CHAPTER: III

LANDUSE LAND COVER (LULC) CHANGE DYNAMICS

3.1 Overview

Historically humans have been modifying land to obtain the essentials for their survival, but the rate of exploitation was not the same as it is today. Recent rapid rate of exploitation has brought unprecedented changes in ecosystems and environmental processes at local, regional and global scales. Presently, land use/land cover changes encompass the environmental concerns of human population including climate change, biodiversity depletion and pollution of water, soil and air. Today, the monitoring and mediating the adverse consequences of land use/land cover change while sustaining the production of essential resources has become a major priority of researchers and policy makers around the world (Erle and Pontius, 2007).

Land use and land cover change is concerned with the detection and quantification of alterations of the land surface and its biotic cover. The difference between land use and land cover is that while land use denotes the human employment of the land and is largely studied by social scientists. Land cover denotes the physical and biotic character of the land surface and is mostly studied by natural scientists (Meyer and Turner II, 1992).The land use/land cover pattern of a region is an outcome of both natural and socio-economic factors and their utilization by man in time and space. Land is becoming a scarce commodity due to immense agricultural and demographic pressure. Hence, information on land use/land cover and possibilities for their optimal use is essential for the selection, planning and implementation of land use schemes to meet the increasing demands for basic human needs and welfare.

Meyer and Turner (1992) defined land cover change as a change that takes place in two forms; conversion from one category of land to another, and the modification of the conditions within a category.

Urban and agricultural land uses are two of the most commonly known land use classes. Rural area land use is quite flexible. In urban areas, the land utilization is much more intensive spatially and temporally and the land use is more inelastic. According to Rajan K.S and Shibasaki R. (2001) Land use and land cover is an important component in understanding the interactions of the human activities with the environment and thus it is necessary to be able to simulate such changes

The study of land use change referred to as change detection and the growth of urban centers have gained prominence in the recent years. This is partly due to the fact that there is an increasing need for proper land use planning to control various urban problems. Remote sensing techniques are of immense practical use for resources evolution and environmental. In fact, it has emerged as the most efficient and effective way to obtain large amounts of timely accurate information about terrain. Urban land use change monitoring compared, using high-resolution remote sensing technology to monitor more efficient time saving, saving a lot of manpower, material resources and time, improve the urban land use database building and database and update efficiency. The growth of city without planning will lead to create many complex urban problems viz. amenities such as water, electricity, sewage etc.

Recently, issues related to LULC change have gained interest among a wide variety of researchers, ranging from those who favor modeling spatio-temporal patterns of land conversion to those who try to understand the causes, impacts and consequences (Verburg et al. 1999; Brown et al. 2000; Theobald, 2001). Human activities which are mainly driven by socio-economic factors bring out changes in non-built-up and built-up land despite restrictions by physical conditions (Long et al. 2007).

3.2 Land Use/Land Cover Studies Using Remote Sensing and GIS Techniques

In order to use land optimally, it is necessary to have the information on existing land use land cover. It is also important to have capability of monitoring the dynamics of land use resulting out of both changing demands of increasing population and forces of nature acting to shape the landscape. Land is in a continuous state of transformation as a result of various natural and man-made processes. The study of spatio-temporal patterns of intra and inter urban form and understanding of the evolution of urban systems are still primary objectives in urban research. Traditionally demographic data has been used to assess urban sprawl (Carlson and Traci, 2000). Meanwhile, the use of aerial photography, become important to update land cover maps. Since land cover changes at regional level occurred increasingly due to human activity, the changes couldn't be realized in the community. Therefore, accurate and updated information is required to design strategies for sustainable development and to improve the livelihood of cities.

Therefore, the information about change is necessary for updating land cover maps and the management of natural resources (Xiaomei and Rong Qing, 1999). Macleod and Congation (1998) list four aspects of change detection which are important when monitoring natural resources. They include; firstly, detecting the changes that have occurred; secondly, identifying the nature of the change; thirdly, measuring the area extent of the change and lastly, assessing the spatial pattern of the change. The basis of using remote sensing data for change detection is that changes in land cover result in changes in radiance values which can be remotely sensed. Techniques to perform change detection with satellite imagery have become numerous as a result of increasing versatility in manipulating digital data and increasing computer power. Conventional ground methods of land use mapping are labor intensive, time consuming and are done infrequently. These maps soon become outdated with the passage of time in a rapid changing environment. In recent years, satellite remote sensing techniques have been developed, which have proved to be of immense value for preparing accurate land use/land cover maps and monitoring changes at regular intervals of time. Despite spatial and spectral heterogeneity challenges of urban environments, remote sensing seems to be a suitable source of reliable information about the multiple facets of urban environment (Jensen and Cowen, 1999; Herlod et al. 2003). So, the analysis of dramatic changes of land use/land cover at global, continental and local levels and further to explore the extent of future changes, the current geospatial information on patterns and trends in land use/land cover are playing an important role.

Remotely sensed imageries provide an efficient means of obtaining information on temporal trends and spatial distribution of urban areas needed for understanding, modeling and projecting land changes (Elvidge et al. 2004). In case of inaccessible regions, this technique is perhaps the only method of obtaining the required data on a cost and time effective basis (Olorunfemi, 1983). Satellite imagery is able to provide more frequent data collection on a regular basis unlike aerial photographs. Although aerial photographs may provide more geometrically accurate maps but is limited in respect to its extent of coverage and expenses. The importance of remote sensing technique was realized by Olorunfemi in 1983 while using traditional method of surveying i.e., aerial photographic approach to monitor urban land use in developing countries with Ilorin in Nigeria as the case study.

A remote sensing device records response which is based on many characteristics of the land surface, including natural and artificial cover. An interpreter uses the element of tone, texture, pattern, shape, size, shadow, site and association to derive information about land cover. The generation of remotely sensed data/images by various types of sensor flown aboard different platforms at varying heights above the terrain and at different times of the day and the year does not lead to a simple classification system. It is often believed that no single classification could be used with all types of imagery and all scales. The successful attempt in developing a generalized classification scheme compatible with remote sensing data has been carried out by Anderson in 1976, which is also referred to as United States Geological Survey (USGS) classification scheme.

Ever since the launch of the first remote sensing satellite (Landsat-1) in 1972, land use/land cover studies were carried out on different scales for different users. For instance, waste land mapping of India was carried out on 1:1 million scales by NRSA using 1980-82 Landsat multi spectral scanner data. About 16.2% of waste lands were estimated based on the study. It has been noted over time through series of studies that Landsat Thematic Mapper is adequate for general extensive synoptic coverage of large areas. As a result, this reduces the need for expensive and time consuming ground surveys conducted for validation of data. In India, National Remote Sensing Agency (NRSA) of Department of Space under National Urban Information System (NUIS) scheme used Cartosat-1, Resourcesat-1 and LISS-VI+PAN merged satellite data to carry out national level urban land use thematic mapping at 1:10,000 scale of 564 cities/towns including State capitals and Union Territories; 23 cities with Million plus population; NCR towns; and one town from each class (from Class I to Class VI) from each State and Union Territories (NRSA, 2008). For this urban land use mapping a classification standard was designed with classes hierarchically arranged with increasing information content as the levels increases from Level I to Level V. The classification also consists of certain land cover classes up to Level II designed to accommodate the rural classes noticed within the urban administrative limits.

A variety of change detection techniques are available for monitoring land use/land cover changes. These techniques can be grouped into two main categories: post classification comparison techniques and enhancement change detection techniques (Nielson, 1998). (a). Post classification techniques The post classification technique involves the independent production and subsequent comparison of spectral classifications for the same area at two different time periods (Mas, 1999). Post classification techniques have the advantage of providing direct information on the nature of land cover changes. The classification process used with these techniques can be either supervised or unsupervised. Sohl (1999) reported accuracies of 96 percent for the identification of new forest land and 62 percent for new agricultural land using a post classification technique in a semi-arid environment. Furthermore, Sohl (1999) noted the strength of the method for providing users with a complete descriptive comparison between images. Pilon et al. (1988) employed post classification in combination with a simple enhancement technique to differentiate areas of human induced change from areas of natural change. Mas (1999) also obtained the highest accuracy with this technique in a study comparing six different techniques. (b). Enhancement change detection techniques Enhancement techniques involve the mathematical combination of images from different dates which, when displayed as a composite image, show changes in distinctive colors (Pilon et al. 1988). The enhancement change detection techniques have the advantage of generally being more accurate in identifying areas of spectral change (Singh, 1989). However, these techniques often require additional analysis to characterize the nature of the spectral change, and also require more accurate image normalization and co-registration. (i). Image differencing Image differencing is a technique by which registered images acquired at different times have pixel DN values for one band subtracted from the corresponding pixel DN values from the same band in the second image to produce a residual image, which represents the change between the two dates (Mas, 1999). Ridd and Liu (1998) reported image differencing was fairly effective in its ability to detect change in an urban environment, with TM band 3 producing the highest accuracies. Sunar (1998) and Sohl (1999) reported that the image differencing technique was extremely straightforward, but with the qualification that image differencing technique becomes slightly more complicated when using multiple bands, instead of single bands, due to the difficulty of interpreting the colors of multiband false color composites. (ii) Principal component analysis Principal component analysis (PCA) is a commonly used statistical method for many aspects of remote sensing image analysis, including estimation of the underlying dimensions of remotely sensed data, data enhancements for geological studies, and land cover change detection (Fung and Le Drew, 1987). The PCA technique for change detection requires the separate images first be stacked in a multi-temporal composite image (Sunar, 1998). The major strength of this technique is its ability to reduce the dimensionality of the data with relatively minor loss of overall information content. The major weakness of this technique is that it can be difficult to interpret. Li and Yeh (1998) compared principal component analysis to post classification techniques and concluded that principal component analysis was much more accurate than post classification techniques and therefore suggested it as an accurate alternative for detecting land use change. (iii) Normalized difference vegetation index (NDVI) The Normalized Difference Vegetation Index (NDVI) estimates the vitality of vegetation by exploiting the known gap in vegetation reflectance between the visible and near infrared channels. Common change detection methods include the comparison of land cover classifications, multi-date classification, band arithmetic, simple rationing, vegetation index differencing and change vector analysis (Jomaa, 2003). The NDVI is calculated as a normalized ratio (ranging from -1 through 1) from the NIR and the red band and emphases apparent vegetation (Sabins, 1996).

3.3 Land Use Change Dynamics in Vadodara Urban Area

3.3.1 Introduction

City areas in the India are growing at unprecedented rates, creating extensive urban landscapes. Many of the agricultural land, wetlands, forests, and natural water bodies have been transformed during the past years into human settlements as urban extensions. These unplanned extensions cause more environmental and societal impacts due to over rush in cities. Therefore; study of land use changes in spatial and temporal scale is essential to monitor environmental and social impacts on urban population.

3.3.2 Data Set and Methodology

The Study of Land use change dynamics has been carried out using LANDSAT Thematic Mapper (TM) and LANDSAT (ETM) dataset. The Thematic Mapper (TM) is an advanced, multispectral scanning, Earth resources sensor designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity and greater radiometric accuracy and resolution than the MSS sensor. TM data are sensed in seven spectral bands simultaneously. Band 6 senses thermal (heat) infrared radiation. Landsat can only acquire night scenes in band 6. A TM scene has an Instantaneous Field of View (IFOV) of 30m x 30m in bands 1-5 and 7 while band 6 has an IFOV of 120m x 120m on the ground (https://landsat.gsfc.nasa.gov/the-thematic-mapper/). Whereas; The Landsat Enhanced Thematic Mapper Plus (ETM+) sensor onboard the Landsat 7 satellite has acquired images of the Earth nearly continuously since July 1999, with a 16-day repeat cycle. Landsat 7 ETM+ images consist of eight spectral bands with a spatial resolution of 30 meters for bands 1 to 7. The panchromatic band 8 has a resolution of 15 meters. All bands can collect one of two gain settings (high or low) for increased radiometric sensitivity and dynamic range, while Band 6 collects both high and low gain for all scenes. Approximate scene size is 170 km north-south by 183 km east-west (https://lta.cr.usgs.gov/LETMP/). Remote sensing data set from Landsat has been acquired for the year 1978, 1990, 2001 and 2011 respectively for the temporal and spatial change analysis.

Table showing the data used with acquisition date

Sensor	Path	Row	Date of acquisition
Landsat 5 TM	148	45	2011-11-14
Landsat 7 ETM+	148	45	2001-11-10
Landsat 5 TM	148	45	1990-10-19
Landsat 3 MSS	159	45	1978-10-16

3.3.3 Methodology

The derivation process of land use and land cover mapping from Landsat TM and Landsat ETM plus dataset used for the study and the visual interpretation method was adopted using maximum interpretation keys viz. tone, texture, shadow, shape and association etc. From a technology perspective, the simplest way to extract information from remotely sensed data is human interpretation. However, significant training and experience are needed to produce a skilled image interpreter. (Campbell, 2007)

Visual image interpretation is a fundamental process that is often the first step in obtaining site-specific information from traditional aerial photographs, single band, and composite band satellite images. Interpretation skills are necessary in order to effectively complete many studies involving Earth system processes and ensuing environmental issues. Interpreting an image begins as a visual process consisting of an ordered sequence of steps including: detection recognition identification classification and analysis. When viewing an image, one first detects the presence or absence of a number of spatial objects in the scene. The brain presumably has some stored experience that enables an interpreter to recognize (to generalize spatial entities by sorting them into general feature classes.) objects based upon some measure of learned knowledge; for example, an ability to recognize water from land. Visual interpretation using key elements (tone, shape, size, pattern, texture, shadow, and association) is regularly a slice of our daily lives. In the present study level 1 USGS classification scheme was followed owing to the limitation of the regional scale level study and satellite resolution was suitable for regional level studies.

As per Anderson et al. (1976) the land classification system includes only the more generalized first, second and third levels. The classification system is capable of further refinement based on more extended and varied use. Land use and land cover classification system for use with remote sensing data is described in Table 3.1. Remote sensing data classified in four major classes in first level and further classified in second level classification system. Whereas level three classifieds objects in finer details.

Table 3.1 Major Classification categories using Remotely Sensed data.

Level I	Level II	Level III
1. Urban or built-up land	1.1 Residential	1.1.1 Dense
		1.1.2 Moderate
		1.1.3 Sparse
		1.4.1 Roads
		1.4.2 Railways
		1.4.3 Airport
	1.2 Mixed built-up Land	
	1.3 Industrial Area	
	1.4 Transportation	
	1.5 Recreational	
2. Agricultural Land		
3.Waste/Barren Land	3.1 Transitional Area	
4. Water	4.1 Rivers	
	4.2 Streams	
	4.3 Lakes	

The land use and land cover classification system presented in table 3.2 includes only the more generalized classification in first and second levels. According to Grigg (1965), the system satisfies the three major attributes of the classification process: (1) it gives names to categories by simply using accepted terminology; (2) it enables information to be transmitted; and (3) it allows inductive generalizations to be made. The classification system is capable of further refi11ement on the basis of more extended and varied use. At the more generalized levels it should meet the principal objective of providing a land use and land cover classification system for use in land use planning and management activities.

Urban or built-up includes land, which provides living space within and around buildings or houses to meet the daily needs of the families of different sizes and composition. This area is predominantly identified for the purpose of living accommodation, and further classified as residential, Commercial & services, industrial land, transportation and utilities, commercial complexes, mixed urban land and other built-up area.

Agricultural Land may be defined broadly as land used primarily for food production. Agricultural land sub categorised in cropland, orchards, confined feeding operations and other agricultural lands. The interface of Agricultural Land with other categories of land use may sometimes be a transition zone in which there is an intermixture of land uses at first and second levels of categorization. Rangeland historically has been defined as land where the potential natural vegetation is predominantly grasses, grass like plants, forbs, or shrubs and where natural herbivory was an important influence in its pre-civilization state. Rangelands sub-classified in herbaceous, shrub and brush, and mixed rangelands. Forest Lands are identified as dense/sparse trees which are stocked with trees capable of producing timber or other wood products, and exert an influence on the climate or water regime. Forest land is categorised in deciduous, evergreen and mixed forest land for further classification. The most important natural or manmade feature to fulfil societal and biological need are water resources which were classified as streams and canals, lakes, reservoirs and bays. Wetlands are generally defined as, areas where the water table is at, near, or above the land surface for a significant part of most years. Further; Wetlands are classified into forested and non-forested wetlands.Land with the limited ability to support life and in which very less area hasvegetation or other cover is defined as Barren Land. In general, it is an areaof thin soil, sand, or rocks. Barren land is categorised into dry salt flats, beaches, sandy areas, bare exposed rocks, strip mines, transitional areas and mixed barren land.Tundra is identified as the treeless regions and it is categorised as shrub,Herbaceous, bare ground, wet and mixed tundra.Due to the environmental factors some land parts is covered by snow or ice is known as Perennial snow or ice, which is categorized in Perennial snow fields and glaciers.

Table 3.2 USGS land use and land cover classification system (Anderson et al. 1976).

	Level I	**Code**	**Level II**
1	Urban or built-up land	11	Residential
		12	Commercial & services
		13	Industrial
		14	Transportation, communications & utilities
		15	Industrial & commercial complexes
		16	Mixed urban or built-up land
		17	Other urban or built-up land
2	Agricultural land	21	Cropland & pasture
		22	Orchards, groves, vineyards, nurseries & ornamental horticultural areas
		23	Confined feeding operations
		24	Other agricultural land
3	Rangeland	31	Herbaceous rangeland
		32	Shrub & brush rangeland
		33	Mixed rangeland
4	Forest land	41	Deciduous forest land
		42	Evergreen forest land
		43	Mixed forest land
5	Water	51	Streams & canals
		52	Lakes
		53	Reservoirs
		54	Bays & estuaries
6	Wetland	61	Forested wetland
		62	Non-forested wetland
7	Barren land	71	Dry salt flats
		72	Beaches
		73	Sandy areas other than beaches
		74	Bare exposed rock
		75	Strip mines, quarries & gravel pits
		76	Transitional areas

	Level I	Code	Level II
		77	Mixed barren land
8	Tundra	81	Shrub & herbaceous tundra
		82	Herbaceous tundra
		83	Bare ground tundra
		84	Wet tundra
		85	Mixed tundra
9	Perennial snow or ice	91	Perennial snowfields
		92	Glaciers

3.4 Land use change analysis

Most major city areas face the growing problems of urban sprawl, loss of natural vegetation and open space, and a general decline in the extent and connectivity of wetlands and wildlife habitat. The public identifies with these problems when they see residential and commercial development replacing undeveloped land around them. Vadodara city, is one of the fast growing city in India, the land use of the city over a period from 1978-2011 showed tremendous rises in the built-up-area from agricultural area, vegetation and vacant land. The city today has its centre at the core areas. Although, the city initially evolved in circular shape on a grid iron pattern outward from the centre. Now it is growing largely towards north, northwest and southeast direction along the main transport routes. There were ample agriculture and vegetation land in outside the urban area. In this period of time industrial and residential areas were dominantly expanded.

3.4.1 Land use in 1978

Land use change analysis carried out for the years 1978, 1990, 2001 and 2011 and year 1978 is considered as a base year for further change detection and change analysis. Figure 3.1 represents visual classifications of Vadodara city, where dark red color shows dense built-up land and area is around 50.23 sq.km, which is 7.11 percent of the entire study area. Table 3.3 represents the number of classes has been analyzed for the study in year 1978, area covered by each class in square kilometers and their respective coverage in total area percent. Figure 3.1

illustrates entire Vadodara Urban Development Authority (VUDA) region was dominated by agricultural land in 1978 which was 80.36 percent of total area and that covers 567.47 square km area of the total area. Airport is situated in North-east direction from built-up cluster in VUDA region, which covers 5.63 Square Km area and 0.80 percent of the total area. Some Built-up clusters were also identified in the North-west direction from the center of the city. Figure 3.1 shows, Waste land is dominated along the river from north to west direction which covers 32.69 square Km area that is of 4.63 percent of the total area. Major river adjacent to VUDA is in north to west direction; whereas major pond situated in west part and many more scattered water bodies were identified within VUDA region in 1978.Area covered by water bodies is 8.83 square Km which is around 1.25 percent of the total VUDA area. Vegetation land was spread in 23.16 square Km and it was around 3.28 percent of total VUDA area; whereas, Open land spread in 4.55 square km as 0.64 percent of total area. In the VUDA region scrubland was spread in 11.73 Km and its percent share of total land was 1.66 percent. Coverage area of alluvium deposits are very less as compare to other classes in VUDA region, which cover 1.88 square Km area and 0.27 percent of total VUDA region. This analysis shows the percent share of each land class in VUDA region along land area coverages by respective classes in Year 1978.Figure 3.2 illustrates percent area shared by each LULC class of total VUDA area.

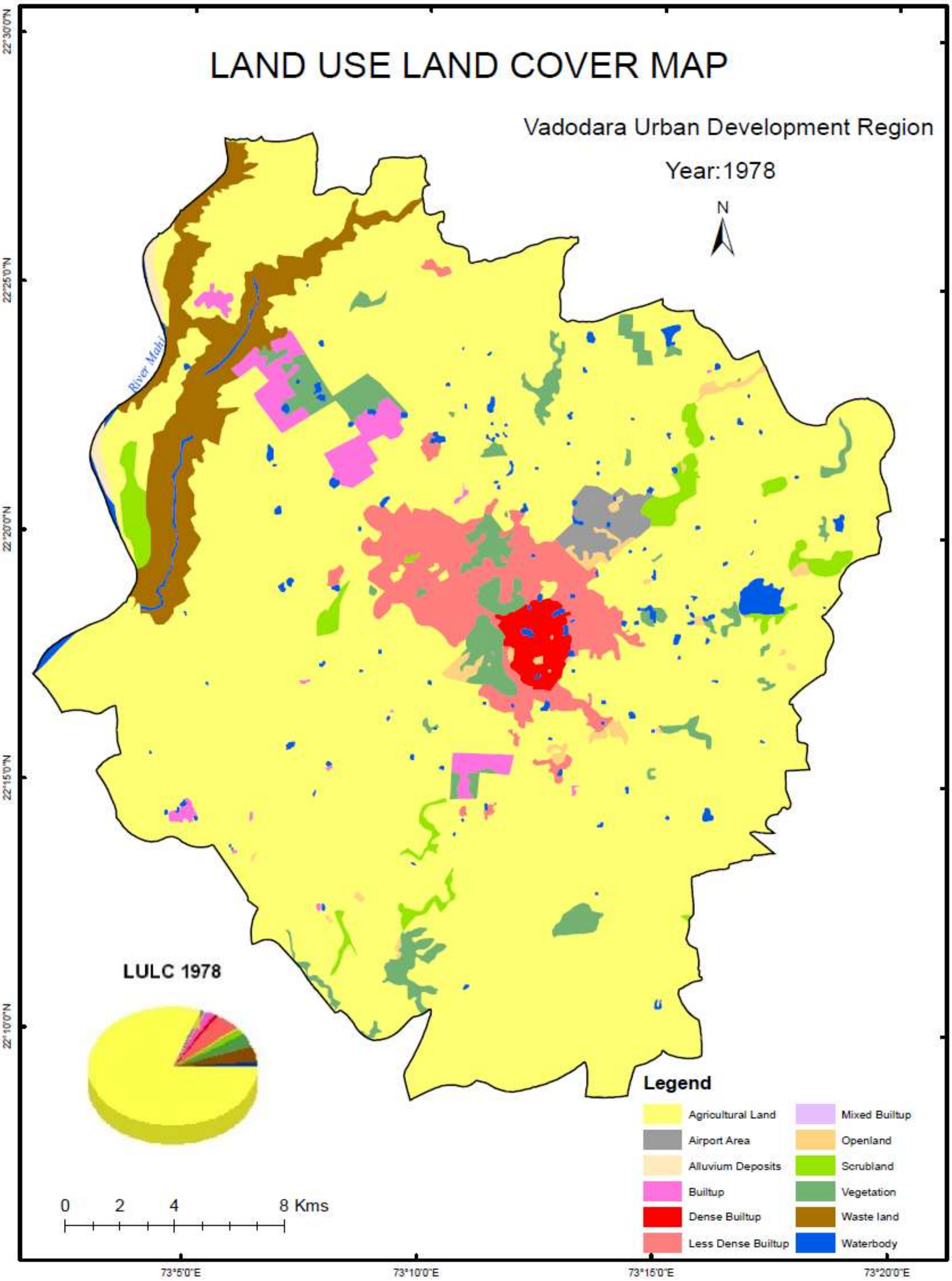


Figure 3.1 Land use Land Cover Map of Vadodara Urban Development Region (year-1978).

