Land Cover Change Detection of Baghdad City Using Multi-Spectral Remote Sensing Imagery

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Abstract
The main goal of this work is study the land cover changes for "Baghdad city" over a period of (30) years using multi-temporal Landsat satellite images (TM, ETM+ and OLI) acquired in 1984, 2000, and 2015 respectively. In this work, the methodology adopted took into consideration different image pre-processing techniques including, geometric correction, radiometric correction, atmospheric correction and satellite image clipping. The principal components analysis transform has been utilized as multi operators, (i.e. enhancement, compressor, and temporal change detector). Since most of the image band's information are presented in the first PCs image. Then, the PC1 image for all three years is partitioned into variable sized blocks using quad tree technique. Several different methods of classification have been used to classify Landsat satellite images; these are, proposed method (ant colony system) using proposed system and supervised method (Maximum likelihood Classifier Technique) using ENVI 5.1 software are utilized in order to get the most accurate results and then compare the results of each method and calculate the land cover changes that have been taken place in years 2000 and 2015 comparing with 1984. The image classification of the study area resulted into five land cover types: Water bodies, vegetation, open land (Barren land), urban area "Residential I" and urban area "Residential II". The results from classification process indicated that water bodies, vegetation, open land and the urban area "Residential I" were increased, while the second type from urban area "Residential II" in decrease to year 2015 comparable with 1984. Despite use of many methods of classification, results of the proposed method proved its efficiency, where the classification accuracies for the ACS algorithm are 83%, 85% and 84% for years 1984, 2000 and 2015 respectively.

Keywords: Landsat satellite images, land cover change detection, ant colony system

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Introduction:

Change detection is a process to measure the extent of the change in the characteristics of a particular area, and the disclosure of this change involves a comparison of aerial photographs or satellite images of the area taken at different time intervals to measure the urban development and environmental changes using two or more of the scenes that cover the same geographical area over two or more times [1].

Remote sensing image classification is regarded as an important mean for quantified remote sensing image analysis. Classification technology as an important branch of remote sensing technology has been the widespread attention of researchers in remote sensing community for many years. In general, the remote sensing image classification has mainly two ways. One is the visual interpretation; the other is computer automatic classification. The computer automatic classification uses the pattern recognition technology and the artificial intelligence technology to carry on the analysis and the deduction, understand the remote sensing image, and complete the interpretation of the remote sensing image finally, according to the land target’s characteristic in the remote sensing image and the goal land target’s interpretation experience and image formation rules in the expert knowledge library, based on the computer system. Minimum distance from means, maximum-likelihood, cluster analysis and Bayesian classification is a simple and conventional classification method [2-3] based on statistical principles. Some new methods for remote sensing classification also have been developed, including machine learning, support vector machine, neural network, fuzzy set and genetic algorithm [4-11].

Artificial Intelligence (AI) techniques have been increasingly incorporated in the classification of remote sensing images [12]. Swarm Intelligence (SI) is actually a complex multi-agents system, consisting of numerous simple individuals (e.g., ants, birds, etc.), which exhibit their swarm intelligence through cooperation and competition among the individuals [13]. SI has currently become a hot topic in artificial intelligence research, and using SI in remote sensing classification is a new research area.

Ant colony optimization (ACO) algorithm is one of the main algorithms in Swarm Intelligence. Dorigo M et.al presented a heuristic bionic evolutionary algorithm based on SI by simulating ants in nature collective search path behavior. It first successfully applied to solve the famous traveling salesman problem. Later, ant colony clustering algorithm was proposed by other scientists. According to the principle of it, ant colony clustering algorithm can be divided into the following four types : (1)
Make use of the pheromone to achieve clustering based on ant foraging theory; (2) Make use of ant self-assembled behavior to achieve clustering; (3) Based on ant reactor forming principle to achieve clustering; (4) Application of ants nests classification model and ant chemical identification system to achieve clustering [14]. In this paper, the first algorithm, namely ant foraging theory, was applied to automatic classify Landsat satellite images. In our work, we classified Landsat satellite images of Baghdad city for years 1984, 2000 and 2015. Classification methods have been used to classify satellite images; these were proposed method (ant colony optimization algorithm) using Visual Basic software and supervised method (Maximum Likelihood Classifier) using ENVI 5.1 software.

**Ant Colony Optimization Concept:**

Ant colony optimization is a probabilistic technique for solving computational problems that can be reduced to finding the best paths through graphs. It is a member of swarm intelligence methods that initially proposed by Marco Dorigo in 1992 in his Ph.D. thesis [15, 16]. The principle of this algorithm is a cooperative search technique that mimics the forging behavior of real life ant colonies. Although ants are blind, they can always be able to find a shortcut between food sources and their nest by indirect communication with each ant whiles it is walking. A special chemical trail (pheromone) is left on the ground during their trips. This chemical trail guides the other ants towards the target solution by choosing a shortest path, which is called “convergence” in mathematical terms [17]. The more ants pass, stronger pheromone achieves. Furthermore, this will cause higher probability of choosing the path by more ants. An ant will move from node i to node j with probability [18]. See Figure-1.

\[
p_{ij}^k(t) = \frac{(\tau_{ij}(t))^\alpha \cdot (\eta_{ij})^\beta}{\sum_{i,j} \tau_{ij}(t)^\alpha \cdot (\eta_{ij})^\beta}
\]

(1)

Where, N is the set of neighboring nodes, \(\tau_{ij}\) is the amount of pheromone on edge i, j. \(\alpha\) and \(\beta\) are important parameters which determine the relative influence of the trail pheromone and the heuristic information. \(\eta_{ij}(t)\) is the desirability of edge i,j (typically 1/d_{ij}). After all ants have completed their solutions, pheromone evaporation on all nodes is triggered, and then according to following equation each ant k deposits a quantity of pheromone, \(\Delta \tau_{ij}^k(t)\) on each node that it has use:

\[
\Delta \tau_{ij}^k(t) = \begin{cases} 
1/L_k^k(t) & \text{if } (i, j) \in T_k^k(t) \\
0 & \text{if } (i, j) \notin T_k^k(t)
\end{cases}
\]

