Land Cover Change Detection in South Tripoli City, Libya

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Abstract

There has been rapid change in the land use and land-cover types in Tripoli, Libya in the past decade. The major change is the conversion of agriculture and woodlands into urban area

Timely determination of change in features at Earth's surface is very important for understanding the relationship between human and natural phenomena in order to encourage better decision making. Detecting regions of change in multi temporal images of the same scene taken at different times is of widespread interest due to a large number of applications in various fields.

Remote sensing data are major sources of information widely used for change detection.

This research is concerned with land cover / land use change in the south Tripoli city, Libya between 1989 and 2015. This study focuses on observed changes in six classes: urban areas, woodland, irrigated area un irrigated , grazing land and bare areas. This study used Boolean classification by applying supervised classification for three Landsat images .

The result shows that, there is a rapid change in land cover and land use due to increase in population, and human activity, this need more urban, more food, the area of urban class are increases from 988.996 hectors in1989 to 4972 hectors in 2015, the people started cut the forest, build new houses and industrial building over the agriculture area without an organize or plane and the area started a complex to study, and the area of woody land decreases from 7310,169 hectors in 1989 to 6321.96 in 2015 , that is why we need to calculate the change detection and give alert to the decision maker to avoid this problem.

Keywords : Remote sensing Change detection, Boolean, supervised classification, urban area, woody land.

1-Introduction

Land cover is the physical material at the surface of the earth; it includes trees, grass, woodland, water, and bare areas. Land cover classes are usually defined by their biophysical properties, such as bio-geographic location and landscape context (Comber, et al. 2005). Land resources are gradually becoming scarce as the increase in population places pressure on these natural resources. Changes in land use and land cover have been recognized as a consequence of human activity which may lead to global change and endanger ecosystem performance and biological diversity. Cihlar (2000) stated that in order to understand the relationship between land use and land cover changes and the global earth system, information is required on what changes happen, when and where they happen, the rates of change and the driving forces. Human activities and population growth are the main driving forces for change that have led to a widespread transition from natural to developed land, which today represents about 3 per cent of earth's land area (Imhoff et al., 2004). As human populations continue to grow, urban areas are expected to increase (Jeffrey et al., 2008). Depending on economics, social preference, and land use policy, urbanization causes significant losses of former agricultural and natural lands that used to maintain social systems and cultural diversity along with natural systems and biodiversity (Alberti, 2008).The rapid increases in population, urbanization and demand for food are considered to be among the most important factors responsible for land cover and land use change in developing countries, mainly in areas where agricultural production is limited by water scarcity, urbanization and desertification. Changes include clearing woodland, building new houses, erecting industrial buildings and encroachment on agricultural areas. Because of these factors, methods of change detection in developing countries are needed to develop a model for predicting land cover and land use changes over time to help in planning. This is because the applications of new spatial techniques in change detection in developing countries are very limited. However, the technique for understanding these changes requires the use of readily available information, integrated with new techniques for more efficient output.In recent times, GIS and remote sensing have been widely used in detecting land cover and land use change. Remotely sensed data from satellites are used to describe and map environmental situations at one particular time; the accessibility of multi-temporal information allows an understanding of land cover and land use processes. Change detection analysis by using GIS and remote sensing software is increasingly providing the required information for land cover and land use such as urban expansion, forestry and agriculture (Guild, 2004).

2- Classification

Image classification is defined as the process of automatically categorizing all pixels according to their spectral properties into land cover classes. Similarly, Dutta et al. (2009) describe image classification as the procedure of creating thematic maps from satellite imagery. The two primary methods of image classification are supervised and unsupervised. Jensen (1996) highlighted that supervised classification is dependent on the input from the user and on informational classes or types known a priori. (Yikalo et al. 2010) also argue that training data from the field and maps form the basis of the supervised classification approach. Supervised classifications identify homogeneous areas or samples of known land cover and land use types.

This means the pixels are assigned to known information classes (Jensen et al., 1999). These areas, which are known as samples or training sites, contain numerical properties that are used to train the classification algorithm. Training is the procedure of defining the criteria by which these patterns are recognized. The outcome of training is a set of signatures, which form the criteria for a set of proposed classes (Lizarazo et al., 2009). With the supervised approach, calibration pixels are chosen and statistics are produced for the classes of interest. The result of such a classification is a thematic map with a label for each pixel of the class for which it has the highest strength of membership.This Boolean classification is based on conventional Boolean set theory. A Boolean classification of remotely sensed imagery models the study area as a number of unique, internally homogeneous classes that are mutually exclusive.

