Spatio-Temporal Modelling of Jammu City Using Remote Sensing and Geographical Information System

Thesis submitted to the Andhra University, Vishakhapatnam in partial fulfillment of the requirement of the award of
Master of Technology in Remote Sensing and GIS

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Declaration

I, Arshdeep Kaur, hereby declare that this dissertation entitled "Spatio-Temporal Modelling of Jammu city using Remote Sensing and Geographic Information System" submitted to Andhra University, Visakhapatnam in partial fulfilment of the requirements for the award of M.Tech in Remote Sensing and GIS, is my own work and to the best of my knowledge and belief. It is a record of original research carried out by me under the guidance and supervision of Dr. Sandeep Maithani Scientist SF, Urban and Regional Studies Department, Indian Institute of Remote Sensing, ISRO, Dehradun. It contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or any other institute of higher learning except where due acknowledgement has been made in the text.

Place: Dehradun Ms. Arshdeep Kaur

Date: 16 July, 2015

CERTIFICATE

This is to certify that the research work entitled "**Spatio-Temporal Modelling of Jammu city using Remote Sensing and Geographic Information System**" is the original record of work carried out by "Arshdeep Kaur" towards partial fulfilment of the requirements for the award of Master of Technology in Remote Sensing and GIS by Andhra University at Urban and Regional Studies Department, Indian Institute of Remote Sensing (IIRS), Dehradun.

The project contains original work carried out by her and she has duly acknowledged the sources of data and resources used. This research project is completed and recommended for evaluation.

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(Dr. Sandeep Maithani)

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Arshdeep Kaur

Dedicated to my brother

Abstract

Urbanization, a phenomenon that is both inevitable and dynamic, shall continue to shape the way the cities are seen worldwide. Increase in the number and extent of cities all across the globe is the mainstay of the global economy these days. Apart from the positive effects of urbanization such as increasing employment opportunities, better educational, transport and communication facilities, convenience, efficiency and social integration (to name a few), there are some adverse consequences as well. The most important of them being overpopulation, cost of living, land insecurity, environmental issues and pollution. Rapid urbanization is the growing trend in almost all the developing countries. In such a fast growing world, the city of Jammu in the state of Jammu and Kashmir is experiencing rapid growth in the urban form having demographic, structural and behavioural bases. This inevitably increases the urban footprint with severe consequences for biodiversity, climate, and environment resources. Urban growth prediction models have been extensively studied with the overarching goal to assist in sustainable management of urban resources. The scarce resources call for their proper utilization else they would not ensure to fulfil the various needs of the masses, the welfare of public and sustainable Development with least consequences to the environment. So, the cities need to be planned beforehand and should not be allowed grow spontaneously and haphazardly. This study thereby aims at studying the causative factors for urbanization in the city of Jammu, identifies the urban growth potential at various places within the city and outside and predicts the future scenarios using several algorithmic approaches.

KEYWORDS

Urban Growth, Artificial neural Networks, Multilayer Perceptrons, Self Organizing Maps, Spatial Metrics, Measures of spatial agreement and disagreement, Urban growth potential, Modelling, Spatial Trend.

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Chapter 1: INTRODUCTION

1.1 Background

We all know that the human population continues to aggregate in urban centres. Urbanization is taking place at such a rapid pace that it comes as severe shock to see the existing growth as well as its consequences where the world is heading. The sub-continent of India alone accounts for more than 17.51 % of the total world population as on 2015 (*World Population Clock*) of which 33% is residing in urban areas. Such mind-blowing statistical figures for India have really changed the perception about urban growth phenomena. Planners, administrators, economists, sociologists, environmentalists have all started predicting the severe consequences of such a trend. Today, the most urbanized regions include Northern America, Latin America & Caribbean, and Europe with 82, 80 and 73% of urbanization respectively in contrast to Africa and Asia with 40 and 48% as their counterparts. It is but natural for Africa and Asia to urbanize faster than the other regions. It is projected that by 2050, the level of urbanization in these two continents will rise up to 56% and 64% respectively. India, China and Nigeria alone are projected to account for 37% of the world's urban population by 2050 (*World Urbanization Prospects, 2014*).

