VEER NARMAD SOUTH GUJARAT UNIVERSITY

# Assessing the significance of land cover prediction in planning using RS & GIS techniques – A case study of Porbandar-Chhaya Municipality

A Dissertation submitted to

**Shri Gijubhai Chhaganbhai Patel Institute of Architecture, Interior Design and Fine Arts, Veer Narmad South Gujarat University, Surat**

for partial completion of

# Master of Urban and Regional Planning


by

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Under the supervision of

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**DECEMBER-JUNE 2021**

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# DECLARATION

I declare that the dissertation entitled **Assessing the significance of land cover prediction in planning using RS & GIS techniques – A case study of Porbandar-Chhaya Municipality** submitted by me for the partial completion of Master of Urban and Regional Planning is the record of research work carried out by me during the period from December 2020 to June 2021 under the supervision **Prof. (Dr.) Dharmesh Juremalani** and this has not formed the basis for award of any degree, diploma, associateship, fellowship, titles in this and any other university or other institute of higher learning.

I further declare that the material obtained from other sources has been duly acknowledged in the thesis. I shall be solely responsible for any plagiarism or other irregularities, if noticed in the thesis.

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Place: Surat, Gujarat, India

# CERTIFICATE

I certify that the work incorporated in the dissertation **Assessing the significance of land cover prediction in planning using RS & GIS techniques – A case study of Porbandar-Chhaya Municipality** submitted by **Nishant Desai** was carried out by the candidate under my supervision. To the best of my knowledge:

(i) The candidate has not submitted the same research work to any other institute for any degree/diploma, associateship, fellowship, or other similar titles
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(iii) The thesis represents independent research work on the part of the student

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# ABSTRACT

An urban area is a complex system consisting of various interrelated sub-systems and is impacted by many factors. Land use/Land cover and transportation systems are two major subsystems in determining urban growth pattern in long term. Study of urban growth pattern and prediction of its future state are believed to be powerful tools to examine the urban growth and provide planning support for future urban planning interventions.

The overall objective of the study is to analyse urban growth pattern based on past land cover change detection and predict its future state. In this study the spatio-temporal growth pattern of Porbandar-Chhaya Municipality (PCM), Gujarat, India was examined from 1991 to 2021 using remote sensing data and GIS techniques. First, four land-use/cover maps of the PCM (i.e., for 1991, 2001, 2011 and 2021) were classified using Landsat data. Second, the temporal pattern of urban growth (i.e., land changes from non-built-up to built-up) across three time-intervals (1991–2001, 2001-2011 and 2011–2021) were examined. Third, the spatial pattern of urban growth along the gradients of various driver variables (e.g., distance to major roads) were examined. Finally, the future urban growth for year 2031 was predicted using MOLUSCE in QGIS, based on CA and ANN.

The results shows that built-up area has increased from 12.40 sq.km. (16.71%) to 26.49 sq.km. (35.71%) between 1991 to 2021, with average change rate of 6.33%. During the same time period barren land has decreased at average change rate of -7.80%. Vegetation and waterbody showed minimal change. The analysis revealed that throughout the three decades more than 94% of the total Built-up Area occurred in close proximity to major roads, i.e., less than 1.0 km from major roads. Also, the PCM's built-up lands have become more fragmented. The existing built-up patches have grown in size and the distance between these patches has reduced because of the process of the cumulative impact of diffusion, expansion and infill development. Growth of built-up in CBD area (Porbandar and parts of Chhaya) was observed to be very low with an average change rate of 0.62%. As infill development has lessened the space in the CBD of PCM for further development, ribbon-type development has radiated from the CBD along the major roads. This lately formed focused urban development in the area of 4 km from CBD, the rest of the PCM area only show scattered built-up. At present, the influence of under construction 45 mt. wide outer ring road (bypass for NH 51), was not observed but the prediction shows increase in built-up along this new road.

As seen in the study the built-up area in PCM has increased however, the change rate of Built-up area in PCM is declining from 10.05% (1991-2001) to 3.77% (2011-2021). The prediction results shows that it will further decline to 3.34% during 2021-2031. Environment sustainability could be adversely affected because of the fragmented development. Also, it makes the task of providing urban infrastructure more difficult compared to compact development. Due to the coalescence of built-up patches, mainly in the CBD and other highly dense built-up areas such as the part of Chhaya and Dharampur, urban open spaces are shrinking. The vegetation and waterbody have largely remained unchanged during past three decades. While delineating the land for future growth, it is to be seen that this green cover area within PCM can be maintained and optimal use of already urbanized areas is achieved.

The study was able to highlight several issues and challenges for future urban development and planning interventions. Suggestions were therefore made at the end of the study to address these issues and challenges and ways to use the information as contained therein in to optimize planning process and make informed planning decisions.

# KEY WORDS

Urban growth; Spatial-temporal pattern; Land use; Land cover; Remote sensing; GIS; Landsat images; Prediction; Porbandar;

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Nishant Desai
Surat
June 2021.

# List of Abbreviations

| | | |
|---|---|---|
| ANN | - | Artificial Neural Network |
| AOI | - | Area of Interest |
| CA | - | Cellular Automata |
| CBD | - | Central Business District |
| CRZ | - | Coastal Regulation Zone |
| FCC | - | False Colour Composite |
| GIS | - | Geographical Information System |
| Ha | - | Hectare |
| IRS | - | Indian Remote Sensing Satellite |
| LANDSAT TM | - | Landsat Thematic Mapper Sensor |
| LC | - | Land Cover |
| LISS | - | Linear Imaging Self-Scanning Sensor |
| LU | - | Land Use |
| LULC | - | Land Use/Land Cover |
| LULCC | - | Land Use/Land Cover Change |
| MDR | - | Major District Roads |
| MOLUSCE | - | Modules for Land Use Change Simulations |
| NDVI | - | Normalized Difference Vegetation Index |
| NH | - | National Highways |
| NIR | - | Near Infrared |
| PCM | - | Porbandar-Chhaya Municipality |
| RGB | - | Red Green Blue |
| RS | - | Remote Sensing |
| SH | - | State Highways |
| SPOT - PLA | - | SPOT Panchromatic Linear Array Sensor |
| Sq.Km. | - | Square Kilometre |
| USGS | - | United States Geological Survey |
| UTM | - | Universal Transverse Mercator |

# List of Figures

# List of Tables

# List of Appendices

# Table of Content

# CHAPTER:1 INTRODUCTION

## 1.1 BACKGROUND OF STUDY

Because of human actions, the Earth surface is mostly changed in many ways and man's existence on the Earth and his utilization of land has had a significant impact upon the indigenous habitat, consequently turning into a visible pattern in the land use/land cover over a period of time.

In India just as in most developing nations, the exorbitant development of populace and the expanded pattern towards urbanization have prompted numerous things, for example, aimless development of industries, impromptu housing and utility organizations, transformation of valuable farming and woodland land into metropolitan land and so forth. Urban land is one of the significant assets given to man by which important human actions are performed. A precise and cutting-edge data about the urban land is basic for planning and the management of urban assets of an area, in the view of environmental consideration. The rational planning and management of urban land is possible through the regular survey of the land cover which helps in delineating land suitable for various activities.

The land use/land cover pattern of a region is a result of natural and socio-economic aspects and their consumption by man in time and space. Land is becoming a rare supply due to immense agronomic and population pressure. Therefore, data on land use land cover and potentials for their best use is important for the choice of planning and execution of land use schemes to encounter the increasing demands for elementary human needs and wellbeing. This data also contributes in monitoring the dynamics of land use ensuing out of changing demands of growing population.

Land use and land cover modification has become an essential component in current policies for managing natural resources and monitoring ecological changes. The progress in the perception of vegetation mapping has greatly improved research on land cover change, providing a precise assessment of the spread and health of the world's forest, grassland. and agricultural resources.

Observing the Earth from space is now decisive to the understanding of the effect of man's actions on his natural resource use, in a given time period. In states of fast and frequently unrecorded land use change, observations of the earth from space offer objective data of how human use the land. Over the past years, data from Earth sensing satellites has become important in mapping the Earth's landscapes and structures, dealing with natural resources and perusing environmental modification.

Remote Sensing (RS) and Geographic Information System (GIS) are now giving new techniques for urban planning process and cutting-edge environment management. Remotely sensed data helps the comprehensive analyses of Earth’s system function, pattering and change at local, regional and global scales over a period of time; such data also provide a significant link between thorough ecological research and regional national and international conservation and management of biological diversity.

Therefore, attempt will be made in this study to map out the status of land cover of Porbandar-Chhaya between 1991 and 2011 with a view to detecting the changes that has taken place in this status particularly in built-up land so as to predict possible changes that might take place in this status in the next 10 years using Geographic Information System and Remote Sensing data.

## 1.2 NEED FOR THE RESEARCH

Certainly, effort has been made to document the growth of urban areas in the past, but that from ground surveys. In current times, the changing aspects of Land use/Land cover and particularly urban expansion in the area needs a more powerful and sophisticated tools such as GIS and Remote Sensing data which provides a general extensive synoptic coverage of large areas compared to land surveys.

The World Bank (The World Bank, 2011)has identified various urban challenges faced by India in the sectors of planning, housing, service delivery, infrastructure and environment. It has expressed its concern that many urban governments lack a modern planning framework and the rigid master plans and restrictive zoning regulations limit the land available for building, constricting cities' abilities to grow in accordance with changing needs.

The process of spatial planning thus requires a scientific backup in the areas of population projection, trend of development, forces behind the development and land requirement. Very few plans have been prepared adopting suitable techniques for forecasting these parameters. Also, continuous updating of the database is an important step in monitoring the performance of the plans. Many spatial plans fail in achieving their goals because of ignoring these aspects. At this age of rapid urbanization, one cannot afford to ignore the adoption of suitable tools and techniques to foresee the trend of urban growth.

The flow chart in Figure 1.1 illustrates how the prediction and simulation-based land use planning fills the gap between the limitations of current planning practices and the anticipated planning support system. The gaps observed between the current land use planning practices and the anticipated planning practices are identified.

The basic problem with the current planning practice is the absence of temporal and spatial urban growth data. The Development Plans are prepared on a macro level, whereas micro level spatial urban growth data during different time periods is not available for planning investigation. Only generic problems are addressed in the plans and specific problems such as location specific in nature are not identified and addressed. Often, the goals and objectives lack space for directional and spatial objectives. In the absence of temporal and spatial urban growth data, the plan preparation is not supported by historic and future spatial trends of development. Lack of specificity in the plan and its objectives affects the implementation of plan and makes it intangible. Owing to time and resource constraints, plans are not evaluated and reviewed in the mid-course of the plan period to find out whether the goals and objectives are realized. Also, no space is available for identifying new problems that crop up and incorporation of suitable solutions in the plan.

The suggested methodology ensures that the limitations in the current land use planning practices are overcome in the planning support system aided by prediction and simulation. It has the advantages of addressing the problems in the current planning practice such as the intermediate verification and evaluation with thorough knowledge on past, present and future growth dynamics.

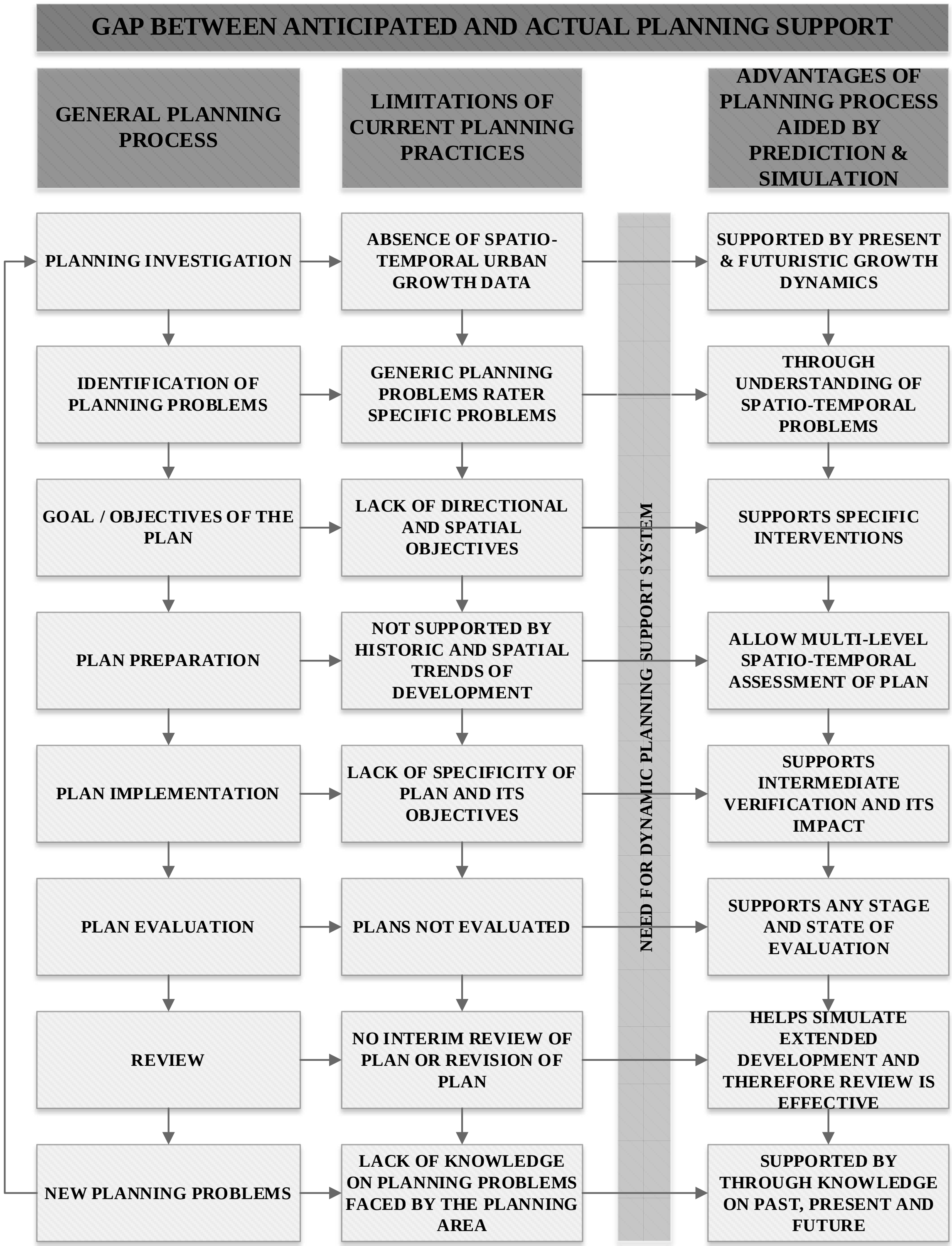



*Figure 1.1 Gap between anticipated and actual planning support*

## 1.3 THESIS STATEMENT

Rapid urbanization & increase in population results in increased land modification and alterations in the status of land use land cover over time. Recently, Government of Gujarat merged Municipalities of Porbandar and Chhaya and also extended its boundary by including three villages (Bokhira, Khapat & Dharmapur) to form Porbandar-Chhaya Municipality. Preparation of Development Plan for the area is undertaken by the government at present.

A detailed and comprehensive attempt to evaluate land cover as it changes over time and also make an attempt to predict the possible changes that may occur in this status in Business-as-Usual scenario, can be an important tool for urban planners. There is a need for a study such as this to be carried out if Porbandar-Chhaya aims to avoid the associated problems of a growing and expanding city like many others.

## 1.4 AIM

The aim of this study is to prepare a land cover maps of study area at different periods in order to detect the changes that have taken place particularly in the Built-up area and subsequently predict the future pattern of land cover, for effective Planning, mid – course review and revision.

## 1.5 OBJECTIVES

1. To prepare land cover maps for the years 1991, 2001, 2011 using Satellite data for the study area by classification of Satellite images for delineation of various land cover categories through image analysis and processing as well as visual interpretation techniques.
2. To analyze the nature, trend, direction and magnitude of land cover change for the study area by transition matrix.
3. To predict the land cover for 2021 using Satellite data & GIS and compare it with current land cover to calibrate prediction model.
4. To predict the pattern of land cover for year 2031 in the study area to visualize the future state of the study area by map.
5. To understand urban growth patterns of study area, identify related issues and challenges and give suggestions.

## 1.6 SCOPE OF THE STUDY

The study will be done for the administrative boundary of newly formed Porbandar-Chhaya Municipality. Historical land cover maps will be generated using satellite archive data and GIS. Landsat images acquired for the study has spatial resolution of 30 meters therefor, land use category classification is difficult and not under taken in this study. Keeping in mind the consistency and suitability for classification of data, maps will be prepared for the year 1991, 2001, 2011 and 2021. The study will be carried out covering limited aspect regarding satellite data as per the objectives. Prediction for future land cover is made only by detecting land cover change in the past using satellite data. Such prediction does not take in to consideration any new planned or unplanned interventions in the study area.

## 1.7 ORGANIZATION OF CHAPTERS

In Chapter 1, in a general outlook, the urbanization process has been studied which urged the need for a research on the urban growth, with specific reference to Porbandar-Chhaya Municipality. Upon establishing the need for the study, aim and objectives of the study are formulated in this chapter. Also, the organization of chapters is outlined.

Chapter 2 deals with the study of literature relevant to the study from a wide variety of sources of literature such as published books, e-books, articles published in journals and websites in order to understand the principles behind the mapping of urban growth process, the tools available for land cover change analysis and prediction of future land cover. Among the various tools available for land cover change analysis, cellular-automata based land cover simulation, is a simple and flexible tool. The proposed method has to be flexible.

The introduction on the study area, namely the Porbandar-Chhaya Municipality is given in Chapter 3. The transportation network in the form of road and rail, the demographic profile, physical character and geographical character are elaborated.

Chapter 4 contains detailed methodology with explanation of different terms used in the study, research process, brief about Landsat satellite and its band designation, properties of satellite images and FCC identification. Also, explain in detail image classification process and different change detection technique.

Chapter 5 includes analysis of land cover classification from thematic maps of year 1991, 2001, 2011 and 2021. Also, contains change detection analysis for built-up area. Built-up growth pattern is analyzed with gradient analysis.

Chapter 6 contains land cover projection methods and its process for future prediction. Also, showing results of thematic map for projection year 2031 of study area and transition probability matrix.

The discussion on results of the study viz., the land cover change detection & prediction using remote sensing and GIS techniques are dealt in detail in Chapter 7. Spatiotemporal pattern of land cover change is discussed and several issues and challenges for future urban development are identified. The ability of the remote sensing and CA based method to predict land cover change and application of the results are discussed. The study is concluded in Chapter 7. Recommendations which emerge out of the study are spelt out. Also, the scope for further research is discussed in the chapter.

# CHAPTER:2 LITERATURE REVIEW

## 2.1 REMOTE SENSING OF URBAN ENVIRONMENT THROUGH GIS TECHNIQUES

Urban expansion is a world phenomenon. Growing cities are creating an alarming situation in all countries of the world. It has led to serious land use problems such as loss of agricultural land, unauthorized urban sprawl, high land values, speculation in land and other related problems, though this phenomenon has assumed great topical significance but it remains a much-neglected area in urban research. In the emerging scenario it is essential to have updated information on urban growth patterns and its impact on the living environment. Collection of all this information by conventional methods requires huge manpower and is a costly and time-consuming process. Planning for urban growth essentially needs the most up to-date and accurate physical maps. The conventional starting point for any urban planner has been the standard topographical map. Topographical maps are general-purpose maps, and several details on the earth's surface are symbolically depicted. It may not give an objective view of the terrain in its true form, particularly when these maps are obsolete. Generally speaking, most of our Survey of India topographical maps could be as old as 25 to 30 years, they, do not depict the ground conditions of the time, when a new plan is to be undertaken (Narayan, 1999). Planning exercises will become purposeful when the decisions are based on sound land, social and environmental information. It is in this area of providing physical inputs that remote sensing has shown the way. In order to comprehend the role of Remote Sensing and GIS in urban planning and management, a brief description of these techniques is discussed below.

### 2.1.1 REMOTE SENSING

Remote sensing has been recognized worldwide as a modern tool for systematic surveying, mapping and monitoring of natural resources for their judicious use and management. It has demonstrated its capability to study these resources economically with greater speed and accuracy and to minimize if not replace fieldwork in management-oriented needs. During the last three decades, this technology has grown tremendously, leading to increased demand for remote sensing data, interpretation techniques and software in various application areas.

According to (Lillesand, Kiefer, & Chipman, 2015) remote Sensing can be defined as "The technique of acquiring information about an object by a recording device (sensor) that is not in physical contact with the object by measuring portion of reflected or emitted electromagnetic radiation from the earth's surface". The two basic processes in remote sensing of earth resources are (a) Data acquisition and (b) Data analysis.

The elements of data acquisition process are: i) energy sources, ii) Propagation of electromagnetic energy through the atmosphere, iii) electromagnetic energy's interactions with surface features, iv) retransmission of energy through the atmosphere, v) recording of these energies by airborne / space borne sensors, and vi) generation of sensor data in pictorial/ digital form, which records the variations in the way earth surface features reflect and emit electromagnetic energy.

Data analysis involves: i) examining the data using various viewing and interpretation devices to analyse pictorial data and a computer to analyse the original data, ii) compiling of the information in the form of hard copy maps and tables or computer files that can be merged with other layers of information in GIS and iii) presenting the information to decision makers. In order to extract and utilize information related to urban processes and forms one must evaluate remote sensing in a variety of ways. The availability of the remotely sensed data products for urban applications, beyond conceptual data requirements, falls under the following two categories.

- Aerial Photography
- Satellite Images

**1. Aerial Photography**

The use of Remote sensing techniques in city planning in India has largely been confined to aerial photography till very recently. It is evident that an enormous amount of detailed information is practically recorded and supplied inferentially by the aerial photographs. This is probably because aerial photography can provide a visualization of the three — dimensional reality of urban spatial structures, which is essential for urban planning. From past experience in planning and development of large urban projects, it is observed by the planners that transformation of paper plans on the ground, takes much more time than simply preparation of the plan (Gupta & Singh, 2010). For example, if the area of a planned project ranges between 2000 hectares to 5000 hectares, identification of land for land acquisition, actual physical possession of land and development of roads etc. takes considerable time. During this incubation period ground realities might have changed and planning proposals become obsolete. Therefore, the rate of implementation of the plan is below the desired level. In such a situation, the urban information extracted from aerial photographs compliments the data available from conventional ground surveys and provide immense opportunities to urban planners for effective planning and management of cities and towns.

Aerial photographs in India are made available by the Survey of India in different modes and at different scales. However, for most urban applications to Indian cities, the black and white photographs at 1:10,000 and large scales are widely used. The data collected from aerial photography is low cost, accurate and reliable and could be obtained at the desired scale and time interval for mapping and interpretation. With the addition of minus blue filtration, black and white photographs provide sharp images of the urban features photographed. The periodically taken aerial photographs reveal changes in urban morphology and land use pattern in the cities.

The aerial photographs however have limitations. First, they can only be taken during daytime. Second, the photographic camera is not capable of penetrating under adverse weather conditions and smog. The urban areas today contain very high concentration of pollutants. The high-altitude panchromatic photography, often fails to penetrate the foreign particles and record sharp images of urban features. Third, obtaining aerial photographs periodically is weather dependent and costly.

**2. Satellite Sensing:**

Satellite data compliments and supplements data available from both aerial photographs and conventional ground sources for urban planning. Although aerial photography remains the principal remote sensing medium for urban applications, space borne remote sensing is gaining wider acceptability today. The biggest strength of satellite-born-sensor data is its periodicity, fastness and economic efficiency. Also, the data being available in analogue and digital form, it is amenable to both visual and digital analysis for extraction of information. The synoptic view provided by the satellite imagery proved very advantageous in assessing the growth of urban areas. Availability of temporal data is an added advantage for realistic monitoring of the city's growth. The remotely sensed data from space borne sensors is most relevant and is perhaps the cheapest means of acquiring information about urban land use/ land cover with reasonable accuracy and in near real time.

The early experiments with first generation Landsat series of satellites were found useful in mapping large urban parcels and urban extensions. The developments during 1980's yielded sensors with both fine resolutions and stereo capabilities. Whereas the Landsat TM data with 30 m resolution helped in mapping level-Il urban land uses and SPOT —PLA provided images with 10 m resolution. The sensors with very high resolutions, i.e., 5.8 m of IRS I C and ID in panchromatic (PAN) mode and 1 to 4 m of IKONOS exhibited capabilities for detailed urban planning and management.

The current satellites allow data to be generated up to scale using IRS (LISS-Il) and up to 1:25,000 scale using SPOT data. Today, with the availability of IRS I C and ID data, it's not only possible to generate data on 1: 50,000, 1: 25,000 scales using LISS-Ill, but with PAN data it is even possible to generate up to the desired scales of 1:20,000, 1:15,000 and 1:12,500 which is useful for urban planning. Over the years, satellite-based remote sensing data have been successfully utilized for mapping, monitoring and planning of urban land use, urban sprawl and urban environment. The salient features of different satellites / sensors and the extractable levels of urban information are given in the Table 2.1 below.

| SATELLITE SYSTEM | SPATIAL RESOLUTION (m) | MAPPING SCALE | EXTRACTABLE INFORMATION |
|---|---|---|---|
| Landsat MSS | 80 | 1:1,000,000 | Broad land use / Land cover, Urban Sprawl. |
| IRS IA and 1B | 72 | 1:250,000 | |
| Landsat (TM) | 30 | 1:50 000 | Broad structural plans and spatial strategies |
| IRS -l A and I B (LISS-II) | 36 | 1:50 000 | |
| IRS -l C and I D (LISS-III) | 23 | 1:50 000 | |
| SPOT HRV -1 (MLA) | 20 | 1:50 000 | |
| SPOT HRV -11 (PLA) | 10 | 1:25 000 | Land use plans / Sector plans |
| IRS -l C and I D (PAN) | 5.8 | 1:10,000 | |
| IKONOS (PAN) | 4 and 1 | 1:6,000, 1.4,000, 1:2,500 | Ground plans and urban desi n |
| RESOURCE SAT -1 IRS P6 (LISS-IV) | 5.8 | 1:10,000 | Land use plans / Sector plans/ Development plans |

*Table 2.1 Salient features of different satellites/sensors*
(Rashid & Sokhi, 1999)

### 2.1.2 GEOGRAPHIC INFORMATION SYSTEM

Urban areas go through many changes that have a spatial-temporal property, which is important to understand for many applications and land management linked problems. So, the planners need detailed information about the amount and spatial spreading of various urban land uses, housing, population growth patterns, urban sprawl, existing condition of infrastructure, services etc. For planning of these services in a better way, planner needs the overall data in a map and statistics related to these features for wholesome planning and management. Urbanisation in the fringe areas brings its own problems including loss of agricultural land.

These problems require direct attention of the planners and administrators. Management and planning of urban areas need spatially accurate and timely data. Because of the Geographic Information System, the course of urban planning in India received a new stimulus. Incorporation of Remote sensing and Geographic Information system (GIS) delivers a way to apprise theme-oriented information and mapping of dynamic landscapes of the earth surface for effective management and planning.

Geographic Information System is a computer-based information system intended to accept large volumes of data resulting from a variety of sources and to competently store, recover, analyse, model and display these data according to user defined requirement. Apprehending the spatial particulars by remote sensing, either by satellite imageries or aerial photographs and organizing that data together with matching attribute data under a GIS offers great potential for undertaking change detection, monitoring and urban planning activities.

GIS handles a number of spatial objects, their properties, and their interrelationship to each other. It allows us to store, process and visualize current and old information. The stored digital map information of the GIS database can be printed in the required format, to yield a map. Retrieval, manipulation and display of all these data are conceivable through a set of GIS applications (Huxhold, 1991). Such as:

- Automated mapping technology: Helps us in managing various spatial map information system effortlessly
- Data base management: help us in handling a diverse attribute data
- Land records information: Helps in handling the cartographic and attribute data accurately and completely
- Topological data structures: Helps in establishing the spatial relationships among point, lines, and polygon features
- Spatial analysis capabilities. Helps to retrieve, manipulate and display map and location related attribute data
- Map making and geographic analysis are being done since centuries. But GIS performs these tasks more efficiently and faster than the old methods.

GIS is a multi-disciplinary integrated approach for monitoring and managing the urban environment, through its various spatial tools. Such as a) through data merging b) through querying. The information in the digitised form (such as contour map, land use maps, land cover maps, etc.) can be merged with one another, in layer form, using the common database such as boundary map, village map or road maps (Rashid & Sokhi, 1999).

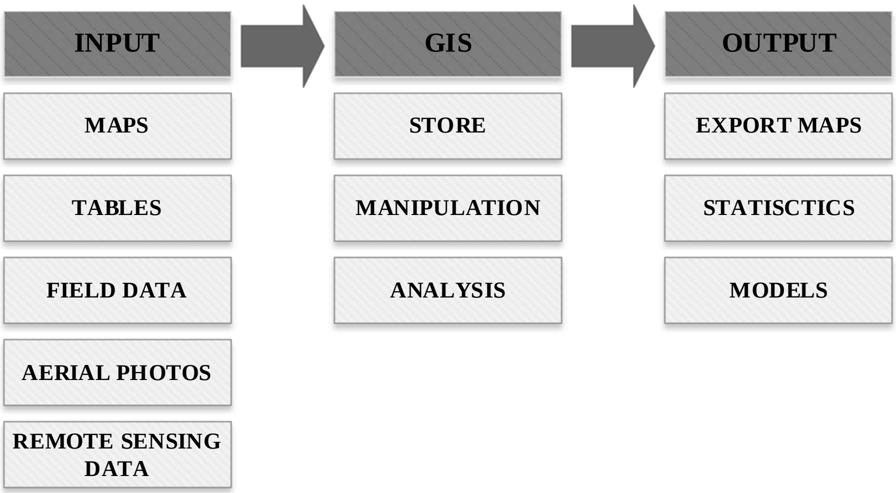



*Figure 2.1 Components of GIS*

Moreover, they enable the assortment and allocation of data to application specific analytical models capable of assessing the influence of possibilities on the chosen area. The main difference or factor, which separates GIS from other information storage and retrieval systems, is the spatial and specific locational features given in the form of maps, which could be showing topography, geology, soil types, forest and vegetation, land use/land cover etc., and stored as layers in a digital form in the computer.

Besides spatial data, we could also have attribute data like statistics, texts and tables. Combining many layers of data in a computer can easily produce new maps. Thus, GIS has a database of multiple information layers that can be manipulated or analysed to assess associations among the particular elements from all that is presented. If we have the right kind of software, any feature on the surface of the earth can be represented on a map by either a point, a line or a polygon and other types of attribute data can also be assigned. Once things are coordinated and geo referenced to the same context and in digital form, it is astonishing to see that we can do any type of analysis with them.

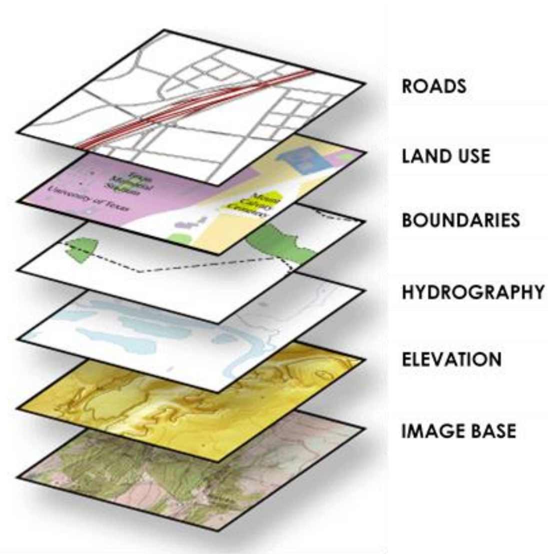



*Figure 2.2 GIS data organization*

### 2.1.3 APPLICATION OF RS AND GIS IN PLANNING

The expression "remote sensing" was first used in the United States in the 1950s by Ms. Evelyn Pruitt of the US office of Naval Research. Remote Sensing (RS) is now frequently used to define the science and art of gaining data about an entity, area or phenomenon of study by a device that records the spectral properties of surface materials on the earth from a distance (Singh, 2010). Fundamentally, there are two types of remote sensing devices, passive and active. Passive devices detect the natural energy that is reflected or emitted from the observed scene whereas active devices provide their own energy (electromagnetic radiation) to illuminate the object or scene they observe. Remote sensing from airborne and space platforms provides an enormous amount of valued data about our earth's surface including aerial photographs, satellite images, spatial data set and other data (Al-doski, Mansor, & Shafri, 2013). The improved availability of varied resolution satellite data since the early 1990s, provides frequent and varying data among themselves in terms of spatial, radiometric, spectral, temporal resolution and its synoptic view (Herold, Gardner, & Roberts, 2003), also the digital format makes them appropriate for many computer image processing software. For all above reasons, remotely sensed data has become the primary source for the applications in the field (Lu, Mausel, Brondízio, & Moran, 2004). Remote sensing satellite imagery has given researchers an outstanding method to identify the reasons for land use/land cover changes and the subsequent consequences owing to human actions (A.Cardille & A.Foley, 2003)

Because of the availability of up to date RS data and spatial analysis tools, researchers has gained a powerful equipment for mapping and identifying land use/land cover changes, particularly in the crop rotation of agriculture, in yield assessment, and yield estimation (A.Cardille & A.Foley, 2003), in coastal area changes (Xie, Zhang, & Lu, 2011) in land degradation detection, vegetation mapping, in wetland landscape changes, in urban change detection (Renzaa, Martinez, Molinab, M., & L., 2017) and other applications.

RS presents a valuable instrument for understanding and managing resources and LULC change detection. Huge efforts have been made to delineate LULC on a local scale as well as global scale by using various multi-temporal and multi-source remotely sensed data from both airborne and space borne sensors.

The commonly used data, for monitoring and mapping LULC changes, are derived from medium resolution satellite sensors like Landsat TM & MSS. These types of data are being used successfully in the studies related to LULC changes, particularly in the regions experiencing rapid urbanization. For example, (Hu, Dong, Lu, & Yan, 2011) used Landsat Multi-Spectral System (MSS). Landsat TM and ETM+ remote-sensing data for land cover changes. (Fan, Weng, & Wang, 2007) used TM and ETM+ images for detecting and predicting land use and land cover in Guangzhou, China.

Also, numerous researchers worked with merging different sensor data in monitoring LULC changes. Like, Landsat Multi-Spectral System (MSSY und Quick Bird data), Landsat TM and Landsat Geo-Cover LC satellite images, multi-temporal and multi-spectral satellite data Landsat MSS, TM, ETM. ASTER, and MODIS.

Different studies show that, due to the limitation of spatial resolution, some multi-temporal and multi-sensor data is suitable for global LULC changes while others are not usable for regional level of studies. Never the less, importance and usability of medium resolution satellite imagery, like Landsat, for monitoring of regional LULC changes is undisputable (Franklin & Wulder, 2002).

## 2.2 LAND USE AND LAND COVER CLASSIFICATION SYSTEMS

The selected method of LULC classification highly affects the analysis of LULC change detection. The amount and type of LULCC is shown in particular LULC classes (ANDERSON, HARDY, ROACH, & WITMER, 1976). To monitor the environmental and socio-economic impacts of LULCC, related feature classes need to be identified for study area. Unless, this is taken care of during the study, the analysis will have little contribution towards policy and planning decision making regarding the study area. This makes it important to study established LULC classification system, which can be adopted to study LULC and temporal change patterns (Briassoulis, 2000).

Representation of “What is” and “What should be” are main choices while making a land classification system. The land available as a resource and its properties as identified by the method used, defines “What is”. At the same time, the possibilities and value derived on the same resource and as a result, decisions taken by the people regarding its proposed use defines “What should be” (Wolman & Fournier, 1987).

The spatial scale and aim for development of study area should be considered first before selecting any land classification system. The spatial scale will decide level of details specified in classification system. The aim of development decides what parameters of the land use types should be included. Apart from this, availability of technology and data plays major role in defining classification system. Most of the classification system does not separate the terms land use and land cover.

Reflected response of different land surfaces like vegetation, waterbody, built-up are recorded by a satellite sensor, or any other remote sensing device. Characteristics of these response data, such as tone, texture, shape, size, pattern, shadow, association are used to interpret information about land cover.

As such data are generated from many different types of satellites and sensors orbiting the earth at different altitudes and gathering information at different points in time, makes classification system more complex. And thus, different classification systems are needed for different imagery, scale and purpose. To date, the most successful attempt in developing a general-purpose classification scheme compatible with remote sensing data has been by Anderson et al, which is also referred to as USGS classification scheme is shown in Appendix 1 (ANDERSON, HARDY, ROACH, & WITMER, 1976). Other classification schemes available for use with remotely sensed data are modification of the above classification scheme.

## 2.3 ASSESSING LAND USE/LAND COVER CHANGE

Natural forces like floods, wild fire, climate changes and volcanic eruptions can also alter the land cover apart from human activities. But, in recent times these changes are by and large governed by direct or indirect human activities like agriculture, husbandry, deforestation and growing urbanization. According to (Meyer, 1995) land cover is also being impacted by many adverse effects of human activities like acid rain, green house effects, depleting ozone layer, GNG emission.

Because of rapid pace of urbanization, maps prepared by conventional ground methods quickly becomes outdated, as they are labor intensive, time consuming, costly and relatively infrequent. As per (Olorunfemi, 1983) monitoring and analysis of LULCC over a period of time is very difficult with ground surveying methods. In past decades the satellite remote sensing technology as evolved dramatically, proving it self to be valuable and accurate data source for preparing LULC maps and monitoring changes at regular time intervals. This has proven indispensable method especially for the study of inaccessible areas, along with saving of cost and time.

The process of observation, at different points in time, of the condition of any object or phenomenon and identification of differences is known as change detection. As it can provide quantitative analysis of spatial distribution and change, change detection has become important process in monitoring and managing land resource and urban development.

(Macleod & Congalton, 1998) list four aspects of change detection, which are important when monitoring natural resources:

1. Detecting the changes that have occurred
2. Identifying the nature of the change
3. Measuring the area extent of the change
4. Assessing the spatial pattern of the change

In some instances, land use land cover change may result in environmental social and economic impacts of greater damage than benefit to the area (Ahadnejad, 2009). This makes study of LULCC and its consequences very important for the planners. In resource management and planning, assessment of LULCC patterns and its future prediction modelling, these types of data are very valuable.

(Shoshany, Kutiel, & Lavee, 1996) investigated the advantages of remote sensing techniques in relation to field surveys in providing a regional description of vegetation cover. The results of their research were used to produce vegetation cover maps that provided new information on spatial and temporal distributions of vegetation in this area and allowed regional quantitative assessment of the vegetation cover.

(Arvind.C.Pandey & M.S.Nathawat, 2009) carried out a study on land use land cover mapping of Panchkula, Ambala and Yamunanger districts, Haryana State in India. The analysis of remote sensing data shows that majority land is used for agriculture in the districts. Also, the fact that there are different LULC in these districts is due to heterogeneous climate and physiographic conditions. Reserved forests are observed in the hilly parts of the districts. The inference drawn from the study is that agro-climatic conditions, availability of ground water and many other factors impacts the LULC pattern in this area.

It has been noted over time through series of studies that Landsat Thematic Mapper is adequate for general extensive synoptic coverage of large areas (Parveen, Bashir, & Praveen, 2018). As a result, this reduces the need for expensive and time-consuming ground survey conducted for validation of data. In most cases, satellite data can be collected at regular intervals and more frequently. Although, aerial photographs have advantage of geometric accuracy, they are limited in terms of special coverage and cost effectiveness, making them used less often.

Objectives of analysis primarily governs the suitable approach for LULCC. The question which needs to be answered and the requirements of the user, decides the theoretical framework adopted and models used. Main categories for the purposes of analysis are description, explanation, prediction, impact assessment, prescription and evaluation. These are discussed in brief below.

For any analysis, descriptive study of LULCC is must to move towards more refined and detailed analysis. Description of LULCC provides conversion of land use from one to another for given time period within study area. The changes are expressed in qualitative and quantitative forms. The spatial scale of study area and availability of data decides the level of detail. Such study provides basis for further research in to the reasons of changes and formation of policies and planning interventions to mitigate negative impacts of such identified changes (Briassoulis, 2000).

For effective policy and planning interventions, description alone is not enough no matter how detailed and precise it may be. These gaps can be filled with explanatory analysis. To answer the question like "What caused these changes?" and to identify parameter having direct or indirect influence on these changes, explanatory analysis needs to be done. The purview of selected spatial and temporal level of analysis decides the level of explanation gained from the study. Macroanalysis deals with changes at global level and relevant determinants of LULCC. For the analysis of smaller spatial levels, socio-economic factors and human behavior analysis are included. Impact of macro-forces like social, cultural and technological changes can be revealed by explanatory analysis over long period of time. In contrast explanatory analysis for short term aims at current factors affecting the land use change. Theoretical framework used for explanatory studies, incorporates major determinants of land use change and their interrelationship (Briassoulis, 2000).

