Land Use Land Cover Mapping with Change Detection: A Spatio-temporal Analysis of NCT of Delhi from 1981 to 2015

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ABSTRACT

Land in urban areas is scarce. There is heavy competition amongst all users of urban a rapid transformation of Land use Land cover (LULC) and inter transferability of one land use function to another is apparent. The NCT of Delhi (India) undergoing rapid urbanization and rapid urban transformation furnishes one of the best examples of the above phenomena. Therefore, the main objective of the present study is to map and monitor the land use land cover (LULC) on one hand and to detect the patterns of LULC changes in spatio-temporal perspective on the other from 1981 to 2015. The study is based upon remote sensing data of Landsat 3(1981) and Landsat 8(2015) multispectral images for the study area. The supervised classification based on maximum likelihood classifier has been used to identify the four major categories of LULC modified from National Urban Information System (NUIS) Standards. The study shows that from 1981 to 2016 the land resources are affected adversely, vegetation cover from 41 percent of the total geographical area of NCT of Delhi in 1981 has recorded a decline of 23 percent in 2015, a decrease of about 50 percent during a span of 34 years. While open area in the above period has decreased to 9% in 2015 from 16% in 1981. The built up has expanded from 42 to 66% mostly at the cost of vegetation cover. The classification accuracy has been established through $K_{hat}$ statistics showing 0.84 and 0.79 for 1981 and 2015 respectively.

Keywords: Land use land cover, Change detection, Maximum likelihood classifier, Accuracy assessment, $K_{hat}$ statistics

1. Introduction

As per the United Nations estimates for 2016, around 54.5 % of the world population is residing in the cities. Amongst the 31 world's megacities (>10,000,000 population), Delhi with 26,454,000 population ranks second after Tokyo, Japan. With its vast population base and limited urban area of 1484 sq.kms, the average density as per 2016 population estimates comes to 17, 846 / sq. km. Therefore, land use land cover (LULC) mapping covering a span of around 35 years and change detection in the LULC major categories is an essential step towards overcoming the problems of degradation of environment and planned development of all major land use categories for a healthy and sustainable urban environment. Land use involves the employment of land management plans placed on the land cover by human agents to exploit the land cover and reflects human activities (Zubair, 2006). The process of land use landcover change is dynamic occurring on the bio-physical surfaces over time and space is an important part of natural resource studies (Rawat, 2013) For sustainable monitoring of urban growth, regular supervision of land use land cover is necessary. Satellite
images and aerial photographs provide synoptic view of areas at different intervals. This data is used at various GIS platforms in order to extract required information.

Urbanisation has multi-dimensional impacts. Continued development is leading to urban sprawl and densification of cities, potentially leading to the impairment of ecosystem function in the urban landscape. Human driven ad intensification of land use is the major effect of urbanization. The study area selected is NCT of Delhi. Land use land cover (LULC) terms though used simultaneously for remote sensing data analysis, are different from remote sensing point of view. While land cover which is directly observable from remote sensing data includes mainly the natural or physical coverage of land features like vegetation/forest, water bodies, wet lands. This also includes land cover arising out of human modification of natural landscape through a particular land use function like agriculture, plantations, built up area and impervious surfaces and so on. Therefore, land use patterns arise out of as a chain of operations on land, carried out by humans, with the purpose to obtain products and benefits from the land. Land use, therefore modifies a given land cover by nature and is a significant parameter for urbanization and urban built up area in a rapidly urbanizing place.

So, natural scientists and social scientists have distinct variable perspectives about land use. The definition of land use as considered by social scientists is based on socio economic utility of land while natural scientists land use in terms of conditions of human activities like construction of buildings, agricultural use, forest use etc. resulting in change of landscape has altered the hydro-geomorphology, biogeochemistry and biodiversity of cities.

Information regarding land use and land cover is crucial for overcoming the problems arising out of uncontrolled urban development and environmental degradation. This defines the need for proper planning and management of land in the city which requires proper monitoring of LULC of the city with a reliable and real time data in spatio-temporal perspectives as provided by remote sensing.

Thus, remote sensing and GIS have emerged effective tools for evaluating LULC patterns in various points of time and also LULC change to focus on ‘how much, where, what type’ (Weng, 2001) of LULC changes have taken place. The present study aims in this direction.

