## Urban Growth Modelling using Remotely Sensed Data: A case study of Kamrej Taluka, Surat district

Thesis submitted in Partial Fulfilment for the Award of the Degree of Master of Urban and Regional Planning

by

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## CERTIFICATE

## Urban Growth Modelling using Remotely Sensed Data:

#### A case study of Kamrej Taluka, Surat district

The contents presented in this Thesis represent my original work and it has not been submitted for the award of any other Degree or Diploma anywhere else.

## Gujarati Harshkumar Lalitbhai

This Thesis is submitted in partial fulfilment of the requirements for the Degree of Master of Urban and Regional Planning at the Department of Architecture Faculty of Technology and Engineering The Maharaja Sayajirao University, Vadodara, Gujarat, India The present work has been carried out under our supervision and guidance and it meets the standard for awarding the above stated degree.

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## Abstract

A rapid global increase in human population has triggered the migration of rural poor towards the cities for a better standard of living, education and income. Urban sprawl (US), propelled by rapid population growth leads to the shrinkage of productive agricultural lands and pristine forests in the suburban areas and, in turn, adversely affects the provision of ecosystem services. There are also instances of population relocation to peripheral areas of cities due to development of planned townships. Such population movements and concentration of population, triggered by economic reasons or caused by land speculation, have led to the occurrence of changes and problems in peri-urban (or peripheral urban) areas.

The spatial metrics values indicate that the existing urban areas became denser and the suburban agricultural, forests and particularly barren lands were transformed into fragmented urban settlements. Globally, remote sensing imageries and techniques showed considerable potentials for urban growth and US analysis. Patterns of sprawl and analyses of spatial and temporal changes could be done cost effectively and efficiently with the help of spatial and temporal technologies such as Geographic Information System (GIS) and Remote Sensing (RS) along with collateral data (such as Survey of India maps, etc.) by taking into consideration the growth, impacts, planning and management of the fringe.

Urban systems have also been identified as a non-linear complex system. With the development of high end computational and visualization environments paved by the advancement computers in frontiers of geographical information systems and remote sensing image processing, modelling complex non-linear urban systems and exploration of new techniques has come to age. Kamrej Taluka (Surat City) has been identified as the study area of this research for parameterization of the model. The model explores the physical factors of urban growth in Kamrej Taluka (Urban fringe) such as transportation network, present development and topographical characteristics. Remote sensing data is employed in providing the calibration data for the model in the form of temporal datasets that allow land use land cover mapping and change detection. The remote sensing data is employed in this study for year 2013,2017 and 2021 to classify it into concern classes, Dem data are used for the

topographic analysis and also distance from major road are used as a physical parameter for the simulation of year 2013 to 2017, 2017 to 2021 and further future urban growth prediction based on previous year simulation and cellular automata method by applying transition rule to neighbourhood cell. The study provides useful metrics for urban planning authorities to address the social-ecological consequences of US and to protect ecosystem services.

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Project work upgrades the vision of a student, it helps in confronting the difficulties, manage senior individuals, and furthermore enhances the communication skills and in addition knows the market request of different things and what is inadequate in the market. Our project would not have been at this phase without the direction of some special people. One by one we might want recognize them.

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# List of Abbreviations

US	Urban Sprawl
UG	Urban Growth
LULC	Land use and Land cover
ANN	Artificial Neural Network
CA	Cellular Automation
RGB	Red, Green, Blue
OSM	Open Street Map

## **Chapter 1: Introduction**

#### **1.1 Background of study**

Urban growth (Growth of Urban area) is defined as the rate at which the population of an urban area increases. This result from urbanization which is the movement of people from rural areas to urban areas. Urban growth may lead to a rise in the economic development of a country. Urban growth is also referred to as the expansion of a metropolitan or suburban area into the surrounding environment. It can be considered as an indicator of the state of a country's economic condition as the effect of urban growth directly impacts the country's economic development. The more the metropolitan area grows, the more employment it generates, and in this way economic growth also takes place.

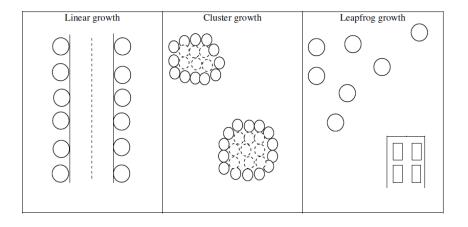
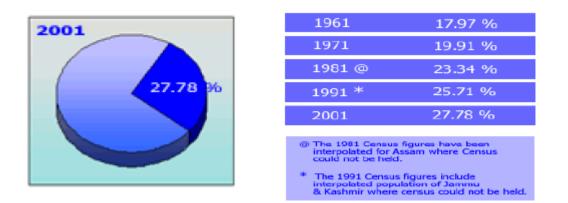


Figure 1 Types of Urban Growth Patterns

As urban growth occurs, that growth is quite relates with urban sprawl. However, there is a difference between urban growth and urban sprawl. Cities may experience growth either physically, by population, or by a combination of both. Urban sprawl is much more complicated because it may or may not qualify as urban growth. How a city grows can create the appearance of sprawl. Such urban growth may appear as a low-density leapfrog pattern, a linear or strip development pattern along highways, or a tightly condensed pattern of new development around pre-existing built-up landscapes. Without urban growth there would be no appearance of urban sprawl.

Urbanization is one of the most glaring realities of the 21st century. All over the world, people are moving towards the cities. The bright lights of the cities, the perception that cities give greater opportunities and the desire to be at the heart of a

'fast life' is drawing people to cities. India is home to some of the world's largest cities.





Urbanization levels in India are increasing. From 28.1% of the population in 2001, we now have 31.16% of the population living in urban areas. Urban areas are growing on a very fast rate in developing countries as well as developed world. It is estimated that by the end of this century, fifty percent population will live in urban areas, which are only three percent of the total landmass. In the present decade, at least eighty percent population growth occurs in towns and cities. The urbanization in India as elsewhere, has catapulted cities as the engines of national development, a source of employment. Urbanization is unequivocal; hence it is better we accept it as an opportunity. We have to strike a balance between the urban and non-urban areas that will take nation to further heights of progress in the 21st century.

## IMPACTS OF URBANIZATION ON VARIOUS COMPONENTS OF ENVIRONMENT

Probably most of the major environmental problems of the next century will result from the continuation and sharpening of existing problems that currently do not receive enough political attention. The problems are not necessarily noticed in many countries or then nothing is done even the situation has been detected. The most emerging issues are climate changes, freshwater scarcity, deforestation, and fresh water pollution and population growth. These problems are very complex and their interactions are hard to define. It is very important to examine problems trough the social-economic-cultural system. Even the interconnections between environmental problems are now better known, we still lack exact information on how the issues are linked, on what degree they interact and what are the most effective measures. One problem is to integrate land- and water use planning to provide food and water security (UNEP 1999).

**1. The creation of heat island** Materials like concrete, asphalt, bricks etc absorb and reflect energy differently than vegetation and soil. Cities remain warm in the night when the countryside has already cooled.

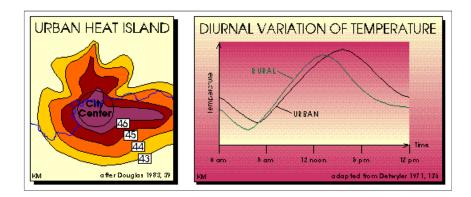


Figure 3 Urban Heat Island

## 2. Changes in Air Quality

Human activities release a wide range of emissions into the environment including carbon dioxide, carbon monoxide, ozone, sulfur oxides, nitrogen oxides, lead, and many other pollutants.

## 3. Changes in Patterns of Precipitation

Cities often receive more rain than the surrounding countryside since dust can provoke the condensation of water vapor into rain droplets.

#### 4. Flow of Water into Streams

Natural vegetation and undisturbed soil are replaced with concrete, asphalt, brick, and other impermeable surfaces. This means that, when it rains, water is less likely to be absorbed into the ground and, instead, flows directly into river channels.

## 5. Flow of Water through Streams

Higher, faster peak flows change streams channels that have evolved over centuries under natural conditions. Flooding can be a major problem as cities grow and stream channels attempt to keep up with these changes.

6. Degraded Water Quality

The water quality has degraded with time due to urbanization that ultimately leads to increased sedimentation there by also increasing the pollutant in runoff.