However, these assumptions are often invalid, especially in areas where transition zones and mixed pixels occur (Cihlar, 2000). Land cover types are rarely internally homogeneous and mutually exclusive; as a result, classes can hardly ever be separated by sharp or Boolean boundaries, in feature space as well as geographic space. In addition, complex relationships exist among spectral responses recorded on the ground and by the sensor, where similar categories, pixels or objects show diverse spectral responses, and similar spectral responses may relate to different classes, pixels or objects .Furthermore, remotely sensed images contain many pixels where boundaries or sub-pixel objects cause pixel mixing, with several land cover classes occurring within a single pixel. Lastly, classes are often hard to define, resulting in vagueness and ambiguity in a classification scheme (Foody, 1996.

2.1Boolean classification

Boolean classification uses a statistical model that attempts to map every pixel by assigning it exclusively to one particular class. The spectrally similar data will explain thematically similar objects for every pixel (Lillesand et al., 2008). Traditional Boolean classification uses binary logic to establish class membership, in that every observation can belong to one class (Foody, 1999).Because of the heterogeneity of land cover and the limitation in spatial resolution of remote sensing imagery, mixed pixels are present in medium- and spatial resolution data. The presence of mixed pixels has been recognized as a major problem affecting the effective employment of remotely sensed data in pixel-based classification (Hu et al., 2010).Boolean classification can be further divided into two broad categories: supervised and unsupervised. The supervised classification for pixel labelling needs the user to select representative training data for each of a predefined number of categories. Moreover, supervised classification techniques use prior knowledge about the field, which is very useful in getting improved classification (Key et al., 2002). Supervised classification is chosen by many researchers because it usually gives more precise class definitions and higher accuracy than the unsupervised method (Jensen, 2000). The most common classifiers in general use are the maximum likelihood algorithm and the minimum distance classifier Dutta et al. (2009). The maximum likelihood process is a supervised statistical method for prototype recognition. The probability of a pixel belonging to each of a pre-defined set of categories is calculated, and the pixel is then assigned to the category for which the probability is the greatest (Mather et al., 2009). The maximum likelihood classifier is the most general supervised classification technique for parametric entry data. The maximum likelihood classifier supposes that a pixel has a certain probability of belonging to a specific class. These probabilities are equivalent for all categories and the input data in every band follow the normal distribution function (Cakir et al., 2006). It is important to recognize that the maximum likelihood method is based on the assumption that the frequency distribution of the category membership can be estimated by the multivariate normal probability distribution (Cakir et al., 2006). Unsupervised classification is a defined by which pixels in an image are assigned to spectral categories without the user having foreknowledge of the existence assignment of those categories. It is performed most frequently using a clustering approach. These procedures can be used to determine the number and position of the spectral categories to determine the spectral class of every pixel.

3- Land use and land cover change detection

Land cover change is one of the main variables in most environmental issues of importance to the human–environmental sciences. According to (Cakir et al., 2006), land use relates to the human activity connected with a particular parcel or area of land. Examples of land use include agriculture, urbanization, grazing and mining. Land cover, on the other hand, relates to the composition and character of land surface elements (Cihlar, 2000). Regions across the world experience rapid changes in land cover due to human activities and natural phenomena, but these changes are mostly determined by human use. Detecting land cover change is important in order to manage and monitor processes such as urbanization and climate change, especially in regions experiencing radical and dramatic changes like those that are commonly found in developing countries (Foody, 2008). These features make it desirable to develop a time series analysis of land use and land cover (LULC) to understand the motivating forces of these changes in addition to projecting the future spatiality of the change (Cakir et al., 2006).

While land use and land cover changes can be monitored by traditional study and surveys, satellite remote sensing gives more information on the geographic distribution of land use and land cover changes, along with the advantages of cost and time efficiencies for larger areas (De Jong et al., 2006). Remotely sensed imagery supplies an efficient means of getting the information on temporal trends and spatial distribution of land cover and land use that is required for understanding and projecting land change (Foody, 2008). The integration of remote sensing and geographic information systems has been broadly applied, and has been documented as a powerful and active tool in monitoring land cover and land use changes throughout the world. Alberti et al. (2004) have shown that satellite remote sensing has the potential to give accurate and timely geospatial information describing changes in land cover and land use in urban regions. According to Coppin et al. (2002), visual and digital analyses are the two approaches for detecting changes in land cover and land use. Visual interpretation using aerial photography will give analysis at better resolutions, but different interpreters may present different results. Automated, repeatable, defensible approaches also give different results. To apply digital change detection techniques, three main steps are outlined:

(1) image pre-processing, which consists of image registration, image enhancement and geometrical rectification.