Prediction of future state of land use is an important objective of such analysis apart from description and explanation. These predictions could be conditional or unconditional. The unconditional prediction or trend extrapolation are able to give map of future land use pattern of study area, given that the past trends are continued and no interventions are made. Hence, they are more mechanistic in nature and more like projections of past trends in land use change in to the future. On the other hand, conditional predictions are able to predict future land use considering impact of hypothetical scenarios. These scenarios could be change in climate, population growth, change in government policy or regulations etc. They are widely used in process of policy making or decision making, affecting at global scale. Spatial and temporal level of analysis are still major concerns in both unconditional and conditional predictions.

Impact assessment in one another important objective of such LULCC analysis. The focus is on study of different impacts of LULCC like, environmental and socio-economic, rather than on change itself. In recent times impact assessment of proposed or implemented policies has gained scientific importance (Briassoulis, 2000).

### 2.3.1 LAND USE CHANGE: ENVIRONMENTAL AND SOCIO-ECONOMIC IMPACTS

The environmental and socio-economic impacts of LULCC is equally important question to be concerned with analysis. What actually made scientific and policy making interested in land use change, is negative impacts of it.

According to (Meyer & Clark, 1990), “the lands of the earth bear the most visible if not necessarily the most profound imprints of humankind's actions”.

The LULCC impacts can be categorized into environmental and socio-economic. Although socio-economic impacts have interested more people and drawn attention. This imbalance of importance could be due to the fact that environmental impacts are subtle, lang-term, affected by many other factors and less visible. Never the less both impacts are closely related with each other.

According to (Blaikie & Brookfield, 1987), in reality environmental impacts are the cause of socio-economic impacts, which in turn are feedback to the first again. This creates cycle of land use change. Shifting cultivators in Latin America and rest of the world, is well known example of such cycle. The cycle starts with clearing of forest, followed by cultivation, after that heavy grazing and finally land is deserted and people move to another location where the cycle repeats.

As per (Briassoulis, 2000), such impacts of LULCC have been identified according to their impacted spatial extent like global, regional and local impacts. Although, these terms do not have precise physical definition when LULCC studies are concerned. For example, a region may be a subdivision of the world (e.g., Latin America, China, the Sahel, large world biomes etc.) or a subdivision of a large nation (e.g., a state or a group of states of the USA) or even a sub-regional Subdivision of a nation's region. From another perspective, for the reasons of examination of the effects of land use change, a locale may characterize dependent on geographic and ecological attributes like the Mediterranean Region, the Baltic Region, and so on. Comparative remarks apply to the outline of neighborhoods where the nearby is utilized as something contrary to the worldwide.

At last, land use change causes a large number of environmental effects at the lower spatial levels in urban, rural, country and open space arear which have been widely archived. Particularly significant are the land use changes and transformation that happen in the outskirts of enormous metropolitan sprawls that are dependent upon urbanization and industrialization pressures and every now and then bring about conversion of prime rural grounds and forest cover.

Their ecological effects could also be changes in the hydrological equilibrium of the zone, increment in the danger of floods and avalanches, air contamination, water contamination, and so forth. Other effects of land use change incorporate soil disintegration, sedimentation, soil and groundwater defilement and salinization, termination of native species marine and sea-going contamination of local water bodies, costal disintegration and contamination. The significance of these effects isn't confined to the neighborhood interest, as they are oftentimes combined emerging out of the choices of numerous individual land and land owner to act in their self-interest. Likewise, land use changes in a single region may have ecological repercussions in other far-off zones. For instance, urbanization or the travel industry improvement in a territory expands the need for water, which nonetheless, is been given by another zone. Abundance water consumption lessens the water accessible for horticulture and plant development in the latter region and may result in saltwater interruption for seaside zones.

According to (Briassoulis, 2000), notwithstanding the natural, the financial effects of land use change are similarly huge and offer ascent to genuine worries at all spatial levels. Worldwide level financial effects concern issues of food security, water shortage, populace relocation and all the more. For the most part, the issue of human security and vulnerability to natural and technological hazards. Global and non-administrative associations, for example, the FAO, the World Bank, the IHDP Program, and so forth embrace methodical evaluations to help strategy and decision making at all spatial levels on the above issues.

(Lonergan, 1998) says that, the food security and the water shortage issues may emerge out of decreases in the zone of rural land and diminishes in accessible water supplies that outcome from soil disintegration, land debasement, desertification, industrialization, urbanization, suburbanization or more all, poor management of ecological assets. In every one of these occasions, unsatisfactory employments of land assume a significant part. These issues concern the essential inquiry of whether there is sufficient food to take care of the developing populace of the earth and enough water to cover present and future requests of an inexorably industrializing and urbanizing world. In equal, they concern whether or not the circulation of the food and water assets is even all through the globe. Populace relocation is another issue that is being examined to recognize the potential pretended by ecological debasement to populace developments from areas encountering natural pressure at last human security and weakness is an aggregate term used to signify each one of those components that may present dangers to human wellbeing. government assistance and prosperity in a given geographic arca. A proposed measure is the "Index of Vulnerability” involving 12 markers; food import dependency ratio, water scarcity, energy imports as a percentage of consumption, access to safe water, expenditures on defense vs. health and education indicator of human freedoms, urban population growth, child mortality, maternal mortality, income per capita, degree of democratization and fertility rates.

Local level financial effects of land use change are more variegated reflecting the assortment of local settings where these progressions happen. These as well, emerge out of similar cycles examined above and develop around such issues as accessibility of land for local food creation changes (decrease), in land efficiency and thusly (lower) productivity and changes in mechanical design, business/joblessness, destitution, populace change and movement and personal satisfaction issues, for example, wellbeing and convenience.

At last. neighborhood level financial effects of land use change contain comparable concerns yet they are limited to the specific areas where these progressions happen. The issue of farmland changes to metropolitan and different uses (for example the travel industry) has arrived at extraordinary exposure and concern has been communicated as, notwithstanding the ecological effects referenced previously, it causes genuine financial effects. On account of the travel industry advancement on already agrarian land, a less noticeable however critical financial effect is the expanded reliance of the traveler district on not privately delivered ranch items and the expanded pressing factors for rural yield filled in and purchased from different regions. Neighborhood level financial, similar to the natural effects, may act aggregately and cause bigger than nearby effects in the more extended term.

### 2.3.2 CHANGE DETECTION TECHNIQUES

(Al-doski, Mansor, & Shafri, 2013) defines change detection as, identifying and analyzing LULCC over large spatial region within given time span and at regular intervals, with medium to high resolution remote sensing satellite data.

As per (Singh, 2010), It is a process of identifying alteration, by monitoring at different points in time, in the state of an object or phenomenon.

According to (Song, Woodcock, & Seto, 2001), this is a significant process in evaluating the LULCC, as it gives quantitative analysis of the spatial distribution. Making LULC study interesting aspect of remote sensing applications.

(Im & R.Jensen, 2005) mentioned six main steps for LULCC detection using remote sensing data, as shown in Figure 2.3.

Although many different techniques for LULC change detection have been applied over the last two decades, (Singh, 2010) summarize eleven different change detection algorithms that were found to be documented in the literature. These include:

1. Mono-temporal change delineation
2. Delta or post classification comparisons
3. Multidimensional temporal feature space analysis
4. Composite analysis
5. Image differencing
6. Multitemporal linear data transformation
7. Change vector analysis
8. image regression
9. Multitemporal biomass index
10. Background Subtraction
11. Image ratioing

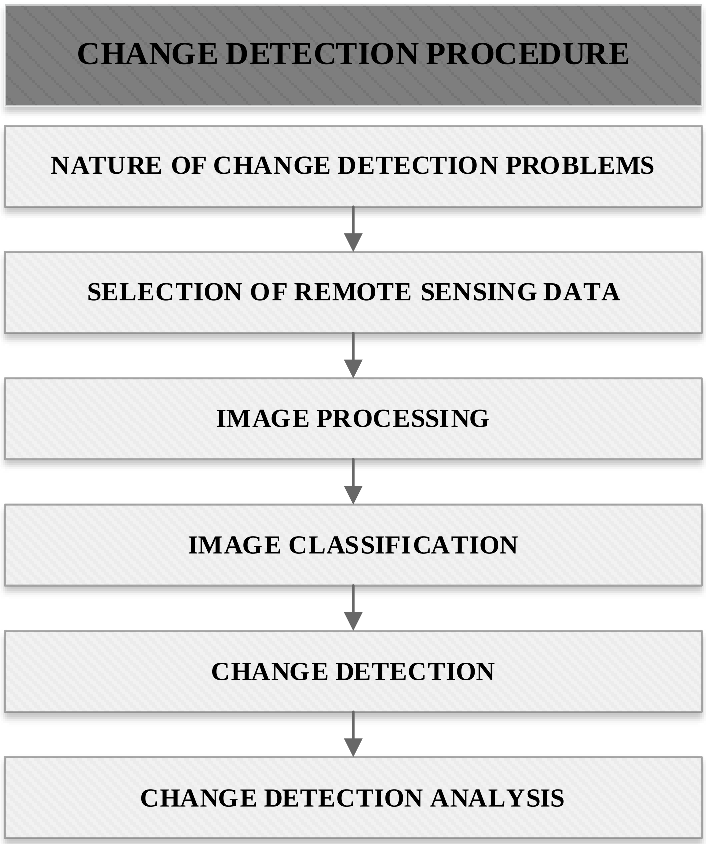



*Figure 2.3 Stepwise change detection procedure*

Since launching, the first of the Landsat satellite system 1972, a wide range of data have been provided (Williams, Goward, & Arvidson, 2006).

According to (Dewidar, 2004), the reason for the development of various LULC change detection techniques is, availability of huge documented satellite data. Various methods have been extensively reviewed and provided with excellent descriptions and comprehensive summaries (Singh, 2010). There are two categories of change detection methods: pre classification and post- classification change detection techniques (Lu, Mausel, Brondízio, & Moran, 2004).

#### 2.3.2.1 PRE-CLASSIFICATION TECHNIQUES

Essentially, the pre-classification techniques produce "change vs no change" maps. This technique is also known as binary change or non-change information detecting techniques and it many methods that directly employ the satellite imagery taken at different points in time.

Various pre-classification techniques have been employed to assess and identify LULC changes. Some of them are listed below:

- Image Differencing (ID)
- Improved Change-Vector Analysis
- Band Image Differencing

- RGB-NDVI Change Detection Method (Yang & Zou, 2009) (Yoon, Yun, & Park, 2003) (Johnson & Kasischke, 2010)
- Spectral Change Vector Analysis
- Principal Component Differencing (PCD)
- Image Ratioing (IR)

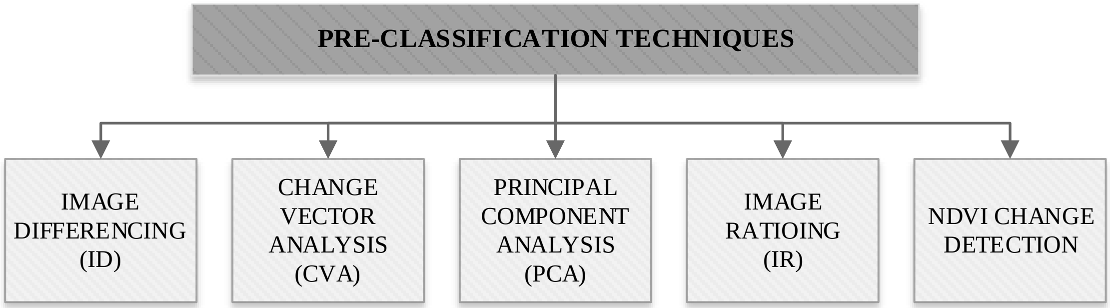



*Figure 2.4 Types of Pre-Classification Change Detection Techniques*

**1. Image Differencing (ID)**

According to (Hayes & Sader, 2001), image differencing means pixel by pixel subtraction of two spatially registered imageries. The pixels of areas, where changes have occurred, are usually distributed at the ends of the histogram in the final image, whereas pixels of unchanged areas are grouped in center. This method makes it easy to interpret the resultant image: though, it is crucial to properly define the thresholds to detect the change from non-change areas.

**2. Change Vector Analysis (CVA)**

According to (Nagaraju Arveti, 2016) and (Yang & Zou, 2009), output received from CVA are a change vector image and a magnitude image. Spatial change vector image provides the direction and magnitude of change from the first to the second point in time (t1 to t2). The total change extent per pixel is calculated by determining the Euclidean distance between end points through dimensional change space. CVA can process any number of spectral bands needed for study. It also gives detailed information regarding detected changes.

**3. Principal Component Analysis (PCA)**

Principal Component Analysis (PCA) technique is useful in reducing the dimensionality of a data set in order to obtain a simple dataset where characteristics of the original dataset that contributes most to its variance are retained. PCA can give improved image classification accuracy by highest visual separability between various feature classes in image, this in turn improves the quality of ground truth gathering.

**4. Image Ratioing (IR):**

Ratioing is also a simple and rapid means to identify changed areas. It implies calculation of the ratio of two registered images from different dates, on a band-by band basis. In the changed areas, the ratio values will be significantly greater than 1 depending on the nature of the change. The issue with this method is non-normal histogram distribution within the final image.

**5. Normalized Difference Vegetation Index (NDVI)**

As per (Yang & Zou, 2009) (Yoon, Yun, & Park, 2003) and (Johnson & Kasischke, 2010), NDVI can find vegetation Index, land cover classification, waterbodies, barren land, hilly areas, agricultural area, dense forest, sparse forest etc. using multi-spectral remotely sensed data. NDVI is calculated as follows:

**NDVI = (NIR - Red) / (NIR + Red)**

Where Red and NIR stand for the spectral reflectance measurements acquired in the red and near-infrared regions, respectively, NDVI itself thus varies between -1.0 and +1.0.

Most of the pre-classification techniques are identified as the most accurate change detection techniques because they are straightforward, elective for identifying and locating change and are easy to implement (Jwan Al-doski, 2013).

As per (Lu, Mausel, Brondízio, & Moran, 2004), there are three important characteristics of pre-classification techniques, selecting suitable thresholds to identify the changed areas, it is sensitive to mis-registration of pixels and inability to provide details regarding the nature of change or provide a matrix of change information.

#### 2.3.2.2 POST-CLASSIFICATION COMPARISON TECHNIQUE

According to (M. Foody, 2002), for change detection analysis, post-classification comparison is proven and widely accepted method. The process adopted in this approach is to classify and rectify each image separately and then generating thematic maps. Which is followed by a comparison of corresponding themes to identify changes. (Figure 2.5).

According to (Lu, Mausel, Brondízio, & Moran, 2004) (Im & R.Jensen, 2005) (Simone Naumann, 2004), advantages to this technique are: minimum sunset, atmospheric, and environmental differences, as data from two time points are separately classified, hence minimizing the problem of normalizing for atmospheric and sensor differences. It also provides a complete matrix of land cover change. A series of "from-to" matrixes can be built by comparing on a pixel-by-pixel basis. Matrices like pixel conversion matrix, percentages conversion matrix and area conversion matrix can be made.

It is noted by (Im & R.Jensen, 2005) and (Basawaraja, Chari, Mise, & Chetti, 2011) that results of such method are influenced by the accuracy of individually classified images. Also suggested by (M.Foody, 2002), that when multi-temporal or different sensor images are used for the study, results could be wrong, due to the differences in the radiometric characteristics of the images.

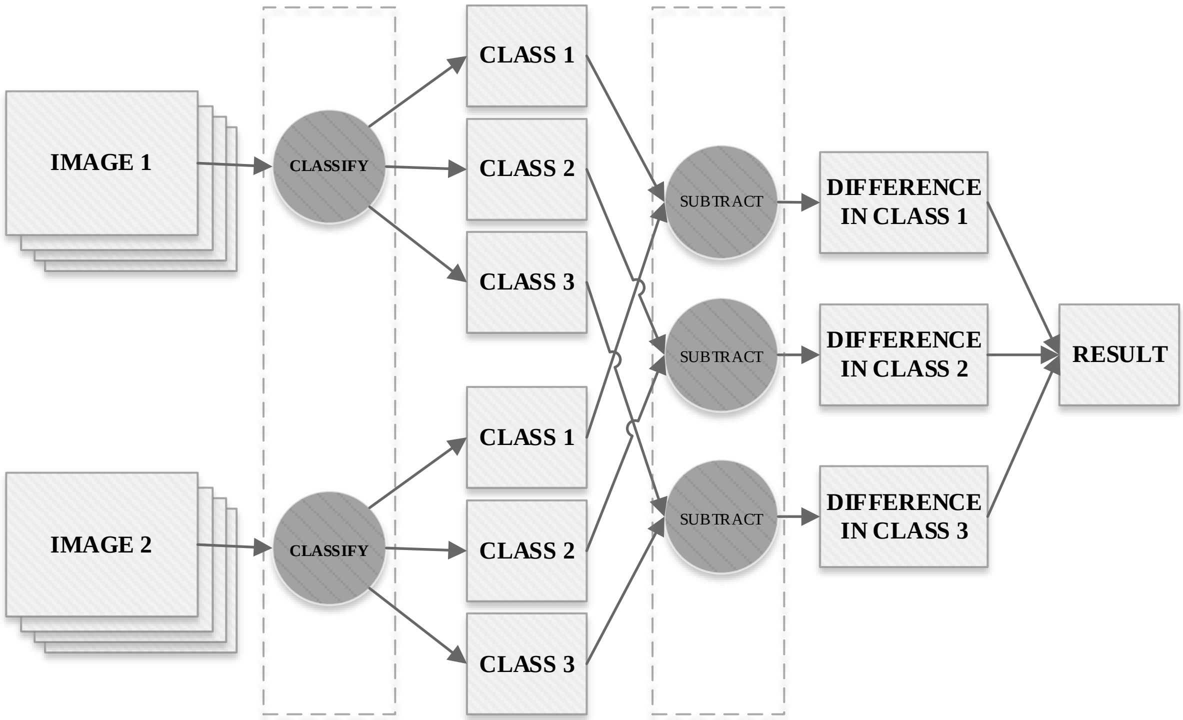



*Figure 2.5 Process of post-classification comparison change detection technique*
(Jwan Al-doski, 2013)

The post-classification comparison approach used by many researchers such as ( (Diallo, Hu, & Wen, 2009) (Bayarsaikhan, Boldgiv, Kim, Park, & Lee, 2009) (Torahi & Rai, 2011) employed post-classification change detection techniques based on Maximum Likelihood Supervised Classification to detect land use/land cover change detection and concluded that it has achieved overall high accuracy for a variety of data.

## 2.4 LAND USE/LAND COVER PREDICTION AND URBAN PLANNING

The land use land cover change and its modeling (LULCC-M) approach has recently been considered by the scientific community to observe environmental changes at local, regional, national, and global level. The term 'land use and land cover changes' (LULCC) refer to human modifications of the terrestrial surface of the earth, as well as the study of land surface change and the term 'transition' defines the process of changing, or the change of something from one form or state to another. As an essential way to learn the urban growth/sprawl phenomena, modeling and simulation is regarded as an efficient way to understand the mechanisms of urban dynamics, to evaluate current urban systems, and to provide planning support in urban growth management, e.g., land-use models may help to build future growth scenarios and to assess possible environmental impacts (Lambin & Geist, 2006).

With the developments of Remote Sensing (RS), Geographic Information Systems (GIS) and large-scale computing and visualization techniques, urban simulation models have been developed to understand urban development dynamics and anticipate urban planning activities (Cabral & Zamyatin, 2006). Urban simulation models can be used to trace urban trajectories in the past and predict urban development scenarios under different "what if" conditions in the future. The outcomes of these models can therefore assist policymakers in evaluating alternative development schemes and are helpful for making urban planning policy recommendations (Herold, Liu, & Clarke, 2003).

To analyze the cause and effect of land use change, land use change models (LUCM) are accepted as effective tool. Moreover, the LULC model is found to be effective when predicting the future state and spatial distribution of LULC using the gained knowledge from previous years. Many scientists, such as (Singh, 2010), have conducted studies related to surface, ocean, and atmospheric parameters associated with the Gujarat earthquake of 26 January 2001.

The remote sensing and GIS techniques have been repeatedly employed to assess LULCC in hard-to-reach areas like mountains. Moreover, high-resolution remote sensing images have also been used in efficient image segmentation and knowledge transfer to automatically update LULCC databases in different areas of China.

Urban models have a long history. Advancement of urban model has increased in last few decades. Each model proposes unique classification system. Therefore, several researchers have proposed many classification rules based on different benchmarks. Recently, (Silva & Wu, 2012) gave a very comprehensive review with several model classification schemes.

Modeling can either be conceptual, symbolic or mathematical. This depends on the purposes of the specific application. Driving forces which are responsible for urban growth needs to be identified before carrying out the modeling. It is well known that a city is a complex system, having many interactive subsystems. This in turn is affected by many different variables or factors. (Hersperger & Bürgi, 2007) distinguished between five major types of driving forces: socioeconomic, political, technological, natural and cultural factors. They also classified these into the primary, secondary and tertiary driving forces, although many times it is not easy to differentiate between impacts and driving factors in reality (Houet, Verburg, & Loveland, 2010). According to (Millera, Douglas, E, Paul, & Salvinic, 2004), an integrated urban system model with a focus on transportation should include socio-demographic parameters, demographics, location choices of housing and businesses, economic variables, transportation and effects on land use and environment.

According to (Lambin & Geist, 2006), land-use change models (urban growth is a significant land-use change, and the urban simulation model, of course, is a branch of land-use change models that focus on urban dynamics) can be summarized into four broad categories, that is, empirical statistical models, stochastic models, optimization models, and process-based dynamic simulation models. Actually, the dynamic simulation models in Lambin's classification systems were usually hybrid models: different methods were coupled in an integrative model. The principles, advantages, disadvantages, and examples of the models are listed briefly in Appendix 2.

Numerous methods, such as mathematical-equation-based, spatiotemporal modeling, system dynamic simulation, statistical, cellular and hybrid models, cellular and agent-based models or a hybrid of the two and the cellular automata–Markov chain (CA-Markov) model have been utilized in different research. The CA-Markov model is one of the most ideal and widely accepted methods for LULCC modeling because it considers 't-1' to 't' to project probabilities of LULCC for the future date ‘t+1’. Past and future changes decide the probabilities. The CA-Markov model has the ability to simulate changes in different LULC and can possibly simulate the transition from one category of LULC change to another (Islam, Rahman, & Jashimuddin, 2018). However, a combined CA-Markov model to simulate future LULC change by integrating natural and socio-economic data is still a challenge due to the different datasets.

### 2.4.1 LAND USE/LAND COVER MODELING APPROACHES

Some related terms need to be clarified before the introduction of modeling. There are various definitions for the term “land”, “land use” and “land use change” according to the context of the use and purpose of the application (Briassoulis, 2000).

In natural science, the term “land” refers to a wide range of natural resources from the atmosphere above the land surface down to some meters below the surface (Wolman & Fournier, 1987). “Land use” indicates the human employment of land (Meyer & Clark, 1990). Land use concerns the function or purpose for which the land is used by the local human population and can be defined as the human activities which are directly related to land, making use of its resources or having an impact on them. “Land-use change”, therefore, indicates quantitative increases or decreases in the area of a given type of land use (Briassoulis, 2000).

The term “model” is the representation of a system through mathematical, logical, physical, and iconic methods. Classifications of urban land-use change models have been proposed by many scientists. Models can be generally classified into four types: descriptive, explorative, predictive and operational models (Echenique, 1994). (Maithani, 2010) divided urban models into three types: urban development, transportation and urban resources. (Briassoulis, 2000) classified land-use change models based on their functional and methodological aspects: statistical and econometric, spatial interaction models, optimization models, integrated models, natural sciences-based models, GIS-based models and Markov chain-based models. Recently, (Silva & Wu, 2012) presented a list of comprehensive classification schemes according to different characteristics, methodologies, application areas and modeling approaches:

- Modeling approaches: mathematical/statistical models, GIS-based models, cellular automata-based models, agent-based models, rule-based models, and integrated models.
- Levels of analysis: micro level, macro level, and cross level models.
- Spatial scales: regional scale, metropolitan scale, local scale, and multi scale models.
- Temporal scales: long term, medium term, and short-term models.
- Spatial emphasis: spatial oriented, aspatial oriented, and integrated models.
- Planning tasks emphasis: land-use/land-cover change, urban growth, transportation land use, impact assessment, and comprehensive projection models.

In the following sections, some of the urban land use models will be discussed in greater detail according to applied approaches.

### 1. Spatial interaction models

The earliest class of land-use models was based on the principle of spatial interaction. In the fields of regional science and quantitative geography, spatial interaction denotes that every movement in space is a consequence of a human process (Sen & Smith, 2012). Adapted from Newton's first law, the gravity model was introduced to describe the spatial relations, which depend on the size of two objects and is in inverse proportion to the distance between them. The total interaction in a system equals the amount of all interactions between any pair of objects. The first operational urban land-use model is assumed to have been developed by Lowry (1964) (Gross, 1982). Many models have been developed based on the basic Lowry's framework.

### 2. Mathematical/statistical models

Almost all models involve a mathematical mechanism, but mathematical models especially lie on equations to reach a static or equilibrium status. The simple mathematical models are a set of equations describing population growth and redistribution to specify the land-use change over time. Economic theories are usually involved in more complex models. The econometric framework normally consists of regional economic models and land market models.

The economic analysis of land use often uses bid rent theory (Alonso, 1965), which focuses on the relationship between types and values of urban land use. Residents and firms estimate and decide the land consumption, land price and transportation costs. Another important concept is discrete choice theory, which means that the probability that an individual chooses one alternative equals the ratio of the utility value of the particular alternative to the total utility value of all alternatives. Statistical techniques are commonly used to model land-use change. Various regression techniques are used to deal with decision making and social phenomena (Mertens & Lambin, 1997). Many successful examples combining theories with statistics have been provided by spatial econometrics.

### 3. Expert models

Expert models integrate expert knowledge with Bayesian probability, Dempster Schaefer theory or artificial intelligence (such as logic-based and knowledge-based) approaches. These methods let users determine where each given land-use type is likely to occur (Klosterman & Pettit, 2005). The rule-based models include the California Urban Futures (CUF) model, the "What-If?" model, and the UPLAN model (Walker, Gao, & Johnston, 2007). The CUF model simulates residential development scenarios by setting specified regulations based on governmental policy. The What-If? model can visualize alternatives of land use allocation once users define input data, development rules and parameters.

### 4. Cellular automata

Cellular models (CM), including Cellular Automata (CA) and Markov models, operate over a grid. The CA concept was first proposed by Stan Ulam and John von Neumann in the late 1940s. In the field of geography, CA was firstly introduced by Tobler (1979). Since then, CA theory has drawn a lot of attention in urban studies (Silva & Wu, 2012).

CA models generally have four basic elements:

- A lattice of regular cells,
- A set of cell statuses,
- A neighborhood defined by the lattice,
- A set of transition rules for individual cells.

Many CA models also add time as the fifth element. CA models are basically deterministic and rule-based as they use logical statements to determine the transition rules. The improvement for CA models includes changes of the structure and dimension of grid, expanded neighborhood definitions, and changes of temporal element (Torrens & O'Sullivan, 2001).

CA models for land-use change include simple state transition models and more complicated designs. The former uses some probability for transition rules, while the latter determine one cell's status based on a function of status in its neighboring cells. The cell space of CA models is set up similar to the raster data structure in GIS. Thus, it can be combined with digital raster data from remote sensing systems and other sources. This grid-based structure is also convenient for programming and visualization. Neighborhoods are considered as one key element since they drive the interaction between land use and the dynamics of the systems (Torrens & O'Sullivan, 2001). The neighborhoods, shown in Figure 2.6, are the most widely used. The former includes eight neighboring cells while the latter includes four neighboring cells (Benenson & Torrens, 2004).

CA has been widely applied to geography and related fields because of four main advantages: spatiality and affinity with GIS, dynamism, micro-simulation, and a bottom-up approach. There are lots of applications, such as: urban form modeling, urban growth, urban and regional development and planning incorporated a density gradient in the model to simulate different urban forms. In recent years, more advanced artificial intelligence techniques are introduced such as genetic algorithms, simulated annealing, and neural network.

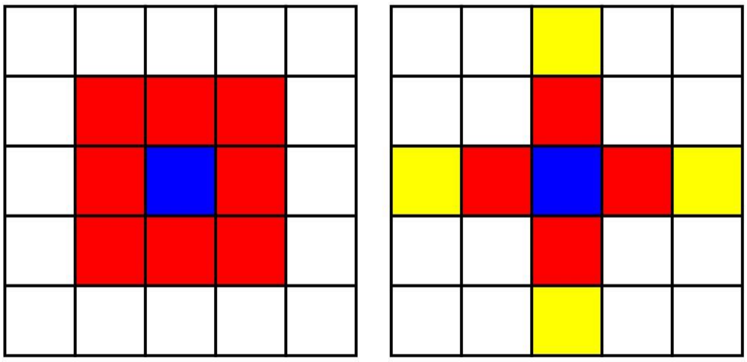


*Figure 2.6 CA neighborhood*

Left: The red cells are the Moore neighborhood for the blue cell.
Right: Red cells are the von Neumann neighborhood for the blue cell, and yellow cells are the extended neighborhood.

CA has been successfully used to simulate urban evolution and development in many cities worldwide, such as Beijing, Shanghai, Wuhan and Pearl River Delta in China; Amsterdam, Groningen, Utrecht and Den Bosch in the Netherlands; Coet-Dan watershed, Central Brittany, France; Sintra-Cascais of Portugal; Calgary, Alberta in Canada; Savannah, Santa Barbara, San Francisco Bay region in California, the Washington/Baltimore corridor and New York Metropolitan Region in USA.

**5. Agent-based modeling**

There are various definitions for the term "agent". However, most of them share some common characteristics (Benenson & Torrens, 2004):

- Autonomy. Agents are autonomous individuals without a centralized control. They can process and exchange information with other agents to make independent decisions.
- Heterogeneity. Agents can represent diverse individuals' attributes such as age, sex, and education.
- Activity. Agents are active in a simulation. They can be pro-active (goal directed), reactive (show awareness of their surroundings) and interactive (they communicate extensively). Agents also have mobility, which is particularly useful for spatial simulations. In complex adaptive systems, agents are designed to be adaptive, i.e., they have a learning ability.

An agent-based model (ABM) consists of multiple interacting agents within a simulated environment. Agents could represent a wide variety of entities in the real world, such as atoms, biological cells, people, organizations, buildings or land parcels (Jager & Janssen, 2002). Rules are defined for the agents' actions and these rules affect their behaviors and relationships. These rules are usually derived from observation, expert knowledge and data analysis. All agents can share one rule or each agent can have its own unique rule. Rules are not always preset and they can evolve as agents having learning ability. Agents can interact with each other within the same type, between two agent types, or with the environment. Agents are spatially explicit, which means they have a geographical location in space, although some agents may not move in some special cases.

Agent-based models have been developed with wide applications such as archaeological reconstruction of ancient civilizations, the biological modeling of infectious diseases, studying the growth of bacterial colonies, modeling economic processes, and investigating social networks of terrorist groups. In the land-use modeling community, five purposes have been identified by (Kumar, Radhakrishnan, & Mathew, 2014): policy analysis and planning, participatory modeling, explaining spatial patterns of land use, examining social science concepts and demonstrating land-use functions. The bottom-up ABM approach claims some advantages over traditional top-down methods.

**6. Multi-agent simulation**

ABM is later extended to a Multi-agent system (MAS), which not only contains an ABM representing disaggregated decision making, but also includes a CA. The CA part describes the land-use changes, while the agents represent human behaviors and perform in the simulated environment. Thus, the complicated interactions among agents or between agents and environment are simulated.

Current Applications of MAS for land-use modeling include: natural resource management, agricultural economics, archaeology, and urban simulation. In urban studies it was only until the past decade MAS started to be used for urban land-use modeling (Bousquet & Page, 2003). In urban modeling, MAS was introduced to micro-simulate land-use changes, incorporating environment, transport, and other economic models in order to build complicated urban systems.

MAS can be applied to simulate how individuals interact with environment to analyze the influence of urban sprawl. Various development scenarios are developed for policy makers to make decision in a spatial planning process. As population growth is the main engine of urban sprawl many studies have focused on residential preference and location choice. Specifying the diversity and behavior of realistic agents is always challenging (Valbuena, Verburg, Bregt, & Ligtenberg, 2009). However, there is no doubt that MAS is a useful tool to explore existing theories and verify assumptions when complex phenomena greatly affect model outcomes.

# CHAPTER:3 OVERVIEW OF STUDY AREA

Porbandar, the birth place of Mahatma Gandhiji, was the biggest city of Junagadh district. It is situated on the western coast of Saurashtra and now become district headquarters of Porbandar district having area of 12.30 sq. km. Chhaya, adjoining town of Porbandar, is the one of town of Porbandar district. It is situated on the eastern part of district headquarter Porbandar having area of 17.76 sq. km.

At present second revised Development Plan is in force at both Municipalities from 31-07-2013. The State Government in Urban Development and Urban Housing Department merged and extended the limits of both Municipalities by adding another surrounding three villages – Bokhira, Khapat and Dharampur. The newly formed entity Porbandar-Chhaya Municipality has now the area of 74.20 sq.km. and generates requirement to prepare new Development Plan.

## 3.1 LOCATION AND REGIONAL LINKAGES

From the day of Gandhi Jayanti, on 2nd October 1997, Government of Gujarat formed Porbandar as a new district from the Junagadh district. Porbandar district has three Talukas, which are Porbandar, Ranavav and Kutiyana.

Porbandar district is one of the 33 districts of Gujarat state in western India. It lies on the Kathiawar peninsula. Adjoining to the district are Jamnagar district and Devbhoomi Dwarka to the north, Junagadh district and Rajkot district to the east and the Arabian Sea to the west and south. Porbandar is located at 21°37′48″N 69°36′0″E. It has an average elevation of 3.66 ft. The district covers an area of 2,316 km$^2$. with density of 253 population per sq.km.

The district has been divided into 3 talukas, with 179 villages and 6 towns with Porbandar city as district head. There are 4 municipalities and 2 Census town in the district. Porbandar is closely linked with Junagadh in the south-east and with Jamnagar in the north. Porbandar has an all-weather port, has direct business relation with indigenous and foreign port. The famous Okha port is the nearest port of Porbandar. Porbandar is well linked on broad-gauge to many important cities like nation capital Delhi and financial capital Mumbai. Porbandar since old days is facilitated by an airport having daily flight to Mumbai.

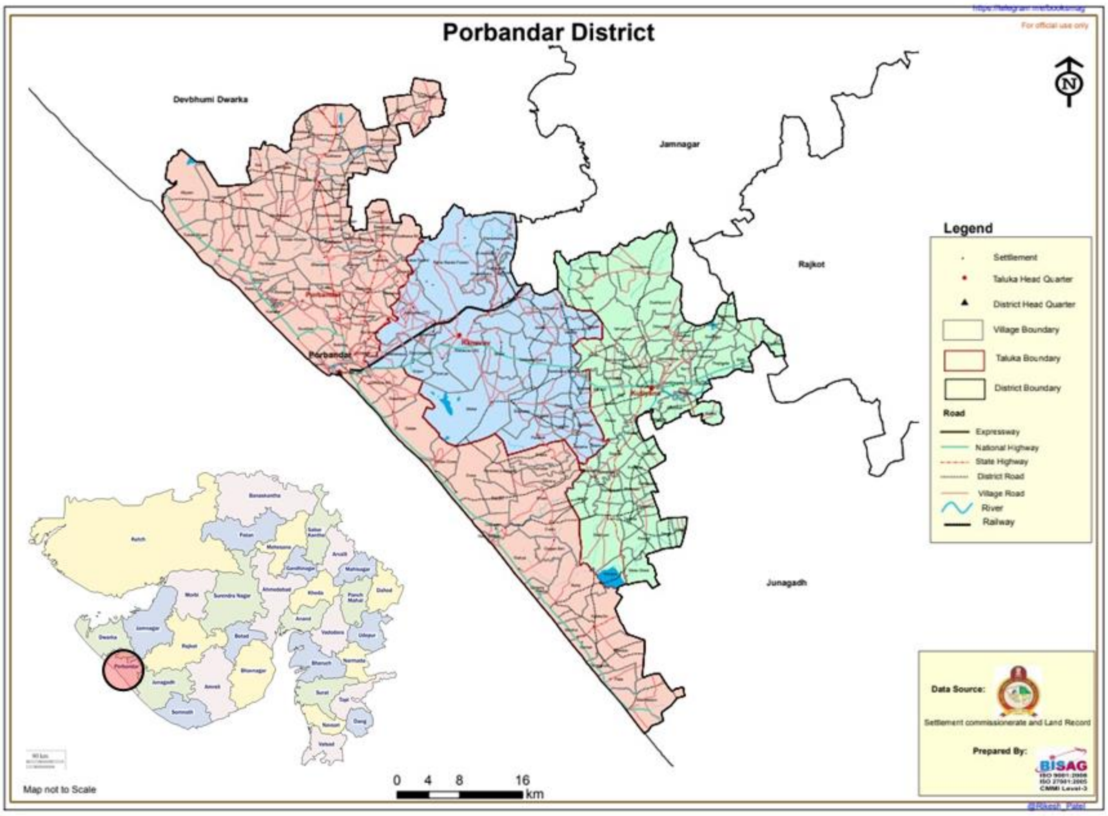



*Figure 3.1 Location of Porbandar District*

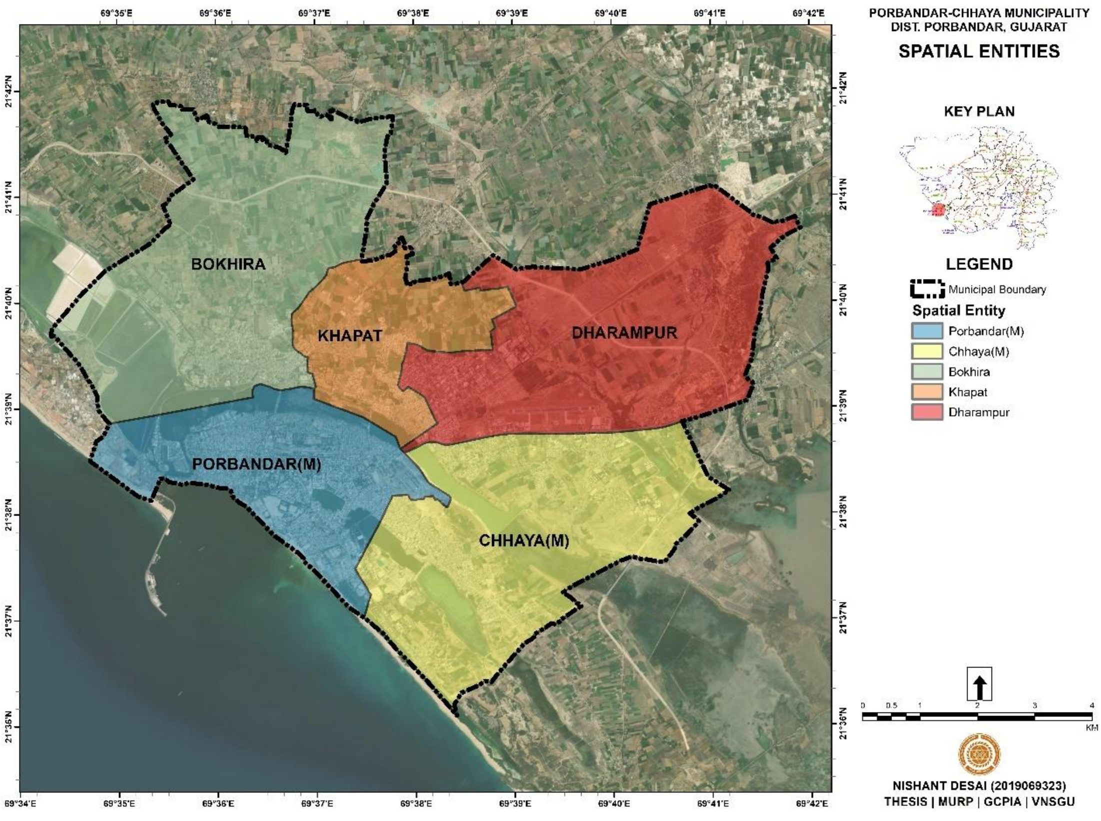



*Figure 3.2 Porbandar-Chhaya Municipality Boundary*

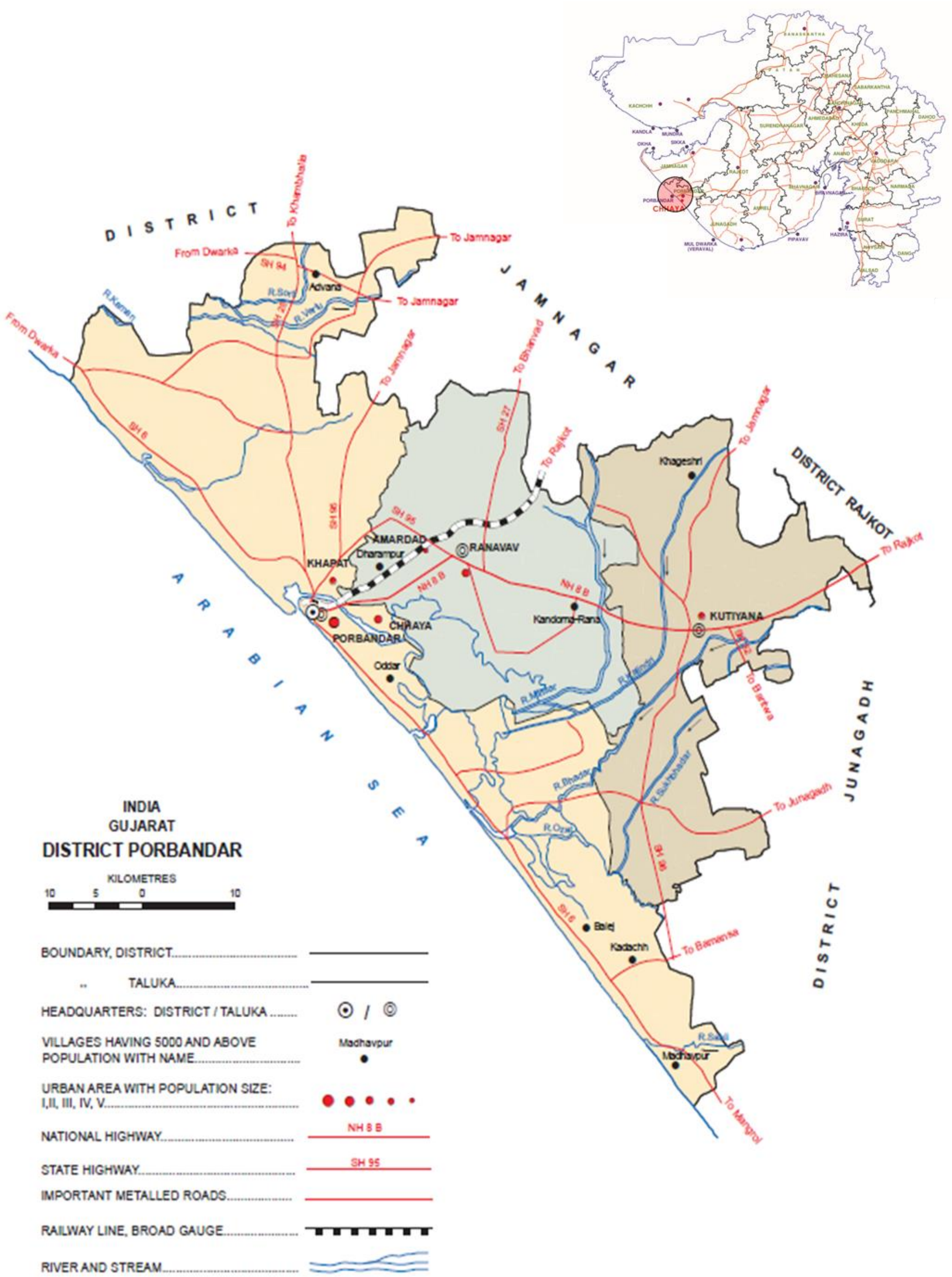



*Figure 3.3 Regional Connectivity*
(Directorate of Census Operations, 2011)

## 3.2 HISTORY

Porbandar stands at shore of Arabian sea, between two famous cities of ancient India, Dwarka and Somnath. Even today, the ancient planning of these cities is case study for town planners around the world. Porbandar is land of Sudama, friend of lord Krishna. The father of nation, Mahatma Gandhi was also born in Porbandar. Today, apart from its historical importance, it is a thriving tourism place for locals and foreigner.

