Digital Approaches for Change Detection in Urban Environment

Abstract

Remote sensing technology has shown its great capabilities to solve many earth resources issues. One of the most important applications of this technology is to detect land use/cover changes happened over a certain period of time. In this study, an attempt has been made to study urban land use/cover changes over a period of 10 years from 19-09-1988 to 04-4-1998. Using PCI Geomatica software package and after careful registration of two Land sat TM image data sets on each other, different digital image processing techniques such as simple image differencing, principal component analysis (PCA) and fuzzy logic were used to generate the change map of the city of Tehran, Iran. Most of the observed changes were in vegetation land use/cover category. The change image generated in this work could be a useful tool to urban managers for investigating and monitoring illegal use of land at urban areas.

Key Words: Remote sensing, Digital change detection, Urban management, Satellite images, Fuzzy logic.

Introduction

In all countries of the world and especially in developing countries, the extensions and developments of urban areas are faster than ever. This is mainly due to the growth of population that is recognized and taken as important measuring urbanization in any region. The three main reasons for this growth may be (i) migration from rural to urban areas; (ii) new town formation; and (iii) natural growth (births over deaths). The population of urban areas was not more than three per cent of the world’s population by the end of last century, but today even in the economically not so advanced countries, urban population constitutes a high percentage. For example, countries like Argentina, Brazil, Mexico, Egypt, Philippines, Malaysia and Nigeria have the high percentages of urban
population of 84%, 73%, 69%, 46%, 39%, 38%, 30% respectively. Some countries like Bangladesh, China, Indonesia, Sri Lanka and Thailand have the low level of urbanization. More than half of the world’s population is expected to live in urban areas by the year 2000. A close look at Table 1.1 in which the world urban population is shown indicates that the world’s urban population has increased from 29% to 41%. The growth of urban population in most developed countries and less developed countries show an increase of 19% and 14% respectively.

Table 1.1. World urban population

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Millions</td>
<td>%</td>
<td>Millions</td>
</tr>
<tr>
<td>North America</td>
<td></td>
<td>105</td>
<td>64</td>
<td>196</td>
</tr>
<tr>
<td>Western Europe</td>
<td></td>
<td>177</td>
<td>60</td>
<td>260</td>
</tr>
<tr>
<td>Oceania</td>
<td></td>
<td>8</td>
<td>64</td>
<td>17</td>
</tr>
<tr>
<td>Latin America</td>
<td></td>
<td>67</td>
<td>41</td>
<td>237</td>
</tr>
<tr>
<td>Eastern Europe/Soviet Union</td>
<td></td>
<td>108</td>
<td>39</td>
<td>243</td>
</tr>
<tr>
<td>North Africa/Middle East</td>
<td></td>
<td>26</td>
<td>26</td>
<td>112</td>
</tr>
<tr>
<td>East Asia</td>
<td></td>
<td>112</td>
<td>17</td>
<td>358</td>
</tr>
<tr>
<td>South East Asia</td>
<td></td>
<td>23</td>
<td>13</td>
<td>90</td>
</tr>
<tr>
<td>South Asia</td>
<td></td>
<td>69</td>
<td>15</td>
<td>199</td>
</tr>
<tr>
<td>Sub-Saharan Africa</td>
<td></td>
<td>17</td>
<td>10</td>
<td>80</td>
</tr>
<tr>
<td>World</td>
<td></td>
<td>712</td>
<td>29</td>
<td>1792</td>
</tr>
<tr>
<td>Most Developed Countries (MDC)</td>
<td></td>
<td>457</td>
<td>53</td>
<td>842</td>
</tr>
<tr>
<td>Less Developed Countries (LDC)</td>
<td></td>
<td>255</td>
<td>16</td>
<td>950</td>
</tr>
</tbody>
</table>

* Estimated

Source: Department of Economic and Social Affairs, New York, 1976.

