International Journal of Plant & Soil Science
3(10): 1266-1289, 2014; Article no. IJPSS.2014.10.007

SCIENCEDOMAIN *international*
www.sciencedomain.org

SCIENCEDOMAIN

The Use of Remote Sensing Data and GIS to Determine and Detect Land Use/Land Cover Change in the Eastern Part of the Tripoli, Libya

Akeel Ellafi[1*] and Julia Meaton[1*]

[1]*Centre for Sustainable and Resilient Communities, The Business School, United Kingdom, University of Huddersfield, United Kingdom.*

Authors' contributions

This work was carried out in collaboration between all authors. Author AE conducted the empirical data collection as the first part of his PhD research under the guidance of author JM. He also wrote the first draft of the literature review. Author JM guided the discussion and worked with author AE to identify the core findings and implications of the research. Author JM edited and framed the paper. Both authors read and approved the final manuscript.

Conference Proceeding Full Paper

Received 13th December 2013
Accepted 21st March 2014
Published 19th July 2014

ABSTRACT

Many areas of the Middle-east and North Africa (MENA) are experiencing land use change. The causes of this vary but include urbanisation, deforestation, and the greater issue of climate change. The implications of such land use change are broad but key problems include desertification and loss of land productivity.

In Libya, there is plenty of anecdotal evidence regarding changes in land use, but very little empirical evidence exists to quantify these changes. This paper is one of the first to quantify land use change in the eastern part of Tripoli. It shows how rapid urbanisation has affected the land use and land cover. Multi-temporal Landsat TM and ETM+ imagery has been used to determine and detect land use/ land cover changes from 1986 to 2009 with the help of land sat images based on remote sensing data. The remote sensing data used the Image Classification method is applied to classify the study area into four categories including urban area, forest land, bare land and irrigated farmland. Between 1986 and 2009, the urban area almost doubled in size from 4,997 ha in 1986 to 9,653ha in 2009 while forest land dropped by 1,793ha during the same period. Bare land,

**Corresponding author: E-mail: akeelallfe@yahoo.co.uk, j.meaton@hud.ac.uk;*
Note: Full paper submitted at the First International Conference on "Food and Agriculture: New Approaches" held in the National Research Centre, Cairo, Egypt from December 2 to 4, 2013.

however, increased in size by 2,353 ha and irrigated farmland had reduced by nearly 65% in size during the study period. The outcomes revealed a significant increase in urban expansion alongside a significant decrease in agricultural land use over the 23 years period. The analysis indicated that this trend has emerged due to a direct exchange of agriculture, forest and bare land, for urban development.
The implications of such massive changes, in a relative short space of time, indicate that there is a significant and growing problem for Libya. If this pattern of land use change is happening throughout Libya the potential impacts on food productivity and water availability could undermine the sustainability of the whole nation. More research needs to be undertaken to find out how communities are affected by these changes and how they are responding to these challenges. This issue needs to be a priority policy area for the new Libyan government.

Keywords: Land use/land cover; remote sensing; urban expansion; Image classification; agricultural land; Libya.

1. INTRODUCTION

The expansion of urban areas is a worldwide phenomenon which has received considerable attention by researchers [1]. While the process of urbanization usually indicates modernization and tends to reflect economic and industrial growth in both the developed and developing countries, there is increasing concern about the impacts of expanding cities, especially on agricultural areas, livelihoods and planning of farmers [2]. The expansion of cities may result in uncontrolled housing development, unplanned use of valuable agricultural lands and natural resources which in turn can give rise to a number of environmental concerns and demands on natural resources, most notably the conversion of agricultural land which can have negative impacts.

Land degradation coupled with desertification, deforestation as well as loss of biodiversity has almost become a global environmental issue [3,4]. Libya is experiencing a swift and significant transition from a rural to urban oriented economy, which has been accompanied by the increasing mobility of production factors such as: capital, labour, technology and information. The urban fringe surrounding Tripoli, in particular, has witnessed significant changes as a result of these pressures.

While pressures on the land intensify and the amount of productive land is reduced, the demand for agricultural products continues to rise, and maintaining the capacity of the land so that it can accommodate the demand is a significant challenge [5].

It should be emphasised that land and culture are two important and complementary segments of any existing culture; their impacts are crucial as they affect the productivity, development, and the state of land use/land cover. However policy needs to be evidence based and very little information about the exact nature and amount of land use change in Libya has been documented. This paper provides some of the first empirical evidence regarding land use change and is the first step in a research project that seeks to explore what is happening and how people are responding to the new pressures.

2. THE STUDY AREA

Libya is sited in the north of Africa, from 20 to 34ºN and 10 to 25ºE. The total area of Libya is 1750000 km^2, [6] of which more than 85% are desert and only 3.6% of the natural land of Libya is cultivated, while the irrigation areas in all Libya were estimated at 400,000 hectares [7]. Most of the agricultural activities are concentrated on narrow strip along the Mediterranean coastline, low mountains and scattered oases in the desert. It is bordered in the east by Egypt and in the west by Tunisia, Algeria and Niger; by Chad and Sudan in the south and by the Mediterranean Sea in the north. It has an important physical asset in its strategic site at the centre of Africa's northern rim. The fertile lands are located in the north of Libya in two main regions: Benghazi and the Jeffara Plain. These areas are economically they are the most important lands in Libya. They are the most cultivated lands which occur in the north. The area under study focused on the eastern part of the Tripoli region. It covers about 24083 ha. The area locates between 13º17' to 13º35' E 32º77' to 32º90' N Libya (Fig. 1).

Fig. 1. Location of the study area in the Libya Sahel

3. DATA SOURCE

Three periods of satellite imageries and diverse ancillary data identifying historical and recent land use/land cover were collected. The satellite images used in this study were one Landsat TM acquired on July 28, 1986, and other two Landsat ETM+acquired on September 29, 2003, and August 26, 2009, respectively. These satellite data were obtained from the Libyan centre for remote sensing data and met the following criteria for its selection: (1) a long time series of images should be available for the study area; (2) the images should be selected in the same season in order to minimise the influence of seasonal variations on the result; (3) all images are required to possess less than 10% of the cloud cover. Against these criteria, Landsat TM Thematic Mapper for both 1986 and 2003 were chosen. The ETM+Enhanced Thematic Mapper plus were selected for 2009.

4. METHODS

4.1. Image Pre-processing

Pre-processing of satellite images prior to image classification and change detection is essential; it is usually comprised of a series of sequential operations including atmospheric correction or normalization, image registration, geometric correction and masking (e.g. for clouds, water, irrelevant features). Therefore accurate geometric rectification is paramount for detecting change, since the potential exists for registration errors to be interpreted as land use change and this may lead to actual change to be overestimated. The satellite images used in the detection of modification along coastlines is processed in a standardized technique to ensure temporal, spatial and spectral compatibility between scenes. Imagery is firstly selected to correlate as thoroughly as probable with season and time-of-year coincident with high biomass and favourable the atmospheric conditions as suitable each area. The details of the satellite imageries data used in the study area are presented in (Table 1). The study area is entirely contained within path 188, row 37, resolution ^{30m} for Landsat TM/ETM+images.

Table 1. Details of satellite imageries data used in study area

No	Satellites	Type of sensor	Date of acquisition	No bands
1	Landsat 5	TM	28/07/1986	7 Bands
2	Landsat 7	ETM+	29/09/2003	8 Bands
3	Landsat 7	ETM+	26/08/2009	8 Bands

İt should be emphasised that the normalization of satellite imagery takes into account the combined, measurable reflectances of the atmosphere, aerosol scattering and absorption, and the earth's surface. It is, however, the volatility of the atmosphere that Could be introducing difference among the reflectance values or the digital numbers (DN's) of satellite images developed at difference times. Even though the influence of the atmosphere upon remotely sensed data is not considered the errors. Since they are portion of signal was received by sensing device, the consideration of this effect is significant. The goal line should be the follows images pre-processing, all images should be appeared as if they were attained from the same sensor.

4.2 Preprocessing Procedure

The procedure before the creation of the minimum images, pre-processing must occur. The pre-processing procedure contains of six stages: (1) collection; (2) downloading; (3) unzipping twice; (4) executing the pre-processing algorithms through the ENVI software; (5) checking the final pre-processed images, and (6) executing the patch procedure, where necessary. The pre-processing procedure is completed, an image containing clouds, surface reflectance and aerosol reflectance is created. However, one time the raw remote sensing digital data have been developed (see Fig. 2), it is processed into usable the information. Analog film photograph is chemically processes in the darkroom whereas digital image is processed within the computer system. The processing digital data includes changing the data to correct to certain type of distortion. Whenever data is changed to correct for one type of alteration, that probability of generating another type of alteration exist. There is changed to remote sensing data include two major operations: the pre-processing and post-processing Similarly, the pre-processing stages of the remotely sensed image generally are performed previously the post-processing enhancement, extraction and analysis of information from the image. Typically, it will be the data provider who will pre-process the image data before delivery of the data to the customer or user. Pre-processing of image data often will include radiometric correction and geometric correction.