It is believed that the city was founded on the day of Shravan Sud Poonam or Nariyeli Purnima on the banks of river Asmavati. According to Sudama Charitra of Skand Puran the city was named after Goddess Porav. In $10^{th}$ century CE it was named Pauravelakul, which was later changed to Sudamapuri. The city is more than 1000 years old.

Art lover Jethwa dynasty of Rajput clan used to rule this land. Under their regime city underwent transformation by construction of wide roads foot paths, symmetrical buildings along the roadsides, having right angular squares, fountains, gardens, public places and temples. Porbandar is also known as “White City” as most buildings were made with intricately carved soft white stone.

As the saying goes, Porbandar is known for Rana, Pana and Bhana. Rana Natwar Sinh was a ruler of Porbandar. Pana in local dialect means “stone”, refers to limestone reserves in area. Bhana refers to well-known Ghee exporting firm Bhanji Lavji. Furthermore, to known that Porbandar has a special life style and folk culture more particularly due to Mehar (MER) community who has put the name of Porbandar on the global map due to its unique dance Maniyara RAS and sward/ Dandiya Ras which reflects the warrior / brave nature of the MER caste. Another community who is never less than the MER in giving unique identity to Porbandar, is KHARVA, famous for fishing (Harvesting Sea and taking Sea crops) and also for fisheries and Sea Voyage.

Chhaya is a town and a municipality in Porbandar district, and is situated on the west bank of Porbandar creek. It is also acted as an extended part of Porbandar city just a thin administrative line makes it separate from Porbandar city in maps only.

Rana Shri Khimoji II Bhanji Jethwa (1574 - 1626), Rana of Chhaya, the elder son of Rana of Ranpur, had founded the state of Chhaya, after he was expelled from Ranpur. It became Jethwa capital after the abandonment of Ranpur and before the adoption of Porbandar. The old palace of Ranas still stands in Chhaya. The Jethwa have had capitals at starting with Morvi in 900 CE, changing with times to Srinagar, Dhank, Chhaya, Ghumli, Ranpur and lastly to Porbandar (from 1685 till 1947).

Chhaya is a popular attraction for shopping related to handicraft collections. Artwork and showpieces made by inhabitants of nearby villages are displayed here. The town is also popular for its enamel work done on gold and silver jewelry apart from seashell toys as well as lacquered wood and metal bells.

### 3.2.1 ARCHITECTURAL HERITAGE OF PORBANDAR

The district boasts many attractive monuments with unique features, proving its architectural heritage passed on by many centuries. For instance, there is the Huzur palace in City which depicts a European style of architecture.

Daria Raj Mahal, near Huzur Palace, exhibits large open spaces with gardens around it. It presents an amalgamation of Indian, Gothic and Arabian Styles of architecture. And then the nationwide famous Kirti Mandir which has some of the artifacts belonging to Mahatma Gandhi.

## 3.3 PORBANDAR CITY EVOLUTION

City emerged as a settlement of fishing community. Legends says that the city was known as Pauravelakul and later renamed Sudamapuri.

**1685**

Porbandar was a prosperous port during the Mughal period and thereafter retained its importance as a seat of maritime activities.

**1785**

The state was subordinate to the Mughal governor of Gujarat until being overrun by the Marathas in the latter half of the 18th century, where after they came under the authority of the Gayakwadi court at Baroda, and eventually of the Peshwa. The state came into British rule in 1807, along with other states of Kathiawar.

**1888**

The ruling family of the state belonged to the Jethwa clan of Rajput which got shifted to Chhaya from Porbandar.

**1926**

During this phase of British rule city witnessed Golden era in terms of development. The state covered 106 villages and population over 100,000, in area of 1,663 square kilometres.

**1975**

With the passage of Municipality act, Porbandar was declared as municipality under Junagadh district in 1975. Sprawl of the city reached till Chhaya making it Municipality. Later on, city marked urbanization due to Industrialisation.

**2017**

Porbandar Nagarpalika boundary is expanded by adding two major villages Bokhira in year 2005 and Khapat in year 2013 located north side of Porbandar city.

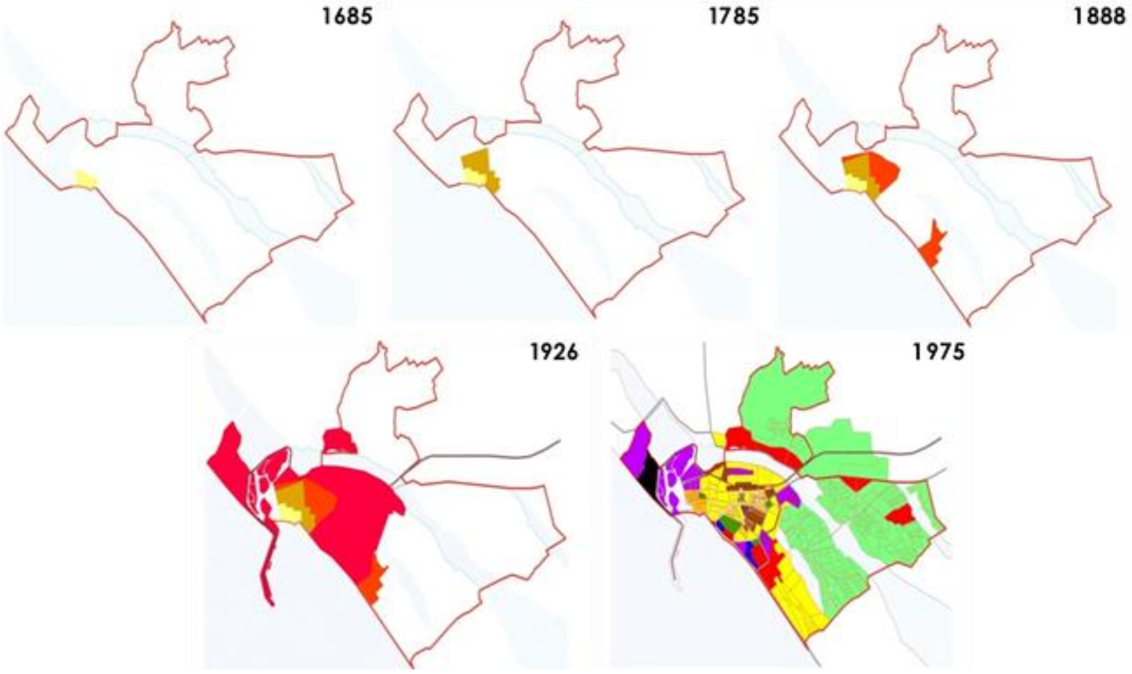



*Figure 3.4 Evolution of Porbandar 1685-1975*

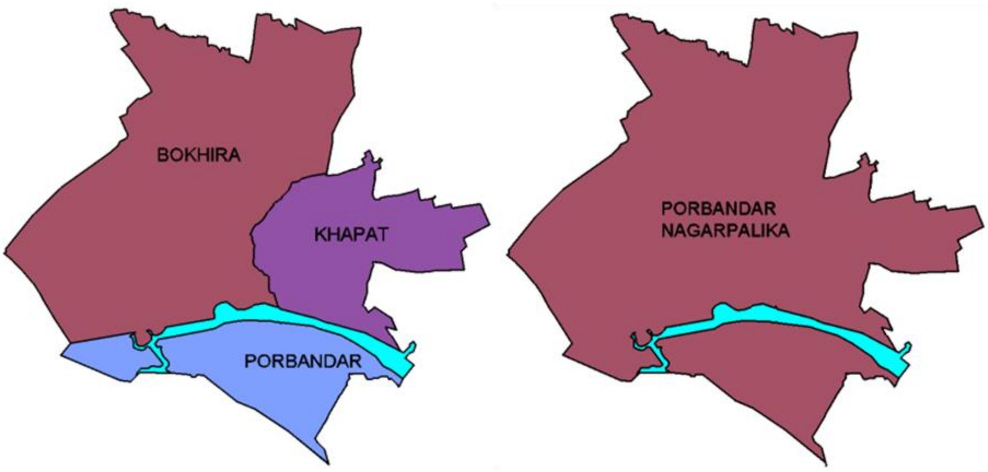



*Figure 3.5 Extension of Municipal boundary in revised development plan 2027*

## 3.4 PHYSICAL CHARACTER

The most part of Porbandar district is flat with gentle slope towards Arabian Sea at south-west. Barda range which lies in northwestern part of the district governs the area around with dense forest, river and streams. The rest of the area is fertile land, locally known as “Ghed”. Barda hills spreads across Ranavav and Kutiyana talukas, having highest altitude of 630 meters. Throughout the district elevation varies from 5 to 630 meters above MSL. The district can be divided in the three main divisions:

1. Hills
2. The River Plain
3. Forest Region

## 3.5 GEOGRAPHICAL CHARACTER

The district's geology consists mostly of Alluvium, Blown Sand, Deccan Trap, Inter Trappe and Beds, etc. Known as Ghed, the reiver plain parts feature alluvial soils. These are fertile soils making agriculture possible in the district. Ranavav and Kutiyana talukas also feature black soil. Limestone and chalk clay deposits are also found in the district.

Almost 75% part of the district have shallow to medium black soil, spread across all talukas. These soils are rich in lime, magnesia and alumina raid poor in phosphorous, nitrogen and organic matters, making them more suitable for agriculture. Most part of coastal area, mainly Porbandar taluka, have coastal alluvial soil. These parts are less productive for agriculture due to their saline nature.

Soil of Porbandar district may be classified into three main categories:

1. Shallow to medium black soils
2. Deep black soil (Ghed area)
3. Coastal alluvial soils

## 3.6 DAMS AND RIVERS

The major three rivers that flows in the district are, Bhadar, Ozat and Minsar. Apart from these there are many seasonal river streams viz. Sorthi, Vartu, Kalinidri and Bilganga. All rivers and streams flow towards Arabian Sea in southwest. There are no major dams in Porbandar District. There are 5 medium and minor dams controlled under state irrigation department and 1 minor dam controlled under the District Panchayat. And there are 4 tidal regulator scheme and one reservoir scheme and 1 minor are under controlled serenity control division Porbandar.

## 3.7 CLIMATE

The climate of the district is varied. The coastal areas enjoy a mild climate; the plain and hilly areas are hot. It receives maximum rainfall during the monsoon period. Porbandar district is semiarid to sub humid type characterized by three well defined seasons viz; monsoon, winter and summer. The winter starts from November and lasts up to February. The normal summer season is from March to end of the May.

### 3.7.1 TEMPERATURE

Porbandar has its own meteorological observatory in the district. The records of these observatories may be taken as representative of the meteorological conditions prevailing in the district as a whole. The temperature ranges from 10°C in winter to 40°C in summer. Most probably January month is the coldest in winter season. The temperature rises from the month of March to June and was the highest in month of April. The details of the maximum and minimum temperatures for the period of ranging from 2001 to 2010 years are given below.

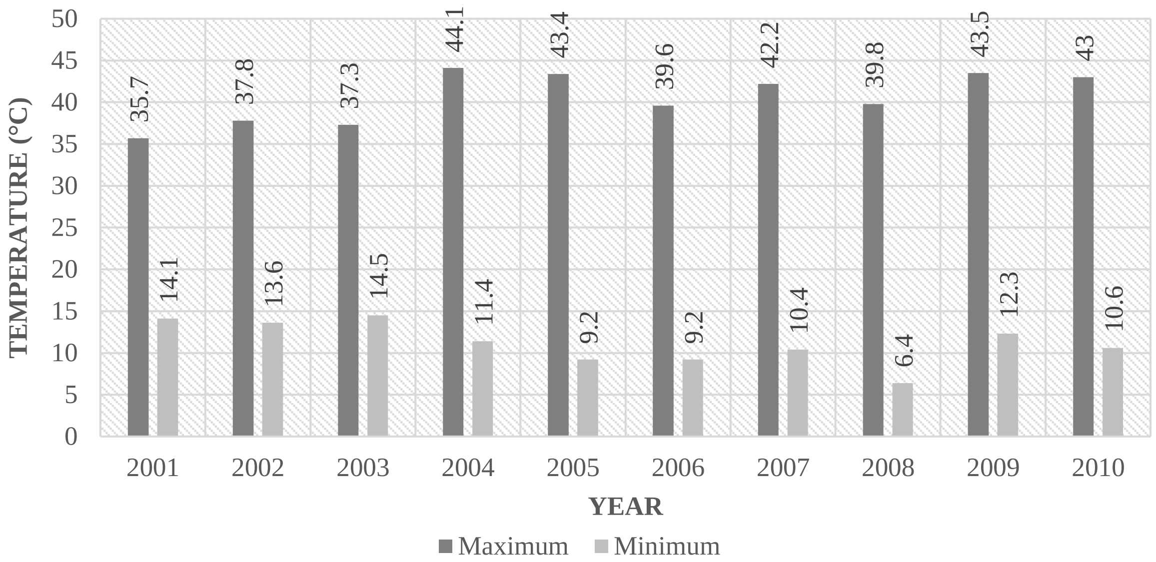



*Figure 3.6 Temperature of last Decade*
(Directorate of Census Operations, 2011)

Above Figure 3.6 gives year wise data with maximum and minimum temperature in the district for the years 2001 to 2010. During the years 2001 to 2010, the highest maximum temperature is recorded at 44.10 centigrade in the year 2004 and lowest minimum temperature of 6.40 centigrade in the year 2008. Average minimum and maximum temperature of the district during the years 2001 to 2010 is 11.170 centigrade and 40.640 centigrade respectively. Figure 3.7 shows the month wise maximum and minimum temperature during the year 2011.

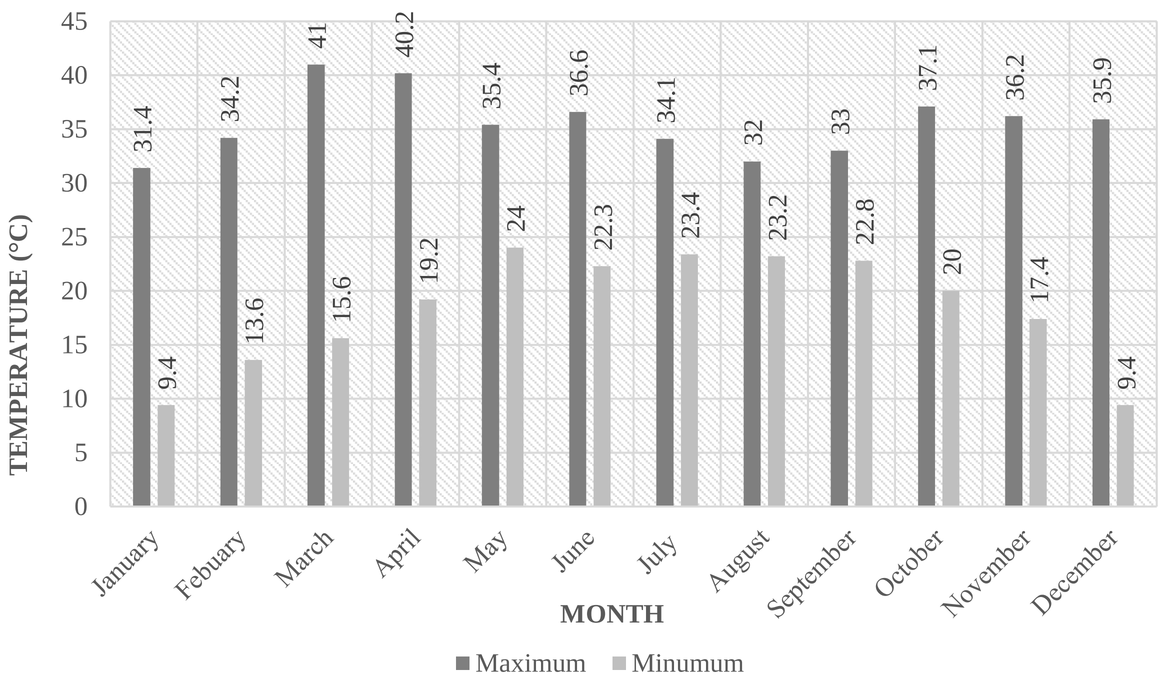



*Figure 3.7 Monthly Maximum and Minimum Temperature for the Year 2011*
(Directorate of Census Operations, 2011)

### 3.7.2 RAINFALL

Generally, rainfall is irregular in the district. Many times, sea cyclone affected the Porbandar district and the district is suffered by heavy flood in the year 1983. Normally monsoon starts from second week of June. The average annual rainfall is recorded 973 mm. The climate of the Ghed area is subtropical and semi-arid and rainfall received between Junes to September due to North West monsoon. The rainfall is very scanty. The Figure 3.8 indicates rainfall for the year 2001 to 2011 and in the year 2010, there is a maximum rainfall found is 1672 mm, while the lowest rainfall occurs during the year 2002, is 271 mm. The average rainfall during the year 2001 to 2011 is 898 mm.

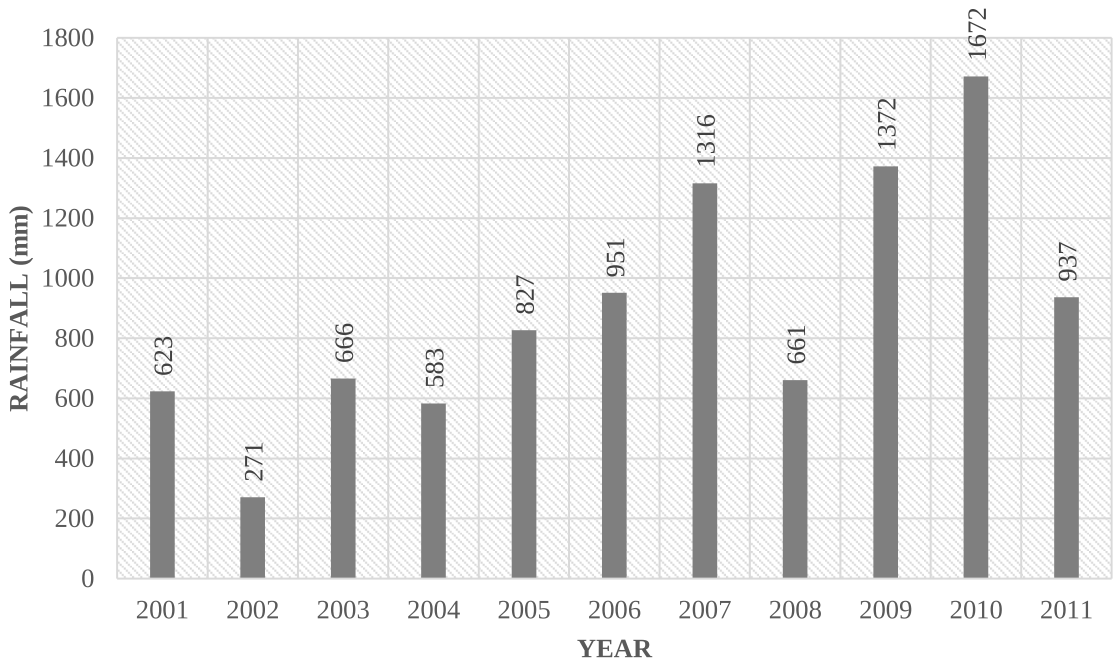



*Figure 3.8 Year wise rainfall*
(Directorate of Census Operations, 2011)

### 3.7.3 FLOOD

Average elevation of the city is 1.5 meters. During high tide and high wind maximum recorded high tides are 4.2 meters. This leads to sea water enter to the city affecting fishermen, fish processing units, Port infrastructure, salt pans, ship building industries, etc.

Sea water enters into the city in every monsoon. This has become part and parcel of life to the people living on the sea coast and on the edge of creek. In Chhaya municipality, Rann area is under water in every monsoon. Few efforts like to draw water through motor pumps are initiated from year 2014 to strengthen infrastructure of the city. Infrastructures have failed in Porbandar city in front of sea dynamics.

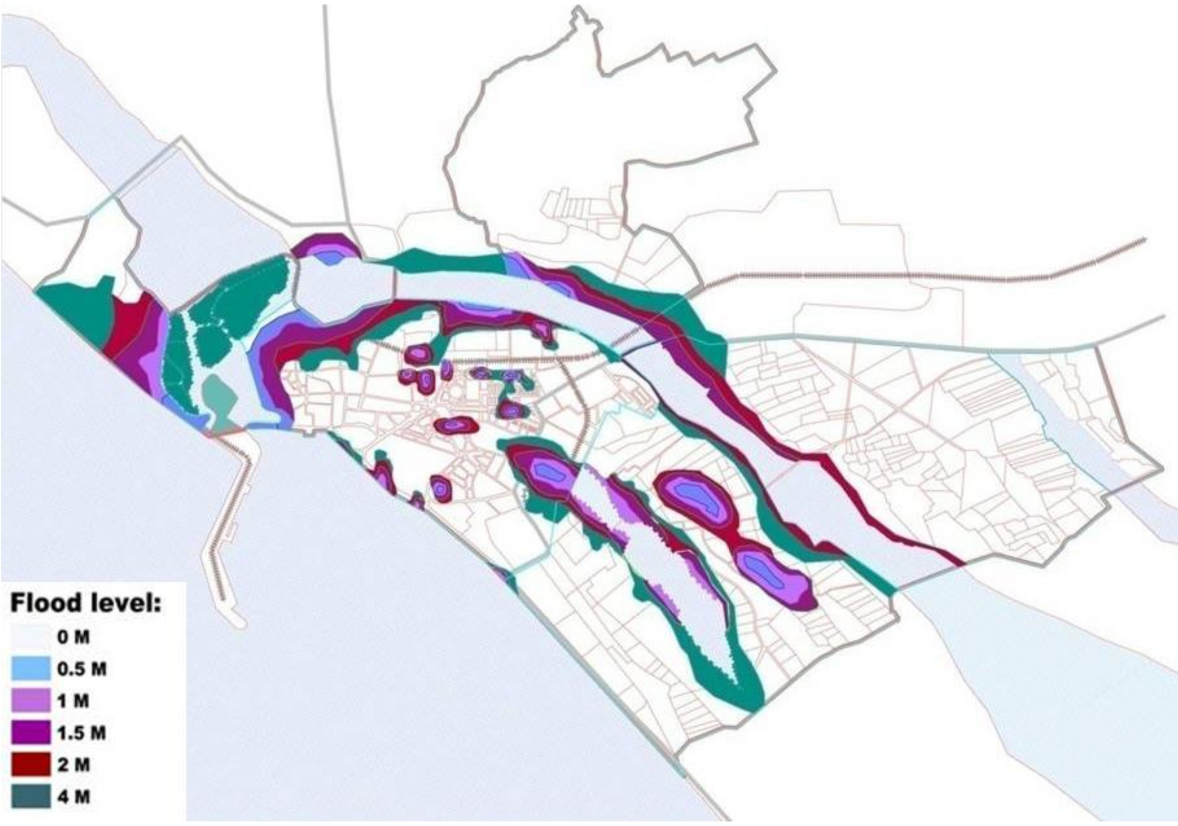



*Figure 3.9 Areas demarked for water logging*

## 3.8 DEMOGRAPHIC PROFILE

As per the Census (2011), the total population of Porbandar district is 5,85,449 with, 3,00,209 (51%) males and 2,85,240 (49%) females. This population of the district forms 1 percent of the state population and rank at 25th place among the districts of Gujarat state. Out of the total population of the district 51.28 percent lives in rural area while 48.72 percent lives in urban areas. Rural population of the district is distributed among 3 talukas and urban population is spread over in 6 towns. The total urban population in the district is 2,85,674 persons comprising 1,46,949 males and 1,38,725 females. The total rural population in this district comes to 2,99,775 persons and is composed of 1,53,260 males and 1,46,515 females as per 2011 Census. 179 villages are inhabited by this rural population. There are 3 uninhabited villages.

The total population of Porbandar taluka is higher than other talukas of the district. The total population of Porbandar taluka is 65.7% of the total population of the district. The total population of Kutiyana taluka is lower than other talukas of the district. The total population of Kutiyana taluka is 14.7% of the total population of the district (Directorate of Census Operations, 2011).

As per the Census (2001), the total population of the district was 536,835. Population has increased by 48,614 persons during the span of 2001-2011. The decadal growth rate of district is 9.1 percent. The growth rates for the rural and urban areas of the district are 8.8 and 9.3 percent respectively. This indicates the rise in urban population in the district. The highest growth of urban population has taken place in Porbandar. The density of population in Porbandar district is 253 persons per Sq.km. against the state’s 308 persons per Sq. Km.

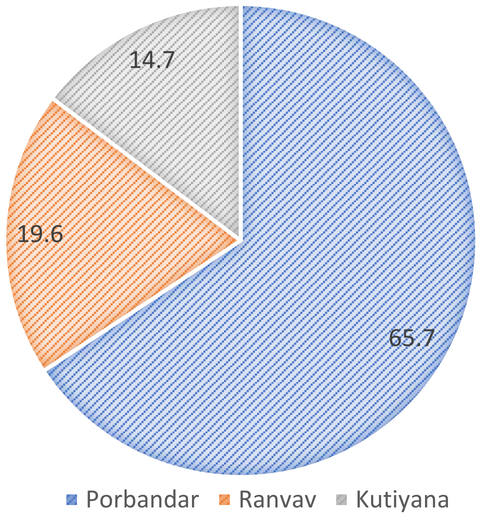



*Figure 3.10 Taluka wise population in 2011 (%)*
(Directorate of Census Operations, 2011)

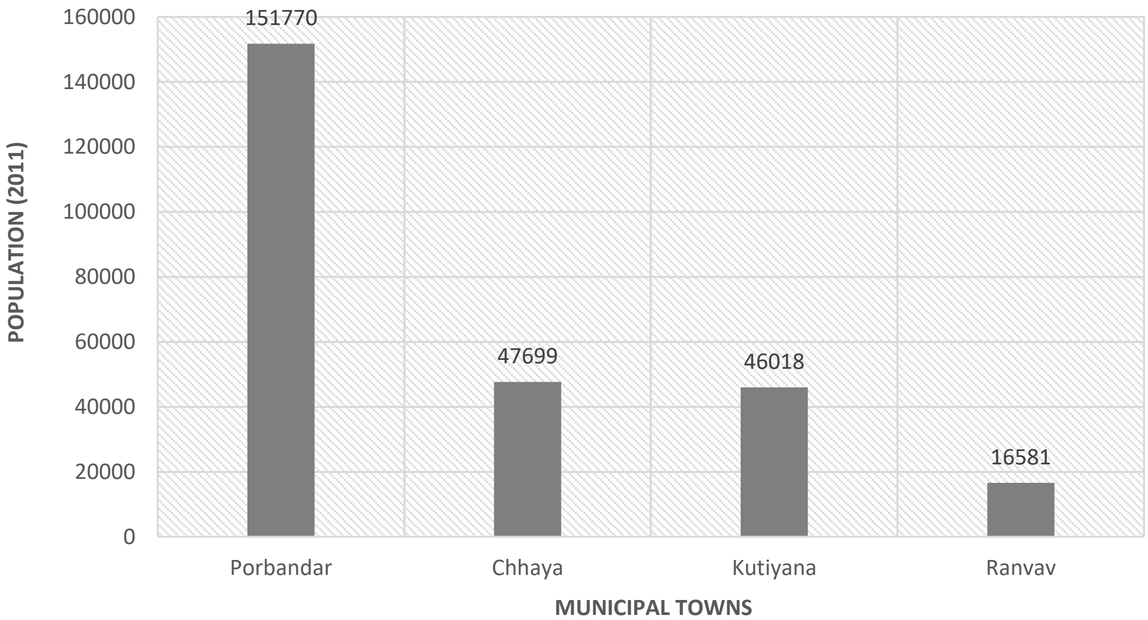



*Figure 3.11 Comparative Population of Towns of Porbandar District (2011)*
(Directorate of Census Operations, 2011)

As compared to other Municipal town in the District, Porbandar has seen highest number of population other than Chhaya, Kutiyana and Ranavav. One of the major reasons is being a district headquarters and other economic and social drivers which help in trade, commerce and better living. Chhaya is second most populated town in the district. Figure 3.11 shows the population (2011) comparison of Municipal towns of Porbandar district.

After the formation of Porbandar-Chhaya Municipality, it has become the urban area catering to 38.42% population of the total district population. Due to this it leads the urbanization & economic development of the region.

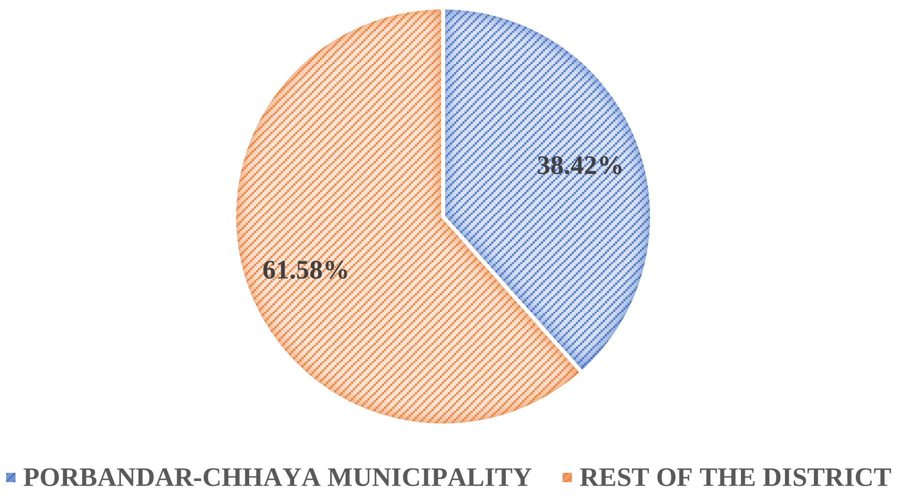



*Figure 3.12 Population comparison Porbandar-Chhaya (M) vs rest of the district*
(Directorate of Census Operations, 2011)

### 3.8.1 POPULATION GROWTH RATE

| YEAR | RURAL POPULATION | URBAN POPULATION | TOTAL POPULATION | DECADAL GROWTH RATE (%) |
|---|---|---|---|---|
| 1901 | 72018 | 34907 | 106925 | - |
| 1911 | 82159 | 36187 | 118346 | 10.7 |
| 1921 | 86666 | 41031 | 127697 | 7.9 |
| 1931 | 107762 | 48090 | 155852 | 18.1 |
| 1941 | 115345 | 75084 | 190429 | 26.2 |
| 1951 | 136849 | 79601 | 216450 | 13.7 |
| 1961 | 174028 | 96606 | 270634 | 25 |
| 1971 | 212071 | 142023 | 354094 | 30.8 |
| 1981 | 246179 | 179720 | 425899 | 20.3 |
| 1991 | 256630 | 212842 | 469472 | 10.2 |
| 2001 | 275460 | 261375 | 536835 | 14.3 |
| 2011 | 300218 | 285231 | 585449 | 9.1 |

*Table 3.1 Population of district at each census 1901-2011*
(Directorate of Census Operations, 2011)

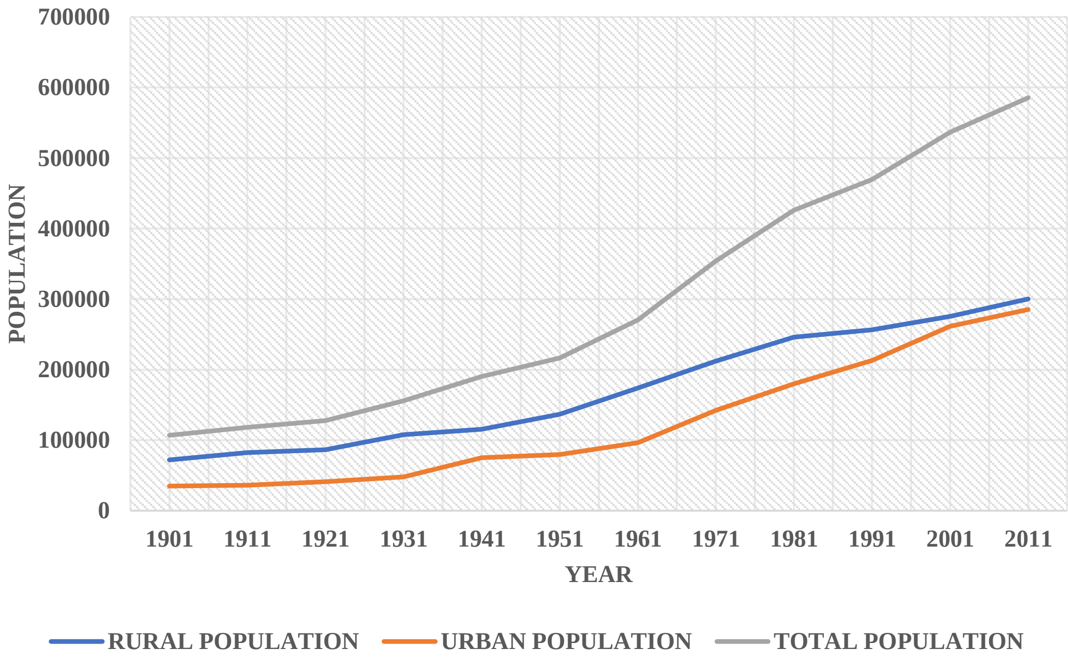



*Figure 3.13 District Population Growth Trend 1901-2011*
(Directorate of Census Operations, 2011)

As per census records, the total population of Porbandar-Chhaya Municipality is 2,24,907 in 2011; 1,99,983 in 2001 and 1,61,348 in 1991. This resulting in decadal growth rate of 12.46% (2001-2011) and 23.95% (1991-2001) in study area, compared to that of district 9.1% (2001-2011). Following Table 3.2 shows population of entities within Porbandar-Chhaya Municipality in last three census (Directorate of Census Operations, 2011). It is observed that Bokhira (OG), Chhaya (M) and Khapat (CT) has seen major population growth between 2001 and 2011. This could also indicate that the Porbandar (M) area is now reaching the saturation and very less land is available for new development.  It is to be seen during the study weather this is reflected in land cover maps for the same time period.

| ENTITY | AREA (sq.km.) | POPULATION | | | POPULATION DENSITY 2011 (PPHa) |
|---|---|---|---|---|---|
| | | 1991 | 2001 | 2011 | |
| **PORBANDAR (M)** | 12.30 | 116671 | 133051 | 152760* | 50.75 |
| **CHHAYA (M)** | 18.80 | 26028 | 38526 | 47699 | 25.37 |
| **KHAPAT (CT)** | 6.90 | 4231 | 9088 | 16744 | 24.26 |
| **BOKHIRA (OG)** | 17.80 | 12391 | 15394 | -- | -- |
| **DHARAMPUR** | 18.40 | 2027 | 3924 | 7704 | 4.18 |
| **TOTAL** | **74.20** | **161348** | **199983** | **224907** | **30.31** |

*Table 3.2 Population of study area census 1991, 2001, 2011*
**Population is including Bokira (OG), as it was merged in to Porbandar (M) in 2005.*

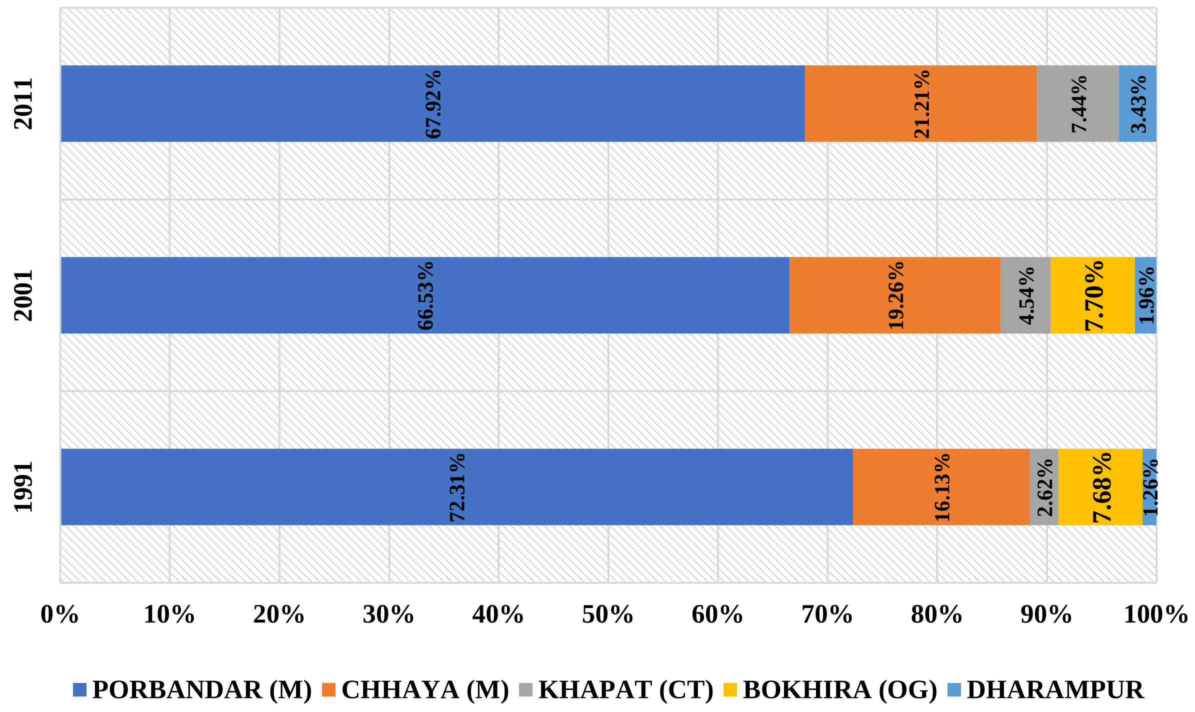



*Figure 3.14 Percentage population for entities of study area – 1991, 2001 & 2011*

## 3.9 TOURISM

Porbandar town is one of the most beautiful, eco-friendly and heritage centers in Porbandar district and can be developed as rich cultural heritage if properly planned and effectively executed. Porbandar has various local sites seeing spots of varieties like tourism, pilgrimage, Barda Sanctuary world famous Blue beach of Madhavpur, Educational centers like Aryakanya Gurukul and Sandipani Ashram to recall our memory to Takshashila and Nalanda school of Vedic Culture. Over all it is pertinent to call Porbandar a place of great import Mythological, Culturally, Historically, Religiously, Socially and on many other contests like Industrial, tourism and education point of view. Porbandar has heritage and dotted with old structures and monuments. Below mention is the list of very important heritage structure within the town. Other religious and recreational facilities are also prominent place of visit in the town.