#### **1.2 Need of Study**

Urban areas are growing on a very fast rate in developing countries as well as developed world. It is estimated that by the end of this century, fifty percent population will live in urban areas, which are only three percent of the total landmass. In the present decade, at least eighty percent population growth occurs in towns and cities.

The magnitude is so large that it warrants a close look into existing policies concerned with planning and development of urban areas.

Many a times the planning objectives are failed due to unprecedented haphazard urban growth. The anticipation of services and opportunities in cities fuels this growth. Due to large number of factors, including organizational structures and procedures, lack of effective planning, implementation of control system etc., urban planners in developing countries feel like running behind the true facts **(Hofstee,1988).** 

In such real time data vacuum, the planner or administrator is forced to take policy decisions concerning vital urban development policies without sufficient and reliable information.

A map provides the visual aspect from which studies on urban sprawl can begin in relation to urban growth. A Geographic Information System is useful for mapping the spatial distribution of urban areas. Unlike traditional cartographic methods, GIS allows for the manipulation of different types of data in one map frame. Mapping urban phenomena is a crucial part of quantifying urban sprawl. While many layers of data are used to create a map of urban growth, ultimately it is the map that tells the story about the level of urban sprawl over a given landscape. This type of mapping involves a temporal signature in which two or more time periods are used for comparing amounts of urbanization? One base map shows urban or built-up land in a starting year and another map shows the developed land from the end year. Therefore, mapping the extent of urbanization over a given period of time is an essential part of understanding urban sprawl.

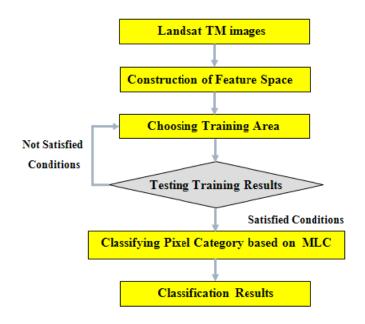


Figure 4 Process of Classification from Remotely sensed Data

The technique of remote sensing provides a powerful tool for studying urban issues, like land use/cover change, urban growth modelling, urban sprawl etc. Remote sensing image classification is one of important application aspects for remote sensing technique, through computer processing with specific software like ERDAS13, the results of the classification of land uses can be auto-outputted.

With the help of modelling and simulation, we can reduce uncertainty and increase our understanding of the urban system. Planning is a future-oriented activity, strongly conditioned by the past and present, planners need to enhance their analytical, problem solving and decision-making capabilities. The urban areas are highly complex systems, so application of Artificial Neural Networks (ANN) to modelling urban growth is quite relevant.

#### **1.3 Scope of study**

The scope of study includes the various Domain that can be analyse using this research work or can be used for different planning process as a tool. The future scope of study in broader scenario are as follows:

- The model predicted the trend of urban growth ahead of the actual growth, raising ambit to take stock of the future urban growth and avoid ill effects, if any, through planning measures.
- The key development variables can be identified as responsible for the spatial growth.
- Evaluation of influence of alternative polices on future land cover patterns in the different planning process like to Revise Development plan, master plan and agricultural planning or environmental planning.

## 1.4 Aim and Objectives

<u>Aim</u>: The aim of this study was to develop a model to predict the urban growth using GIS and artificial neural networks, remote sensing data helped in model calibration by providing a temporal dataset.

## Research Objectives

The main objective of the research is to develop Artificial Neural Network based model

Using Cellular Automata Method for urban growth modelling and forecasting. The research is aimed at demonstration of ANN in modelling complex urban systems and effectiveness of use of GIS and remote sensing in such study. Research objectives in this broader scenario are as follows:

- To demonstrate the use of GIS and remote sensing as spatial data providers in the urban modelling.
- Exploring the process of land cover change and variable that drive it.
- To develop Artificial Neural Network based model (Cellular Automata Method) for urban growth modelling and forecasting the future land cover scenarios.
- To methodically check the accuracy of the model.

## 1.5 Methodology

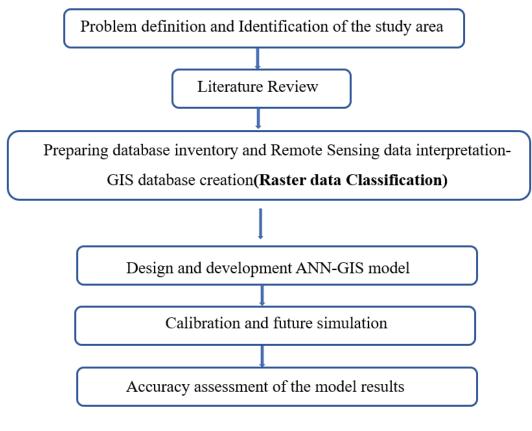


Figure 5 Methodology of the Study

#### **Chapter 2: Review of Literature**

#### 2.1 Background

Doing a careful and thorough literature review is essential when you write about research at any level. A literature review helps to create a sense of rapport with the audience or readers so they can trust that the work is referred by all that research papers. A literature review in any field is essential as it offers a comprehensive overview and recapitulation on the given scholarship from past to present, giving the reader a sense of focus as to which direction the new research is headed.

#### 2.2 Literature on effects on Environment due to urbanization

**(S.Uttara,Nishi Bhuvandas,Vanita Aggarwal, 2012)** presented that due to uncontrolled urbanization in India, environmental degradation has been occurring very rapidly and causing many problems like land insecurity, worsening water quality, excessive air pollution, noise and the problems of waste disposal. This paper emphasizes on the effect of urbanization on environmental components mainly climate, biosphere, land and water resources and also discuss about the pattern and trend of urbanization in India (1901-2001), Impact of urbanization on the environmental quality in the metropolitan cities. The paper concludes that some causes of damage to the environment due to urbanization lies in the legislation and the regulating agencies of the country and Serious attention should be given to the need for improving urban strategies, which promote efficiency in resource use.

(Rai, 2017) This paper emphasizes on the effect of urbanization on environmental components mainly public health and habitat, climate, biosphere, land and water resources. A case study of urbanization in India has been carried out leading to conclude on the existing causes of damage to the environment due to urbanization. Although it is impossible to restrict urbanization it has to be ensured that urbanization proceeds in the right path causing minimum impact on environment.

(Neelmani Jaysawal, Sudeshna Saha, 2014) presented how urbanization is closely linked to modernization, industrialization, and the sociological process of rationalization. Urbanization is not merely a modern phenomenon, but a rapid and historic transformation of human social roots on a global scale, whereby predominantly rural culture is being rapidly replaced by predominantly urban culture in Indian context. With changes in the land-use pattern when the city grows in size, it expands both horizontally and vertically. The horizontal expansion engulfed the nearby fringe villages and converted the agricultural lands, so that there is decrease in water level and also discussed about various basic problems of Urbanisation, Effects of urbanization on society and reasons behind it.

(Arpit Tiwari, 2017) has illustrate that Global trend of expanding cities to meet the requirement of increasing population always have been concern for environmental exploitation. The solution of the problem lies in strengthening the sense of our cities where the focus is not only development but also the quality of space, resource utilization and reducing effects on nature. Also, it has analysed and evaluate the urban happening and their effects on the urban quality in terms of space as well as on the public of any city.

(Ali, 2017) includes Urbanization scenario of India, causes of Urbanization in India. A sociological analysis of urban community contains several salient features of Indian Urban centres. Trends of Urban process in India is an integral part of economic development, as the economy develops; there is an increase in the per capita income and also the demand for non-farm goods in the economy, As the country urbanizes, the share of national income that originates in the urban sector also increases. In last this paper also provides the distribution of Indian cities in various class and categories based on different factor like size, Population, Growth rate and their growth pattern.

## 2.3Literature on Urban Growth Modelling Using Remote Sensing Techniques

(**Iyad Dhaoui, 2013**) focuses on the issues widely and frequently used in the examination of the urban spread out, which are scattered in the literature. The paper follows the GIS assessment conducted along some different ways that consist of the most influential advantages. The technique of Remote Sensing imagery which provides several information bases for analysis of the sprawl feature. The Literature also illustrated, types of urban sprawl, issues related to urban sprawl and also states the distinction between urban growth and sprawl. At last, discussed how GIS reveals

spatial patterns of urban sprawl by measuring distances of new urban growth areas from town centres and roads. Because urban development is irreversible, GIS simulates future land development (Lee et al 1998). A Geographic Information System is a decision support system that can facilitate urban planning. GIS can better understand all the information on one-way and becomes a guide for the best choice of urban traffic. It also allows to update the dynamic that know the ways in urban areas as new development will be done automatically updated in the information system, more specifically.