Table 3.3 Land use classes, total area and percent of area covered by each class in 1978.

LULC class_1978	Area 1978(Sq. Km)	% Area 1978
Agricultural Land	567.47	80.36
Airport Area	5.63	0.80
Alluvium Deposits	1.88	0.27
Built up	50.23	7.11
Open land	4.55	0.64
Scrubland	11.73	1.66
Vegetation	23.16	3.28
Waste land	32.69	4.63
Water body	8.83	1.25

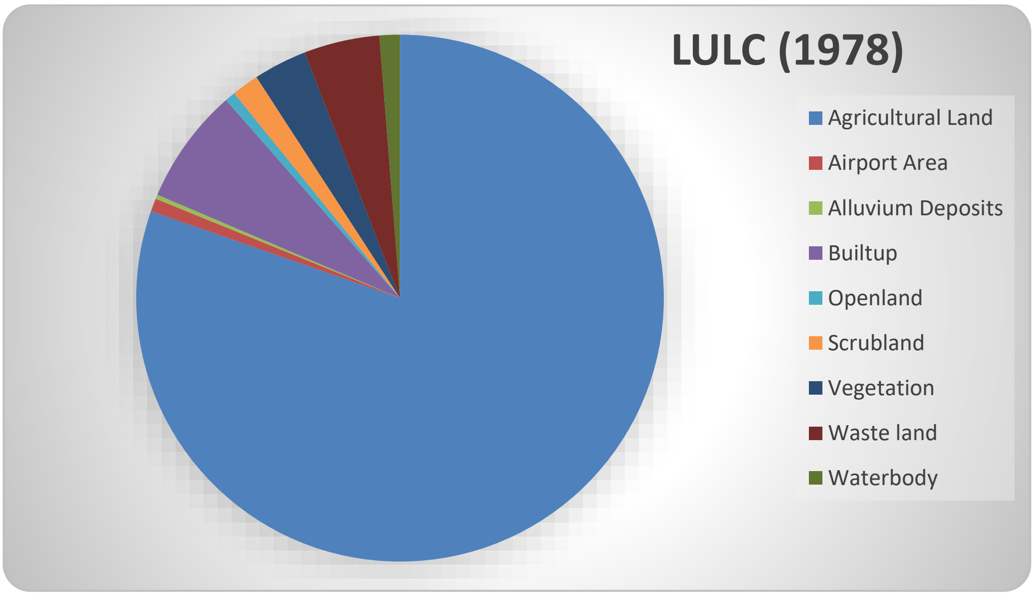


Figure 3.2 Percent area shared by LULC class of Total VUDA area in 1978.

3.4.2 Land use 1990

Figure 3.3 shows classified output of VUDA for the year 1990.Land use land cover area and statistical information for respective classes shown in the table 3.4; whereas the percent of area covered by each class out of total area are shown in figure 3.4. Agricultural land still occupies highest area by 77% and built up is 10%, 4% waste land while scrub land and vegetation occupy 2.48 and 2.45% respectively. It is interesting that there is 3% decrease of agriculture area and compensating 3% simultaneous increase of built up. This may be due to slow and steady growth of urbanization by the way of residential and commercial constructions.

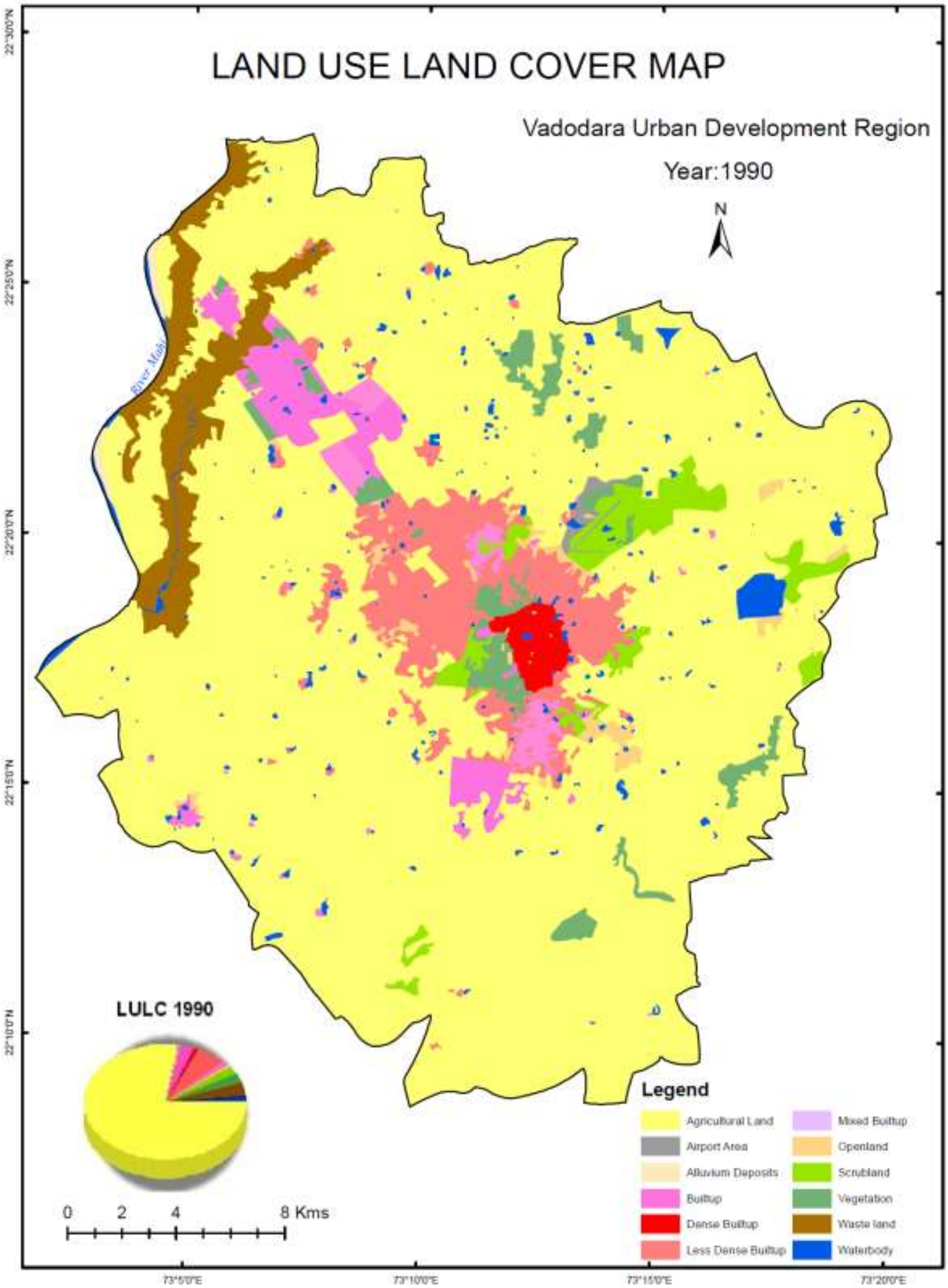


Figure 3.3 Land use Land Cover Map of Vadodara Urban Development Region (year-1990)

Table 3.4 Land use classes, total area and percent of area covered by each class in 1990.

LULC class 1990	**Area 1990 (Sq. Km)**	**% area1990**
Agricultural Land	545.36	77.21
Airport Area	1.60	0.23
Alluvium Deposits	1.49	0.21
Built up	77.09	10.91
Open land	6.27	0.89
Scrubland	17.54	2.48
Vegetation	17.28	2.45
Waste land	28.73	4.07
Water body	10.95	1.55

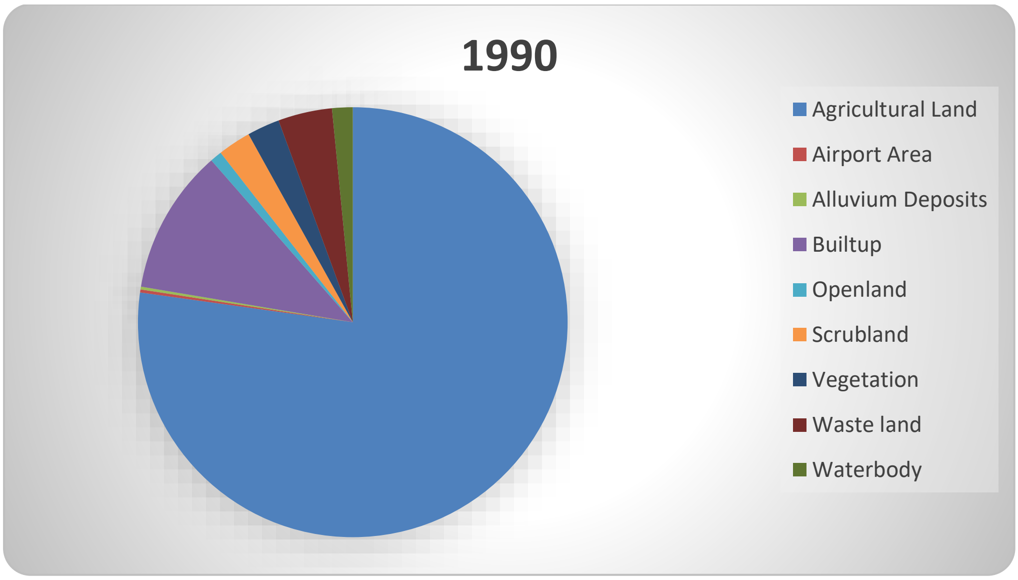


Figure 3.4 Percent area occupied by various LULC class of Total VUDA area in 1990

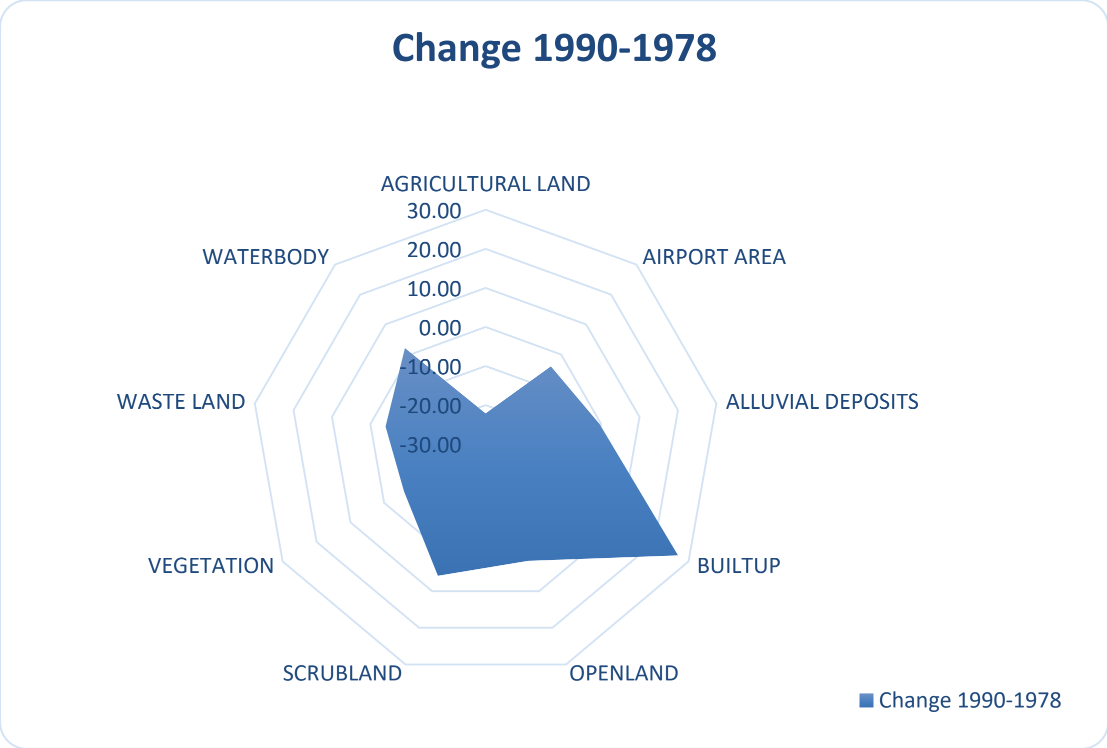


Figure 3.5 Percent changes in LULC classes from 1978 to 1990

3.4.3 Land Use 2001

Land use land cover map for the year 2001 is presented in figure 3.6. Year 2001 is second last decadal year for which study have been carried out. Land use Land cover map represents agricultural land spread in 513.82 square Km; airport area covers 6.61 square Km. Alluvium deposits were spread in 1.65 square Km. Built-up area: 98.78, open land: 15.27, scrub land: 12.23, vegetation land: 12.31, waste land 38.35 and water body: 7.16 square Km area covered out of total area 706.18 Km. Class inclinations towards the increasing or decreasing trends were also analyzed for the year 2001 from1990. Figure 3.7 illustrates the percent area changes in each class towards the positive or negative changes.

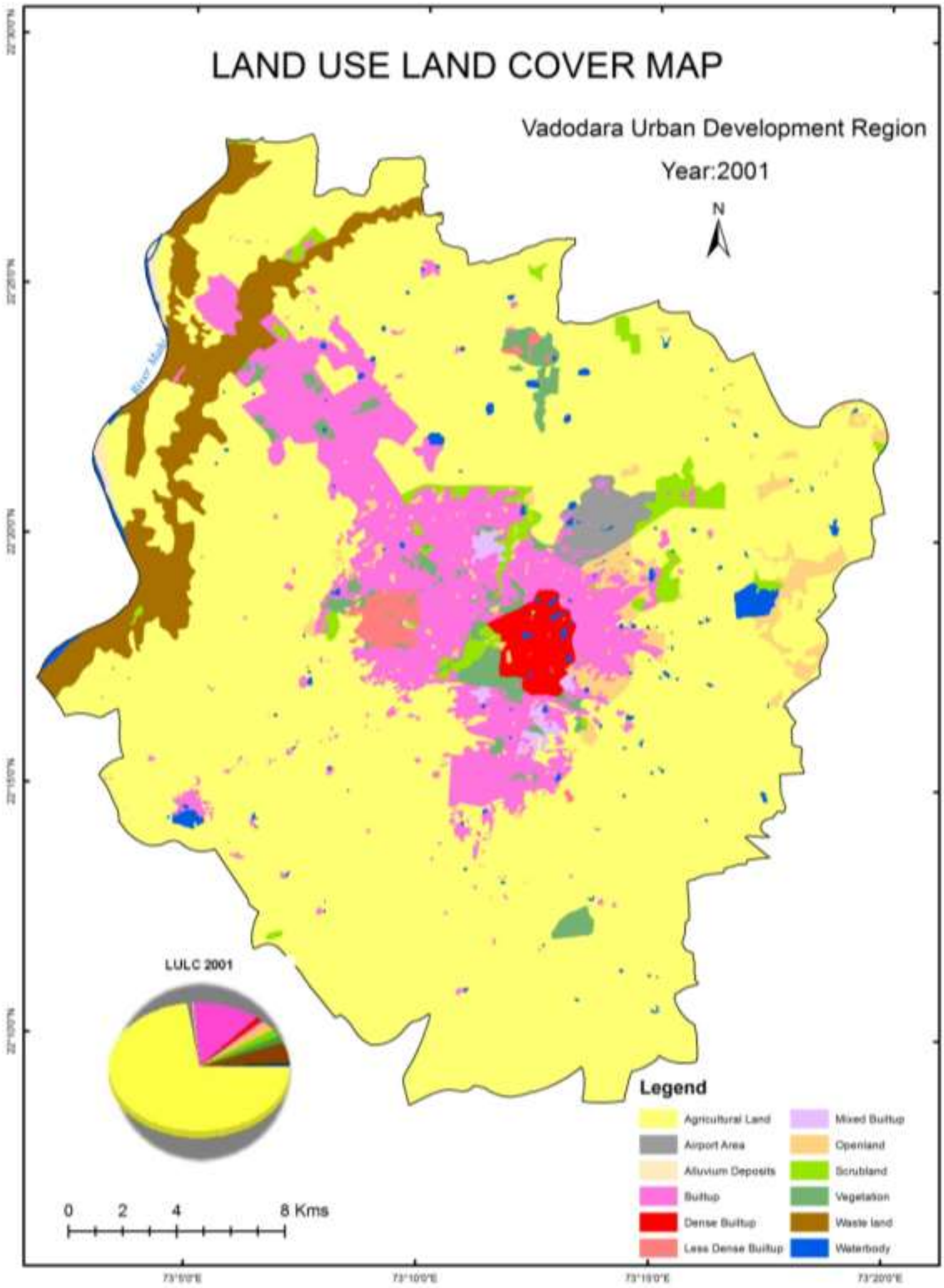


Figure 3.6 Land use Land Cover Map of VUDA (year-2001)

Table 3.5 Land use classes, total area and percent of area covered by each class in 1990.

LULC_class_2001	Area_2001(Sq. Km)	% area2001
Agricultural Land	513.82	72.76
Airport Area	6.61	0.94
Alluvium Deposits	1.65	0.23
Built up	98.78	13.99
Open land	15.27	2.16
Scrubland	12.23	1.73
Vegetation	12.31	1.74
Waste land	38.35	5.43
Water body	7.16	1.01

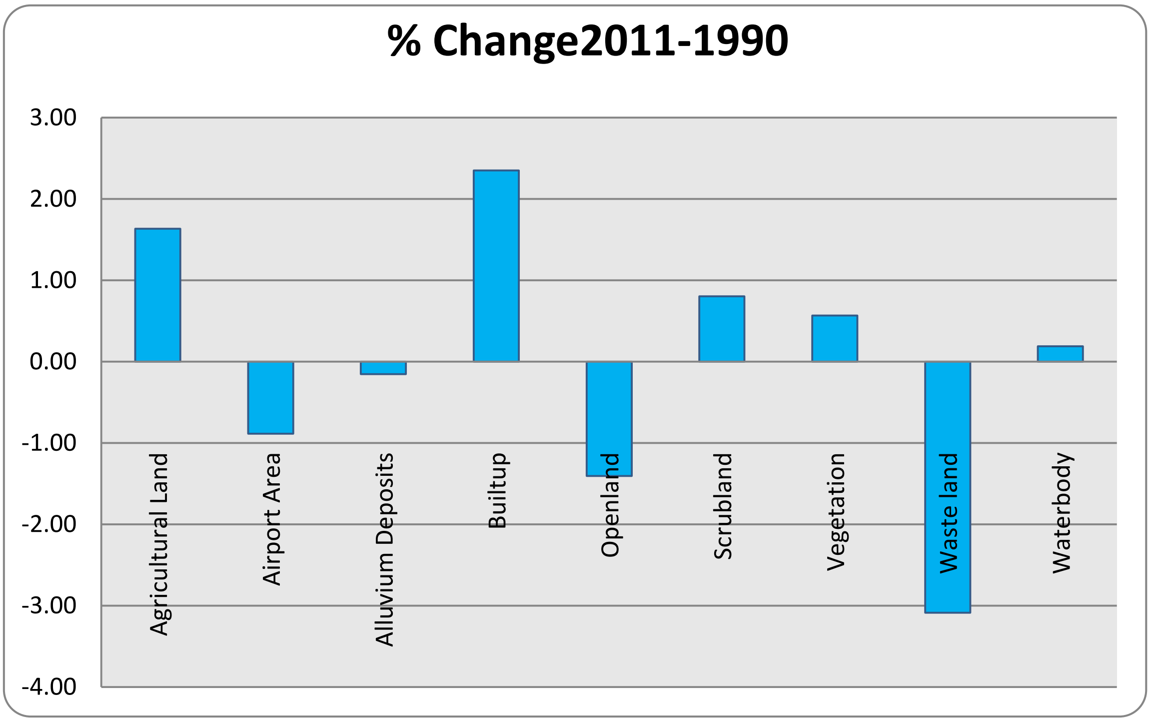


Figure 3.7 Percent area changes in LULC classes from 1990, to 2011

It is observed that agriculture area is decreased by 53.65sq.km for time period between 1978-2001 i.e. 2.334 sq. km in 23 years and 31.54 sq.km (5%) for the period between 2001- 1990 at an annual rate of 3.154 sq.km, while built up have gone up to 3% compared to 1990 and 6% compared to 1978.It was 50.23 sq.km which doubled almost to 98.78 sq.km by 2001 this suggest urban the land-use pattern changed from a semi-urban and semi-agrarian, to a highly industrialized and urban area. Thus on an approximation of more than two-fold rise in the built up area was accounted and this mainly due to the population rise and pressure for built up land increased. Vegetation has reduced to half from 23.16 sq. km to 12.31 sq. km in 2001.This shows the destruction of green cover which my lead to climate change impacts on urban areas. Whereas;

Open land is steadily increased by four times from 1978-2001 from 4. 55 sq.km to 15.27 sq .km.i.e. by 2%; whereas, waste land increased from 28 .73 sq.km in 1990 to 38.35 sq. km from in 2001. This may be attributed to erosion and gullies

Furthermore, water body seems to remain at 1% though there are slight differences in the total hectare between this periods.

Table 3.6 Land use classes, total area and percent of area covered by each class in 2011.

LULC class	**2011**	**% area2011**
Agricultural Land	525.38	74.40
Airport Area	0.35	0.05
Alluvium Deposits	0.56	0.08
Built-up	115.39	16.34
Open land	5.33	0.75
Scrubland	17.92	2.54
Vegetation	16.30	2.31
Waste land	16.56	2.34
Waterbody	8.50	1.20

Built up area is now 115 sq. km which was 7% of total land use is now 16% more than double in 33 years but the steadily increased by 3% rate. However, agriculture slightly increased which can be attributed to Narmada Canal introduced in area. Open land, scrub land, vegetation also has declined. In an urban situation, it is the hinterlands where agricultural activities that are predominant supply the food materials to the inhabiting population of the city. Threat to the agricultural land implies a future threat on the food material supply and on inflation. Figure 3.8 represents, percent of area change in land use land cover classes between 2001 and 2011.

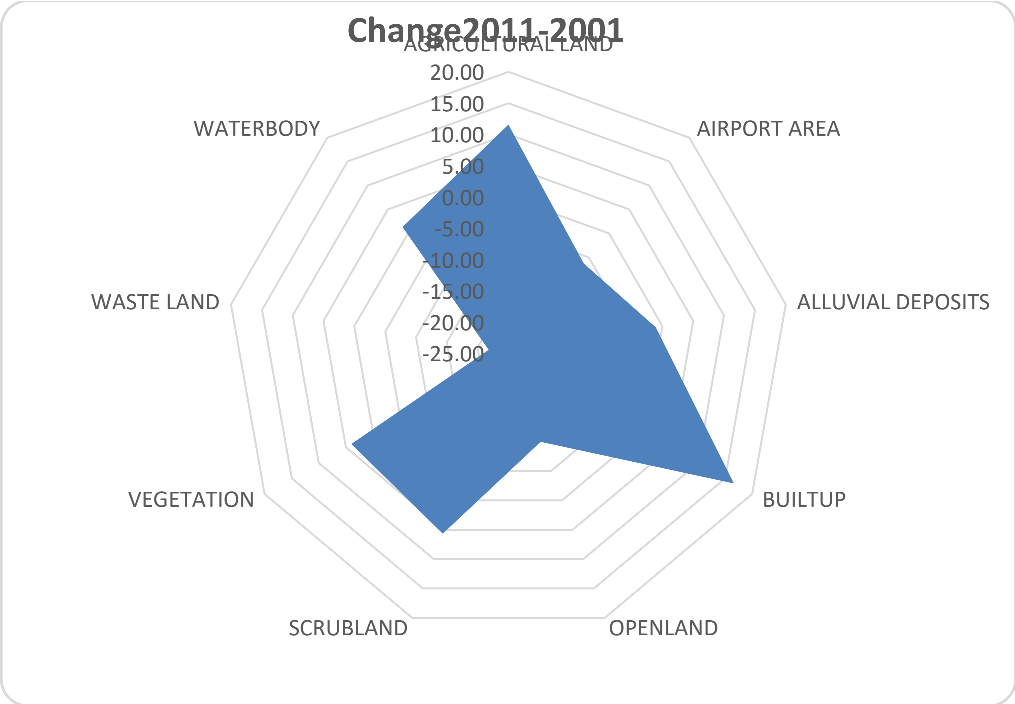


Figure 3.8 Percent of changes in LULC classes from 2001 to 2011

3.5Analysis of land use change 1978-2011

Comparative analysis of LULC absolute changes in years 1978 to 2011, has been summarized in table 3.6. Maximum absolute change in Agricultural land has been observed during 1990 to 2001. During 1990 to 2001-time period 31.54 Sq. km area of agricultural land decreased, whereas, year 1978 to 1990 -22.11 Sq. Km. agricultural land decreased. Built-up area is increased in mentioned time period respectively, 1978 to 1990: 26.86 Sq. Km, 1990 to 2001: 21.69 Sq. Km and 2001 to 2011 16.61 Sq. Km. as mentioned in Table 3.7.