1.1 Scope of the work

The LULC change detection studies coupled with identification of critical areas going through rapid changes in land use categories from one to another are the basis for a variety of application in spatial sciences. For geographers, the effective land management plans for resource utilization, conservation of biodiversity and planned urban development for an environmentally secure planning in a highly vibrant urban society as found in NCT of Delhi is of prime significance. The change detection further enables to probe deeper into the impacts of any ongoing phenomena in an urban environment like shrinking of urban forest cover and water bodies, changing hydro-geomorphology of the terrain, increase in built up area which finally impacts the rise of temperature and increase in air water and land pollution. Remote sensing and GIS has proved to be the most effective tool from its inception for planning of urban areas. However, with increasing development in geospatial technology, the scope of remote sensing data utilisation has widened. Therefore, the present study has taken up Landsat 3 and Landsat 8 images for studying the LULC of the NCT of Delhi.
1.2 Aims and objectives

1. To identify major LULC categories in NCT of Delhi for two point of time, 1981 and 2015.


3. To identify the magnitude and extent of urban problems arising out of LULC changes over a span of 34 years in NCT of Delhi from 1981 to 2015.

1.3 Study Area

The NCT of Delhi is located at 28.61°N, 77.23°E in north India (Figure 1). The city is surrounded by Indo-Gangetic plains in north and east, Thar Desert in the west, Aravalli Hills in the south. It is bounded by the states of Haryana in the north, west and south, by Uttar Pradesh in the east and Aravallis in the south. The terrain is mostly flat except in the north–northeast and south-southwest from the Aravallis of Rajasthan. Delhi ridge starts from the Aravalli range in south which encircles west with parts at a height of 318 m. River Yamuna which is very prone to periodic floods, flows through NCT of Delhi.

NCT of Delhi has always been a political, economic, social and cultural hub. Being a part of NCR and socio-economic hold over the surrounding states, it has always attracted in migrants from other states within the country and from different countries for availing better opportunities. Hence, this indicates an increase in population by immigration. Influx of population is specifically very high from adjoining states of Haryana, Uttar Pradesh and Rajasthan. This has turned to elevated infrastructural demands on a daily basis. Population pressure has resulted in exponential growth of demands from all socio-economic aspects. In spite of efforts from the Government satisfactory results with regards to demand-supply relationship is still not been achieved.

2. Database

Landsat images of NCT of Delhi were acquired 1981 and 2015 for the study. Both 1981 and 2015 data were obtained from USGS. The survey of India map was used to prepare the base map. Details of remote sensing data used have been shown in table 1.
Table 1: Details of remote sensing data

<table>
<thead>
<tr>
<th>Satellite</th>
<th>Sensor</th>
<th>No. of Bands</th>
<th>Spatial Resolution</th>
<th>Path</th>
<th>Row</th>
<th>Date of Acquisition</th>
</tr>
</thead>
<tbody>
<tr>
<td>LANDSAT 3</td>
<td>MSS</td>
<td>4</td>
<td>80m</td>
<td>148</td>
<td>40</td>
<td>1st July 1981</td>
</tr>
<tr>
<td>LANDSAT 8</td>
<td>OLI</td>
<td>11</td>
<td>30m</td>
<td>146</td>
<td>40</td>
<td>8th April 2015</td>
</tr>
</tbody>
</table>

3. Methodology

For obtaining the statistics of LULC patterns and change detection, the following methodology is adopted (Figure 2):

1. The toposheet map 53H from the Survey of India was used for mosaic and digitized to prepare the base map.

2. The Landsat 3 MSS 1981 and Landsat 8 OLI 2016 data obtained from USGS website, were geometrically and radiometrically corrected. The re-projected images are clipped by using the base map. A Level-I Classification based on the scheme given by National Urban Information System (NUIS) Standards has been done using feature-based supervised classification technique. This was done for two time period remote sensing data (1981 and 2015). The supervised classification method is based on Maximum likelihood classifier.

3. The change detection map was prepared based on the 1981 and 2015 LULC maps.

Figure 2: Methodological chart for land use land cover and change detection from 1981 to 2015

The steps involved in generating the LULC and change detection maps are as follows:

3.1 Image processing

After data acquisition image preprocessing is the most important step. This involves the techniques of 'geometric corrections, image enhancement, noise removal and topographic correction' (Butt et. al., 2015). In order to enhance the quality of an image, as perceived by human, image enhancement techniques are used. Satellite images when inspected in a computer by the user, may display inadequate information, which can become functional using the enhancement techniques.
For the present study, the survey of India Toposheet no. 53H was used for mosaic and digitized to prepare the base map. The base map was used to geometrically rectify the Landsat 3MSS and Landsat 8 OLI images which were downloaded from the USGS site. These images were imported to ERDAS Imagine version 9.3. Radiometric enhancement was done using contrast stretch. Image convolution filtering was also used for spatial enhancement through Kernel matrix. The layer stack option was used to generate the False Colour Composite (FCC) images. The images were geometrically rectified using image rectification, as poor geometric correction created problem of geo-linking the images for change detection. The Landsat1981 image was geo-referenced to the 2015 image. A second degree polynomial was used to rectify the images. Extraction of the Area of Interest (AOI) was done through subset option.