(SANDEEP MAITHANI, 2007) The present study attempts to develop an Artificial Neural Network (ANN) based model for simulating urban spatial growth. In this model remote sensing data is used to provide the empirical inputs about urban growth and other spatial information. GIS is used for handling of this spatial data, to obtain site attributes and training data for neural network, and to provide spatial functions for constructing the model. The Artificial Neural Network is used to reveal the relationships between future urban growth probability and site attributes, as ANN can capture the non–linear complex behaviour of urban systems. A three-layer feed forward neural network architecture is used in this study, which is trained using the back propagation algorithm to calculate the land use transition probability. The model results are evaluated using the percent correct match (PCM) metric and Moran spatial autocorrelation index to find out how accurately the model is able to predict the urban morphology. The model was applied to simulate the urban growth of Saharanpur city in Uttar Pradesh.

(Rajchandar Padmanaban, 2017) this study states that Urban sprawl (US), propelled by rapid population growth leads to the shrinkage of productive agricultural lands and pristine forests in the suburban areas and, in turn, adversely affects the provision of ecosystem services. The quantification of US is thus crucial for effective urban planning and environmental management. The paper includes Random Forest (RF) classification on Landsat imageries from 1991, 2003, and 2016, and computed six landscape metrics to delineate the extent of urban areas within a 10 km suburban buffer of Chennai. The level of US was then quantified using Renyi's entropy. A land change model was subsequently used to project land cover for 2027. The study

provides useful metrics for urban planning authorities to address the socialecological consequences of US and to protect ecosystem services.

(Yasmine Megahed, 2015) This study modelled the urban growth in the Greater Cairo Region (GCR), one of the fastest growing mega cities in the world, using remote sensing data and ancillary data. Three land use land cover (LULC) maps (1984, 2003 and 2014) were produced from satellite images by using Support Vector Machines (SVM). Then, land cover changes were detected by applying a high-level mapping technique that combines binary maps (change/no-change) and post classification comparison technique. The spatial and temporal urban growth patterns were analysed using selected statistical metrics developed in the FRAGSTATS software. Major transitions to urban were modelled to predict the future scenarios for year 2025 using Land Change Modeler (LCM) embedded in the IDRISI software. The model results, after validation, indicated that 14% of the vegetation and 4% of the desert in 2014 will be urbanized in 2025.

(L.R.B.Jitendrudu) The research work presents a framework for integrating artificial neural networks and geographical information systems that is implemented for modelling of urban growth and forecasting the land development in the future. Urban systems have also been identified as a non-linear complex system. Dehradun city has been identified as the study area of this research for parameterization of the model owing to its tremendous growth since becoming an interim Capital of newly formed Uttaranchal State. The model explores the physical factors of urban growth in Dehradun such as transportation network, present development and topographical characteristics. The ANN's are used to learn the patterns of development in the study area. While GIS is used to develop the spatial and predictor drivers and perform spatial analysis on the results. Remote sensing data is employed in providing the calibration data for the model in the form of temporal datasets that allow land use land cover mapping and change detection.

**(Yongjiu Feng, 2018)** illustrated that Cellular automaton (CA) is a spatially explicit modelling tool that has been shown to be effective in simulating urban growth dynamics and in projecting future scenarios across scales. At the core of urban CA models are transition rules that define land transformation from non-urban to urban. The objective is to compare the urban growth simulation and prediction abilities of

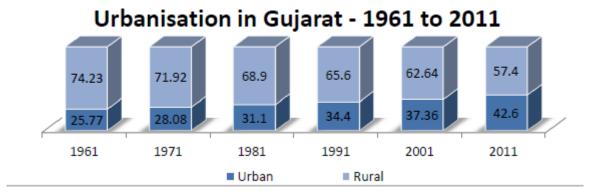
different metaheuristics included in the R package optimx. Simulation for the year 2035 were constructed considering the overall effect of all candidate influencing factors and the enhanced effects of county centres, road networks and population density. These scenarios can provide insight into future urban patterns resulting from today's urban planning and infrastructure, and can inform future development strategies for sustainable cities. different metaheuristics included in the R package optimx.

(Mohamed Benchelha, 2020) In this study, our goal was to research land-use change by combining spatial-temporal land use/land cover monitoring (LULC (1989–2019) and urban growth modelling (1999–2039) in Benslimane, Morocco, to determine the effect of urban growth on different groups based on cellular automata (CA) and geospatial methods. A further goal was to test the reliability of the AC algorithm for urban expansion modelling. To do this, four years of satellite data were used at the same time as population density, downtown distance, slope, and ground road distance. The LULC satellite reported a rise of 3.8 km2 (318% variation) during 1989–2019. Spatial transformation analysis reveals a good classification similarity ranging from 89% to 91% with the main component analysis (PCA) technique. The statistical accuracy between the satellite scale and the replicated built region of 2019 gave 97.23 %t of the confusion matrix overall accuracy, and the region under the receiver operational characteristics (ROC) curve to 0.94, suggesting the model's high accuracy.

## Chapter 3: Research Approach & Analysis of the study

#### 3.1 Study Area Selection

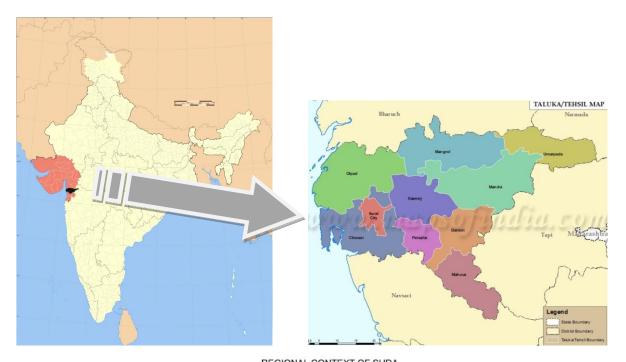
The state of Gujarat is not untouched by the phenomena of fast urbanization(3rd). State is accelerating towards the process of urbanization and modernization due the fast-growing economy of the State. The rapid pace of industrialization during the past five decades in Gujarat is one of the prime factors contributing to urban growth. With the total population of 6.03 crores (10th most populous Indian state), the urban population has risen from 37% in 2001 to 43% in 2011, making it one of the fastest growing urbanized states.

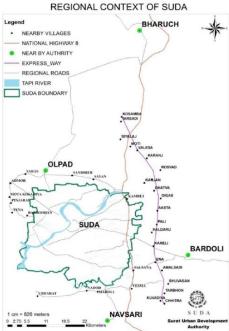




- Surat city is located on the southern part of Gujarat state in the western India. It lies near the mouth of the Tapti River at the Gulf of Khambhat (Cambay). It is one of the most dynamic cities of India with one of the fastest growth rates due to immigration from various part of Gujarat and other states of India. It is major urban center on the Ahmedabad-Mumbai regional corridor. The city has grown on both the sides of river Tapi.
- Surat's population grew from 2.8 million in 2001 to 4.5 million in 2011 a phenomenal rise of 58.68%.
- Surat is Gujarat's 2nd most populas city, India's 8th most populas city. It is the 73rd largest urban area in the world. Surat ranks 4th fastest growing city in a global study of fastest developing cities conducted by The City Mayors Foundation, an international think tank on urban affairs.

- In 2013 Surat was conferred with two awards 'Best Urban City of India' and 'Best City to Live in India' constituted by Annual Survey of India's City-Systems (ASICS). UK-based charity, The Ecological Sequestration Trust (TEST) in 2013, has selected Surat as one of the three cities in the world, to be developed as 'Global Eco-cities'.
- The SUDA area is located between latitudes 21°03' and 21°19' North and longitudes 72°41' and 73°00' East which covers 715 sq.km. It is 13 m above mean sea level.





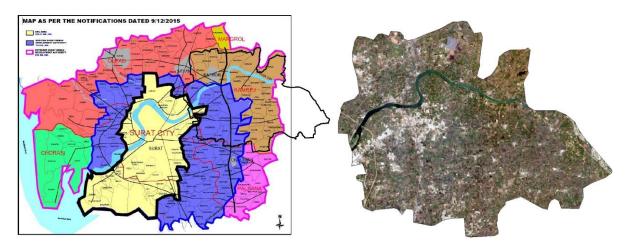


Figure 7 Kamrej Taluka - Study Area

## Demography & Salient Features of Kamrej Taluka (2011 Census)

Area: 375 sq. km

No of Town: 1 (Amboli (CT))

No of Villages: 68

Table 1 Demographic details of Kamrej

Town	Total/ Rural/ Urban	Area in square Kilometre	Number of households	Total Population (including institutional and houseless population)		Population in the age- group 0-6			
				Persons	Male	Female	Persons	Male	Femal
Kamrej	Total	375.06	39445	184554	97277	87277	22661	11890	10771
	Rural	371.31	38128	178417	94003	84414	21703	11403	10300
	Urban	3.75	1317	6137	3274	2863	958	487	471

## 3.2 Data Collection

The following materials and datasets are used for the study.