Table 3.7Comparative analysis of Land use classes and absolute changes in decadal years.

LULC class	**Geographical Area (In Sq. Km)**				**Absolute Change**		
	1978	**1990**	**2001**	**2011**	**Change 1990-1978**	**Change 2001-1990**	**Change2011-2001**
Agricultural Land	567.47	545.36	513.82	525.38	-22.11	-31.54	11.56
Airport Area	5.63	1.6	6.61	0.35	-4.03	5.01	-6.26
Alluvium Deposits	1.88	1.49	1.65	0.56	-0.39	0.15	-1.08
Built up	50.23	77.09	98.78	115.39	26.86	21.69	16.61
Open land	4.55	6.27	15.27	5.33	1.72	9	-9.94
Scrubland	11.73	17.54	12.23	17.92	5.81	-5.31	5.68
Vegetation	23.16	17.28	12.31	16.3	-5.88	-4.97	3.99
Waste land	32.69	28.73	38.35	16.56	-3.96	9.62	-21.79
Water body	8.83	10.95	7.16	8.5	2.12	-3.79	1.34

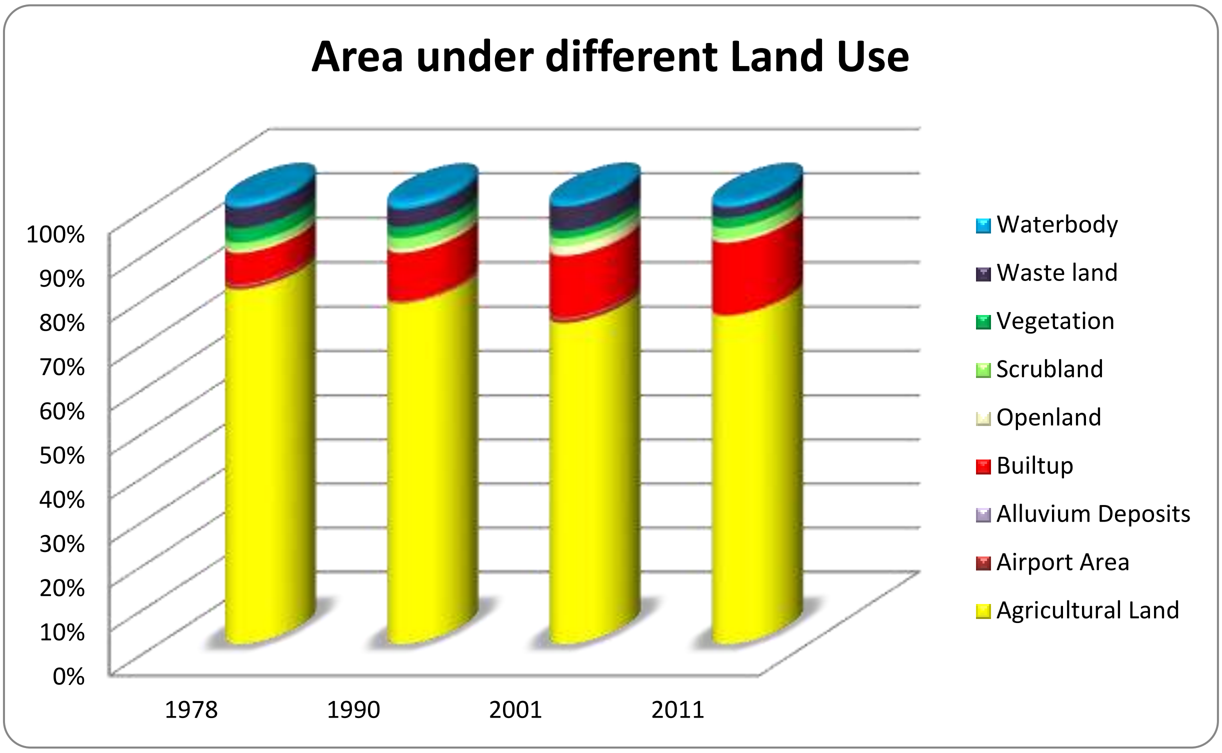


Figure 3.9 Area under different LULC classes for the years 1978, 1990, 2001 and 2011

Table 3.8Comparative analysis of Land use classes and percent area changes in decadal years (1978, 1990, 2001 and 2011).

LULC class	Area In %				% change		
	1978	1990	2001	2011	1990-1978	2001-1990	2011-2001
Agricultural Land	80.36	77.21	72.76	74.4	-3.15	-4.45	1.64
Airport Area	0.8	0.23	0.94	0.05	-0.57	0.71	-0.89
Alluvium Deposits	0.27	0.21	0.23	0.08	-0.06	0.02	-0.15
Built up	7.11	10.91	13.99	16.34	3.8	3.07	2.35
Open land	0.64	0.89	2.16	0.75	0.24	1.27	-1.41
Scrubland	1.66	2.48	1.73	2.54	0.82	-0.75	0.8
Vegetation	3.28	2.45	1.74	2.31	-0.83	-0.7	0.57
Waste Land	4.63	4.07	5.43	2.34	-0.56	1.36	-3.09
Water body	1.25	1.55	1.01	1.2	0.3	-0.54	0.19

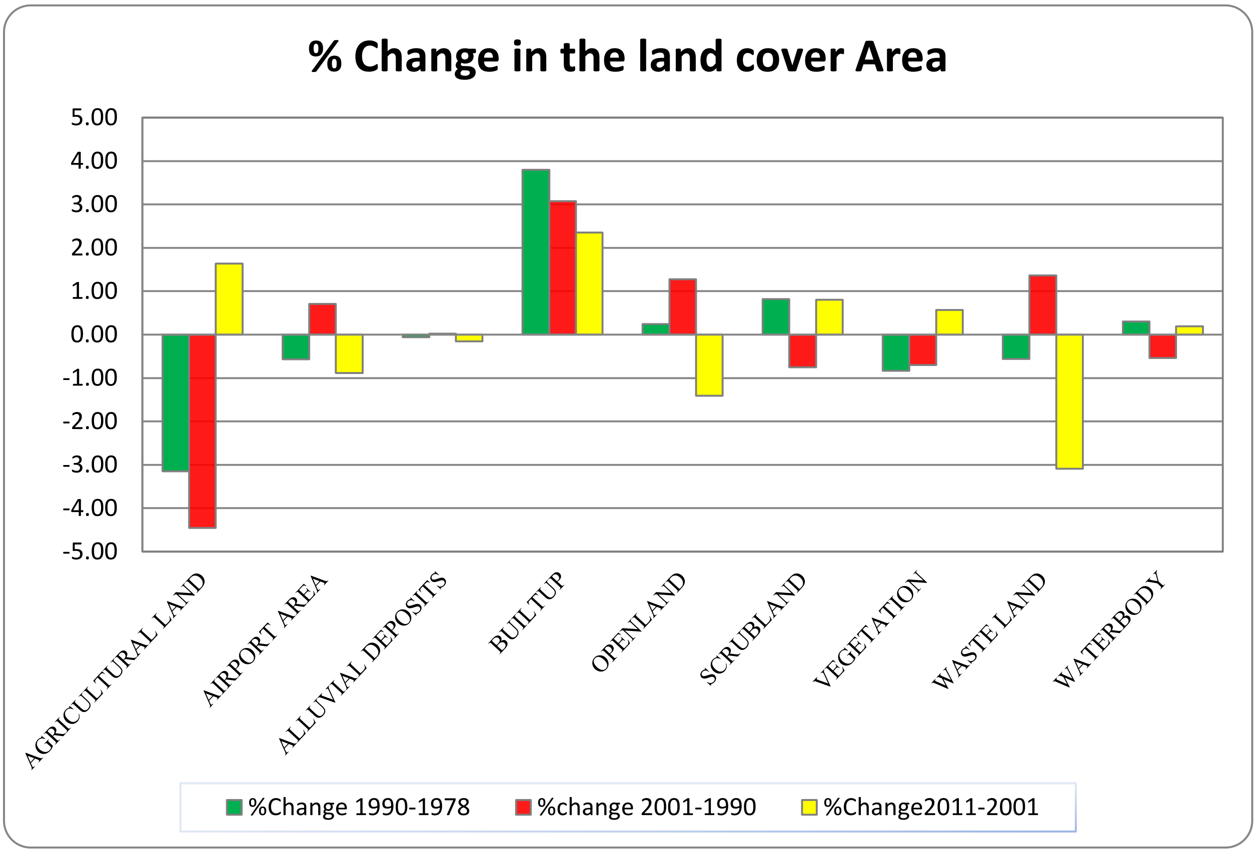


Figure 3.10 Percent of changes in land use land cover classes.

Table 3.9 Comparative analysis of Land use classes and percent area changes in decadal years (1978, 1990, 2001 and 2011).

Land Use Class	Area Change(In Sq Km)			% area				%Change			
	1990-1978	2001-1990	2011-2001	1978	1990	2001	2011	1990-1978	2001-1990	2011-2001	2011-1990
Agricultural Land	-22.11	-31.54	11.56	80.36	77.21	72.76	74.4	-3.15	-4.45	1.64	1.64
Airport Area	-4.03	5.01	-6.26	0.8	0.23	0.94	0.05	-0.57	0.71	-0.89	-0.89
Alluvial Deposits	-0.39	0.15	-1.08	0.27	0.21	0.23	0.08	-0.06	0.02	-0.15	-0.15
Built-up	26.86	21.69	16.61	7.11	10.91	13.99	16.34	3.8	3.07	2.35	2.35
Open land	1.72	9	-9.94	0.64	0.89	2.16	0.75	0.24	1.27	-1.41	-1.41
Scrubland	5.81	-5.31	5.68	1.66	2.48	1.73	2.54	0.82	-0.75	0.8	0.8
Vegetation	-5.88	-4.97	3.99	3.28	2.45	1.74	2.31	-0.83	-0.7	0.57	0.57
Waste Land	-3.96	9.62	-21.79	4.63	4.07	5.43	2.34	-0.56	1.36	-3.09	-3.09
Water body	2.12	-3.79	1.34	1.25	1.55	1.01	1.2	0.3	-0.54	0.19	0.19

The figure 3.11 shows the expansion of the built-up area from the 50.23 to 115.39 sq. km. the graphical representation clearly depicts the fragmented growth of the Vadodara city in year 2001 and 2011. This may be due to provision of the efficient transport network and cheaper land prices in the periphery.

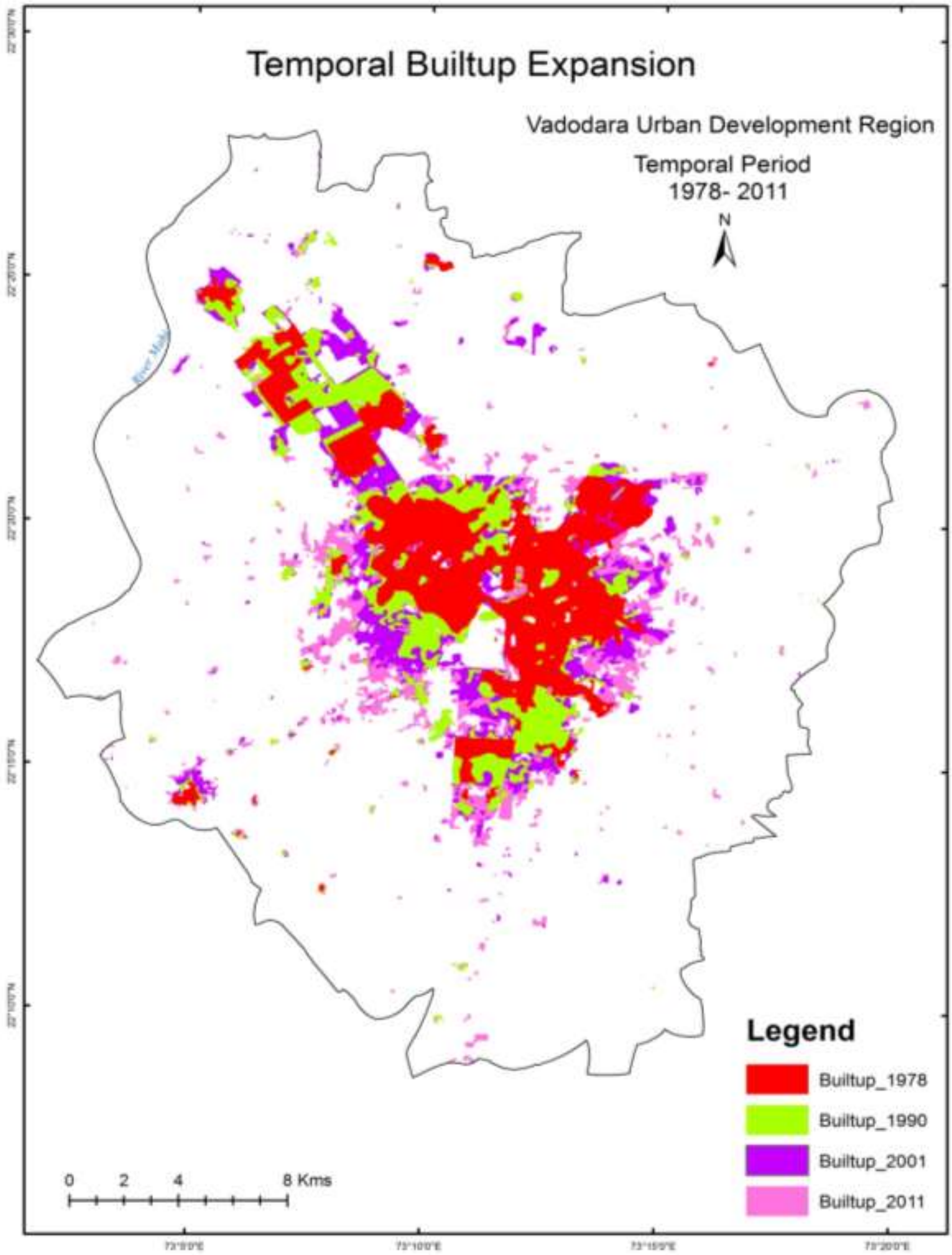


Figure 3.11: Temporal Built-up change

3.6 Urban sprawl analysis

Urban expansion take place when the population load increases in the centre of the city, in simpler words, as population increases in an area or a city expands to accommodate the growth; this expansion is considered as sprawl. Usually sprawls take place on the urban fringe or at the edge of an urban area.

3.6.1 Urban Sprawl Index (U.S.I.): It is a measure of the built environment in a city.

$$\text{Urban Sprawl Index (U.S.I)} = \frac{\text{Urban Expansion}}{\text{Population Increase}} \quad \text{…Equation (3.1)}$$

Table 3.10 Decadal U S I

Year	Urban Expansion (ha)	Population growth	U.S. I
1978-1990	2685.78	355832	0.35
1990-2001	2169.30	303353	0.22
2001-2011	1661.22	542709	0.14

Table 3.11 Builtup Expansion in the study area

Year	Urban Expansion (Sq Km)	Rate of expansion
1978-1990	26.85781244	2.24
1990-2001	21.69308091	1.97
2001-2011	16.61219058	1.66

3.6.2 Land consumption rate (L.C.R.):

It estimates the rate at which the land is consumed by the developing area, in other words a measure of compactness which indicates a progressive spatial expansion of a city. LCR is computed using equation (3.2).

$$\text{Land Consumption Rate (L.C.R.)} = \frac{\text{Areal Extent of City}}{\text{Population}} \quad \text{…Equation (3.2)}$$

Table 3.12 L.C.R. of the study area (VMC)

Year	Area (A) (ha)	Population (P)	L.C.R. (A/P)
1978(1981)	8700	7,34,473	0.011
1990(1991)	10800	10,31,346	0.010
2001	10800	13,06,227	0.007
2011	15800	17,52,371	0.009

The consumed land rates by developing area are presented in Table 3.10. The LCR of the study area for the year 1978 represents higher rate, which is 0.011. Whereas; LCR for the Year 2001 is very less as compare to other years. Year 1990 shows comparatively less LCR from the year 1978 and higher from the year 2001. These trends suggest that now city is tending to have the compaction.

3.6.3 Land Absorption Coefficient (L.A.C.): It estimates the rate at which the developing city absorbs the new urban land (Yeates and Garner, 1976). LAC was calculated using equation (3.3) that represents, a measure of change in consumption of new urban land by each unit increase in urban population.

$$\text{Land Absorption Coefficient (L.A.C.)} = \frac{A2-A1}{P2-P1} \qquad \text{… Equation (3.3)}$$

Whereas; A1 and A2 are the areal extents for the early and later years.P1 and P2are population for the early and later years respectively.

Table 3.13 L.A.C. of the study area.

Year	Area (A) (ha)	Population (P)VUDA	L.C.R. (A/P)
1978(1981)	5023.19045	10, 01,167	-
1990(1991)	7708.971694	13,47,033	0.0939
2001	9878.279785	17,51,699	0.0078
2011	11539.49884	22,90,703	0.0037

3.7 The longitudinal expanse Scenario of the Vadodara city

The region has shown the expansion of the area coverage under the built-up class and shrinkage of the open land and agricultural Land.

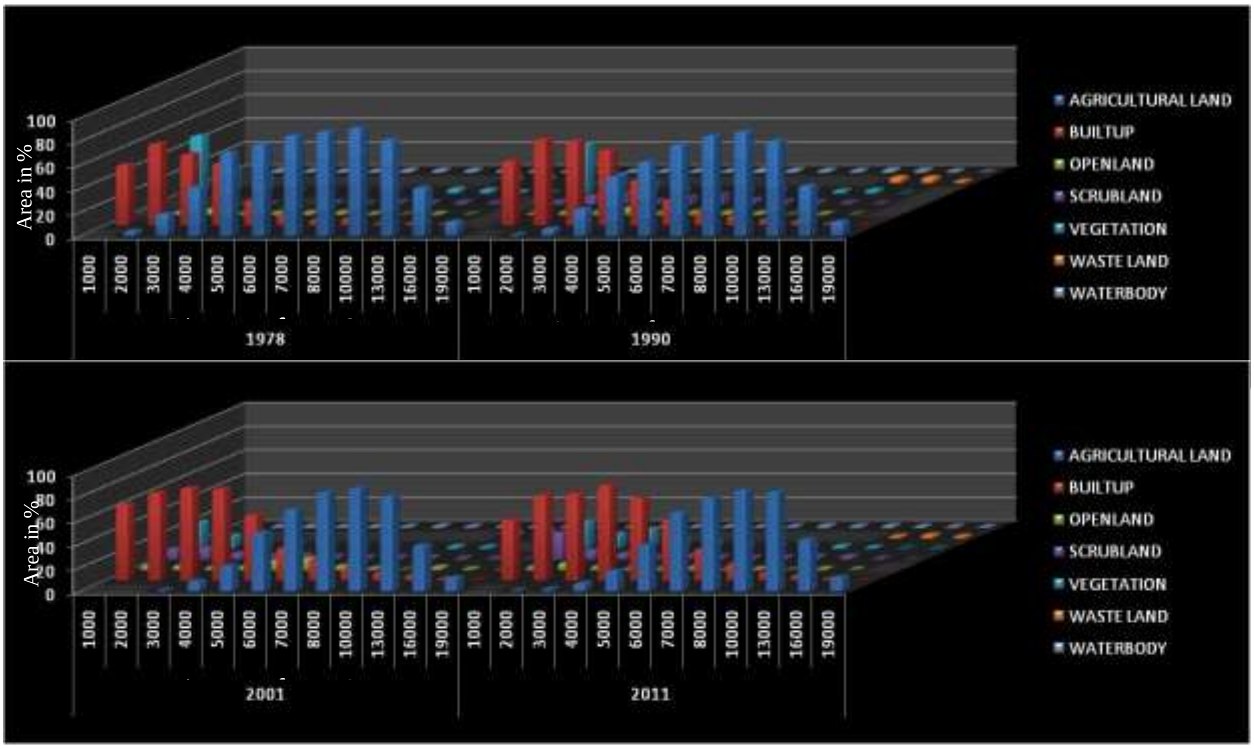


Figure 3.12: Temporal Longitudinal changes

The scenario shown in the figure shows how the inliers vacant plots came into built-up in the temporal duration as built-up percentage increases from 40 to 60. In 2001 and 2011 construction of the vacant land in the interior up to 4 km radius. New out growth development have triggered from the 3 km radius reducing the percentage share of agricultural land. It is worthwhile to mention that the analysis uses circular buffer and the decreasing share of the agricultural space after 13 km is due to non-geometrical boundary. Overall the scenario suggest that the tendency of the agrarian economy has shown the decline in the peri-urban limits owing to the short-term price it offers in lieu of transformation to built-up. Secondly it was also observed that the proximity to city and accessibility has change the living of the surrounding villages and education improvement and uncertainty of the agriculture yield has because the change in the preference of the job in the youngsters and this large scale trend was witnessed in this region.

3.8 Land use change analysis by Supervised Classification

Supervised classification uses the spectral signatures obtained from training samples to classify an image (ESRI). For Vadodara city were classified by the supervised classification based on Level I NRSC classification with Accuracy Assessments. Agriculture Crop, Agriculture Fallow, Built-up Dense and Sparse, Open land or Wasteland, Vegetation and Waterbodies this are the LULC classes were identified. The Classification has done from year of 1978- 2011 showed the various changes in builtup area which increased in simultaneously in inner and outer part of the city and other changes in agriculture area, vegetation and open land.City is growing largely towards north, northwest and southeast direction along the main transport routes. Year wise detail changes area and percentage are carried out from 1978 to 2011.

3.8.1 Land use in 1978

The Figure 3.13 represents supervised classifications of Vadodara city, where dark red color shows dense built-up land and area is around 26.14 sq.km, which is 3.70 percent of the entire study area. Table 3.14 represents the number of classes has been analyzed for the study in year 1978, area covered by each class in square kilometers and their respective coverage in total area percent. Figure 3.13 illustrates entire Vadodara Urban Development Authority (VUDA) region was dominated by agricultural which is some land under fallow and crop land in 1978 which was 32.09 and 42.36 percent respectively of total area and that covers 526.23 square km area of the total area. Some Built-up clusters were also identified in the North-west direction from the center of the city. Figure 3.13 shows, Waste land or open land is dominated along the river and upper part of the builtup area and south east direction of city which covers 89.26 square kilometer area that is of 12.70 percent of the total area.

Major River adjacent to VUDA is in north to west direction; whereas major pond situated in west part and many more scattered water bodies were identified within VUDA region in 1978.Area covered by water bodies is 3.81 square kilometer which is around 0.54 percent of the total VUDA area. Vegetation land which is combination of grassland, scrubland, open pasture which was spread in 60 square kilometer and it was around 8.61 percent of total VUDA area.

This analysis shows the percent share of each land class in VUDA region along land area coverages by respective classes in Year 1978.Figure 3.14 illustrates percent area shared by each LULC class of total VUDA area.