India has a gigantic urban structure by having more than over 12000 settlements and 7500 towns and cities and it is known that some 5-6 million people are continually being added to urban India every year thereby creating it as one of the largest urban systems. The situation is no different in case of Jammu And Kashmir State. The urban population of over 2.5 million is distributed in 80 towns in the state but it is largely concentrated in the cities of Jammu and Srinagar which account for about 63% of the total urban population.

What happens in such a condition is that many of the planning initiatives fail to combat with the pace of unprecedented haphazard urban growth. It is felt that there is a mismatch to anticipate the level of services, utilities, facilities and planned opportunities that the cities can offer to thrive on this continuous systematic growth. Urban planners in the developing countries are constantly confronting with the problems and taking policy decisions without adequate and reliable information (Hofstee, 1988). Urban growth manifests various problems such as putting pressure on infrastructure, stress on natural resources and consequently leading to the formation of slums, squatters and shanty towns. Increase in traffic volumes on roads, congestion, jamming besides reducing farmlands, green covers causing environmental problems of various types. In this regard, modelling tool is an innovation which provides solution to all these problems by being able to perform analysis and prediction of urban growth dynamics of an area (Silva & Clarke, 2002). Urban growth modelling provides valuable insight to policy makers and planners who anticipate, forecast and evaluate the change detection and envisage futuristic changes or trends of development. This also lets them understand the impacts of future spatial development and explore the potential impacts of different policies and regulatory schemes on

the land use patterns (Pettit et al., 2002, Verburg et al., 2002). Urban growth dynamics is a highly complex and nonlinear phenomena which can be modelled using various mathematical models each coming with their own sets of merits and de-merits. Which model is suitable for a particular situation is a highly subjective thing. Depending on the particularity of an area and its differentiation, a decision is made much before selecting a model. The key question is to know the factors responsible for urbanisation that is taking place in an area and its cumulative impact on the quality of life.

1.2 What is an Urban Area?

The Census Organization of India has set up its own criteria to determine and define the urban areas. As per 1981Census, an urban area is defined as any place which satisfies all of the following conditions:

a) A minimum population of 5,000
b) With at least 75% of the male working population engaged in non-agricultural activities and
c) A population density of at least 400 persons per square kilometre.

1.3 Demographic Changes in India

The population explosion in developing countries is a major issue concerning all. In the context of India, we observe that the rapid urbanization has led to compounding of problems such as scarcity of service-lands, and qualitative physical and social infrastructural facilities (Sivaramakrishnan and Singh, 2005a). The urbanisation of India some decades ago had a unique characteristic that it tended to concentrate more in larger cities like Delhi, Mumbai, Hyderabad, Kolkata etc. but in the recent past, the situation is reversed and the small and medium sized towns are also picking up at a fast rate. The trend in urban growth is depicted in the below given graph.