In this study, the area was seen to be flat and relatively small. Thus, from 1986 an image that was used for the mapping of the transformation method, georeferenced the Landsat TM5 satellite image. The geometric corection was selected as the most appropriate model due to the fact that a first order polynomial is seen to be sufficient for medium spatial resolution images as far as flat areas are concerned.

From both the image and map, the Ground Control Points were selected in order to be spread over the area within the image. Then the corrected Lansat TM5 1986 image which is considered as the reference image, was used for the application of image to image registration. İn addition, all other images were referenced based on the corrected Landsat TM5 1986 image.

This study has selected twenty-five ground control points (GCP) from the topographic map for the correction of the Landsat TM imagery resampling which produced less than 1.0 pixel of Root Mean Square error (RMS) for each Landsat TM5, TM7 and TM8 images (1986, 2003 and 2009) by incorporating clear image features including the control points such as cross-sections. Thus, in order to reference each image to the original 1986 image, a first order polynomial model was applied. To check the geometric correction of the images, data collected in the field were used through the selection of reference points based on the images that are situated in similar points of the field visit.

The process of geocoding was completed through Geometric Correction Package which includes a regression analysis between two variables, uncorrected image and master data. However, there are two ways to run this regression. First, image with input coordinate which considers input by user and second, image to image where coordinates for each point are mapped to the geocoded image. This study has made use of these two methods.

In the majority of cases, the atmosphere can have negative effects on the pixel values in each image. Thus, the adverse effects must be eliminated before analysing remotely sensed data [8]. Thus, the normalisation of the imagery based on radiometric parameters is important for avoiding these adverse effects.

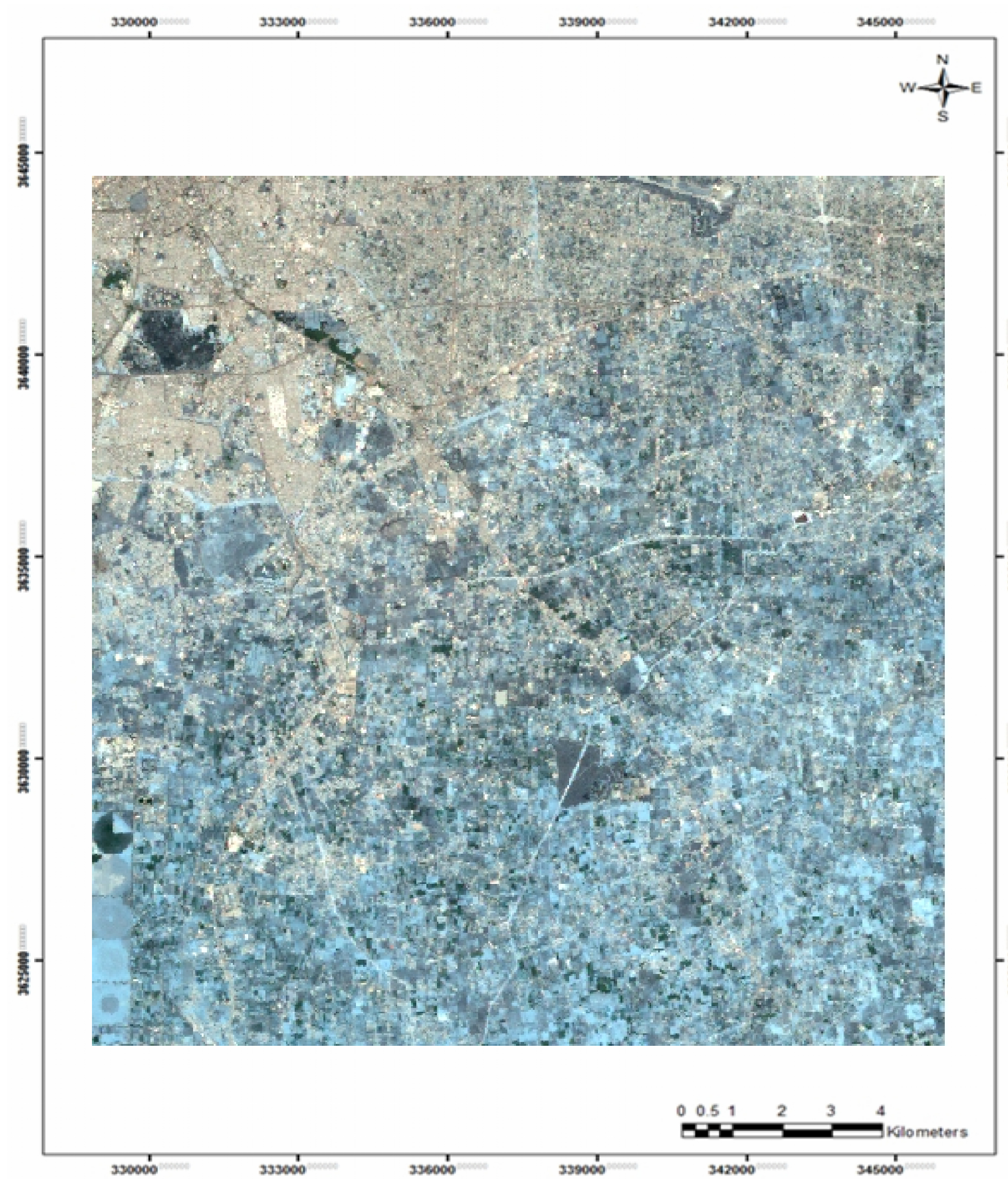


Fig. 2. Raw image of the study area

This study has made use of the correction of the TM dataset using the improvement method of the darkest pixel which is the approach considered to be the simplest one [9,10].

4.3 Image Classification

Image classification is the process of creating a meaningful digital thematic map from an image data set. The classes in the map are derived either from known cover types (wheat, soil) or by algorithms that search the data for similar pixels. Once data values are known for the distinct cover types in the image, a computer algorithm can be used to divide the image into regions that correspond to each cover type or class. The classified image can be converted to a land use map if the use of each area of land is known. The term land use refers to the purpose that people use the land for (e.g. city, national parks or roads), whereas cover type refers to the material that an area is made from (e.g. concrete, soil or vegetation). In other words, the objective of the image classification is to identify and portray, as a unique grey, the features occurring in an image in terms of the object or type of land use/ cover the features actually represent on the ground [11].

Hence, image classification is one of the techniques in the domain of the interpretation of digital images based on the different spectral characteristics of different materials in the earth's surface. In other words, as [12] and [13] pointed out the image classification can also be thought of as the interpretation of remote sensor data at various scales and resolutions which led to many algorithms or producers to be developed for this purpose [12]. Similarly, the classification process intends to categorize all pixels in a digital image into one of several land use and land cover classes. These categorized data were then used to produce thematic maps of the land use/land cover prevailing in the image. Overall, multispectral data are used to perform the classification. Moreover, the spectral data pattern per pixel is used as a numerical basis for subsequent categorization.

Image classification can also be done using a single image data set, multiple images acquired at different times, or even image data with additional information such as elevation measurements or expert knowledge about the area. Pattern matching can also be used to help improve the classification. The discussion here concentrates on the use of a single image dataset to create a classified thematic map where each pixel is classified based on its spectral characteristics. The process that would be used for multiple images is essentially the same with perhaps some extra effort needed to match the images together. If soil type or elevation are used the algorithm would need to take into account the fact that thematic soil classes need to be treated differently than measured radiance data.

It is to be understood that Classification algorithms are grouped into two types of algorithms: supervised and unsupervised classification. With the supervised classification the analyst identifies pixels of known cover types and then a computer algorithm is used to group all the other pixels into one of those groups. With the unsupervised classification a computer algorithm is used to identify unique clusters of points in data space, which are then interpreted by the analyst as different cover types. The resulting thematic image shows the area covered by each group or class of pixels. This image is usually called a thematic image, or classified image.