(2) the choices of suitable change detection methodology: many change detection approaches have been developed since the 1970s, such as image differencing, image rationing, post-classification comparison, vegetation index differencing, background subtraction, image regression, and fuzzy set operation;

(3) accuracy assessment of any error encountered during the classification procedure, mainly due to the interaction between the spatial structure of the landscape, sensor resolutions and classification algorithms. The reliability of the change detection procedure is strongly affected by different environmental characteristics and atmospheric effects (Alberti, (2008)). For effective use of remote sensing for change detection, data applied for monitoring should be taken by the same sensor using the same spatial resolution, spectral band, and viewing geometry, at the same time of day (Cakir et al., 2006). In order to detect change, many methods have been developed to define change features using remotely sensed data.

The post-classification approach is one of the most commonly used techniques (Brian et al., 2011). Given that it is possible to overcome issues of required expert knowledge to produce reliable land cover classifications, the major advantages of this method is the amount of information that can be obtained from the produced change matrix and the limited impact of image calibration and environmental differences. Another advantage of the post-classification approach is its intuitive interpretation as opposed to numerically based image analysis methods that need careful interpretation to evaluate what the identified changes mean. This advantage is mainly due to the rich semantics of land cover class labels; however the semantics is also noted by many authors as problematic because of the generally limited descriptions of the precise meanings of land cover labels (Comber et al., 2004b). Moreover, some studies have found that data on land cover and land use from different times are classified using different classification methods (Comber et al., 2004a). In these situations a normal post-classification change assessment can be very complicated.

4. The study area

The study area is located in the north-western part of Libya (South of the Tripoli city), as shown in Figure 1. This region is heavily populated, mostly along the Mediterranean coast; it comprises the city of Tripoli, the capital of Libya, and major towns such as Janzour, Tajura, soq-Aljoma, Al-Suany, Azhra, Al-Qarabulli, and Bin-Ghashir. These settlements are experiencing growth and expansion due to population increase and migration; the built-up area of Tripoli city increased from 8,011.4 ha in 1966 to 19,236 ha in 2000 (El-Zannan, 2000). The increase in people, settlements and infrastructure consequently decreases the areas of agricultural land and woodland around the cities, and increases pressure on other natural resources, particularly water. The uncontrolled settlement growth may also lead to increasing amounts of waste generation, and improper dumping of waste causes land and water pollution. In Libya, the demands of a rapidly increasing population have been the main driving force of land cover and land use change in the study area. The total population of Libya has increased over recent decades. In 1970 it was 1.986 million, whereas in 2003 it had risen to 5.551 million. Compared with the figure for 1970, the total population had doubled by 1980 and trebled by 2003 (FAOSTAT, 2004). And in 2008, the total population was 6,173,579, with annual growth at 2.216 per cent (National Information Authority of Libya, 2008). According to the General Authority for Information elementary census of 2006, the population of Libya will be more than 10 million in 2025. Approximately 90 per cent of the Libyan people will be living in urban areas and only 10 per cent will be residing in rural areas. Increased supplies of food are needed to match this growth. Population growth plus the absence of control and planning policies has resulted in some serious problems in Libya. One of these problems is the increased competition between urban and agricultural lands (*Libyan Statistics Book*, 2007). Increases in population have been a significant and important driver of land cover changes in urban areas and are expected to continue and to place significant demands on the land resources.

