Chapter 9 Assessing Pattern of Spatio-temporal Change in NCT of Delhi and its Peri-urban Areas using Geospatial Techniques

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Abstract Big Cities like Mumbai, Kolkata and Delhi, etc., are expanding very fast mainly due to changing socio-economic activities which in turn put pressure on land and natural environment of the cities. Rapid development of cities without proper planning and ecological concern has been a great challenge to the urban planners as well the policy makers to manage a livable environment for city dwellers. Development of new urban areas and expansion of existing cities is inevitable as it's an essential part of sustainable economy but uncontrolled and haphazard urban growth may raise serious problems related to environmental pollution, changes in urban micro climate, loss of biodiversity and ecological balance, human and traffic congestion, etc. Actual information on spatial distribution of different land use and land cover has multi-dimensional utility in planning and management of the land resources which is perceived as a key factor in the process of development of an area. However, optimal use of land resource requires quantitative information on spatial distribution as well as spatio-temporal changes of various land use and land cover in an area. In this context remote sensing data and GIS techniques are well accepted and established tool for assessing the land dynamics. For this paper landsat data of 1977, 2003 and 2014 were used to assess the spatio-temporal change over NCT of Delhi and its per-urban areas within a buffer of 15 km from the outer boundary of NCT of Delhi. In order to identify the urban growth and associated land use land cover changes, change detection analysis was carried out. The study reveals that areas under different land use and land cover has changed during 1977–2003 and the level of change recorded maximum 14.5% increase in low-density built-up and 8.79% high-density built-up areas but sparse vegetation recorded 12.20% decrease in the NCT of Delhi. On the other hand there

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is just little change, i.e. an increase of about 9.09% in the low-density built-up and almost little change in the rest of the classes in the peri-urban areas. Furthermore the result shows that during 2003–2014 there is large scale change, i.e. 19.63% in high-density built-up area has been recorded at the cost of 8.4% sparse vegetation and 4.4% agricultural in the NCT of Delhi. In the peri-urban areas there is decrease of agricultural land of about 13% during last decades.

Keywords Spatio-temporal change \cdot Land use/land cover \cdot Geospatial technique \cdot NCT of Delhi \cdot Peri-urban area

Acronyms

9.1 Introduction

Megacities like Delhi are being changed everyday mainly due to anthropogenic activities which are causing increasing pressure on land and natural environment (Dutta et al. [2015a\)](#page-14-0). Rapid development of cities without proper planning and ecological concern has been a great challenge to the urban planners as well the policy makers to manage a livable environment for city dwellers. Development of new urban areas and expansion of existing cities is inevitable as it is an essential part of sustainable economy but uncontrolled and haphazard urban growth may raise serious problems related to environmental pollution, changes in urban micro climate, loss of biodiversity and ecological balance, human and traffic congestion and moreover quality of urban life. Since land resource is limited and over-exploitation of land may exaggerate problem of land degradation, optimum land use is required to achieve maximum benefit. Such types of studies are very important because the spatial characteristics of land use/land cover (LULC) are useful for understanding the various impacts of human activity on the overall ecological condition of the urban environment (Yeh and Li [1999](#page-15-0)). In this context, proper planning and management is essentially required for best utilization of land to meet the socio-economic demand as well as to preserve the sustainability.

Actual information on spatial distribution of different land use and land cover has multi-dimensional utility in planning and management of the land resources which is perceived as a key factor in the process of development of an area. However, optimal use of land resource requires quantitative information on spatial distribution as well as spatio-temporal changes of various land use and land cover in an area. Remote sensing technique has become an established and well accepted tool for acquiring information on land dynamics. In order to convert the satellite based data into reliable LULC information several image classification techniques are being used. Throughout the last decades researches have put their efforts towards minimizing the error and increasing the level of accuracy of image classifiers. As a result, a number of new algorithms for image classification (e.g. neural network, decision tree classification, SVM, LSU) have come up and become popular. Sub-pixel based linear spectral unmixing (LSU) is another important model which is used as a combined effect of transformation of built-up and vegetation cover to assess the growth of Dehradun city (Dutta et al. [2015b](#page-14-0)).