3.2 Image classification

Image classification aims at classifying all the pixels an image into desired land use land cover categories. Classification methods can be supervised or unsupervised classification. In supervised classification training sets are selected which statistically set apart the land use land cover categories. Whereas, in unsupervised classification identifies spectrally homogeneous groups which are later assigned to various land use land cover classes. Both classification techniques encompass pros and cons; however supervised method of classification is expected to give more precise result than the unsupervised one. (Iqbal and Khan, 2014).

For the present study feature based supervised classification has been used. Polygons were delimited to select the training samples for the pre-defined LULC categories. The pixels enclosed in the polygons were used to record the spectral signatures for the LULC categories. Then maximum likelihood classification technique was used for supervised classification of the imageries.

Maximum likelihood classifier has been used for supervised classification. The maximum likelihood process assumes each training class as normal distribution. Training data with bi or n nodal histograms in band are not suited. In certain cases individual nodes represent unique classes which should be looked upon individually labeled as separate training classes. Probability of a pixel of a particular set of n classes is calculated and then given to the class with highest probability.

3.3 Change detection

Observing the process of temporal and spatial change is done by the technique of change detection. This technique specifically involves analyzing multi temporal remote sensing details from the datasets quantitatively which helps in understanding the changes associated with LULC properties. Change detection is the process of identifying temporal change from one period to another to find out the total rate of change in LULC (Table 2) The change detection was also carried out to assess the inter transferability of one land use category to another on an overall basis. It further helps in identifying the most vulnerable parcel of land under a particular function being encroached upon by some other LULC function.
3.4 Accuracy assessment of image classification

Accuracy assessment evaluates the classified map with independent data. Accuracy of the classification is the probability in percentage that the classifier has labelled an image pixel into the ground truth class. It is the probability of a reference pixel being correctly classified.

The *Observed accuracy* is determined by diagonal in the error matrix. Chance agreement incorporates off-diagonal sum of product of rows and columns, totals of each class. The *producer’s accuracy* ‘provides the user with the number of pixels correctly classified in a particular category as a percentage of the total number of pixels actually belonging to that category in the image.’ The *user’s accuracy* is ‘determined using the number of correctly classified pixels to the total number of pixels assigned to a particular category’.

Kappa coefficient (*K_hat*): ‘a discrete multivariate technique of use in accuracy assessment’ and reflects the difference between actual agreement and agreement expected by chance and also measures the relationship between beyond chance agreement and expected disagreement.

**Quantifying Accuracy Assessment: K_hat Statistics**

*K_hat* is a numerical measure of the extent to which the percentage correct values of an error matrix are due to ‘true’ agreement versus ‘chance’ agreement.

\[
\hat{k} = \frac{\text{Observed accuracy} - \text{chance agreement}}{1 - \text{chance agreement}}
\]

The formula used is:

\[
\hat{k} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}
\]

Where:

N=total number of samples
r=number of classes
\(x_{ii}\) = diagonal values in the matrix
\(x_{i+}\) =total samples in row i
\(x_{+i}\)=total samples in column i

*K_hat* ranges between 0 and 1.0 in where 1 means true agreement (100% accuracy).

4. Results and discussion

The classification result provided a general idea of the key LULC features of the NCT of Delhi for the selected years. A comprehensive dataset with tabulations and area calculations can provide insight into the defined classes and changes across the landscape and this has to be shown graphically for better representation. (Johnson et.al. 2002).
For analyzing the given LULC in the landscape of the city for the period of 34 years, the remote sensing data of Landsat 3 MSS and Landsat TM OLI have been used for LULC classification and change detection. The four LULC categories opted from NSUI Scheme clearly reveals the role of interplay of both demographic and economic factors bringing about rapid changes in LULC in NCT of Delhi. The role of urbanization and urban development can be seen over the selected time period. The urban land use has impacted inter transferability of natural land cover to built up land cover from 1981 to 2015 as seen from the following analysis.