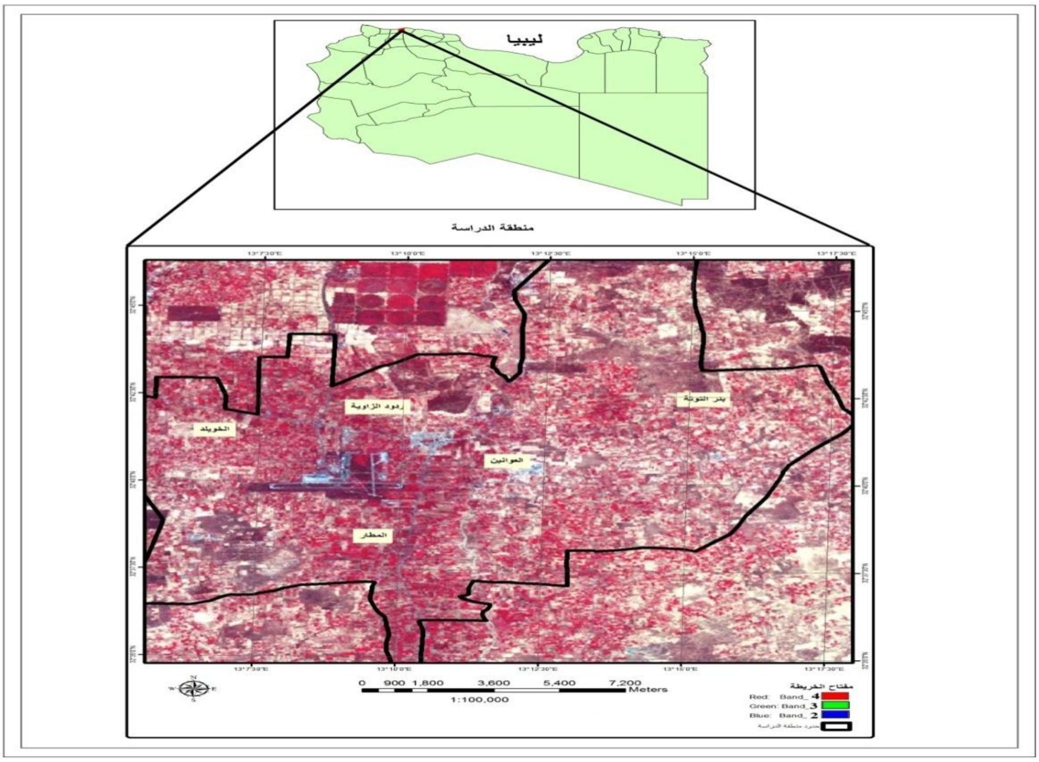

Figure 1 study area

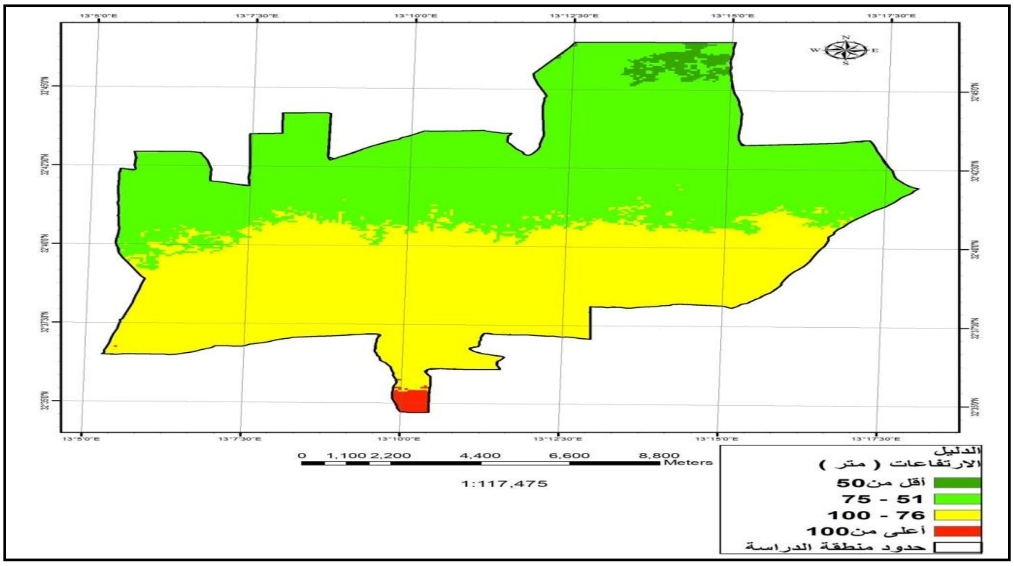

Figure 2 height of the study area

5 – Methodology

5.1 Image pre-processing

Multi-resolution and multi-temporal time series, including historical satellite imagery, aerial photographs and other data, were used to determine land use and land cover changes over the study period between 1989 and 2015. Mosaic and image enhancement processes using edges, texture and high- and low-frequency components extract important information that could otherwise be missed. Were applied for data preparation and pre-processing for reliability. Two partially overlapping images covering the study area were merged to the same map projection and datum using the same pixel size. Image-to-image registration one of the images was selected as the base to which the other was compared. Topographic maps were used as base maps and the geometric registration was done on all images, using triangulation registration points.

5.2 Mosaicing and image-to-image registration

Mosaicing is when two, partially overlapping images, are merged together. The two images were be rectified to the same map projection and datum using the same resampling logics and pixel size and then one image is selected as the base image to which the other one will be related to. In the study area the mosaicing has been done for two images to cover the study area. The image registration is the most important step in order to get precise change detection results. Geometric registration requires resampling to interpolate the new brightness values and there are three usually used methods; nearest neighbor, bi-linear or cubic convolution. Cubic convolution is similar to the bilinear interpolation except that it weight values of 16 surrounding pixels, this method has been applied in this study. In this paper the topographic map has been chosen as a bas map then the Geometric registration has been done for all images, many points were taken and distributed in all parts of the image to get a good result. This process has been done in ER-Mapper soft ware, by using Geodetic Datum WGS84 and map projection NUTM 33.