In this study, Landsat data of three dates were independently classified using the supervised classification method of maximum likelihood algorithm and requires the user to identify the cover types of interest. The supervised classification relies on the analyst who provides the 'training' for computers to recognise different cover types. Usually there are three basic steps involved in a typical supervised classification procedure. First the selection of training regions through defining training regions in image which is considered to be areas of known feature types or cover classes. The second procedure involves calculating region statistics. This is achieved by the calculation of statistics for pixels in each training region. Furthermore, the evaluation of class signatures falls under the third process. This is about viewing and evaluating statistics using tables and graphs. The fourth step requires classifying the Image by selecting a classification type or decision rule which assigns each pixel to one of the feature classes. Finally, the display and the evaluation of classification are needed. This is achieved by displaying the output classification image, assigning colours to classes and overlaying classes or using statistical means to assess accuracy. Samples of pixels are then selected based on available ground truth information to represent each cover type. Hence, the study area was classified into four categories: urban area, forest land, bare land, irrigation farm. Explanation of these land use classes are presented in (Table 2).

Table 2. Definitions of the different land-use/land-cover classes in study area

No	land use/land cover classes	Explanation
1	Bare land	characterized by sandy soil and dominated by non-natural vegetation
2	Irrigated land	tree crop areas such as, almond, olive, citrus and fig, also vegetables areas and all these are cultivated by irrigation
3	Urban land	residential sites characterized by intensity residential
4	Forest land	forest vegetation type including evergreen, deciduous, and wetland forest vegetation type

4.4 SAVI (Soil Adjusted Vegetation Index)

To minimize the soil “noise” [14] developed the Soil Adjusted Vegetation Index (SAVI) to account for these soil effects in areas of low vegetation cover. However, SAVI as well as other vegetation indices are simply a measure of the relative abundance of vegetation and gives no indication of the species composition of the vegetation cover Some of the specific problems involved with remote sensing of arid vegetation include multiple scattering of light (nonlinear mixing) between vegetation and soil [14,15]. This paper puts much focus on vegetation cover changes in the years 1986, 2003 and 2009 using digital satellite such as Landsat images TM ETM+ as the source of data to generate the Soil Adjusted Vegetation (SAVI) which is considered to be a modified version of the NDVI that Huete suggested in 1988 and it is primarily related to vegetation biophysical parameters. However, with this type of indices there are problems because of external factor effects, such as soil background variations [16]. To reduce the soil background effects, [14] proposed using a soil-adjustment factor L to account for first-order soil background variations and obtained a Soil-adjusted vegetation index (SAVI). In other words, [14] successfully normalised differences in soil substrate, consequently allowing a more accurate estimate of vegetation cover. The SAVI was calculated using the near-infrared band and red-reflectance band according to [14] where L is a constant soil adjustment factor. It is calculated by the following equation.

$$SAVI = \frac{(1+L)(\rho nir - \rho red)}{\rho nir + \rho red + L}$$

Where ρ_{nir} is the near-infrared-reflected radiant flux, ρ_{red} is the red-reflected radiant flux, and L is the optimal adjustment factor to vary with vegetation density and it accounts for differential red and near-infrared extinction thorough the canopy [14]. L is a correction factor and its value varies between 0 and 1 and its value is dependent on vegetation cover or soil moisture conditions [14] and [17]. However, an L value of 0.5 had been proved to minimize soil brightness variations.

The reflectances between red and near infrared fluctuate proportionally, when the moisture content changes, those two values are said to be correlated and have a linear relationship. This means that whenever one changes, the other changes according to the relationship that binds the two. The line that describes that relationship is known as the soil line, which is unique for each soil.

In order to map vegetation of various densities, three digital satellite images (Landsat TM and ETM+) were used to generate the soil-adjusted vegetation index (SAVI) images in the study area: TM 1986, ETM+ 2003 and ETM+ 2009. The first step in this method made use of the algorithm classification technique to map vegetation of various densities. In the second step, however, the Landsat TM & ETM+ images were classified to give the actual vegetation over the entire study area using SAVI. The third step, by contrast, used the image difference technique to calculate the changes and the trend of the changes between 1986, 2003 and 2009. In this way, the ability to map sparse vegetation in the study has been enhanced by the use of the SAVI index.

4.4 Accuracy Assessment

Classification accuracy analysis is one of the most active research fields in remote sensing. Meaningless and inconclusive assessment on the image classification results sometimes precludes the application of automated land cover classification techniques even when their cost is more favourable with more traditional means of data collection. It is always claimed in the remote sensing community that “a classification is not complete until its accuracy is assessed” [18]. While the Accuracy assessment is a general term for comparing the classification to geographical data that is assumed to be true, it also helps to determine the quality of the information which are derived from remotely sensed data and the accompanying land resource statistics. It is most reliable when using reference data collected in the field or from aerial photographs at or near the time of satellite overpasses [19].

One of the most common methods of expressing classification accuracy is the preparation of a classification error matrix or sometimes referred to as confusion matrix; it compares the relationship between known reference data and the corresponding results of the classification. In other words, the most common and typical method used by researchers to assess classification accuracy is the use of a confusion matrix calculating in ERDAS IMAGIN 9.2 software. The confusion matrix is square assortment of numbers defined in rows and columns that represent the number of sample units (i.e., pixels, clusters of pixels, or polygons) also a simplest descriptive statistic used to compare a classification result with ground truth information using global positioning system (GPS) points obtained during fieldwork study [20]. In addition, the Arc view GIS version 10.1 was also used to complement the display and processing of the data while Microsoft Excel was used in producing the bar graphs and statistical analyses.

The overall accuracy of the classification map is determined by dividing the total number of correct pixels (sum of the major diagonal) by the number of pixels in the confusion matrix. Overall accuracy is the proportion of all reference pixels, which are classified correctly (in the sense that the class assignment of the classification and of the reference classification agree). For the global assessment of classification accuracy, a measurement called Cohen’s kappa coefficient ($\kappa_{\eta\alpha\tau}$) is often employed. The kappa coefficient is a measure that considers significantly unequal sample sizes and likely probabilities of expected values for each class. It is computed by dividing the total number of correctly classified pixels (the sum of the elements along the main diagonal) by the total number of reference pixels [20].

The Kappa analysis is a discrete multivariate technique used in accuracy assessment for statistically determining if one confusion matrix is significantly different to another [21]. The result of performing a Kappa analysis are K_{HAT} statistics (actually K, an estimate of Kappa), which are another measure of agreement or accuracy. This measure of agreement is based on the difference between the actual agreements in the confusion matrix [22].

4.5 Change Detection

Change detection is a technique that can be defined as a process by which one can identify whether there exist differences in the state of an object by observing it at different times [23]. There is another definition provided by [24] is that "change detection is a technique used to determine the change between two or more time periods of a particular area" [23].

That hanged the detection aim is to realize temporal difference of the similar objects at altered time. In this method, that the initially should extract objects features before change detection and describe them. When data is remote sensing images, the feature of detected object can be the image gray and can also be the extracted features by classification or other pattern appreciation methods. And these extracted features should replicate the temporal change of ground object.

There are several methods for the determination of change, but basically, there are two main approaches, comparative analysis of independently produced classifications and simultaneous analysis of multi-temporal data [23]. The post classification comparison method for change detection is one of the common methods least affected by differences in image characteristics used in the change detection. It is also rather straightforward for implementation producing relatively acceptable results [25].

It is to be acknowledged that changed detection is a complex processes, due to related several process stages. The several factors have effect on accuracy of the detection results, such as the precision of geometric co-registration. The accuracy of radiometric co-registration or regularized precision. The insertion of temporal features for the detected objects. The knowledge of the operative, the analysis ability and experience, the change detection methods and etc. In these factors, the precision of radiometric co-registration, the accuracy of geometric co-registration, the extraction of temporal features for detected objects and the change detection method is more important. When the detection method created on post classifications are accepted. The detection precision is the product of each classification result accuracy of different temporal remote sensing images [26].

However, in this study the post classification method was used because it is considered as the most accurate process. It involves stacking of at least two classified images. The study made use of three images from different periods namely 1986, 2003 and 2009 in order to classify and label them, and this has allowed knowing the nature of changes that had happened. Furthermore, the extraction of the area of change is achieved through direct comparison of the classification result.

5. RESULTS AND DISCUSSION

5.1 Classification Accuracy

With the advent of more advanced digital satellite remote sensing techniques, the necessity of performing an accuracy assessment has received considerable interest. This is not to say that accuracy assessment is unimportant for the more traditional remote sensing techniques. However, given the complexity of digital classification, there is more of a need to assess the reliability of the results. Hence, the accuracy assessment is principally based on the reference field data which were not in use during the classification stage.

The results of the accuracy assessment of the classification which was obtained firstly for land use/land cover map of the study area are shown in (Table 3).