(2)

Where \(T_k^k(t)\) is the tour done by ant k iteration t, and \(L_k^k(t)\) is its length [19,20]. It is clear from equation (2) that the value \(\Delta \tau_{ij}^k(t)\) depends on how well the ant has performed, the shorter the tour done, the greater the amount of pheromone deposited. Practically, the addition of new pheromone by ants and pheromone evaporation are implemented by the following rule applied to all the nodes.

\[
\tau_{ij}(t) \leftarrow (1 - p) \cdot \tau_{ij}(t) + \Delta \tau_{ij}(t)
\]

(3)

Where \(\Delta \tau_{ij}(t) = \sum_{k=1}^{m} \Delta \tau_{ij}^k(t)\), m is the number of ants at each iteration and \(p \in [0,1]\) represents the evaporation degree of pheromone concentration on path (i,j) after one cycle, and 1-p represents the factor of residual pheromone. The main role of pheromone evaporation is to avoid stagnation. All ants can update the pheromone according to equation (3) and the best ant deposits additional pheromone on nodes of the best solution. This leads to the exploration of ants around the optimal solution in next iteration [21]. The survey shows the use of Ant Colony Optimization Algorithm applied to various applications such as Vehicle Routing, Travelling Salesman Problem (TSP), Job Scheduling problem and Telecommunication Network as an optimizer, but not used as a recognizer [22].
The Study Area:

The study area is Baghdad city. It is the capital and the main administrative center of Iraq. Baghdad is located in the central part of Iraq on both sides of Tigris River with geographic coordinates: Latitude (33°25′46″) to (33°24′21″) N, Longitude (44°15′55″) to (44°17′38″) E. Baghdad is the largest and most heavily populated city in Iraq. Baghdad is suited in a plain area of an elevation between (31-39 m) above sea level. So, no natural boundaries exist that limits the aerial extension of the city. The Tigris River passes through the city dividing it into two parts; Karkh (Western part) and Rusafa (Eastern part). The area is bounded from the east by Diyala River, which joins the Tigris River southeast of Baghdad. The Army Canal, 24km long, recharges from the Tigris River in the northern part of the city and terminates in the southern part of Diyala River. Figure-2 shows the study area "Baghdad city" for period 1984, 2000 and 2015.

Figure 2- Area of study "Baghdad city"
(A) Landsat- 5 (TM) satellite image (1984), false color composite (Band 4, Band 3, Band 2)
(B) Landsat- 7 (ETM+) satellite image (2000), false color composite (Band 4, Band 3, Band 2)
(C) Landsat- 8(OLI) satellite image (2015), false color composite (Band 5, Band 4, Band 3)
Satellite Imagery Acquisition:

In our work, Landsat satellite images were used, because of its low cost, especially in relation to the area covered. Another advantage of Landsat images is the copyright, which permits a legal sharing of data among government department, academia and donor agency. Three types of satellite image were consulted during the work, Landsat-5 TM satellite image (27/8/1984), Landsat-7 ETM+ satellite image (31/8/2000) and Landsat-8 OLI satellite image (1/8/2015) with (Path 168/ Row 37). The images used in this work were taken during the same season (summer season), were not highly affected by atmosphere (scattering and absorption) and were clouds free. Detail of Landsat images are given in Table-1. Satellite images used for this work were obtained from the USGS Earth Explorer database (http://earthexplorer.usgs.gov/).

Table 1- Details of data used

<table>
<thead>
<tr>
<th>ID</th>
<th>Satellite Image</th>
<th>Sensor</th>
<th>Path / Row</th>
<th>Acquisition Date</th>
<th>Bands</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Landsat- 5</td>
<td>Thematic Mapper (TM )</td>
<td>168 / 37</td>
<td>27 /8 /1984</td>
<td>(1,2,3,4,5,7)</td>
<td>USGS Earth Explorer database</td>
</tr>
<tr>
<td>2</td>
<td>Landsat- 7</td>
<td>Enhanced Thematic Mapper Plus (ETM+)</td>
<td>168 / 37</td>
<td>31 /8 /2000</td>
<td>(1,2,3,4,7)</td>
<td>USGS Earth Explorer database</td>
</tr>
<tr>
<td>3</td>
<td>Landsat- 8</td>
<td>Operational Land Imager (OLI)</td>
<td>168 / 37</td>
<td>1 /8 / 2015</td>
<td>(2,3,4,5,6,7)</td>
<td>USGS Earth Explorer database</td>
</tr>
</tbody>
</table>

Satellite Image Pre-Processing:

Generally, raw satellite image contain some errors and will not be directly utilized for features identification and any applications. It needs some correction. Pre-processing is done before the main data analysis and extraction of information. Pre-processing involves two major processes: geometric correction and radiometric correction or haze correction. [23]. In this paper, ENVI 5.1 software was used to perform most satellite image pre-processing stages.

1. Importing of Landsat Images:
   In this stage, all downloaded Landsat TM, ETM+ and OLI satellite images for years 1984, 2000 and 2015 were unzipped and imported to ENVI 5.1 software environment. Then all the bands of each satellite image were gathered together in a single layer "layer stacks" or "multiband images" using the layer-stack function of ENVI 5.1 software and saved with ENVI format. Bands 1 to 5 and band 7 were utilized for the Landsat TM and ETM+ images. While, bands 2 to 6 and band 7 were utilized for the Landsat OLI images. Bands 1 to 4 are categorized as the visible bands (Blue band, Green band, Red band) or the near Infrared (NIR) band. Meanwhile bands 5 and 7 are considered the short wave infrared bands.