The satellite images were classified into six land-cover categories – urban areas, woodland, irrigated area un irrigated , grazing land and bare areas – using Boolean classification model. The analysis was performed in a variety of software, including ER-Mapper and Erdas for image processing,. The following steps were applied:

Step 1. Mosaic:

Image-to-image registration and image enhancement were applied for data preparation and pre-processing for reliability. Two partially overlapping images covering the study areas were merged to the same map projection and datum using the same resembling logics and pixel size. One of the images was selected as the base to relate the other. Nearest neighbour, bi-linear or cubic convolutions are the commonest image registration methods. However, the study adopted cubic convolution for all resolution up-scaling and down-scaling because it is similar to the bilinear interpolation except that it weighs the values of sixteen surrounding pixels. Topographic maps were used as base maps, and the geometric registration was done on all images, using triangulation registration points. This process has been done in ER-Mapper software, using Geodetic Datum WGS84 and NUTM 33 map projection. At this stage the study also applied histogram equalization to all the images for enhancement. The image enhancement process uses edges, texture and high and low frequency components to extract important information that could otherwise be missed.

Step2. Training sites development

Determining the training set is an essential step in supervised image classification. A training set can be defined as a sample of pixels of known category membership collected from reference data such as existing maps, ground data, and aerial photographs (DeFries et al., 1998). These training pixels are used to obtain various statistics such as standard deviation and mean for every land cover category. A training sample in soft supervised classification differs in practice from the traditional training set in training-site selection. Traditionally, training sites are chosen for every training category and the sites must be sufficiently homogeneous on the ground. Therefore, these are selected subjectively and purposefully to exclude mixed pixels containing two or more categories. For soft classification, the condition for being homogeneousis less important, and a training sample can be used to produce statistical factors for more than one category (Alberti, (2008)). In the current research, training sites were selected in areas which contained pure and mixed pixels.