Table 3. Results of accuracy assessment of the land use map produced from landsat data

Land use/land cover classes	Over all accuracy	Kappa coefficient
1986	75.62 %	0.70
2003	83.57 %	0.76
2009	90.81 %	0.86

This accuracy measure indicates the probability of a reference pixel being correctly classified and is really a measure of omission error. This is often referred to as producer's accuracy because the producer of the classification is interested in how well a certain area can be classified. It should be known that the accuracy of the classification is likely to be affected by many factors including data availability and quality, data validity used as a reference, the difference in time between the validation date and classified images, and some land use/ land cover classes being similar and sometimes difficult to separate; all these factors can have an influential effect and produce different results despite similarity in data and procedure being used. In addition, mixed pixel and atmospheric effects can also act to reduce the accuracy of the results. For example, in the 1986 land use map, the table shows that there has been an overall accuracy of 75.62% with a kappa coefficient of about 0.70. Based on these results of 1986, all the land-use/land-cover classes were classified with accuracy as they were all above 70%. For the 2003 land-use/land-cover map, the (Table 3) shows that an overall accuracy assessment of 83.57% have been recorded and an agreed kappa coefficient of 0.76, which clearly demonstrates that the land use classes have been accurately classified. With respect to producer's and user's accuracy, all classes were above 80%. However, for all land-use/land-cover classes, the agreed kappa coefficients were above 70%. However, for the 2009 land-use/land-cover map, accuracy assessment result depicted in (Table 3) clearly shows that there has been an overall accuracy assessment of 90.81% with a kappa coefficient of 0.86. This is a clear indication that the accuracy assessment result is accurate and acceptable.

5.2 Land-use/Land-cover Change

The areas that changed of the four land use classes (urban, bare land, Forest land and Irrigation land) for 1986, 2003 and 2009 are presented in (Table 4). Thus, Land-use change in any area involves a shift to a different use whereas land-cover changes fall into two categories namely conversion and modification. The results show that there have been a lot of changes of the urban land area in the eastern part of Tripoli which has undergone a rapid urban growth during the periods of 1986, 2003 and 2009 which is consistent with the increasing trend of population of the region (Fig. 3). As it can be seen throughout this study, the growth in urban land has resulted in a big drop in the vegetated and barren land use.

To demonstrate the degree to which the losses and gains have occurred between the four land-use/land-cover classes, all changes are presented in (Table 5c, but 5a and 5b) are included to illustrate how these changes occurred between 1986 and 2003 and 2003 and 2009, respectively.

Table 4. Results of land use/land cover distribution (1986-2009) showing area changed (ha) of each class

Land use/ land cover classes	1986		2003		2009	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Urban area	4996.8	20.7	6383.3	26.5	9652.5	40.2
Bare land	1602	6.6	4238.1	17.5	2775.2	11.5
Forest land	11183.3	46	10077.8	41.8	9390.7	39
Irrigation land/farms	6240.7	26	3323.5	13.7	2204.3	19.2

5.2.1 Urban area

The (Table 4) shows that urban areas have risen from 4996.8ha in 1986 to 9652.5ha in 2009 during the study period. This represents a positive change of around 1386.5ha (40.2%) in land area. It can clearly be seen that the urban area has been expanding at an increasing rate (Figs. 4). In 1986, for example, urban area was small and mainly located in the Tripoli and eastern part. By 2003, it has expanded taking almost the whole east start capturing the north-east. In other words some new highly concentrated areas have emerged. From 2003 to 2009, further expansion had been seen. Urban expansion is also noticed in rural villages surrounding Tripoli. Population in Tripoli and areas around it (Fig. 3) increased from 797000 in 1980 to 2.300 million in 2010 [27]. The urban population of Tripoli has increased largely because there of rapid economic development since 1960 when Libya discovered and started exploiting the oil reserves. This has resulted in urban transformation, which is centred around the major cities and has encouraged rural-urban migration. It explains the observed expansion of the urban area (Table 5c), it can be clearly seen that the urban area has gained in total 5,470.7ha from 1986 to 2009. Most of its gain came from forest (2799ha), followed by irrigation farm (2381.4ha) and from bare land, 290.3ha from.

(Table 5c) indicate that the increase in urban area was largely at the expense of forest land and irrigated farmland. Of the 4655.8ha of the total growth in urban land-use/land-cover, 60% was the result of the conversion from forest land, 51% from irrigation farm and 9% from bare land. From 1986 to 2009, 2799ha of forest land was transformed into urban area. However at the same time the results suggest that 647.5ha of urban land were converted into forest land. This may be due to errors from classification; however it is known that forested areas are among the areas many people seek especially when it comes to developing new housing.

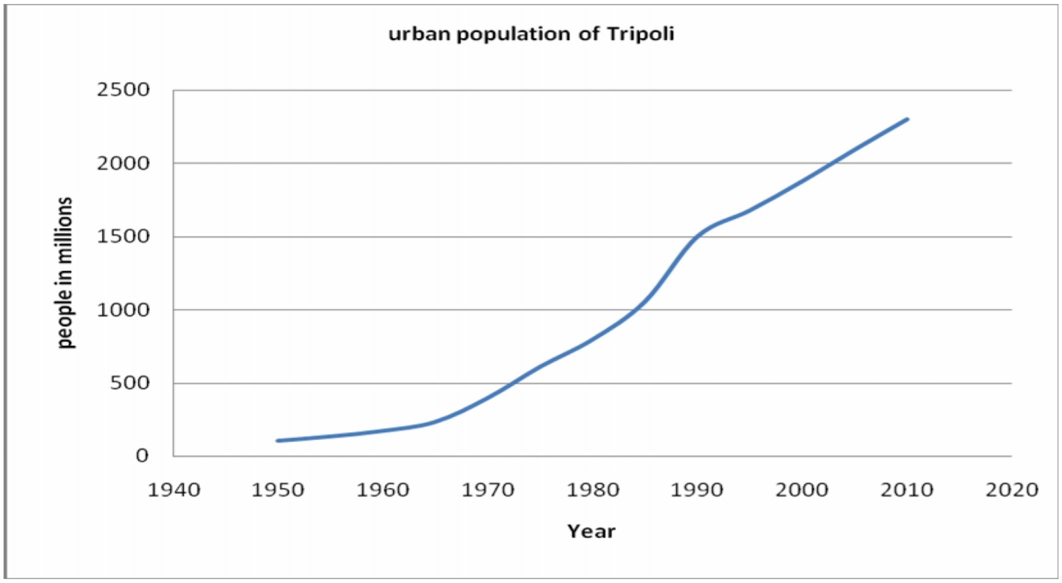


Fig. 3. Urban Population growth of Tripoli

5.2.2 Forest land

The quantitative statistics from (Table 4) show that forest land areas reduced continuously from 1986 to 2009. The (Table 4) indicates that forest land had an area of 11,183.3ha in 1986, 10,077.8ha in 2003, and 9,390.7ha in 2009 which represented a net decrease of 16% (-1792.6ha) from 1986 to 2009. Only about 5,227ha of forest land in 1986 were not changed in 2009 (around 47%) (Table 5c).The decrease in forest land was mainly due to deforestation for urban use. According to (Table 5c), about 2799ha, 1953ha and 1204.3ha was lost to urban area, bare land and irrigation farm respectively while it only gained 2866 ha and 647.5ha from irrigation farm and urban areas respectively, at the same time. The net loss was about 5956.3ha, which is nearly 53.2% of net decrease of forest land during 1986 to 2009. This loss of forested land is associated with a rural exodus; people leaving rural areas to settle in urban areas as well as on bare land. The loss to bare land may be as a result of the abandonment of some forest plots. It is also evident that some forest plots may not have been detected by the satellite at the time of the observation. As a result these lands might have been considered as bare land. (Figs. 4) clearly show that the most remarkable deforestation happened in the southeast.

5.2.3 Bare land

Bare land increased 2353ha (147%) of its 1986 area from other classes and decreased 1180.3ha (73.7%) to other classes leading to a net increase of 1172.7ha (5% of the total study area) in bare land area during the study period (Table 5c). Of the 2353 ha increase in bare land from 1986 to 2009, 1953ha (70.4%) was at the expense of forest lands, 323.4ha (11.7%) from irrigation farm and only 77ha (2%) from urban areas (Table 5c). Of the 1180.3 ha decrease in bare land during the same period, 650.6ha (40%) appears to have become forest land, 290.3ha (18%) converted to urban areas and 239.4ha (15%) became irrigation farm. In brief, bare land gained more from forest than forest did.