2. Geometric Correction:
   Geometric correction of the data is critical step for performing a change detection analysis [23]. In this work, the geometric correction of the satellite data has not been performed; all satellite images obtained from the "(http://earthexplorer.usgs.gov/)" site were geo-registered to the same Universal Transversal Mercator (WGS_1984_UTM_Zone_38N) coordinate system. Subsequently, all satellite images (Landsat-5 TM 1984, Landsat-7 ETM+ 2000 and Landsat-8 OLI 2015) carried out according to WGS_84 datum and UTM _Zone_38N projection, using nearest neighbor re-sampling method.

3. Radiometric and Atmospheric Correction:
   Since digital sensors record the intensity of electromagnetic radiation from each spot viewed on the Earth’s surface as a Digital Number (DN) for each spectral band, the exact range of DN that a sensor utilizes depends on its radiometric resolution [24]. Therefore, normalizing image pixel values for differences in sun illumination geometry, atmospheric effects and instrument calibration is necessary specially because a time series of Landsat imageries will be used, from 1984 to 2015 (TM, ETM+ and OLI), and compared to each other. The radiometric correction was used to restore the image by using sensor calibration concerned with ensuring uniformity of output across the face of the image, and across time. ENVI 5.1 software has been used to perform the radiometric correction and atmospheric correction using "Radiometric Correction Tools" and "Dark Object Subtraction Tools" respectively.
4. Clipping the Area of Study:

The study area "Baghdad city" locates in center of Iraq with the following geographic coordinate: ULX (44˚13΄ W), LRX (44˚32΄ E), ULY (33˚26΄ N) and LRY (33˚10΄ S). The image is clipped to the rectangular boundary "square size" of the study area. The clipped image consists of 1024 columns and 1024 rows. All images were secured to have the same number of rows and columns. This step is performed using subset data with region of interest (ROIs) tools in ENVI 5.1 software.

Proposed Classification Method:

The proposed classification method includes three main stages: The principle component analysis (PCA) transform is first employed to create newly integrated image with dense information and best contrast due to the information of all used bands are concentrated in one image (PC1 image). Then, the PC1 image is segmented into variable sized blocks using quad tree technique. Later stage, the ant colony optimization algorithm is adopted to perform the automatic classify Landsat satellite images that classifies the study area and obtains the members of each class. Figure-3 illustrate the block diagram of the proposed classification method. More details for each step can be shown in following subsections.
**Figure 3-** Block diagram of the proposed classification method

1. **Principal Component Analysis Transform (PCA):**

   The main idea of PCA transform is to reduce the dimensionality of a set of bands, which contains numerous interconnected variables. The PCA algorithm transforms those variables into a new set of decorrelated ones. The order of new variables is such that usually only the first few are responsible for most of the variances in the original bands. PCA transform uses the input image bands to create new principles components (PCs). The newly images will have characteristics of dense information and best contrast [25, 26]. Therefore, the first principle component is suitable for classifying the multiband satellite images. The chosen PC image is the most descriptive and ready to apply the partitioning stage on it.
The principal components analysis of KL-transform has been utilized as multi operators, (i.e. enhancement, compressor, and temporal change detector). Since most of the image band’s information are presented in the first PCs, therefore image classification and change detection procedures are performed with little consuming time. The linear “PCA” transformation can be used to translate and rotate data into a new coordinate system that maximizes the variance of the data. It can also be implemented for enhancing the information content. In this section, and after achievement satellite image pre-processing stages, we will be perform PCA transform on the Landsat images of study area for years 1984, 2000 and 2015 using proposed system. See Figure-4. The mechanism of this transform can be illustrated in the following algorithm.

Algorithm 1- PCA Transform for Landsat Satellite Images

**Input:**
- No. Bands: number of the image bands for landsat sensor (6 Bands)
- Width: width of image band
- Height: height of image band

**Output:**
- Six PCs images resulted from the PCA transform (PC1, PC2, PC3, PC4, PC5 and PC6)

**Procedure:**

**Step 1:** Set the multi-band images $f(x, y, r)$, each of size $(M*N)$ and “$r$” bands

**Step 2:** Convert each image band in form of an $n$-dimension vector $(D_{n,b})$, where $n=(M*N)$

**Step 3:** Arrange the whole image bands into a matrix $(D_{n,r})$ of $n$-rows and $r$-columns

**Step 4:** Compute the mean of each column in step (3), by taking the arithmetic averages of each column by:
\[
\overline{D}_{n,b} = \frac{1}{n} \sum_{i=1}^{M} f(i, j, b), \quad b=1, 2, 3, \ldots, r
\]

**Step 5:** Compute “Mean corrected matrix” $(P_{n,r})$ (n-row, r-column) by subtracting the mean of each column $(\overline{D}_{n,b})$ from that column values $(D_{n,b})$ by:
\[
P_{j,b} = \sum_{i=1}^{D_{i,b}} - \overline{D}_{l,b}, \quad j=1, 2, 3, \ldots, n \quad \text{and} \quad b=1, 2, 3, \ldots, r
\]

**Step 6:** Compute the covariance matrix of the $(P_{j,b})$ matrix by:
\[
CM_P = E \left\{ (D - \overline{D})(D - \overline{D})^T \right\}
\]
Where: $E \{ . \}$ is the expectation operation, "$T$" indicates transposition and $CM_P$ is an $(r * r)$ matrix.