1. Huzoor Palace
2. Kirti Mandir (Birthplace of Mahatma Gandhi)
3. Porbandar Beach (Chowpati)
4. Sudama Mandir
5. Sandipani Mandir
6. Jambuvan Cave
7. Porbandar Bird Century

**1. Huzoor Palace**

The last Maharaja of the Princely State of Porbandar, Rana Natwarsinhji built the Huzoor Palace in early 20th century. Even today the palace is used by his family, and is closed for tourists. Clearly the European influence can be seen on architecture of the palace with many wings and a slanting roof. There are large windows offering view of Arabian Sea. The various wings of the palace have front and backyards, and arranged so that they present a natural scenic ambiance surrounded by gardens and fountains. The façade boasts many semi-circular shaped ornamental porticos with neoclassical columns.

**2. Kirti Mandir**

Built like a Haveli, this three storied building was home to Mahatma Gandhi. His great grandfather, Shri Harjivan Raidas Gandhi, had purchased the house in 17th century. Over a period of time upper floors were added to the existing building. Mahatma Gandhi’s father and uncle, Tusidas along with grandfather Uttamchand lived. Shri Uttamchand was Dewan to the Jethwa Rajput rulers of the princely state of Porbandar.

In 1947 restoration of Kirti Mandir started, making it attractive and modern structure we see today, by Shri Darbar Gopaldas Desai. The well-known industrialist, Nanjibhai Kalidas Mehta, took initiative to build a memorial to Mahatma Gandhi. He also funded the purchase of house and development around making new complex called Kirti Mandir.

By 1950, the construction of Kirti Mandir was complete. Then Home Minister, Sardar Patel, inaugurated this place on May 27, 1950. Currently Central Government of India controls the management of Kirti Mandir.

**3. Porbandar Beach**

At walking distance from core city area of Porbandar, Chowpati beach is favored spot for locals and tourists alike. Huge crowds can be seen here on every Sunday. The beach offers outstanding scenic beauty. Shoreline adores many boats and ships floating in the sea. At night shimmering lights of sea port creates mesmerizing view.

**4. Sudama Temple**

Located at the center of Porbandar and dedicated to Sudama, the temple is one of the revered sites of Gujarat. Sudama was the childhood friend of Lord Krishna. The temple attracts devotees by thousands. Many newly married Rajasthani Kshatriya couples visit the temple for blessings.

**5. Sandipani Temple**

Situated near the airport and almost 5 km away from the Porbandar city, is Shri Hari Mandir in Sandipani. Started with vision and dream of Bhaishri, it took 13 years to complete. Today it is one of the outstanding and unique temples of Saurashtra, thanks to many experts and contributors around the world.

**6. Jambuvan Cave**

Located near Saurashtra Cement factory, almost 15 km from Porbandar, these caves fall in Ranvav taluka. According to the legends, Ramayana age worrier Jambuvan resided here. He was born in Satyuga and seen Treta yug and Dwaper waiting for the arrival of next Vishnu, Lord Krishna. He had given a beautiful diamond to his daughter Jambuvati, which was taken from a king by a lion. Jambuvan had killed the lion and took the diamond.

Lord Krishna was in search for same diamond. First Jambuvan fought with Krishan over the diamond, later he realized that Lord Krishna is the Vishnu, he had been waiting for. Realizing his mistake, he asked for forgiveness from Lord Krishna and married his daughter to him. The cave is deep with one small opening to let in sun light. Inside there is Shiv ling made by sand. When water falls from roof of cave, we can see nature carving too. Outside cave there is Lord Shiva temple and Samadhi of Guru Ramdasji who did Tapsya there.

**7. Porbandar Bird Century**

Porbandar Bird Sanctuary has an area of less than 1 sq.km., making it one of the smallest bird sanctuaries. It encircles a small lake providing legal protection to the bird's nests. Local and migratory birds like flamingos, ibis, curlews, fowls and teals can be seen here. Though lacking in the flora life, the sanctuary is richly blessed with its avifauna.


*Figure 3.15 Places of tourism in Porbandar*

# CHAPTER:4 METHODOLOGY

## 4.1 RESEARCH PROCESS

Research Process for the study is divided into four stages each stage contains some respective details which are used or read or analyzed in order to complete the stages and to achieve aim and objective for this research within prescribed time frame.

1. **Study instigation**
    - Background study, formulation of thesis statement, aim & objectives.
    - Identification and overview of study area.
    - Literature review. Collection of relevant literature from secondary source (research papers, books, reports, maps, census satellite images etc.).
    - Formulation of detailed methodology for data collection & analysis.

2. **Data collection, land cover maps and assessing land cover change**
    - Collect raw satellite data for different year is the year 1991, 2001 and 2011.
    - Preparation of FCC and develop land cover classification scheme.
    - Preparation of land use land cover thematic maps for each year by supervised classification method.
    - Accuracy assessment of thematic maps.
    - Change detection analysis based on the land cover map for the different years.
    - Area calculation for different land cover categories and making transition matrix.

3. **Prediction of future land cover**
    - Develop a future pattern of land cover thematic map using Cellular Automata based simulation in QGIS.

4. **Summary, Conclusion & Recommendations**
    - Based upon the data, analysis, findings and inferences, conclusions are derived & recommendations are given.
    - Scope of further extension.

Above stages and details of methods followed in this study are elaborated in Chapter 4.2 & 4.3.

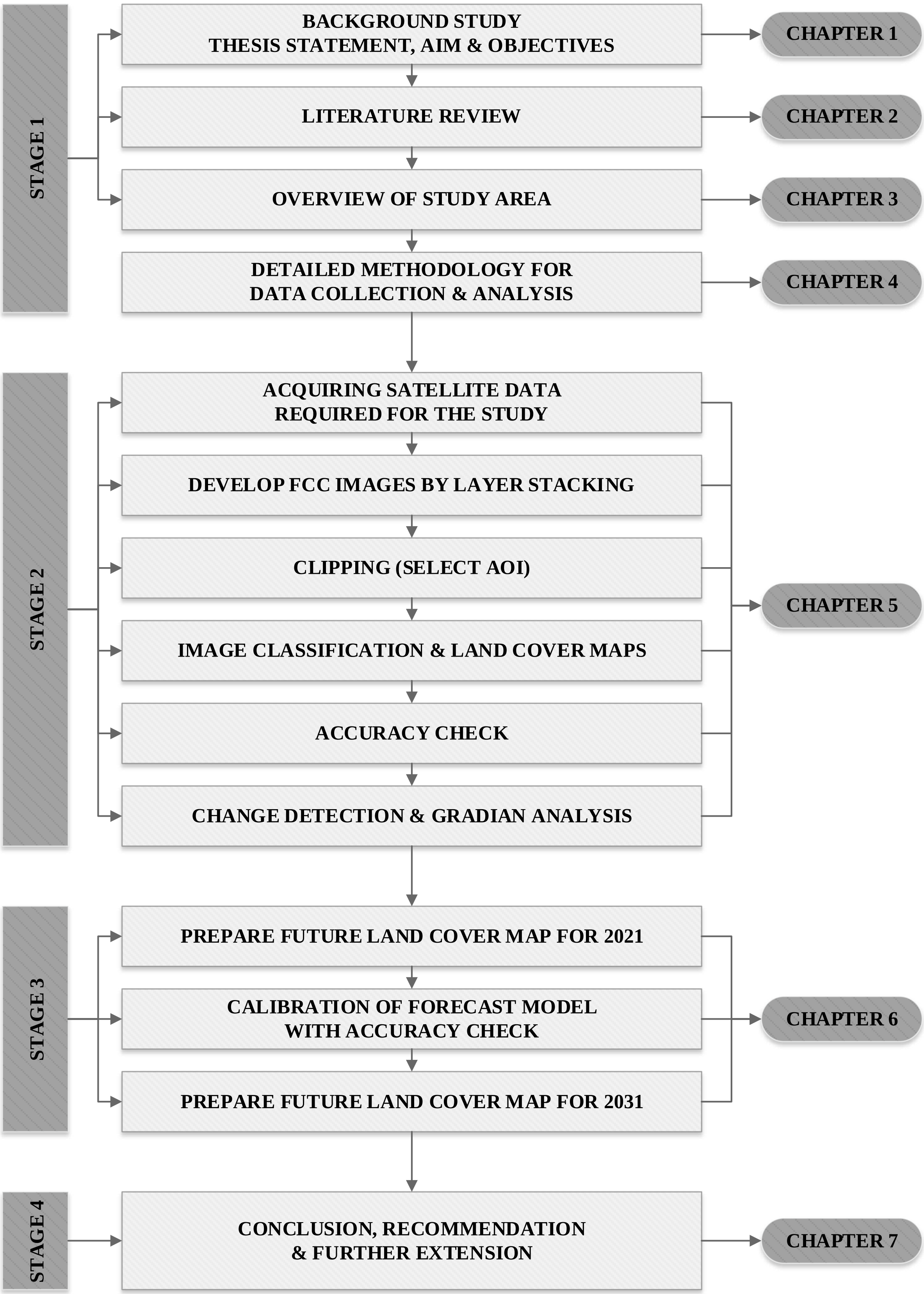



*Figure 4.1 Flowchart of Research Process*

## 4.2 DATA COLLECTION, LAND COVER MAPS & ASSESSING LAND COVER CHANGE

Numerous image classification and analysis techniques have been developed to support the interpretation of remote sensing data and to derive as much information as possible. The selection of definite techniques or algorithms to use be subject to the aim of each individual study. Stepwise image classification procedure adopted for the study is described below.

1. Data Collection
2. Develop FCC Images by Layer Stacking
3. Clipping (Select AOI)
4. Image Classification & Generation of Land Cover Maps
5. Accuracy check for Land Cover Maps
6. Assessing land cover change

### 4.2.1 ACQUIRING LANDSAT DATA FOR THE STUDY

For the study, Landsat-5 & 8 satellite images for different years i.e., 1991, 2001, and 2011 collected from earth explorer (USGS).

On July 23, 1972, the Earth Resources Technology Satellite was launched. This was eventually renamed to Landsat. Since 1972. Landsat satellites have provided Earth Observation (EO) data to support work in agriculture, geology, forestry. education, urban mapping, emergency response and disaster relief, as well as providing a long-term record of natural and human-induced changes to the Earth.

In United Sates and worldwide variety of communities like government, commercial, industrial, civilian, military, and educational are benefited by the data collected by Landsat Project. In 1979, operation of Landsat was transferred to the National Oceanic and Aspheric Administration (NOAA)by Presidential Directive, issued by then President Jimmy Carter. Till 1979 Landsat Project was under NASA. In 1998, operation was transferred to U.S. Geological Survey and Space Imaging (EOSAT) has been operating since 2001. In 2008, all Landsat data was made available to public for free to use.

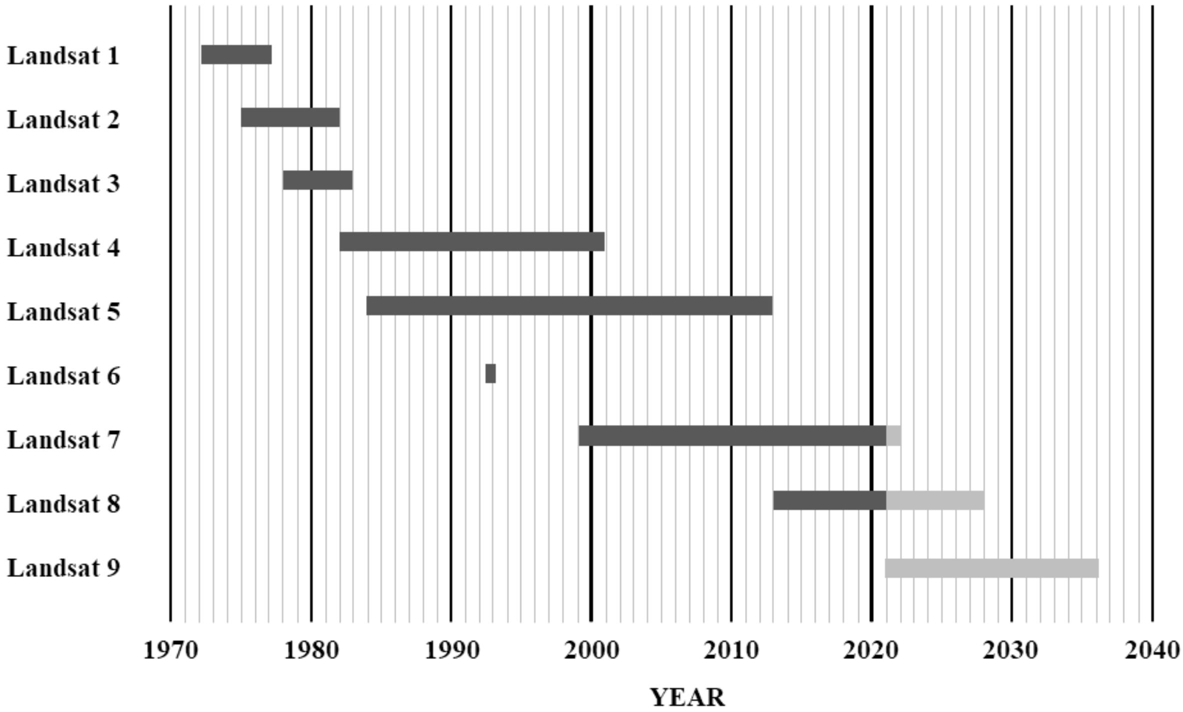



*Figure 4.2 Timeline of Landsat Satellites*
(Landsat Science, 2021)

For the study, Landsat-5 and 8 satellite images for Porbandar-Chhaya, Gujarat has been acquired for different years like 1991. 2001 and 2011. Which obtained from the United States Geological Survey Georeferencing properties shown in below Table 4.1

| SR. NO. | SATELLITE | WRS PATH | WRS ROW | ACQUISITION DATE | RESOLUTION (m) | UTM ZONE | DATA FORMAT |
|---|---|---|---|---|---|---|---|
| 1 | Landsat 5 | 150 | 45 | 20.10.1991 | 30 | 42N | Geotiff |
| 2 | Landsat 5 | 150 | 45 | 15.10.2001 | 30 | 42N | Geotiff |
| 3 | Landsat 5 | 150 | 45 | 21.10.2011 | 30 | 42N | Geotiff |
| 4 | Landsat 8 | 150 | 45 | 16.02.2021 | 30 | 42N | Geotiff |

*Table 4.1 Properties of Satellite data used for the study*

For the study, 7 bands Landsat 5 and 8 satellite data were used. Below Table 4.2 showing band properties of Landsat-5 satellite:

| BAND NUMBER | BAND NAME | WAVELENGTH (μm) | RESOLUTION (m) | BAND APPLICATIONS |
|---|---|---|---|---|
| 1 | Visible Blue | 0.45 - 0.52 | 30 | Bathymetric mapping distinguishing soil from vegetation, and deciduous from coniferous vegetation |
| 2 | Visible Green | 0.52 - 0.60 | 30 | Emphasizes peak vegetation, which is useful for assessing plant vigor |
| 3 | Visible Red | 0.63 - 0.69 | 30 | Discriminates vegetation slopes |
| 4 | NIR | 0.76 - 0.90 | 30 | Emphasizes biomass content and shorelines |
| 5 | SWIR 1 | 1.55 - 1.75 | 30 | Discriminates moisture content of soil and vegetation; penetrates thin clouds |
| 6 | Thermal | 10.40 - 12.50 | 30 | Thermal mapping and estimated soil moisture |
| 7 | SWIR 2 | 2.08 - 2.35 | 30 | Hydrothermally altered rocks associated with mineral deposits |

*Table 4.2 Band classification for Landsat-5 Satellite (Sensor TM)*
(Survey, U.S. Geological, n.d.)

### 4.2.2 DEVELOP FCC IMAGES BY LAYER STACKING

For developing FCC images and image classification, we need to stack multiple images, usually single band images, as bands/layers into a single output multi-band image file. This was done in QGIS software as Landsat 5 satellite images are available in 7 different bands.

### 4.2.3 CLIPPING (SELECT AOI)

Creating a subset of satellite raster data is called Clipping. The process removes data outside the area of interest reducing the file size and improving the processing time for many operations to follow. The satellite data was clipped to the administrative boundary of study area, Porbandar-Chhaya Municipality.

### 4.2.4 IMAGE CLASSIFICATION & LAND COVER MAPS

Categorization of all pixels within a digital image into one of many land cover classes is called image classification. This categorized data may be used to produce thematic maps of the land cover present in an image: Unsupervised and supervised image classification techniques are the two most common approaches. In supervised classification selects representative samples for each land cover class in the digital image. These simple and cover classes are called training sites. User provided training samples are used by classification software to recognize the land cover classes. Essentially, training samples segregate spectral signature of different land cover classes.

Classification of entire raster image is helped by statistical decision criterion, Maximum likelihood. In case of overlapping signatures, class with highest probability is assigned to the pixel. Band combinations used to identify different land cover classes in FCC for this study are as below:

| | LANDSAT 5 & 7 | | | LANDSAT 8 | | |
|---|---|---|---|---|---|---|
| | **R** | **G** | **B** | **R** | **G** | **B** |
| Natural colour | 3 | 2 | 1 | 4 | 3 | 2 |
| False colour (urban) | 6 | 5 | 3 | 7 | 6 | 4 |
| Colour Infrared(vegetation) | 4 | 3 | 2 | 5 | 4 | 3 |
| Agriculture | 5 | 4 | 1 | 6 | 5 | 2 |
| Atmospheric Penetration | 6 | 5 | 4 | 7 | 6 | 5 |
| Healthy Vegetation | 4 | 5 | 1 | 5 | 6 | 2 |
| Land/Water | 4 | 5 | 3 | 5 | 6 | 4 |
| Atmospheric removal (Natural) | 6 | 4 | 2 | 7 | 5 | 3 |
| Shortwave Infrared | 6 | 4 | 3 | 7 | 5 | 4 |
| Vegetation Analysis | 5 | 4 | 3 | 6 | 5 | 4 |

*Table 4.3 Band combinations used for FCC*

For the study. Maximum likelihood supervised classification techniques used to develop thematic maps. Images are classified in four different land cover category that are listed below.

1. **Waterbody**
2. **Vegetation**
3. **Built-up Area**
4. **Barren Land**

False color composites allow us to visualize the wavelengths the human eye does not see (near the infrared range). To increase spectral separation and improve interpretability of data bands like near infrared (NIR) are used. Representation of multispectral image, using many different band combinations, is called False Colour Composite (FCC) (Appendix 3). Feature in an optical remote sensing image could be identified using their colour. radiance texture, shape, shadow. tone, and associative features around. What makes classification of pixels into different feature classes is their unique digital signature. Individual class has an inimitable signature, which makes the classification of feature classes conceivable. Visual keys like shapes, colours and band combinations use for classification for different feature classes in FCC image are listed below.

**1. Water Body (River, Lake, Sea)**

For waterbody uses band composition 4,5,3 in Landsat 5 & 8 image and 5,6,4 in Landsat 8 image. This band combination is very helpful when you intend to pick out land from water. In the image, water appears in shades of blue and black. Creek can be seen as an irregular shape seen in dark blue colour. Whereas sea can be seen in black. (Figure 4.3).

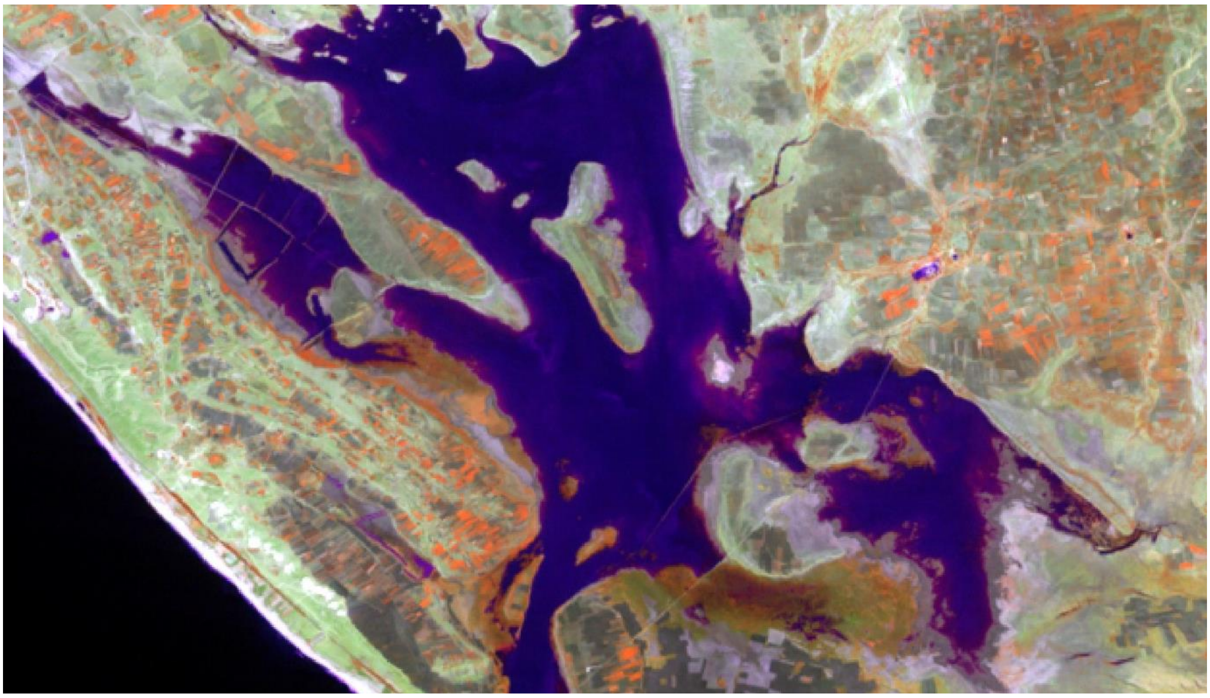


*Figure 4.3 Identification of Waterbody in FCC Image*

**2. Vegetation**

This band combination is also called color infrared composite.  For uses band composition 4,3,2 in Landsat 5 & 8 image and 5,4,3 in Landsat 8 image. This band combination is suited for vegetation to be easily detected in the image. Vegetation emerges in shades of red. (Figure 4.4).

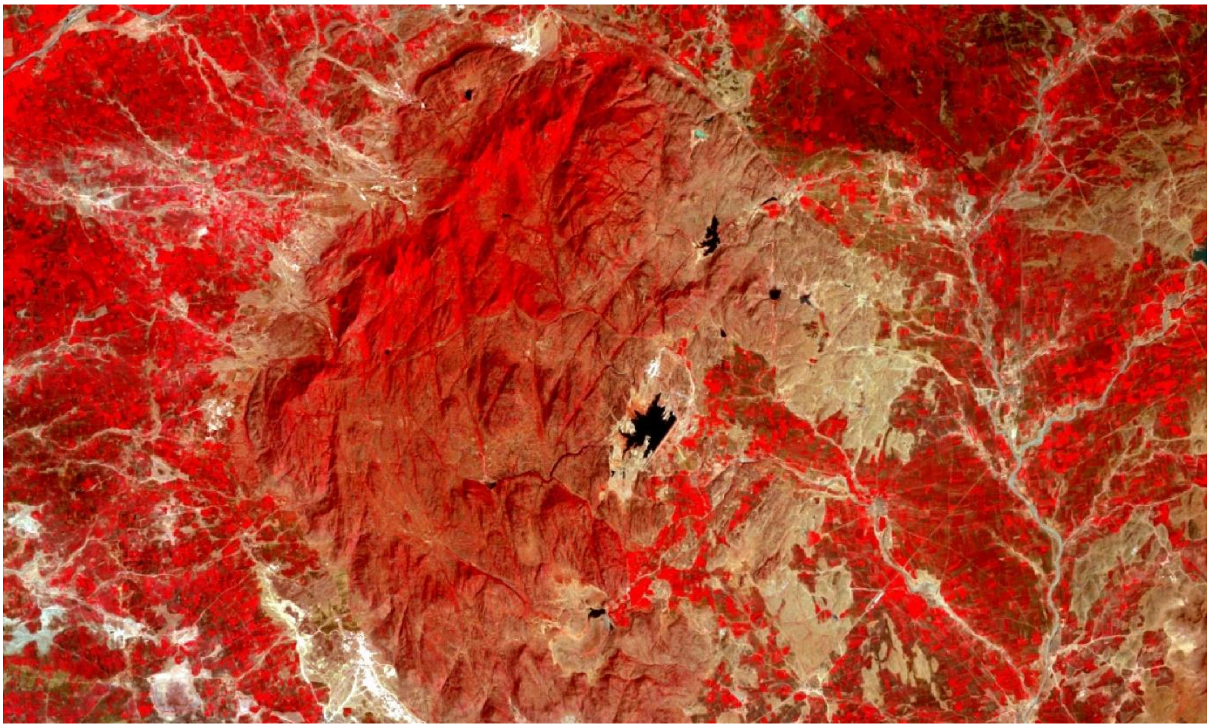


*Figure 4.4 Identification of Vegetation in FCC Image*

**3. Built-up Area (Urban area, settlement area)**

For Built-up Area uses band composition 6,5,3 in Landsat 5 & 8 image and 7,6,4 in Landsat 8 image. Built-up area emerges in cyan and white color. (Figure 4.5).

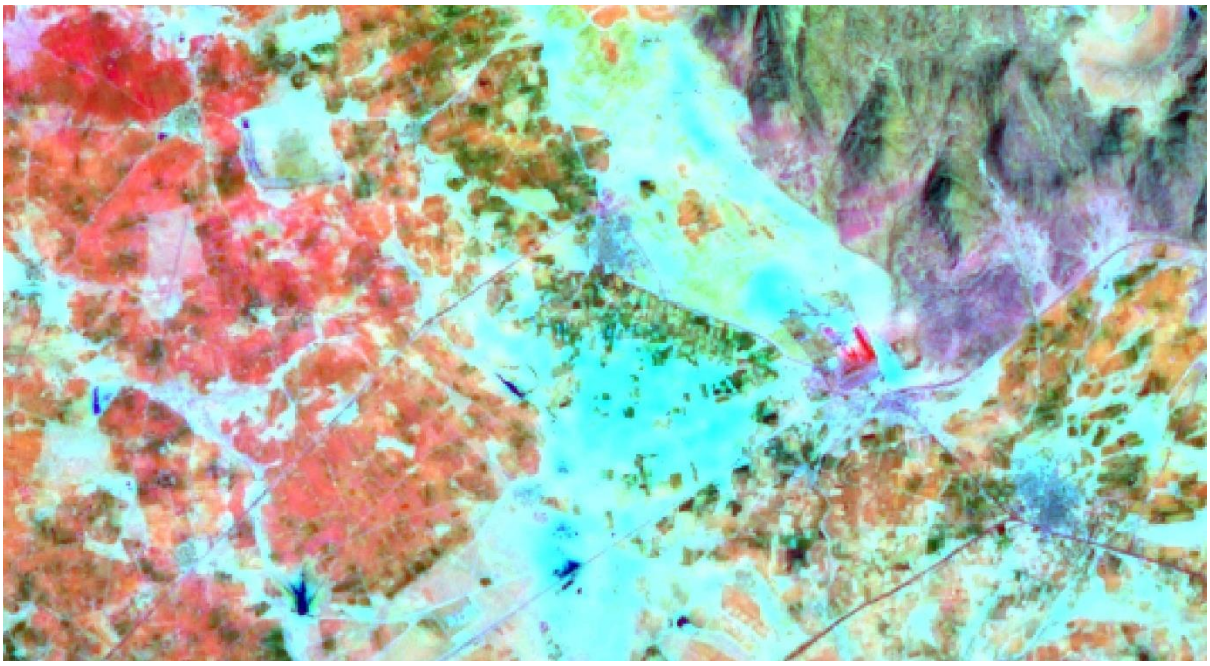


*Figure 4.5 Identification of Urban Settlement in FCC Image*

**4. Barren Land**

For Barren land Area uses band composition 3,2,1 in Landsat 5 & 8 image and 4,3,2 in Landsat 8 image. Built-up area emerges in light brown color. (Figure 4.6).

*Figure 4.6 Identification of Wasteland in FCC Image*

### 4.2.5 ACCURACY CHECK & FINALIZING LAND COVER MAPS

Accuracy assessment is an important part of any classification project. It compares the classified image to another data source that is considered to be accurate or ground truth data. One way of collecting ground truth data is field survey, although it is an expensive and time-consuming method. Also, this method does not provide ground truth for historical land cover. Hence, for this study ground truth data has been collected from visual interpretation of high-resolution (1m) satellite imagery available from Google Earth.

Accuracy Assessment uses a Reference Dataset to determine the accuracy of your classified result. The values of your reference dataset need to match your classified map. Setting random points to collect ground truth data and comparing them to the classified data in confusion matrix is the well accepted method to check accuracy of a classified map. Ideally, the source of ground truth data should be different than that used for generating classification maps. In this study classification maps are generated using Landsat data, whereas for ground truth Mexar Technologies, TeraMetrics and other satellite data is used. This ground truth provides information about the actual land cover types present on the ground at the location of selected test pixels.

The function of error matrix is to compare the association between ground truth data and corresponding data presented in map by semi-automated classification, on a category-by-category basis. In an error matrix, column represent true land cover derived from ground truth test pixels and rows represent corresponding land cover from classified map. The major diagonal, running from top left to bottom right, shows the test pixels that are correctly classified (TCS). Other nondiagonal entries in the matrix shows errors of omission or commission.

#### Accuracy Assessment Formulas

$$\text{Users Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total number of Classified Pixels in that Category (The Row Total)}} \times 100$$

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (Column Total)}} \times 100$$

$$\text{Overall Accuracy} = \frac{\text{Total Number of Correctly Classified Pixels (Diagonal)}}{\text{Total Number of Reference Pixels}} \times 100$$

$$\text{Kappa Coefficient (k)} = \frac{(\text{TS}\times\text{TCS}) - \sum(\text{Column Total}\times\text{Row Total})}{\text{TS}^2 - \sum(\text{Column Total}\times\text{Row Total})} \times 100$$

Where, TS = Total Sample

TCS = Total Correctly Classified Sample

The workflow adopted in the study consists of the following steps:

1. Create point shape file
2. Take ground truth point that are representative for our land cover classes (samples not taken during Supervised classification are mostly used)
3. Add new field in Attribute (user and procedure) and number them according to class in user field and ground truth numbering according class in procedure field
4. Prepare Error Matrix
5. Find out accuracy and Kappa Coefficient (k) of land cover map using above equations

### 4.2.6 ASSESSING LAND COVER CHANGE

MOLUSCE plugin for QGIS has been used for change detection in the study. Based on QGIS, MOLUSCE (Modules for Land Use Change Simulations) is a tool to do analysis of LULCC. As a researcher who analyses changes in landscape through time, we often deal with questions like:

- What are the changes and where did they happen?
- Which factors can explain the changes and strong is their explanatory power?
- What changes are expected in future and where?

The answer for the first question can be obtained by visual estimation, but to answer other questions one will need to set hypotheses, verify them, derive conclusions and see how they meet the reality. The process of answering these questions is partially automated by the tool MOLUSCE. The workflow consists of the following steps:

1. Obtain landcover map for few time slices and a set of potential explanatory variables
2. Calculate probabilities of transitions from class to class

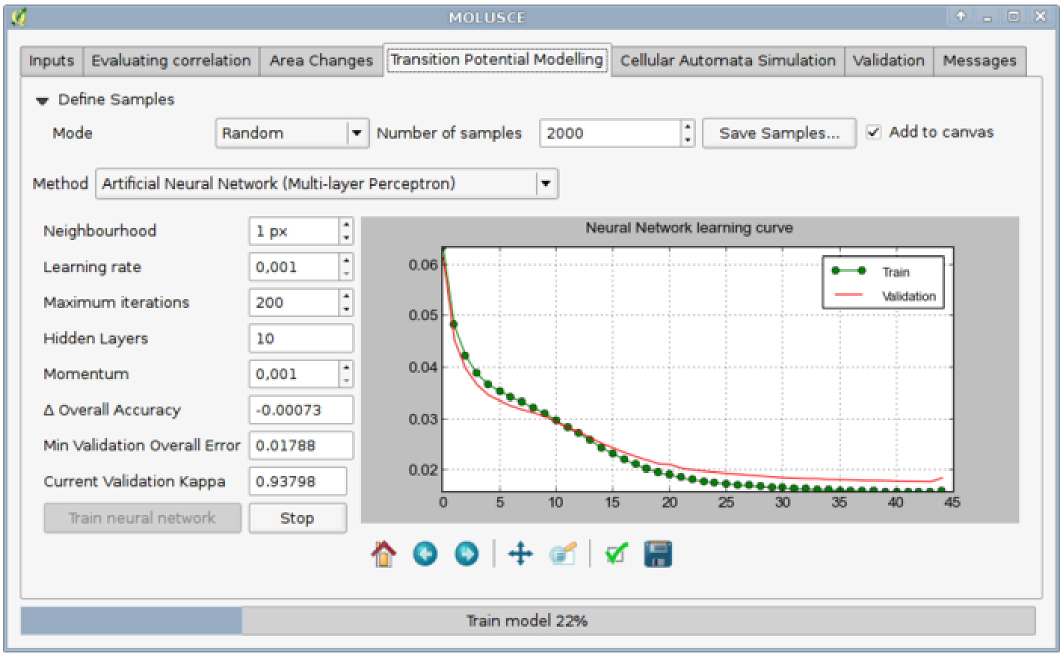



*Figure 4.7 Change detection using MOLUSCE*

## 4.3 FUTURE LAND COVER PREDICTION

For the study land cover prediction maps are generated using MOLUSCE Plugin of QGIS. After the preparation of LC map, variable maps like DEM, Distance from Road, Distance from River/Ocean and Slope, that can influence the change in future land cover, are added to database. Thereafter the workflow for prediction consists of the following steps:

**1. Load all data**

**2. Evaluating correlation**

Within evaluating correlation module, there are three techniques to perform analysis:

- Pearson's correlation
- Cramer's coefficient
- Joint information uncertainty

For this study Pearson's correlation is used.

**3. Area Changes – Transition Matrix**

To produces class statistics and transition matrix tables. The class statistics table shows the initial and final land cover (LC) areas. The transition matrix shows the proportions of pixels changing from one land cover to another.

**4. Transition potential modelling**

To model land use/land cover transition potential, MOLUSCE uses Artificial Neural Network (ANN), Multi Criteria Evaluation (MCE), Weights of Evidence (WoE) and Logistic Regression (LR) methods.

The probability or potential to change from one to another land cover class is displayed in transition potential map.

Transition potential values range from 0 to 100. Where, 0 represent low transition potential of change, and 100 represent high transition potential. From the corresponding land cover changes (e.g., “agricultural to barren land” transition potential, “barren land to built-up” transition potential), transition potential maps will be generated. Number of samples and sampling mode can be defined by “samples” function, these sampling points so created can be saved and displayed on a map.

**5. Cellular Automata Simulation**

The simulation result produces a simulated land cover map for future date. For the study LC maps for 2021 and 2031 are generated.

**6. Validation**

To check, validate and compare the simulation results. Also generate the graph can be edited and saved as image and the overall the overall accuracy (% of correctness), kappa (overall), kappa (histogram) and kappa (location) can be executed.

# CHAPTER:5 LAND COVER CHANGE ANALYSIS

## 5.1 IMAGE CLASSIFICATION AND LAND COVER MAPS

As per adopted methodology of post-classification comparison technique separate land cover maps of study area are prepared for the year 1991, 2001 and 2011. Land cover classification is done using supervised classification method. Four level 1 land cover classes are identified viz. Built-up Area, Vegetation, Water Body and Barren Land. Image classification and land cover maps of the study area are prepared using QGIS software. The land cover maps are checked for accuracy using error matrix method. Randomly selected sample points are compared with ground truth, derived from Google Earth historical data. The error matrix compares test points from ground truth, known as "Producer" (columns) versus the mapped cover type from the classified maps, known as "User" (rows). The results of matrix are used to calculate accuracy of map and kappa coefficient. The maps and quantitative data thus generated are presented hereafter in form of maps, charts, and statistical tables.