Most of these extensions and developments are in urban fringe wherein the agricultural land and rural settlements are converted to urban and industrial areas. Apart from new economic opportunities through provision of employment in new industries, including the provision of several other infrastructure facilities (e.g., transport, communication and electricity lines), a number of problems like air and water pollution, water scarcity, transportation etc. are associated with the development and extension of urban areas.
One of the most important applications of remotely sensed data is to find changes from one date to another. Many investigators like agricultural scientists, urban planners, geologists, etc. use these data to find and locate changes over a certain period of time. For most of them, it is a necessity to know where and what the type and magnitude of the change is. The basic idea behind any change detection is to compare two or more images/maps or in general compare the data of the same geographical area to find and mark non-similar features on the available data. The way of doing these comparisons could be divided into two broad categories.

The first way is to use conventional methods that are mainly based on the simple overlay of the raw/interpreted data and draw the boundaries of changed areas. The second method is to use advanced computer processing facilities and digital satellite remote sensing data. As far as time, cost and accuracy are concerned, the second way has advantages over the first one.

In the concept of change detection using satellite images, a number of different methods have been adopted. Lo (1986) classified these methods into three major approaches: (1) band rationing; (2) transformation enhancement of multi-temporal data; and (3) post classification comparison change detection. Later on in a review article, Singh (1989) classified these techniques into ten different approaches: (1) univariate image differencing; (2) image regression; (3) image rationing; (4) vegetation index differencing; (5) principal components analysis (PCA); post classification comparison; (7) direct multi-date classification; (8) change vector analysis; (9) background subtraction; and (10) other methods which include Kalmogorov-Smirnov test and the use of correlation coefficient as an indicator of change.

According to Lo (1986), the digital nature of most satellite data makes it amenable to computer-aided analysis. In digital analysis, although the information content of the satellite data can be fully utilized, so many factors should be considered before implementing any analysis. For example, successful remote sensing change detection requires careful attention to both (1) the remote sensing system and (2) environmental characteristics. Failure to understand the impact of the various parameters on the change detection process can lead to inaccurate results (Dobson et al. 1993).

Jensen (1996) offers a useful and more generalized review of digital change detection approaches. He describes some of the change detection algorithms that are commonly used: (1) change detection using write function memory insertion (band overlay); (2) multi-date composite image change detection; (3) image algebra change detection (band differencing or rationing); (4) post-classification comparison change detection; (5) multi-date composite image change detection using a binary
mask applied to date 2; (6) multi-date composite image change detection using ancillary data source as date 1; (7) manual, on-screen digitization of change; (8) spectral change vector analysis; and (9) knowledge-based vision system for detecting change. He has also summarized the advantages and disadvantages of all the above techniques.

Change investigators have used one or a combination of the above techniques to demonstrate changes over a certain period of time for a particular geographical area. In the work carried out by Howarth and Boasson (1993), the capabilities of digital enhancement for displaying change were investigated. They suggested that change enhancements could be used effectively by agencies responsible for monitoring urban development over large areas. Jensen (1993b) used overlay method to detect changes using SPOT panchromatic data of Par Pond in South Carolina. Byrne et. al. (1980), Richards (1984), Fung and LeDrew (1987, 1988) and Bauer et. al. (1994) used PCA to detect changes. Jiaju (1988) formed a three-dimensional three-date Landsat TM data set of an area between two cities of Motala and Mjolby, in the south of Sweden and applied PCA to it. Jensen et. al. (1993a) demonstrated the post classification comparison method by classifying two Landsat TM images of Kittredge and Fort Moultrie, S.C. and then compared the resultant maps using an n × n GIS matrix. Spell et. al. (1995) used Multi-Date Change Detection method using a Binary Change Map Applied to Date 2 to map changes over an area centered on the lower Columbia River between Washington and Oregon. Cowen et. al. (1991), Westmoreland and Stow (1992) and Cheng et. al. (1992) used the concept of On-Screen Digitization of changes to detect changes. The Change Vector Analysis Technique has been successfully applied to monitor changes in mangrove and reef ecosystem along the coast of the Dominican Republic (Michalek et. al. 1993) and for forest change mapping in the northern Idaho (Malila, 1980). Gong (1993) introduced a preprocessor to automatically perform a number of digital change detection techniques including image differencing, mask creation using principal component analysis, fuzzy supervised classification and attribute extraction.