**Step 7:** Calculate the Eigen values and Eigen vectors of the covariance matrix $CM_P$

**Step 8:** Compute the transform matrix "A" which, whose rows are the eigenvectors of $CM_P$

**Step 9:** Compute the principal components vectors using the transform:
\[
Y_i = A (D_i - \overline{D}_i), \quad i = 1, 2, 3, \ldots, r
\]
Such formed PCA bands have the highest contrast or variance in the first band and the lowest contrast or variance in the last band. Therefore, the first factor of PCA bands often contain the majority of information residing in the original multi spectral Landsat images and can be used for more effective and accurate analyses because the number of image bands and the amount of image noises are reduced.

**Results of Principal Component Analysis Transform:**

In our work, the PCA algorithm is applied to transform six multibands 1, 2, 3, 4, 5 and 7 of Landsat (TM), (ETM+) images and six multibands (2, 3, 4, 5, 6 and 7) of Landsat-8 (OLI) images to six principal component images. Only first PCA was chosen because it has higher potential information. The higher potential image is indicated by its PCA eigenvalue. The higher eigenvalue shows higher variance in the image, which means that the image has (lower data redundancy) and a PCA transformation is done by transforming each image into a new PCA image. Although six components are generated from the original bands, PCA1 is responsible for more than 95% of the total variation for each satellite image. It is provide the most information about different ground features. Apply PCA transform of each band in Landsat images; enable PCA to highlight different features and land cover classes on the satellite images. PCA1 is the index of the spectral signature of each feature on the ground. The PCA1 containing the least degree of noise and the most ground feature information. Consequently, we can use it to extract the change information during the period of study. Tables-2, 3 and 4 show the percent and accumulative eigen-values for each eigen-channel in each satellite image Landsat-5 (TM) 1984, Landsat-7 (ETM+) 2000 and Landsat-8 (OLI) 2015 respectively.

**Table 2** The percent and accumulative eigen-values for Landsat-5 (TM) satellite image (27/8/1984)

<table>
<thead>
<tr>
<th>PCA Layers</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigen values (Variances)</td>
<td>22769.42856</td>
<td>684.15612</td>
<td>126.94174</td>
<td>114.89866</td>
<td>45.73805</td>
<td>16.91121</td>
</tr>
<tr>
<td>Percent of Eigen values (%)</td>
<td>95.8387</td>
<td>2.8797</td>
<td>0.5343</td>
<td>0.4836</td>
<td>0.1925</td>
<td>0.0712</td>
</tr>
<tr>
<td>Accumulative of Eigen values (%)</td>
<td>95.8387</td>
<td>98.7184</td>
<td>99.2527</td>
<td>99.7363</td>
<td>99.9288</td>
<td>100.0000</td>
</tr>
</tbody>
</table>

**Table 3** The percent and accumulative eigen-values for Landsat-7 (ETM+) satellite image (31/8/2000)

<table>
<thead>
<tr>
<th>PCA Layers</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigen values (Variances)</td>
<td>16666.40580</td>
<td>356.04279</td>
<td>141.05243</td>
<td>86.07097</td>
<td>39.27142</td>
<td>18.34102</td>
</tr>
<tr>
<td>Percent of Eigen values (%)</td>
<td>96.2976</td>
<td>2.0572</td>
<td>0.8150</td>
<td>0.4973</td>
<td>0.2269</td>
<td>0.1060</td>
</tr>
<tr>
<td>Accumulative of Eigen values (%)</td>
<td>96.2976</td>
<td>98.3548</td>
<td>99.1698</td>
<td>99.6671</td>
<td>99.8940</td>
<td>100.0000</td>
</tr>
</tbody>
</table>

**Table 4** The percent and accumulative eigen-values for Landsat-8 (OLI) satellite image (1/8/2015)

<table>
<thead>
<tr>
<th>PCA Layers</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigen values (Variances)</td>
<td>46102.64873</td>
<td>285.79167</td>
<td>837.55498</td>
<td>91.11189</td>
<td>59.89008</td>
<td>22.00381</td>
</tr>
<tr>
<td>Percent of Eigen values (%)</td>
<td>95.8387</td>
<td>0.6145</td>
<td>0.1801</td>
<td>0.0441</td>
<td>0.0310</td>
<td>0.0020</td>
</tr>
<tr>
<td>Accumulative of Eigen values (%)</td>
<td>95.8387</td>
<td>99.7427</td>
<td>99.9229</td>
<td>99.9670</td>
<td>99.9980</td>
<td>100.0000</td>
</tr>
</tbody>
</table>

The first PC layer shows 95.8387%, 96.2976% and 99.1282% of the total variance for 1984, 2000 and 2015 Landsat images respectively. The first PC contains the most ground information and can be used to compare the changes in land cover classes in different years for the study area. The second PC layer has the second variance of 2.8797%, 2.0572% and 0.6145% for 1984, 2000 and 2015 Landsat images respectively. The variances of the PC3 layer for all three-satellite images are lower. Tables-2, 3 and 4, show variances of 0.5343%, 0.8150% and 0.1801% for the PC3 layer of the 1984, 2000 and 2015 Landsat images respectively. Finally, the variances of the PC4, PC5, and PC6 for three years are lower with high degree of noise. The PC1, PC2 and PC3 layers for the 1984, 2000 and 2015 satellite images are shown in Figures 5, 6 and 7 respectively.
2. Satellite Image Segmentation:

One of the most familiar partition techniques is the quad tree method, which subdivides a region of an image into four equal blocks when a given homogeneity criterion is not met by that region. It continues to divide each sub-division until the criteria is met or minimum block size is reached. Typically, an image is initially divided into a set of large blocks (their size equal to the maximum allowable block size). The variance is computed and compared to a threshold for each of these blocks. Any sub-blocks created by failure of the homogeneity test undergo the same procedure. The subdivision will continue until a block either reaches a minimum size or it satisfies the homogeneity criterion. Each block test constitutes a node of the quad tree. A node for which no further subdivision is needed is called a leaf [27]. In this work, a quad tree algorithm is proposed; it is based on the image
uniformity criterion. In this section, we applied quad tree algorithm to partition the first principle component (PCA 1) image for years 1984, 2000 and 2015 into sub regions represents the area of study. The efficiency of such method is due to its ability to effectively partitioning diversity regions in the satellite image. Satellite image segmentation algorithm can be given in algorithm 2 as the following [27]:

**Algorithm 2- Satellite Image Segmentation using Quad Tree Algorithm**

**Input:**
PcImg: first PCA image band
Width: width of the first PC image
Hght: height of the first PC image

**Output:**
Llist: One-dimensional array represents grid of quad tree partitioning

**Procedure:**

**Step 1:** Compute the global mean ($M$) and the standard deviation ($\sigma$) of the whole input (initial) image, this factor will be used to automatically determine the threshold value of the dispersion level (in the uniformity criterion).

**Step 2:** Set the values of some partitioning control parameters, which can be considered as attributes of the partitioning process, these parameters are the:

A. Maximum block size ($S_{\text{max}}$): represent the maximum size of the block corresponds to the minimum depth of the tree partitioning.
B. Minimum block size ($S_{\text{min}}$): represent the minimum size of the block corresponds to the maximum depth of the tree partitioning.
C. Inclusion factor ($\alpha$): represent the multiple factor, when it is multiplied by the global standard deviation ($\sigma$) it will define the value of the extended standard deviation ($\sigma_e$), i.e.

$$\sigma_e = \alpha \sigma.$$ 
D. Acceptance Ratio ($R$): represent the ratio of the number of pixels whose values differ from the block mean by a distance more than the expected extended standard deviation.

**Step 3:** In order to store information about quad tree partitioning process, quad tree link list was utilized, it is defined as an array of records, each record of type quadtree link list consist of the following parameters:

(i) Position: represented by the $X$ and $Y$ coordinates of the upper left corner of each block
(ii) Size: represent the size of each image block, which is equal either to width or height of the image block, since in quad tree the blocks have square shape
(iii) Next: it is a pointer to the next block in the quad tree

**Step 4:** The segmentation process by quad tree algorithm start with partitioning the image into blocks whose size is equal to the maximum allowable block size.

**Step 5:** Check the uniformity criteria for each sub-block as follows:

A. Compute the local mean of the sub-block ($m$).
B. Compute number of undesired pixels within the sub-block ($N_p$), which may differ from the mean value ($m$) by distance more than ($\sigma_e$), those pixels satisfy the condition

$$|f(x, y) - m| > \sigma_e,$$

Where, $f(x, y)$ is the pixel value.
C. If the ratio of undesired pixels ($N_p/S$), where $S$ is the block size, is less than the acceptance ratio then the block is considered uniform (i.e., don’t partition), otherwise the block should be partitioned into four child sub-blocks (corresponding to create new four quad tree link list records). Each block should be examined by measuring its uniformity if it does not satisfy the uniformity criteria, then the partitioning is repeated until the uniformity condition is satisfied or the child block reach the minimum size. After completing the partitioning sequence, the constructed quad tree will consist of partitions whose size value will be between the minimum and maximum block size.

Figure-8 show the segmentation results using quad tree algorithm of the PCA1 image with different segmentation control parameters for Landsat-5 TM (27/8/1984) satellite image. It is observed that the sizes of the image blocks are variable. In all parts, the block size was automatically determined according to the details variety. The testing results had indicated that the used algorithm is a simple
and powerful framework for the quad tree segmentation. The control parameters have different influence on the segmentation results. In our work, the best results were obtained when the control parameters as the following: maximum block size=8, minimum block size=4, inclusion factor =0.5, acceptance ratio=0.1 and mean factor=0.05.

![Quad Tree Segmentation Results](image)

**Figure 8**- Results of quad tree segmentation applied on the PCA-1 image generated from Landsat-5 (TM) satellite image (1984) with different partitioning control parameters

3. Satellite Image Classification:

This section aims to investigate the ability of the ACS algorithm to solve the problem of classifying varsity areas of satellite images in terms of its semantic concepts. ACS algorithm is used to estimate the number of classes that may be found in the satellite image, and then classify the image according to the determined classes. Image classification stage begins with computing the median ($M_i$) and variance ($V_i$) for each image part, where the subscript ($i$) is pointer refers to the current part of the image. Initially assign the values of number of iteration ($n$), number of ants ($m$), and initial pheromone value ($\tau_0$). For each part, the initial amount of pheromone is ($\tau_0$), and there are ($m$) of ants begin to moving. Each ant should select a part for the next movement that is not selected previously. To find out the parts is been selected or not, a flag value is assigned for each part. The flag values are set to be "0" at each time when new ant gets down; once the part is selected the flag is changed to "1". The first ant remains moving until there is no choices are found, another ant will be get down in the same part, and so on until the last ant. This procedure is followed for all the parts. Each time when the ant...
randomly selects the \((k^{th})\) part, the median \((M_k)\) and variance \((V_k)\) are stored in the solution matrix, and the pheromone updated using the following equation.

\[
\tau_{\text{new}} = (1 - \rho)\tau_{\text{old}} + \rho \tau_{\text{old}}
\]  

(4)

Where, \((\tau_{\text{new}})\) and \((\tau_{\text{old}})\) are the new and old pheromone values of the current part, and \((\rho)\) is rate of pheromone evaporation parameter \((0<\rho<1)\). When the ant completes its tour, calculate the average of the medians \((A_m)\) and the average of variances \((V_m)\) of the selected parts by each ant using the solution matrix. The \((A_m)\) is the average of the parts median that individual ant chooses them in one tour. After completing all parts, the process of ants getting down is repeated \((n)\) times. The number of labels in the solution matrix is the number of classes in the image. The ACS for classification was applied with the following setting; \(n=40, m=50, \rho=0.9, \tau_c=0.001, \alpha=1, \beta=1\) and \(\Omega\) (implies the tolerable ant’s movement range; \(8\)-connectivity neighborhoods). Therefore, the optimal number of classes determined by ACS was five-land cover classes. Then the image is now unsupervised classified by minimizing the distance between its average medians \((A_m)\) and the class that belong to. The following steps summarize the algorithm of ACS for Landsat image classification.