### 5.1.1 LAND COVER FOR YEAR 1991

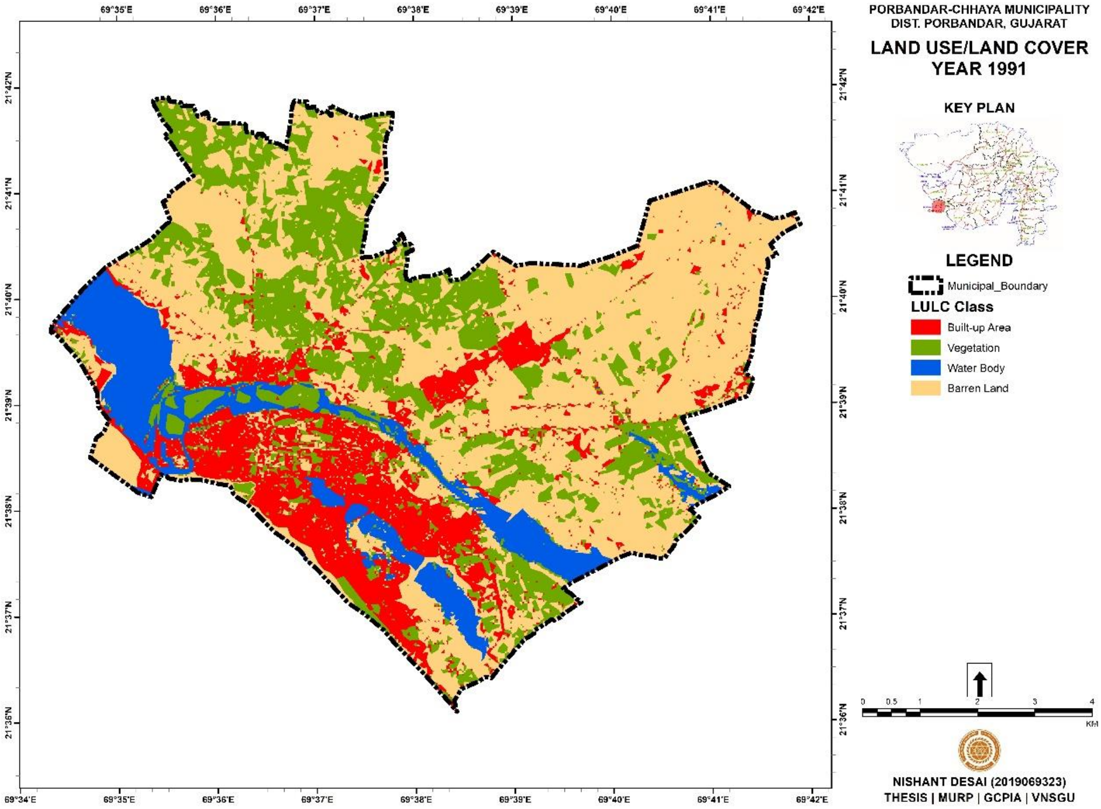



*Figure 5.1 Land cover map of the study area for year 1991*

Areas covered by each class derived from classified land cover map (1991) are mentioned in Table 5.1. The data shows that area of Barren Land is higher than any other class, covering 36.02 sq.km. (48.55%). Followed by Vegetation 18.01 sq.km. (24.27%). Built-up area occupies 12.40 sq.km. (16.71%). Lastly Waterbody covers 7.77 sq.km. (10.47%).

| LAND COVER CLASS | AREA IN SQ.KM | PERCENTAGE (%) |
|---|---|---|
| **Built-up Aera** | 12.40 | 16.71 |
| **Vegetation** | 18.01 | 24.27 |
| **Water Body** | 7.77 | 10.47 |
| **Barren Land** | 36.02 | 48.55 |
| **Total** | **74.20** | **100.00** |

*Table 5.1 Land cover classification (Year 1991)*

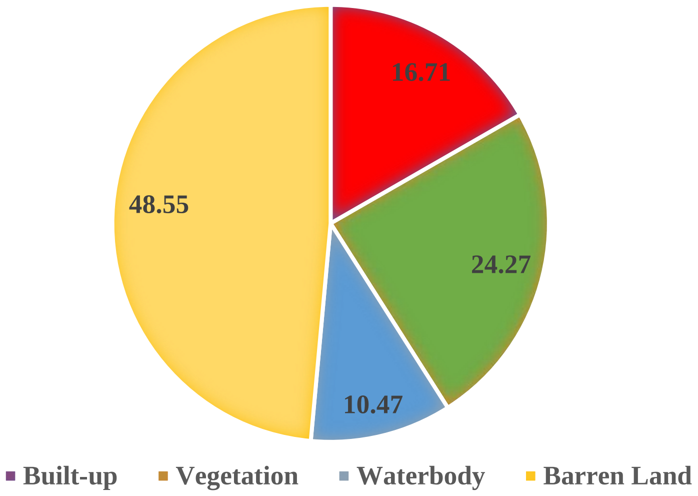



*Figure 5.2 Percentage of land cover classification (Year 1991)*

**Accuracy assessment of land cover map**

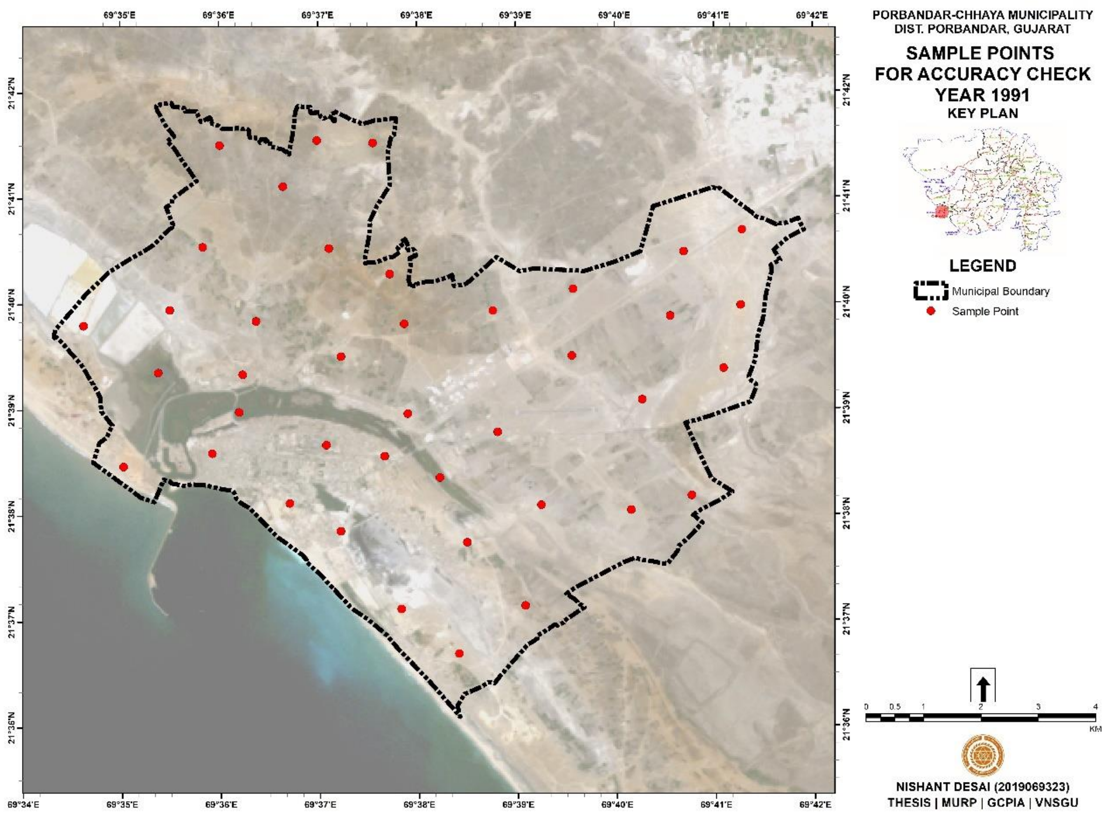



*Figure 5.3 Random sample points taken for accuracy check (Year 1991)*

| | Built-up Aera | Vegetation | Water Body | Barren Land | Total (User) |
|---|---|---|---|---|---|
| **Built-up Aera** | 6 | 1 | 0 | 1 | 8 |
| **Vegetation** | 0 | 7 | 0 | 4 | 11 |
| **Water Body** | 0 | 0 | 5 | 0 | 5 |
| **Barren Land** | 1 | 1 | 0 | 14 | 16 |
| **Total (Producer)** | 7 | 9 | 5 | 19 | 40 |

*Table 5.2 Error matrix (Year 1991)*

$$\text{Overall Accuracy}=\frac{\text{Total Number of Correctly Classified Pixels (Diagonal)}}{\text{Total Number of Reference Pixels}}\times 100$$

= 80.00%

$$\text{Users Accuracy}=\frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total number of Classified Pixels in that Category (The Row Total)}}\times 100$$

- Built-up Area = (6/8) *100 = 75%
- Vegetation = (7/11) *100 = 63.63%
- Water Body = (5/5) *100 = 100%
- Barren Land= (14/16) *100 = 87.5%

$$\text{Producer Accuracy}=\frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (The Column Total)}}\times 100$$

- Built-up Area = (6/7) *100 = 85.71%
- Vegetation = (7/9) *100 = 77.77%
- Water Body = (5/5) *100 = 100%
- Barren Land= (14/19) *100 = 73.68%

$$\text{Kappa Coefficient (k)}=\frac{(TS\times TCS)-\sum(\text{Column Total}\times\text{Row Total})}{TS^2-\sum(\text{Column Total}\times\text{Row Total})}\times 100$$

- Kappa Coefficient (k) = 71.32%
- Here, TS = Total Sample = 40 and TCS = Total Correctly Classified Sample = 32

**So, above calculation find out the accuracy of land cover map of study area in 1991, is 80.00% and Kappa Coefficient is 71.32%.**

### 5.1.2 LAND COVER FOR YEAR 2001

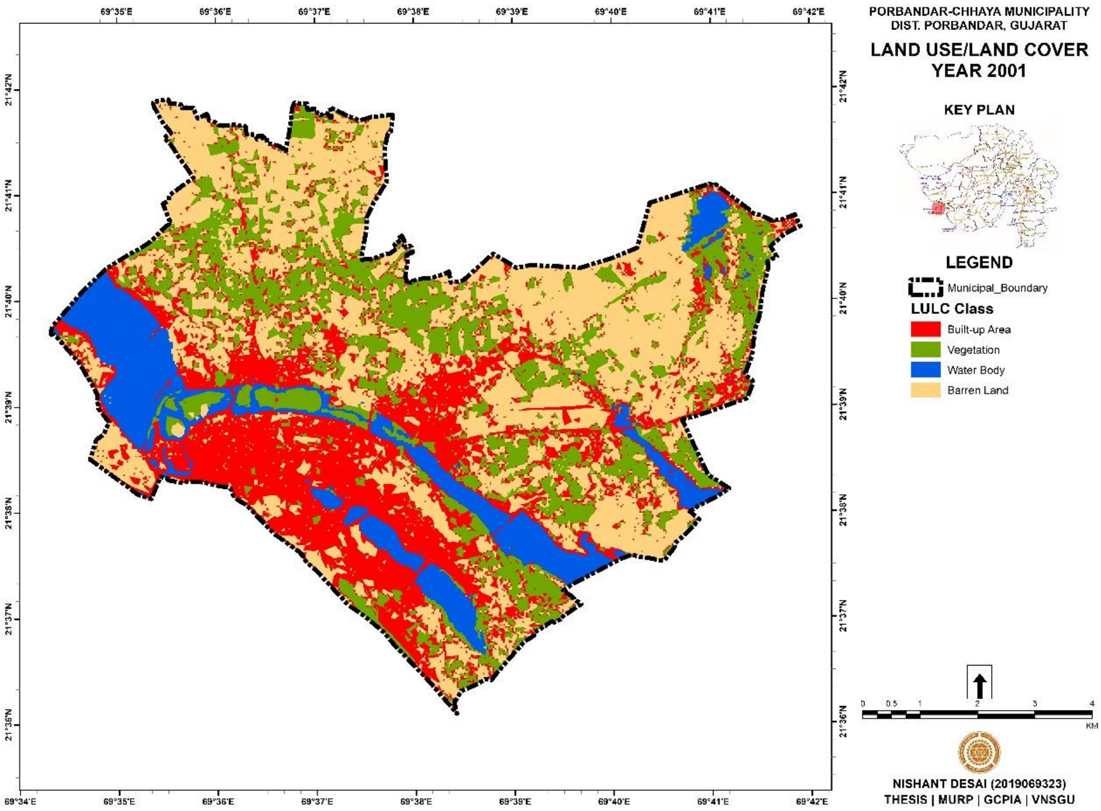



*Figure 5.4 Land cover map of the study area for year 2001*

Areas covered by each class derived from classified land cover map (2001) are mentioned in Table 5.3. The data shows that area of Barren Land is higher than any other class, covering 28.58 sq.km. (38.52%). Followed by Built-up 19.86 sq.km. (26.76%). Vegetation occupies 17.06 sq.km. (22.99%). Lastly Waterbody covers 8.70 sq.km. (11.73%).

| LAND COVER CLASS | AREA IN SQ.KM | PERCENTAGE (%) |
|---|---|---|
| **Built-up Aera** | 19.86 | 26.76 |
| **Vegetation** | 17.06 | 22.99 |
| **Water Body** | 8.70 | 11.73 |
| **Barren Land** | 28.58 | 38.52 |
| **Total** | **74.20** | **100.00** |

*Table 5.3 Land cover classification (Year 2001)*

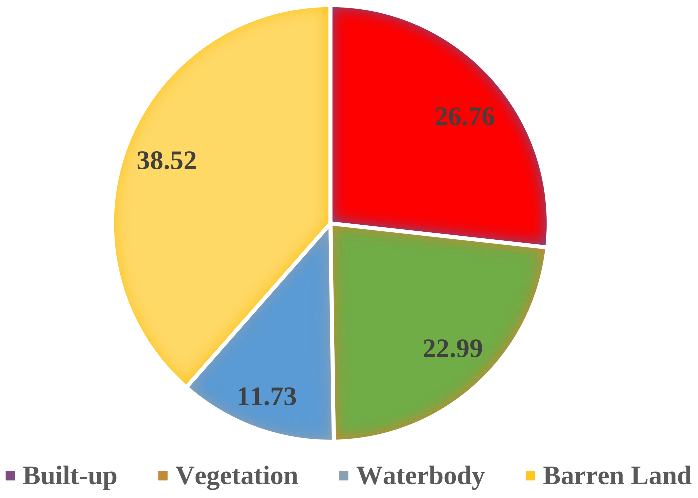



*Figure 5.5 Percentage of land cover classification (Year 2001)*

**Accuracy assessment of land cover map**

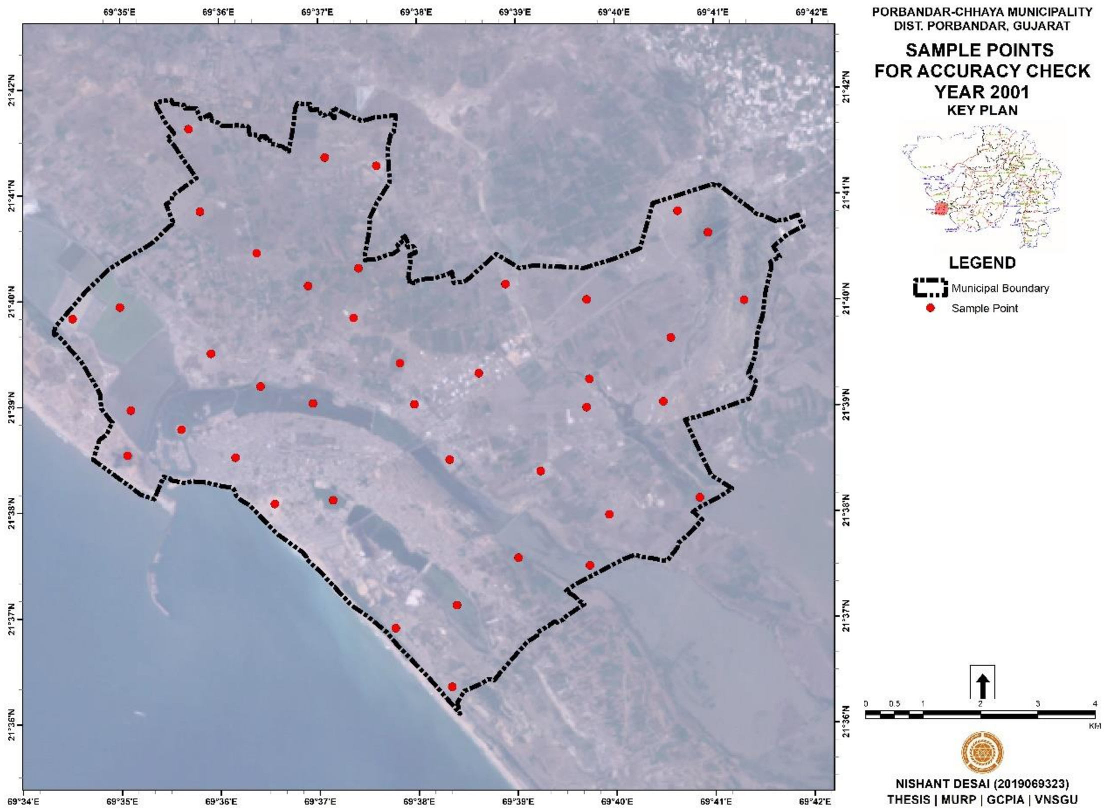



*Figure 5.6 Random sample points taken for accuracy check (Year 2001)*

| | Built-up Aera | Vegetation | Water Body | Barren Land | Total (User) |
|---|---|---|---|---|---|
| **Built-up Aera** | 8 | 0 | 0 | 0 | 8 |
| **Vegetation** | 0 | 6 | 0 | 1 | 7 |
| **Water Body** | 0 | 0 | 6 | 3 | 9 |
| **Barren Land** | 0 | 1 | 1 | 14 | 16 |
| **Total (Producer)** | 8 | 7 | 7 | 18 | 40 |

*Table 5.4 Error matrix (Year 200s1)*

$$\textbf{Overall Accuracy}=\frac{\textbf{Total Number of Correctly Classified Pixels (Diagonal)}}{\textbf{Total Number of Reference Pixels}}\times 100$$

= 85.00%

$$\textbf{Users Accuracy}=\frac{\textbf{Number of Correctly Classified Pixels in each Category}}{\textbf{Total number of Classified Pixels in that Category (The Row Total)}}\times 100$$

- Built-up Area = (8/8) *100 = 100%
- Vegetation = (6/7) *100 = 85.71%
- Water Body = (6/9) *100 = 66.66%
- Barren Land= (14/16) *100 = 87.5%

$$\textbf{Producer Accuracy}=\frac{\textbf{Number of Correctly Classified Pixels in each Category}}{\textbf{Total Number of Reference Pixels in that Category (The Column Total)}}\times 100$$

- Built-up Area = (8/8) *100 = 100%
- Vegetation = (6/7) *100 = 85.21%
- Water Body = (6/7) *100 = 85.21%
- Barren Land= (14/18) *100 = 77.77%

$$\textbf{Kappa Coefficient (k)}=\frac{(TS\times TCS)-\sum(\text{Column Total}\times\text{Row Total})}{TS^2-\sum(\text{Column Total}\times\text{Row Total})}\times 100$$

- Kappa Coefficient (k) = 78.87%
- Here, TS = Total Sample = 40 and TCS = Total Correctly Classified Sample = 34

**So, above calculation find out the accuracy of land cover map of study area in 2001, is 85.00% and Kappa Coefficient is 78.87%.**

### 5.1.3 LAND COVER FOR YEAR 2011

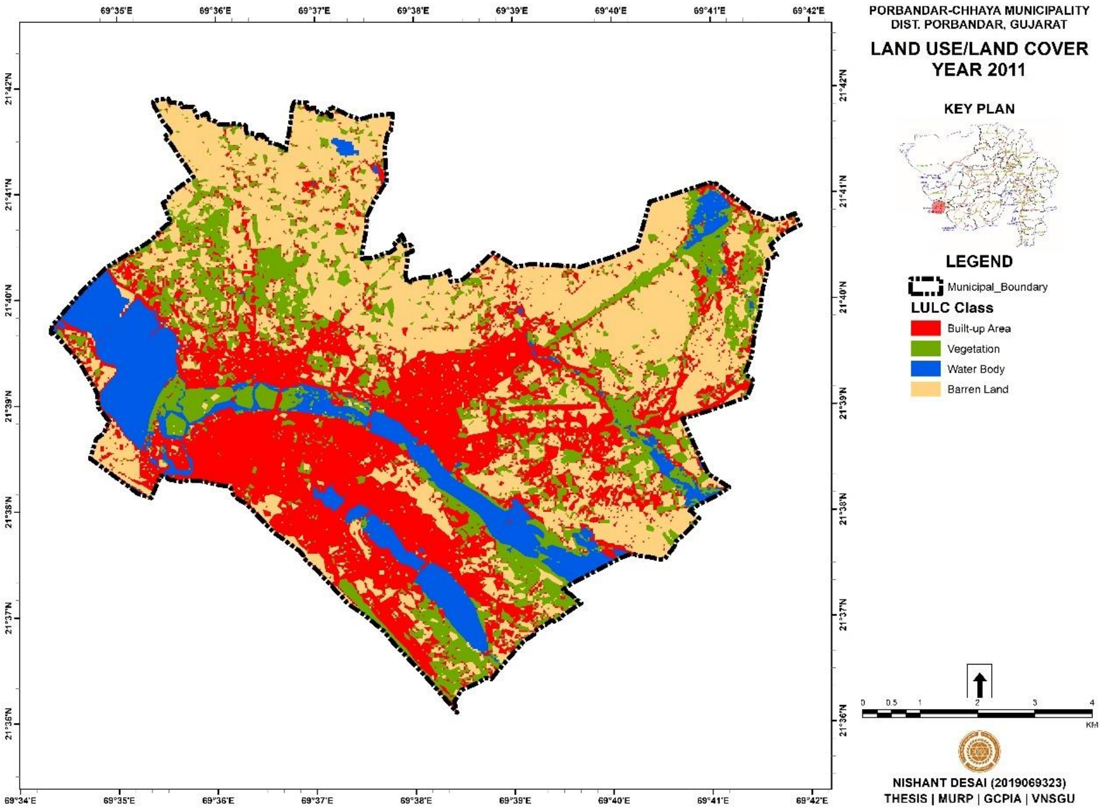



*Figure 5.7 Land cover map of the study area for year 2011*

Areas covered by each class derived from classified land cover map (2011) are mentioned in Table 5.5. The data shows that area of Barren Land is higher than any other class, covering 28.01 sq.km. (37.75%). Followed by Built-up 23.69 sq.km. (31.93%). Vegetation area occupies 14.05 sq.km. (18.93%). Lastly Waterbody covers 8.45 sq.km. (11.39%).

| LAND COVER CLASS | AREA IN SQ.KM | PERCENTAGE (%) |
|---|---|---|
| **Built-up Aera** | 23.69 | 31.93 |
| **Vegetation** | 14.05 | 18.93 |
| **Water Body** | 8.45 | 11.39 |
| **Barren Land** | 28.01 | 37.75 |
| **Total** | **74.20** | **100.00** |

*Table 5.5 Land cover classification (Year 2011)*

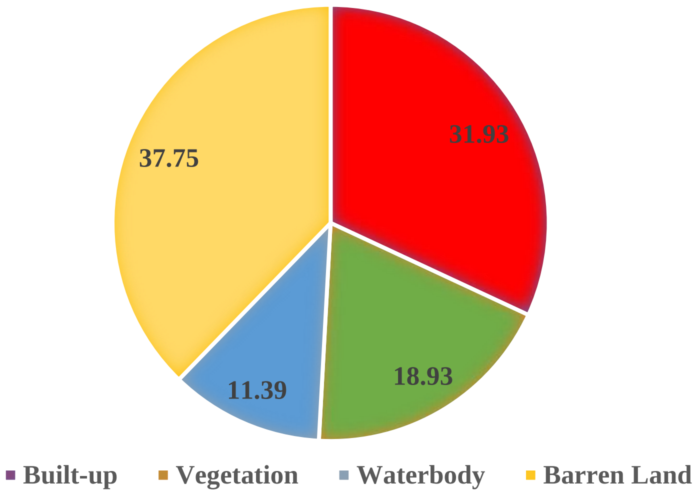



*Figure 5.8 Percentage of land cover classification (Year 2011)*

**Accuracy assessment of land cover map**

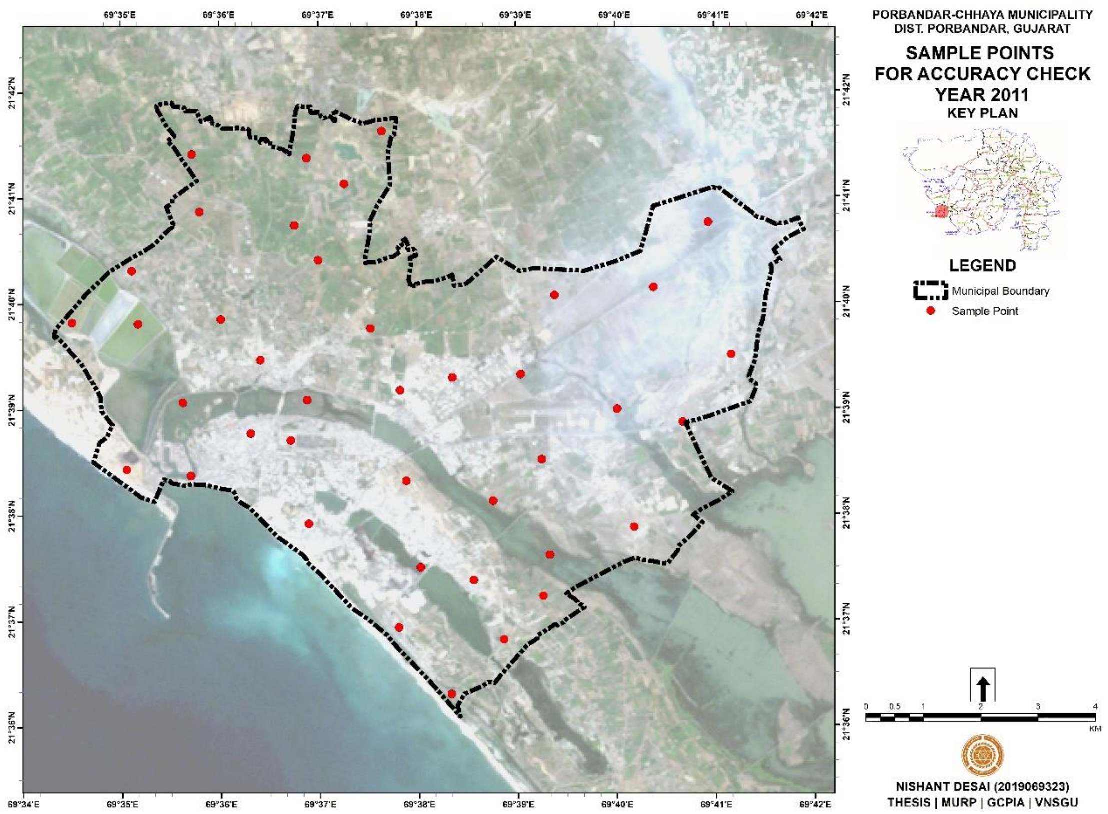



*Figure 5.9 Random sample points taken for accuracy check (Year 2011)*

| | Built-up Aera | Vegetation | Water Body | Barren Land | Total (User) |
|---|---|---|---|---|---|
| **Built-up Aera** | 10 | 0 | 0 | 1 | 11 |
| **Vegetation** | 0 | 6 | 0 | 1 | 7 |
| **Water Body** | 0 | 2 | 6 | 0 | 8 |
| **Barren Land** | 0 | 2 | 0 | 12 | 14 |
| **Total (Producer)** | 10 | 10 | 6 | 14 | 40 |

*Table 5.6 Error matrix (Year 2011)*

$$\text{Overall Accuracy}=\frac{\text{Total Number of Correctly Classified Pixels (Diagonal)}}{\text{Total Number of Reference Pixels}}\times 100$$

= 85.00%

$$\text{Users Accuracy}=\frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total number of Classified Pixels in that Category (The Row Total)}}\times 100$$

- Built-up Area = (10/11) *100 = 90.90%
- Vegetation = (6/7) *100 = 85.71%
- Water Body = (6/8) *100 = 75%
- Barren Land= (12/14) *100 = 85.71%

$$\text{Producer Accuracy}=\frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (The Column Total)}}\times 100$$

- Built-up Area = (10/10) *100 = 100%
- Vegetation = (6/10) *100 = 60%
- Water Body = (6/6) *100 = 100%
- Barren Land= (12/14) *100 = 85.71%

$$\text{Kappa Coefficient (k)}=\frac{(TS\times TCS)-\sum(\text{Column Total}\times\text{Row Total})}{TS^2-\sum(\text{Column Total}\times\text{Row Total})}\times 100$$

- Kappa Coefficient (k)= 79.56%
- Here, TS = Total Sample =40 and TCS = Total Correctly Classified Sample = 34

**So, above calculation find out the accuracy of land cover map of study area in 2011, is 85.00% and Kappa Coefficient is 79.56%.**

### 5.1.4 LAND COVER FOR YEAR 2021

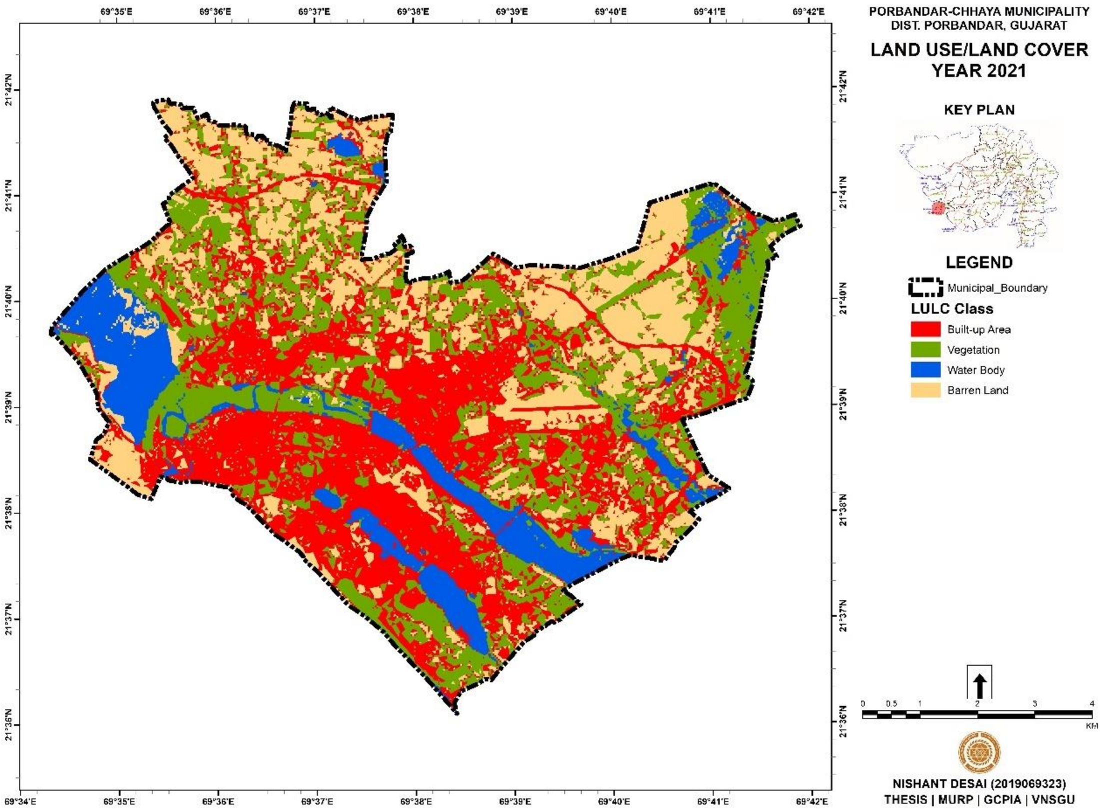



*Figure 5.10 Land cover map of the study area for year 2011*

Areas covered by each class derived from classified land cover map (2021) are mentioned in Table 5.7. The data shows that area of Built-up Area is higher than any other class, covering 26.49 sq.km. (35.71%). Followed by Vegetation 20.81 sq.km. (28.04%). Barren Land occupies 18.66 sq.km. (25.15%). Lastly Waterbody covers 8.24 sq.km. (11.10%).

| LAND COVER CLASS | AREA IN SQ.KM | PERCENTAGE (%) |
|---|---|---|
| **Built-up Aera** | 26.49 | 35.71 |
| **Vegetation** | 20.81 | 28.04 |
| **Water Body** | 8.24 | 11.10 |
| **Barren Land** | 18.66 | 25.15 |
| **Total** | **74.20** | **100.00** |

*Table 5.7 Land cover classification (Year 2021)*

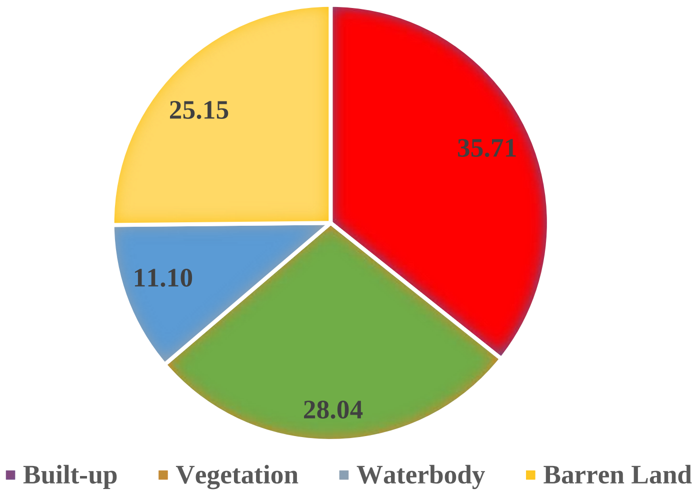



*Figure 5.11 Percentage of land cover classification (Year 2021)*

**Accuracy assessment of land cover map**

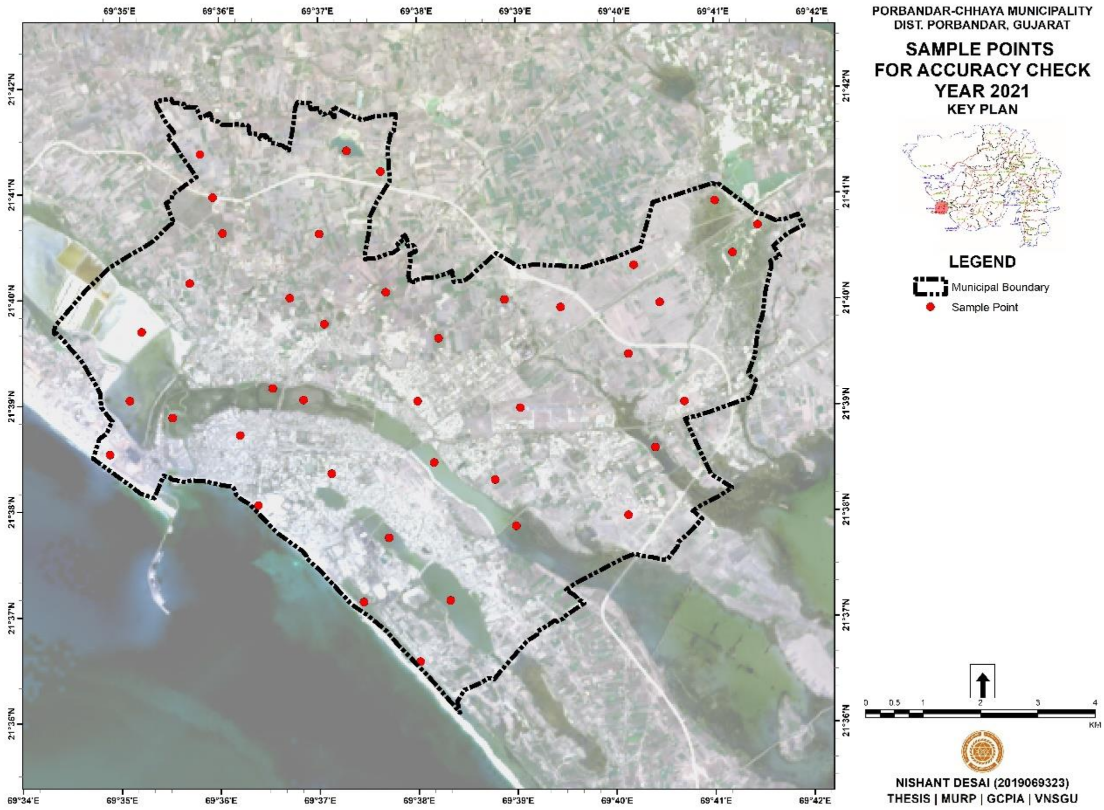



*Figure 5.12 Random sample points taken for accuracy check (Year 2021)*

| | Built-up Aera | Vegetation | Water Body | Barren Land | Total (User) |
|---|---|---|---|---|---|
| Built-up Aera | 8 | 0 | 0 | 2 | 10 |
| Vegetation | 0 | 8 | 0 | 0 | 8 |
| Water Body | 0 | 0 | 10 | 1 | 11 |
| Barren Land | 0 | 1 | 0 | 10 | 11 |
| Total (Producer) | 8 | 9 | 10 | 13 | 40 |

*Table 5.8 Error matrix (Year 2021)*

$$\text{Overall Accuracy} = \frac{\text{Total Number of Correctly Classified Pixels (Diagonal)}}{\text{Total Number of Reference Pixels}} \times 100$$

= 90.00%

$$\text{Users Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total number of Classified Pixels in that Category (The Row Total)}} \times 100$$

- Built-up Area = (8/10) *100= 80%
- Vegetation = (8/8) *100= 100%
- Water Body = (10/11) *100= 90.90%
- Barren Land= (10/11) *100= 90.90%

$$\text{Producer Accuracy} = \frac{\text{Number of Correctly Classified Pixels in each Category}}{\text{Total Number of Reference Pixels in that Category (The Column Total)}} \times 100$$

- Built-up Area = (8/8) *100= 100%
- Vegetation = (8/9) *100= 88.88%
- Water Body = (10/10) *100= 100%
- Barren Land= (10/13) *100= 76.92%

$$\text{Kappa Coefficient (k)} = \frac{(TS \times TCS) - \sum(\text{Column Total} \times \text{Row Total})}{TS^2 - \sum(\text{Column Total} \times \text{Row Total})} \times 100$$

- Kappa Coefficient (k)= 86.61%
- Here, TS = Total Sample =40 and TCS = Total Correctly Classified Sample = 36

**So, above calculation find out the accuracy of land cover map of study area in 2011, is 90.00% and Kappa Coefficient is 86.61%.**

## 5.2 ASSESSMENT OF LAND COVER CHANGE

Land cover over the study area has been analyzed for the years 1991, 2001, 2011 and 2021. The comparison of results is presented below in Table 5.9 & Figure 5.13.

| | Area (sq.km.) | | | | Area (%) | | | |
|---|---|---|---|---|---|---|---|---|
| **Land Cover class** | **1991** | **2001** | **2011** | **2021** | **1991** | **2001** | **2011** | **2021** |
| **Built-up** | 12.40 | 19.86 | 23.69 | 26.49 | 16.71 | 26.76 | 31.93 | 35.71 |
| **Vegetation** | 18.01 | 17.06 | 14.05 | 20.81 | 24.27 | 22.99 | 18.93 | 28.04 |
| **Waterbody** | 7.77 | 8.70 | 8.45 | 8.24 | 10.47 | 11.73 | 11.39 | 11.10 |
| **Barren Land** | 36.02 | 28.58 | 28.01 | 18.66 | 48.55 | 38.52 | 37.75 | 25.15 |
| **Total** | **74.20** | **74.20** | **74.20** | **74.20** | **100.00** | **100.00** | **100.00** | **100.00** |

*Table 5.9 Comparison of area of land cover classes*

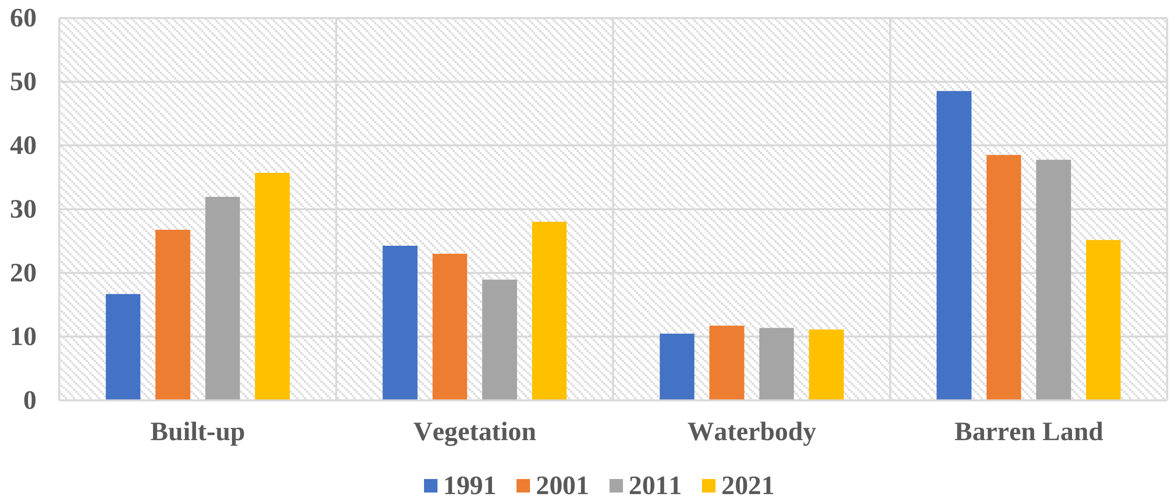



*Figure 5.13 Comparison of area of land cover classes*

The analysis of land cover for study area, for different time periods (the year 1991, 2000, 2011, 2021), indicate substantial changes which are summarized in below Table 5.10 and Figure 5.14. From that statistics, it is helpful to identifying percentage change rate, trend and magnitude.

The magnitude of change is a degree of expansion or reduction in the land cover area. A negative value will present a decrease in land cover, while a positive value an increase in the area of land cover class. The magnitude of change and percentage of change (trend) are calculated by below equations.