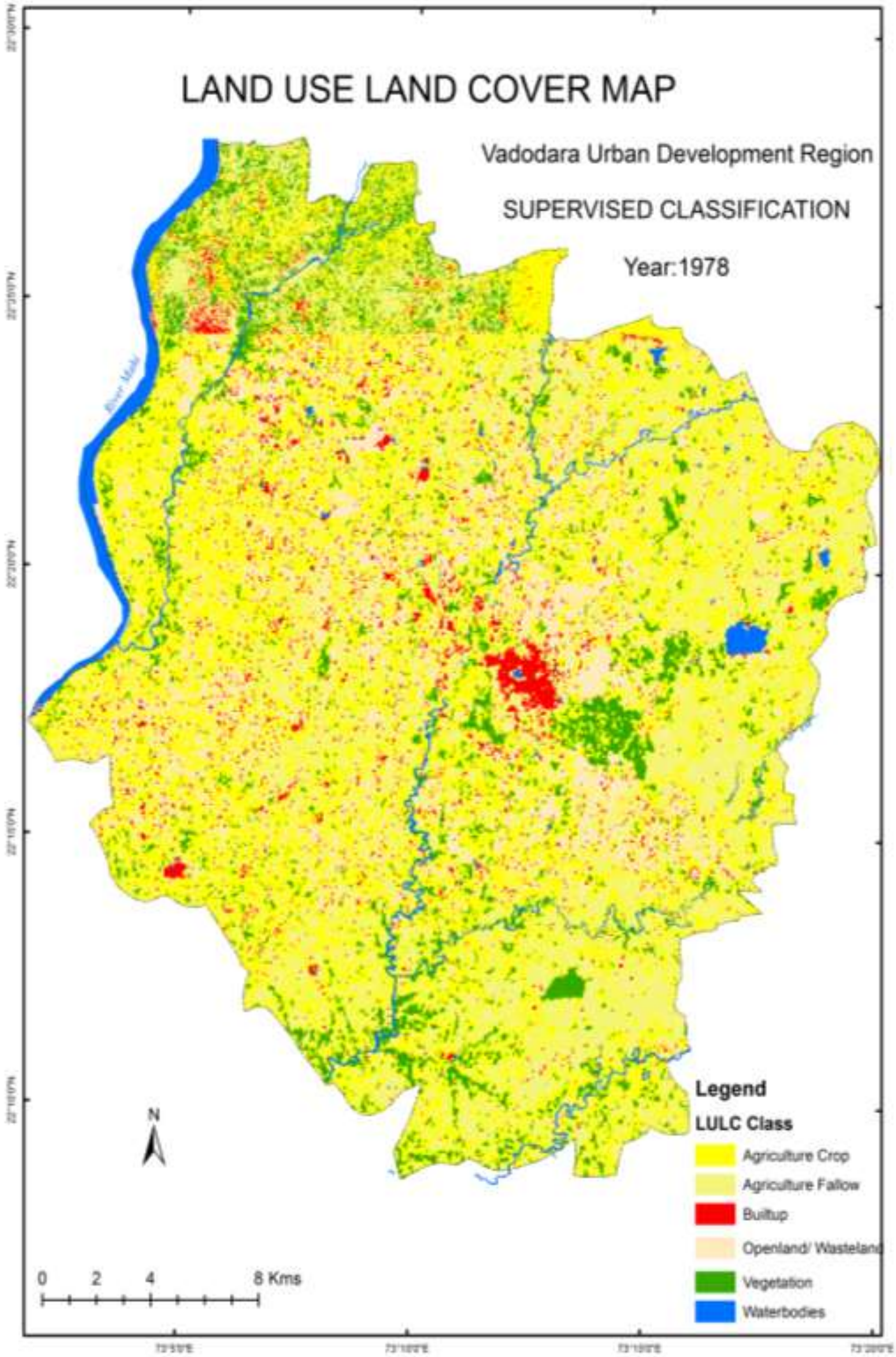


Figure 3.13 Land use Land Cover Map of Vadodara Urban Development Region (year 1978).

Table 3.14 Land use classes, total area and percent of area covered by each class in 1978.

LULC Class	Area In sqkm	Area in %
Builtup	26.14	3.70
Waterbodies	3.81	0.54
Agriculture Fallow	226.81	32.09
Vegetation	60.86	8.61
Open land/ Wasteland	89.78	12.70
Agriculture Crop	299.42	42.36

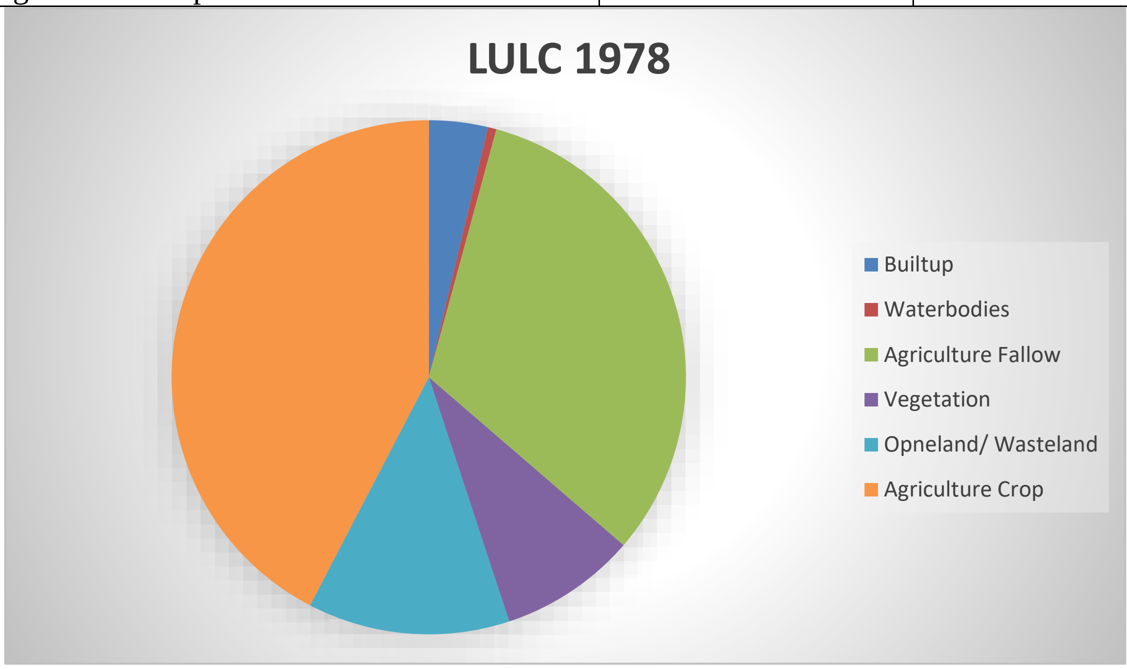


Figure 3.14 Percent area shared by LULC class of Total VUDA area in 1978.

3.8.2 Land use in 1990

The figure 3.15 shows classified output of VUDA for the year 1990.Land use land cover area and statistical information for respective classes shown in the table 3.15; whereas the percent of area covered by each class out of total area are shown in figure 3.16.

Agricultural crop and fallow land still occupies highest area by 57.84% and 16.99 respectively. Built up is 6%, open and wasteland is 9.61% while scrub land and vegetation occupy 8.18%. Built-up is divide into sparse and dense where dense settlement identified in center part of the city and sparse is outward. Compare to inner part the built up is increase in outward of the city. Its increase 2% than 1978 this may be due to slow and steady growth of urbanization by the way of residential and commercial constructions.

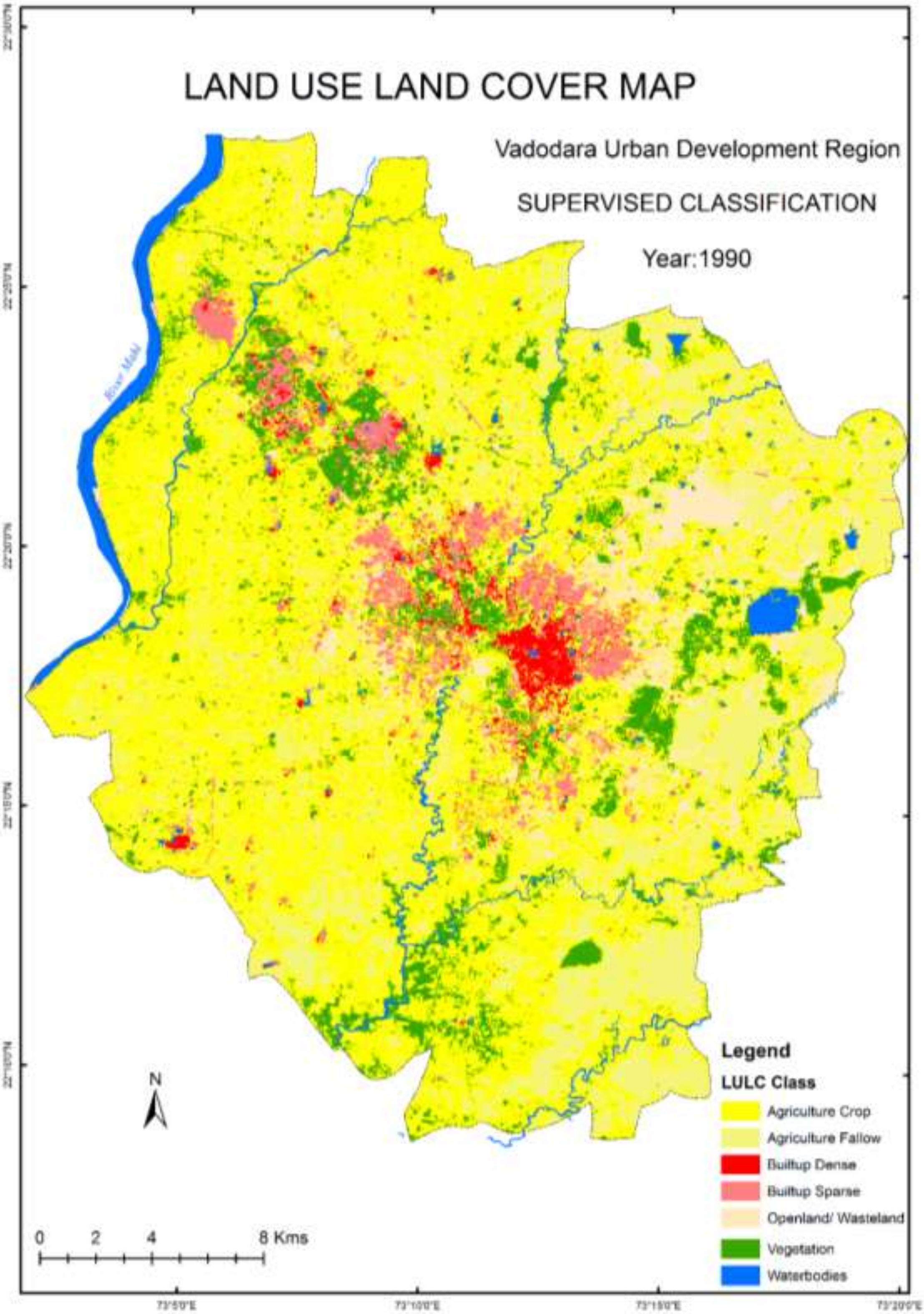


Figure 3.15 Land use Land Cover Map of VUDA (year 1990).

Table 3.15 Land use classes, total area and percent of area covered by each class in 1990

LULC Class	Area in sqkm	Area in %
Builtup Sparse	33.81	4.77
Agriculture Crop	409.52	57.84
Open land/ Wasteland	68.04	9.61
Waterbodies	6.75	0.95
Builtup Dense	11.74	1.66
Agriculture Fallow	120.30	16.99
Vegetation	57.91	8.18

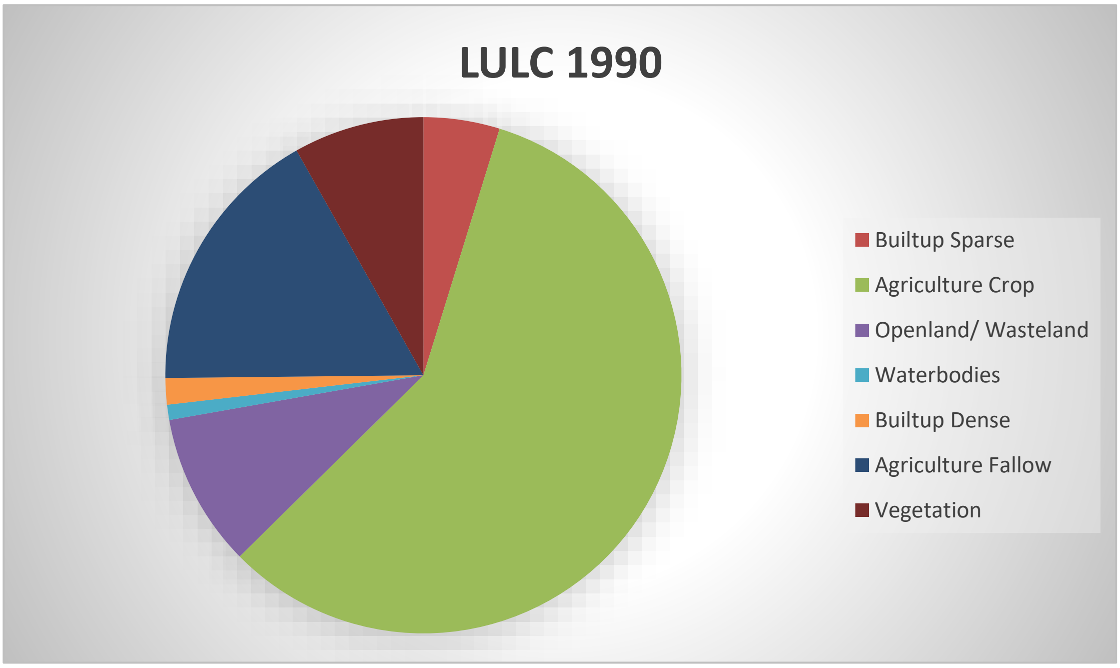


Figure 3.16 Percent area shared by LULC class of Total VUDA area in 1990.

3.8.3 Land use in 2001

LULC map for the year 2001 is presented in figure 3.17. Year 2001 is second last decadal year for which study have been carried out. Land use Land cover map represents agricultural land spread in 398.09 square kilometer; builtup were spread in 148 square kilometers this is tremendous change happened in this year, open land and wasteland is 62.58vegetation land: 95.52, water body: 4.24 square kilometer area covered out of total area 706.18 kilometers.

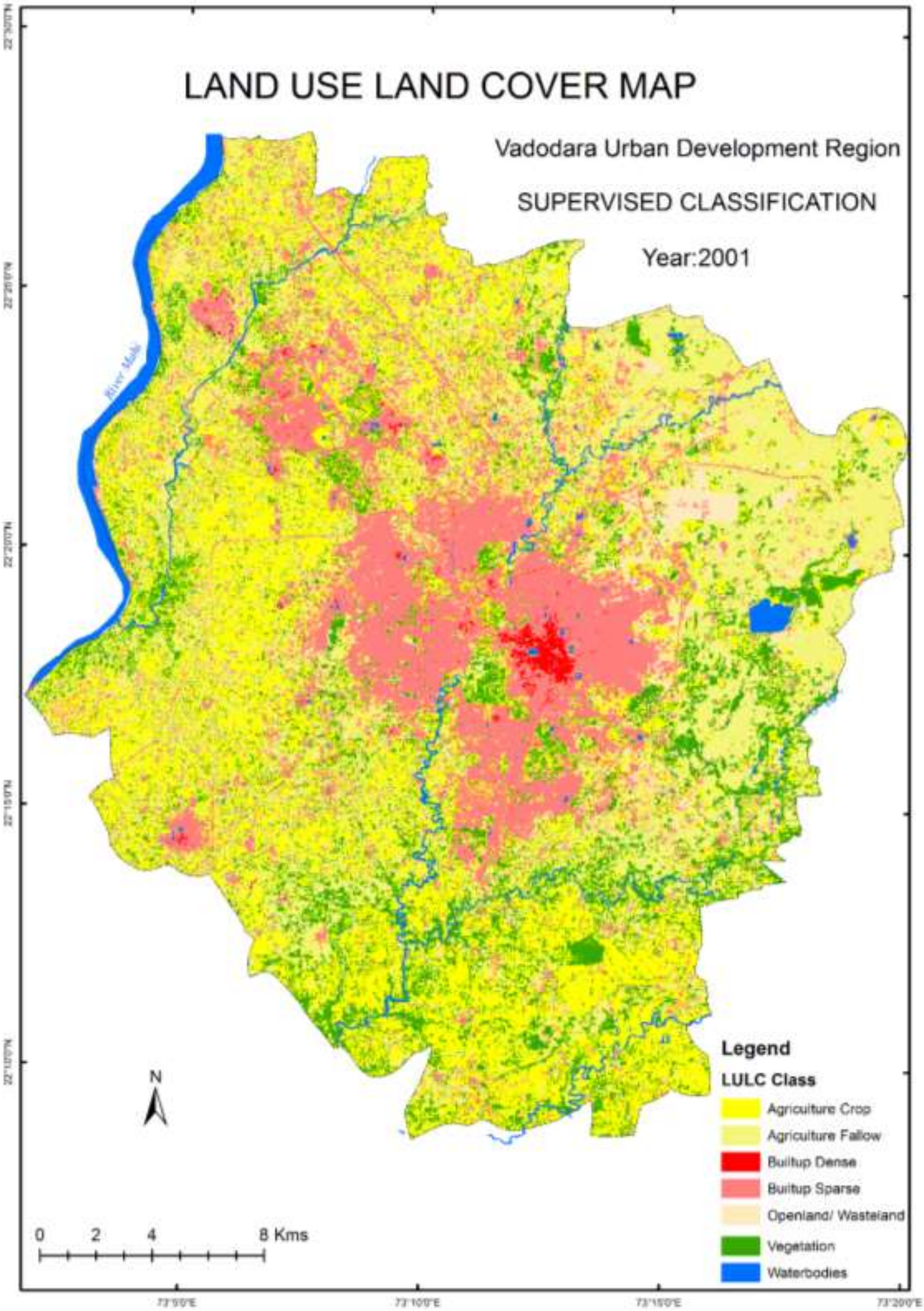


Figure 3.17 Land use Land Cover Map of Vadodara Urban Development Region (Year 2001)

Table 3.16 Land use classes, total area and percent of area covered by each class in 2001.

LULC Class	Area in sqkm	Area in %
Waterbodies	4.24	0.60
Agriculture Crop	181.18	25.58
Builtup Dense	3.67	0.52
Builtup Sparse	144.03	20.34
Agriculture Fallow	216.91	30.63
Vegetation	95.52	13.49
Open land/Wasteland	62.58	8.83

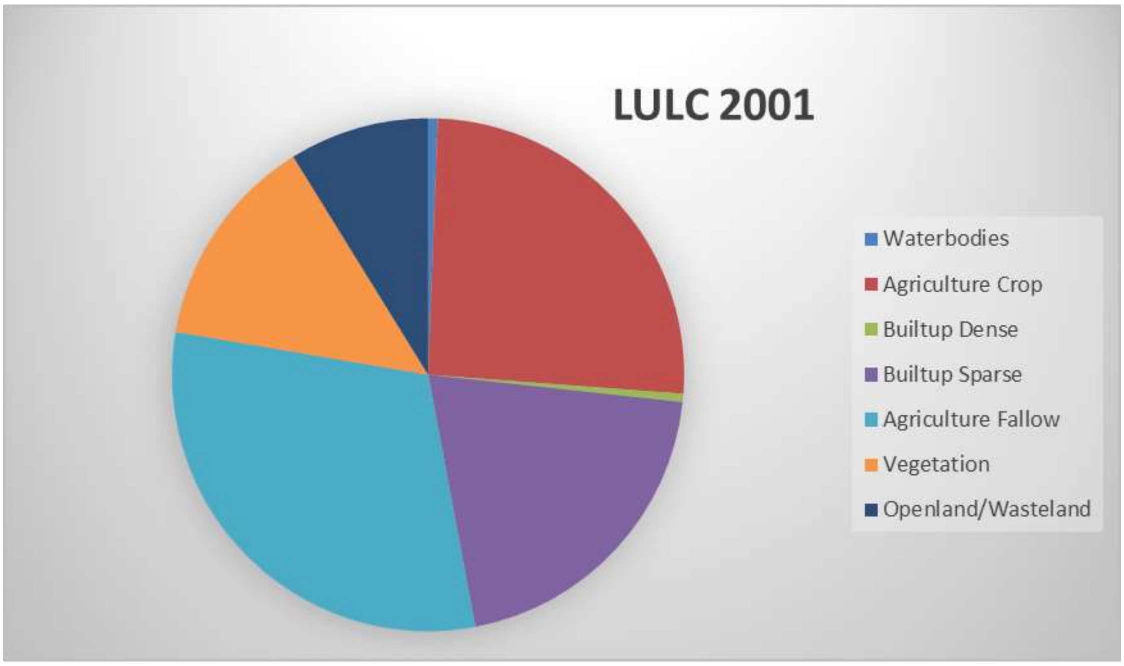


Figure 3.18Percent area shared by LULC class of Total VUDA area in 2001.

3.8.4 Land use in 2011

In this year builtup area are increased in tremendous scale. It is now 166.1 sq. km which was 23.40 % of total land use is now 20 % more than double in 33 years. However, agriculture slightly increased which can be attributed to Narmada Canal introduced in area. Open land slightly increase with 11.90%, vegetation also has declined. In an urban situation, it is the hinterlands where agricultural activities that are predominant supply the food materials to the inhabiting population of the city. Threat to the agricultural land implies a future threat on the food material supply and on inflation. Figure 3.20 rep resents, percent of area change in land use land cover classes between 2001 and 2011.

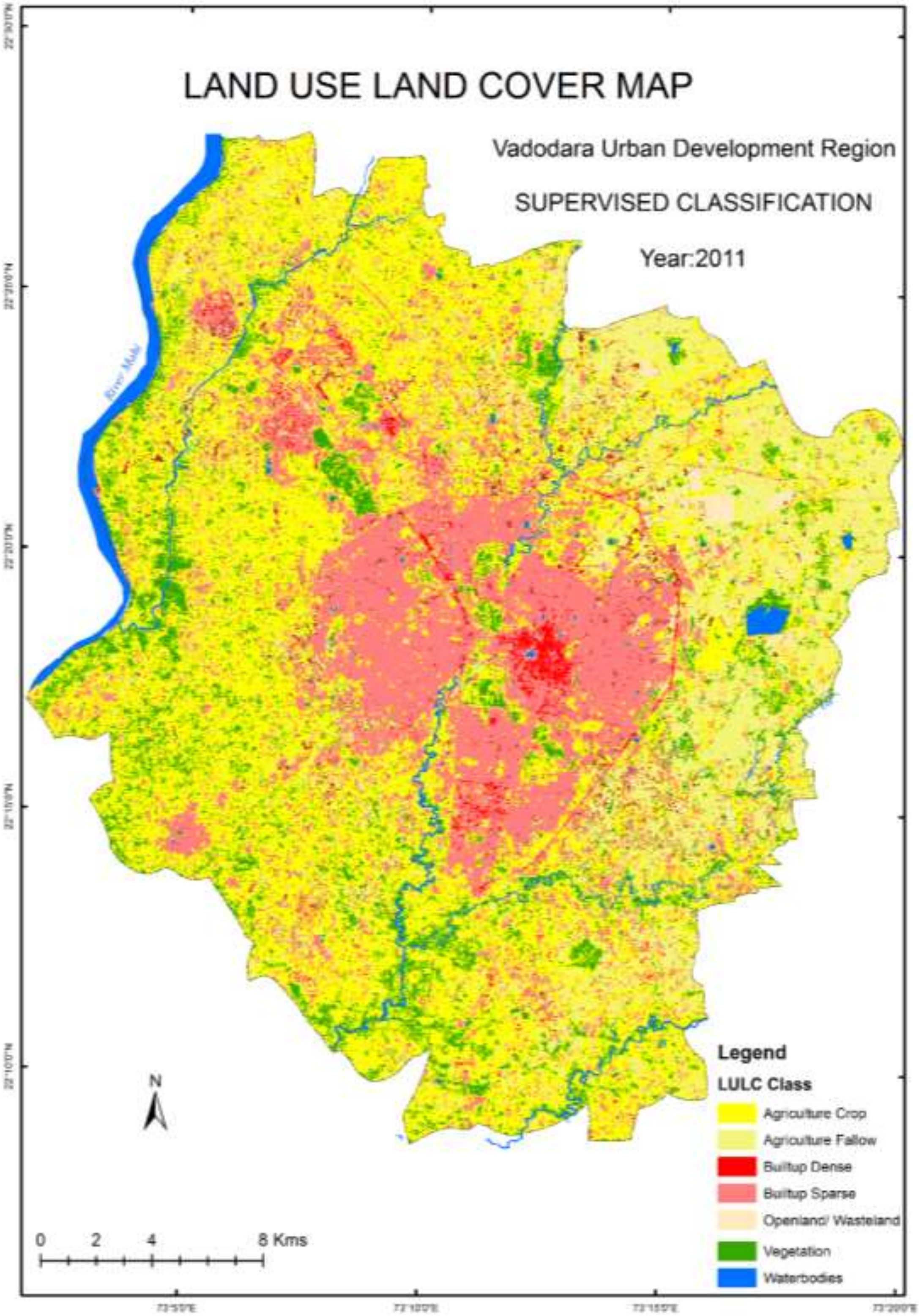


Figure 3.19 Land use Land Cover Map of VUDA (year 2011).