The Support Vector Machines (SVMs) originally rooted from Statistical Learning Theory has been adopted as a robust classifier in the arena of remote sensing due to its unparallel performance in detecting land use and land cover features (Huang et al. [2002;](#page-14-0) Mahesh and Mather [2003](#page-14-0); Guo et al. [2005;](#page-14-0) Pal and Mather [2005\)](#page-14-0). The SVM algorithms has achieved better results than traditional parametric classifiers (Pal and Mather [2005;](#page-14-0) Nooni et al. [2014\)](#page-14-0) and even better than nonparametric decision tree classifiers in terms of accuracy, simplicity, and robustness (Foody and Mathur [2004](#page-14-0)). The remote sensing implementations of SVMs is acknowledged as a promising machine learning methodology (Mountrakis et al. [2011;](#page-14-0) Nooni et al. [2014\)](#page-14-0) which can be applied for the purpose of mapping urban land cover, using medium spatial resolution imagery (Griffiths et al. [2010;](#page-14-0) Poursanidis et al. [2015\)](#page-14-0).

Monitoring the degree and extent of urban growth using geospatial techniques has been attempted by classifying satellite based images and quantifying the amount of area under various land use and land cover classes (Rahman et al. [2012;](#page-15-0) Elizabeth et al. [2008](#page-14-0); Rahman et al. [2009](#page-15-0); Netzband and Rahman [2007](#page-14-0); Rahman [2006;](#page-14-0) Netzband et al. [2005\)](#page-14-0). Addressing the estimation of urban growth has been a major topic of research considering its demand in urban planning as well as policies. Satellite-based data coupled with geo-information techniques have made this study more accurate, robust without spending much time and cost. The urban growth within a given area is characterized by increasing amount of built-up surface which is actually the area converted from other land use and land cover classes. In this context, the present study attempts to estimate the area under different land use and cover classes from multi-temporal images and identify the spatio-temporal extent of changes during 1977–2015.

9.2 Data Base and Methodology

9.2.1 Data Base

The landsat data of 1977, 2003 and 2014 were chosen for the present study (Table [9.1](#page-3-0)). Although the landsat archive in GLOVIS provides a large number of temporal datasets for the study area, landsat data of these years were selected considering the phenological and seasonal effect. For the present study, the data of

Sensors	Spectral bands (in μ m)	Spatial resolution (in mts.)	Spectral region	Time of acquisition	
Landsat MSS	Band 1: 0.50-0.60	60	Green	February,	
	Band2: 0.60-0.70		Red	1977	
	Band 3: 0.70-0.80		Reflected IR		
	Band 4: 0.80-1.11				
Landsat	Band 1: 0.45–0.52	30	VNIR	February, 2003	
TM	Band2: 0.53-0.60	30			
	Band 3: 0.63-0.69				
	Band 4: 0.75–0.90				
	Band 5: 1.55–1.75		SWIR		
	Band 6: 1.04-12.5	120	TIR		
	Band 7: 2.09–2.35	30	SWIR		
Landsat	Band 1: 0.45–0.52	30	Visible	February,	
OLI/TIRS	Band 2: 0.52–0.60		Visible	2014	
	Band 3: 0.63–0.69		Visible		
	Band 4: 0.77-0.90		Near-infrared		
	Band 5: 1.55–1.75		Near-infrared		
	Band 6: 10.40–12.50		Thermal		
	Band 7: 2.09–2.35	60(30)	Mid-infrared		
	Band 8: 0.52–0.90	15	Panchromatic		

Table 9.1 Characteristics of the Landsat 7 TM, MSS and Landsat OLI/TIRS sensor

late winter season (February–March) was targeted because of availability of cloud free and good quality images during the time.

9.2.2 Field Survey

Field verification was carried out during February, 2014 and seventy sample points were collected using a Trimble GPS. The sample points were selected according to the stratified sampling method where each land use land cover class was considered as a stratum and equal number of sample points was collected from all classes. Apart from this, few areas were visited particularly for clarifying confusion regarding their land surface feature.