Table 5a. Change matrix of land use/land cover from 1986 to 2003

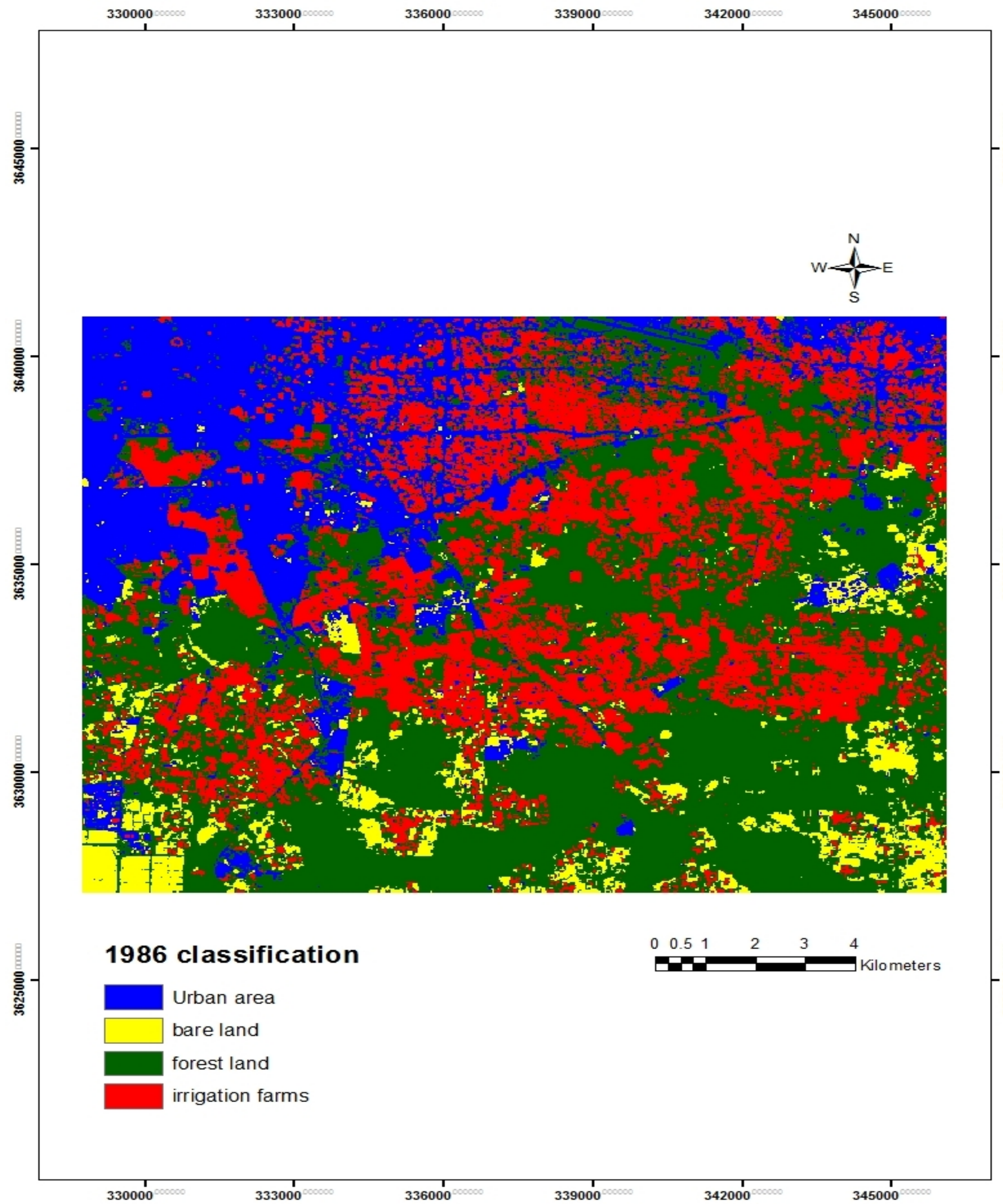
		2003				Total 1986
	LU/LC classes	**Urban area**	**Bare land**	**Forest land**	**Irrigation farm**	**Hectare**
1986	Urban area	4299.66(ha)	86.76(ha)	582.93(ha)	27.45(ha)	4996.8(ha)
	Bare land	66.51(ha)	696.87(ha)	650.7(ha)	187.83(ha)	1601.91(ha)
	Forest land	957.33(ha)	3060.18(ha)	5667.57(ha)	1498.23(ha)	11183.31(ha)
	Irrigation farm	1059.84(ha)	394.29(ha)	3176.55(ha)	1610(ha)	6240.68(ha)
Total 2003		6383.34(ha)	4238.1(ha)	10077.75(ha)	3323.51(ha)	24022.7(ha)

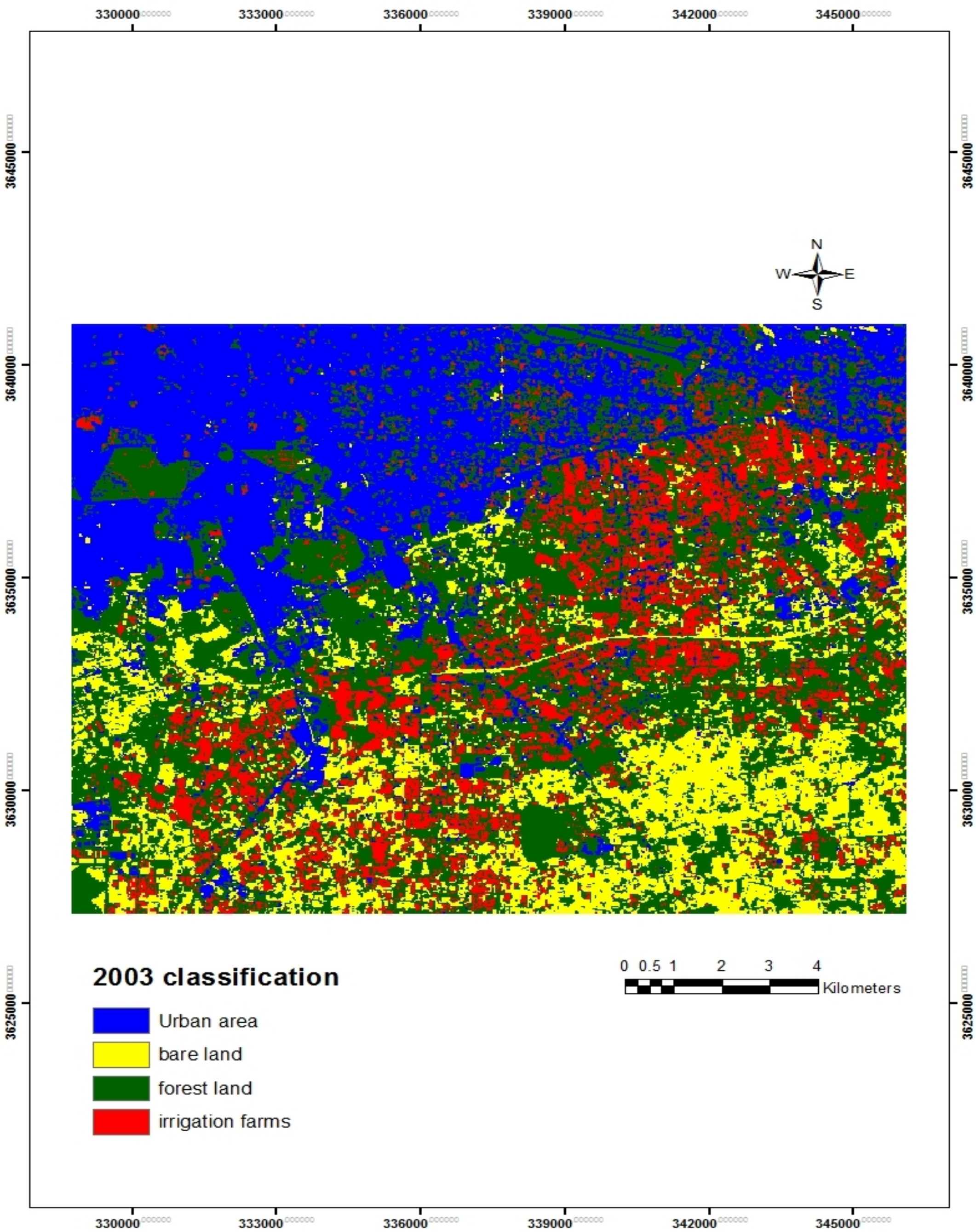
Table 5b. Change matrix of 2003 and 2009