**Magnitude of change (sq.km.) = Area Year (t) – Area Year (t-10)**

$$\textbf{Change Rate \% (trend)} = \frac{\textbf{Magnitude of change}}{\textbf{Total area of spatial entity}} \times 100$$

By using above equations, the magnitude of change and change rate in percentage for land cover classifications clarify in detail below.

| Land Cover class | 1991-2001 | | 2001-2011 | | 2011-2021 | | Average Decadal Change | |
|---|---|---|---|---|---|---|---|---|
| | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) |
| **Built-up** | 7.46 | 10.05% | 3.83 | 5.16% | 2.80 | 3.77% | 4.70 | 6.33% |
| **Vegetation** | -0.95 | -1.28% | -3.01 | -4.06% | 6.76 | 9.11% | 0.93 | 1.26% |
| **Waterbody** | 0.93 | 1.25% | -0.25 | -0.34% | -0.21 | -0.28% | 0.16 | 0.21% |
| **Barren Land** | -7.44 | -10.03% | -0.57 | -0.77% | -9.35 | -12.60% | -5.79 | -7.80% |

*Table 5.10 Magnitude and Change Rate in different land cover classes*

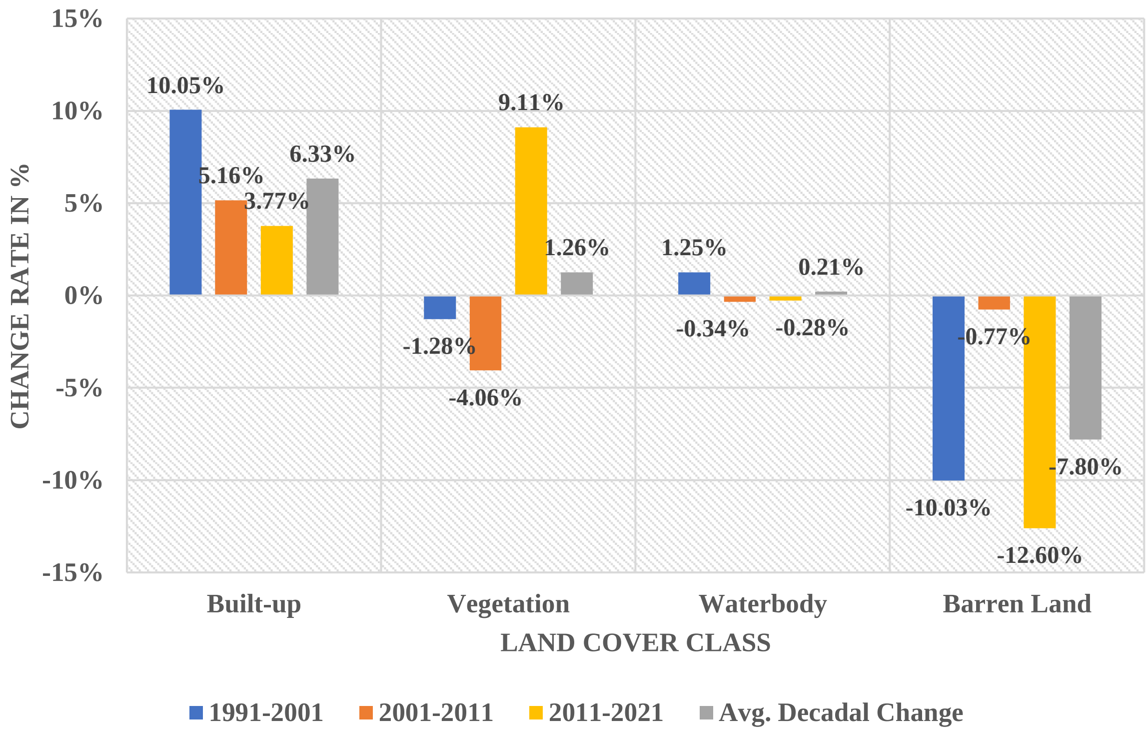



*Figure 5.14 Change rate in different land cover classes*

### 5.2.1 SUMMARY

**1. Built-up area**

Continuous rise in built-up area is observed during the period of 1991-2021. Built-up area increased from 12.40 sq.km. (16.71%) in 1991 to 19.86 sq.km. (26.76%) in 2001 to 23.69 sq.km. (31.93%) in 2011 to 26.49 sq.km. (35.71%) in 2021. During 1991-2001 built-up area increased by 7.46 sq.km. with change rate of 10.05%. During 2001-2011 built-up area increased by 3.83 sq.km. with change rate of 5.16%. During 2011-2021 built-up area increased by 2.80 sq.km. with change rate of 3.77%.

**2. Vegetation**

Vegetation area is observed to be decreasing during the period of 1991-2011. Vegetation area decreased from 18.01 sq.km. (24.27%) in 1991 to 17.06 sq.km. (22.99%) in 2001 to 14.05 sq.km. (18.93%) in 2011 to 20.81 sq.km. (28.04%) in 2021. During 1991-2001 vegetation area decreased by 0.95 sq.km. with change rate of -1.28%. During 2001-2011 vegetation area decreased by 3.01 sq.km. with change rate of -4.06%. During 2011-2021 vegetation area increased by 6.76 sq.km. with change rate of 9.11%.

**3. Water body**

Area of waterbody has shown only slight overall change. It increased from 7.77 sq.km. (10.47%) in 1991 to 8.70 sq.km. (11.73%) in 2001 and decreased to 8.45 sq.km. (11.39%) in 2011 and then decreased to 8.24 sq.km. (10.10%) in 2021. During 1991-2001 waterbody area increased by 0.93 sq.km. with change rate of 1.25%. During 2001-2011 waterbody area decreased by 0.25 sq.km. with change rate of -0.34%. During 2011-2021 waterbody area decreased by 0.21 sq.km. with change rate of -0.28%.

**4. Barren land**

Continuous decrease in Barren Land is observed during the period of 1991-2011. It decreased from 36.02 sq.km. (48.55%) in 1991 to 28.58 sq.km. (38.52%) in 2001 to 28.01 sq.km. (37.75%) in 2011 to 18.66 sq.km. (25.15%) in 2021. During 1991-2001 barren land area decreased by 7.44 sq.km. with change rate of -10.03%. During 2001-2011 barren land area decreased by 0.57 sq.km. with change rate of -0.77%. During 2011-2021 barren land area decreased by 9.35 sq.km. with change rate of -12.60%.

## 5.3 CHANGE DETECTION ANALYSIS FOR BUILT-UP AREA

While the above study includes all land use/land cover classes, it is Built-up Area which is of prime consideration, while study of urban growth or expansion. Hence, further analysis based on findings of LULC maps generated above, focuses on the growth of Built-up Area in the study area that took place between the year 1991 to 2021. This is shown below in map.

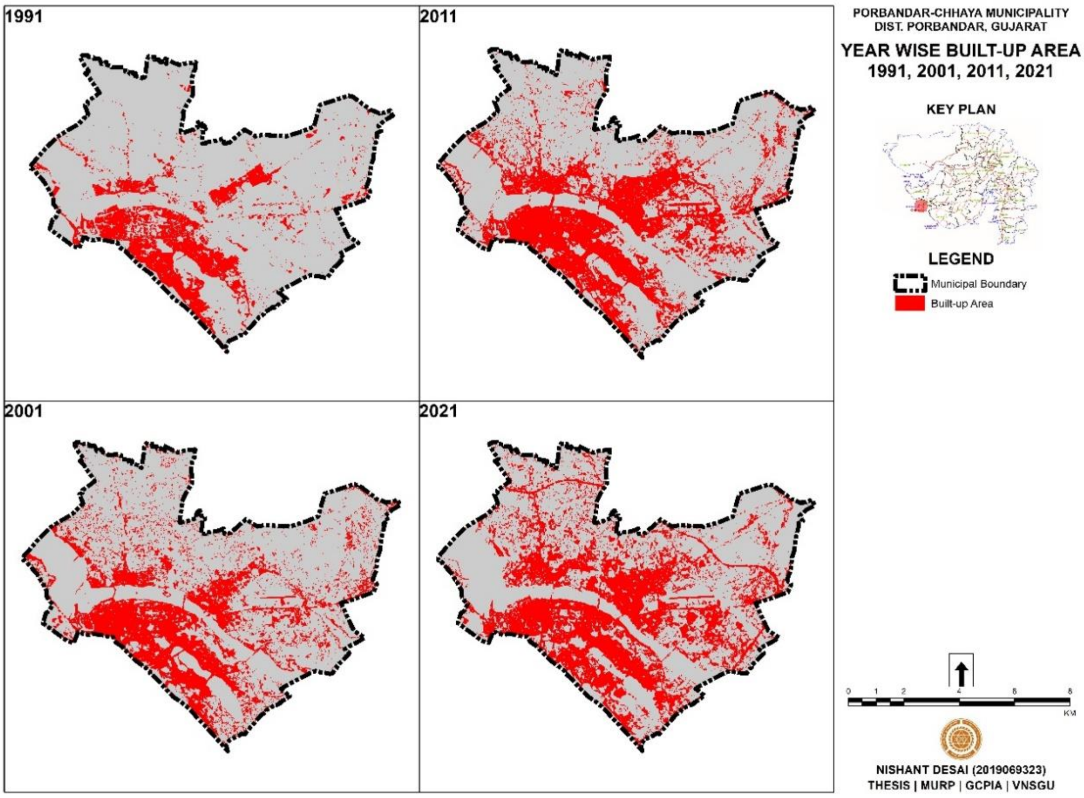



*Figure 5.15 Year wise built-up area*

The built-up area has increased from 16.71% of total land area (74.20 sq.km.) in 1991 to 35.71% in 2021. However, the growth rate during these three decades has not remained constant. Growth rate was observed to be continuously decreasing from 10.05% to 5.16% to 3.77% between 1991-2001, 2001-2011 and 2011-2021.

The emergence of land use/ land cover change knowledge, including developments in GIS and remote sensing, has provided a base to observe landscape changes throughout space and time. In urban environments, landscape transformations are mainly dominated by human activities and are greatly influenced by the spatial expansion of built-up area. The methods proposed by Aldwaik and Pontius for analysing the intensity of land change allows an understanding of the extent and growth rate of land change during several time intervals. Though, portraying the extent and growth rate of land changes is important, it is also important to inspect the explanatory variables, or the factors responsible for such changes. Such driving factors can help in the understanding of the spatiotemporal patterns of land use/land cover change.

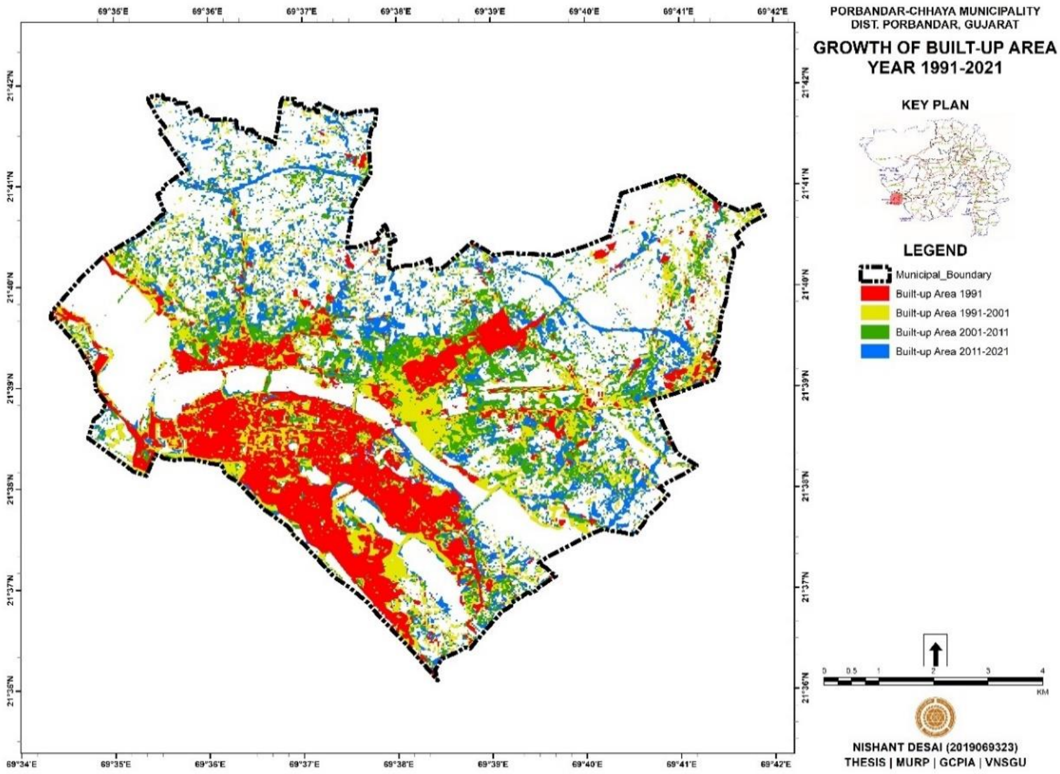



*Figure 5.16 Growth of Built-up Area in study area (1991-2021)*

Gradient analysis, a normally used idea in land use analysis, can be used to describe the spatiotemporal patterns of land use changes. Gradient, is defined as the variation in the values of a given variable, e.g., distance to the major road. Based on the knowledge of the study area, four important factors that are potentially driving the spatial pattern of Built-up Area in study area are identified. These are: the distance to major roads, distance to CBD, elevation level and spatial entity (village or municipality area). First, a multiple ring buffers around each driver variable was created within the study area boundary. Then, the magnitude and growth rate of built-up area was examined along the gradient of each variable during the three time-intervals (1991-2001, 2001-2011 and 20011-2021). Results and findings of these analysis is described in the following sections.

### 5.3.1 BUILT-UP AREA CHANGE ANALYSIS - SPATIAL ENTITY WISE

As mentioned earlier the study area, Porbandar-Chhaya Municipality, comprises of five spatial entities or administrative areas. They are Porbandar (M), Chhaya (M), Bokhira (OG), Khapat (CT) and Dharampur (V). Below map shows the boundary of each entity.

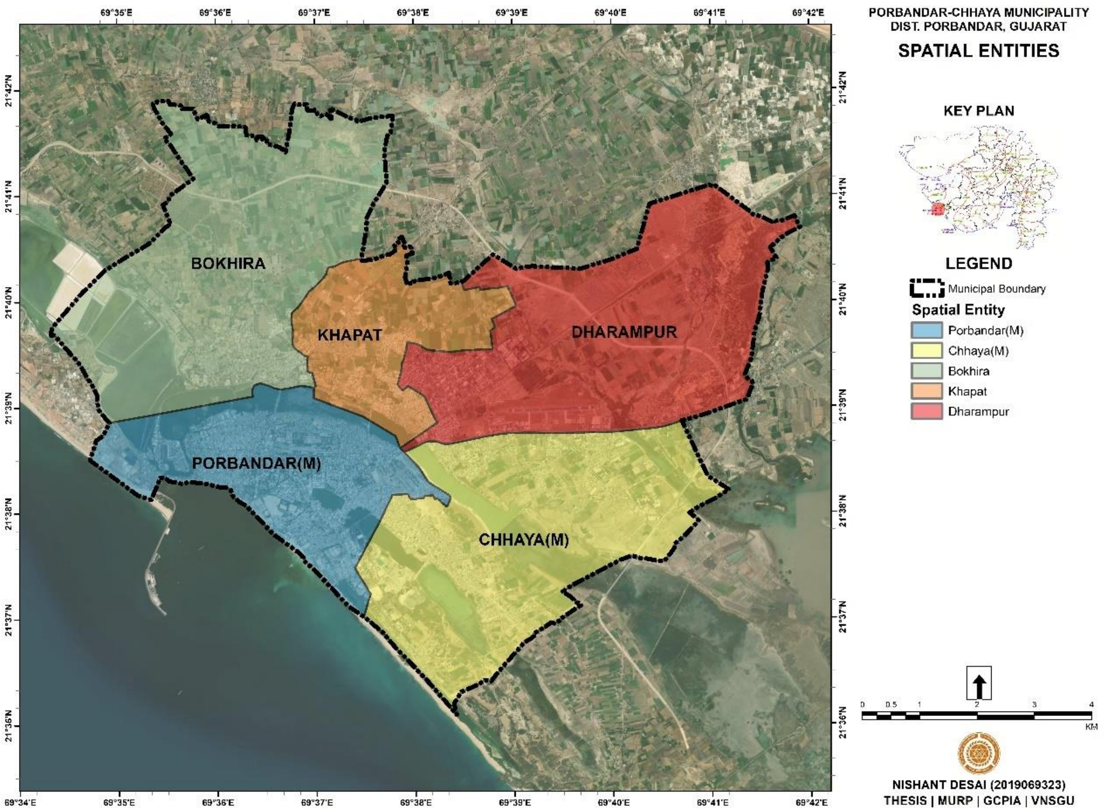



*Figure 5.17 Spatial entities within Porbandar-Chhaya Municipality*

| ENTITY | AREA (sq.km.) | POPULATION | | | POPULATION DENSITY 2011 (PPHa) |
|---|---|---|---|---|---|
| | | 1991 | 2001 | 2011 | |
| **PORBANDAR (M)** | 12.30 | 116671 | 133051 | 152760* | 50.75 |
| **CHHAYA (M)** | 18.80 | 26028 | 38526 | 47699 | 25.37 |
| **KHAPAT (CT)** | 6.90 | 4231 | 9088 | 16744 | 24.26 |
| **BOKHIRA (OG)** | 17.80 | 12391 | 15394 | -- | -- |
| **DHARAMPUR** | 18.40 | 2027 | 3924 | 7704 | 4.18 |
| **TOTAL** | **74.20** | **161348** | **199983** | **224907** | **30.31** |

*Table 5.11 Area and population of spatial entities within study area*

The magnitude and growth rate of built-up area within the boundary of each entity was analyzed between the year 1991-2021. The results are shown below.

| Spatial Entity | Built-up Area in 1991 | | Built-up Area in 2001 | | Built-up Area in 2011 | | Built-up Area in 2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) |
| **Porbandar** | 5.57 | 7.50 | 6.48 | 8.73 | 6.88 | 9.28 | 6.56 | 8.84 |
| **Chhaya** | 3.13 | 4.22 | 5.35 | 7.21 | 6.15 | 8.29 | 7.43 | 10.02 |
| **Bokhira** | 1.33 | 1.79 | 3.19 | 4.30 | 3.45 | 4.65 | 4.58 | 6.17 |
| **Khapat** | 0.48 | 0.65 | 1.43 | 1.93 | 1.88 | 2.53 | 2.68 | 3.61 |
| **Dharampur** | 1.89 | 2.55 | 3.41 | 4.60 | 5.33 | 7.18 | 5.24 | 7.06 |

*Table 5.12 Built-up Area within each spatial entity (1991-2021)*

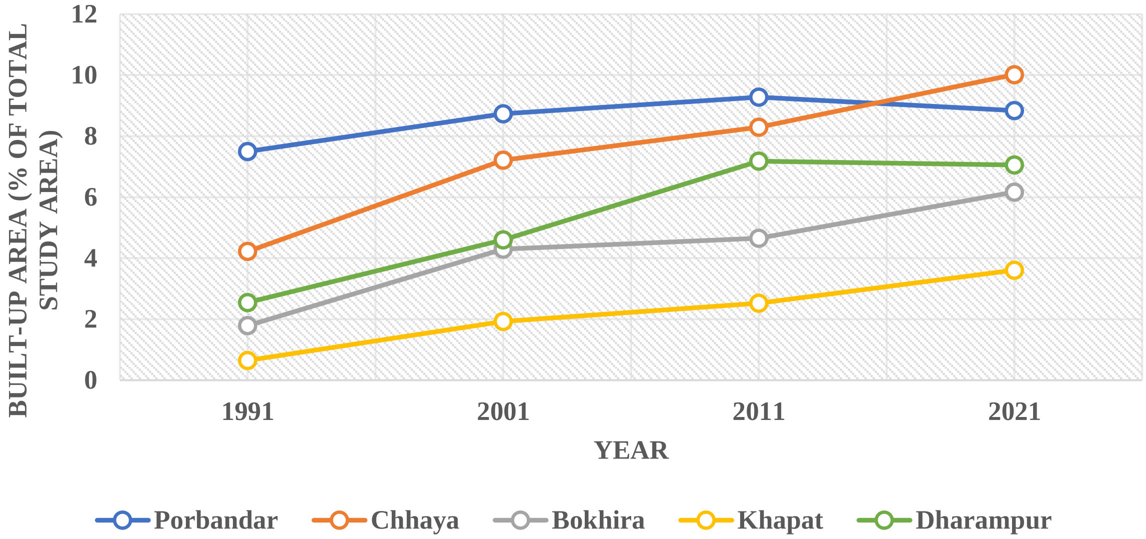



*Figure 5.18 Built-up Area within each spatial entity (1991-2021)*

| Spatial Entity | Change Rate (%) | | | |
|---|---|---|---|---|
| | 1991-2001 | 2001-2011 | 2011-2021 | Average |
| **Porbandar** | 1.23 | 0.55 | -0.44 | 0.45 |
| **Chhaya** | 2.99 | 1.08 | 1.73 | 1.93 |
| **Bokhira** | 2.51 | 0.35 | 1.52 | 1.46 |
| **Khapat** | 1.28 | 0.60 | 1.08 | 0.99 |
| **Dharampur** | 2.05 | 2.58 | -0.12 | 1.50 |

*Table 5.13 Change rate (%) of built-up area within each spatial entity (1991-2021)*

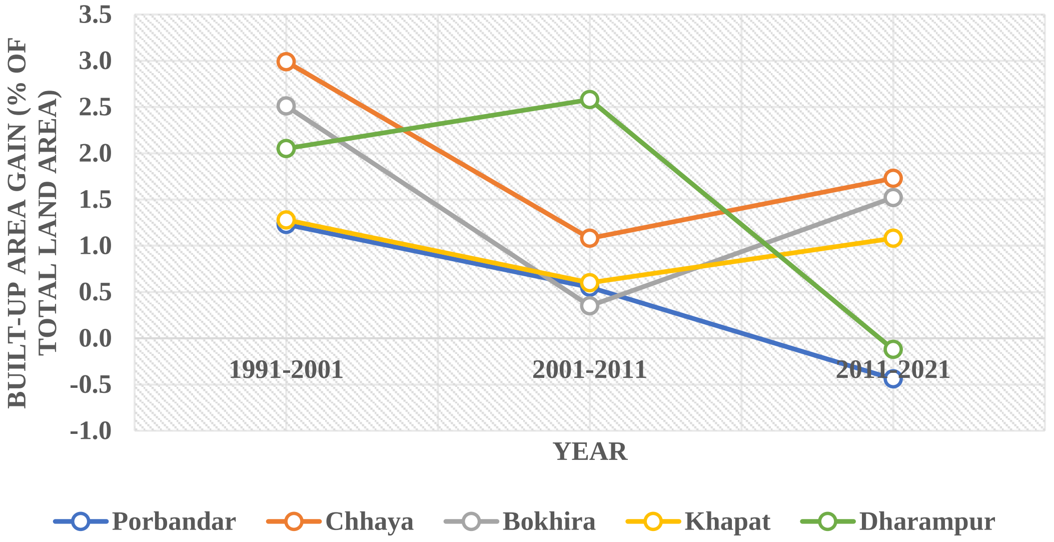



*Figure 5.19 Change rate (%) of built-up area within each spatial entity (1991-2021)*

### 5.3.2 BUILT-UP AREA CHANGE ANALYSIS – DISTANCE FROM MAJOR ROADS

Based upon data of road map and understanding of study area, major roads within the study area are identified. Road buffers were made at the interval of 500m (on both sides), resulting in 5 buffer areas viz. 0-500 mt, 500-1000 mt, 1000-1500 mt, 1500-2000 mt and 2000-2500 mt. Road network and buffers from major roads are shown in map below.

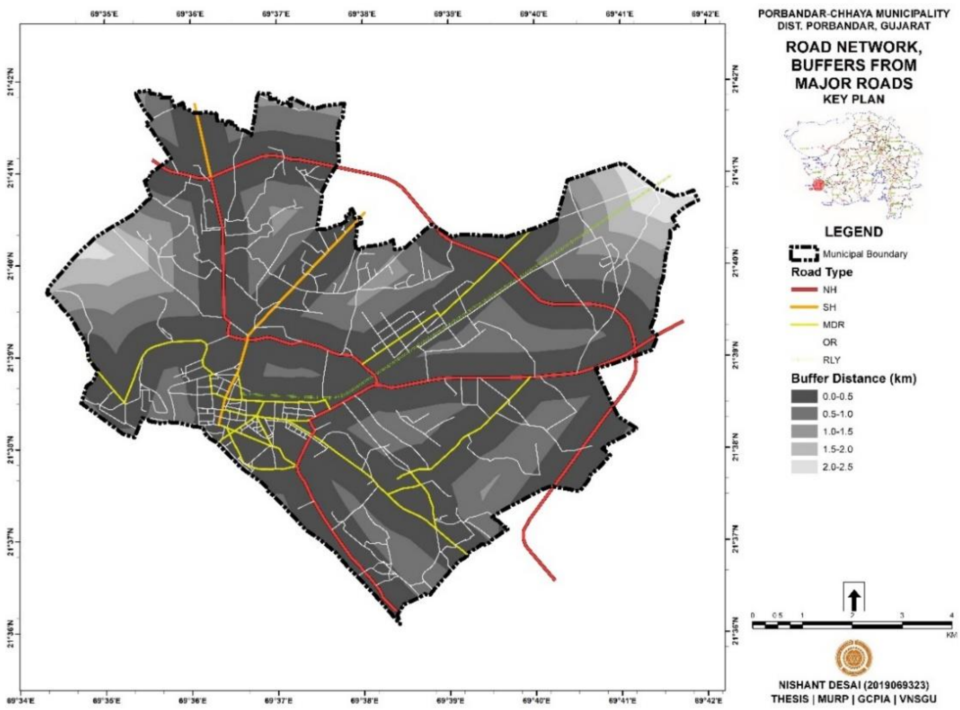



*Figure 5.20 Road network and buffers from major roads*

The magnitude and growth rate of built-up area within each buffer area was analyzed between the year 1991-2021. The results are shown below.

| Road Buffer (km) | Built-up Area in 1991 | | Built-up Area in 2001 | | Built-up Area in 2011 | | Built-up Area in 2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) |
| **0-0.5** | 10.77 | 14.51 | 15.33 | 20.66 | 18.74 | 25.27 | 20.51 | 27.64 |
| **0.5-1.0** | 1.31 | 1.77 | 3.38 | 4.56 | 3.80 | 5.12 | 5.09 | 6.86 |
| **1.0-1.5** | 0.17 | 0.23 | 0.60 | 0.81 | 0.56 | 0.75 | 0.62 | 0.84 |
| **1.5-2.0** | 0.11 | 0.15 | 0.37 | 0.50 | 0.41 | 0.55 | 0.17 | 0.23 |
| **2.0-2.5** | 0.04 | 0.05 | 0.18 | 0.24 | 0.18 | 0.24 | 0.10 | 0.13 |

*Table 5.14 Built-up Area within each buffer from major road (1991-2021)*

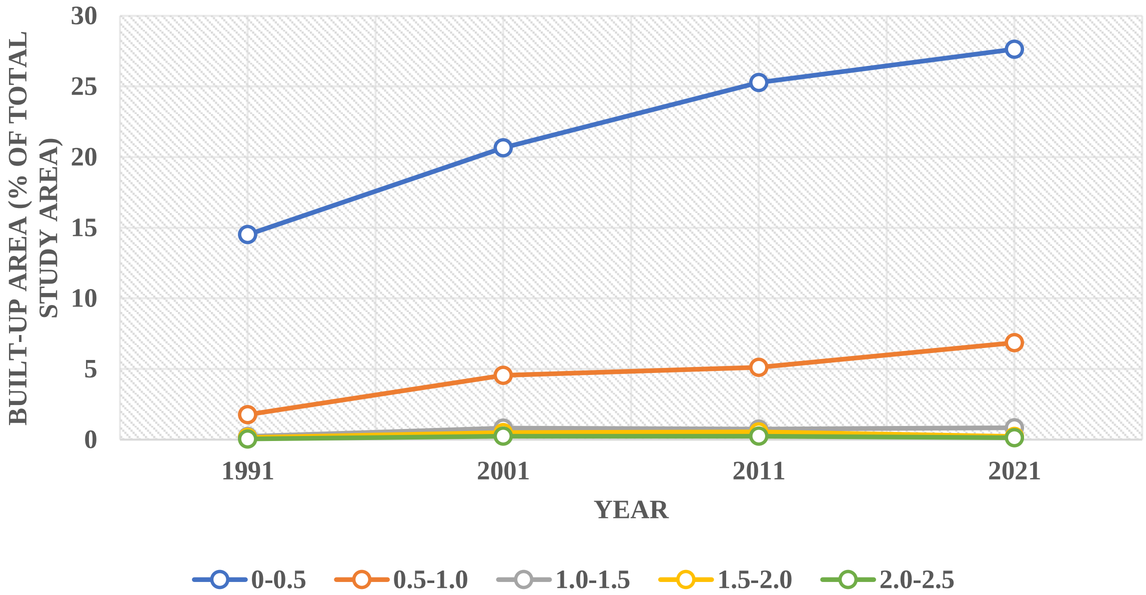



*Figure 5.21 Built-up Area within each buffer from major road (1991-2021)*

| Road Buffer (km) | Change Rate (%) | | | |
|---|---|---|---|---|
| | 1991-2001 | 2001-2011 | 2011-2021 | Average |
| **0-0.5** | 6.15 | 4.61 | 2.37 | 4.38 |
| **0.5-1.0** | 2.79 | 0.56 | 1.74 | 1.70 |
| **1.0-1.5** | 0.58 | -0.06 | 0.09 | 0.20 |
| **1.5-2.0** | 0.35 | 0.05 | -0.32 | 0.03 |
| **2.0-2.5** | 0.19 | 0.00 | -0.11 | 0.03 |

*Table 5.15 Change rate (%) of built-up area within each road buffer (1991-2021)*

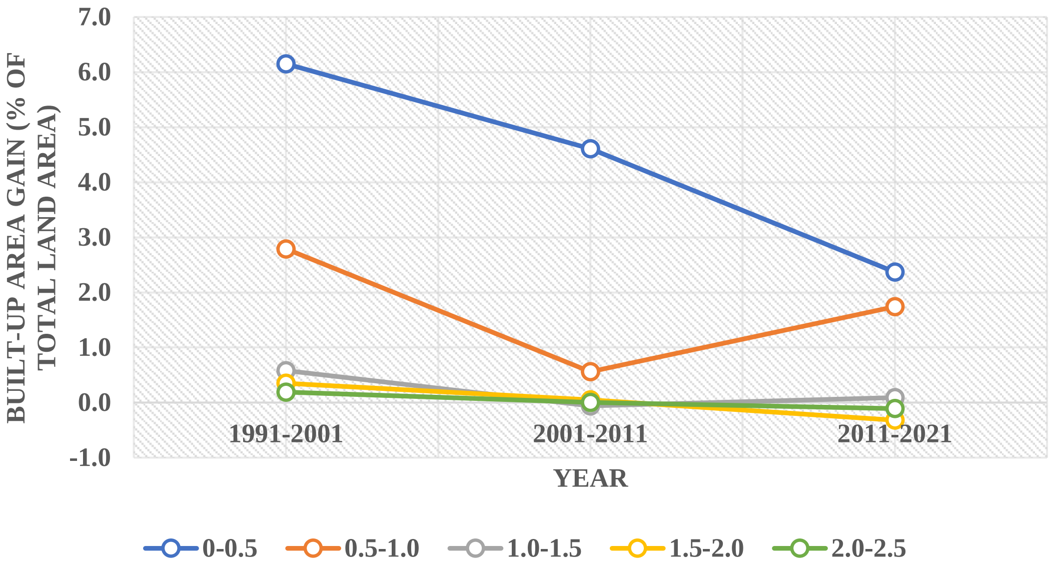



*Figure 5.22 Change rate (%) of built-up area within each road buffer (1991-2021)*

### 5.3.3 BUILT-UP AREA CHANGE ANALYSIS – DISTANCE FROM CBD

Based upon the data of evolution of the study area, CBD area was identified. Buffers from CBD were made at the interval of 2.0 km, resulting in 5 buffer areas viz. CBD, 0.0-2.0 km, 2.0-4.0 km, 4.0-6.0 km and 6.0-8.0 km. CBD area and buffers from it are shown in map below.

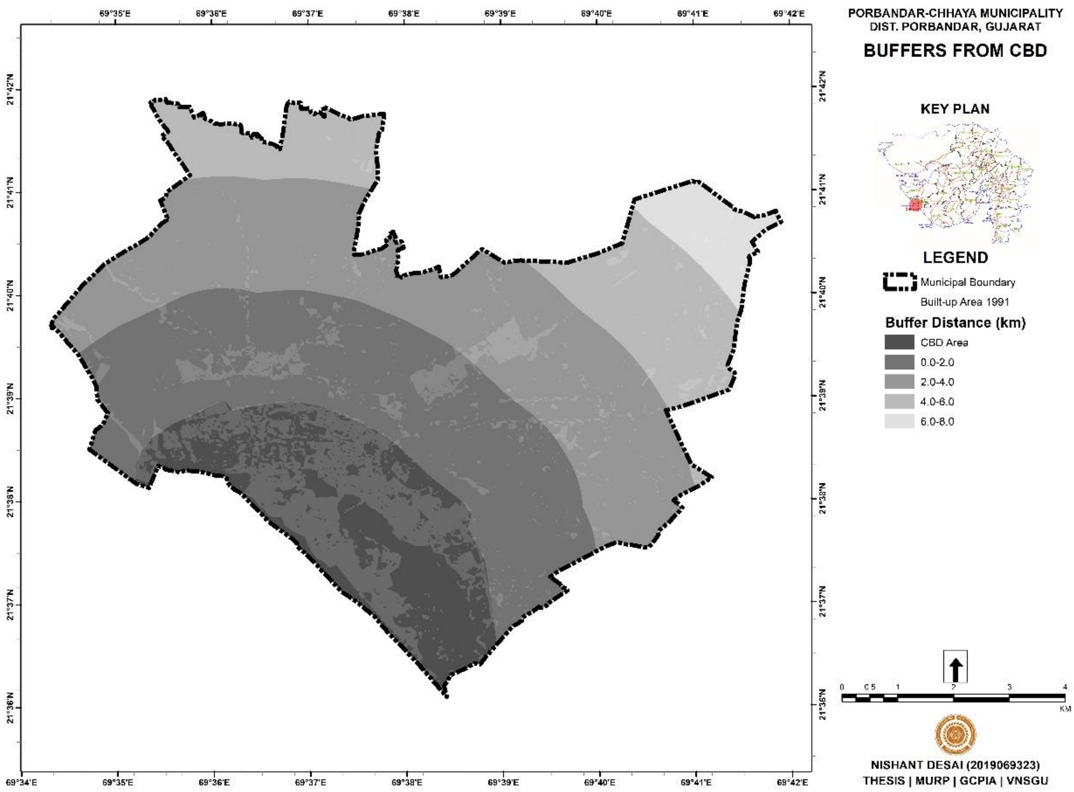



*Figure 5.23 CBD area and buffers from CBD*

The magnitude and growth rate of built-up area within CBD and each buffer area was analyzed between the year 1991-2021. The results are shown below.

| Distance to CBD (km) | Built-up Area in 1991 | | Built-up Area in 2001 | | Built-up Area in 2011 | | Built-up Area in 2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) |
| **CBD** | 8.05 | 10.86 | 9.17 | 12.37 | 9.63 | 12.98 | 9.45 | 12.73 |
| **0.0-2.0** | 2.54 | 3.42 | 5.88 | 7.92 | 7.86 | 10.59 | 8.82 | 11.89 |
| **2.0-4.0** | 1.3 | 1.75 | 3.36 | 4.53 | 4.78 | 6.44 | 6.10 | 8.22 |
| **4.0-6.0** | 0.44 | 0.59 | 1.12 | 1.51 | 1.05 | 1.42 | 1.93 | 2.60 |
| **6.0-8.0** | 0.07 | 0.09 | 0.33 | 0.44 | 0.37 | 0.50 | 0.19 | 0.26 |

*Table 5.16 Built-up Area within CBD and each buffer area (1991-2021)*

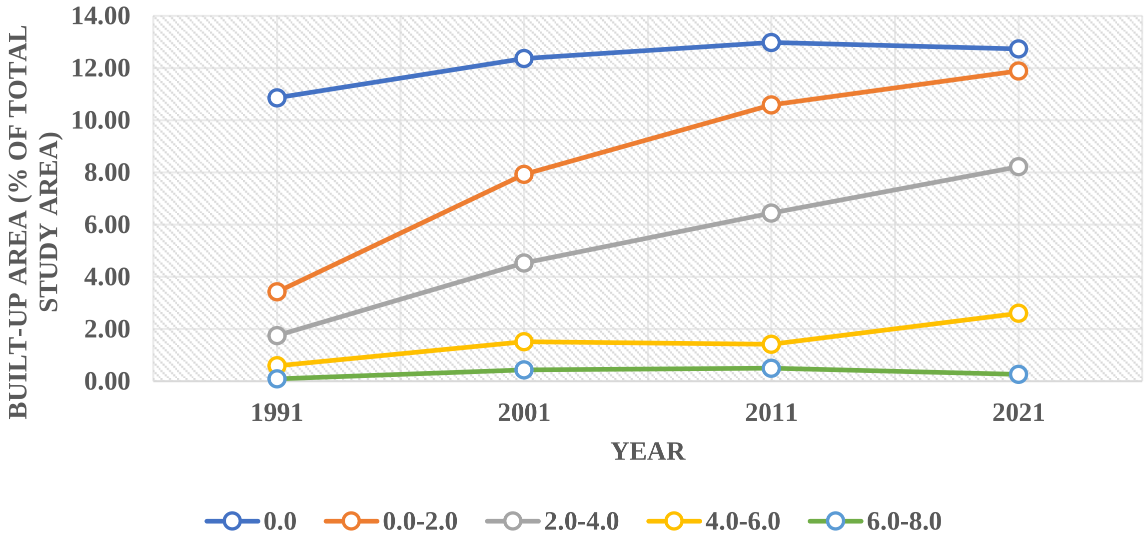



*Figure 5.24 Built-up Area within CBD and each buffer area (1991-2021)*

| Distance to CBD (km) | Change Rate (%) | | | |
|---|---|---|---|---|
| | 1991-2001 | 2001-2011 | 2011-2021 | Average |
| **CBD** | 1.51 | 0.61 | -0.25 | 0.62 |
| **0.0-2.0** | 4.50 | 2.67 | 1.30 | 2.82 |
| **2.0-4.0** | 2.78 | 1.91 | 1.78 | 2.16 |
| **4.0-6.0** | 0.92 | -0.09 | 1.18 | 0.67 |
| **6.0-8.0** | 0.35 | 0.06 | -0.24 | 0.06 |

*Table 5.17 Change rate (%) of built-up area within CBD and each buffer (1991-2021)*

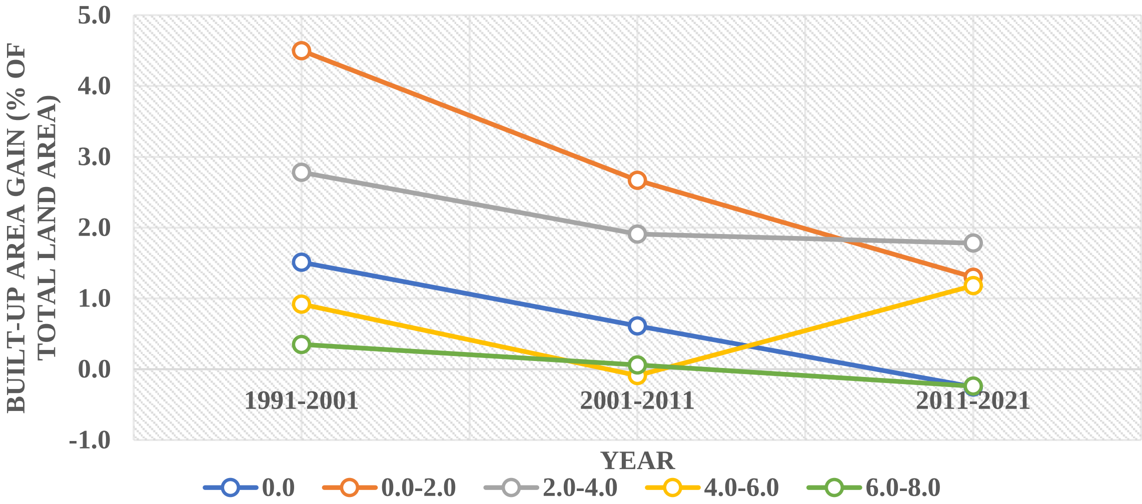



*Table 5.18 Change rate (%) of built-up area within CBD and each buffer (1991-2021)*

### 5.3.4 BUILT-UP AREA CHANGE ANALYSIS – ELEVATION

Using the DEM for the study area, highest and lowest elevation points were identified, which are to be 25.07 mt and -0.65 mt respectively. The total difference of elevation level is then divided in to five equal ranges, resulting in 5 different elevation ranges viz. -0.65-4.50 mt, 4.50-9.64 mt, 9.64-14.78 mt, 14.78-19.93 mt and 19.93-25.07mt. These are shown in map below.