Methods of modeling and detecting a general pattern of change associated with construction and potentially other kinds of activities in a 15,000 km² region in central Iraq using ten Landsat TM images were presented by Carlotto (1997). He included a new nonlinear prediction technique for measuring changes between images and temporal segmentation and filtering techniques for analyzing patterns of change over time. The theory of fuzzy subsets was first introduced by Zadeh in 1965. Wang (1990a) in a case study carried out in Southwest of Hamilton city, Ontario, Canada has shown the importance of fuzzy information representation for improving remote sensing data analysis and has emphasized the information loss in spectral space partition and classier
training, fuzzy partition of spectral space and improvement in overall classification accuracy. This study has also provided valuable input to develop a fuzzy maximum likelihood classification software in the VAX operating VMS environment to analyze the Indian Remote Sensing Satellite (IRS-1A) LISS-II data of 36.25 meter resolution of a mangrove land cover in Pichavaram which is located in the south-eastern coast of India (Zaeiyan Firouzabadi et. al., 1995a).

Also in another attempt, Madras metropolitan city urban land use/land cover areas were analyzed by using the same software (Zaeiyan Firouzabadi et. al., 1995b). This study showed a better performance of fuzzy classification over maximum likelihood classification and also showed better discrimination of mixed and unmixed land use/land cover categories. Zeaiean firouzabadi et.al. (1997, 2000) introduced a new visualization technique based on fuzzy logic to show urban changed areas over Madras city, India.

In this research work, an attempt was made to investigate urban land use/cover changes over a period of ten years using available remotely sensed data.

Study Area

Tehran, being the capital of Iran, has become a metropolitan during a period of 80 years. As a result of rapid political, economic and social change in Iran, Tehran had the chance of becoming more expanded. In 1920, Tehran had an area of about 7.2 km2. This was 60.6 km2 and 515 km2 in 1951 and 1981 respectively (Ghanavati, 1992). Figure 1 shows the physical expansion of this city during the last 80 years.

Figure 1. Expansion of Tehran During 1863 till 1988
Tehran is located in northern part of Iran in an area between desert and mountainous land. Its geographical latitude/longitudes are 35° 33’ N/51° 10’E and 35° 50’ N/51° 31’E respectively. The present land use/land covers of the study area are dense/less dense settlement area, roads, parks/forested park, orchards, open spaces, industrial area and agricultural fields. The average altitudes of southern, central and northern part of Tehran are 1100 m, 1200 and 1700 respectively. This means that there is a 600 meters height difference between the low and highest points in this city. In resent years, due to different factors such as population growth, immigration, and social and economic developments, the adjacent lands around Tehran have been occupied by people seeking a better living condition (Nazarian, 2002).

Data and Methodology

Landsat TM data pertaining to the study area acquired in 19-9-1988 and 04-04-1998 were used in this study. Figure 2 is the False color composite (FCC) of these data. Also 1:50000 topographic maps were used. PCI Geomatica V8.2 image processing software was used for data analysis and modeling.

Satellite digital data sets were imported by PCI Geomatica image processing software (version 8.2). Image to image registration module of this software was used to geometrically register the images of the subsequent dates. A first order polynomial transformation with a nearest neighborhood re-sampling scheme with 13 ground control points was used for registration purposes. The Root Mean Square errors of less than one pixel were the result of registration. After registration, different enhancement techniques like band subtraction, principal component analysis and combination of them were used to investigate the changed areas over a period of ten years. The fuzzy logic has also been used to combine the changes derived from enhancement techniques.