- (1) Remote Sensing Datasets (Raster Datasets)
  - Landsat 8 OLI/TIRS C2 L1-For the year 2013, 2017,2021 and Bhuvan LISS-III Datasets (Availability)-for supervised and unsupervised classification.
  - DEM Data: SRTM 1 ARC-Second Global-Digital Elevation

- (2) OSM: Open Street map (Major Road)-To create Distance from major road map
- (3) District Census Handbook-Surat (2011)
- (4) Administrative Map of Surat city- Suda Authority Shape file of Administrative Boundary of Gujarat
- (5) GIS and Image processing software: ESRI ArcGIS (10.3), Qgis (3.8.3)
- (6) ANN Software: Qgis (2.18.0)-MOLUSCE (Cellular Automata Simulation)

#### **3.3 Urban Growth Theory and Modelling (Artificial Neural Network)**

It is apparent form the above discussion that the neural networks derive its computing power through, first, its massively parallel distribution framework and second, its capability to learn and therefore generalize; these two-information processing capability makes it possible for the NN to solve complex problems.

The use of Neural Networks offers the following useful properties & capabilities:

I) Non-linearity: A neuron is elementarily a non –linear entity. Consequently, an interconnected system of neurons, neural network is itself a nonlinear distributed across the whole network.

II) Input and output mapping: A popular paradigm of learning called supervised learning involves modification of synaptic weights (free parameters) of a neural network by applying a set of labelled training samples. Each sample has a unique input signal and a desired response. The free parameters are modified so as to minimize the difference between desired and actual response of the network. The training us repeated several times till the system stabilizes where there is no significant change in the synaptic weights of the network. Thus, the network learns from the examples by constructing an input and output mapping for the problem in hand.

III) Adaptivity: Neural Networks have a built-in capability to adapt to their synaptic weights to change in the surrounding environment. In particular, a neural network can be retained to suit with minor change in the operating environment.

IV)Contextual information: Knowledge is represented by the very structure and activation state of the neural network. Every neuron in the network is affected by the global activity of all neurons in the network. Consequently, a neural network deals contextual information naturally. The neural networks have a capability to perform associative recall of memory and fill in the incomplete information.

V) Fault tolerance: A neural network implementation has to deal with abundance of data with randomness and noise within, but neural network has a fault tolerance capability to deal with it.

The manner in which the neurons of a NN are structured is intimately linked with learning algorithm of the network. In general, four basic classes of network architectures are identified, namely:

i) Single layer feed forward networks

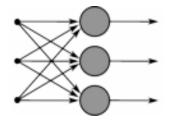


Figure 8 Single layer feed forward networks

ii) Multi layered feed forward networks

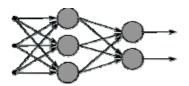


Figure 9 Multi layered feed forward networks

iii) Recurrent networks

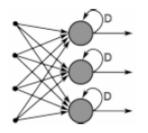


Figure 10 Recurrent networks

A salient feature of the neural networks that is significant in the ability of the network to learn from its environment and to improve its performance. There are many definitions of learning process, being a matter of viewpoint. Recognizing the interest lying in neural networks, following definition is adopted (Mendel & MacLaren, 1970):

This definition reveals the following sequence of events in neural network operation:

I) Neural Network simulated by and environment.

II) Neural Network undergoes changes as a result of simulations.

III) Neural network responds in new way to the environment due to changes in

the internal structure.

**Supervised learning** is a machine learning technique for creating a function from training data (teacher). The training set consist of pairs of input objects, and desired outputs.

**Unsupervised learning** is a method of machine learning where a model is fit to observations. It is distinguished from Supervised learning by the fact that there is not *a priori* output. In unsupervised learning, a data set of input objects is gathered. Unsupervised learning then typically treats input objects as a set of Random variables. A joint density model is then built for the data set.

#### Cellular Automata method For Urban growth modeling

A Cellular automation is a cellular entity that varies its state based on its Previous state and that of its Immediate Neighbors According to a specific Rules.

$$\{s_{t+1}\} = f\bigl(\{s_t\}, \{I_t^h\}\bigr)$$

 $\{s_{t+1}\}$  =is the state of the cell at time (t+1)

 $\{s_t\}$  = is the state of the cell at time (t)

 $\{I_t^h\}$  =refers to the neighbourhood

{V}=refers to the suitability of a cell for urban growth

f() = is the transition rule

## h= is neighbourhood size

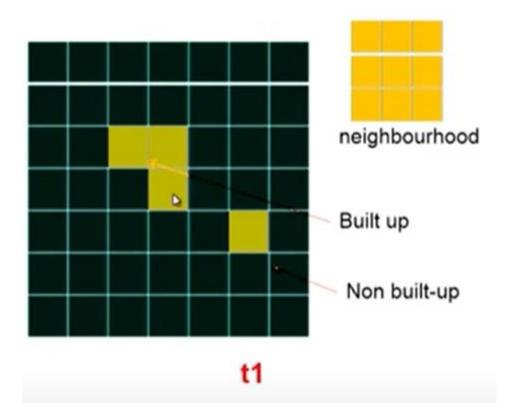


Figure 11 Cellular Entity

Transition rule:

- 1. If cell is non built up
- 2. If no. of built-up pixels in neighborhood >=3 convert to built up.
- There is not any changing in state of the cell at simulation periods if the state of a cell is urban.
- There is not any changing in state of the cell at simulation periods if the state of a cell is constrained.
- Probability of a cell for transformation to the urban state will increase if affecting factors are closer to the cell.

- The probability for transformation to urban state will increase if cells have more urban state neighbours.
- The state of the cell will transform to urban state if calculated of a cell has the maximum value between the other cells.

## **Chapter 4: Results & Discussion**

## 4.1 Development of Urban Growth Model

The urban growth model has been designed and developed to simulate the growth pattern of Kamrej Taluka. The model couples the Geographical Information Systems (GIS) and Artificial Neural Networks (ANN) routines, remote sensing and geospatial tools. The chapter discusses the development of model framework for forecasting the urban growth.

#### **Pre-Processing of Satellite Data and Maps**

The cardinal step towards the use of remote sensing data for preparation of GIS database is to geometrically correct and register the maps and satellite image data sets. This process has been identified as a very important step in the model data preparation for the reason that from serial temporal image sets.