**Algorithm 3- Satellite Image Classification using ACS Algorithm**

**Input:**
- PC Img: two-dimensional array is the first PC image
- Width: width of the image band
- Height: Height of the image band

**Output:**
- ClasImg: two-dimensional array represents the colored map of classification results

**Procedure:**

**Step 1:** For each pixel \((k^{th})\) in the image, compute the median \((M_k)\) and variance \((V_k)\) values.

**Step 2:** Initialize the values of number of iterations \((n)\), number of ants \((m)\), initial pheromone value \((\tau_c)\) and a constant value for pheromone update \((\rho)\).

**Step 3:** Create a solution matrix \((S)\) to store the labels, \(M_k, V_k, \) flag, pheromone for each pixel.

**Step 4:** take new \((k^{th})\) pixel in the target image.

**Step 5:** Let new ant get down to the \((k^{th})\) pixel, make the flag to be zeros.

**Step 6:** Select a random part, which is not selected previously, according to a probabilistic choice.

**Step 7:** Update the pheromone values for the selected pixel by the current ant.

**Step 8:** Perform steps (6-7) until no possible choices for the current ant.

**Step 9:** Assign unique label for the pixels visited by the current ant, store them in solution matrix \((S)\).

**Step 10:** Perform steps 5-9 for \((m)\) ants.

**Step 11:** Do steps (4-10) until last pixel found in the target image.

**Step 12:** Back to step 5 for \((n)\) times.

**Step 13:** Pixels with same pheromone have same labels.

**Step 14:** Assign a specific color for each label in the solution matrix, and draw the image \((\text{ClasImg})\) with the new coloring, which is the classified image.

In this method, Landsat images at different time classified into five land cover classes. These classes represent five major features in the study area (water bodies, open land (barren land), vegetation, residential I and residential II). The results from applying ACS classification algorithm are shown in Figure-9 for Landsat (TM, ETM+ and OLI) satellite images. Table-5 shows the results of classification statistics for all three Landsat satellite images (TM 1984, ETM+ 2000 and OLI 2015) using ACS algorithm.
Figure 9- Result of Landsat satellite images classification using ACS algorithm
(A) Landsat-5 (TM) satellite image (27/8/1984), (B) Landsat-7 (ETM+) satellite image (31/8/2000)
(C) Landsat-8 (OLI) satellite image (1/8/2015)

Table 5 - Results of classification statistics for all three Landsat satellite images using ACS algorithm

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Area (KM²)</td>
<td>Percent</td>
<td>Area (KM²)</td>
</tr>
<tr>
<td>Water</td>
<td>Blue</td>
<td>12.4901985</td>
<td>1.7672</td>
<td>11.5169638</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Green</td>
<td>63.0892139</td>
<td>8.9263</td>
<td>132.375466</td>
</tr>
<tr>
<td>Residential I</td>
<td>Red</td>
<td>246.335098</td>
<td>34.8532</td>
<td>226.970061</td>
</tr>
<tr>
<td>Residential II</td>
<td>Magenta</td>
<td>341.212405</td>
<td>48.2771</td>
<td>246.270782</td>
</tr>
<tr>
<td>Open Land</td>
<td>Yellow</td>
<td>43.6527914</td>
<td>6.1763</td>
<td>89.645728</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>706.7797068</td>
<td>100%</td>
<td>706.7790008</td>
</tr>
</tbody>
</table>

Satellite Image Classification using Envi 5.1 Software:

The methodology adopted for this stage including different image techniques: geometric correction, radiometric correction, atmospheric correction, false color composite (bands 4, 3, 2 for TM and ETM+ images and bands 5, 4, 3 for OLI images) and image enhancement. Supervised classification was used in satellite image classification process. The algorithm used in supervised classification was the maximum likelihood classifier method to produce the land cover maps from Landsat TM, ETM+, and OLI satellite images for years 1984, 2000 and 2015. The block diagram of this methodology is shown in Figure-10.
The training area collected from all imageries by selecting the region of interest (ROIs) using Envi 5.1 Software Tools, the study area classified into five classes (residential I, residential II, vegetation, open land and water bodies). Therefore, five ROIs were collected for Landsat images. Figure-11 shows the results of supervised classification for Landsat (TM, ETM+ and OLI) satellite images using maximum likelihood classifier method. The image classification of the study area resulted into five land cover types. Table-6 show the results of supervised classification statistics for all three years (1984, 2000 and 2015) using maximum likelihood classifier method.
Figure 11- Result of supervised classification using maximum likelihood classifier method
(A) Landsat-5 (TM) satellite image (27/8/1984), (B) Landsat-7 (ETM+) satellite image (31/8/2000)
(C) Landsat-8 (OLI) satellite image (1/8/2015)

Table 6- Results of supervised classification statistics for all three Landsat satellite images using Maximum Likelihood method