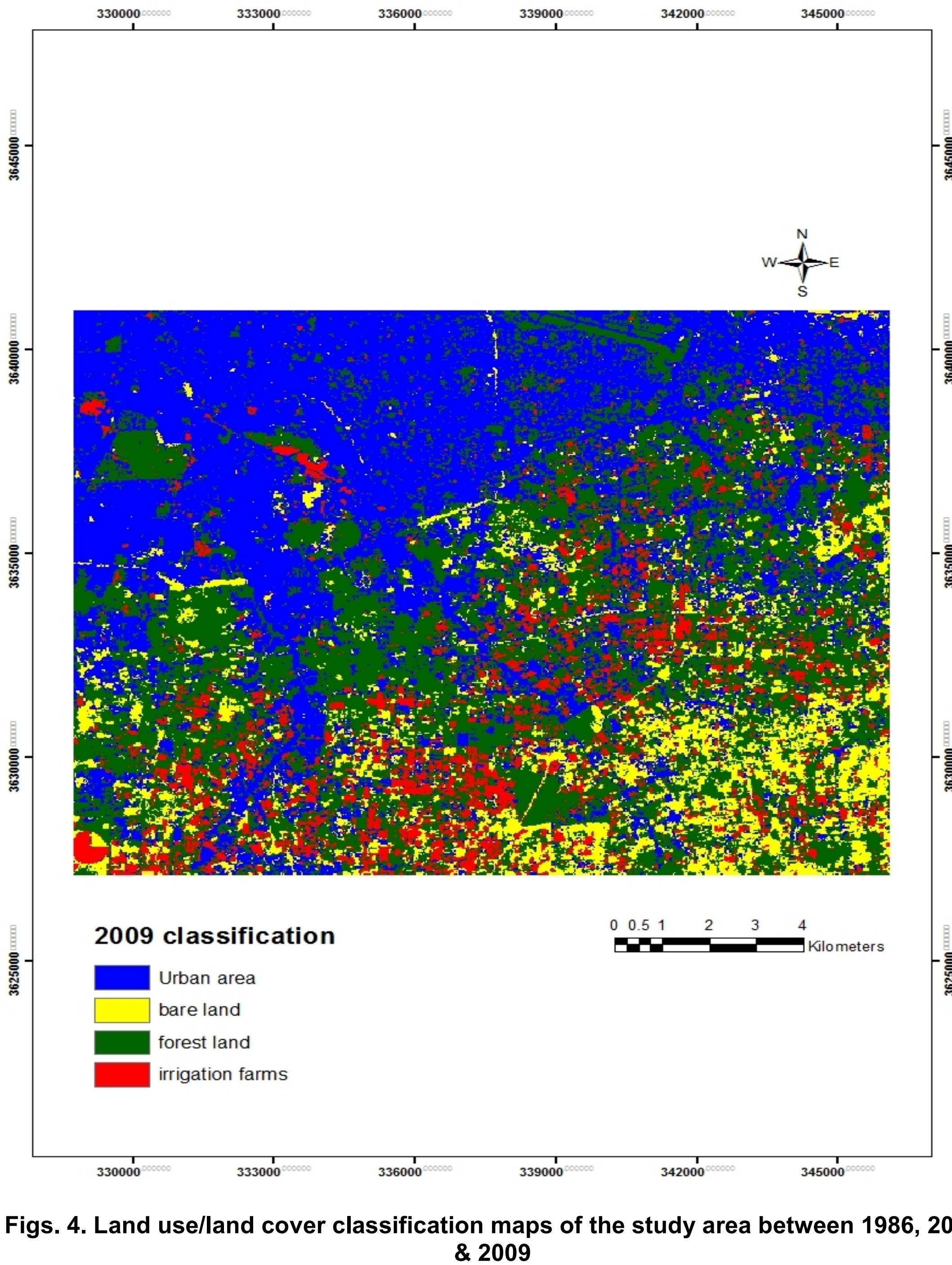
		2009				Total 2003
	LU/LC classes	**Urban area**	**Bare land**	**Forest land**	**Irrigation farm**	**hectare**
2003	Urban area	5402.4	78.2	783.3	119.4	6383.3
	Bare land	852.2	1303.1	1673.5	409.2	4237.8
	Forest land	2782	11	5271.6	913.4	8978
	Irrigation farm	616	283	1662.3	762.2	3323.5
Total 2009		9652.6	1675.3	9390.7	2204.2	22922.6

Table 5c. Change matrix of 1986 and 2009

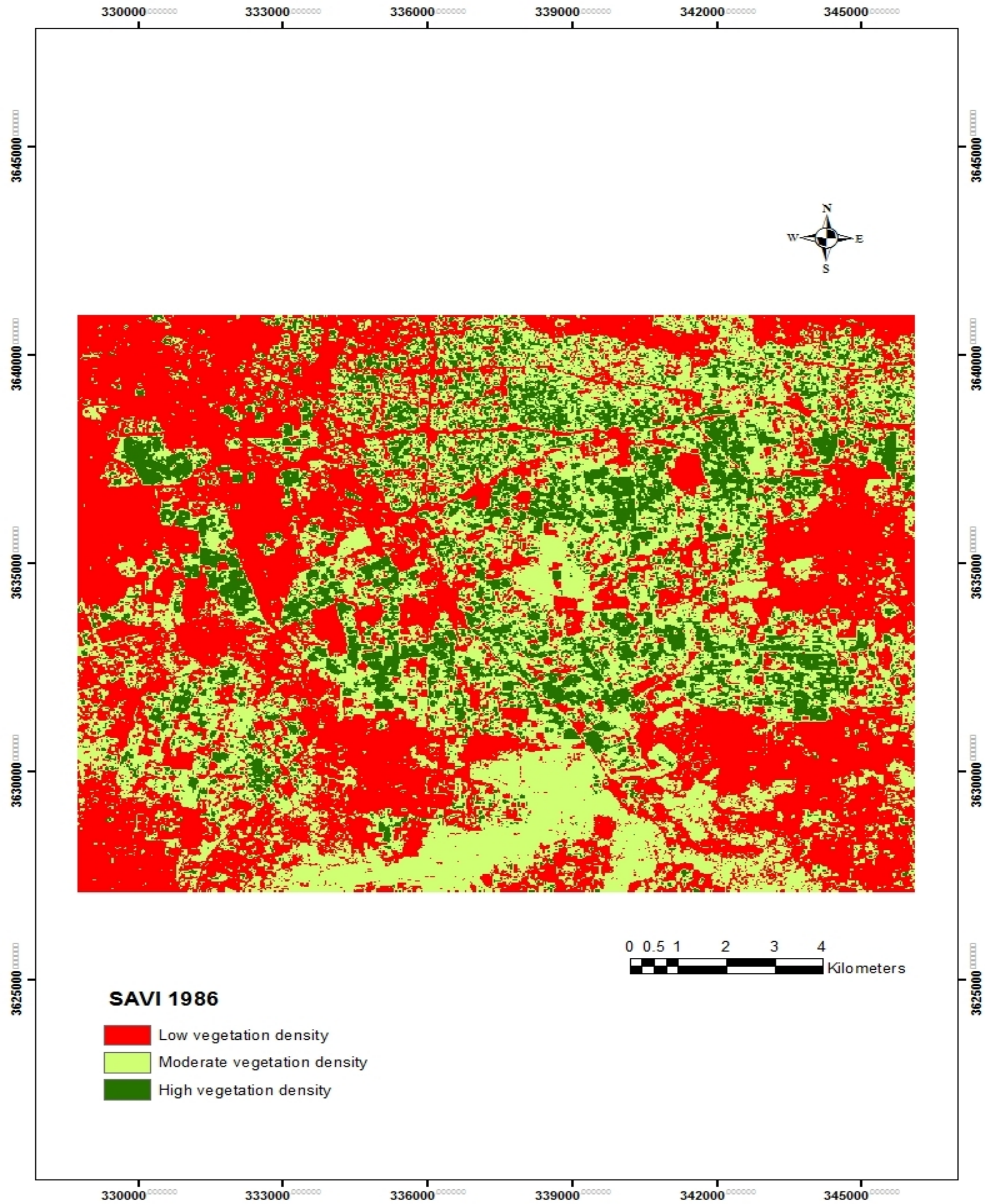
		2009				Total 1986
	LU/LC classes	**Urban area**	**Bare land**	**Forest land**	**Irrigation farm**	**Hectare**
1986	Urban area	4182	77	647.5	90.4	4996.9
	Bare land	290.3	421.6	650.6	239.4	1601.9
	Forest land	2799	1953	5227	1204.3	11183.3
	Irrigation farm	2381.4	323.4	2866	670.2	6241
Total 2009		9652.7	2774.6	9391.1	2204.3	24022.7