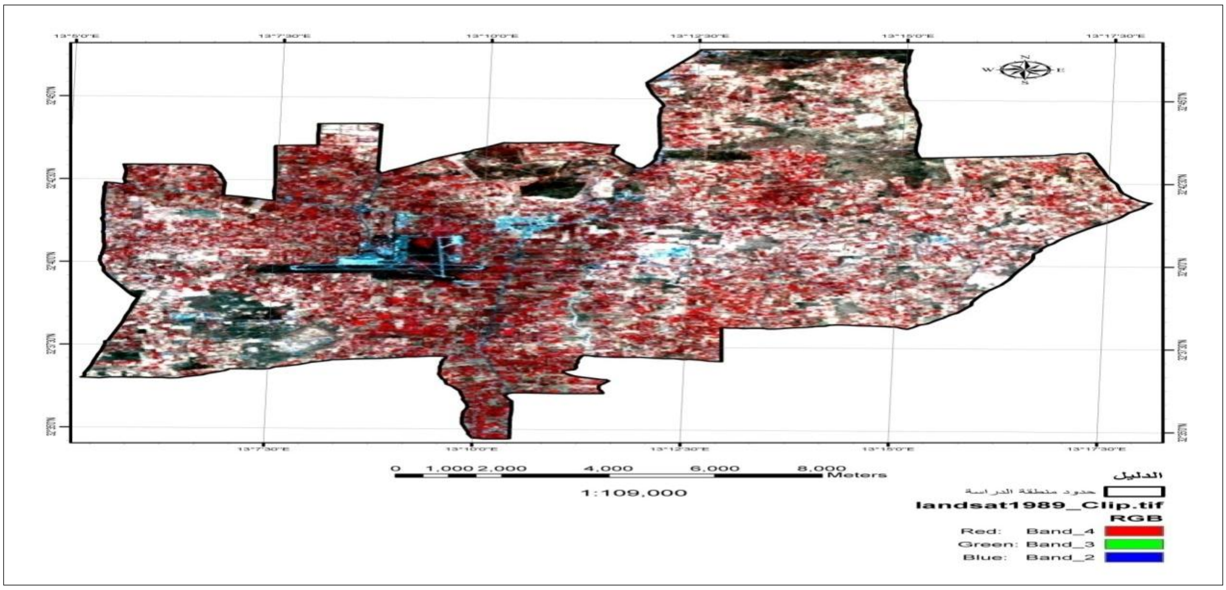

Figure 3 landsat image 1989

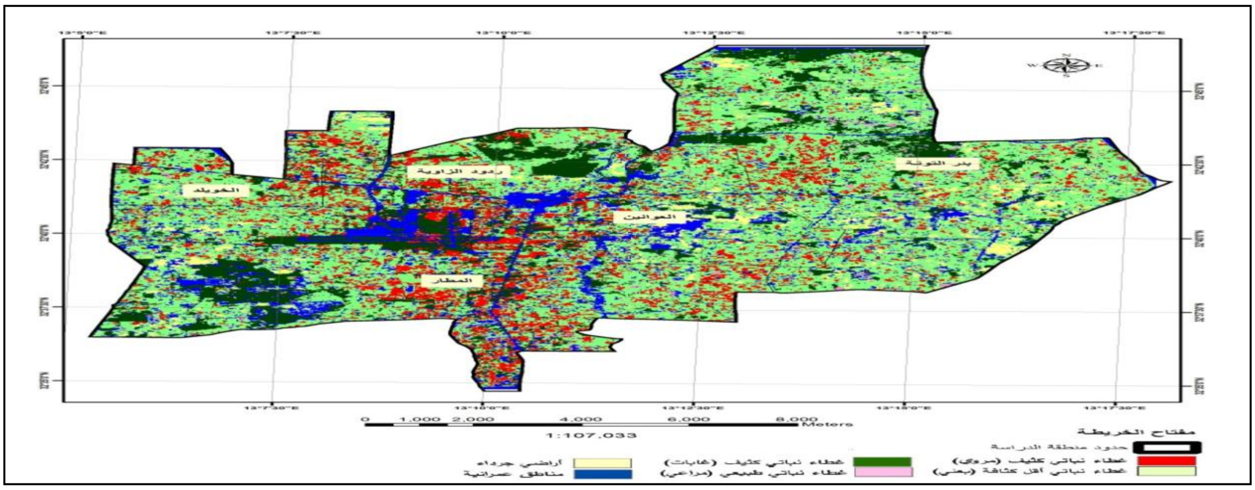

Figure 4 Classified image Landsat 1989

Table1classified image 1989

Classes	Area by hector	Percentage
Urban	988.996	2.2
Woodland	7310.169	16.3
Bare area	5425.749	9.9
Grazing land	10399.749	23.1
Irrigated area	7594.944	16.9
Un irrigated area	14194.962	31.6
Total area	44925.142	% 100.0