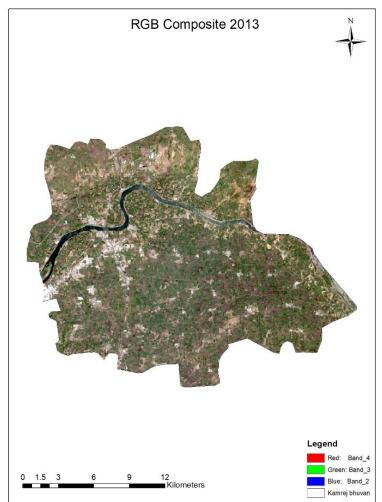


Figure 12 RGB Composite 2013

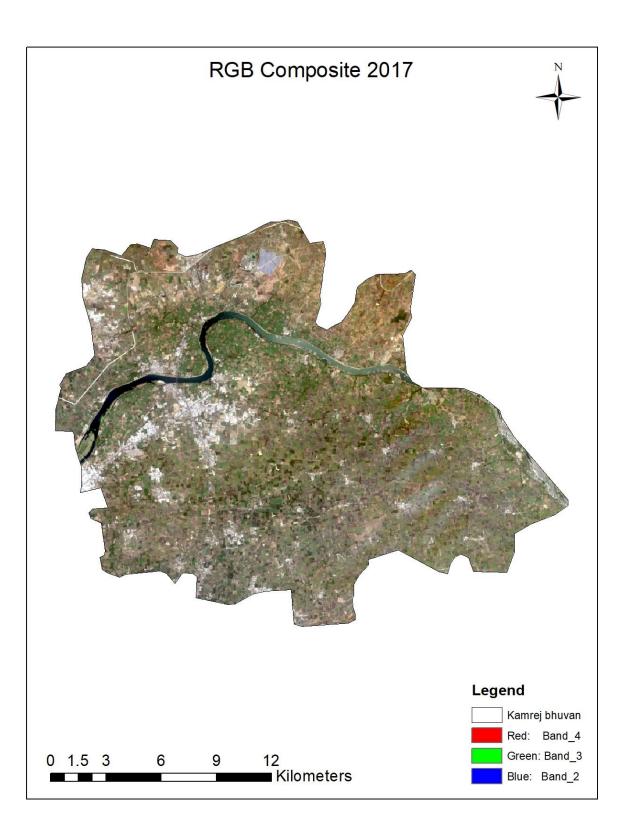


Figure 13 RGB Composite 2017

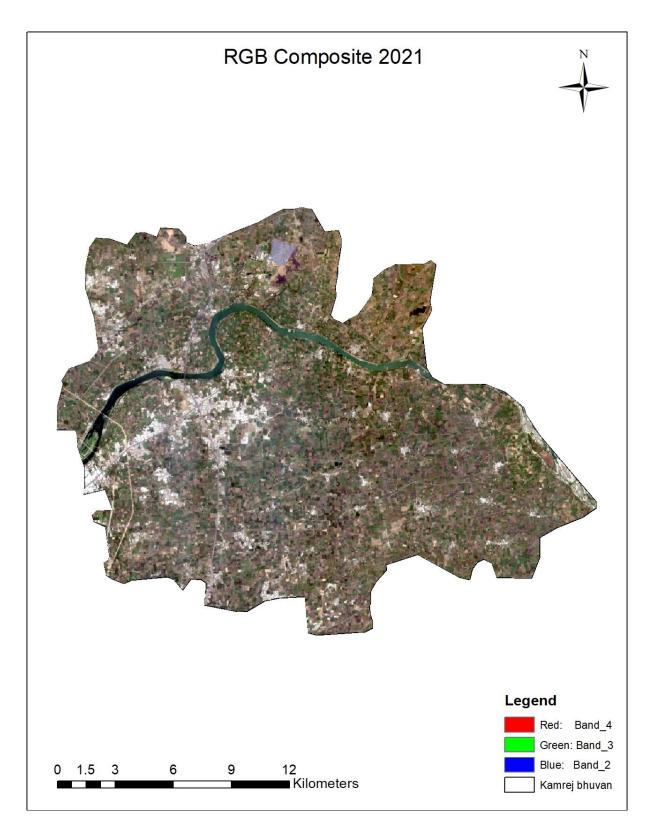


Figure 14 RGB Composite 2021

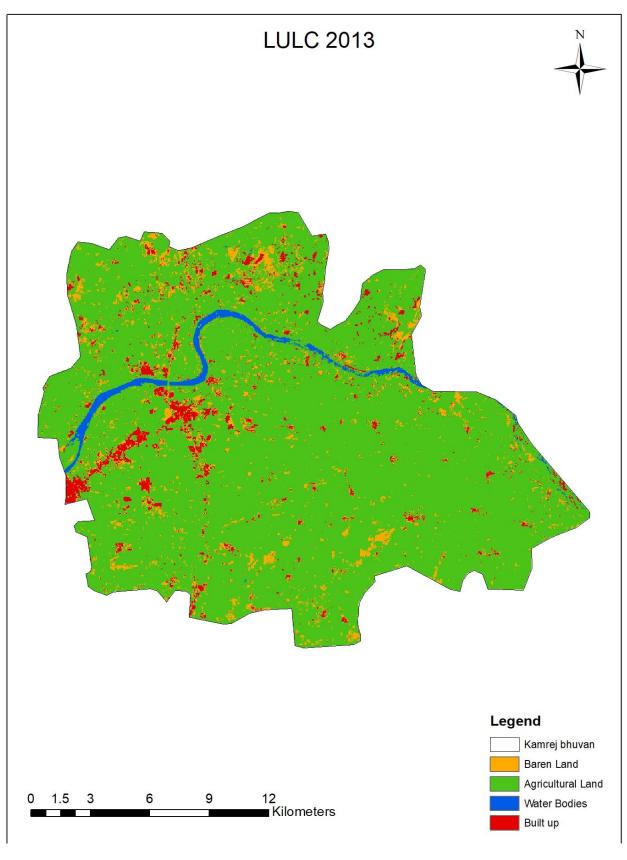


Figure 15 Supervised Classification for the year 2013

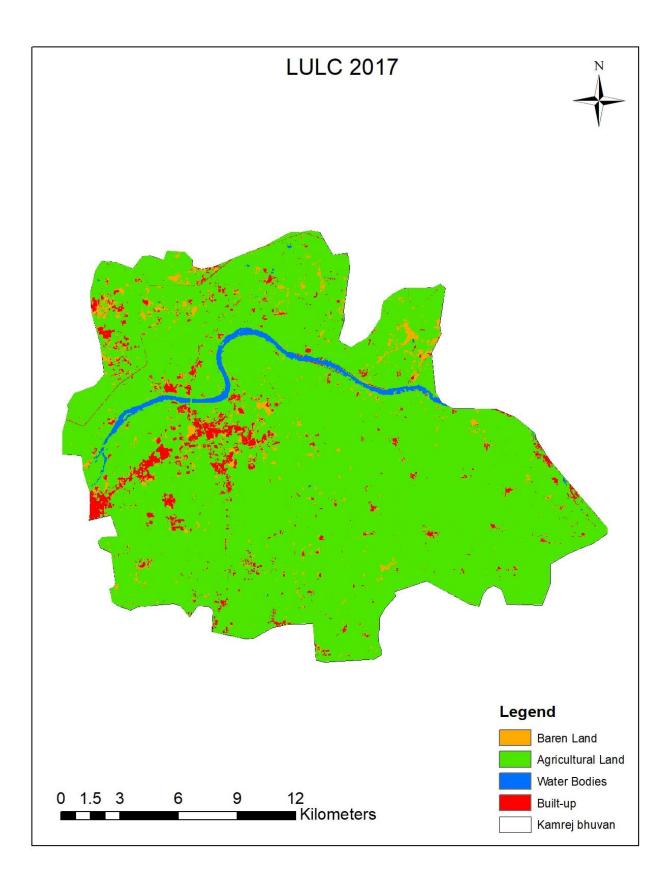


Figure 16 Supervised Classification for the year 2017

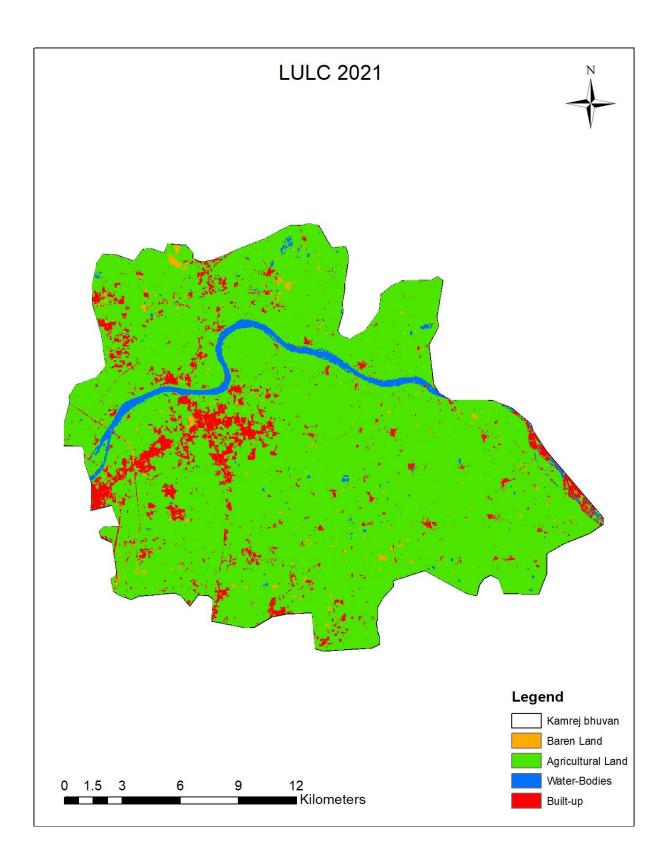


Figure 17 Supervised Classification for the year 2021

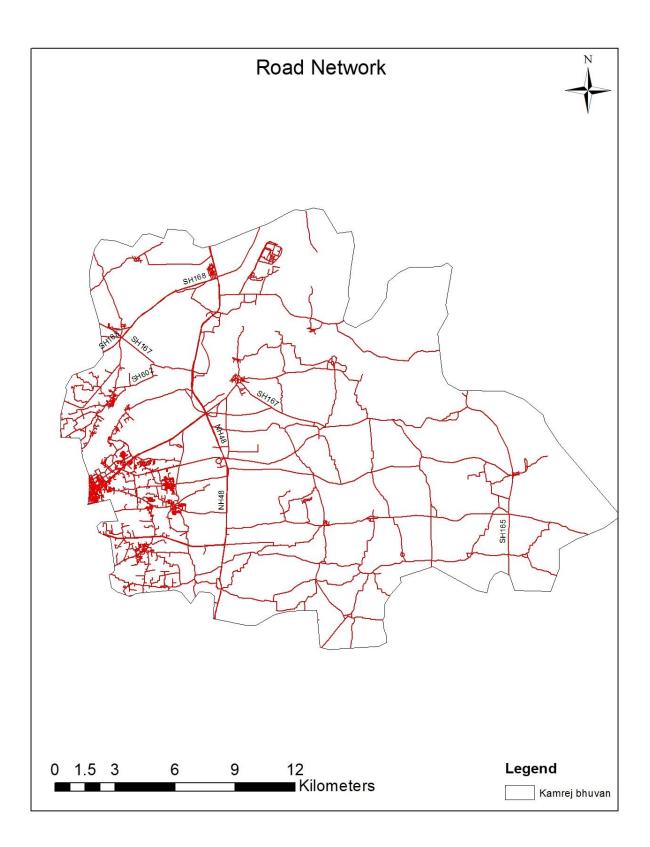


Figure 18 OSM Transportation Network within study area

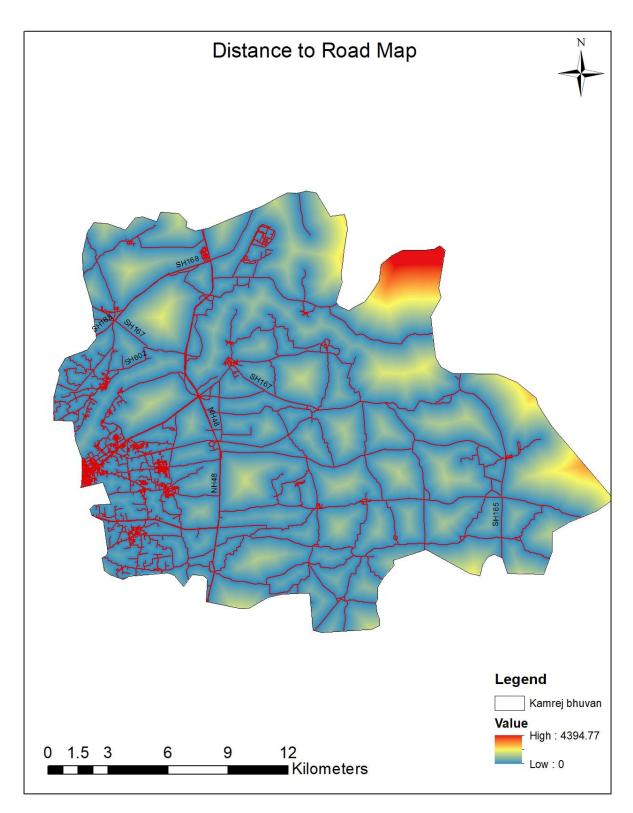


Figure 19 Distance to Road Map

The Layer created by Eclidean Distance Arc-tool.

The Modelling process was carried out in Qgis(2.18.0) With the help of Plugin named MOLUSCE.

There are generally five steps in the training process:

- 1. Assemble the training data.
- 2. Create the Transition Potential modelling.
- 3. Train the Neural network.
- 4. Simulate the network response to new input by means of Cellular Automata Simulation.
- 5. Validate the Simulated Mao with Reference Map.

Assembling the training data is the main important thing in this study because the training data helps to network for learning the training data. It also necessary that the input or training data to be used must be in same geometry and sources. Therefore, in this step the input data has to be check if its geometry does not match with each other, then the further step will not succeed that is to create the Transition Potential Modelling.

In this study, the input data were corrected and edited to match the geometry of different training data. The process involved various Arc-tools and the changes are carried out to match geometry are Cell-size of raster layer, Reference Geometric Co-ordinate System and the Classification Values of different class that are used in this study (4-Baren Land, Agricultural Land, Water-Bodies, Built-up).

#### Process of Simulating the LULC Map of 2021

- 1. Training data used in this process
  - As initial Layer LULC 2013
  - As Final Layer LULC 2017
  - As spatial Variable Distance to Road Map

Evaluating correlation Area Changes Transition	Potential Modelling	Cellular Automata Simulation	Validation Messages
013	Initial >>	2013	2013
017	Initial >>	2013	2015
FF2021 ucDist_shp41	Final >>	2017	2017