Table 3.17 Land use classes, total area and percent of area covered by each class in 2011

LULC Class	Area in sqkm	Area in %
Builtup Dense	9.70	1.37
Builtup Sparse	156.40	22.09
Agriculture Crop	289.56	40.89
Waterbodies	4.77	0.67
Vegetation	58.92	8.32
Agriculture Fallow	104.51	14.76
Open land/Wasteland	84.28	11.90

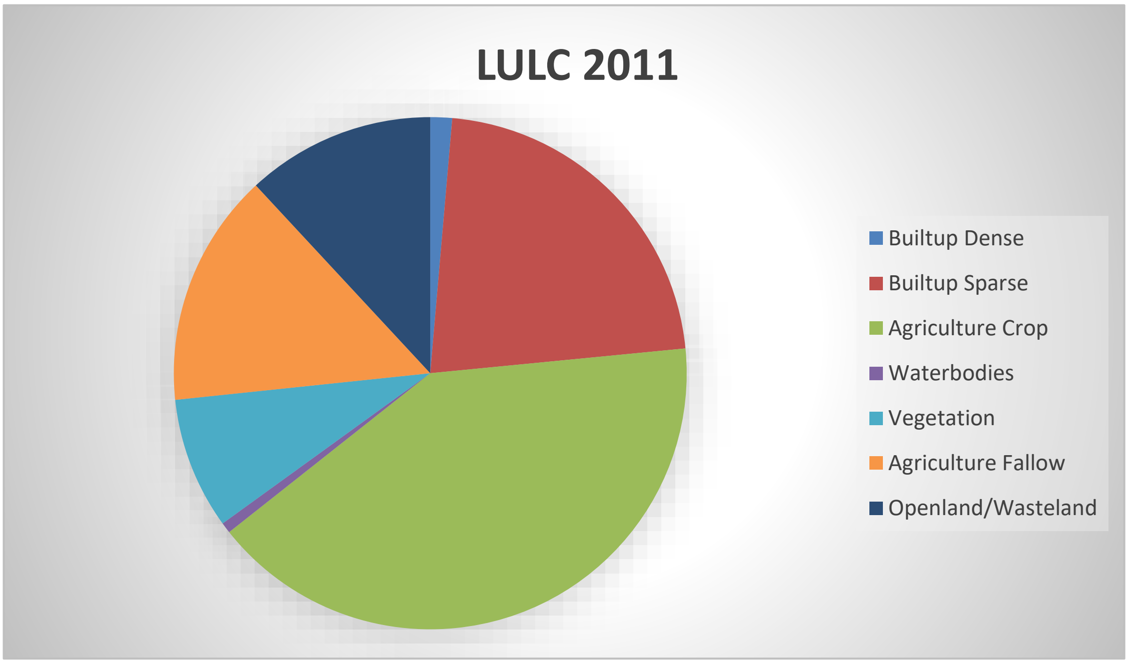


Figure 3.20 Percent area shared by LULC class of Total VUDA area in 2011.

3.9 Accuracy Assessment:

Accuracy Assessment uses a Reference Dataset to determine the accuracy of classified result. The values of reference dataset need to match the schema (ESRI). The VUDA region, supervised classification were applied and for the checking accuracy of classified image overall accuracy and Kappa Statistic of the LULC feature were calculated by the accuracy assessment

Process. Accuracy Assessment for 1978, 1990, 2001 and 2011 were calculated with producer and user accuracy, which is describe in following table:

Table: 3.18 Accuracy Assessment of LULC from 1978 to 2011(In %)

Years	**1978**		**1990**		**2001**		**2011**	
LULC Classes	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
Built-up Dense	40.00%	85.71%	100%	75%	100.00%	100.00%	100.00%	87.50%
Built-up Sparse	-	-	61.54%	88.89%	75.00%	75.00%	64.71%	91.67%
Agriculture Crop	83.33%	83.33%	93.75%	83.33%	100.00%	87.50%	100.00%	93.33%
Agriculture Fallow	72.73%	72.73%	64.71%	100.00%	77.78%	87.50%	90.91%	100.00%
Vegetation	100.00%	100%	100.00%	100.00%	88.89%	100.00%	90.00%	100.00%
Open / Wasteland	83.33%	62.50%	100.00%	100.00%	100.00%	85.71%	100.00%	100.00%
Water body	100%	100%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Overall Accuracy	**73.33%**		**83.75%**		**91.67%**		**90.00%**	

Table: 3.19 Kappa Statistics of all LULC feature from 1978 to 2011

LULC Classes	**1978**	**1990**	**2001**	**2011**
Builtup Dense	0.8095	0.7297	1.0000	0.8630
Builtup Sparse	-	0.8673	0.7115	0.8942
Agriculture Crop	0.7917	0.7917	0.8585	0.9192
Agriculture Fallow	0.6660	1.0000	0.8529	1.0000
Vegetation	1.0000	1.0000	1.0000	1.0000
Open / Wasteland	0.5833	1.1026	1.8413	1.3506
Waterbody	1.0000	1.0000	1.0000	1.0000
Overall Kappa	**0.6872**	**0.8115**	**0.9047**	**0.8845**

A table is created listing each random point as a record along with a field for ground truth and a field for the classified image.

3.10 Analysis of land use Change 1978-2011

Comparative analysis of LULC absolute changes in years 1978 to 2011 summarized in table 3.22. Maximum absolute change in Agricultural crop land has been observed during 1990 to 2001. During 1990 to 2001-time period 228 Sq. km (32%) area of agricultural land decreased, whereas, agriculture fallow land is increased with 13.64 %. Year 2001 to 2011 crop land increased because of the irrigation network available due to Narmada branch canal; it was 108.38 Sq. Km increased.

Table: 3.20 Comparative analysis of Land use classes and absolute changes in decadal years.

LULC class	Geographical Area (In Sq. Km)				Absolute Change		
	1978	1990	2001	2011	Change 1990-1978	Change 2001-1990	Change2011-2001
Builtup Dense	26.14	11.74	3.67	9.70	19.41	-8.07	6.03
Builtup Sparse		33.81	144.03	156.40		110.22	12.37
Agriculture Crop	299.42	409.52	181.18	289.56	110.1	-228.34	108.38
Agriculture Fallow	226.81	120.30	216.91	104.51	-106.51	96.61	-112.4
Vegetation	60.86	57.91	95.52	58.92	-2.95	37.61	-36.6
Open / Wasteland	89.78	68.04	62.58	84.28	-21.74	-5.46	21.7
Waterbody	3.81	6.75	4.24	4.77	2.94	-2.51	0.53

Table 3.21 Comparative analysis of Land use classes and percent area changes in decadal years (1978, 1990, 2001 and 2011).

LULC class	Area In %				Change in %		
	1978	1990	2001	2011	1990-1978	2001-1990	2011-2001
Builtup Dense	3.70	1.66	0.52	1.37	2.73	-1.14	0.85
Builtup Sparse		4.77	20.34	22.09		15.57	1.75
Agriculture Crop	42.36	57.84	25.58	40.89	15.48	-32.26	15.31
Agriculture Fallow	32.09	16.99	30.63	14.76	-15.1	13.64	-15.87
Vegetation	8.61	8.18	13.49	8.32	-0.43	5.31	-5.17
Open / Wasteland	12.70	9.61	8.83	11.90	-3.09	-0.78	3.07
Waterbody	0.54	0.95	0.60	0.67	0.41	-0.35	0.07

Built-up dense and sparse area is increased or decreased in mentioned time period respectively, 1978 to 1990: 19.41 Sq. Km area is increased, 1990 to 2001:dense area decreased whereas sparse areas increased with 110.22 Sq. Km and 2001 to 2011 12.37 Sq. Km. Water body and Open land was slight increased and decreased refer Table3.21.

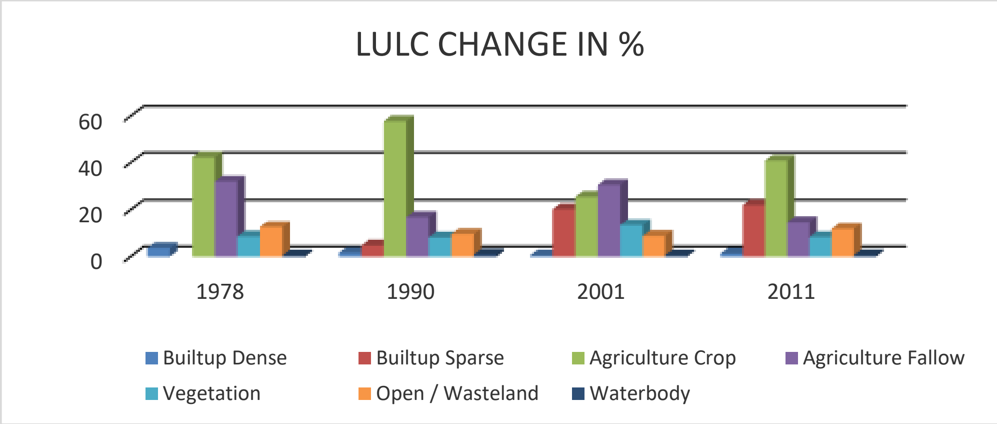


Figure 3.21 Percent of changes in land use land cover classes.

The change analysis shows that agriculture area were increased in 1991 compared to previous decade, whereas this features decreased in 2001 and 2011 with increasing the builtup land. The waterbodies increased and decreased with changed the decade. In 1990 waterbody has increased 0.41%, then this was decreased 0.35 %. In compare to 2001 it has increased 0.07% in 2011. So movement of change of water based on the availability of rainfall and human activities. Thus the changes in LULC in percentage by decade that expressed in figure 3.21.

3.11 Digital Image processing Technique: Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a dimension-reduction tool that can be used to reduce a large set of variables to a small set that still contains most of the information in the large set. Principal component analysis (PCA) is a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components.The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

Principal Component Analysis: Principal Component Analysis (PCA) is a mathematical technique for reducing the dimensionality of a data set. In multi-band remote sensing images, some of the original bands may be highly correlated. To save on data storage space and computing time, such bands could be combined into new less correlated Eigen images by PCA. Principal Component Analysis applies either the covariance matrix or the correlation matrix to transfer data to an uncorrelated set. The Eigen vectors of the resultant matrices are sorted in descending order where first principal component (PC) expresses most of the data variation. The next largest variation is defined by the succeeding component and is independent (orthogonal) of the preceding principal component. In PCA the areas of no change are highly correlated whereas areas of change are not. In multi temporal image analysis it was assumed that the PC1 and PC2 tend to represent the unchanged areas, where as PC3 and later PCs contain the change information (Masroor Hussain Dongmei et al, 2013)

Christopher et al., (2004) implements Principal Component Analysis method to detect changes in an inland wetland system in southern Zambia using a combination of Landsat MSS and TM images. PCA was found to be useful to identify where changes occurred but it was difficult to interpret the changes. Knowledge of the land cover characteristics of the study area is essential to use PCA as a change detection technique (Christopher Munyati, 2004).

Li and Yeh (1998) compared principal component analysis to post classification techniques and concluded that principal component analysis was much more accurate than post classification techniques and therefore suggested it as an accurate alternative for detecting land use change.

PCA is expected to estimate dimensionality of dataset and identify the principal axes of variability within the data. The purpose of principal components analysis is to define the number of dimensions that are present in a data set and to fix the values of the coefficients which specify the positions of that set of axes which point in the directions of greatest variability in the data (Mather and Koch, 2011).

Satellite remote sensing digital images are numeric; therefore, their dimensionality can be reduced using PCA. Dimension reduction leads to visualization of the data clearly and subsequent data analysis more manageable (Connese, C., G. et al, 1988). In multi-band remote sensing images, the bands are the original variables. Some of the original bands may be highly correlated and to save on data storage space and computing time, such bands could be combined into new, less correlated eigen images by PCA. In addition to its use in this way, PCA can be used as a change detection technique in remote sensing.(Ding, J.L et al 2011, ERDAS Inc., 1994, Eastman, J.R. and M. Fulk, 1993) Many studies have been used PCA for various purpose including detect geomorphologic features and sediment textural classes7 as one of the index in decision tree classifier for land use classification8 and to distinguish between geologic features9. Furthermore, this technique could be used to evaluation internal vegetation anomalies10. The aim of this study was to investigate the accuracy of the classification using the combination of PCA1 with original bands.

PCA-based change detection, which captures maximum variances in a finite number of orthogonal components based on an eigenvector analysis of the data correlation matrix, has been used in change detection for many years and has become one of the most popular techniques because of its simplicity and capability of enhancing the information on change (Ingebritsen and Lyon 1985, Yeh and Li 1997, Li and Yeh 1998, Lu et al. 2005,). The central idea of PCA is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables (Jolliffe 2002)

By employing this technique, data were placed in new space that correlation between bands vanished and created independent bands. Due to the more variance, first component among the other components of the principal components analysis selected. Some authors in the literature have found the first component has maximum variance for each class and helps to better separation phenomena. In a study, Bonyad18 used principal component analysis to reduce the correlation satellite images and overall accuracy was estimated 99.37%.

3.11.1 Data Set

Temporal satellite data from various satellites were chosen for monitoring the spatial and temporal changes in the land-use/land-cover. Landsat TM, Landsat ETM and ETM+ is used. The Landsat TM image for the year 1978 has shortfall in the coverage in the northern region of the study area due to shift in path and row. And the nearest temporal image available for the patch was at the gap of 6 years of different season. And using that the PCA showed undesirable result thus the image was left unpatched.

3.11.2 Methodology

Principal Component Analysis (PCA): Principal component analysis[13] is a linear transformation which de-correlates multi variate data by translating and/or rotating the axes of the original feature space, so that the data can be represented without correlation in a new component space. This technique has been chosen over traditional direct image classification after visual interpretation in order to ensure maximum separability between the various classes. Computationally, three steps are involved in the principal component transformation

The first step is the calculation of a covariance or correlation matrix using the input data sets, the second step is the calculation of eigen values and eigen vectors and the third one is the calculation of principal components. The principal components calculated using the covariance matrix are referred to as un-standardized principal components and those calculated using the correlation matrix are referred to as standardized principal components[11,14]. The use of a correlation matrix in calculating principal components implies scaling of the axes so that each feature has unit variance. This normalization process prevents certain features from dominating the analysis because of their large numerical values. An IRS image can be expressed in matrix format in the following way:

$$X_{n,b} = \begin{pmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{4,1} & \cdots & x_{4,n} \end{pmatrix}$$

Where, n represents the number of the pixels and b the number of bands. Considering each band as a vector, the above matrix can be simplified as follows:

$$X_k = \begin{pmatrix} x_1 \\ . \\ . \\ x_4 \end{pmatrix}$$

Where, k is the number of bands.

To reduce the dimensionality of the original bands, the eigenvalues of the covariance matrix must be calculated as follows:

$$C_{b,b} = \begin{pmatrix} \sigma_{1,1} & \cdots & \sigma_{1,4} \\ \vdots & \ddots & \vdots \\ \sigma_{4,1} & \cdots & \sigma_{4,4} \end{pmatrix}$$

Where, $\sigma_{i,j}$ is the covariance of each pair of different bands.

$$\sigma_{i,j} = \frac{1}{N-1}\sum_{p=1}^{N}(DN_{p,i} - \mu_i)\left(DN_{p,i} - \mu_j\right)$$

Where, $DN_{p,i}$ is a digital number of a pixel p in the band i, $DN_{p,i}$ is a digital number of a pixel P in the band j, μ_j and μ_j are the averages of the DN for the bands i and j, respectively.

From the variance-covariance matrix, the eigenvalue (λ) are calculated as the roots of the characteristic equation:

$$\det(C - \lambda I) = 0$$

Where, C is the covariance matrix of the bands and I is the diagonal identity matrix.

The eigenvalues indicate the original information that they retain. From these values, the percentage of original variance explained by each principal component can be obtained calculating the ratio of each eigenvalue in relation to the sum of all those. Those components which contain minimum variance and thus minimum information can be discarded.

The principal components can be expressed in matrix form:

$$Y_6 = \begin{pmatrix} y_1 \\ \cdot \\ \cdot \\ y_4 \end{pmatrix} = \begin{pmatrix} w_{1,1} & \cdots & w_{1,4} \\ \vdots & \ddots & \vdots \\ w_{4,1} & \cdots & w_{4,4} \end{pmatrix} \begin{pmatrix} x_1 \\ \cdot \\ \cdot \\ x_4 \end{pmatrix}$$

Where, Y is the vector of the principal components, W is the transformation matrix and X is the vector of the original data. The coefficients of the transformation matrix W are the eigenvectors that diagonals' the covariance matrix of the original bands. These values provide information on the relationship of the bands with each principal component. From these values it is possible to link a main component with a real variable.

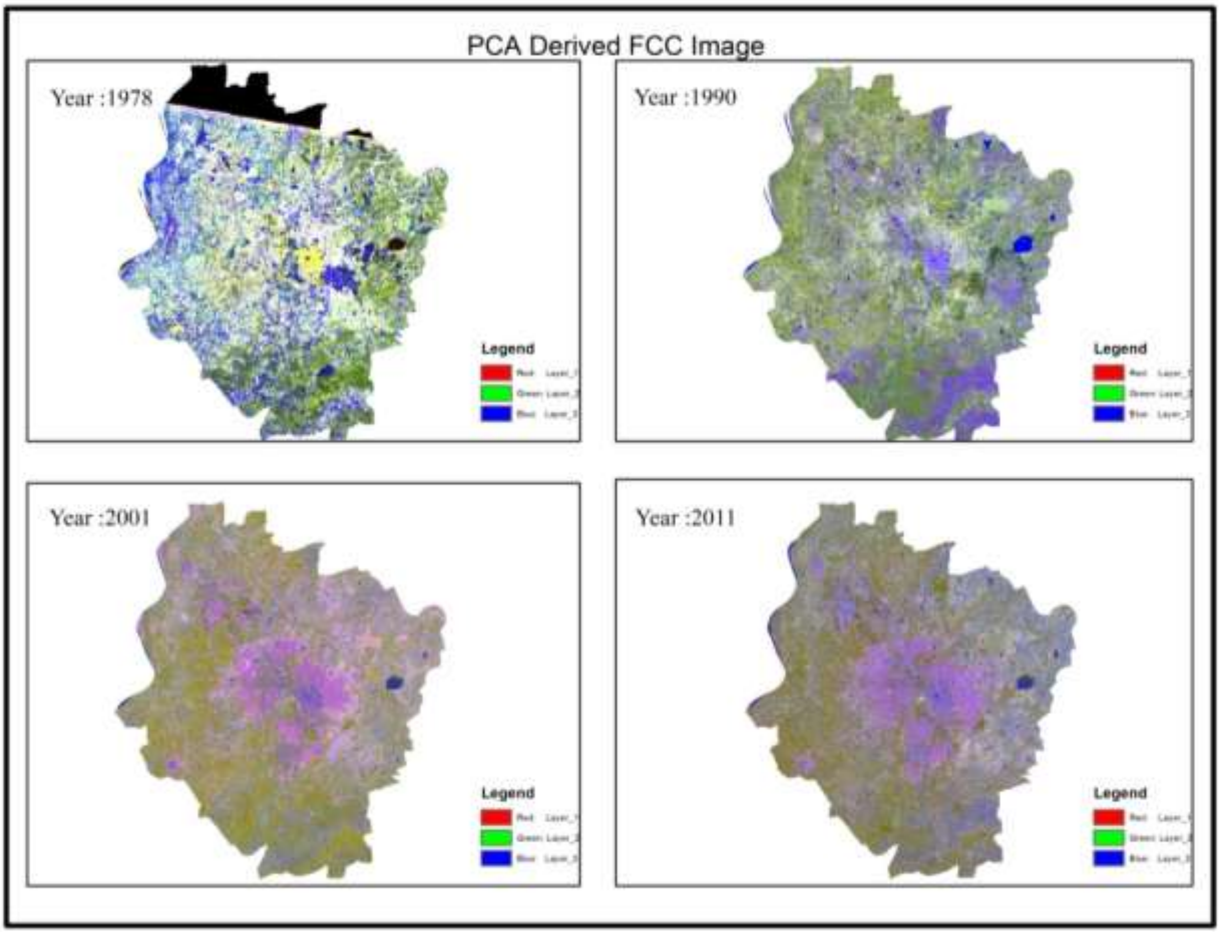
The eigenvectors can be calculated from the vector - matrix equation for each eigenvalue λ_k:

$$(C - \lambda_k I) w_k = 0$$

Where, C is the covariance matrix, λ_k is the k eigen values (four in our example), I is the diagonal identity matrix and w_k is the k eigenvectors.

3.12 Results and Discussion

The properties of PCA prove to be useful for data compression, also it helps to eliminate the redundant information and compressed files become easy for transmission over a slow connection. Also, relationships between different groups of pixels representing different land cover types may become clearer if they are viewed in the principal axis reference system rather than in terms of the original spectral bands, especially as the variance of the data set is concentrated in relatively fewer principal components. Variance is often associated with information. The data compression property is useful if more than three spectral bands are available. The Landsat TM provides seven bands of data; hence a decision must be made regarding which three of these seven bands are to be used as source image for classification. If the basic dimensionality of the TM data is only three, then most of the information in the seven



bands will be expressible in terms of three principal components.

The principal component images could therefore be used to generate a RGB false-color composite. Such an image contains more information than any combination of three spectral bands.

The use of lower-order (higher numbered) components depends on the aims of the project. If the aim is to capture as much as possible of the information content of the image set in as few principal components as possible then the lower-order principal components should be omitted. If the PCA is based on the correlation matrix is used, then the ‘Eigen value greater than 1’ (or ‘Eigen value – 1’) criterion have been used to determine how many principal components to retain. If an individual standardized band of image data has a variance of one, then it might be possible to argue that all retained principal components should have a variance of at least one. The Eigen values and scaled eigenvectors, or principal component loadings, derived from the correlation matrix measure the concentration of variance in the data in six orthogonal directions. Using the generated Eigen values sum of the Eigen values has been calculated and cumulative sum for each PC level have been computed for cumulative variance calculations.

For the year 1990 PCA-1 shows 84.22 % variability in the data lies in the direction defined by the first principal component. Over 96% of the variability in the data lies in the direction defined by the second principal component and Over 99% variability lies in the direction defined by the Third principal component (Table 3.22).