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Area (KM²)</td>
<td>Percent %</td>
<td>Area (KM²)</td>
</tr>
<tr>
<td>Water</td>
<td>Blue</td>
<td>12.636</td>
<td>1.787829</td>
<td>12.4146</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Green</td>
<td>63.8127</td>
<td>9.028664</td>
<td>134.8038</td>
</tr>
<tr>
<td>Residential I</td>
<td>Red</td>
<td>251.2566</td>
<td>35.549528</td>
<td>223.5699</td>
</tr>
<tr>
<td>Residential II</td>
<td>Magenta</td>
<td>335.1609</td>
<td>47.420891</td>
<td>241.6968</td>
</tr>
<tr>
<td>Open Land</td>
<td>Yellow</td>
<td>43.9128</td>
<td>6.213088</td>
<td>94.2939</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>706.779</td>
<td>100%</td>
<td>706.779</td>
</tr>
</tbody>
</table>
Land Cover Change Detection:

In our work, monitoring land cover changes was achieved using three Landsat satellite images taken at different times represented by three dates; 1984, 2000 and 2015. The changes in land cover occurred in the study area in the period from 1984 to 2015 have been calculated by the subtraction processes. The results or the changes in land cover classes are illustrated in Tables-7 and 8 for ACS classification algorithm. While, tables 9 and 10 show the results of changes in land cover classes for maximum likelihood classifier method. Where the changes are given in square kilometers and in percent. The type of change (decrease or increase) is also shown.

Table 7- Changes in the Land Cover of the Period from 1984 to 2000 for Baghdad city using ACS Classification algorithm

<table>
<thead>
<tr>
<th>CLASS NAME</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Relative Changes for Area (km²)</th>
<th>(2000-1984) Relative Changes %</th>
<th>Type of Change in Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>12.4901985</td>
<td>1.7672%</td>
<td>11.5169638</td>
<td>1.6295%</td>
<td>-0.9732347</td>
<td>-7.79 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Vegetation</td>
<td>63.0892139</td>
<td>8.9263%</td>
<td>132.375466</td>
<td>18.7294%</td>
<td>69.2862521</td>
<td>109.82 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Residential I</td>
<td>246.335098</td>
<td>34.8532%</td>
<td>226.970061</td>
<td>32.1133%</td>
<td>-19.365037</td>
<td>-7.86 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Residential II</td>
<td>341.212405</td>
<td>48.2771%</td>
<td>246.270782</td>
<td>34.8441%</td>
<td>-94.941623</td>
<td>-27.82 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Open Land</td>
<td>43.6527914</td>
<td>6.1763%</td>
<td>89.645728</td>
<td>12.6837%</td>
<td>45.9929366</td>
<td>105.36 % increase</td>
<td>increase</td>
</tr>
</tbody>
</table>

Table 8-Changes in the Land Cover of the Period from 1984 to 2015 for Baghdad city using ACS Classification algorithm

<table>
<thead>
<tr>
<th>CLASS NAME</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Relative Changes for Area (km²)</th>
<th>(2015-1984) Relative Changes %</th>
<th>Type of Change in Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>12.4901985</td>
<td>1.7672%</td>
<td>19.3127362</td>
<td>2.7325%</td>
<td>6.8225377</td>
<td>54.62 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Vegetation</td>
<td>63.0892139</td>
<td>8.9263%</td>
<td>118.285827</td>
<td>16.7359%</td>
<td>55.1966131</td>
<td>87.48 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Residential I</td>
<td>246.335098</td>
<td>34.8532%</td>
<td>266.110068</td>
<td>37.6511%</td>
<td>19.77497</td>
<td>8.02 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Residential II</td>
<td>341.212405</td>
<td>48.2771%</td>
<td>229.710243</td>
<td>32.5010%</td>
<td>-111.502162</td>
<td>-32.67 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Open Land</td>
<td>43.6527914</td>
<td>6.1763%</td>
<td>73.3601263</td>
<td>10.3795%</td>
<td>29.7073349</td>
<td>68.05 % increase</td>
<td>increase</td>
</tr>
</tbody>
</table>

Table 9- Changes in the Land Cover of the Period from 1984 to 2000 for Baghdad city using Maximum Likelihood Classifier Method

<table>
<thead>
<tr>
<th>CLASS NAME</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Relative Changes for Area (km²)</th>
<th>(2000-1984) Relative Changes %</th>
<th>Type of Change in Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>12.636</td>
<td>1.787829%</td>
<td>12.4146</td>
<td>1.756504%</td>
<td>-0.2214</td>
<td>-1.75 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Vegetation</td>
<td>63.8127</td>
<td>9.028664%</td>
<td>134.8038</td>
<td>19.072978%</td>
<td>70.9911</td>
<td>111.24 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Residential I</td>
<td>251.2566</td>
<td>35.549528%</td>
<td>223.5699</td>
<td>31.63222%</td>
<td>-27.6867</td>
<td>-11.01 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Residential II</td>
<td>335.1609</td>
<td>47.420891%</td>
<td>241.6968</td>
<td>34.196941%</td>
<td>-93.4641</td>
<td>-27.88 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Open Land</td>
<td>43.9128</td>
<td>6.213088%</td>
<td>94.2939</td>
<td>13.341356%</td>
<td>50.3811</td>
<td>114.72 % increase</td>
<td>increase</td>
</tr>
</tbody>
</table>

Table 10- Changes in the Land Cover of the Period from 1984 to 2015 for Baghdad city using Maximum Likelihood Classifier Method