9.2.3 Methodology

In order to extract actual quantitative information of the earth surface and measuring the changes of dynamic earth in a quantitative way, the noises carried by signals must be removed. Since the raw images consist of radiometric and

geometric errors, before classification they were pre-processed (Fig. 9.1) using the FLAASH atmospheric correction followed by image to image rectification. Unlike other atmospheric models of image calibration that interpolate radiation transfer properties from a pre-calculated database of modelling results the FLAASH model uses MODTRAN4 code and considers elevation, water vapour and aerosol distribution. It estimates the actual reflectance of earth surface by removing the atmospheric effects caused by molecular and particulate scattering and absorption from the radiance at the sensor.

The image of recently launched landsat-8 of February 2014 was registered using the coordinates of sample points collected during field survey in February 2014. The resultant image was resampled using nearest neighbour method and a first-order polynomial was applied for the transformation. Since the urban growth analysis is entirely based on multi-temporal satellite datasets, image to image co-registration was applied using the base image, 2014 and other two sets of images were co-registered accordingly. In order to extract maximum information from the images, the Principal Component Analysis was employed and the original multispectral bands were transformed into principal components. Finally, the images were classified using support vector machine classifier for analyzing the land use and land cover of the study area. In order to assess the long term spatio-temporal changes, a simple change detection analysis was performed in pixel basis. The spatial pattern and distribution of several land use land cover as well as their pattern of temporal changes were analyzed.

9.3 Study Area

The study area comprises Delhi NCT and its peri-urban area. The peri-urban area was delineated by 15 km buffer from the outer boundary of Delhi NCT which comprises part of Gurgaon, Faridabad, Sonepat, Jhaijar districts of Hariyana and

Gautam buddha nagar, Ghaziabad, Baghpat districts of Uttar Pradesh (Fig. 9.2). The total area of the study region is 4095.90 km² within which NCT area is having 1480.07 km² . Since the satellite data was not available for the similar time period the left part of the region could not be taken into account. This area falls under extreme tropical climate with hot dry summer and cold winter season. Rainfall occurs mainly during the month of July and August.

Fig. 9.2 Study area

9.4 Results and Discussion

9.4.1 Land Use and Land Cover in 1977, 2003 and 2014

The classified image (Fig. [9.3](#page-7-0)a) depicts that most of the areas were under agricultural and sparse vegetation during 1977. Agriculture was dominant class in the peri-urban area of Delhi NCT although many patches of sparse vegetation and small settlements can be found throughout the area. The development of high-density built-up areas took place towards the eastern part of Delhi NCT along the Yamuna River. Low-density built-up areas can be observed in the central and eastern part of Delhi NCT surrounding the high-density built-up areas.

Although, high-density built-up areas are mainly located in the core and central part of the city, small patches are also visible towards the outskirts of NCT region during 2003 (Fig. [9.3](#page-7-0)b). Distinct patches of low-density built-up areas can be detected in the extreme east and southern part of peri-urban areas. A large patch of sparse vegetation is depicted in the southern part of study area which represents the famous Delhi ridge. This area is characterized by undulating parallel ridges, folds and faults covered by sparse vegetation.

It is also observed from the classified image of 2014 (Fig. [9.3c](#page-7-0)) that numerous small patches of built-up areas are scattered throughout the peri-urban area which actually indicate the growth of small towns. A distinct green patch can be identified in the core of the city that represents Delhi ridge forest. Towards the eastern part of the city, some patches of wasteland just adjacent to the low-density built-up area can be observed. While visited this place during fieldwork it was found that these areas are actually vacant lands being ready for new construction. Earlier, these areas were agricultural land and now it has become converted for the development of new urban centers. It was observed that these areas have experienced a huge real estate boom in recent years followed by mushrooming of high rises and cluster of new apartments.