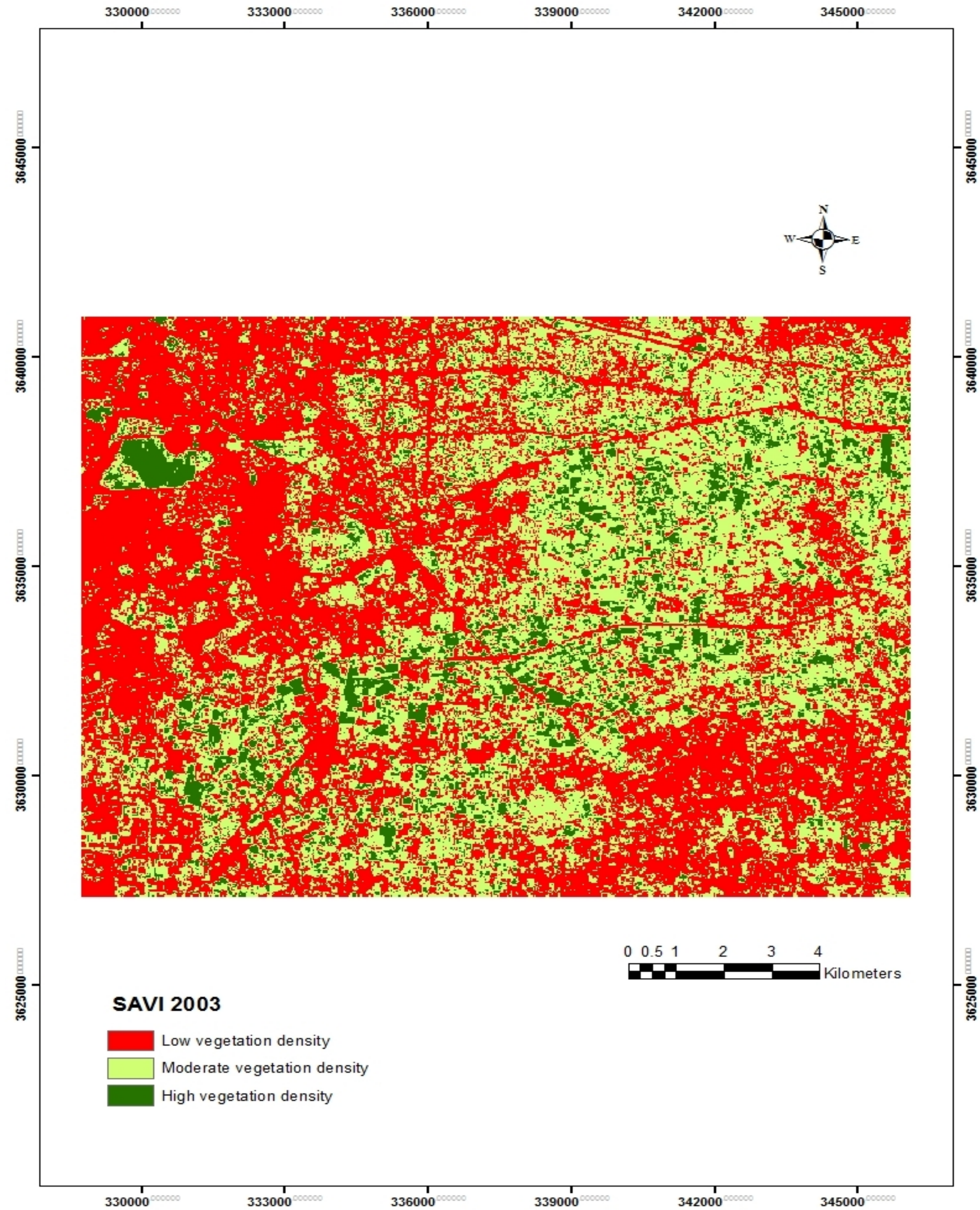

330000
333000
336000
339000
342000
345000
3645000
3640000
3635000
3630000
3625000
N
W
E
S
1986 classification
Urban area
bare land
forest land
irrigation farms
0 0.5 1 2 3 4
Kilometers

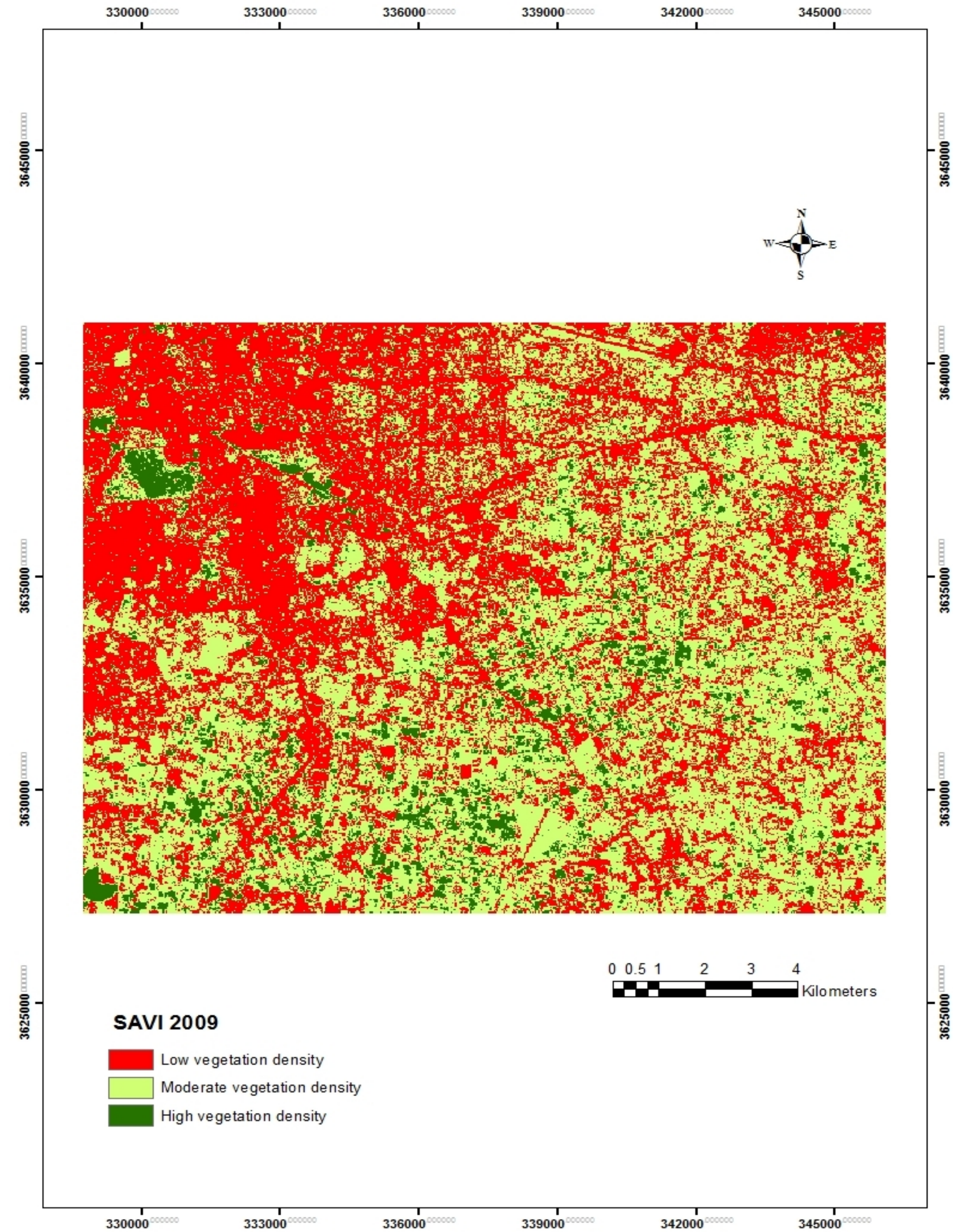

330000
333000
336000
339000
342000
345000
3645000
3640000
3635000
3630000
3625000
N
W
E
S
2003 classification
Urban area
bare land
forest land
irrigation farms
0 0.5 1 2 3 4
Kilometers



Figs. 4. Land use/land cover classification maps of the study area between 1986, 2003 & 2009


330000
333000
336000
339000
342000
345000
3645000
3640000
3635000
3630000
3625000
N
W
E
S
0 0.5 1 2 3 4
Kilometers
SAVI 1986
Low vegetation density
Moderate vegetation density
High vegetation density


330000
333000
336000
339000
342000
345000
3645000
3640000
3635000
3630000
3625000
N
W
E
S
0 0.5 1 2 3 4
Kilometers
SAVI 2003
Low vegetation density
Moderate vegetation density
High vegetation density



Figs. 5. Vegetation various density maps using SAVI in study area between 1986, 2003 and 2009

5.2.4 Irrigation farm

A total of 4036.3ha of irrigation farm use was lost between 1986 to 2009, 64.7% of its 1986 area by 2009 (Table 4). (Table 5c), shows that only 670.2ha (10.7%) irrigation farm remained unchanged from 1986 to 2009. 2381.4ha had changed to become classified as (38%) to urban area and 2866 ha (45.9%) became forest land. However, irrigation farmland also appeared to increase in some areas gaining 239.4ha from bare land and 1204.3ha from forest land, respectively. Despite these small positive shifts the overall loss of irrigated farm land is significant.