Table 3.22 Eigen Values for 1990

S.no.	Eigen Value	Cumulative Sum (Eigenvalue)	Cumulative Variance %
1	3481.692955	3481.692955	84.2204405
2	514.1823028	3995.875258	96.65825756
3	125.7943453	4121.669603	99.70116091
4	8.922980743	4130.592584	99.91700343
5	2.769350445	4133.361934	99.98399265
6	0.661747525	4134.023682	100
Total	**4134.023682**		

Table 3.25 illustrates the cumulative % variance in year 2001 dataset using PCA, where First principal component shows more than 85% variability covered in the dataset. Over 95% of the variability in the data lies in the direction defined by the second principal component and Over 99% variability lies in the direction defined by the Third principal component (Table 3.23).

Table 3.23 Eigen Values for 2001

S.no.	Eigen Value	Cumulative Sum (Eigen Value)	Cumulative Variance %
1	0.035125226	0.035125226	85.8807764
2	0.003868422	0.038993648	95.33902317
3	0.001566604	0.040560252	99.16935214
4	0.000193474	0.040753726	99.6423929
5	0.000112214	0.04086594	99.91675522
6	3.40E-05	4.09E-02	100
Sum	**0.040899987**		

Variance analysis using principal component analysis for the year 2011 is analyzed in table 3.26, where PCA-1 shows over 85% cumulative variance in dataset. Over 95% of the variability in the data lies in the direction defined by the second principal component and Over 98% variability lies in the direction defined by the Third principal component (Table 3.24).

Table 3.24 Eigen Values for 2011

S.no.	Eigenvalue	Cumulative Sum(Eigenvalue)	Cumulative Variance %
1	0.027703196	0.027703196	85.07901641
2	0.003499633	0.031202828	95.82670401
3	0.000971848	0.032174677	98.81133748
4	0.000199687	0.032374363	99.42459375
5	0.000138494	0.032512858	99.84992191
6	4.89E-05	0.032561726	100
Sum	**0.032561726**		

It was noted that the principal components transform is defined by the characteristics of the into-band correlation or covariance structure of the image. It is observed by cumulative percent variance in Table 3.24, Table 3.25 and Table 2.26 for the respective year 1990, 2001 and 2011, variance values 99%, 99% and 98% have been covered in third principal component.

The Study have been carried out with PCA level 3 for further classification procedure in mentioned years (1990,2001 and 2011).

The three Principal components (PC) were used by stacking them as the layers and FCC were generated. The images were then subjected to the supervised classification and as the images showed the promising result, the concentrations were focused on the built-up class. It was subjected to the accuracy assessment and the built-up class was having the accuracy of the 89 % and overall accuracy of 92%. Thus, the output land use maps were used as input for future prediction of the Urban Growth.

3.25 Land Use Land Cover Change Analysis:

LULC class	Area_1978	Area_1990	Area_2001	Area_2011	Change		
					1978-1990	1990-2001	2001-2011
Built-up	42.4116	50.3874	82.5849	91.0035	7.9758	32.1975	8.4186
Waterbody	6.7019	8.9784	6.2001	9.5661	-2.27	-2.7783	3.366
Agriculture	297.658	406.724	317.187	258.089	109.066	-89.537	-59.098
Vegetation	53.6256	88.8282	92.5524	89.3448	35.2026	3.7242	-3.2076
Scrubland	96.1515	20.5452	67.8771	173.079	-75.6063	47.3319	105.2019
Open space	158.834	106.544	125.022	75.1284	-52.29	18.478	-49.8936
Other	10.9449	24.1695	14.7879	10.2	13.2246	-9.3816	-4.7879

A major change is observed in decline in agriculture area, open land and water body, at the same time built up area has drastically increased. The analysis goes in the similar line of shrinking agricultural land with expansion of the Built-up land. The transition shows an interesting reflection of the policies in action. The time scale of the study shows the different phase how the built-up has evolved during the temporal period.

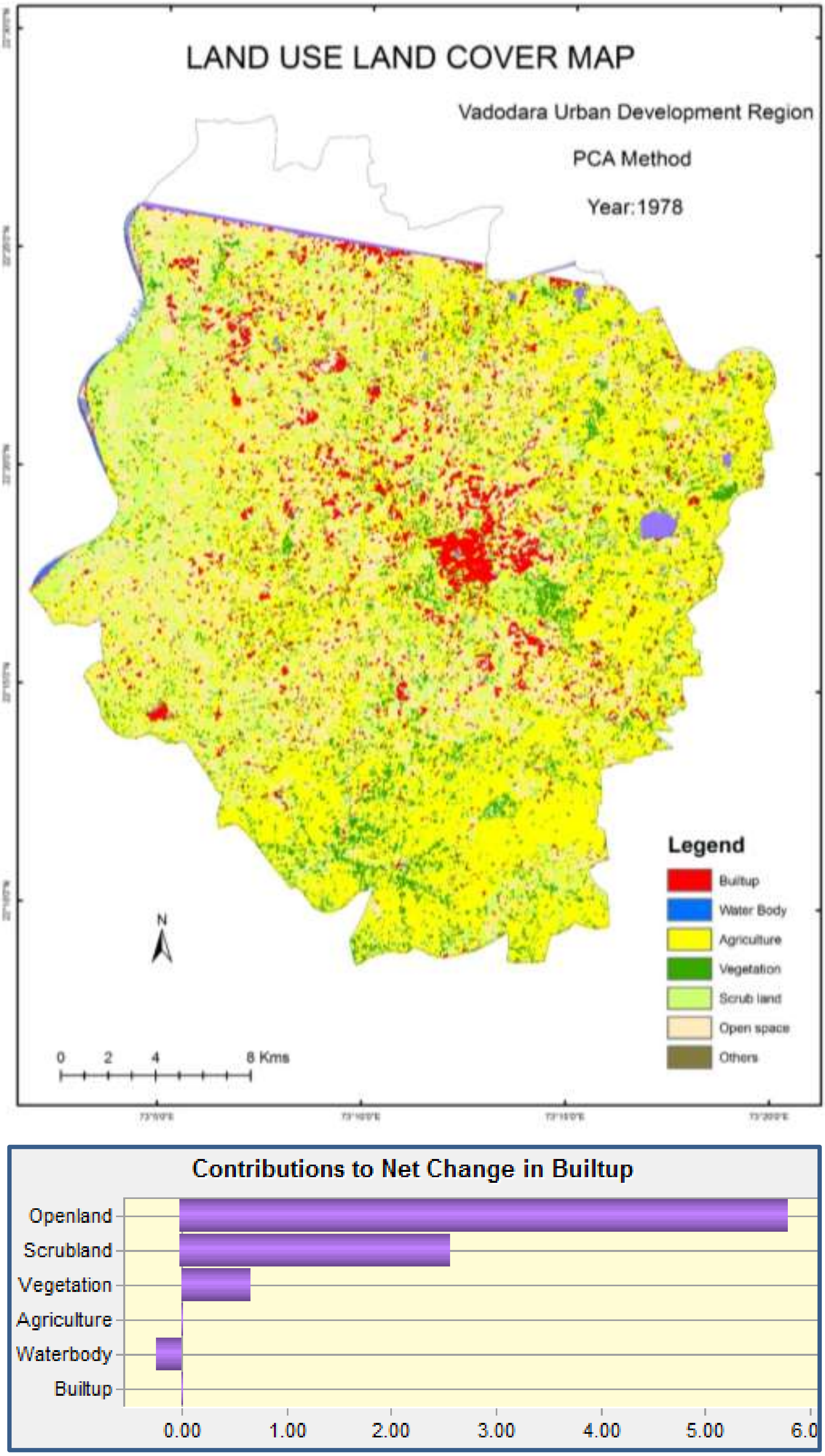


Figure 3.22 LULC Map & Contribution to Net Change in Built-up during 1978-90 (Sq. Km)

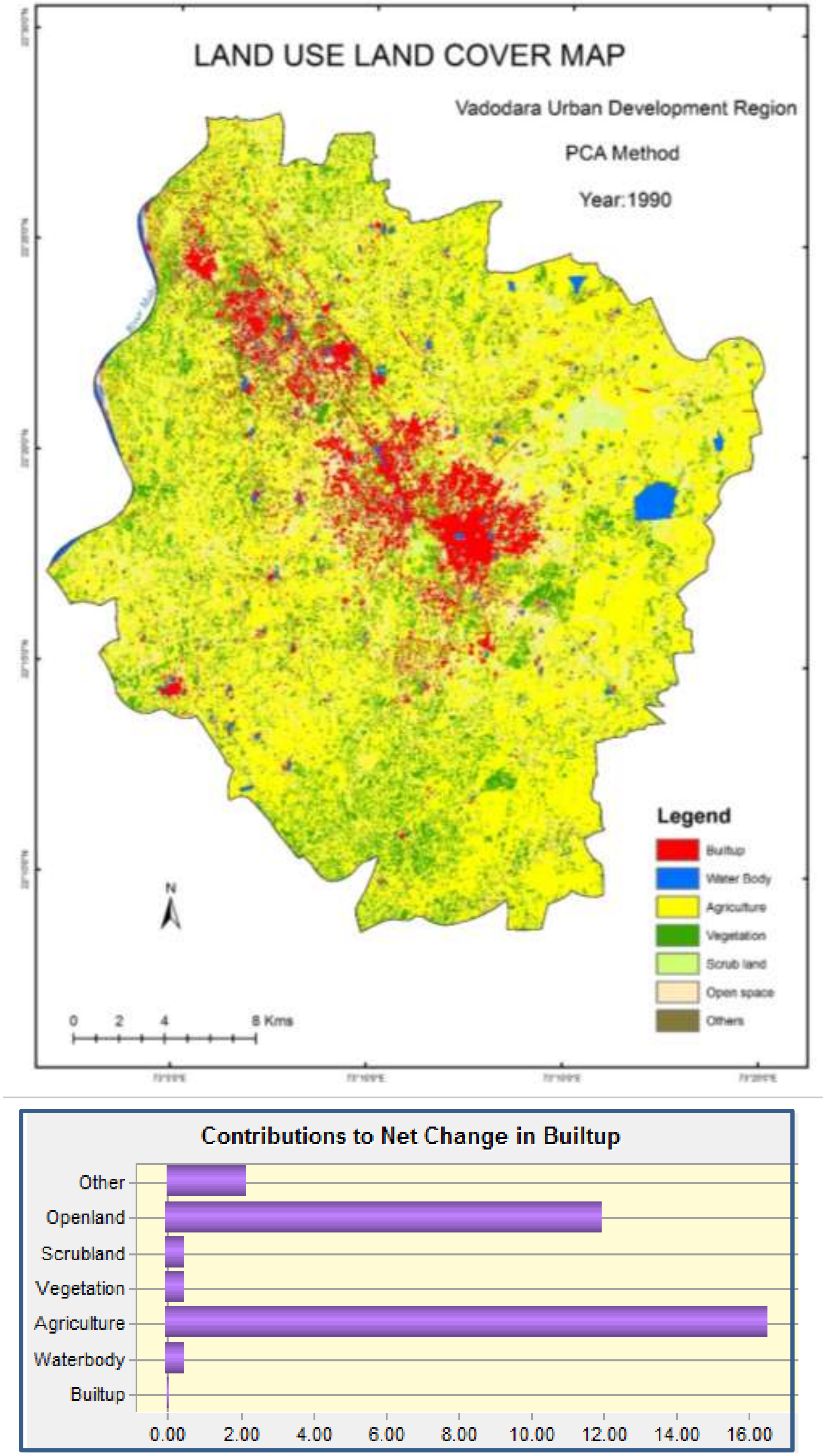


Figure 3. 23 LULC Map & Contribution to Net Change in Built-up during 1990-2001 (Sq. Km)

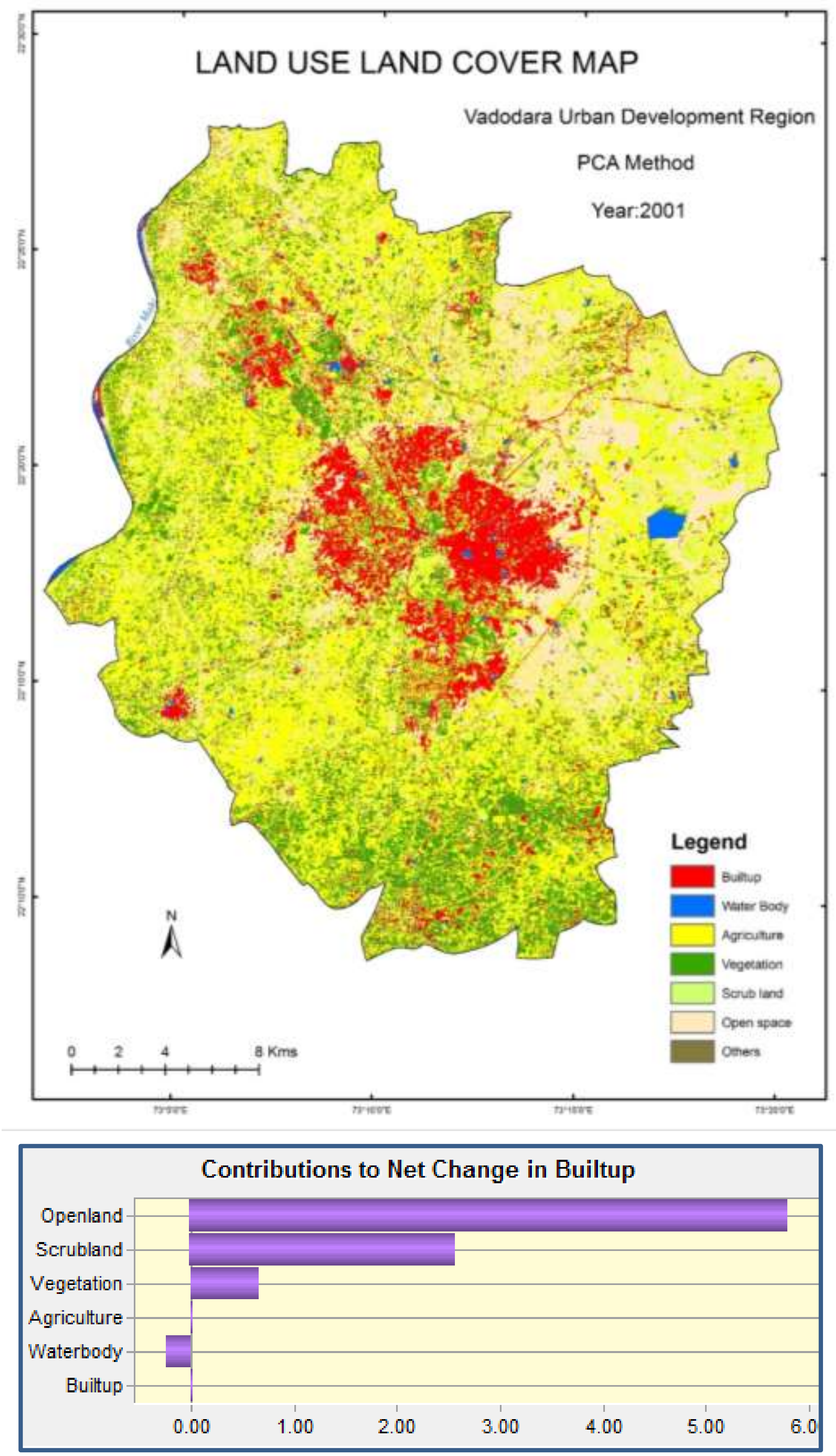


Figure 3.24. LULC Map & Contribution to Net Change in Built-up during 2001-2011 (Sq. Km)

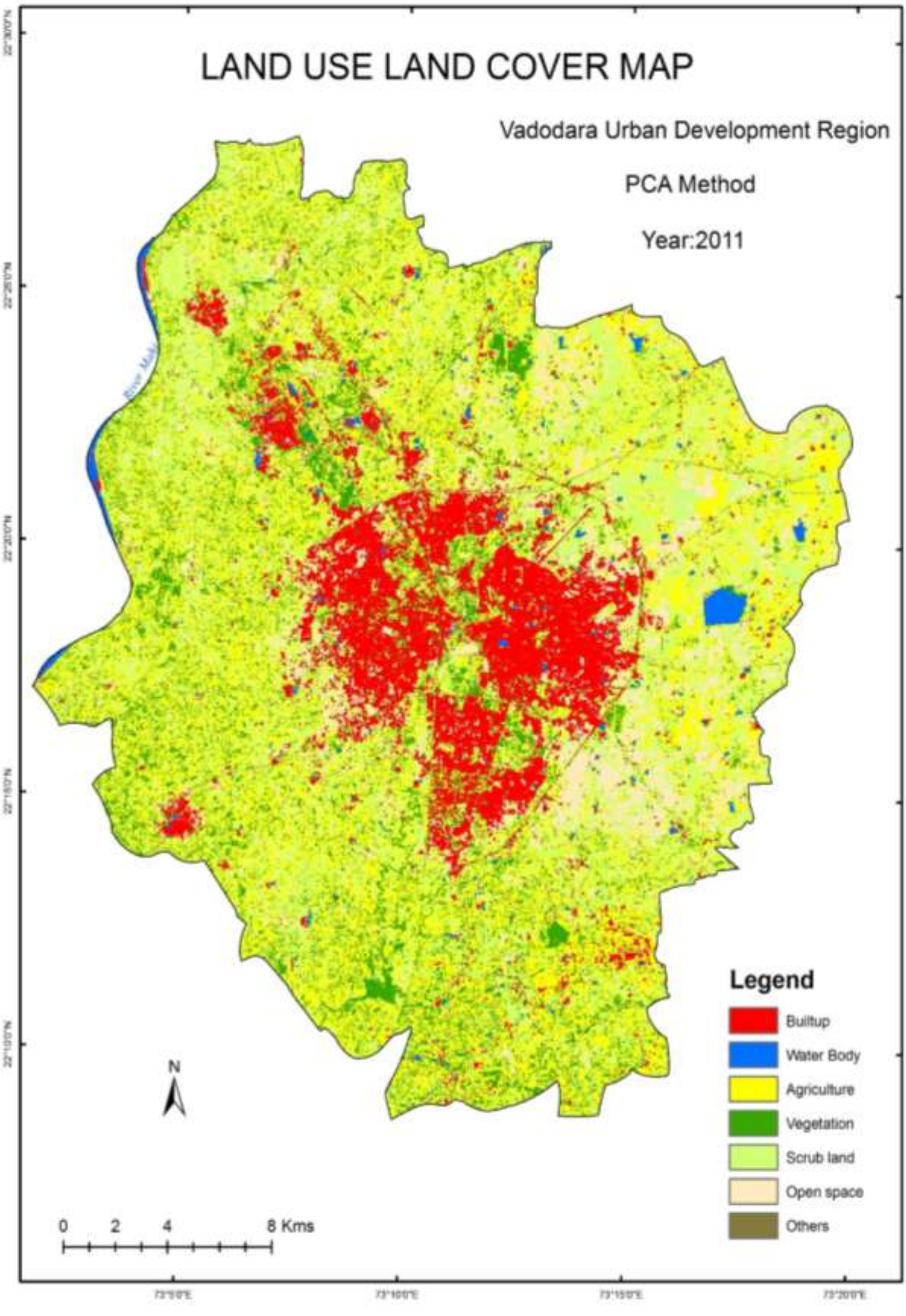


Figure 3.25 Land Use Land Cover by PCA Method of 2011.

The Land use Land cover for the VUDA Region classified by the PCA method for the Year of 1978,1990, 2001,and 2011.Comparing to all above maps it was easily identified that, built-up was going to increased whereas agriculture and open space was decreased. After 1990 built-up land was highly increasing west and south direction from the city and linear direction towards the northwest direction. Figure 3.26 is the area of % LULC Classes, which shows the increasing trend in built-up feature from the 1978 to 2011.

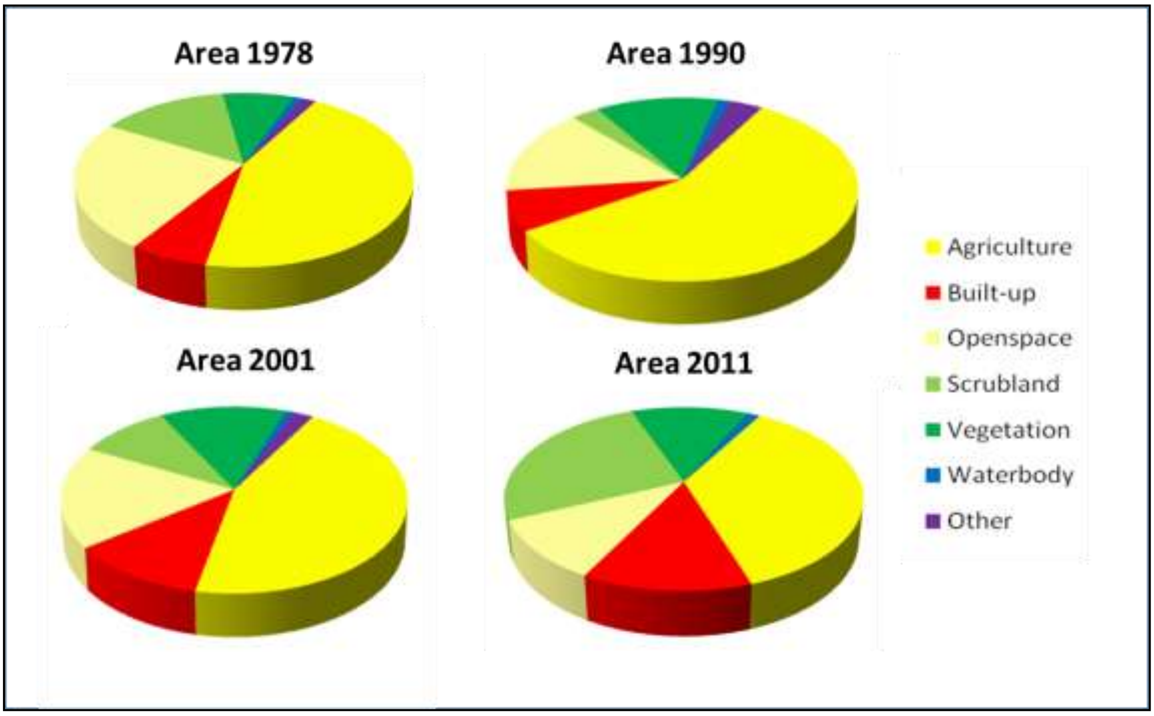


Figure 3.26 Area under Land Use Land Cover Classes (1978, 1990, 2001, and 2011)

Conclusion

The rapid urbanization process and economic development are assumed to have caused an unparalleled scale and rate of urban growth in VUDA area. Thus, the land-use patterns have undergone a remarkable change. Urbanization and economic development of the city is at the expense of the loss of other valuable lands, especially croplands. This presents a formidable challenge for urban planners and managers to maintain a sustainable development and to ensure that unnecessary urban development on valuable cropland lands be prevented as far as possible.

3.13 Digital Change Detection Techniques using remotely sensed data urban mapping based on a Combined Spectral Spatial Methodology.

3.13.1 Introduction

Spectral change detection methods based on the principle that land cover changes result in constant changes in the spectral signature of the affected land surface. These techniques demand the transformation of two original images to a new single-band or multi-band image in which the areas of spectral change are highlighted. The spectral change data must be further processed by other analytic methods, such as a classifier, to produce a labeled land cover change product. Most of the spectral change detection techniques are based on some style of image differencing or image rationing (Weismiller et al., 1977; Toll et al., 1980). It has been shown that image equalization in the data pro-processing stage usually improves the result of change detection (Hall et al., 1991).

Urbanization is an expected effect of human social growth taking place rapidly and is worldwide. One of the apparent problems caused by urbanization is the harm to natural ecosystem and segregate people from nature. Urban vegetation is one of the major land use category which plays a major role in quality and worth of urban areas. It is used as one of the important inference areas of urban image classification techniques. Satellite derived vegetation indices (VIs) are valuable tool to evaluate the role of vegetation in the exchange of radiation, momentum and heat during atmosphere-biosphere interactions (Kasturirangan, 1996).