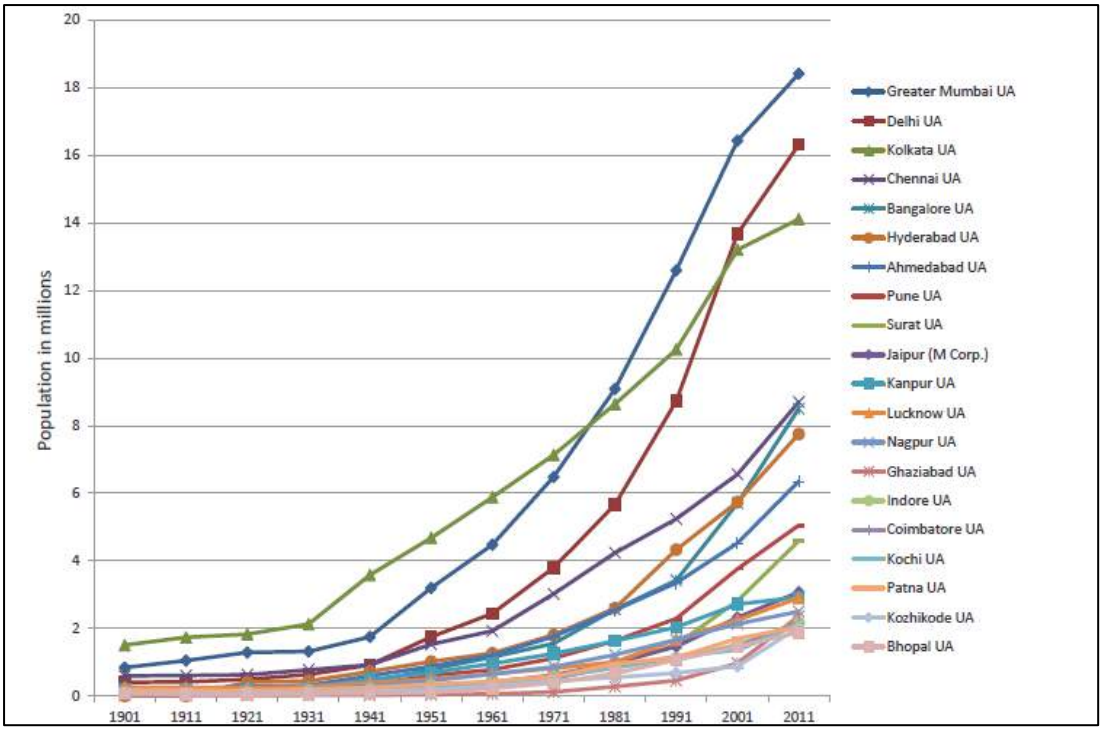


Figure 1: Largest 20 Urban Agglomerations (UA) in India as per population in 2011

Figure 1 shows the rapid growth of the largest metropolitan cities in the 20th century. It clearly indicates how it is now slowing down and the trend is towards the expansion of smaller cities at a much faster rate.

As per Census 2001, there were about 35 million plus urban agglomerations and cities which then rose to 53 as on 2011 and are still on the rise. It is also noticed that a total of 43% of the urban population of India lives in these cities, the population in each case being confined to the statutory limits of the respective Municipal Corporations only and devoid of inclusion of any outgrowths (Census 2011).