		Spatial variables EucDist_shp41	
	Add >>	]	
	<< Remove		
	<< Remove all	] [	
		Check geomet	in.

Figure 20 Training Data to be used

### 2. Evaluating correlation with Pearson's correlation

nputs Evalu	ating correlation	Area Changes	Transition Potential Modelling	Cellular Automata Simulation	Validation	1	
	European and a					-	
First Raster	EucDist_shp41						
Second Raster	er EucDist_shp41						
	X Check all raste	ers					
Method	Pearson's Correla	ation				ŀ	
		EucDist_shp41					
	EucDist_shp41						
Result							
Count							
			Check				
	0						

Figure 21 Evaluating correlation with Pearson's correlation

# 3.Change Detection

Inp	outs Eva	luating corre	elation	Area Changes	Transition P	otential Modelling	Cellular Autom	ata Simulation Val	idation	Message	es	
las	ss statistics					sq. k	:m.					•
	Class colo	r 20:	13	2017	Δ	2013 %	2017 %	Δ%				
)		25.87 sc	q. km.	12.12 sq. km.	-13.74 sq. km.	6.80833422172	3.19036281582	-3.6179714059				
		333.21	sq. km.	346.50 sq. km.	13.29 sq. km.	87.7080890279	91.206898594	3.49880956611				
2		6.07 sq.	. km.	5.81 sq. km.	-0.26 sq. km.	1.59743197944	1.52991483364	-0.0675171458015				
3		14.76 so	q. km.	15.47 sq. km.	0.71 sq. km.	3.88614477097	4.07282375656	0.186678985584				
ar	nsition matri	1										
	0	1	2	3								
,	0 0.152893	1 0.757542	0.00013	9 0.089426								
5	0 0.152893 0.021257	1 0.757542 0.960454	0.00013 0.00268	9 0.089426 8 0.015601								
0 1 2	0 0.152893 0.021257 0.000000	1 0.757542 0.960454 0.185822	0.00013 0.00268 0.80869	9 0.089426								
012	0 0.152893 0.021257 0.000000	1 0.757542 0.960454 0.185822	0.00013 0.00268 0.80869	9 0.089426 8 0.015601 0 0.005487								

# Figure 22 Class Statistics, Area Changes and Transition Matrix

# Table 2 Area Changes 2013-2017

Class	Class Name						
Value		2013	2017	Δ	2013%	2017%	Δ%
	Baren Land	25.87 sq.	12.12 sq.				
0		km.	km.	-13.74 sq. km.	6.808334	3.190363	-3.61797
	Agricultural Land	333.21 sq.	346.50 sq.				
1	-	km.	km.	13.29 sq. km.	87.70809	91.2069	3.49881
	Water Bodies	6.07 sq.	5.81 sq.				
2		km.	km.	-0.26 sq. km.	1.597432	1.529915	-0.06752
	Built-up	14.76 sq.	15.47 sq.				
3		km.	km.	0.71 sq. km.	3.886145	4.072824	0.186679

### Table 3 Transition Matrix 2013-2017

Class Value	0	1	2	3
0	0.152893	0.757542	0.000139	0.089426
1	0.021257	0.960454	0.002688	0.015601
2	0	0.185822	0.80869	0.005487
3	0.073336	0.389295	0.000366	0.537003