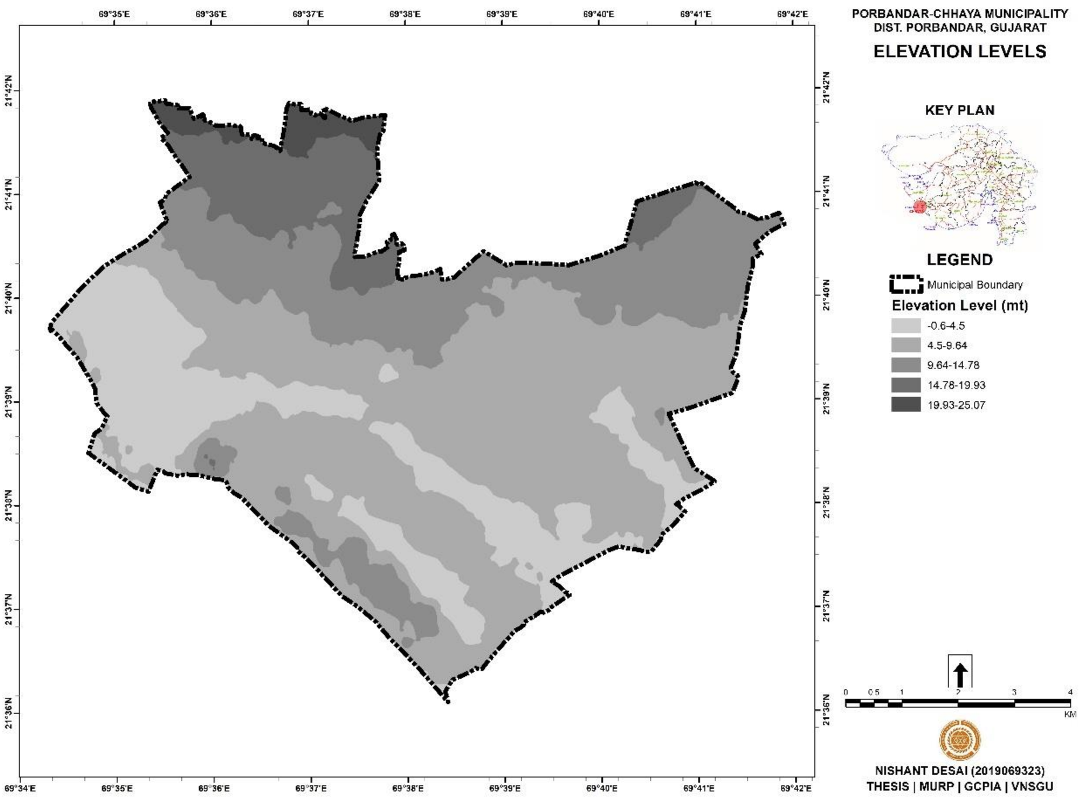



*Figure 5.25 Elevation ranges within study area*

The magnitude and growth rate of built-up area within these elevation range areas were analyzed between the year 1991-2021. The results are shown below.

| Elevation (mt) | Built-up Area in 1991 | | Built-up Area in 2001 | | Built-up Area in 2011 | | Built-up Area in 2021 | |
|---|---|---|---|---|---|---|---|---|
| | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) | Area (sq.km.) | Area (%) |
| **-0.65-4.50** | 1.65 | 2.22 | 3.01 | 4.06 | 2.82 | 3.80 | 2.89 | 3.89 |
| **4.50-9.64** | 8.66 | 11.68 | 12.98 | 17.50 | 17.06 | 23.00 | 17.70 | 23.85 |
| **9.64-14.78** | 1.94 | 2.61 | 3.20 | 4.31 | 3.26 | 4.39 | 4.48 | 6.04 |
| **14.78-19.93** | 0.14 | 0.19 | 0.53 | 0.71 | 0.49 | 0.66 | 1.20 | 1.62 |
| **19.93-25.07** | 0.01 | 0.01 | 0.14 | 0.19 | 0.06 | 0.08 | 0.22 | 0.30 |

*Table 5.19 Built-up Area within each elevation range (1991-2021)*

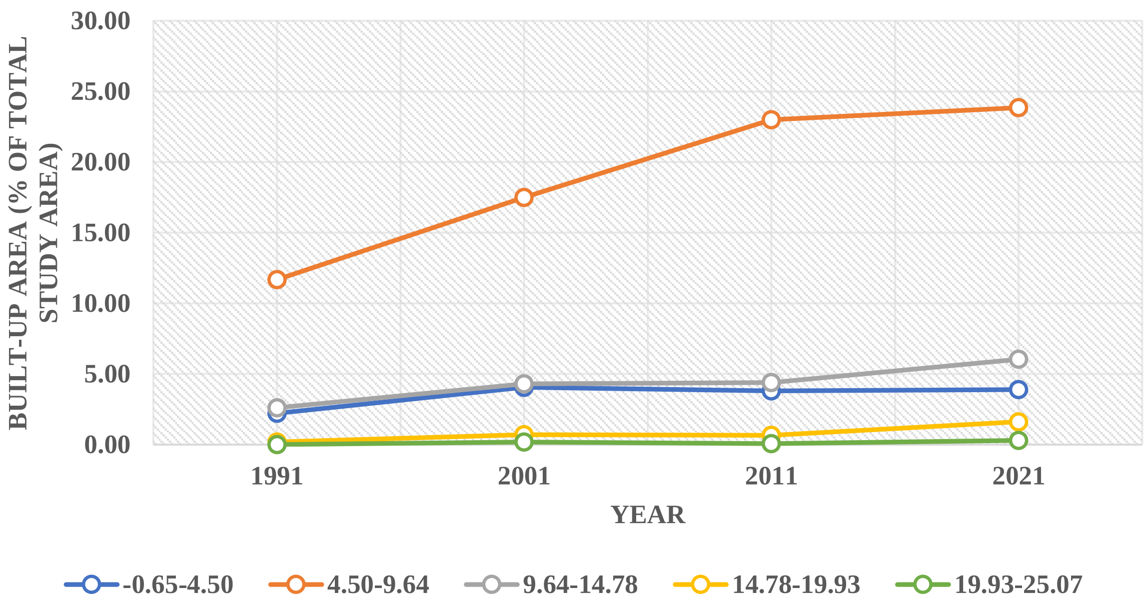



*Figure 5.26 Built-up Area within each elevation range (1991-2021)*

| Elevation (mt) | Change Rate (%) | | | |
|---|---|---|---|---|
| | 1991-2001 | 2001-2011 | 2011-2021 | Average |
| **-0.65-4.50** | 1.84 | -0.26 | 0.09 | 0.56 |
| **4.50-9.64** | 5.82 | 5.50 | 0.85 | 4.06 |
| **9.64-14.78** | 1.70 | 0.08 | 1.65 | 1.14 |
| **14.78-19.93** | 0.52 | -0.05 | 0.96 | 0.48 |
| **19.93-25.07** | 0.18 | -0.11 | 0.22 | 0.10 |

*Table 5.20 Change rate (%) of built-up area within each elevation range (1991-2021)*

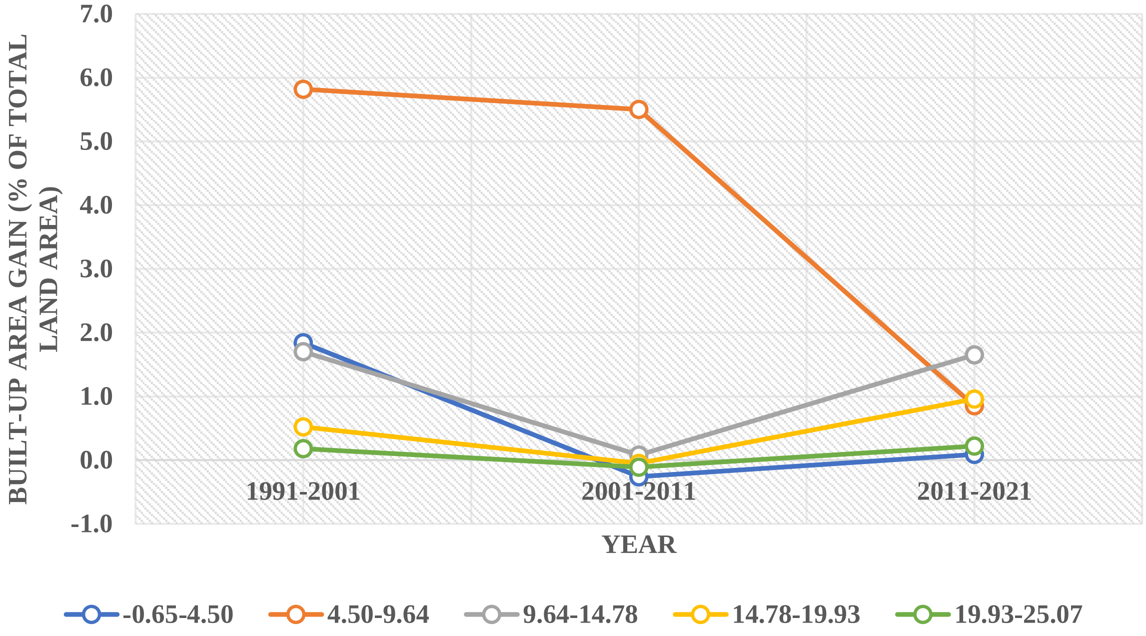



*Figure 5.27 Change rate (%) of built-up area within each elevation range (1991-2021)*

### 5.3.5 SUMMARY

Spatial distribution of Built-up Area along the gradients of the variables (i) spatial entity, (ii) Distance from major roads, (iii) Distance from CBD, (iv) Elevation level; was quantified in previous sections.

The results show that till 2011 Porbandar covered largest percentage share of built-up area. But, by 2021, Chhaya has the largest percentage share of built-up area (10.02%), followed by Porbandar (8.84%), Dharampur (7.06%), Bokhira (6.17%) and Khapat (3.61%). Although, Porbandar has remained major area for built-up percentage, the change rate within it is lowest amongst all spatial entities (average 0.45%). Chhaya has highest average built-up area change rate (1.93%), followed by Dharampur (1.50%), Bokhira (1.46%) and Khapat (0.99%). This observation suggest that Porbandar has very small amount of land available for expansion and is almost saturated. As a result, the future expansion of built-up area will take place in remaining spatial entities.

Throughout the time period (1991-2021) maximum percent of built-up area is observed at distance of 0.0-0.5 km from major roads, followed by the buffer area of 0.5-1.0 km. This is same for change rate, as average 4.38%of change rate is observed in 0.0-0.5 km area followed by 0.5-1.0 km (1.70%), 1.0-1.5 km (0.20%), 1.5-2.0 km (0.03%) and 2.0-2.5 km (0.03%). As expected, built-up area growth follows the major roads.

Maximum percent of built-up area is observed within CBD area (12.73%) followed by 0.0-2.0 km buffer area (11.89%), 2.0-4.0 km (8.22%), 4.0-6.0 km (2.60%) and 6.0-8.0 km (0.26%). However, average growth rate is highest within 0.0-2.0 km area (2.82%) followed by 2.0-4.0 km (2.16%), 4.0-6.0 km (0.67%), CBD area (0.62%) and 6.0-8.0 km (0.06%). Built-up area growth within CBD is less compared to 0.0-6.0 km area and expected to be even lesser in the future. As expected, built-up area growth is higher near CBD and reduces as we move away from CBD.

Maximum percent of built-up area is observed within the elevation range of 4.50-9.64 mt (23.85%), followed by 9.64-14.78 mt (6.04%). -0.65-4.50 mt (3.89%), 14.78-9.93 mt (1.62%) and 1993-25.07 mt (0.30%). This pattern is followed in terms of change rate. Elevation range of 4.50-9.64 mt showed the change rate of 4.06%, followed by 9.64-14.78 mt (1.14%). -0.65-4.50 mt (0.56%), 14.78-9.93 mt (0.48%) and 1993-25.07 mt (0.10%). It is also observed that the elevation gradient follows the distance from CBD gradient and that distance to CBD could have greater impact on these results than that of elevation level.

While predicting the LULC map for year 2031 these variable maps will be used and will be taken in to consideration.

# CHAPTER:6 LAND COVER PREDICTION

Land cover prediction was done using Cellular Automata and Artificial Neural Network based MOLUSCE plugin in QGIS. Details of the process and results are discussed in following section.

## 6.1 LAND COVER PREDICTION USING MOLUSCE

### 6.1.1 INPUT DATA

The prediction model uses already prepared land cover maps (year 1991, 2001, 2011 & 2021), four variable maps (spatial entity, distance to major roads, distance to CBD & elevation) and map defining areas where "No land cover change" should take place. The areas like airport, existing water bodies, lands owned by navy, area under CRZ regulations etc. are defined as "No land cover change" areas.

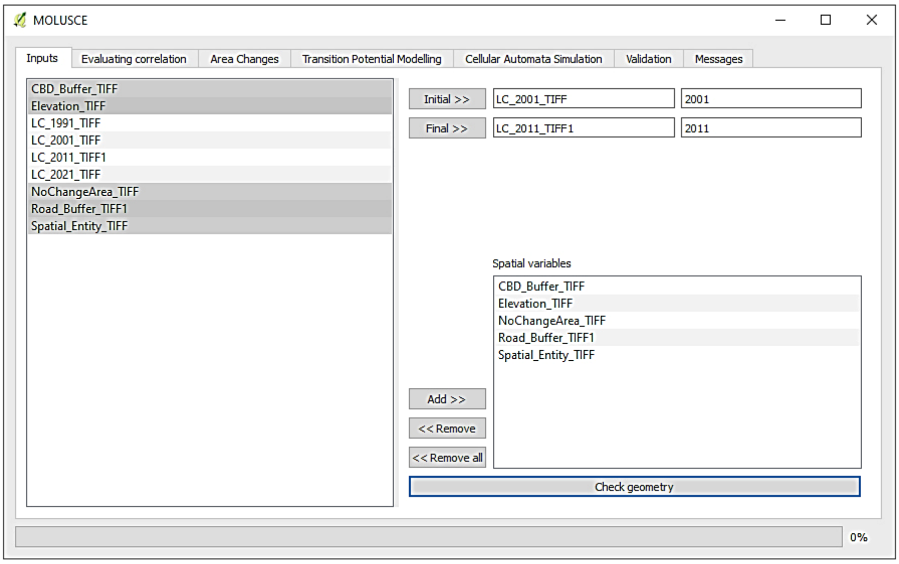



*Figure 6.1 Input data for land cover prediction*

### 6.1.2 CORRELATION ASSESSMENT

Strength of the connections between variables are calculated to measure the dependence of the input variables. Pearson's correlation coefficient can be calculated for continuous values. For nominal values Cramer coefficient can be calculated. As input data are in continuous Geotiff format, Pearson's correlation coefficient was calculated in the study.

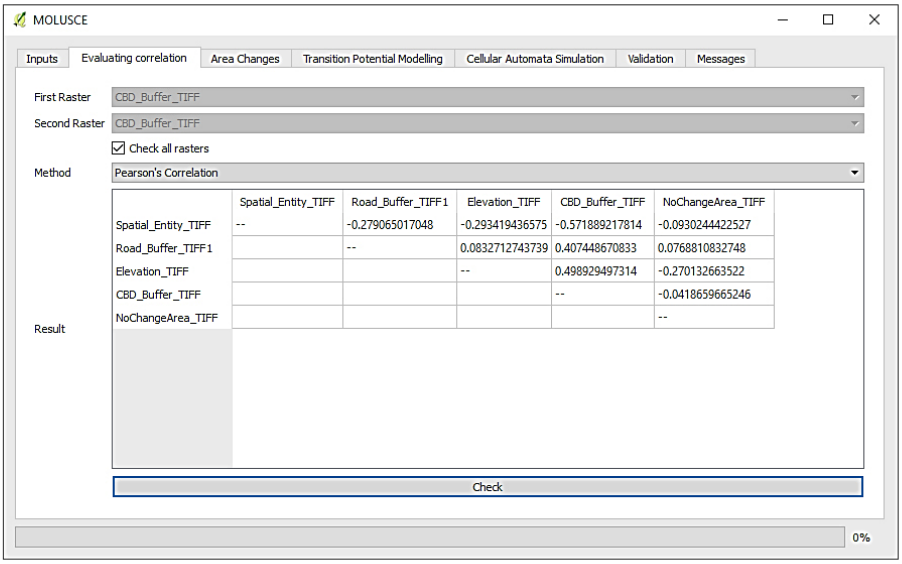



*Figure 6.2 Correlation assessment*

### 6.1.3 TRANSITION PROBABILITY MATRIX

Probability of each land cover class changing to another is described by transition probability matrix. This matrix is produced by the multiplication of each column in the transition probability matrix by the number of cells of corresponding land use in the later image. In the 4 by 4 matrix table presented below, rows represent the previous land cover categories during the time (t1), white the column represents the later land cover categories (t2). For example, the row represents actual LULC classes of the year 2001 while the column represents the simulate year 2011 LULC categories.

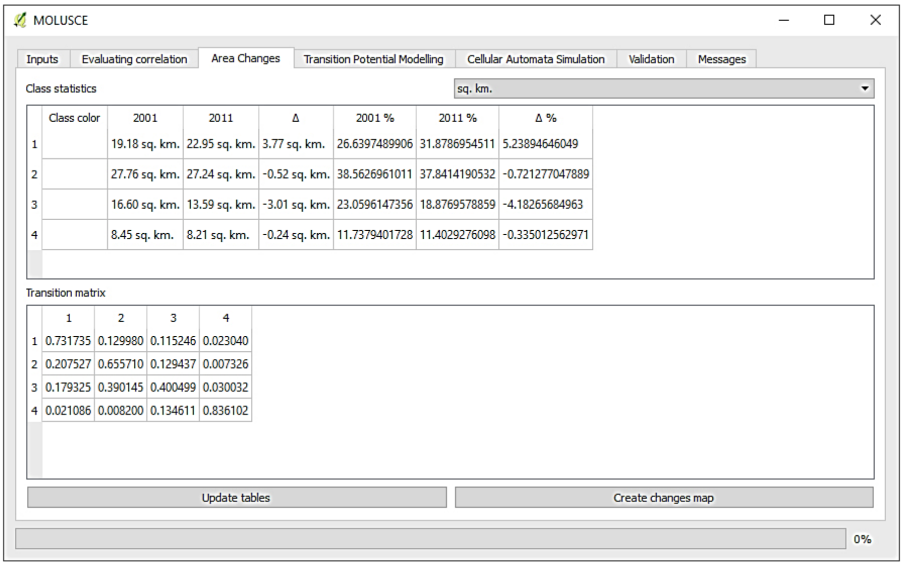



*Figure 6.3 Generating Transition probability matrix*

| LULC Class | Built-up Area | Vegetation | Waterbody | Barren Land |
|---|---|---|---|---|
| **Built-up Area** | 0.731735 | 0.12998 | 0.115246 | 0.02304 |
| **Vegetation** | 0.207527 | 0.65571 | 0.129437 | 0.007326 |
| **Waterbody** | 0.179325 | 0.390145 | 0.400499 | 0.030032 |
| **Barren Land** | 0.021086 | 0.0082 | 0.134611 | 0.836102 |

*Table 6.1 Transition probability matrix*

### 6.1.4 TRAINING THE MODEL

In order to assess the significance of the factors, considering the change map and transition probability matrix, model training needs to be done. The extension provides options of the following models:

- Artificial Neural networks (ANN)
- Logistic regression
- Weights of Evidence method
- A multi-criteria assessment method

All methods are widely known and are actively used in GIS. For this study ANN was used. As a result of tuning the model, each factor receives one or another weight, depending on its contribution, the probability of changes occurring. Weight can be either positive (a close relationship between a factor and the possibility of changes occurring) or negative (feedback - if a factor is present, then changes are unlikely). Depending upon the selected method, the plugin provides various customizations. For ANN, numbers of samples and iterations can be specified by the user.

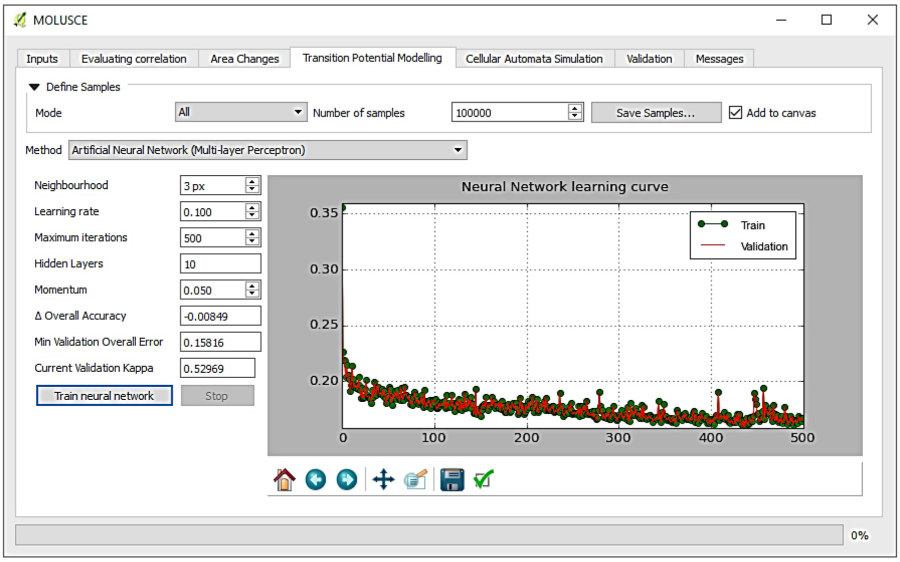



*Figure 6.4 Model training using ANN*

### 6.1.5 PREDICTION AND VALIDATION (YEAR 2021)

Following the above steps land cover map for year 2021 was predicted. The predicted map was then compared with the observed land cover map for year 2021, to validate the accuracy of prediction model. The predicted map was found to be 82.60% accurate with overall Kappa of 75.74%.


*Figure 6.5 Validation of Predicted land cover map for year 2021*

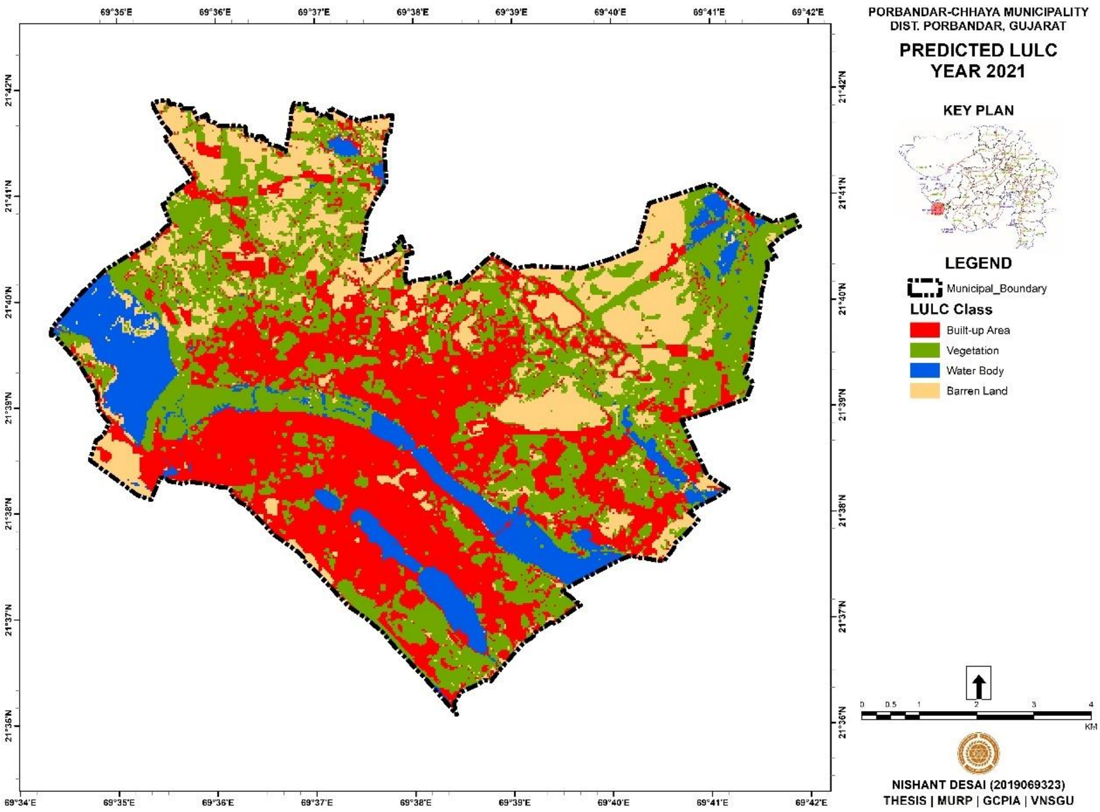



*Figure 6.6 Predicted Land cover map of the study area for year 2021*

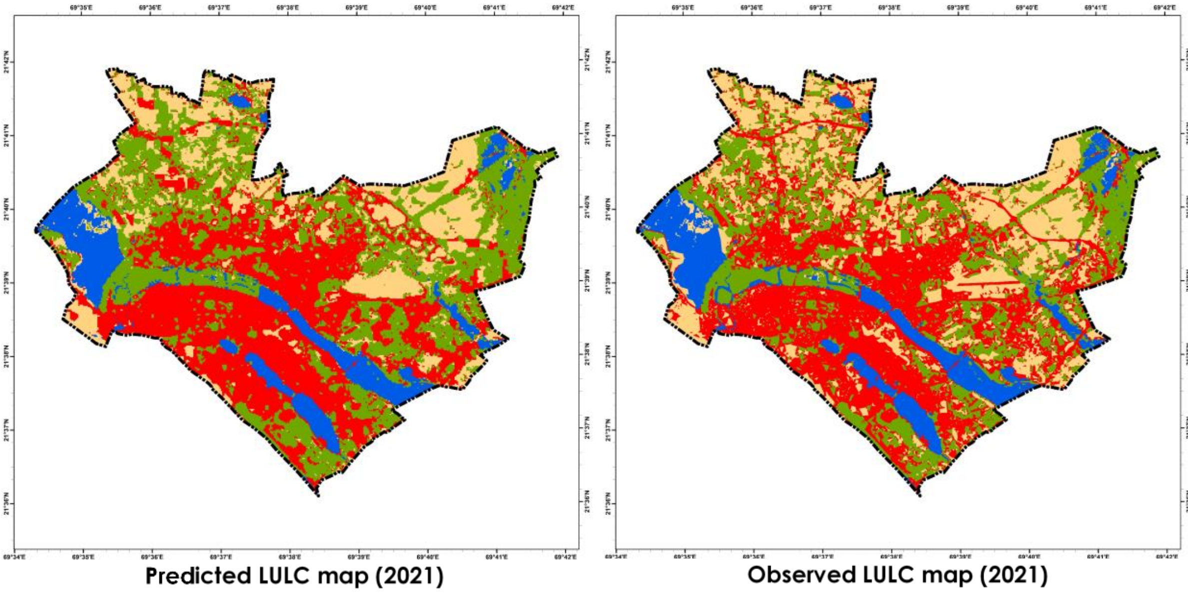



*Figure 6.7 Predicted vs Observed Land cover map of the study area for year 2021*

## 6.2 LAND COVER PREDICTION FOR THE YEAR 2031

As the predicted map for year 2021 was found to be fairly accurate, the trained model was used to predict the future land cover for the year 2031, which is discussed in following sections.

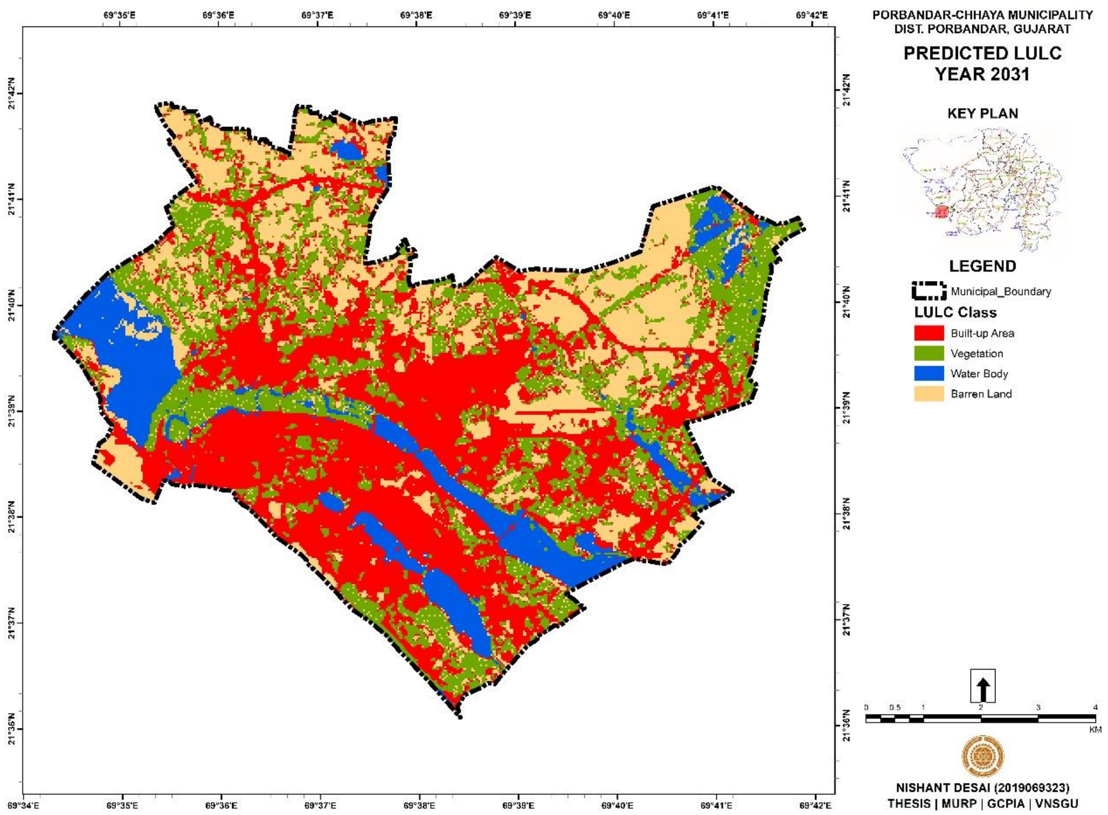



*Figure 6.8 Predicted Land cover map of the study area for year 2031*

Areas covered by each class derived from predicted land cover map (2031) are mentioned in Table 6.4. The data shows that area of Built-up is higher than any other class, covering 28.97 sq.km. (39.04%). Followed by Vegetation 18.68 sq.km. (25.18%). Barren land occupies 18.47 sq.km. (24.89%). Lastly Waterbody covers 8.08 sq.km. (10.89%).

| LAND COVER CLASS | AREA IN SQ.KM | PERCENTAGE (%) |
|---|---|---|
| **Built-up Aera** | 28.97 | 39.04 |
| **Vegetation** | 18.68 | 25.18 |
| **Water Body** | 8.08 | 10.89 |
| **Barren Land** | 18.47 | 24.89 |
| **Total** | **74.20** | **100.00** |

*Table 6.2 Predicted Land cover classification (Year 2031)*

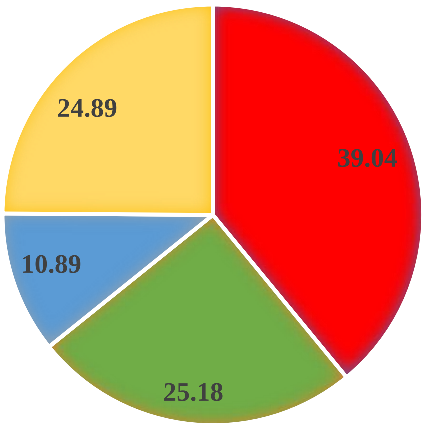



*Figure 6.9 Predicted Percentage of land cover classification (Year 2031)*

| | Area (sq.km.) | | | | | Area (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Land Cover class** | **1991** | **2001** | **2011** | **2021** | **2031 (Predicted)** | **1991** | **2001** | **2011** | **2021** | **2031 (Predicted)** |
| **Built-up** | 12.40 | 19.86 | 23.69 | 26.49 | 28.97 | 16.71 | 26.76 | 31.93 | 35.71 | 39.04 |
| **Vegetation** | 18.01 | 17.06 | 14.05 | 20.81 | 18.68 | 24.27 | 22.99 | 18.93 | 28.04 | 25.18 |
| **Waterbody** | 7.77 | 8.70 | 8.45 | 8.24 | 8.08 | 10.47 | 11.73 | 11.39 | 11.10 | 10.89 |
| **Barren Land** | 36.02 | 28.58 | 28.01 | 18.66 | 18.47 | 48.55 | 38.52 | 37.75 | 25.15 | 24.89 |
| **Total** | **74.20** | **74.20** | **74.20** | **74.20** | **74.20** | **100.00** | **100.00** | **100.00** | **100.00** | **100.00** |

*Table 6.3 Comparison of area of land cover classes (1991-2031)*

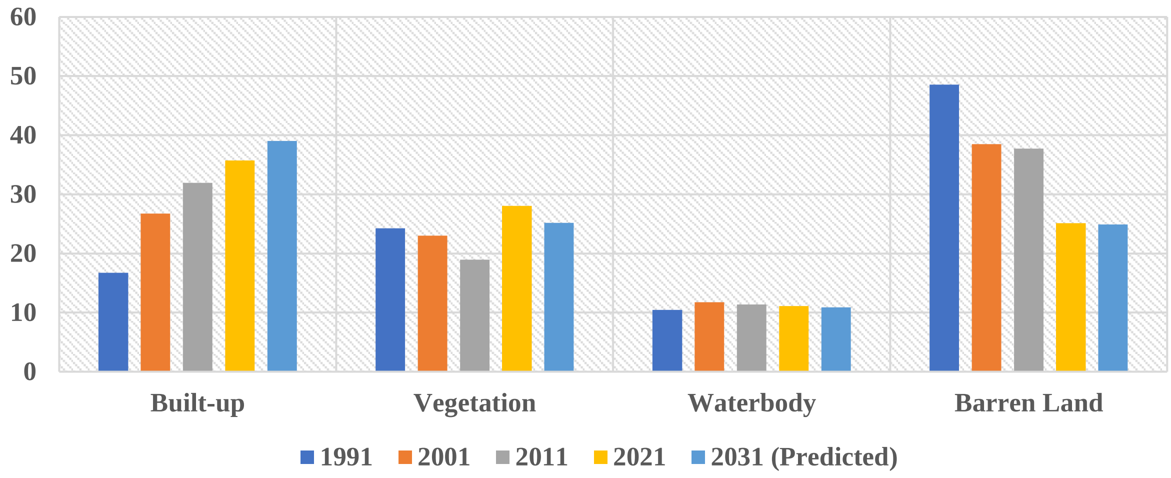



*Figure 6.10 Comparison of area of land cover classes (1991-2031)*

| Land Cover class | 1991-2001 | | 2001-2011 | | 2011-2021 | | 2021-2031 (Predicted) | | Average Decadal Change | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) | Area (sq.km.) | Change Rate (%) |
| **Built-up** | 7.46 | 10.05 | 3.83 | 5.16 | 2.80 | 3.77 | 2.48 | 3.34 | 4.14 | 5.58 |
| **Vegetation** | -0.95 | -1.28 | -3.01 | -4.06 | 6.76 | 9.11 | -2.13 | -2.87 | 0.17 | 0.23 |
| **Waterbody** | 0.93 | 1.25 | -0.25 | -0.34 | -0.21 | -0.28 | -0.16 | -0.22 | 0.08 | 0.10 |
| **Barren Land** | -7.44 | -10.03 | -0.57 | -0.77 | -9.35 | -12.60 | -0.19 | -0.26 | -4.39 | -5.91 |

*Table 6.4 Magnitude and Change Rate in different land cover classes*

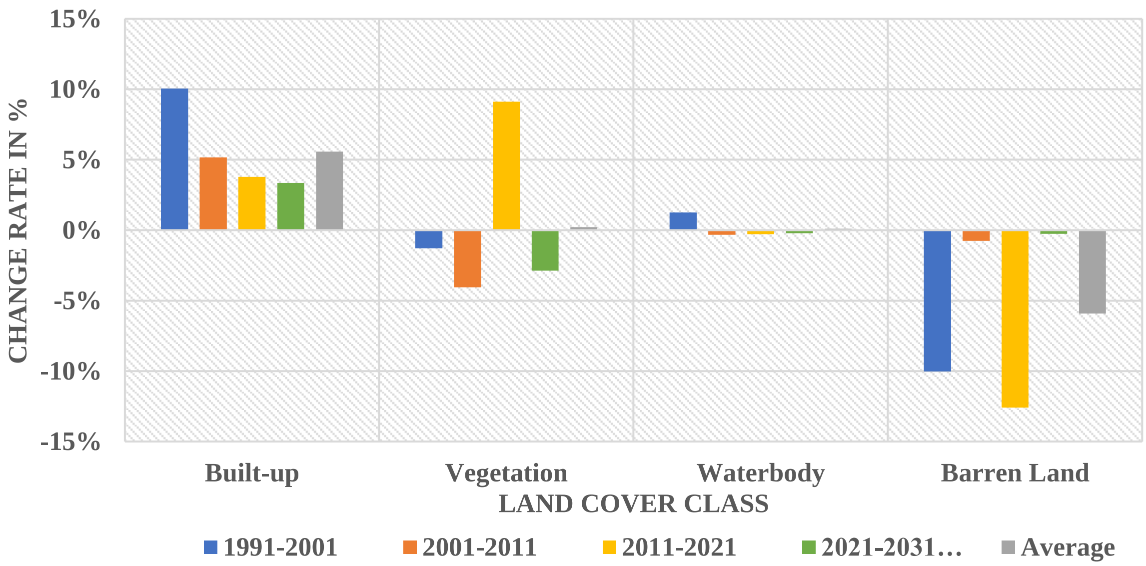



*Figure 6.11 Change rate in different land cover classes*

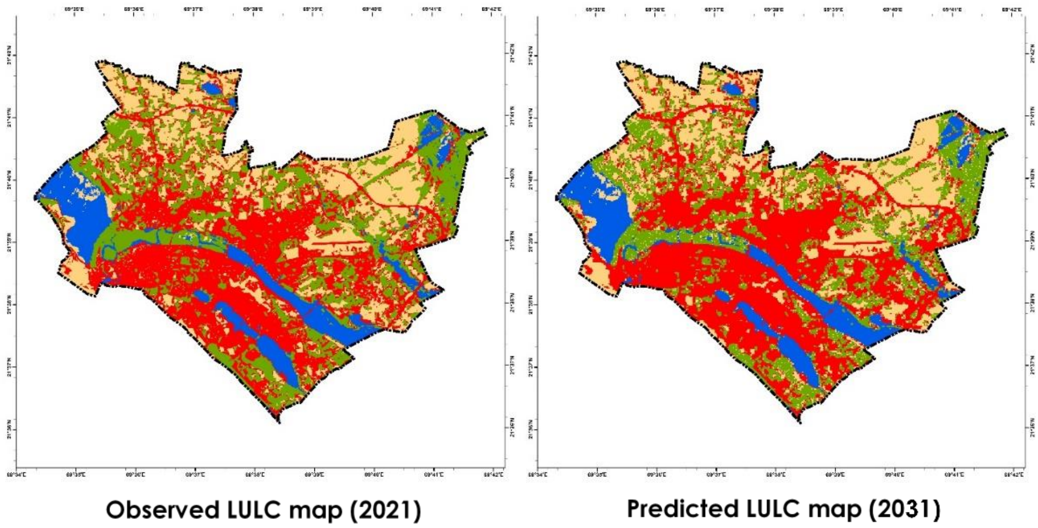



*Figure 6.12 Observed LULC (2021) vs Predicted LULC (2031)*

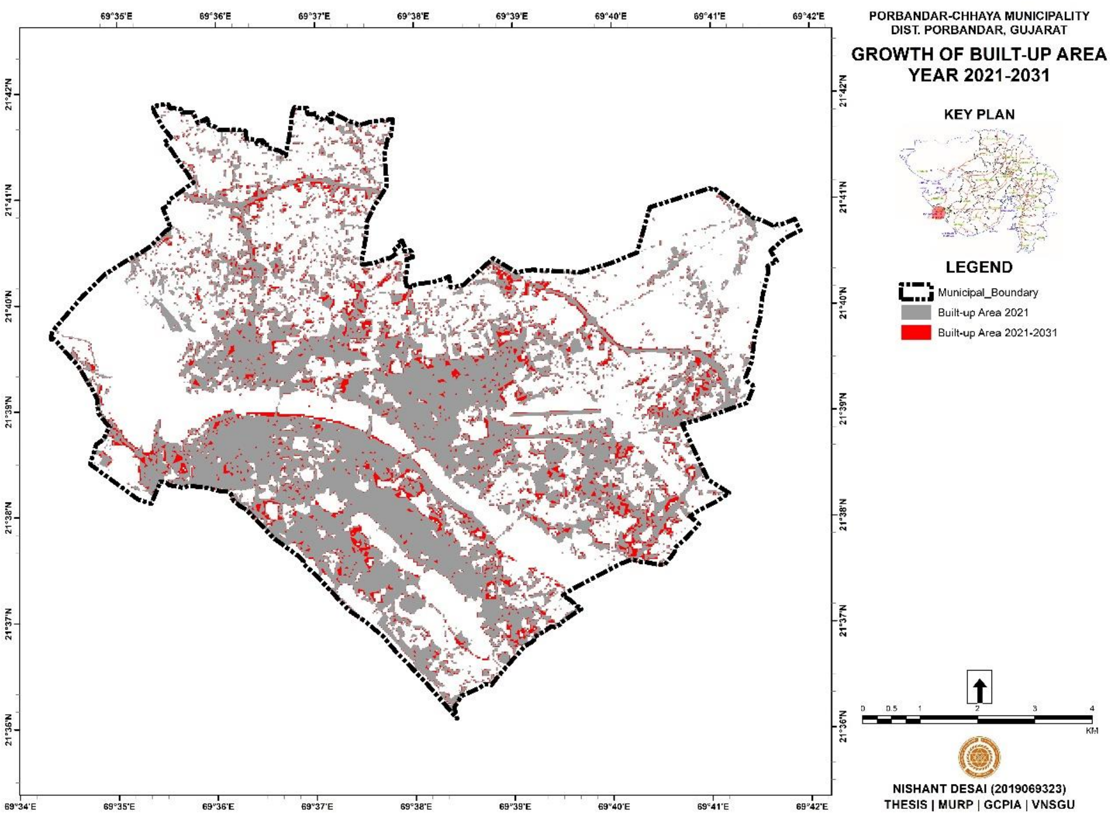



*Figure 6.13 Growth of built-up area (2021-2031)*

## 6.3 SUMMARY

The model predicted increase in Built-up area between 2021 and 2031 from 26.49 sq.km. (35.71%) to 28.97 sq.km. (39.04%) respectively. Although, the Built-up area has increased the change rate has decreased from 3.77% to 3.34%, which is following the trend of last three decades.