In the last decade, more than forty vegetation indices are introduced in the remote sensing literature to assess the vegetation cover for different applications. Among the different VIs studied, TNDVI and NDVI seems to provide best results for vegetation analysis in urban environment. Tucker (1979) presented a transformed normalized difference vegetation index (TNDVI) by adding a constant 0.5 to NDVI and taking the square root, which always has positive values and the variances of the ratio are proportional to mean values. TNDVI indicates a slight better correlation between the amount of green biomass and that is found in a pixel (Senseman et al. 1996).

The three different thematic indices have been used in constructing the IBI viz., Soil Adjusted Vegetation Index (SAVI), Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Built-up Index (NDBI), which together represent the three major components of vegetation, water and built-up land, respectively (Xu et al., 2008).

3.13.2 Methodology

This study is carried out using both methods such as descriptive and analytical. To identify and monitor the urban growth, the urban land-use was grouped into three other oversimplifying categories: vegetation, surface water, bare soil and built-up-land. Based on these mechanism, the following thematic indices were generated:

- The Normalized Differences Vegetation Index (NDVI),
- Normalized Differences Water Index (NDWI) ,
- Bare Soil Index (BSI) And
- Normalized Differences Built-Up Index (NDBI) ,

So the intention is to disintegrate the information for vegetation and water to ascertain the built-up land. The study also aims of the Land Surface temperature (LST) derivation to understand the heat exchange of the region.

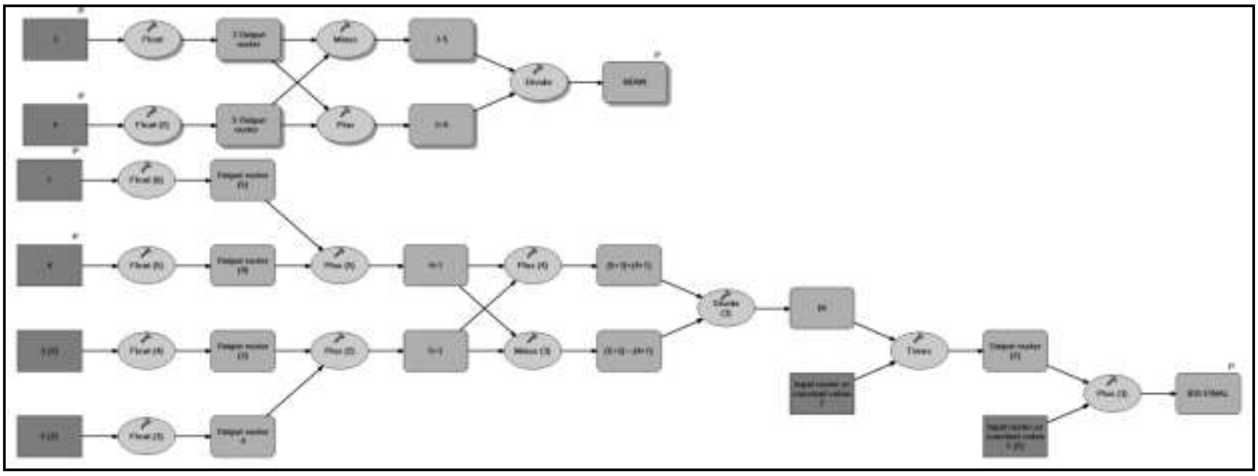


Figure 3.27 The calculation was done by preparing the model example

3.13.3 Normalized Difference Vegetation Index (NDVI)

NDVI: A Normalized Difference Vegetation Index (NDVI) is an equation that takes into account the amount of infrared reflected by plants. Live green plants absorb solar radiation, which they use as a source of energy in the process of photosynthesis (Rouse, et al., 1974). The procedure of NDVI related to vegetation is that healthy vegetation reflects very well in the near-infrared part of the electromagnetic spectrum. Green leaves have a reflectance of 20% or less in the 0.5 to 0.7-micron range (green to red) and about 60% in the 0.7 to 1.3-micron range (near-infrared).The NDVI ratio is calculated by dividing the difference in the near-infrared (NIR) and red color bands by the sum of the NIR and red colors bands for each pixel in the image as follows:

NDVI= (NIR-RED)/(NIR+RED)

The use of NDVI allows transforming multispectral data into a single image band representing vegetation distribution, as the amount of green vegetation present in the pixel. Therefore, NDVI values range from −1 to +1, where negative values correspond to an absence of vegetation (Pettorelli et al., 2005).

NDVI is generally used to express the density of vegetation (Purevdorj et al., 1998). The notion behind NDVI is that plants' chlorophyll absorbs sunlight, which is captured by the red light region of the electromagnetic spectrum, whereas a plant's spongy mesophyll leaf structure creates considerable reflectance in the near-infrared region of the spectrum (Tucker, 1979; Jackson et al., 1983). For this reason, greener and dense vegetation has low red-light reflectance and high near-infrared reflectance, and thus high NDVI values. On the other hand, near zero and negative values of the index indicate non-vegetated surface features such as rock, soil, water, ice and clouds (USGS, 2010).

Vegetation density

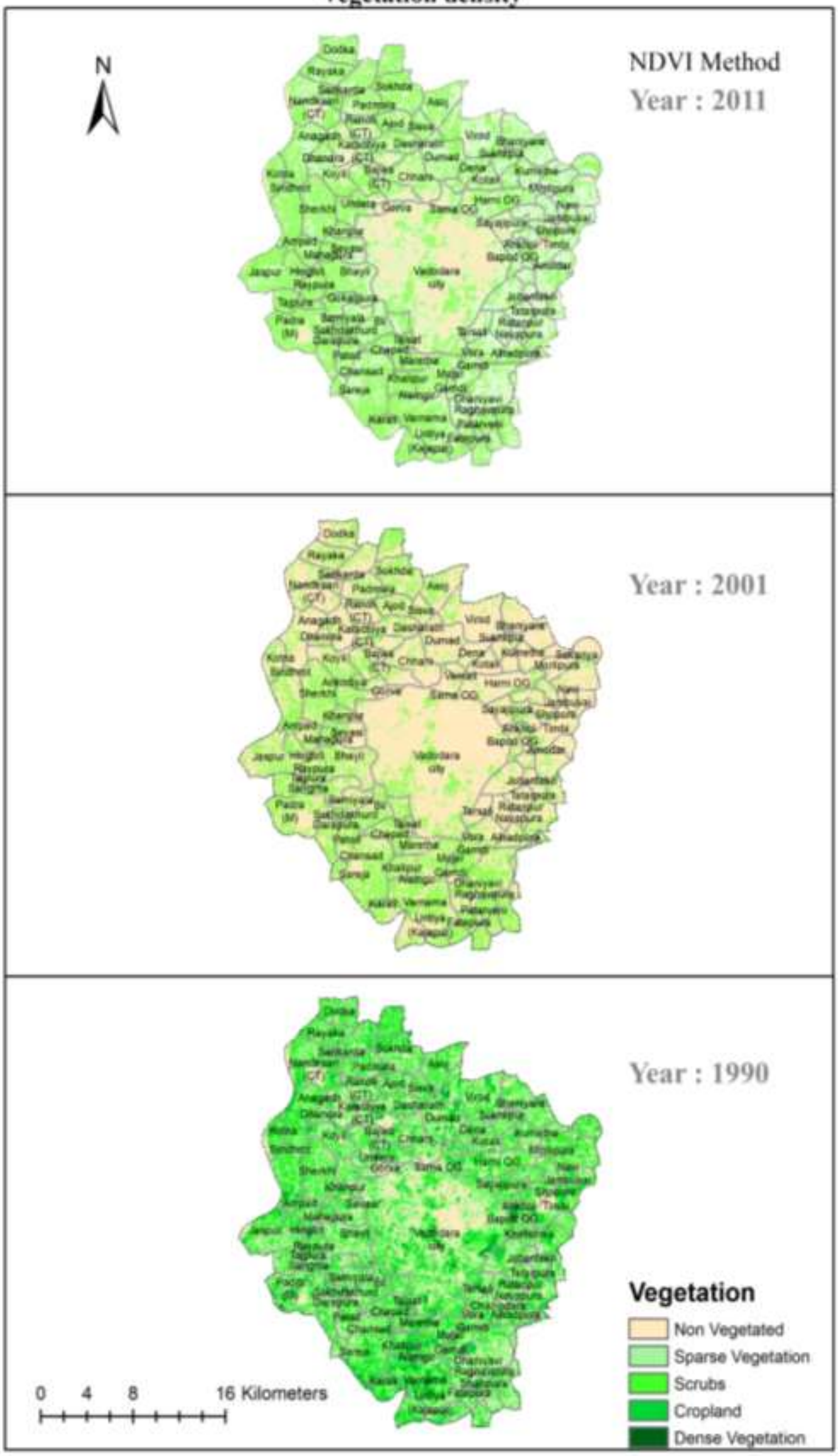


Figure 3.28 Vegetation Density (1990, 2001, and 2011)

NDVI is first calculated for each image (Figure 3.28) For Landsat TM & ETM+, NDVI is defined as (band4 - band3) / (band4 + band3). NDVI images from subsequent dates are then subtracted, producing a map of NDVI in which positive values represent ‘greening’ (increased vegetation) and negative values represent ‘browning’ (decreased vegetation). Later, then choose a threshold NDVI value by visual assessment to differentiate true urban growth as in figure 2 (large negative NDVI) from noise (small negative NDVI). Typically, threshold values are found within recently-developed residential areas where the spatial pattern of roads evidently indicates intensification but the introduction of landscaping typically modulates NDVI values (Jensen, J.R., 1999).

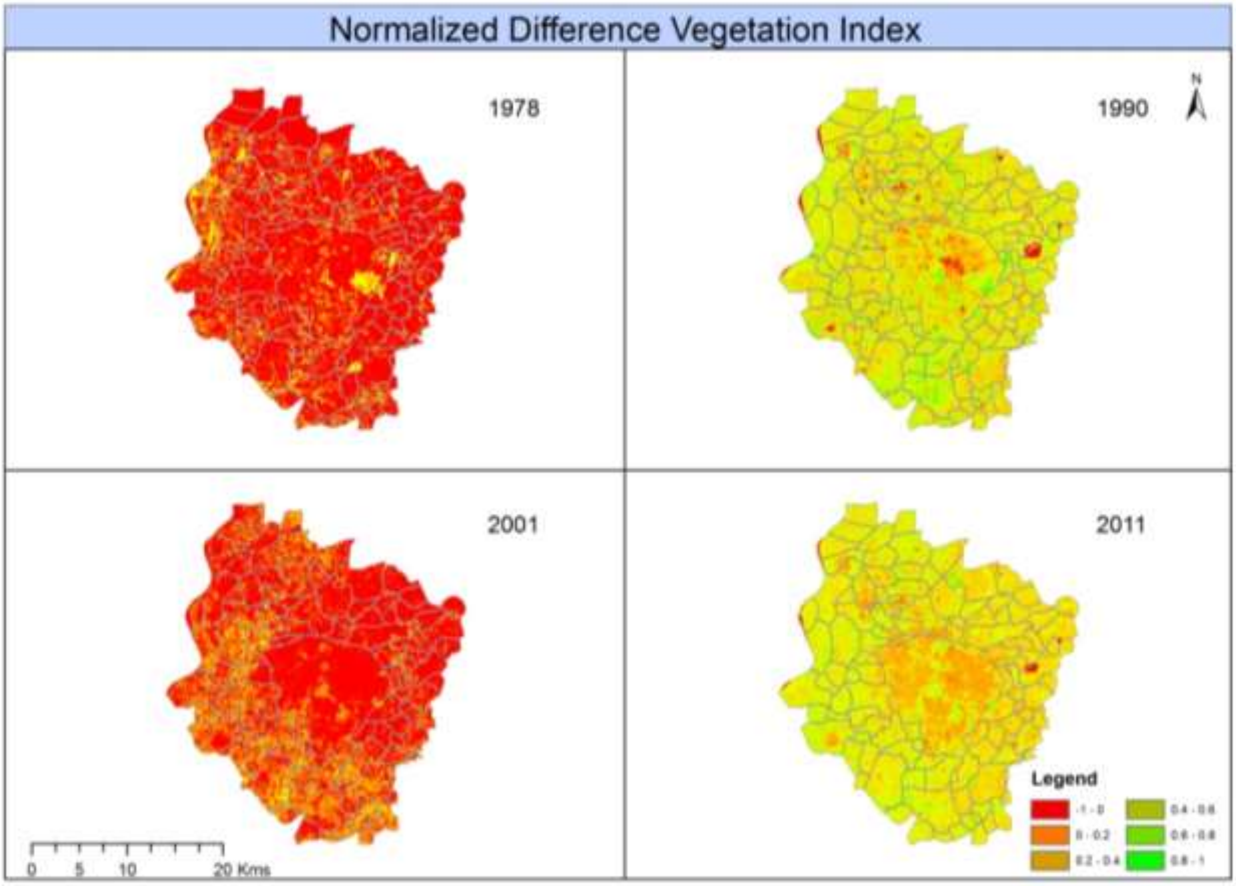


Figure 3.29 Normalized Difference Vegetation Index (1978, 1990, 2001, and 2011)

3.13.4 Normalized Difference Water Index (NDWI)& Modified NDWI (MNDWI)

McFeeters (1996) proposed the Normalized Difference Water Index (NDWI) to delineate open water features, which is expressed as follows:

NDWI = (GREEN- NIR)/ (GREEN + NIR)

Where, GREEN is a green band such as TM2, and NIR is a near infrared band such as TM4. This index maximizes reflectance of water by using green light wavelengths and minimizes low reflectance of NIR by water features while taking advantage of the high reflectance of NIR by vegetation and soil features. As a result, water features are enhanced owing to having positive values and vegetation and soil are suppressed due to having zero or negative values. However, the applications of the NDWI in the water regions with built-up land background like the cases of study area were not as successful as expectation. The extracted water in sequence in these regions was consistently mixed up with built-up land noise because many built-up lands also have positive values in the NDWI derivative image.

To remedy this problem, Xu (2005) modified the NDWI by using a middle infrared (MIR) band such as TM5 to substitute the NIR band in the NDWI.

The modified NDWI (MNDWI) is expressed as follows:

MNDWI = (GREEN -MIR) / (GREEN + MIR)

Accordingly, the enhanced water features will no longer have built-up land noise in a MNDWI image. This substitution has no impact on vegetation, as vegetation still has negative value when calculated using equation. Therefore, this test employed MNDWI instead of NDWI to enhance water features in the built-up land-dominated urban area. Moreover, MNDWI can enhance the contrast between built-up land and water much more than NDWI because built-up lands reflect MIR radiation much higher than NIR radiation. The increase in difference between them would help the delineation of these two classes

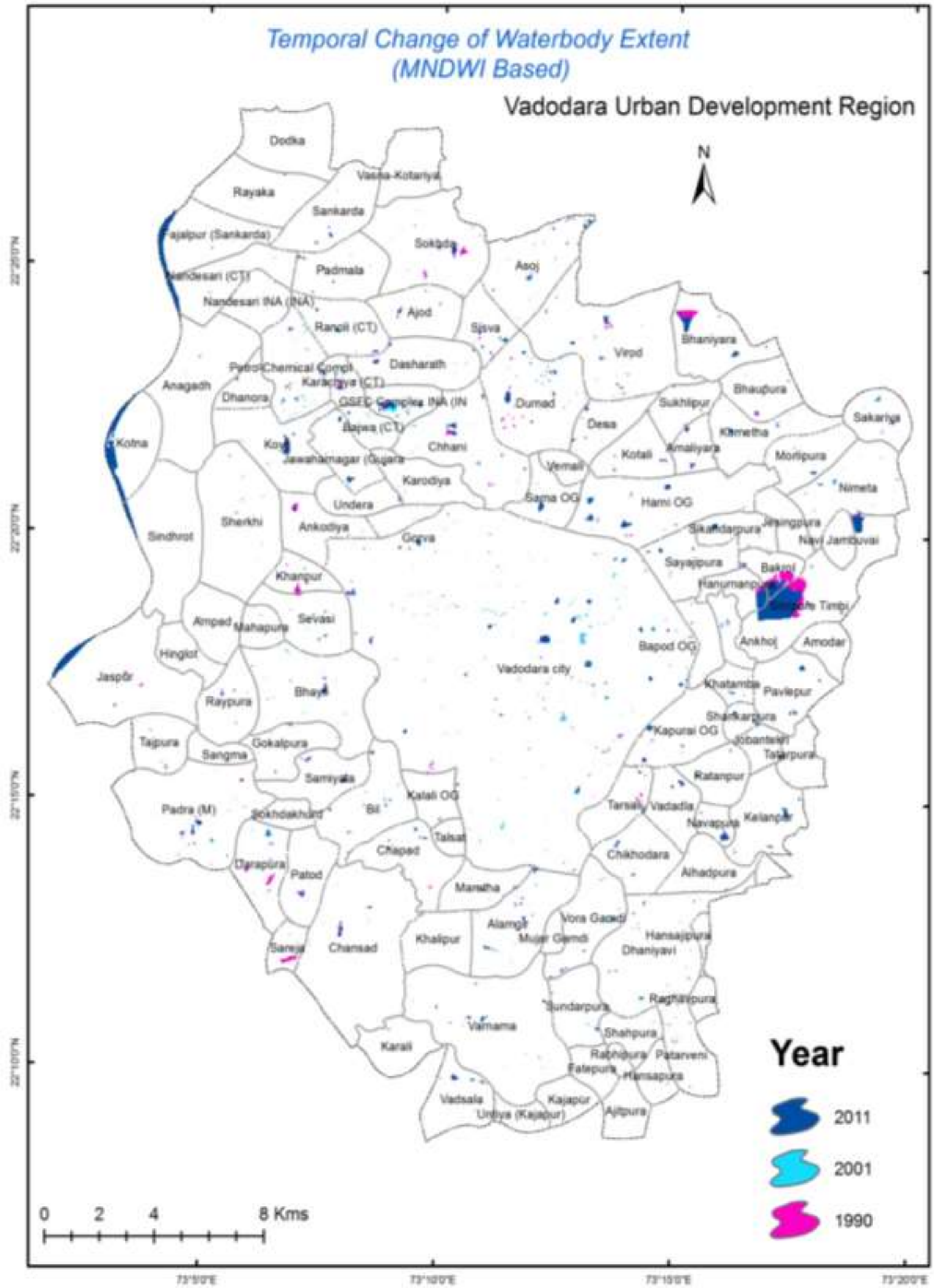


Figure 3.30 Normalized Difference Vegetation Index (1978, 1990, 2001, and 2011)

Table 3.26 Temporal Waterscape Characteristics

Year		Shallow Water	Deep Water Body
1990	Area	1.3	11.73
	Perimeter	154.07	280.04
2001	Area	2.11	8.67
	Perimeter	239.64	208.44
2011	Area	6.94	8.88
	Perimeter	504.6	159.48
Change 1990-2001	Area	0.81	-3.04
	Perimeter	85.57	-71.60
Change 2011-2001	Area	4.83	0.18
	Perimeter	264.96	-48.96

The temporal characteristic identified by assigning logical threshold to the values of MNDWI, shows the capacity to identify the fluctuating limits of the water body. The analysis also suggest that the core water body area has declined during 1990- 2001, whereas, it remained more or less same during 2001-2011(Table 3.26). The main hint towards the encroachments on the water body with satellite image lies with the perimetric change study as the edge of the water body and shallow water bodies are the vulnerable and at risk zones liable to be encroached subsequently. The decreases in the perimeter of the deep water bodies suggest that the siltation has reduced the extent on the other hand it is also observed that eutrophication, growth of algae on the surface has resulted in showing of the signature of vegetation not the water such Larger cases are seen in the rural counterpart in the region. But in the vicinity of built-up it is the perimetric landfill which has resulted in the shrinkage and blockade on the catchment due to random plinth level of construction has resulted in the formation of the water pools easily observed by the residents.

3.13.5 Difference Bare Soil Index (BSI)

Bare-soil plays an important role in the ecosystem. There are different soil indices needed to remotely distinguish areas that are truly bare, from urban surfaces, agricultural practices, areas with varying density of plant recovery. It is also important to monitor the bare-soilareas, but there was no good idea to automatically extraction bare-soil areas using existing method. Southworth

(2004) find that the thermal infrared band (TIR) of Landsat TM measures the emission of energy from the Earth's surface and, as this is a function of the surface cover, it can be used as a determinant of land cover type based on the temperatures measured. According to this principle, Zhao &Chen (2005) build a normalized difference bareness index (NDBaI) for mapping of the bare-soil areas from the satellite images. This index is based on the difference between strong reflection of TIR radiation and near total absorption of middle infrared (MIR) wavelengths by bare-soil (Chen, et al., 2006). It is effective in distinguishing bare-soil from similarly built-up and vegetation.

The bare soil index proposed by Jalalabad and Akbar, 2004 is useful to identify the agricultural and non-agricultural land cover. It is the indicator of the soil characteristics, which is combination of the blue red SWIR and NIR .

$$\mathbf{BSI} = \frac{\mathbf{(SWIR - RED) - (NIR - BLUE)}}{\mathbf{(SWIR + RED) + (NIR + BLUE)}}$$

In the classified map pink and yellow shades the area under the built-up cover and the shades of the blue shows high moisture contend indicating the wet soil and presence of water interaction land cover.

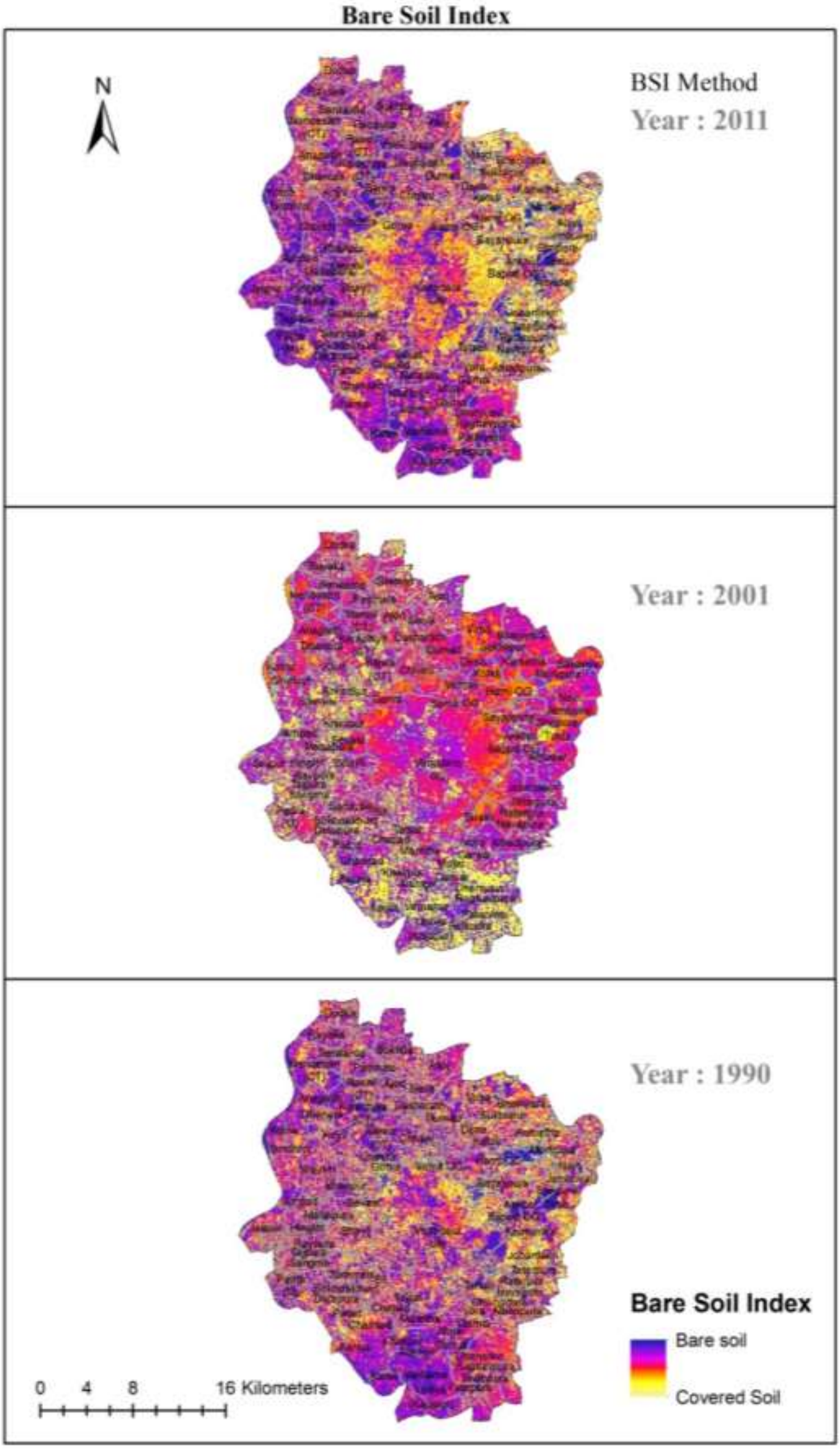


Figure 3.31 Difference Bare Soil Index (1990, 2001, and 2011)

3.13.6 Normalized Difference Built-up Index (NDBI)

The NDBI was calculated using the following equation

NDBI = (SWIR-NIR) / (SWIR+NIR)

The equation proposed by the zha et al is based on the characteristics of the built-up land to have the higher reflectance in SWIR range.