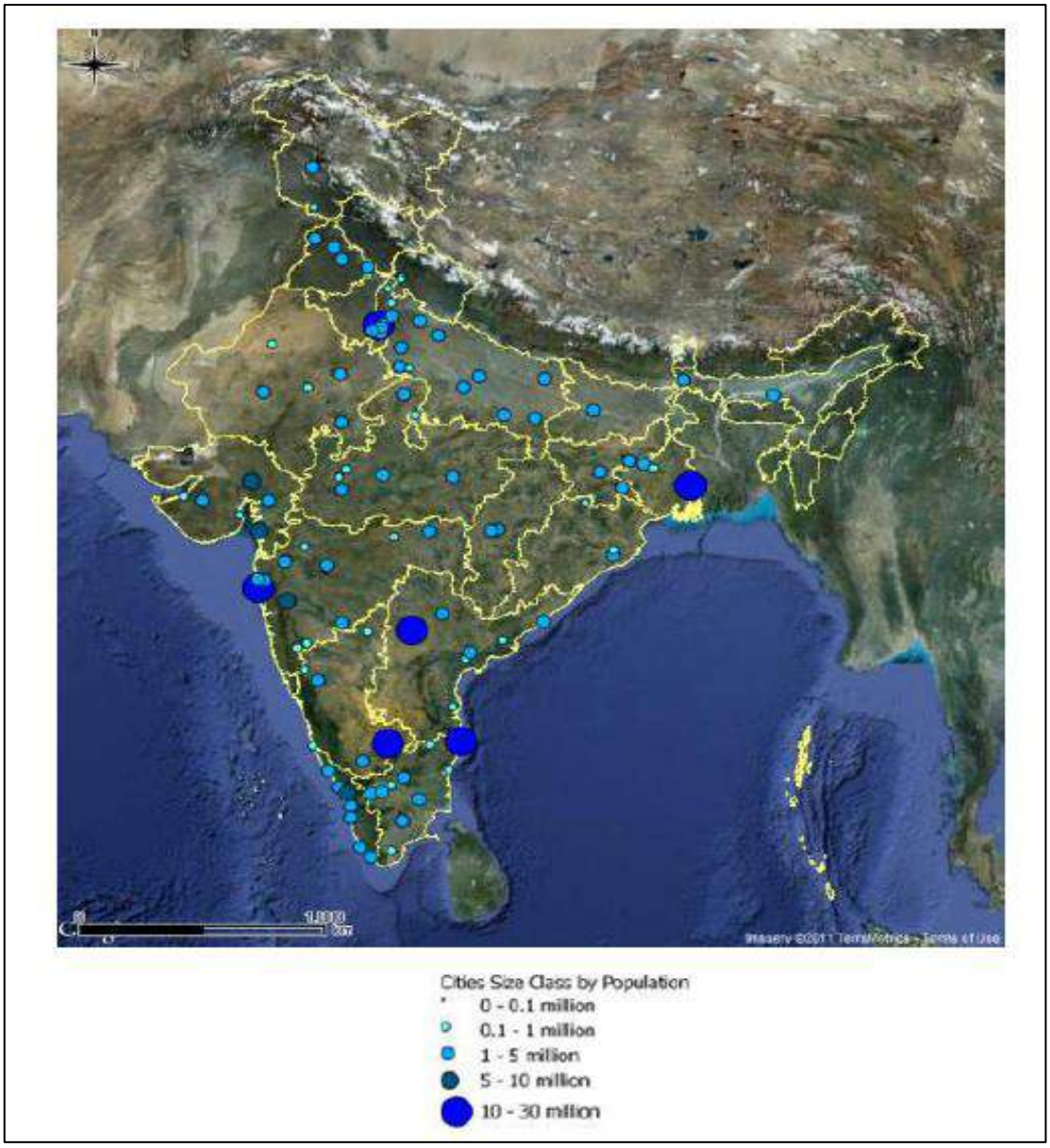


Figure 2: Scenario of Indian Cities

It is also noted that among these fast growing cities, Srinagar was the first to become the first agglomeration in the state of Jammu and Kashmir to cross one million. As per Census 2011, Jammu had a total population of 951,373 and a density of 5697 persons per square kilometre. With the pace of urbanization witnessed in the last five years, Jammu City too has attained the metropolitan status as of now (Master Plan 2021 projections).

The outcome of the projections and calculations can be used as a basis for suggesting alternative sustainable urban development plans for the cities. It is highly imperative to study the causes and dynamics of urban growth and provide models of urban growth to the planning bodies so as to be able to predict and forecast urban growth patterns and structure the policies in short and long term to implement the intended plans.

1.4 Role of Remote Sensing and GIS in Urban Growth Prediction and Modelling

The availability of high resolution satellite imagery and remote sensing data has made it possible to deliver any type of geographical information at any point of time with a click of a button. Remote sensing data is an asset because of its real-time data acquisition, synoptic view and repetitive coverage.

Geographic Information System (GIS) and Remote Sensing (RS) along with collateral data (such as Survey of India maps, etc.) together can help perform various types of analysis. Some of them concerning us include the patterns of city growth, spatial distribution, and identifying the temporal changes. Mapping the urban growth provides a pictorial representation of where the growth is occurring, it also helps identify the environmental and natural problems caused by this unprecedented growth, and also suggests the likely future directions and patterns of expected sprawling growth (Michael and Gabriela, 1996). The availability of up to centimetre level of high-resolution satellite imageries and the ever-growing advancements in computer hardware and software has opened doors for greater GIS analysing capabilities than ever before. The highly specialized image processing software is quite effective in capturing the features on ground. The spatio-temporal information of different time-periods obtained from the various satellites can be easily utilized to find out the pattern of development in the cities over the years. Change analysis helps in the formulation of better future plans.

The current study utilizes three time-period data of Landsat Satellite for the years 2003, 2008 and 2014 respectively. The growth in the city structure over these years is assessed and calculated and is subsequently employed in the prediction of the future urban form. This will have added benefits for the planning bodies and administrative authorities to make well-informed and intelligent decisions.