The principal component transformation, also referred to as the eigenvector transformation, the Hotelling transformation and the Karhunen-Loeve (K-L) transformation in the remote sensing and pattern-recognition literature, is a multivariate statistical technique, which is often used for determining the underlying statistical dimensionality of the image data set (Ready and Winz, 1973). In order to identify the changed and unchanged areas within the images, in the present study, PCA was applied to difference data sets. As discussed by Gong (1993), there are two problems associated with the above-mentioned traditional method of band differencing.
Landsat TM fcc image of Tehran 91-09-88

Landsat TM fcc image of Tehran 04-04-1998

Figure 2. FCC images of the study area
The first problem is that different types of change information are contained in different spectral bands; thus, the use of one spectral band usually does not allow every type of change to be detected. The second problem is that once threshold is applied to a difference image, change information occurring at smaller magnitudes will be lost. Also, noise could be included as change if its magnitude falls outside range (Gong, 1993). Of interest, scaled difference images derived from subtraction of four bands of Landsat TM images of 88 and 98 were put together to create a new data set. PCA was applied to this new data set and four new principal component difference (PCD) images were generated. The first two PCD images carry most of the change information and the others carry noise.

To overcome such problems, the following procedure suggested by Gong (1993) can be implemented after registration and band subtraction of two images.
1. Application of PCA to the difference images.
2. Determination of change membership functions for a number of selected change component images.
3. Application of fuzzy operations to combine change information in the different change component images into a single image.
4. Determination of change areas in the image derived from previous step.

High and low levels of redundancies have been observed in the difference images. This suggests that two transformed images would result from the PCA analysis containing most of the change information. After applying PCA to the difference image, the resultant principal component images (PCD’s) were analyzed to find out their statistical parameters like average, maximum, minimum and standard deviation. Each pixel value in the PCD images is the result of a linear transformation of the difference images with the transformation coefficients determined with PCA. Because the variance in a difference image represents primarily change information and the purpose of PCA is to preserve most variances into the first few principal components, the application of PCA to difference images will result in most change information preserved in the first few PCD images (Gong, 1993). The statistical parameters (average, maximum and minimum) of the PCD 1 and PCD 2 having histograms close to normal were then used to construct fuzzy membership function of change defined by Gong (1993). A fuzzy membership function of change, \( \mu_{cj}(\delta c) \), can be defined as:
Where \( \mu_{cj}(\delta e) \) represents the degree of pixel value \( \delta e \) in the image PCD\(_j\) belonging to a fuzzy set of change, C. \( L_\delta, \) ave, and \( H_\delta \) are the three parameters defining the inverse triangular-shaped function. To apply this formula to the PCD images, a procedural programme was developed and used in the modeling module of PCI image processing software. For the period between 88 to 98, equations (2) and (3) are the constructed fuzzy functions of change for PCD1 and PCD2 respectively.

\[
\begin{align*}
1 & \quad 0 \leq \delta e < L_\delta \\
(\delta e - \text{ave})/ (L_\delta - \text{ave}) & \quad L_\delta \leq \delta e < \text{ave} \\
(\delta e - \text{ave})/ (H_\delta - \text{ave}) & \quad \text{ave} \leq \delta e < H_\delta \\
1 & \quad H_\delta \leq \delta e \leq 255
\end{align*}
\]

By applying fuzzy membership function of change to the PCD images, a change membership (CM) image can be created. The change membership images (CM1 and CM2) of change can then be integrated into one image by applying the fuzzy set theory (Zadeh, 1965). In this study, the fuzzy union operation (maximum rule) was used to integrate the CM1 and CM2 images into the combined change membership (CCM) image. The resultant image (CCM) is the integration of the change information of the four bands. PCD3 and PCD4 did not account for to construct this function due to the shape of their histograms. Modeling module of PCI image processing software was used to apply fuzzy membership of change and fuzzy union. Figure 2 shows the combined change membership (CCM) image. In this figure, the white areas are the most changed areas and the black areas are the less changed area.
To identify the type of the change, images of two dates were classified using Maximum likelihood classification algorithm with 24 different training areas for 88 image and 26 training areas for 98 image. Only TM band 1, 2, 3 and 4 were used for the classification and equal prior probabilities were assigned to each class. The resultant classified outputs of this stage are shown in figure 4.

Statistics generated from classification of images of the years 88 and 98 are given in table 1.2 below. From this table, one cannot get the real changes happened during the study period. With masking out the real changed areas from Fuzzy Combined Change Membership (CCM) Image, the correct statistics were then generated.