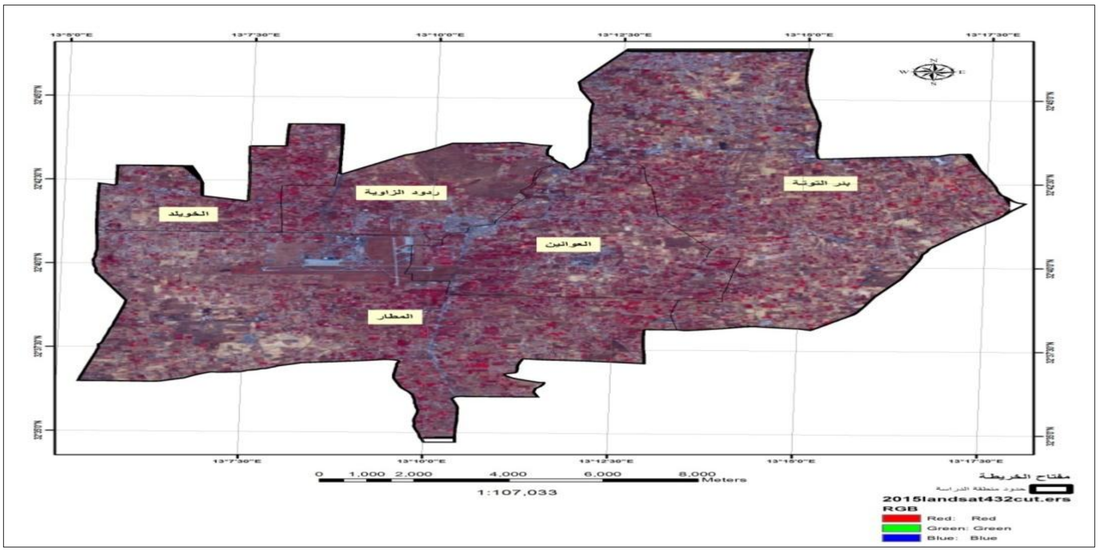

Figure 5 landsat image 2001

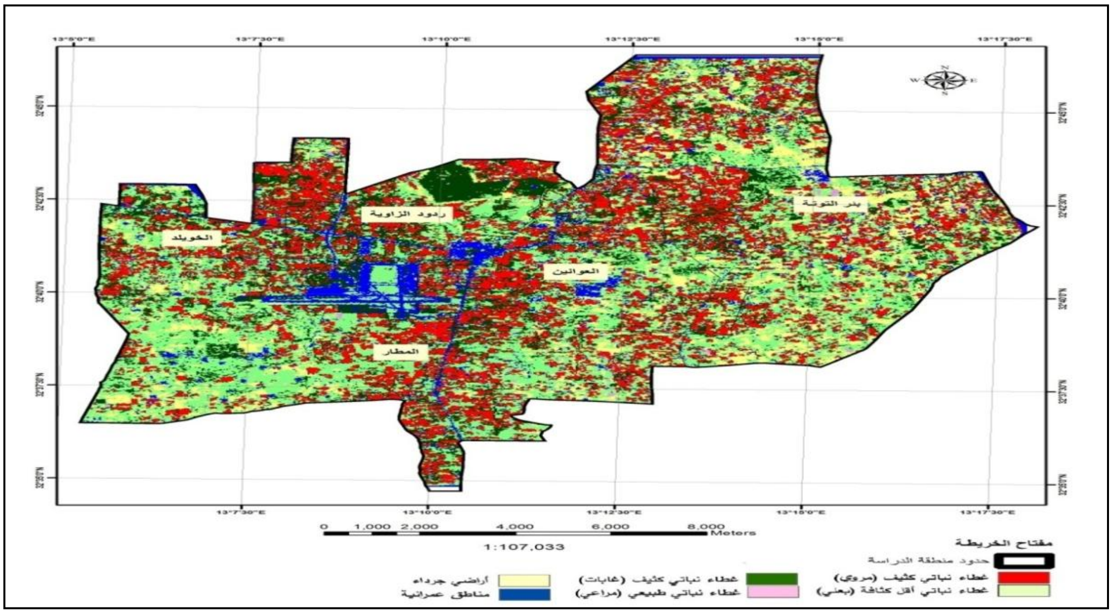

Figure 6 Classified image Landsat2001

Table 2 Classified image Landsat 2001

classes	Area by hector	Percentage
Urban	2724.611	6.1
Woodland	6982.67	15.5
Bare area	7194.099	16
Grazing land	16643.246	37
Irrigated area	8004.155	17.8
Un irrigated area	3376.361	7.5
Total area	44925.142	% 100.0