A value greater than the threshold is built up area and is assigned value as 1 and pixels value equal to or less than threshold value can be assigned as non-built up area and assigned 0 value. The resultant image shown in the figure 3.32 is a continuous image showing extracted built-up area in red color shade. The mixed response is received due to the bareness of the peripheral region due to which clear separation of the built-up land from the processed image could not be attempted. The NDBI clearly demarcates the dense settlement in the shades of the brown color and darker shade showing the newer built-up area having relatively higher brightness.

Relationships among NDBI, NDVI and MNDWI: Densely vegetated areas appear dark in this image, whereas water and a few areas with less dense vegetation are shown in bright tones. However, for extracting the built-up areas, both vegetation and water were later filtered using NDVI and MNDWI, respectively. A very clear separation between vegetation and other land-cover types is evident in this output. The MNDWI gives a clear separation of Water and the Areas with dense vegetation appear dark whereas the built-up areas are shown in variable tones of colour.

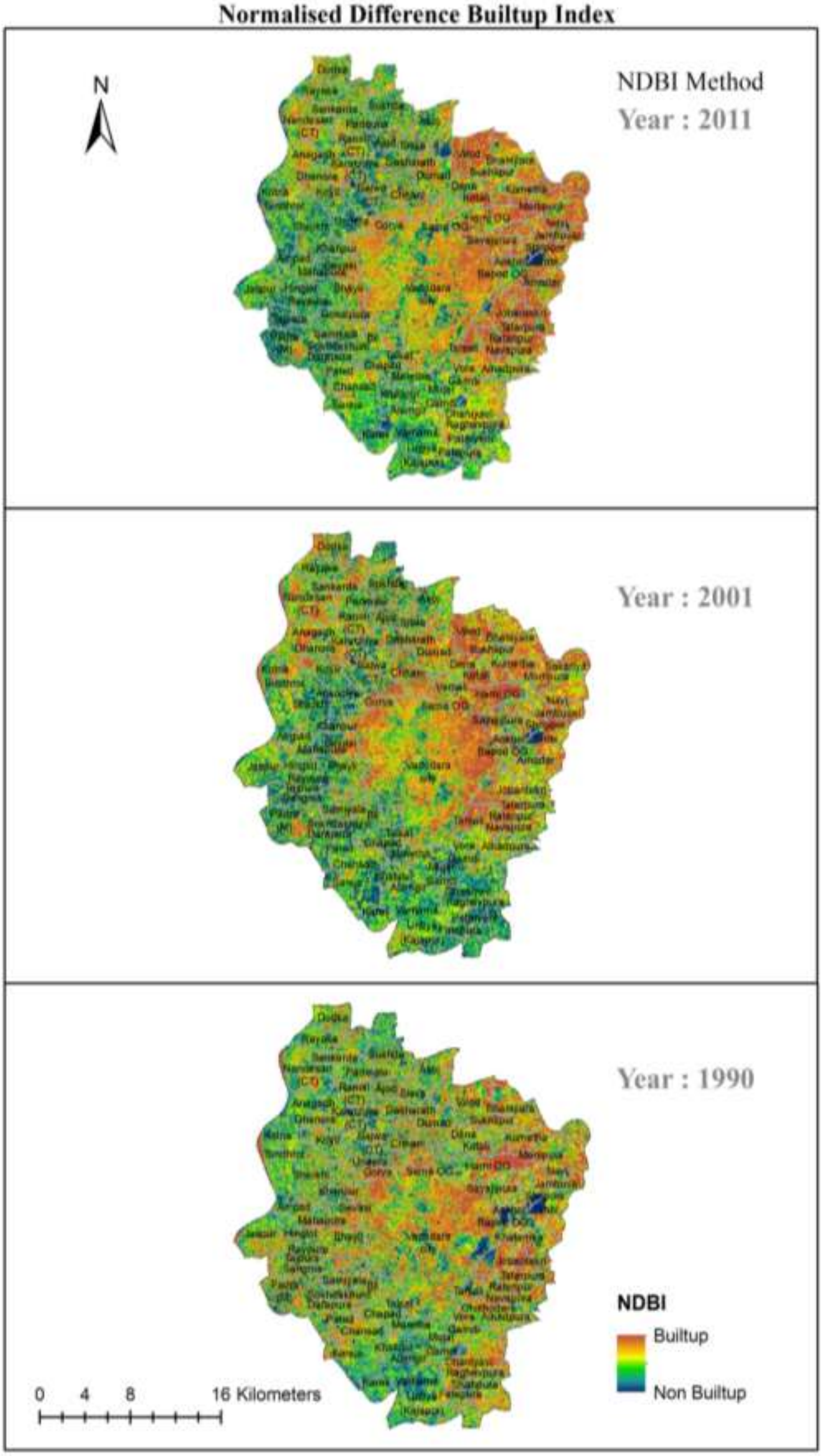


Figure 3.32 Normalized Difference Built-up Index (1990, 2001, and 2011)

3.14 Land Surface Temperature

An important advantage of the RS is in its availability to map the thermal regime within the spatial resolution of the sensor. Conventionally, the farther located weather station and its interpolated values were used to generalize the weather phenomenon.

Knowledge of the LST is necessary for many environmental studies and management activities of the Earth's surface resources (Li & Becker, 1993). It is one of the key parameters in the physics of land surface processes on regional and global scales, combining the results of all surface–atmosphere interactions and energy fluxes between the atmosphere and the ground (Mannstein, 1987). LST plays an essential role in interactions and energy fluxes at the surface–atmosphere interface (Coll et al., 2005; Sobrino, Kharraz, & Li, 2003). In detail, spatio-temporal variabilityin LST reveals spatial and temporal changes in the state of the land surface which has been widely implemented insurface energy and water budget estimations (Bastiaanssen, Menenti, Feddes, & Holtslag, 1998; Karnieli et al., 2010; Roerink, Su, & Menenti, 2000). The LST plays an important role in maintain several ecosystem services and also understanding the changes in those services (Patel et al., 2017).which is retrieved from satellite, remote is captured in the thermal infrared region of the electromagnetic spectrum (Gusso & Fontana, 2005) and is an indicator for measuring the spatio-temporal temperature dynamics and climate change analysis. According to Intergovernmental Panel on Climate Change (2001), increase in greenhouse gas concentrations has influenced the annual mean global temperature by 0.6 _ 0.2 °C since the late 19th century. Various environmental studies and management activities of the Earth surface resources require the knowledge of LST (Li & Becker, 1993). Therefore, the studies using LST is of great importance with respect to the environmental and climate change scenarios (Patel et al., 2017). A study of VUDA (Joshi et al.2011) shows the temporal variation of the LST in which importance of water body and heat was stressed.

Figure 3.33 illustrates the spatial variability of Land Surface Temperature in study area at different time scale 2011, 2001 and 1990 respectively.

The spatial distribution of LST for the year 1990 is described in Figure 7, where the maximum LST is in the south-east part of VUDA region, and the rest of the study area is experiencing normal surface temperature. From Figure 7, it can be concluded that the year 2001 has high temperature as compared to year 1990 in VUDA region. From the visual analysis it is observed that high surface temperature patches scattered in western and northern part of study area and year 2011 experienced comparatively higher temperature with respect to the year 2001 and 1990. In all the respective years 1990, 2001 and 2011 South-West, West and North-west part from the centre of the study area received very less surface temperature as compared to the entire VUDA region.

Average LST has been calculated at village level to identify the temperature severity of the concerned villages and amount of temperature received by villages to analyse spatial variability of LST at Village level. Figure 8 represents village level calculated zonal mean of LST shown in degree Celsius. In Year 1990 approximately 5 villages show very high LST, from south east part of the study area and 6 villages experiencing moderate high surface temperature and rest of the study area is in normal LST ranges; where as in year 2001 approximately 2 villages experiencing very high LST from the north east part of the study area and 15 villages covered under moderate LST of VUDA region. Figure 3.34 illustrates LST variations of VUDA region in year 2011 where 2 villages in high LST and approximate 10 villages in moderate LST ranges. Village wise LST analysis is useful in local level planning and analysis.

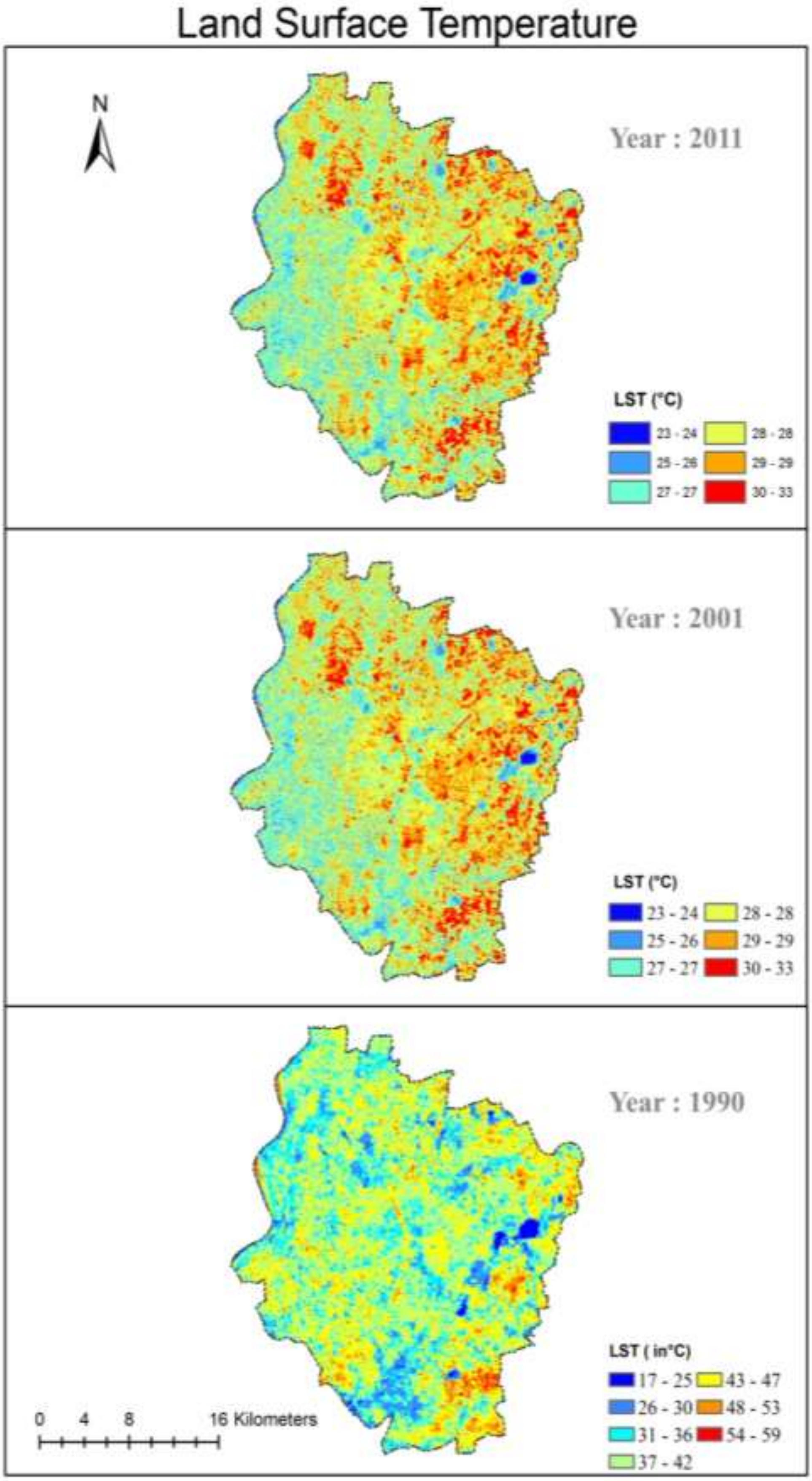


Figure 3.33 Land Surface Temperature (1990, 2001, and 2011)

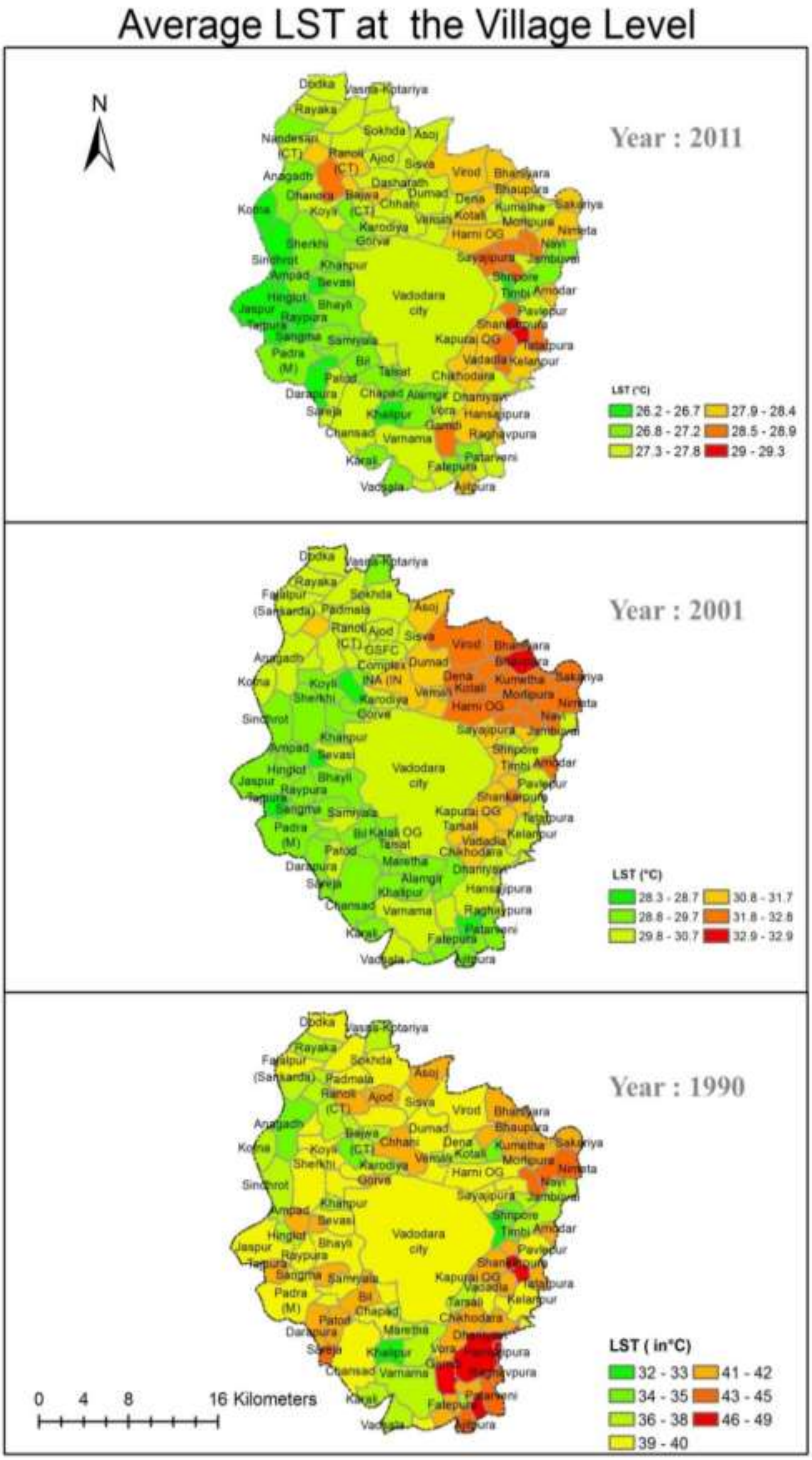


Figure 3.34 Average Land Surface Temperature at Village Level (1990, 2001, and 2011)

3.15 Discussion

The present study tried to understand the LST regime of the study area for the month of the October. The study showed that city does represent the thermal contrast between the rural and urban region and peri-urban being at the transition. The dissecting river vishwamitry and the scrubs along the flood banks of the river act as the heat sink resulting into discontinuity of the thermal behavior of the city.

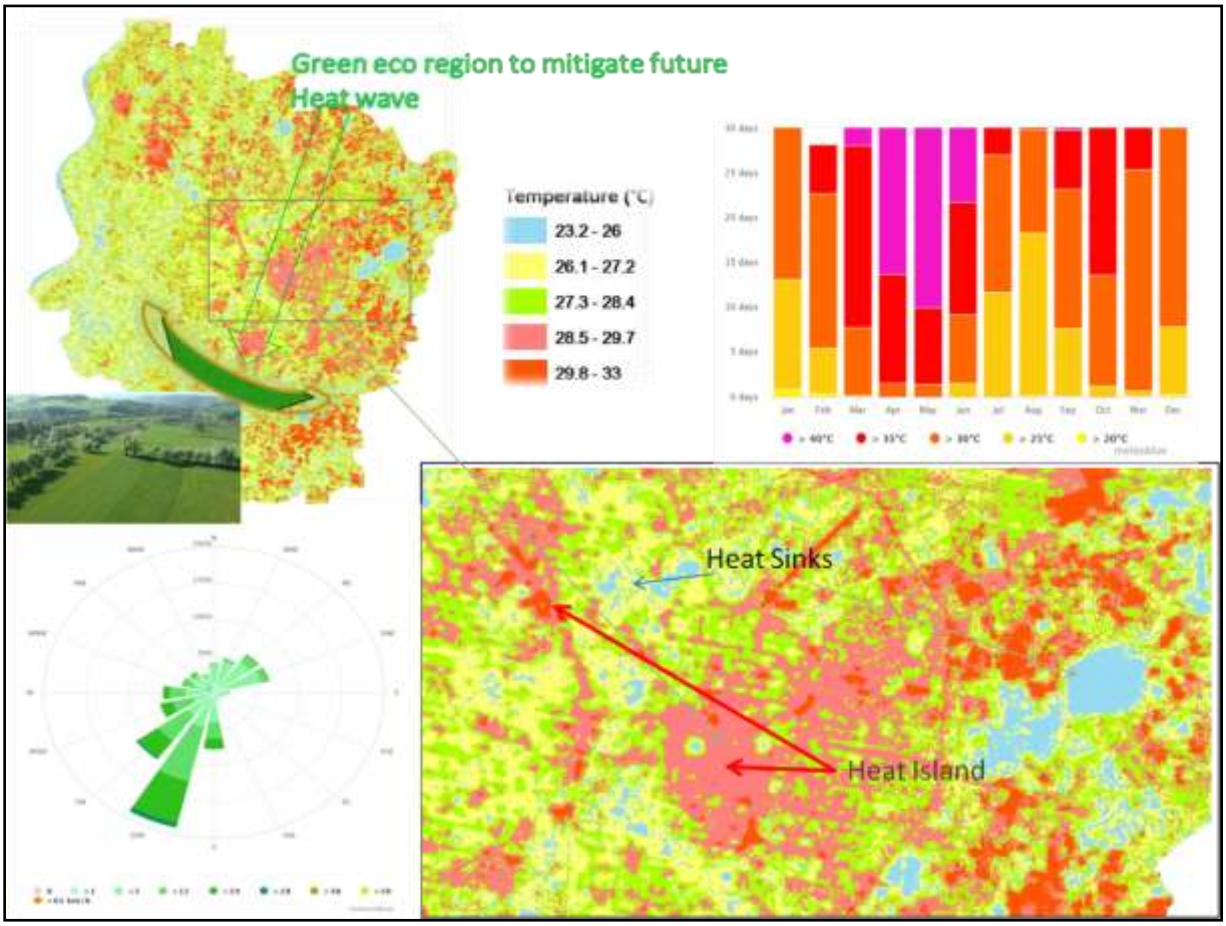


Figure 3.35 Conceptualization of Heat Sink Island and its mitigation plan in region.

It is noticed that the city is still having the formation of thermal island which is the part of the old city, characterized by small road width dense built-up and lack of open space, green space, vegetation. This prevents heat diffusion, absorption resulting into extended time for cooling. Moreover in the evening the breeze from the SW direction makes weather comforting but due to rampant development and margin to margin construction the wind tunneling has come up in the city. One can witness breeze either in the open land or on road. The building height permission takes into consideration the road width accordingly FSI are issued, so for each road side building are permissible with proportionate height. The plots beside road side turned out in low rise building and Interior Island is formed with wind blockades of the building. Resulting into multiple reflection in day, more heat trapped and delayed cooling in night. This phenomenon is hazardous as it enables constant temperature regime and season diseases can extend prolonged as now a day we see mosquito menace, cholera, jaundice, dengue cases round the year. This is due to weakened environmental control in the urban regime.

The region is under developmental pressure and is expanding in varied direction and planned to develop in west part as per existing TP schemes. The region stretch out for its serene nature and greenery, but as the demand and area usage will change there will be formation of the large UHI and thus we are required to efficiently reserve and develop the green space with thick vegetation and other heat sinks in the form of the lake conservation maintenance of the water circulation in the pond. This will adjust the surrounding temperature and will give a shade effect to the surrounding.

Secondly as the region is in the sub humid and tropical region the region temperature of more than 35 degree Celsius for more than three month and it exceeds 41 also. In such situation the south west wind will result in aggravating the temperature or resulting in to the heatwave effect in the city and more sun stroke are likely. The remedial measure remains in the form of increasing the tree canopy cover, maintaining the water bodies, lakes etc. but to large in the city, the lack of open space and shrinkage of the ponds are irreversible. Other suggestion lies in the form of ecofriendly designs of the new developmental fabric and not the continuum of the developmental plan. In which wedge/ sectoral belts with alternate green cover and waterscape, water flowing channels are planned in. to balance the heat islands and the heat sinks, in the direction of the wind movement, Figure 3.35. Even the lining tree along road, river, pond and farm boundaries will help to ease the issue instead of Lake Concretization for the beautification purpose. Such that it will acts as the ecoservice provider to the region. The region will also ease the stress on resource, will attract recreational value. Conventional parcel level planning with its ease of allocation tends to scatter the fabric of development which goes on self-replication and thus we find the planned development as unorganized patched development increasing pressure on resource, posing demand for the service and infrastructure ultimately reducing the ecoservice.

Conclusion

Monitoring the growth of built-up areas at regional level has been attempted by various authors using the Landsat data. Researchers have worked out BI approaches to delineate built-up regions from diverse remotely sensed data. The existing NDBI algorithms is used to identify built-up regions and their growth in the entire study area. From NDVI study it has been observed that in three new bands were generated directly from three thematic indexes, NDVI, MNDWI, and NDBI. This considerably reduced data correlations and redundancy between multispectral bands, significantly avoided the spectral confusion between the land-use classes, and thus largely improved the extraction accuracy. Besides, using NDVI and MNDWI instead of NDVI and NDWI also contribute to the improvement because this can significantly increase the spectral contrast between different land-use classes. Thus, the high accuracy of extraction of urban built-up land features was attained through a simplified band spectral signature analysis.

The LST is one of the best data to integrate in the planning which can help to plan the space along with the material to be used so as to minimize the climate change impact. Also it will help to restore the ecological services by remedial planning approach.