1.5 Motivation and Problem Statement

Urban analysis emerged from the field of city planning. Much of the theory of urban analysis was generated as a result of amalgamation of ideas borrowed from other disciplines such as economics, quantitative geography, operations research and spatial statistics. As different methods vary in terms of their specificity to different fields, these were not guaranteed to fit into the field of urban planning practice directly. 1980s was a time of great critical debate on whether urban analysis contributes to city planning at all or not. Urban planning in the earlier years was not advanced enough to incorporate quantitative methods as no spatial databases covering urban spaces or cities were available, however, the development of urban databases and the application of geographic information systems (GIS) to city planning changed the situation drastically. India is on its way to becoming a nation to utilize such spatial databases and other tools for effective policy making related to land use patterns, allocation of urban facilities, and urban environments.

Spatial analysis which resonates clearly with urban analysis is greatly facilitated in today's world as a result of the advancement in the field of high resolution data availability, data management strategies,

improvements in visualisation environments, fast-paced information interchange and a skilled workforce. In contrast, however, spatial analysis itself, especially statistical analysis is lagging behind. Major statistical methods for spatial analysis suffer a lot because of their conventionalism and their inability to present a better picture in a detailed space. Many endeavours are being undertaken to this end, whereby behavioural and psychological methods too will be employed for the betterment of spatial statistical techniques (Ishikawa et al., 2008).

Land use change is of prime concern in urban analysis. The question is what changes are caused by what factors and in what structure? The new technology of RS and GIS since the last two decades has enabled development of modelling, prediction and evaluation of urban phenomena including several what-if scenarios. Since 1990s, new models have been attempted by various authors such as Markov Chain Model (Osaragi and Masuda, 1995), the genetic algorithm (Takizawa et al., 1997), cellular automaton model (Arai et al., 1999) etc. Most of the models are mainly parametric in nature and cannot assimilate multi-source and categorical data. Secondly, it is extremely time consuming to find proper values for the model parameters during the calibration process.

The present study aims to overcome some of the short-comings of the previous models using diverse ANN (Artificial Neural Networks) and machine learning techniques to model the urban growth in a reliable manner. Such non-parametric techniques for modelling complex patterns (such as city growth) have the following advantages:

a) Being non-parametric techniques, hence no assumptions about the distribution of the data.
b) Multi-source data and measurement data of different types can be used.
c) They can solve highly non-linear problems.
d) These techniques are also resistant to noise in the data-sets.
e) These methods generate a number of parameter values automatically, thus saving the calibration time.

This study aims to estimate quantitatively the various factors responsible for growth in the study area and constructing various machine-learning based Neural Network Models to investigate the structure of the changes and predict the future.

1.6 Research Objectives:

The prime focus of the study is to explore various machine learning based approaches for urban growth modelling and forecasting. The research is aimed at the demonstration of adequacy, reliability and accuracy of such techniques in modelling complex non-linear phenomena of urban growth and the effectiveness and use of GIS and remote-sensing data in such a study. Research objectives in the current study are as follows:

- To analyse the various forms of urban spatial growth in the study area.
- To identify the causative factors inducing urban growth.

- To simulate the urban growth as a function of the causative factors using various machine-learning algorithms.
- To evaluate the simulation results using various spatial matrices.
- To generate future growth and what-if scenarios.

1.7 Research Questions:

The following are the research questions that will be addressed:

- What is the urban growth trend of Jammu City?
- What are the determinants or variables that affect the urban growth in the study area?
- What different spatial growth models can be applied to model the future urban growth?
- How can the accuracy of each respective algorithm be assessed?
- How will the growth pattern be affected under different circumstances?

1.8 Scope and Limitations:

The whole study encompassing the understanding of structural profile of the Jammu city will bring out the causes of urbanization in the study area. The study aims at discovering the potential of various machine-based learning algorithms to understand the existing pattern and trying to predict/speculate the future conditions. The entire exercise tries to give us a realistic and a much understandable future land use pattern after the application of different modelling techniques. Also, various what-if scenarios will be generated indicating the change in the growth pattern and direction under various growth constraints. This study is going to be extremely useful for the planning bodies by allowing them assistance in decision-making and effective planning.

The main limitation of the study is that it is based on two classes: Built Up and Non Built Up, so it does not give an elaborative land use classification (which includes Residential, Commercial, Industrial, Public and Semi-Public etc.), the limiting factor being data availability (Landsat imagery with 30 meter resolution).