Vegetation will decrease from 20.81 sq.km. (28.04%) to 18.68 sq.km. (25.18%). This results in overall small change during four decades (1991-2031).

Waterbody will decrease from 8.24 sq.km. (11.10%) to 8.08 sq.km. (10.89%). Again, this results in overall small change during four decades.

Barren land will decrease from 18.66 sq.km. (25.15%) to 18.47 sq.km. (24.89%). Although, in past decades, Barren land has shown considerable decrease (10.03% and 12.60%), the model predicted nominal change in future.

# CHAPTER:7 SUMMARY, CONCLUSION & RECOMMENDATIONS

## 7.1 SPATIOTEMPORAL PATTERNS OF LAND COVER CHANGE

Many cities experience ribbon type urban development along the major transport corridors. The gradient analysis in the study showed that, throughout the three decades more than 94% of the total Built-up Area occurred in close proximity to major roads, i.e. less than 1.0 km from major roads (Table 5.14). These results confirm that the road network has been influential in the spatial pattern of urban growth in the Porbandar-Chhaya Municipality (PCM).

The visual analysis of land cover maps revealed that the PCM's built-up lands have become more fragmented (Figure 5.15). Growth of new built-up areas along the major roads and the diffusion of new built-up patches near existing built-up areas contributes to this fragmentation of built-up. The analysis also showed expansion process of existing built-up patches as they grow in size. Also, the distance between these patches is reducing, because of the process of the cumulative impact of diffusion, expansion and infill development.

These results are aligned with the urban growth theory of diffusion and coalescence (Nong, et al., 2014) (Dietzel, Oguz, Hemphill, Clarke, & Gazulis, 2005) (Liu, Li, & Ai, 2010). "Diffusion is a process in which new urban areas are dispersed from the origin point or 'seed' location, while coalescence is the union of individual urban patches, or the growing together of the individual urban patches into one form or group" (Estoque & Murayama, 2015). Based on the results, we can say that the PCM is still in the early stages of urban development process; i.e., it is experiencing more diffusion and less coalescence.

The built-up fragmentation and diffused growth of the PCM might be the result of several factors. Apart from the Arabian sea on South and Bokhira Khadi, there are no major physical constraints, such as high altitude or steep grades, in the land side of the PCM, which boosts fragmentation and diffused growth of built-up. In the study it was observed that road network has expanded during last three decades. This road development reduced the travel time from the peripheries to central areas or the business district (CBD) and has encouraged land fragmentation. Thus, people moved out to the peripheries, inducing fragmentation and diffused urban growth. Majorly, the non-built-up lands in near to the major roads were slowly transformed into built-up lands.

The coalescence of built-up patches was largely detected in the CBD and other highly dense built-up areas such as the part of Chhaya (areas adjacent to Porbandar) and Dharampur (areas near Porbandar along railway track). The existing Development Plan 2021 for Porbandar was enacted in 2006 (Appendix 4). Under this development plan, the urban planning interventions presented in the CBD are one major factor that motivates the coalescence of built-up patches. Under these, new road networks and purposeful zones were planned for the area of the Porbandar, resulting in the coalescence of built-up patches with infill development.

Infill growth pattern is result of coalescence and ongoing process of diffusion and expansion characterize urban sprawl. The infill growth pattern offers several advantages like optimized use of existing infrastructures, preservation of non-built land by controlling urban sprawl and creation of walkable neighborhoods. Nevertheless, it also has some possible disadvantages, including reduced urban open spaces, increased traffic issues, inflated land prices and overburdened services (Estoque & Murayama, 2015).

The gradient analysis shows that the growth rate of built-up area within Porbandar has remained lowest (average 0.45%) during last three decades (1991-2021) among all spatial entities (Table 5.13). Although, CBD area (Porbandar and parts of Chhaya) performed little better with an average of 0.62% growth rate of built-up (Table 5.17), due to the infill development. As infill development has lessened the space in the CBD of PCM for further development, ribbon-type development has radiated from the CBD along the major roads. This lately formed focused urban development in the area of 4 km from CBD, the rest of the PCM area only show scattered built-up.

At present, the influence of under construction 45 mt. wide outer ring road (bypass for NH 51), is not observed. However, the prediction shows increase in built-up along this new road. This new development can help avoid any further congestion of the CBD, while giving prospects to other parts of the PCM to develop. However, not only can these new roads and growth nodes influence urban sprawl in the future, they can also lead to economic separation, environmental degradation and the loss of agricultural land.

There are many local and external factors influencing the urban growth. It is not possible to understand the process of urban growth from standalone point of view. Collective impact of various factors and their interrelationship must be studied for comprehensive understanding of urban growth patterns.

## 7.2 ISSUES AND CHALLENGES FOR URBAN DEVELOPMENT

As seen in the study the population of Porbandar district is moving towards urban areas. Being the largest urban center in the district, the built-up area in PCM has increased from 16.71% to 35.71% between 1991 to 2021. However, the change rate of Built-up area in PCM is declining from 10.05% (1991-2001) to 3.77% (2011-2021). The prediction results shows that it will further decline to 3.34% during 2021-2031.

Environment sustainability could be adversely affected because of the fragmented development. The results divulge that the major roads are very significant for the urban growth of the area and promotes ribbon-type development. This fragmentation and ribbon development makes task of providing urban infrastructure more difficult compared to compact development. Earlier it was not possible for urban authorities to control the development within these areas, as they were under rural administration. After the delineation of PCM area, planning initiatives need to address this factor when the new urban planning interventions are introduced.

Due to the coalescence of built-up patches, mainly in the CBD and other highly dense built-up areas such as the part of Chhaya and Dharampur, urban open spaces are shrinking. Although, coalescence has its advantages, its negative impacts need to be controlled in future planning efforts.

The vegetation (green cover and agriculture land) has increased and decreased during 1991-2021, it has mostly remained unchanged with average change rate of 1.26% (Table 5.10). The prediction results show decrease in vegetation area (2.87%) between 2021 and 2031 (Table 6.5 & 6.6). Mostly the Barren Land has been converted in to Built-up area. While delineating the land for future growth, it is to be seen that this green cover area within PCM can be maintained and optimal use of already urbanized areas is achieved.

PCM's urban development planning needs to pay attention to the coastal area. Although, it has been projected to experience little change in the future. The waterbody has shown very small change during 1991-2021, it has mostly remained unchanged with average change rate of 0.21% (Table 5.10). The prediction results show decrease in waterbody area (0.22%) between 2021 and 2031 (Table 6.5 & 6.6). However, future planning efforts needs to consider the preservation and enhancement of coastal area (especially area under CRZ regulations) and Bokhira Creek edges.

The prediction results show that: (a) ongoing urban growth will expand, covering a small area, (b) fragmented built-up patches will increase in size, (c) the major roads will have a vast impact on the future spatial patterns and (d) the PCM's built-up area will be consolidated due to infill development (Figure 6.10).

This study and its findings show that continuous urban growth, decreasing non-urban land and land fragmentation with diffused urban growth in the PCM needs to be resolved by urban planning interventions and policies. Currently the Development Plan sanctioned in 2006 is in effect for Porbandar area only, which needs to be revised in 2021. Development Plan for Chhaya was prepared but was not sanctioned by the Government and didn't came in effect.

There are numerous aspects like preservation and enhancement of coastal areas and creek edges, buildings with historical and cultural values, tourism etc. which needs to be taken in to account for urban planning. Important issues and challenges which are highlighted in this study and should be considered in the PCM's urban development planning are identified as below.

1. Declining growth rate of Built-up Area.
2. Fragmented development in parts of PCM, which are far from CBD and major roads.
3. Shrinking urban open spaces in CBD and other high density built-up areas due to infill development.
4. Retaining existing green cover as much as possible, while delineating land for future urban growth.

## 7.3 RECOMMENDATIONS FOR FUTURE URBAN DEVELOPMENT

### 1. LOCAL ECONOMY BOOST

- Although, being major urban center in the district, compared to the other cities in the region (like Rajkot, Jamnagar), Porbandar lacks in terms of employment opportunities and economic growth.
- At present, agriculture and fishing are main sectors of local economy. Initiatives should be taken to boost these sectors can help in employment generation and economic growth.
- In recent decades, due to climate change, Kathiawar region has seen increased annual rainfall. Which has worked in positive way for agriculture. Promotion of agro-product based industries can help recover the declining growth rate of Porbandar. Modernization of fishing industry with supporting infrastructure can help growth.

- Since its establishment Porbandar has been a Port city. Development of port related activities like Inland Container Depot (ICD) can boost the economic activities and create employment opportunities.

**2. CULTURAL HERITAGE AND TOURISM**

- Porbandar is also the birth place of Mahatma Gandhi, father of our nation. There are many buildings associated with him. This cultural heritage combined with existing natural coast line can be exploited for development of tourism industry.
- Open land parcels, owned by the government, which can be utilized for tourism projects.
- Such development has potential to generate employment and economic growth.

**3. IMPROVEMENT OF PUBLIC INFRASTRUCTURE & SERVICES**

- It was also observed in the study that Porbandar lacks in terms of public services like water supply, drainage, solid waste management, road condition etc. The current situation of these services, within the Porbandar, is somewhat comparable to rural areas with open drainage, inadequate water supply, lack of solid waste management.
- The ULB of this newly formed area needs to prioritize the improvement and expansion of these public services.
- Future planning efforts also needs to consider new mechanisms for financing these required infrastructure and public services projects.
- These improvements in urban infrastructure and services can attract in-migration and consequently boost the growth of the city.

**4. ZONING FOR FUTURE DEVELOPMENT**

- PCM needs planned zoning for future growth. Controlling the existing fragmented and ribbon development should be the priority along with limiting the amount of land to be urbanized. This will ensure that the future demand for urban land is met with optimal use of available resources.
- As per population of 2011 (population 224907, built-up 2369 Ha) the net population density for built-up area comes around 95 PPHa. If we consider entire urbanized area (area of land parcels having built-up) net density will be lesser than this. This density is quite low compared to the recommendation of URDPFI (for Medium Town 100-125).
- Hence, zoning which promotes higher density development (whitin recommended range) should be adopted. This will ensure compact development with minimum amount of non-urban land being converted to urban areas and mostly preserving existing green cover.

**These recommendations can be implemented through the statutory mechanism of development plan, town planning scheme and local area planning.**

## 7.4 CONCLUSION

This study has examined the spatiotemporal patterns of urban growth of the Porbandar-Chhaya Municipality - administrative and urban headquarter of Porbandar district, Gujarat - from 1991 to 2021 using remote sensing data and GIS techniques. The analysis showed that growth of built-up area was faster during the 1991-2001 (10.05%) and since decreasing. Predicted change rate of built-up area for 2021-2031 was 3.44%, lowest in four decades (1991-2031). The results also showed that most of the built-up during this period occurred in close proximity to major roads, while also showing some indications of built-up fragmentation and infill development patterns. The predicted land cover showed that by 2031, the PCM's built-up land would increase to 28.97 sq.km. (39.04%) and that major roads would be more likely to influence the future spatial pattern of built-up area. The findings of the study provide important insight for future urban planning interventions and policies. In context of the study, four issues were identified which needs to be addressed in future urban planning efforts and recommendations were given within the limited aspect of the study. Overall, this study provided valuable information on the land cover transformation of the PCM.

Overall, the study successfully shows the importance and application of land cover change detection and prediction to identify urban growth patterns and related issues & challenges. This gives valuable inputs for informed decision making in planning process.

## 7.5 LIMITATIONS & FURTHER RESEARCH

The spatial resolution of satellite data plays a major role in prediction of land cover, for this study 30m resolution data was used in CA based prediction model. A higher resolution data can generate more accurate land cover maps and prediction.

The limited numbers (four) of variables were used in prediction model, these variables were able to predict considerably accurate land cover for 2021. More variables like social infrastructure, travel pattern, employment pattern, land value, ownership of land parcels etc. could be incorporated in the model subjected to availability of data. This will not only improve prediction accuracy but, also provide more insight to the impact of these variables on growth patterns.

Currently in many cases development plans (land use plans), infrastructure development and transportation / mobility plans are prepared and implemented separately. Instead, preparation of integrated and comprehensive plans would save human efforts and financial resources. The prediction model would be of great help for preparing such plans.

Furthermore, rather than the unconditional prediction, conditional prediction model - which can access the impact of vast numbers of variables and can predict alternate scenarios in case of proposed planning intervention are implemented – needs to be prepared.

# APPENDICES

## APPENDIX 1: LAND USE AND LAND COVER CLASSIFICATION SYSTEM FOR USE WITH REMOTE SENSING DATA

(ANDERSON, HARDY, ROACH, & WITMER, 1976)

| LEVEL I | | LEVEL II | |
|---|---|---|---|
| 1 | Urban or Built-up Land | 1.1 | Residential |
| | | 1.2 | Commercial and Services |
| | | 1.3 | Industrial |
| | | 1.4 | Transportation, Communications and Utilities |
| | | 1.5 | Industrial and Commercial Complexes |
| | | 1.6 | Mixed Urban or Built-up Land |
| | | 1.7 | Other Urban or Built-up Land |
| 2 | Agricultural Land | 2.1 | Cropland and Pasture |
| | | 2.2 | Orchards, Groves, Vine-yards, Nurseries and Ornamental Horticultural Areas |
| | | 2.3 | Confined Feeding Operations |
| | | 2.4 | Other Agricultural Land |
| 3 | Rangeland | 3.1 | Herbaceous Rangeland |
| | | 3.2 | Shrub and Brush Rangeland |
| | | 3.3 | Mixed Rangeland |
| 4 | Forest Land | 4.1 | Deciduous Forest Land |
| | | 4.2 | Evergreen Forest Land |
| | | 4.3 | Mixed Forest Land |
| 5 | Water | 5.1 | Streams and Canals |
| | | 5.2 | Lakes |
| | | 5.3 | Reservoirs |
| | | 5.4 | Bays and Estuaries |
| 6 | Wetland | 6.1 | Forested Wetland |
| | | 6.2 | Non-forested Wetland |
| 7 | Barren Land | 7.1 | Dry Salt Flats |
| | | 7.2 | Beaches |
| | | 7.3 | Sandy Areas other than Beaches |
| | | 7.4 | Bare Exposed Rock |
| | | 7.5 | Strip Mines, Quarries and Gravel Pits |
| | | 7.6 | Transitional Areas |

| | | | |
|---|---|---|---|
| | | 7.7 | Mixed Barren Land |
| 8 | Tundra | 8.1 | Shrub and Brush Tundra |
| | | 8.2 | Herbaceous Tundra |
| | | 8.3 | Bare Ground Tundra |
| | | 8.4 | Wet Tundra |
| | | 8.5 | Mixed Tundra |
| 9 | Perennial Snow or Ice | 9.1 | Perennial Snowfields |
| | | 9.2 | Glaciers |

**APPENDIX 2: SUMMARY OF LAND-USE CHANGE MODELS**
(Lambin & Geist, 2006)

| MODEL | PRINCIPLE | CONVENTIONAL TECHNIQUES | ADVANTAGES | DISADVANTAGES | EXAMPLES |
|---|---|---|---|---|---|
| **Empirical statistical models** | Identify explicitly the causes of land-use changes using multivariate analyses of possible exogenous contributions to empirically derived rates of changes | Multiple linear regression (MLR) | They are mainly an exploratory tool to test for the existence of links between candidate driving forces and land-use change. | (1) They are only able to explain, in a statistical sense, patterns of land-use changes which are represented in the calibration data set. (2) They cannot be used for wide-ranging extrapolations. (3) They are intrinsically not spatial. | CLUE-S |
| **Stochastic models** | Generally, assume that land-use change is a first-order process; that is the conditional probability of land use at any time, given all previous uses at earlier times, depends at most upon the most recent use and not upon any earlier ones | Transition probability models, e.g. Markov chain | (1) Mathematical and operational simplicity. (2) They can be used where no information on the driving forces and mechanisms of land-use changes is available. | (1) The stochastic nature of the Markov chain masks the causative variables, so the model has little explanatory power. (2) They only predict when changes in land use might take place in the short term, under a strict assumption of stationarity of the process, in contrast to a spatial model. | Markov chain; Spatial diffusion models; CA |

| | | | | | |
|---|---|---|---|---|---|
| **Optimization models** | Any parcel of land, given its attributes and its location, is modeled as being used in the way that yields the highest rent. | Econometric approaches (linear programming, general equilibrium models) | They usually assume that the agents whose behavior is described within the model do have the capacity to make informed predictions and plans, so as to try to avoid disasters. | They use a somewhat arbitrary definition of objective functions and non-optimal behavior of people, e.g. due to differences in values, attitudes. and cultures. | Thunen model; ABM; Econometric models |
| **Process based dynamic simulation models** | Condense and aggregate complex ecosystems into a small number of differential equations in a stylized manner. Different branches of methods were coupled in an integrative model. | System dynamic model, within GIS framework, CA+MAS+Markov+MLR, etc. | They are well suited to representing non-stationary processes since they mimic the underlying processes in the system and include feedbacks and thresholds in the system dynamics. They allow the testing of scenarios on future land-use changes, and take full advantage of different methods. | Many individual processes of decision-making cannot be modeled deterministically; it is possible to identify the main determinants of decisions on when and where to change land use. The dynamic landscape simulation models developed to date are specific to narrow geographic situations and cannot easily be generalized. It takes time to develop the model and initiate model parameters. | IMAGE IMPEL SLEUTH |

**APPENDIX 3: BAND COMBINATION USED FOR CLASSIFICATION OF FCC**

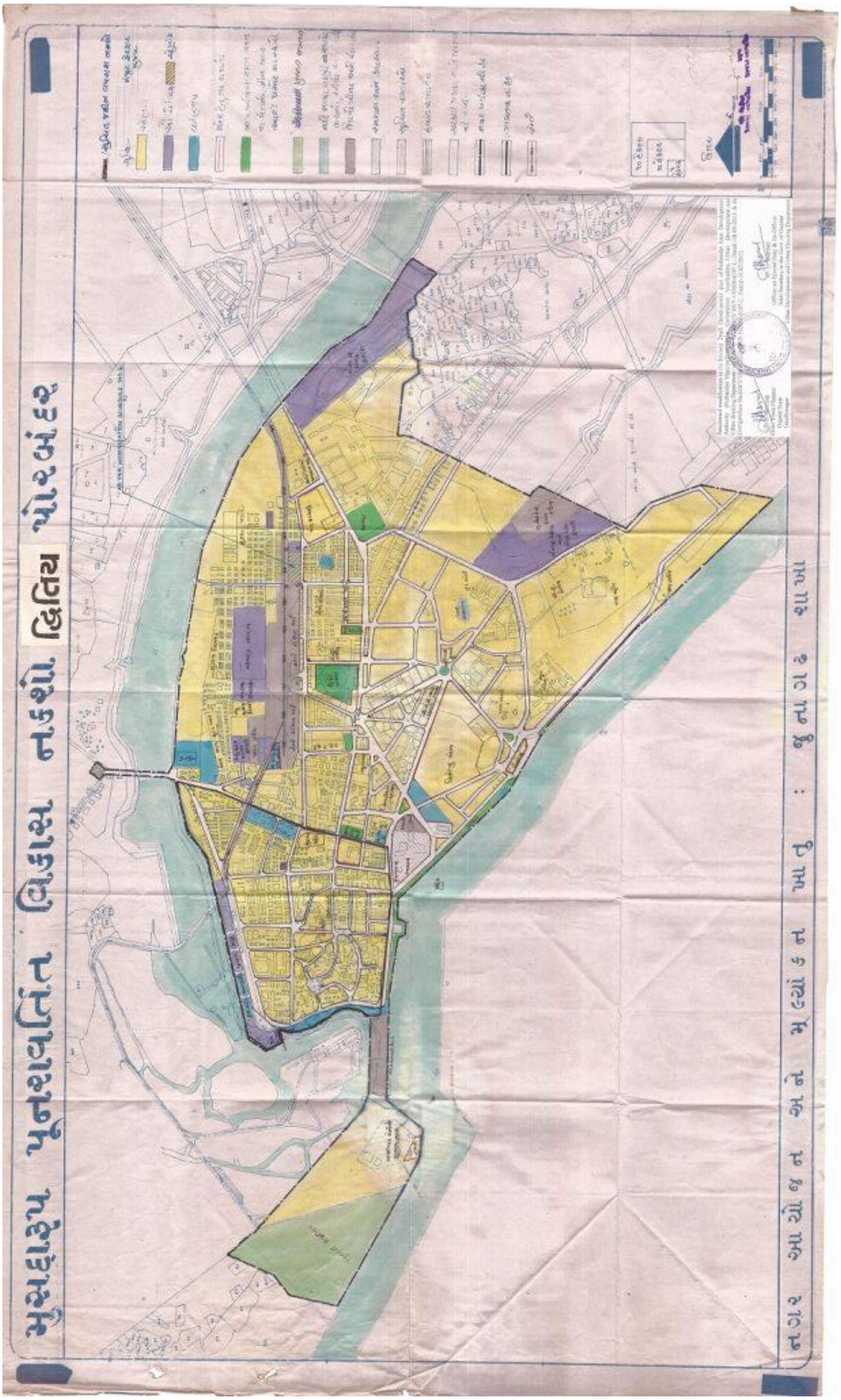
(Quinn, 2001)

| R,G,B | POTENTIAL INFORMATION CONTENT |
|---|---|
| **4,3,2** | The standard "false colour" composite. Vegetation appears in shades of red, urban areas are cyan blue, and soils vary from dark to light browns. Ice, snow and clouds are white or light cyan. Coniferous trees will appear darker red than hardwoods. This is a very popular band combination and is useful for vegetation studies, monitoring drainage and soil patterns and various stages of crop growth. Generally, deep red hues indicate broad leaf and/or healthier vegetation while lighter reds signify grasslands or sparsely vegetated areas. Densely populated urban areas are shown in light blue. This TM band combination gives results similar to traditional colour infrared aerial photography. |

| | |
|---|---|
| **3,2,1** | The "natural colour" band combination. Because the visible bands are used in this combination, ground features appear in colours similar to their appearance to the human visual system, healthy vegetation is green, recently cleared fields are very light, unhealthy vegetation is brown and yellow, roads are grey, and shorelines are white. This band combination provides the most water penetration and superior sediment and bathymetric information. It is also used for urban studies. Cleared and sparsely vegetated areas are not as easily detected here as in the 4 5 1 or 4 3 2 combination. Clouds and snow appear white and are difficult to distinguish. Also note that vegetation types are not as easily distinguished as the 4 5 1 combination. The 3 2 1 combination does not distinguish shallow water from soil as well as the 7 5 3 combination does. |
| **7,4,2** | This combination provides a "natural-like" rendition, while also penetrating atmospheric particles and smoke. Healthy vegetation will be a bright green and can saturate in seasons of heavy growth, grasslands will appear green, pink areas represent barren soil, oranges and browns represent sparsely vegetated areas. Dry vegetation will be orange and water will be blue. Sands, soils and minerals are highlighted in a multitude of colours. This band combination provides striking imagery for desert regions. It is useful for geological, agricultural and wetland studies. If there were any fires in this image, they would appear red. This combination is used in the fire management applications for post-fire analysis of burned and non-burned forested areas. Urban areas appear in varying shades of magenta. Grasslands appear as light green. The light-green spots inside the city indicate grassy land cover - parks, cemeteries, golf courses. Olive-green to bright-green hues normally indicate forested areas with coniferous forest being darker green than deciduous. |
| **4,5,1** | Healthy vegetation appears in shades of reds, browns, oranges and yellows. Soils may be in greens and browns, urban features are white, cyan and grey, bright blue areas represent recently clear-cut areas and reddish areas show new vegetation growth, probably sparse grasslands. Clear, deep water will be very dark in this combination, if the water is shallow or contains sediments it would appear as shades of lighter blue. For vegetation studies, the addition of the Mid-IR band increases sensitivity of detecting various stages of plant growth or stress; however, care must be taken in interpretation if acquisition closely follows precipitation. Use of TM 4 and TM 5 shows high reflectance in healthy vegetated areas. It is helpful to compare flooded areas and red vegetated areas with the corresponding colours in the 3 2 1 combination to assure correct interpretation. This is not a good band combination for studying cultural features such as roads and runways. |
| **4,5,3** | This combination of near-IR (Band 4), mid-IR (Band 5) and red (Band 3) offers added definition of land-water boundaries and highlights subtle details not readily apparent in the visible bands alone. Inland lakes and streams can be located with greater precision when more infrared bands are used. With this band combination, vegetation type and condition show as variations of hues (browns, greens and oranges), as well as in tone. The 4,5,3 combination demonstrates moisture differences and is useful for analysis of soil and vegetation conditions. Generally, the wetter the soil, the darker it appears, because of the infrared absorption capabilities of water. |
| **7,5,3** | This band combination also provides a "natural-like" rendition while also penetrating atmospheric particles, smoke and haze. Vegetation appears in shades of dark and light green during the growing |

| | |
|---|---|
| | season, urban features are white, grey, cyan or purple, sands, soils and minerals appear in a variety of colours. The almost complete absorption of Mid-IR bands in water, ice and snow provides well defined coast lines and highlighted sources of water within the image. Snow and ice appear as dark blue, water is black or dark blue. Hot surfaces such as forest fires and volcano calderas saturate the Mid-IR bands and appear in shades of red or yellow. One particular application for this combination is monitoring forest fires. During seasons of little vegetation growth, the 7 4 2 combination should be substituted. Flooded areas should look very dark blue or black, compared with the 3 2 1 combination in which shallow flooded regions appear grey and are difficult to distinguish. |
| **5,4,3** | Like the 4 5 1 combination, this combination provides the user with a great amount of information and colour contrast. Healthy vegetation is bright green and soils are mauve. While the 7 4 2 combination includes TM 7, which has the geological information, the 5 4 3 combination uses TM 5 which has the most agricultural information. This combination is useful for vegetation studies, and is widely used in the areas of timber management and pest infestation. |
| **5,4,1** | This will look similar to the 7 4 2 combination in that healthy vegetation will be bright green, except the 5 4 1 combination is better for agricultural studies. |
| **7,5,4** | This combination involves no visible bands. It provides the best atmospheric penetration. Coast lines and shores are well defined. It may be used to find textural and moisture characteristics of soils. Vegetation appears blue. If the user prefers green vegetation, a 7 4 5 combination should be substituted. This band combination can be useful for geological studies. |
| **5,3,1** | This combination displays topographic textures while 7 3 1 may display differences in rock types. |

**APPENDIX 4: PORBANDAR DEVELOPMENT PLAN 2021**



# REFERENCES

1. A.Cardille, J., & A.Foley, J. (2003). Agricultural land-use change in Brazilian Amazônia between 1980 and 1995: Evidence from integrated satellite and census data. *Remote Sensing of Environment*, 551-562.
2. Ahadnejad, M. (2009, 01 09). Environmental land use Change detection and assessment using with multi-temporal satellite imagery. *www.geospatialworld.net*.
3. Al-doski, J., Mansor, S. B., & Shafri, H. Z. (2013). Change Detection Process and Techniques. *Civil and Environmental Research, IISTE*, 37-45.
4. Alonso, W. (1965). *Location and Land Use: Toward a General Theory of Land Rent.* Harvard University Press.
5. ANDERSON, J. R., HARDY, E. E., ROACH, J. T., & WITMER, R. E. (1976). A Land Use and Land Cover Classification System for Use with Remote Sensor Data. *U.S. Geological Survey*.
6. Arvind.C.Pandey, & M.S.Nathawat. (2009). Landuse-Land cover mapping through digital image processing of satellite data- A case study from Panchkula, Ambala and Yamunanagar districts, Haryana state, India. *www.geospatialworld.net*.
7. Azmat, A., Kazmi, J., Shahzad, A., & Shaikh, S. (2020). Mapping Change in Spatial Extent and Density of Mangrove Forest at Karachi Coast Using Object Based Image Analysis. *International Journal of Economic and Environmental Geology*, 118-122.
8. Basawaraja, R., Chari, K. B., Mise, S. R., & Chetti, S. B. (2011). Analysis of the impact of urban sprawl in altering the land-use, land-cover pattern of Raichur City, India, using geospatial technologies . *Journal of Geography and Regional Planning*, 455-462.
9. Bayarsaikhan, U., Boldgiv, B., Kim, K.-R., Park, K.-A., & Lee, D. (2009). Change detection and classification of land cover at Hustai National Park in Mongolia. *International Journal of Applied Earth Observation and Geoinformation*, 273-280.
10. Benenson, I., & Torrens, P. M. (2004). *Geosimulation: Automata-Based Modeling of Urban Phenomena.* John Wiley & Sons.
11. Blaikie, P., & Brookfield, H. (1987). *Land Degradation and Society.*
12. Bousquet, F., & Page, C. L. (2003). Multi-agent simulations and ecosystem management: a review. *Ecological Modelling*.
13. Briassoulis, H. (2000). *Analysis of Land Use Change: Theoretical and Modeling Approaches.* West Virginia University.

14. Cabral, P., & Zamyatin, A. (2006). Using Cellular Automata-Markov Analysis and Multi Criteria Evaluation for Predicting the Shape of the Dead Sea. *Advances in Remote Sensing*.

15. Dewidar, K. (2004). Detection of land use/land cover changes for the northern part of the Nile delta (Burullus region), Egypt. *International Journal of Remote Sensing*.

16. Diallo, Y., Hu, G., & Wen, X. (2009). Applications of Remote Sensing in Land Use/Land Cover Change Detection in Puer and Simao Counties. *Journal of American Science*, 157-166.

17. Dietzel, C., Oguz, H., Hemphill, J. J., Clarke, K. C., & Gazulis, N. (2005). Diffusion and coalescence of the Houston Metropolitan Area:. *Environment and Planning B: Planning and Design*.

18. Directorate of Census Operations, G. (2011). *District Census Handbook, Porbandar, Gujarat.*

19. Echenique, M. H. (1994). Urban and Regional Studies at the Martin Centre: Its Origins, its Present, its Future. *Environment and Planning B: Planning and Design*.

20. Estoque, R. C., & Murayama, Y. (2015). Intensity and spatial pattern of urban land changes in the megacities of Southeast Asia. *Land Use Policy*, 213-222.

21. Fan, F., Weng, Q., & Wang, Y. (2007). Land Use and Land Cover Change in Guangzhou, China, from 1998 to 2003, Based on Landsat TM /ETM+ Imagery. *Sensors for Urban Environmental Monitoring*.

22. Franklin, S. E., & Wulder, M. A. (2002). Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography: Earth and Environment*.

23. Gross, M. (1982). The Lowry model of land use simulation and its derivatives. *Computers, Environment and Urban Systems*.

24. Gupta, A., & Singh, D. J. (2010). An Investigation of Reliability on Remote Sensing and GIS Data as an Aid to Urban Development Plan: A Case Study on Bhopal. *Institute of Town Planners, India Journal*, 90-100.

25. Hayes, D., & Sader, S. (2001). Comparison of change-detection techniques for monitoring tropical forest clearing and vegetation regrowth in a time series. *Photogrammetric Engineering and Remote Sensing*, 1067-1075.

26. Herold, M., Gardner, M. E., & Roberts, D. A. (2003). Spectral resolution requirements for mapping urban areas. *IEEE Transactions on Geoscience and Remote Sensing*, 1907-1919.

27. Herold, M., Liu, X. H., & Clarke, K. (2003). Spatial Metrics and Image Texture for Mapping Urban Land Use. *Photogrammetric Engineering and Remote Sensing*.

28. Hersperger, A., & Bürgi, M. (2007). Driving Forces of Landscape Change in The Urbanizing Limmat Valley, Switzerland. *Modelling Land-Use Change*.

29. Houet, T., Verburg, P. H., & Loveland, T. R. (2010). Monitoring and modelling landscape dynamics. *Landscape Ecology*.

30. Hu, G., Dong, Z., Lu, J., & Yan, C. (2011). Land use and land cover change monitoring in the Source Region of Yellow River by remote sensing technology. *International Conference on Remote Sensing, Environment and Transportation Engineering (RSETE).* Nanjing, China: IEEE.

31. Huxhold, W. E. (1991). *An Introduction to Urban Geographic Information Systems (Spatial Information Systems).* Oxford University Press.

32. Im, J., & R.Jensen, J. (2005). A change detection model based on neighborhood correlation image analysis and decision tree classification. *Remote Sensing of Environment*, 326-340.

33. Islam, K., Rahman, M., & Jashimuddin, M. (2018). Modeling land use change using Cellular Automata and Artificial Neural Network: The case of Chunati Wildlife Sanctuary, Bangladesh. *Ecological Indicators*.

34. Jager, W., & Janssen, M. (2002). The Need for and Development of Behaviourally Realistic Agents. *Multi-Agent-Based Simulation, Third International Workshop,.* Bologna, Italy.

35. Jin Chen, P. G. (2003). Land-Use/Land-Cover Change Detection Using Improved Change-Vector Analysis. *Photogrammetric Engineering & Remote Sensing*, 369-379.

36. Johnson, R. D., & Kasischke, E. S. (2010). Change vector analysis: A technique for the multispectral monitoring of land cover and condition. *International Journal of Remote Sensing* , 411-426.

37. Jwan Al-doski, S. B. (2013). Change Detection Process and Techniques. *Civil and Environmental Research* .

38. Klosterman, R. E., & Pettit, C. J. (2005). An update on planning support systems. *Environment and Planning B: Planning and Design*.

39. Kumar, S., Radhakrishnan, N., & Mathew, S. (2014). Land use change modelling using a Markov model. *Geomatics, Natural Hazards and Risk*, 145-156.

40. Lambin, E. F., & Geist, H. J. (2006). *Land-Use and Land-Cover Change: Local Processes and Global Impacts.*

41. Landsat Science. (2021). *Landsat Science*. Retrieved from Landsat Science: https://landsat.gsfc.nasa.gov/about/landsat-timeline

42. Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). *Remote Sensing and Image Interpretation.* Wiley.

43. Liu, X., Li, S., & Ai, B. (2010). A new landscape index for quantifying urban expansion using multi-temporal remotely sensed data. *Landscape Ecology*.

44. Lonergan, S. (1998). *The Role of Environmental Degradation in Population Displacement.* Environmental Change and Security Project Report.

45. Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, 2365-2401.

46. M. Foody, G. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 185-201.

47. M.Foody, G. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 185-201.

48. Macleod, R., & Congalton, R. (1998). uantitative Comparison of Change-Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data. *Photogrammetric Engineering and Remote Sensing*, 207-216.

49. Maithani, D. S. (2010). Application of Cellular Automata and GIS Techniques in Urban Growth Modelling: A New Perspective. *Institute of Town Planners, India Journal*, 36-49.

50. Mertens, B., & Lambin, E. F. (1997). Spatial modelling of deforestation in southern Cameroon: Spatial disaggregation of diverse deforestation processes. *Applied Geography*.

51. Meyer, W. B. (1995). Past and Present Land Use and Land Cover in the USA. *Consequences*.

52. Meyer, W. B., & Clark, W. C. (1990). *The Earth as Transformed by Human Action: Global and Regional Changes in the past 300 years.* Cambridge University Press.

53. Millera, E. J., Douglas, J., E, H. J., Paul, A., & Salvinic, A. (2004). Microsimulating urban systems. *Computers, Environment and Urban Systems*.

54. Nagaraju Arveti, B. E. (2016). Land Use/Land Cover Analysis Based on Various Comprehensive Geospatial Data Sets: A Case Study from Tirupati Area, South India. *Advances in Remote Sensing*.

55. Narayan, L. R. (1999). *Remote Sensing and Its Applications.* Universities Press, UNESCO.

56. Nong, D., Lepczyk, C., Miura, T., Fox, J., Spencer, J., & Chen, Q. (2014). Quantifying spatiotemporal patterns of urbanization: The case of the two fastest growing metropolitan regions in the United States. *East-West Center Working Papers*.

57. Olorunfemi, J. F. (1983). Monitoring urban land use in developing countries—an aerial photographic approach. *Environment International*, 27-32.

58. Parveen, S., Bashir, J., & Praveen, B. (2018). A LITERATURE REVIEW ON LAND USE LAND COVER CHANGES. *International Journal of Advanced Research*, 1-6.

59. Quinn, J. W. (2001). Retrieved from http://web.pdx.edu/~nauna/resources/10_BandCombinations.htm

60. Rashid, S. M., & Sokhi, B. S. (1999). *REMOTE SENSING OF URBAN ENVIRONMENT*. Manak Publications Pvt Ltd.

61. Renzaa, D., Martinez, E., Molinab, I., M., D., & L., B. (2017). Unsupervised change detection in a particular vegetation land cover type using spectral angle mapper. *Advances in Space Research*, 2019-2031.

62. Sen, A., & Smith, T. E. (2012). *Gravity Models of Spatial Interaction Behavior*. Springer Science & Business Media.

63. Shoshany, M., Kutiel, P., & Lavee, H. (1996). Monitoring temporal vegetation cover changes in Mediterranean and arid ecosystems using a remote sensing technique: case study of the Judean Mountain and the Judean Desert. *Journal of Arid Environments*, 9-21.

64. Silva, E., & Wu, N. (2012). Surveying Models in Urban Land Studies. *Journal of Planning Literature*.

65. Simone Naumann, A. S. (2004). Object-oriented image analysis and change detection of land-use on Tenerife related to socio-economic conditions. Spain: Remote Sensing for Environmental Monitoring, GIS Applications, and Geology IV.

66. Singh, A. (2010). Review Article Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, 989-1003.

67. Song, C., Woodcock, C. E., & Seto, K. C. (2001). Classification and Change Detection Using. *Remote Sensing Enviornment*, 230-244.

68. Survey, U.S. Geological. (n.d.). Retrieved from Earth Observing System: https://eos.com/landsat-5-tm/

69. The World Bank. (2011, July 14). *The World Bank*. Retrieved from https://www.worldbank.org/en/news/feature/2011/07/04/indias-urban-challenges

70. Torahi, A., & Rai, S. (2011). Land Cover Classification and Forest Change Analysis, Using Satellite Imagery-A Case Study in Dehdez Area of Zagros Mountain in Iran. *Geographic Information System*, 1-11.

71. Torrens, P. M., & O'Sullivan, D. (2001). Cellular Automata and Urban Simulation: Where Do We Go from Here? *Environment and Planning B: Urban Analytics and City Science*.

72. Valbuena, D., Verburg, P., Bregt, A., & Ligtenberg, A. (2009). An agent-based approach to model land-use change at a regional scale. *Landscape Ecology*, 185-199.

73. Walker, W. T., Gao, S., & Johnston, R. A. (2007). UPlan: Geographic Information System as Framework for Integrated Land Use Planning. *Transportation Research Record: Journal of the Transportation Research Board*.

74. Wikipedia. (n.d.). Retrieved from Wikipedia: https://en.m.wikipedia.org/wiki/False_color

75. Williams, D., Goward, S., & Arvidson, T. (2006). Landsat: Yesterday, Today, and Tomorrow. *Photogrammetric Engineering & Remote Sensing, 72*.

76. Wolman, M. G., & Fournier, F. G. (1987). Land transformation in agriculture. In *Land transformation in agriculture.* New York: John wiley & sons.

77. Xie, H., Zhang, Y., & Lu, X. (2011). Land use/cover change study of Lianyungang coastal zone based on remote sensing. *International Conference on Geoinformatics.* Shanghai, China: IEEE.

78. Yang, W., & Zou, T. (2009). Supervised Land-cover Classification of TerraSAR-X Imagery over Urban Areas Using Extremely Randomized Clustering Forests . *Urban Remote Sensing Joint Event*.

79. Yoon, G.-W., Yun, Y. B., & Park, J.-H. (2003). Change vector analysis: detecting of areas associated with flood using Landsat TM. *International Geoscience and Remote Sensing Symposium.*