4.1 LULC Analysis of NCT of Delhi: 1981 and 2015

Data interpretation basically involves comparing the classes during the term of 34 years. The Figure 3 shows the classified images of NCT of Delhi showing different LULC classes for the years 1981 and 2015.

Massive LULC changes can be noticed during this period (Table 2). Built-up area of the city has expanded immensely. Urban structures cover around 40 percent of the land in NCT of Delhi. Jain et. al. In their study has cited Mazumder (2010) who states that in the mid 1990s there had been rapid economic growth which was driven by reinforcement of private segment service sectors. This was the outcome of the economic reform policy of 1991. Service sector rise led to the increasing demand for land for residential and infrastructural development. This also reduced contribution in agricultural sector, especially in case of Delhi. This also attracted population from outside thus increasing population pressure in the city. Mazumder attributed the dramatic change in built up area to the economic reform of the 1990s. In Delhi the changing pattern of economy played a major role in changing the LULC of the NCT of Delhi.

Table 2: Area under each LULC categories in NCT of Delhi:1981 and 2015
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<table>
<thead>
<tr>
<th>LULC categories</th>
<th>Area (in hectares)</th>
<th>Total Area (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up</td>
<td>63147.4</td>
<td>99721.2</td>
</tr>
<tr>
<td>Vegetation</td>
<td>61841.4</td>
<td>35069</td>
</tr>
<tr>
<td>Open area</td>
<td>23337.3</td>
<td>13500.3</td>
</tr>
<tr>
<td>Water bodies</td>
<td>2110.4</td>
<td>2146</td>
</tr>
</tbody>
</table>

**Figure 4:** Area (%) under each land use land cover category for 1981 and 2015

The figure 4 represents the area under LULC category for the years 1981 and 2015 in NCT of Delhi. Built up area has increased from contributed 42 percent (63147.4) of the total area in 1981 which increased to 66 percent (99721.2 hectares) in 2015. In 1981 contribution of vegetation and built up in the total land cover was almost same but by 2015 vegetation decreased considerably. In 1981 vegetation occupied 41 percent of the total land and in 2015 it was reduced to 23 percent, a decrease of 26772.4 hectares. This shows that built up expansion to vegetative land have been maximum. The other two categories show relatively less change. Open area has reduced from 12 percent in 1981 to 9 percent in 2015, while water body has remained almost same, as the River Yamuna is the only major water body in the city.

**4.2 Change detection in land use land cover in NCT of Delhi from 1981 to 2015**

Change detection involves various techniques aiming at reflecting the differences in digital image values in multi-date satellite images. Changes in LULC are complex and multidirectional. In many cases the net percent change of a certain class can show no considerable temporal change but can show changes in spatial terms (Jain et. al., 2016). Vegetation, for example, can decrease in spatial coverage in one area and at the same time can increase in another area, showing no change. But built-up classes do not get generally demolished rather their expanse is expected to be increased with time. Quantitative change in the landscape is reflected in from-to algorithm, thus allowing assessing the LULC changes.
Digital change detection is very useful to recognize the changes that have taken place from one land use category to another (Hegazy et al.). Net change in the LULC classes in NCT of Delhi from 1981 to 2015 has been shown in figure 5.

Table 3: Over all change detection matrix (1981-2015)

<table>
<thead>
<tr>
<th>Change Detection Matrix (in thousand hectares)</th>
<th>Built-up area</th>
<th>Vegetation</th>
<th>Open area</th>
<th>Water bodies</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up area</td>
<td>36.179</td>
<td>22.915</td>
<td>9.172</td>
<td>0.763</td>
<td>69.029</td>
</tr>
<tr>
<td>Vegetation</td>
<td>12.274</td>
<td>24.233</td>
<td>6.187</td>
<td>0.188</td>
<td>42.882</td>
</tr>
<tr>
<td>Open Area</td>
<td>13.668</td>
<td>13.501</td>
<td>7.729</td>
<td>0.273</td>
<td>35.171</td>
</tr>
<tr>
<td>Water bodies</td>
<td>0.940</td>
<td>1.098</td>
<td>0.208</td>
<td>0.394</td>
<td>2.640</td>
</tr>
<tr>
<td>Total</td>
<td>63.061</td>
<td>61.747</td>
<td>23.296</td>
<td>1.618</td>
<td>149.721</td>
</tr>
</tbody>
</table>