9.4.2 Accuracy Assessment of LULC Maps of 1977, 2003 and 2014

In order to examine the accuracy of the classification, accuracy assessment was carried out for individual LULC maps (Table [9.2\)](#page-8-0). It can be seen that percentages of overall classification accuracy as well as Kappa statistics were acceptable for all of the years. It is also significant that the accuracy of the LULC map of 1977 $(K^{\wedge} = 0.84)$ was lowest among the classified maps. This can be explained by low spatial, spectral and radiometric resolution of Landsat MSS data that hinders the accuracy of the classifier. Also, the purity of spectral signature of LULC features

Fig. 9.3 Land use and land cover maps of the study area in 1977 (a), 2003 (b) and 2014 (c)

gets degraded in low resolution data and thus, the problem of mixed pixels hampers the accuracy.

The accuracy of classified LULC map of 2014 ($K^{\wedge} = 0.91$) was significantly high due to better radiometric and spectral resolution of Landsat 8 data. However, the SVM classifier with principal components has proved a close agreement between classified and referenced data.

Land use and	1977		2003		2014	
land cover Class	Producers accuracy $(\%)$	Users accuracy (%)	Producers accuracy $(\%)$	Users accuracy (%)	Producers accuracy $(\%)$	Users Accuracy (%)
High-density built-up	83.67	82.00	90.20	92.00	97.92	94.00
Low-density built-up	80.36	90.00	95.65	88.00	93.88	92.00
Dense vegetation	89.36	84.00	88.24	90.00	84.91	90.00
Agricultural land	83.02	88.00	90.38	94.00	97.87	92.00
Sparse vegetation	86.00	86.00	85.19	92.00	88.46	92.00
Water body	95.83	92.00	95.92	94.00	97.96	96.00
Wasteland	87.23	82.00	89.36	84.00	86.54	90.00
Overall classification accuracy	0.86		0.91		0.92	
Overall Kappa statistics	0.84		0.89		0.91	

Table 9.2 Classification accuracy and Kappa statistics

9.4.3 Comparison of Land Use and Land Cover of Delhi NCT and Its Peri-urban Area During 1977–2014

It was found from the statistical extracts of the proportion of area under different land use and land cover that agriculture was dominant land use class in NCT region till 2003, after that the high-density built-up land took dominant position (Fig. [9.4a](#page-9-0)–c). Whereas, in the peri-urban area agricultural land remained as a dominant land use class throughout the whole period of study. The percentage of areas under high- and low-density built-up, dense and sparse vegetation and water body were higher in Delhi NCT during 1977–2003. The percentage of area under low-density built-up land was increased in peri-urban area during 2003–2014. It was also found that the percentage of area under water bodies was always higher in Delhi NCT than its peri-urban areas. This is mainly due to the course of Yamuna River and its canals flowing through the Delhi NCT region. The proportion of wasteland was comparatively higher in peri-urban areas than NCT region (Table [9.3](#page-9-0)). Since the pressure on land was much higher in NCT than the peri-urban areas, the wastelands of NCT have been utilized for other purposes like settlement, agriculture or manufacturing industries.

The Fig. [9.5](#page-10-0) shows temporal trend of change in land use land cover in the study area over the years. It can be observed that as a whole four land use and land cover features, i.e. agricultural land, sparse vegetation, water bodies and wasteland have

Fig. 9.4 Proportion of LULC in Delhi NCT and its Peri-urban area in 1977, 2003 and 2014

Land use and land	1977		2003		2014	
cover classes	Area in km ²	Percentage	Area in $km2$.	Percentage	Area in $km2$.	Percentage
High-density built-up	25.45	0.62	162.43	3.97	636.22	15.53
Low-density built-up	235.67	5.75	688.02	16.80	839.48	20.50
Dense vegetation	198.48	4.85	253.44	6.19	266.16	6.50
Agricultural land	2048.72	50.02	2001.26	48.86	1598.22	39.02
Sparse vegetation	1069.88	26.12	636.19	15.53	412.42	10.07
Water body	51.75	1.26	43.22	1.06	43.51	1.06
Wasteland	465.95	11.38	311.33	7.60	299.88	7.32
Total	4095.90	100.00	4095.90	100.00	4095.90	100.00