<table>
<thead>
<tr>
<th>CLASS NAME</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Area (km²)</th>
<th>Percent %</th>
<th>Relative Changes for Area (km²)</th>
<th>(2015-1984) Relative Changes %</th>
<th>Type of Change in Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>12.636</td>
<td>1.787829%</td>
<td>19.7073</td>
<td>2.788326%</td>
<td>7.0713</td>
<td>55.96 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Vegetation</td>
<td>63.8127</td>
<td>9.028664%</td>
<td>126.2628</td>
<td>17.864538%</td>
<td>62.4501</td>
<td>97.86 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Residential I</td>
<td>251.2566</td>
<td>35.549528%</td>
<td>274.7979</td>
<td>38.880315%</td>
<td>23.5413</td>
<td>9.36 % increase</td>
<td>increase</td>
</tr>
<tr>
<td>Residential II</td>
<td>335.1609</td>
<td>47.420891%</td>
<td>212.1552</td>
<td>30.017191%</td>
<td>-123.0057</td>
<td>-36.70 % decrease</td>
<td>decrease</td>
</tr>
<tr>
<td>Open Land</td>
<td>43.9128</td>
<td>6.213088%</td>
<td>73.8558</td>
<td>10.449631%</td>
<td>29.943</td>
<td>68.18 % increase</td>
<td>increase</td>
</tr>
</tbody>
</table>
From classification results using (ACS and maximum likelihood algorithms), the present study allows estimating the amount of significant land cover changes occurred at the study area during the two periods. The most significant change for the period 1984-2015 is represented by increasing the water body, area of vegetation, open land and urban area "residential I" (positive change), while, the change was negative represented by decrease of urban area “residential II”. The results from applying ACS classification algorithm showed that the water, vegetation area, residential I and open land are in increase, water increased about 54.62%, vegetation area about 87.48%, "residential I" about 8.02% and finally open land increased about 68.05% in 2015 comparable with 1984, while, the second type from urban area “residential II” in decrease, about 32.67% in 2015 comparable with 1984. The results from applying maximum likelihood classifier method showed that the water, vegetation area, residential I and open land are in increase, water increased about 55.96%, vegetation area about 97.86%, "residential I" about 9.36% and finally open land increased about 68.18% in 2015 comparable with 1984, while, the second type from urban area "residential II" in decrease, about 36.70% in 2015 comparable with 1984.

Classification Accuracy Assessment:

Accuracy assessment is a procedure for quantifying how good a job was done by a classifier or how accurate out classification is. Accuracy assessment is an important part of classification. It is usually done by comparing the classification product with some reference data that is believed to reflect the true land cover accurately [28]. Sources of reference data include ground truth, higher spatial resolution images, and maps refer to Google map or Google Earth as needed. Assessing of the final classification results has been performed manually on a field basic. In our work, number of random points have been chosen on each of classified images. These points compared with reference points. The results of accuracy assessment for all classification methods (ACS and maximum likelihood methods) are shown in Table-11.

Table 11- Accuracy Assessment Results

<table>
<thead>
<tr>
<th>Classification Type</th>
<th>Satellite Image</th>
<th>Year</th>
<th>Accuracy Assessment (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACS Classification Algorithm</td>
<td>Landsat-5 (TM)</td>
<td>1984</td>
<td>83%</td>
</tr>
<tr>
<td></td>
<td>Landsat-7 (ETM+)</td>
<td>2000</td>
<td>85%</td>
</tr>
<tr>
<td></td>
<td>Landsat-8 (OLI)</td>
<td>2015</td>
<td>84%</td>
</tr>
<tr>
<td>Maximum Likelihood Classification Method</td>
<td>Landsat-5 (TM)</td>
<td>1984</td>
<td>92%</td>
</tr>
<tr>
<td></td>
<td>Landsat-7 (ETM+)</td>
<td>2000</td>
<td>93%</td>
</tr>
<tr>
<td></td>
<td>Landsat-8 (OLI)</td>
<td>2015</td>
<td>95%</td>
</tr>
</tbody>
</table>

Conclusions:

The basic idea of our work is to classify Landsat satellite images at different times for the study area using several methods and then compare the results of each method. From the results obtained, the following points are chosen for the present conclusions:

1. The study showed that the first factor of PCA bands often contain the majority of information residing in the original multi spectral Landsat images and can be used for more effective and accurate analyses because the number of image bands and the amount of image noises are reduced.

2. The first PCA layer is responsible for more than 95% of the total variation for each satellite image (95.8387%, 96.2976% and 99.1282% of the total variance for 1984, 2000 and 2015 Landsat images respectively). Therefore, the first principle component is suitable for classifying the multiband satellite images because, its contain the most ground information in study area and can be used to compare the changes in land cover classes in different years.

3. The primary stage of partitioning was accurately segmenting the image depending on the spectral uniformity, such that the founded block size differs from region to another in the image depending on the details found in that region. Therefore, the partitioning mechanisms using quad tree method produce small blocks when it contains high details, while the large blocks are produced if low details exit within the block.

4. The use of ACS algorithm was successfully determining the number of classes in the satellite image and showed good classification results. The classification accuracy for the proposed method ACS algorithm are 83%, 85% and 84% for years 1984, 2000 and 2015 respectively.
5. This research demonstrated the interest and efficiency of proposed method (PCA-transform, quad tree technique and ACS algorithm) as tools for detecting and monitoring changes of land cover processes of multi-spectral analysis with all spectral bands for different temporal intervals of satellite images.

6. Some factors such as selection of suitable change detection approach, suitable band and optimal threshold, may affect the success and accuracy of the classification.

7. Land cover dynamics is a result of complex interactions between human activities and natural factors. The effects of human activities are immediate and often radical, while the natural effects take a relatively longer period of time.

8. The results from classification process for study area indicated that water body, vegetation, open land and the first type from urban area “Residential I” are in increase (positive land cover change), while the second type from urban area “Residential II” in decrease (negative land cover change) for year 2015; comparable with 1984.

References:

1. Mamdouh, M. Abdeen and Fatima Al Masoudi. Utilization of Multi-Dates and Multi-Sensors Remote Sensing Data in Monitoring Land Use/Land Cover Changes in Kuwait, Geography Department, Kuwait University, Alshuwaykh, State of Kuwait.