Change/no-change matrix (Table 3) was prepared for the 1981-2015 time intervals. ‘In these matrices, the element in the (i)th row and the (j)th column are the number of pixels of class i from the first image (i.e. initial date) and of class j from the second image (i.e. later date). The land-cover proportion of the (i)th class of the first image corresponds to its relative marginal frequency ni.'
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\[ n_i' = \frac{n_i}{n} = \sum_{j=1}^{q} \frac{n_{ij}}{n} \]

Where, \( n_i \) is the marginal frequency of the class i, \( n_{ij} \) is the number of pixels of the class i from the first image that were changed to the class j in the second image, \( n \) is the total number of pixels of the images.” (Petit et. al., 2001)

\[ q \]

\[ ni \]

\[ nij \]

\[ n \]

\[ ni' = \frac{n_i}{n} = \sum_{j=1}^{q} \frac{n_{ij}}{n} \]

Figure 6: Change in LULC from 1981 to 2015 in NCT of Delhi

During the span of 34 years, vegetation, open area and water bodies have shown negative change, while built-up has increased tremendously (Figure 6). From 1981 to 2015 a total of 6073.8 hectares has gone to the built-up category from the other categories. All the other categories have shown negative changes. 38772.4 hectares of vegetative land has been lost during this period.

4.3 Accuracy assessment of the classified maps of NCT of Delhi: 1981 and 2015

In order to assess the quality of a classification, it is very necessary to evaluate the accuracy of the classification. A discrete multivariate technique has been used to determine the accuracy of the classified map. The technique used is known as Kappa Coefficient. The observations based on which the classification is evaluated were selected using simple random sampling.

The most common way to access the accuracy of a classification is by calculating the error matrix. Overall accuracy, User’s accuracy and Producer's accuracy, and omission and commission errors (Table 4, 5) are then calculated using the error matrix from which kappa statistics have been calculated (Reis, 2008; Torahi et. al.,2011).

Table 4: Producer’s accuracy and User’s accuracy

<table>
<thead>
<tr>
<th>Landsat 3 MSS 1981</th>
<th>Producer's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waterbodies</td>
<td>91.9598</td>
<td>68.79699</td>
</tr>
<tr>
<td>Vegetation</td>
<td>98.30202</td>
<td>91.2169</td>
</tr>
<tr>
<td>Open Area</td>
<td>90.93231</td>
<td>60.90676</td>
</tr>
</tbody>
</table>
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<table>
<thead>
<tr>
<th>Built up</th>
<th>89.47019</th>
<th>Builtup</th>
<th>98.98434</th>
</tr>
</thead>
</table>

### Landsat 8 OLI 2015

<table>
<thead>
<tr>
<th>Product's Accuracy</th>
<th>User's Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Builtup</td>
<td>81.19474</td>
</tr>
<tr>
<td>Vegetation</td>
<td>69.7006</td>
</tr>
<tr>
<td>Open Area</td>
<td>95.87251</td>
</tr>
<tr>
<td>Waterbodies</td>
<td>82.77808</td>
</tr>
</tbody>
</table>

Table 5: Omission errors and commission errors

<table>
<thead>
<tr>
<th>Landsat 3 MSS 1981</th>
<th>Omission Errors</th>
<th>Commission Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waterbodies</td>
<td>8.040201</td>
<td>Waterbodies</td>
</tr>
<tr>
<td>Vegetation</td>
<td>1.697977</td>
<td>Vegetation</td>
</tr>
<tr>
<td>Open Area</td>
<td>9.067688</td>
<td>Open Area</td>
</tr>
<tr>
<td>Builtup</td>
<td>10.52981</td>
<td>Builtup</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Landsat 8 OLI 2015</th>
<th>Omission Errors</th>
<th>Commission Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Builtup</td>
<td>18.80526</td>
<td>Builtup</td>
</tr>
<tr>
<td>Vegetation</td>
<td>30.2994</td>
<td>Vegetation</td>
</tr>
<tr>
<td>Open Area</td>
<td>4.127494</td>
<td>Open Area</td>
</tr>
<tr>
<td>Waterbodies</td>
<td>17.22192</td>
<td>Waterbodies</td>
</tr>
</tbody>
</table>

The overall accuracy assessment for 1981 and 2015 classified images is 91.5 percent and 91.8 percent respectively which is highly reliable.