<table>
<thead>
<tr>
<th>Land use cover</th>
<th>Snow cover</th>
<th>Mountains</th>
<th>Open spaces</th>
<th>Industrial area</th>
<th>Urban area/with or without vegetation</th>
<th>Clouds</th>
<th>Vegetation cover</th>
<th>Water body</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Pixels 88</td>
<td>399513</td>
<td>551234</td>
<td>345278</td>
<td>12039</td>
<td>954321</td>
<td>105056</td>
<td>645321</td>
<td>2021</td>
</tr>
<tr>
<td>No. of Pixels 98</td>
<td>0</td>
<td>481234</td>
<td>457345</td>
<td>10671</td>
<td>569787</td>
<td>8873</td>
<td>524564</td>
<td>1811</td>
</tr>
</tbody>
</table>

Figure 3. Fuzzy Combined Change Membership (CCM) Image
MLC classified output 1988

MLC classified output 1998

Figure 4. Classified outputs of MLC Algorithm.
Results

Though change information existing in different bands could be combined by the application of the band differencing, PCA and Fuzzy logic, no more information on the type of the change could be obtained. The image derived from these procedures shows the areas of major change. One can easily get information on the magnitude of the change based on the CCM image. Although most of the changes were in the southern part of Tehran (where the agricultural practices are undergone), these are not the real changes. This is due to the difference between the acquisition dates of the satellite data. Most of the agricultural fields were under cultivation in the image of 98 and without crops in 88.

Based on the study made on statistics derived from the classified outputs, it could be concluded that the Urban land use of Tehran was expanded during this period with an area of 243 Km². Approximately, an area of 120 Km² of open space was converted to urban land use. Agriculture lands have been converted to urban land use with an area of 81 Km². Orchards have been changed to urban areas with an area of 40 Km². It is worth mentioning that there have been no ground truth investigations for the above results. This is because of the difference between the data acquisition and the analysis date.

Discussion

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multi-temporal data sets. In this context, an attempt has been made to study the land use/land cover changes over the coastal urban city of Tehran. The major metropolitan city in Iran, Tehran is known to be affected by different factors such as urbanization. This factor is studied through digital change detection of satellite images. The techniques used in this study are from the simple band differencing to the complex fuzzy logic methods. The methodology adopted here mainly depends on digital image processing technique related to change detection. In the band subtraction method, pixels that have changed in brightness value between dates can be identified. There is no information about the land use/cover type of change between dates. Also, it requires a careful selection of change/no-change threshold (Jensen, 1996). Difficulties related to application of principal component analysis in change detection are mainly interpretation and labeling each component image. Fuzzy logic has proved its ability to combine change information between dates to one image. Different steps involved in this technique make it very complex. In classification of images using the MLC, due to complexity of the study.
area, several difficulties like separation of classes, the more number of rejected or unclassified pixels and the difficulties in selecting a suitable representative training site for specific land use/land cover are observed.

The results of classification showed that the area converted from green areas to built-up land is the major change in this study area. This result is most important to the urban planners to look at the issues related to the conversion of green areas to built-up land. Since many of the remote sensing data analyses for urban land cover classes mainly depend on the accuracy of classification algorithm as well as the resolution of satellite data, the fuzzy supervised classification can be used for accurate classification of mixed land cover categories (Zaeian Firouzabadi et.al. 1995b).

It is possible to produce dynamic change detection maps based on classified remotely-sensed images of several different dates. However, methods of assessing the uncertainties of these change detection maps are woefully inadequate and need to be further investigated. It is important for a user to understand the nature and spatial distribution of uncertainties when analyzing change detection results, as this minimizes the risk of making wrong decision based on uncertain data. Therefore, in decision making related to change detection, one needs to analyze not only the results of change but also the uncertainties of the detected results (Shi and Ehlers, 1996). New techniques of change analysis through membership of each pixel coupled with change type information can provide valuable information on the proportion of land use/land cover change to the planner.

References