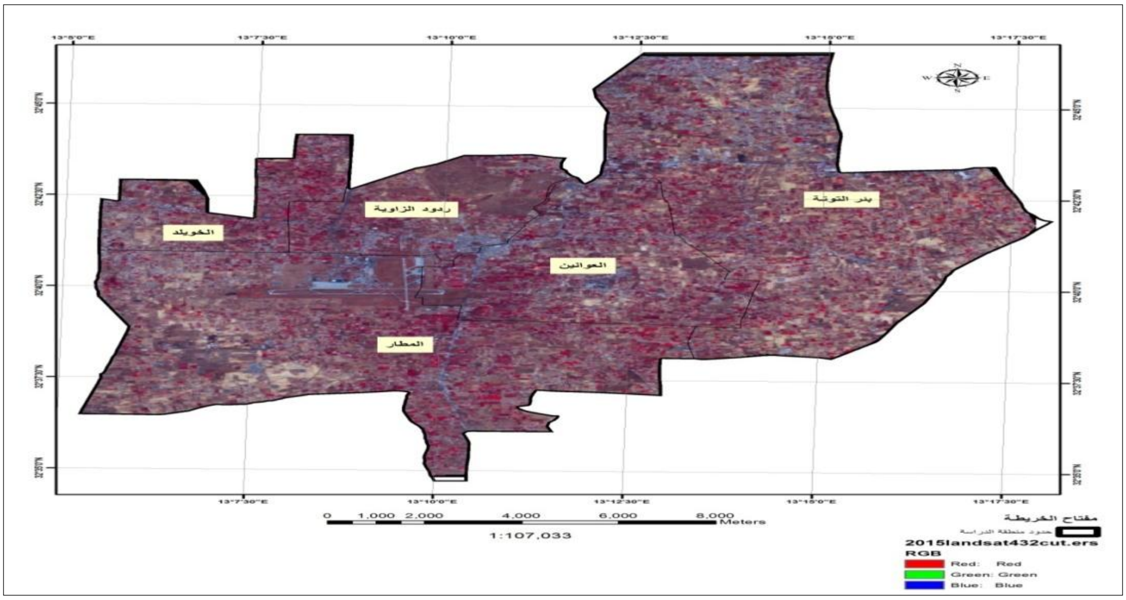

Figure 7 Landsat image 2015

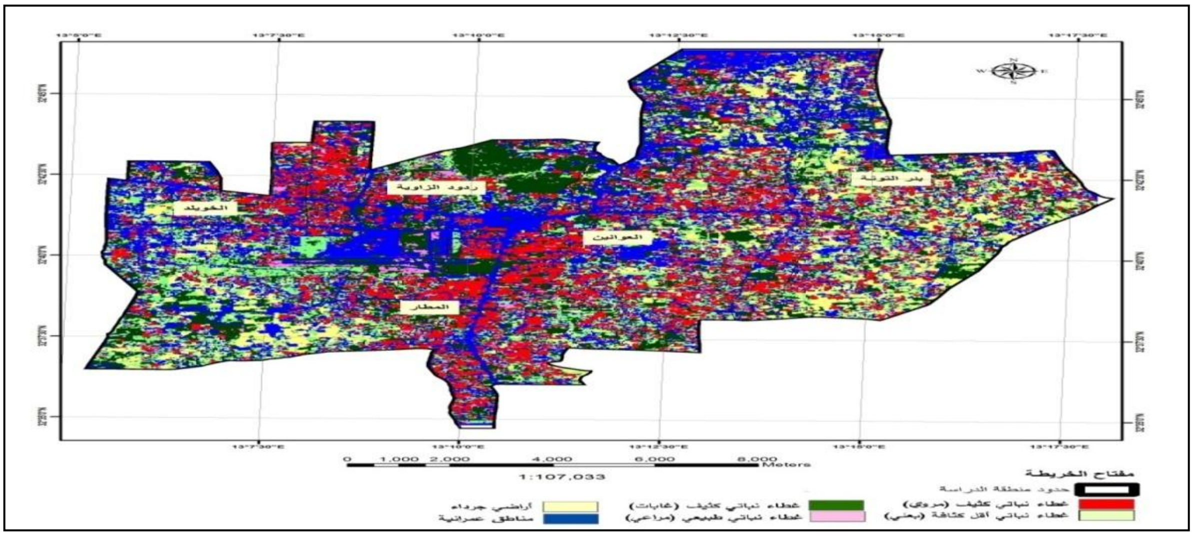

Figure 8 Classified image Landsat2015

Table3Classified image Landsat2015

Classes	Area by hector	Percentage
Urban	4972.01	11.1
Woodland	6321.96	14.1
Bare area	720.262	1.6
Grazing land	12984.49	28.9
Irrigated area	8004.155	17.8
Un irrigated area	14955.52	33.3
Total area	44925.142	% 100.0

6. Results of Boolean classification

Figures 4, 6 and 8 show the classified images produced by the Boolean classification model in 1989 and 2001; 2015 from the figures it is clear that the urban class in
creases while the woodland decreases. Table 4below shows the area of classes in hectares at different dates using Boolean classification. The area of the urban class is 988.9hectares at T1 (1989), starts to increase at T2 (2001) (2724.6hectares), and is 4972.01hectares at T3 (2015) ; the difference in area between T1 and T3 is equal to 3983hectares, which means there has been a huge increase in the area of the urban class. Table 4also shows that the area of woodland is 7310.1hectares at T1 (1989), then starts to decrease at T2 (2001) (6982.6hectares), and is 6321.9hectares at T3 (2015); the difference in area between T1 and T3 is equal to -944.209 hectares, which means that there has been a huge decrease in the woodland class.

Table 4 shows the area of classes in hectares

Classes	1989 TM	2001 TEM	2015 TEM	Difference 2015-1989
Urban	988.996	2724.611	4972.01	3983.014
Woodland	7310.169	6982.67	6321.96	-944.209
Bare area	4436.322	7194.099	720.262	-3716.06
Grazing land	10399.749	16643.246	12984.49	2584.741
Irrigated area	7594.944	8004.155	4970.9	-2624.044
Un irrigated area	14194.962	3376.361	14955.52	760.558

7. Recommendations

For future analyses of land cover change in the study area of south Tripoli, Libya, it is important that the decision makers take the following recommendations into consideration:

1. Libyan decision makers should take the current research results into consideration for present and future land use planning.
2. The methods developed can be adapted for all parts and the same methodology can be implemented for different land cover changes.
3. Some awareness should be provided in the study area specially to the woodland and reforestation the area surrounded by Tripoli city
4. Funding is needed for studying land cover change in Libya, to control and monitor the changes in the study area every five years.
5. From the study it is clear that the study area is covered by heterogeneous and mixed pixels; there is a need to specify management methods to be used in future and to find suitable places to extend the city of Tripoli.

6. Grazing activities in the study area need improvement and management.

8. Summary

Land use and land cover classification is one of the most important applications of remote sensing data. Either Boolean (pixel-by-pixel) or (sub-pixel) classification may be performed to obtain land use and land cover maps. However, in general, and particularly in medium spatial resolution images such as Landsat, most of the pixels may be mixed. Detecting regions of change in multi temporal images of the same region taken at different times is of widespread interest due to a large number of applications in various fields. This paper is concerned with land cover and land use change in the Tripoli, Libya between 1989 and 2015. Mixed pixels are common within the area, and normal methods of classification assume that land cover classes have crisp boundaries in space and attributes; this vagueness in the boundaries of land cover classes is a continuing problem for image classification.

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