User’s accuracy (Table.4) leads to errors of commission or inclusion of one category to another. The user accuracy for the most dominant category, built up category of 1981 is 98.9 percent, which shows strong agreement but the user accuracy for built up has come down to 74.3 percent in 2015, which shows moderate agreement. It reflects that for 1981 the image classification from the Landsat 3 MSS data results are highly reliable for built up category but for Landsat 8 OLI data, the built-up signatures were confused with open area signatures due to rise in the soil cover in Delhi which must have interfered with the spectral signature of built-up area. This requires further in-depth analysis and extensive field verification to obtain an accuracy of at least 80 percent.

Producer’s Accuracy leads to error of omission or exclusion i.e., lack of particular pixels from one class giving to another class. Therefore, producer’s accuracy is important from the point of view of classifying a map or how accurate is the map. For 1981 image, 10.5 percent of the built-up is identified as something else, while for 2015 image was 18.8 percent of the built-up is identified as something else (omission error). For 1981 image 1.01 percent of the classified built-up are not built-up and for 2015 image 25.6 percent of the classified built-up are not built-up (commission error). The signature confusion between built-up and non built-up as identified under user accuracy is also reflected here for both Landsat 3 MSS 1981 and Landsat 8 OLI 2015.
The Kappa Statistics are 0.84 and 0.79 respectively for the 1981 and 2015 images respectively.

The $K_{hat}$ of 0.84 for 1981 corresponds to both high overall accuracy and suitability of Landsat 3 data for assessing all major LULC categories like vegetation, built up, water bodies and open area. However the Kappa coefficient of 0.79 highlights confusion in separating spectral signatures between open area and built up area worked out from Landsat 8 data. Therefore to improve accuracy of classification scheme from Landsat 8 OLI data, it is required that prior probabilities in maximum likelihood classifier to be set up first especially in case of land use classes as these affect the assessment of land cover classes as found in case of open area and built up area.

5. Outputs and its applications

“Land-use planning is defined as a systematic assessment of land and water potential, alternatives for land use, and the economic and social conditions required to select and adopt the best land-use options” (Sharma et.al, 2009). Though GIS and RS technique is an essential tool for analyzing the LULC and change detection in a fast urbanizing landscape like NCT of Delhi, the selection and suitability of image classification can affect final results. However, for the present study the all aims formulated have been almost met out satisfactorily as confirmed by statistical analysis.

An important characteristic of the study was to note the erosion of landscape elements i.e. loss of vegetation, water bodies etc. Though, the study shows the degree of such loss, the effects of such loss was not attempted (Sudhira et.al., 2004).

In NCT of Delhi, the emerging sectors of commercial, industrial and institutional status have attracted population and still acting as pull factors due to which existing land cover in NCT of Delhi is going through rapid urban transformation.

Regarding LULC and its change in spatio-temporal perspective from 1981 to 2015, the study reveals:

1. NCT of Delhi has recorded an exuberant increase of 36573.8 hectares (57.92%) of land during a span of 34 years.
2. In the same period, there has been a loss of 36, 6772 hectares (-43.29%) of vegetative land.
3. Open areas have also recorded a sharp decline of 9,873 hectares (-42.15%) but water bodies has rather increased by 35.6 hectares (1.69%).
4. The spatial pattern of built up area increase has shown that urban growth has spread outwards from central eastern parts in NCT of Delhi to the surrounding areas mostly in northern, western and southern parts in a radial pattern. While south and eastern Delhi Shahadra, Old Delhi and Mehrauli especially part lying along River Yamuna have been almost saturated from 1981 itself. Therefore, the vegetation loss has mostly been in fast urbanizing areas.

Thus in NCT of Delhi, built up areas has extended predominantly in the city. This leads to nearly spatial saturation in urbanization as seen in the Trans Yamuna region. If this trend of built up area growth continues, the vegetative land would become substantially less and this
may led to a major threat to the environment of NCT of Delhi. The results of LULC analysis and change detection patterns in NCT of Delhi in the span of 34 years has highlighted many aspects which can be of help to urban land management policy decisions.

Finally, urban development in a fast urbanizing city like in NCT of Delhi cannot be stopped but it can be restrained with the help of proper planning and management and directed towards a healthy city development. To achieve this target, satellite remote sensing has come out as an essential tool for observing and quantification of LULC change across different spatial and temporal scales. But its application requires undertaking micro level urban development studies and intensive field verification of urban objects/features especially with GPS to work out more efficiently the high resolution multi spectral data as felt during the course of present study.

6. References


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