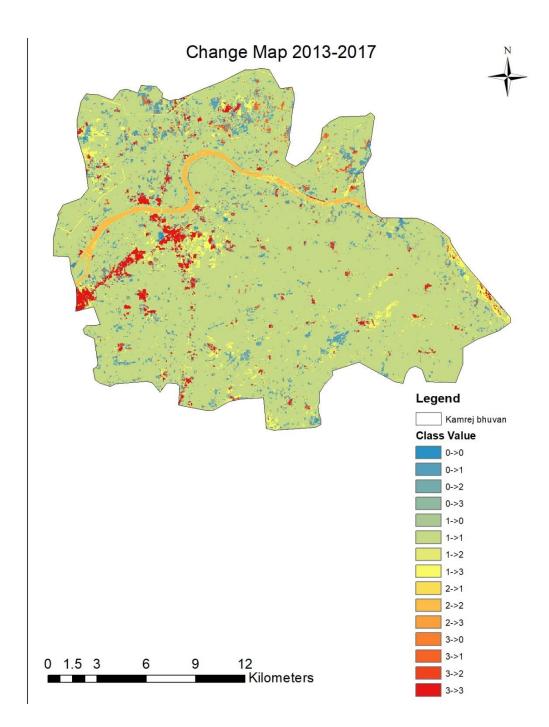
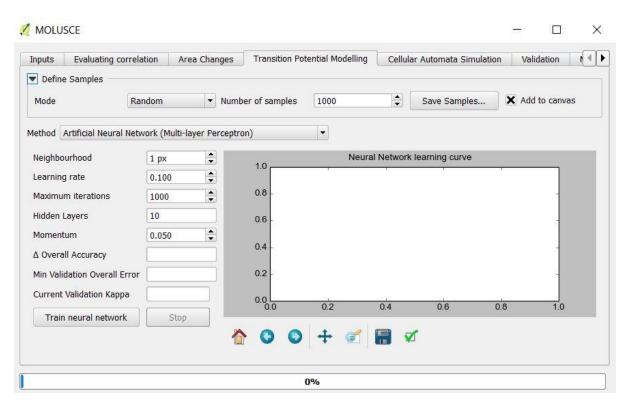


Figure 23 Change Map 2013-2017

### 4. Transition Potential Modelling



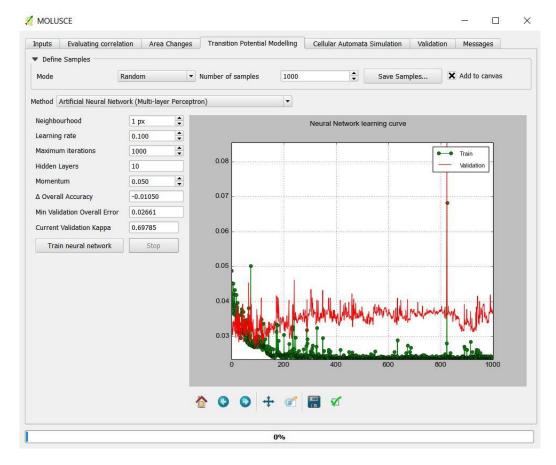


Figure 24 Transition Potential Modelling to Train Neural Network

5. Simulation based on Cellular automata Simulation for the year 2021.

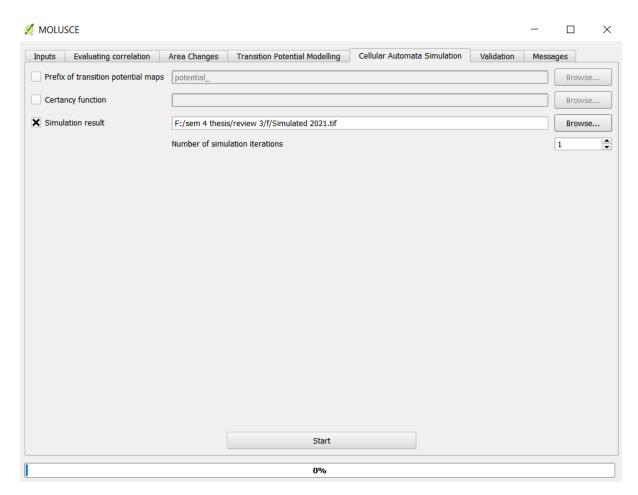


Figure 25 Simulation based on Cellular automata Simulation for the year 2021.

In this step, the output is simulated 2021 with the references the area changes, transition matrix, Transition potential Modelling to Tarin Neural Network.

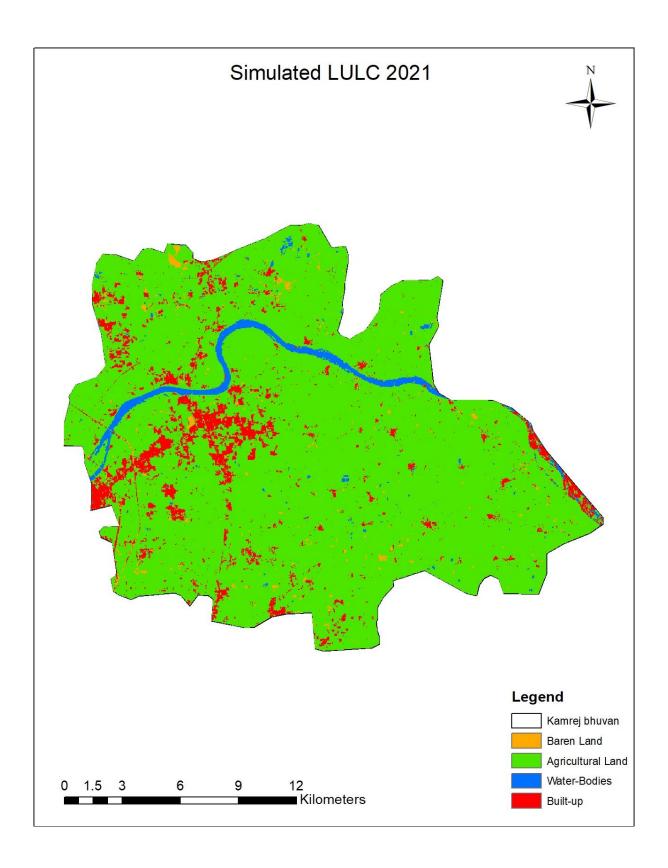


Figure 26 Simulated 2021 (2013-2017)

6. Validation of Simulated 2021 Map with Reference Map for Accuracy of Simulation

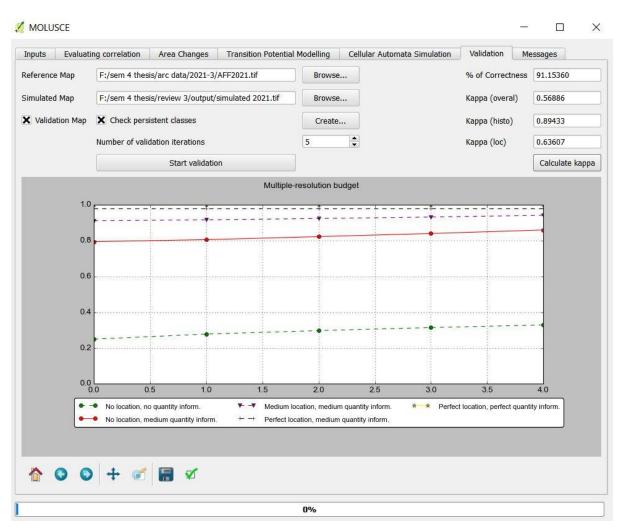


Figure 27 Validation of Simulated 2021 Map with Reference Map for Accuracy of Simulation

### Accuracy (Kappa) = 91.15%

#### Prediction Urban Growth for the year 2025

- 1. Training data used in this process
  - As initial Layer LULC 2017
  - As Final Layer LULV 2021

	Evaluating correlation	Area Changes	Transition Potential Modelling	Cellular Automata Simulation	Validation	Messages	
2013							
2017			Initial >>	2017	2017		
2021			Final >>	2021	2021	1	_
	t_shp41		T mar 2 2				
	2013-2017						
	ted 2021 ted 2025						
				Spatial variables EucDist_shp41			
			Add >> << Remove				

- As spatial Variable Distance to Road Map

Figure 28 Training Data to be added

2. Evaluating correlation with Pearson's correlation

nputs Evalu	ating correlation	Area Changes	Transition Potential Modelling	Cellular Automata Simulation	Validation	Messages	
First Raster	EucDist_shp41						-
Second Raster	EucDist_shp41						
	X Check all raste	rs					
Method	Pearson's Correla	tion					-
		EucDist_shp41					
	EucDist_shp41		_				
Result							
Result							
Result							
Result							
Result							
Result							
Result							
Result							
Result							