Table 9.3 Spatial statistics of LULC in the study area in 1977, 2003 and 2014

followed a decreasing trend whereas, built-up (both high- and low-density) and high-density vegetation class have experienced a positive trend throughout the last 37 years. The growth of built-up areas and the shrinkage of agricultural land, sparse vegetation, water bodies and wasteland certainly indicate the process of urbanization. It is noteworthy that in spite of rapid urban development, the area under high-density vegetation has increased during the period 1977–2014. The study also reveals that growth of low-density built-up areas was higher during 1977–2003 whereas the high-density built-up areas increased rapidly during 2003–2014.

9.4.4 Land Use and Land Cover Dynamics

9.4.4.1 Spatio-temporal Change Detection During 1977–2003

In order to identify the urban growth and associated land use land cover changes, change detection analysis was carried out. The study reveals that areas under different land use and land cover has changed within the period 1977–2003 although the extent of change was not same for all classes (Fig. [9.6](#page-11-0)). It depicts that low-density built-up areas and sparse vegetation classes have experienced maximum changes. Both high and low-density built-up and dense vegetation have undergone positive changes in Delhi NCT region. The positive growth of these classes is contributed from spatial reduction of other land use land cover classes (Table [9.4](#page-11-0)), i.e. sparse vegetation (12.20%), agricultural land (6.81%), wasteland (3.52%) and water body (0.44%). The degree of change was quite different in peri-urban region where area under agricultural land has increased along with the built-up and dense vegetation classes. The study reveals that areas under sparse vegetation and wasteland were eaten up by agricultural class and this expansion of agricultural area in peri-urban region is due to increasing pressure of population and demand for food. The multi-utility and multi-potentiality of land in urban areas stimulate extension of secondary and tertiary activities which in turn acts as a pulling factor for growth of new urban settlements. As a consequence, primary activities pushed away from core city. Nevertheless, the increasing demand of food

Fig. 9.6 Percentage of change in LULC features during 1977–2003

LULC classes	Area in percentage (Delhi NCT)		Change $(\%)$	Area in percentage (peri-urban)		Change $(\%)$
	1977	2003		1977	2003	
High-density built-up	1.62	8.79	7.16	0.05	1.24	1.19
Low-density built-up	11.03	25.52	14.50	2.77	11.86	9.09
Dense vegetation	7.61	8.91	1.31	3.28	4.64	1.36
Agricultural land	38.23	31.42	-6.81	56.69	58.72	2.04
Sparse vegetation	29.01	16.81	-12.20	24.49	14.81	-9.68
Water body	1.98	1.54	-0.44	0.85	0.78	-0.08
Wasteland	10.52	7.00	-3.52	11.86	7.94	-3.92
Total	100.00	100.00		100.00	100.00	

Table 9.4 Proportion of LULC features and their net change during 1977–2003

Source Author

for the densely populated core city is catered by the extensive agricultural land of the fringe area. Thus, expansion of built-up area surrounding the core city is closely associated with increasing cultivable area in its peri-urban areas. It can be observed that percentage of change in both high and low-density built-up classes of peri-urban region were comparatively less than the Delhi NCT. However spatial increase in built-up area and consecutive alteration of other land covers indicates the process of urbanization.

9.4.4.2 Spatio-temporal Change Detection During 2003–2014

The spatial growth of the study area, during the period 2003–2014 was quite different from the earlier period, 1977–2003. Large scale transformation of land use land cover has been noticed in this period which was mainly driven by

establishment of new real estate projects and expansion of existing built-up areas. As it is shown in Fig. [9.5](#page-10-0), the maximum change has occurred in high-density built-up class of Delhi NCT which has increased about 20% of its total area (Table 9.5). This massive growth of high-density built-up class within Delhi NCT was mainly contributed from low-density built-up, sparse vegetation and agricultural land. However, the areas under dense vegetation class in Delhi NCT region experienced positive growth during the period. Although the rate of growth is very less (1.7%), still it is significant from the ecological point of view. The growth of areas under dense vegetation was a successful outcome of "Green Delhi" campaign. Also, Delhi Development Authority (DDA) has played major role in greening of Delhi NCT by taking several measures like increasing the number of city parks, densification of city forests, development of biodiversity parks, afforestation and maintaining the ridge forest. The study estimates that about 6.5% of the total area under low-density built-up has decreased. Further studies reveal that these areas were transformed into high-density built-up class.