5.3 Identifying Vulnerability Land Using SAVI Model

The purpose of using (SAVI) model is about mapping the areas of vulnerability land to land degradation and desertification. This has led to the definition of degrees of vulnerability for each type of land degradation such as vegetation degradation. Using satellite digital multispectral data, a simple model has been developed that allows an image to be generated which emphasizes areas with low vegetation density and high reflectance soils.

In order to assess the degree of vulnerability, the Soil Adjusted Vegetation Index (SAVI) was implemented to the 1986, 2003, and 2009 satellite images. The visual differences of the land use/land cover were clearly depicted and are shown in (Figs. 5 above) Looking at the picture, there was an overall decrease in SAVI vegetation reflectance values in the whole study area. Vegetation cover indicates serious vegetation degradation over time. The mean SAVI values obtained for July 28, 1986, September 29, 2003 and August 26, 2009, was 0.6, 0.3, and 0.1 respectively. Therefore, SAVI values were more variable. The first results clearly indicate that there is a proportion distribution of vegetation cover areas using SAVI created images during the period in the study area; hence, the most important factor indicating degradation of vegetation cover is the decline of land productivity.

On the whole, SAVI vegetation values decreased from 0.6 in 1986 to 0.1 in 2009 of the study area. The areas are classified into three classes which have been calculated from the Landsat TM and ETM+. They are as follows:

- Low vegetation density less than 0.2 (red colour) represents the distribution of vegetation cover (considered to be highly affected by degradation)
- Moderate vegetation density between 0.2 and 0.4 (slight green colour) represents the distribution of vegetation cover (considered to be moderately affected by degradation).
- High vegetation density greater than 0.4 (dark Green colour) represents the distribution of vegetation cover (considered not to be affected by degradation).

6. CONCLUSION

This paper presented the significance of using remotely sensed data as a means for the mapping and the detection of changes of land use/land cover in the eastern part of Tripoli-Libya. Remotely sensed data helps the analysis of data from a large study area. The results demonstrate clearly the significance of the use of multi-temporal Landsat data which offers an accurate and economical way of mapping and conducting analysis on the changes in land-use/ land-cover during the study period 1986-2009. The study has identified several patterns and trends of the changes in land-use/land-cover in the eastern part of Tripoli. These key findings are summarised below:

1. Urban area has gone up by 109% from 1986 (4996.8ha) to 2009 (9652.5ha), mainly caused by the conversion of Forest land, Irrigation farm and Bare land.
2. Forest land has reduced by 16% (-1792.6ha) from 1986 to 2009. This decrease is mainly caused by the conversion of Forest land to urban area and bare land.
3. Bare land gained 2353ha (147%) of its 1986 area from other classes and lost 1180.3 ha (73.7%) to other classes leading to a net increase of 1172.7ha (5% of the total study area) in bare land area during the study period.
4. The amount of land classified as irrigation farmland reduced by 64.7% between 1986 and 2009.

It is clear that urban expansion is happening at the expense of all the other land classifications. In short, the results have shown that there is a significant increase in urban expansion leading to a significant drop in agricultural land use during the study period (1986-2009). As can be seen from the analysis, the trend has emerged because of the direct exchange of forest, agriculture and bare land. It is thought that the main explanation for the rapid increase in urban area is population growth, migration from rural areas to the city of Tripoli and more general economic development. These assumptions will be explored in the second stage of this research when field visits will explore conditions on the ground using a range of qualitative and quantitative methods. The combined findings will provide policy makers with scientific evidence of land use change and will identify the problems and/or opportunities for Libya that have emerged as a result of these changes. At this point, however it can be concluded that significant change is happening and it appears to be having a direct impact of the amount of productive land under cultivation. Policy makers have to start considering methods of mitigating some of the more worrying problems that might emerge as a result, namely national food and water security.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. UN-Habitat. The challenge of slums. Global report on human settlements. Earthscan, London; 2003.
2. Rahman A, Agarwal S. Environmental impact assessment of urban expansion using remote sensing and GIS techniques, in Starrett SK, et al. (eds) Proceedings of the 3rd International Conference on Environmental Science and Technology. American Sciences Press, Houston (USA). 2007;2:349-363.
3. Luc Gnacadja. The global environment facility. Investing in land stewardship. GEF'S efforts to combat land degradation and desertification globally; 2009.
4. Lunetta RS, Ediriwickrema J, Johnson DM, Lyon JG, McKerrow A. Impacts of vegetation dynamics on the identification of land-cover change in a biologically complex community in North Carolina, USA. Remote Sens Environ. 2002;82:258–270.
5. Turner MG, Naiman RJ, Bisson PA. Approaches to management at the watershed scale. In: Kohm KA, Franklin JF (eds) Creating a forestry for the 21st century: The science of ecosystem management. Island Press, Washington, DC. 1997;239–253.

6. Libyan Planning Council. Report about agricultural policies. Tripoli, Libya; 2005.
7. Mahmoud R, Mansur S, Al-Gomati A. Land degradation and desertification in Libya, Land Degradation and Desertification Research Unit. Libyan Center for Remote Sensing and Space Science, Tripoli, Libya; 2000.
8. Schott JR. Remote sensing: The image chain approach. Oxford University Press, New York; 1997.
9. Chavez PSJ. An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data. Remote Sensing of Environment, 1988;24:459-479.
10. Chavez PSJ. Radiometric calibration of Landsat Thematic Mapper multispectral images. Photogrammetric Engineering and Remote Sensing. 1989;55:1285-1294.
11. Lillesand TM, Kiefer RW. Remote sensing and image interpretation, New York etc. 1994;724.
12. Anderson R, Hardy EE, Roach JT, Witmer RE. A land use and land cover classification system for use with remote sensor data. USGS Professional Paper 964, Sioux Falls, SD, USA; 1976.
13. Jensen JR, Cowen DC. Remote sensing of urban/suburban infrastructure and socio-economic attributes. Photogr Eng Remote Sens. 1999;65:611–622.
14. Huete AR. A soil adjusted vegetation index (SAVI). Remote Sensing of Environment. 1988;25:295-309.
15. Murray BC, Ray TW. Nonlinear spectral mixing in desert vegetation. Remote Sensing of Environment. 1996;55:59-64.
16. Huete A, Liu HQ. An error and sensitivity analysis of the atmospheric and soil-correcting variants of the NDVI for the MODIS-EOS. IEEE Trans Geosci Remote Sens. 1994;32:897–905.
17. Jensen JR. Introductory digital image processing. A remote Sensing Perspective (Third Edition). Prentice Hall Inc. New Jersey. 2005;526.
18. Lillisand TR, Keifer W. Remote Sensing and Interpretation. 5th edition, UG/ USGS Information service, the Lehigh Press; 2004.
19. Congalton RG, Green K. Assessing the accuracy of remotely sensed data, Principles and Practices. 2nd edition. CRC Press, Taylor & Francis Group, Boca Raton London New York; 2009.
20. Congalton R. A review of assessing the accuracy of classification of remotely sensed data. Remote sensing of Environment. 1991;37:35-46.
21. Cohen I. A coefficient of agreement of nominal scales. Educational and Psychological Measurement. 1960;20(1):37-46.
22. Congalton RG, Green K. Assessing the accuracy of remotely sensed data: principles and practices. Lewis Publishers, Boca Raton; 1999.
23. Singh A. Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing. 1989;10(6):989-1003.
24. Macleod, Russell G. Congalton. A quantitative comparisons of change-detection algorithms for monitoring eelgrass from remotely sensed data; 1998.
25. Foody G. Status of land cover classification accuracy assessment. Remote sensing of environment. 2002;80:185-201.

26. Steve NG, Nicholas CC, Michael AW, Sarah EG. Multi temporal remote sensing of landscape dynamics and pattern change: Describing natural and anthropogenic trends. Department of Forest Resource Management, SAGE Publications, Toronto; 2008.
27. National Information Authority of Libya. 2010. General census of population in Libya, Available: http://www.nidaly.org/index.htm 02.03.2010.

Peer-review history:
The peer review history for this paper can be accessed here:
http://www.sciencedomain.org/review-history.php?iid=600&id=24&aid=5373