Figure 29 Evaluating Correlation

# 3.Change Detection

Inp	outs Eva	luating corr	elation	Area Changes	Transition	Potential Modelling	Cellular Autor	nata Simulation	Validation	Message	S	
las	ss statistics					sq.	km.					
	Class colo	r 20	017	2021	Δ	2017 %	2021 %	۵ %				
0		12.12 s	q. km.	4.73 sq. km.	-7.39 sq. km.	3.19036281582	1.24397379861	-1.94638901721				
1		346.50	sq. km.	337.76 sq. km.	-8.74 sq. km.	91.206898594	88.9072882982	-2.29961029577				
2		5.81 sq	ı <mark>. km.</mark>	9.53 sq. km.	3.72 sq. km.	1.52991483364	2.50808428983	0.978169456191				
3		15.47 s	iq. km.	27.89 sq. km.	12.41 sq. km.	4.07282375656	7.34065361335	3.26782985679				
	poition mate	iw.										
rar	nsition matr	ix										
	0	1	2	3								
5	0 0.122744	1 0.674018	0.000594	4 0.202643								
0	0 0.122744 0.009088	1 0.674018 0.944646	0.000594 0.01045	4 0.202643 7 0.035808								
0	0 0.122744 0.009088 0.000000	1 0.674018 0.944646 0.010220	0.000594 0.01045 0.98807	4 0.202643 7 0.035808 7 0.001703								
0 1 2	0 0.122744 0.009088 0.000000	1 0.674018 0.944646 0.010220	0.000594 0.01045 0.98807	4 0.202643 7 0.035808								
0	0 0.122744 0.009088 0.000000	1 0.674018 0.944646 0.010220	0.000594 0.01045 0.98807	4 0.202643 7 0.035808 7 0.001703								

### Table 4 Area Changes (Class Statistics) 2017-2021

	Class						
Class Value	Name	2017	2021	Δ	2017%	2021%	Δ%
	Baren	12.12 sq.	4.73 sq.	-7.39 sq.			
0	Land	km.	km.	km.	3.190363	1.243974	-1.94639
	Agricultural		337.76 sq.	-8.74 sq.			
1	Land	km.	km.	km.	91.2069	88.90729	-2.29961
	Water	5.81 sq.	9.53 sq.	3.72 sq.			
2	Bodies	km.	km.	km.	1.529915	2.508084	0.978169
	Built-up	15.47 sq.	27.89 sq.	12.41 sq.			
3		km.	km.	km.	4.072824	7.340654	3.26783

The increase in Built-up is 3.26 %.

The Decrease in Agricultural land is 2.29 %.

# Table 5 Transition Matrix 2017-2021 as per Class Value

Class Value	0	1	2	3
0	0.122744	0.674018	0.000594	0.202643
1	0.009088	0.944646	0.010457	0.035808
2	0	0.01022	0.988077	0.001703
3	0.005758	0.143148	0.010005	0.841089

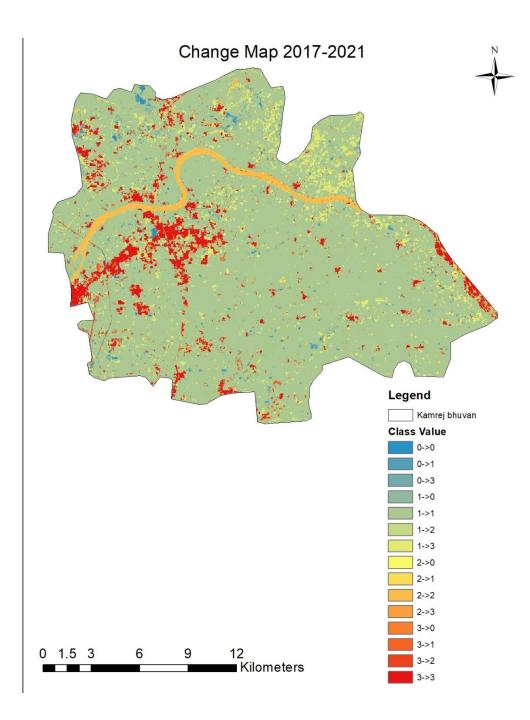


Figure 30 Change Map 2017-2021

# 4. Transition Potential Modelling

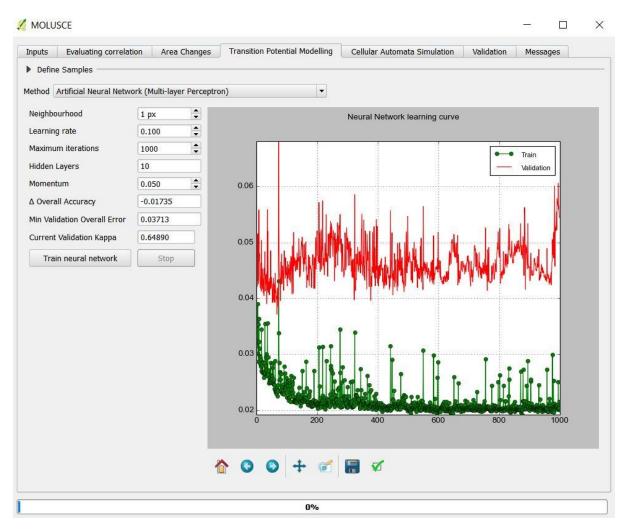


Figure 31 Transition Potential Modelling to Train Neural Network

5. Prediction of Urban Growth based on Cellular automata Simulation for the year 2025

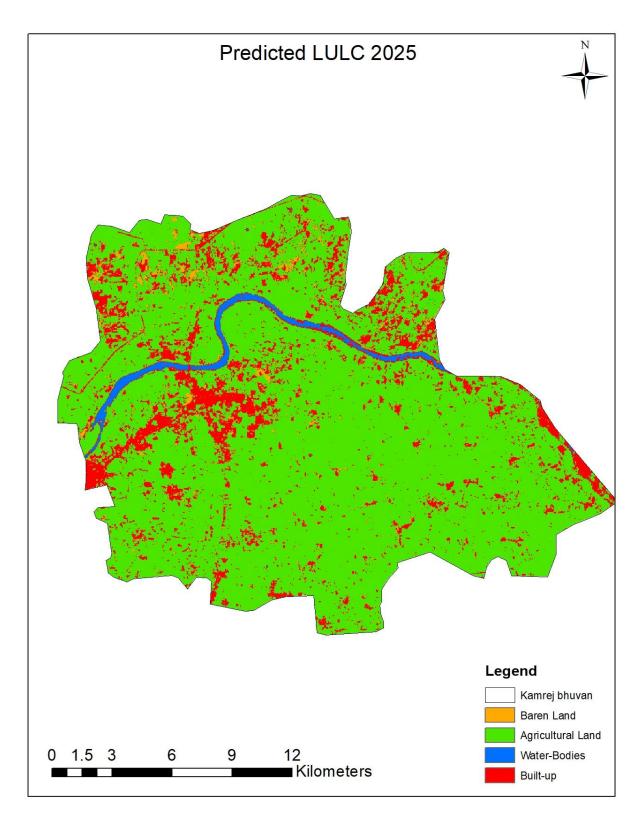


Figure 32 Predicted 2025

# **Chapter 5: Conclusion & Recommendation**

- The study has simulated Urban Growth (LULC) for the year 2021 with the input layers are LULC 2013, LULC 2017 and Spatial Variable (Road Network, Distance to road Map) with the help of remotely Sensed data and MOLUSCE Arc-Tool (Cellular Automata Method), The Model has provided the Accuracy of Modelling by validating Simulated LULC 2021 Map with Reference layer (LULC 2021). The Accuracy of Simulated LULC Map for the year 2021 is 91%.
- After that, the study has Predicted Urban Growth (LULC) for the year 2025 with the input layers are LULC 2013, LULC 2017 and Spatial Variable (Road Network, Distance to road Map) with the help of remotely Sensed data and MOLUSCE Arc-Tool (Cellular Automata Method), The Model also provides Change Map that includes Change Value of Different Class.
- The accuracy is primarily based on the accuracy of Classified input data (Training data) and more Spatial variables. Further accuracy of Modelling can be increase by increasing different class of Remotely Sensed data. In short it is Trial & Error process.
- The Modelling provides Change Map of different class and amount of Area change of Different class. Therefore, Growth pattern and their contributing variables can be identified.

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