The spatio-temporal change detection of peri-urban areas of Delhi depicts different scenario (Fig. [9.7](#page-13-0)). Here, both high- and low-density built-up areas have undergone a positive change though the percentage of increase was higher in low-density built-up class. This positive increase was mainly attributed from the transformation of agricultural land (12.88%) and sparse vegetation class. It is clearly evident that urban growth in NCT and peri-urban area follows two distinct patterns. The urban growth in Delhi NCT region was occurred through development of new high-density built-up areas converted from low-density built-up, agricultural and sparsely vegetated areas whereas in peri-urban areas numerous pockets of low-density built-up land come up by the conversion of agricultural land and sparsely vegetated land.

LULC classes	Area in percentage (Delhi NCT)		Change $(\%)$	Area in percentage (peri-urban)		Change $(\%)$
	2003	2014		2003	2014	
High-density built-up	8.79	28.42	19.63	1.24	8.25	7.01
Low-density built-up	25.52	19.01	-6.51	11.86	21.34	9.47
Dense vegetation	8.91	10.62	1.70	4.64	4.17	-0.48
Agricultural land	31.42	26.96	-4.46	58.72	45.84	-12.88
Sparse vegetation	16.81	8.41	-8.40	14.81	11.01	-3.80
Water body	1.54	1.47	-0.07	0.83	0.78	-0.05
Wasteland	7.00	5.11	-1.89	7.94	8.62	0.68
Total	100.00	100.00		100.00	100.00	

Table 9.5 Proportion of LULC and their net change during 2003–2014. Source Author

Fig. 9.7 Percentage of change in LULC during 2003–2014

9.5 Recommendations

The Government of NCT of Delhi and the NCR Planning Board who are responsible for looking and administrating the developmental aspects of the Delhi as well as whole of this region should look into different dimensionality of the growth and development patterns. In this context the present study recommends that the authorities may use land use and land cover map and other such map of this study. It will be very useful for them to prepare the base map for the entire city and the peri-urban region and also for preparing long term Perspective plan and the Master Plan 2041. The study clearly demonstrated and further recommends the use of remote sensing datasets for creating a detailed and accurate multi-temporal, multi-scale geospatial data base and to update the existing land use and land cover maps for the better growth and development of the region. Further, the study recommends exploring other remote sensing data sets for better and sustained growth of the region and especially hyper-temporal vegetation products for policy interventions that will surely help in the smart city project of Delhi.

9.6 Conclusions

The study shows that the area under built-up class has undergone large scale change by conversion of surrounding agricultural, wasteland and vegetated land. Large scale development occurred in the peri-urban areas especially towards Gurgaon (southwest), Faridabad (southeast) and Ghaziabad (east) area. Numerous small pockets of low-density built-up land observed in the northeastern and northwestern part of peri-urban area were come up due to conversion of sparsely vegetated areas. However, the growth of built-up areas was mainly confined within the NCT until 2003. Though, three distinct nuclei of built-up areas were formed outside the NCT region which can be identified in eastern (Ghaziabad), southeastern (Faridabad) and southwestern (Gurgaon) directions. The peri-urban areas experienced large scale development mainly during the period 2003–2014 (shown in red colour). The expansion of built-up land in and around Delhi NCT is greatly shaped by several policies implemented by the DDA and other Government organizations. For instance, the process of urbanization could not affect the ridge forests of the area and these green pockets were remained unchanged. In fact, the green areas have become greener due to afforestation, densification and proper maintenance of forests and parks.

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