1.9 Organisation of the Thesis

The whole thesis is divided into six chapters. The first chapter lays the background of the study providing general introduction about the research work including the problem statement, research objectives and questions. The second chapter deals with literature survey in which the related works as have been performed by various other researchers are presented. In the third chapter, information about the chosen study area is given and how the several data layer maps are generated, also outlining the methodology of carrying out the task and the data sources utilized. The fourth chapter discusses about the various CA-based Artificial Neural Networks and how they can be utilized for generating the potential maps specifying the location of urban growth and also about the what-if scenarios depending upon the various conditions/constraints in the urban growth. Chapter five presents the

findings of this research work and a detailed discussion on the results obtained. In the sixth chapter, a conclusion is drawn based on the results obtained along with future research possible and some recommendations.

Chapter 2: LITERATURE SURVEY

2.1 General

Urban growth/sprawl is a much talked about word in today's planning practices of the developed as well as the developing world. 'Urban growth' is a constant process of growth and decline of economic agglomerations. The study of urban growth has been taking place from a very long time. Studies have revealed that by the year 2030, an estimated 60% of the world's total population will live in urban areas (*United Nations, 2004b*). The expected population projections suspect the inadequacy of the cities to sustain the urban growth in the upcoming years. Understanding the urban growth in an area and the various models that are applicable to map the future urbanization is an essential task for urban planning bodies to provide for better planning and proper utilization of resources.

2.2 Spatial Models in Urban Simulation

Various models have been tried and tested to perform the task of urban growth mapping since a long time with variable levels of success. We discuss a few of them below, however, many new models get discovered from time to time and thus lead to the realization of the fact that the process of model refinement is something that lies at the very heart of spatial growth prediction and modelling.

2.2.1 Cellular Automata (CA) Models

CA is one of the earliest and the most widely used models to study the phenomena of urban growth. A finite state automaton is a kind of mathematical formulation which has basic input, processing and output units each of which is connected to each other and made understandable by a set of grammar rules. These grammar rules work as a source of information exchange between any two units. CA is discrete in nature and is a dynamically, rapidly changing system constituted of a series of cells which behave like finite-state automata. Any CA system is composed of four components – cells, states, neighbourhoods and transition rules. The interactions operating in the CA are all local. So, a functional relationship can be formulated whereby the next state of a cell is a function of the current state as well as its neighbours (Flake, 2000). Cellular automata have been used as a simulation technique in various urban phenomena including regional growth, gentrification, expanding residential areas, economic activity and employment structure, historical basis of urbanization, evolution of land use, and poly-centricity to name a few.

CA being a decentralized approach helps model complex physical phenomena with greater ease. It provides a connection of form with functions, patterns and processes. The ease with which the model results can be visualized is still another attraction. CA also proposes the advantages of dynamics, simplicity, flexibility, computational efficiency and capability of mimicking real life behaviour. CA

has a very high compatibility with geographic information systems and remotely sensed data thus favouring them over other techniques.

2.2.2 SLEUTH Model

SLEUTH (Slope, Land-use, Exclusion, Urban Extent, Transport and Hill-shade) is another eminent simulation model for speculating the urban growth. It is also based on cellular automata techniques. Basically, it comprises of a set of rules called growth rules. The prime use of this model is to predict the future urban extent under different planning scenarios. Some of the key attributes of this model include independent scalability, transportability, transparency and capability to predict the urban extent over some future time by re-generating the past and forecasting the growth into the future time. The SLEUTH simulation model actually incorporates two different models i.e. Clarke Urban Growth Model and Delta-tron Land Use/Land Cover Model.

2.2.3 Clarke Urban Growth Model (CUGM)

The Clarke UGM is again a cellular automaton based urban growth model. It not only considers transportation networks and slopes but also the urban regions so as to bring out the predictions of urban growth in an area within a certain span of time. This model simulates the urban growth in terms of topography, adjacency and transportation networks which operate through time (Clarke et al. 1996). The behaviour of this model can be controlled by varying several parameters and by modifying the urban growth rules. Different growth types like spontaneous, diffusive, organic and road-influenced growths can be studies using this model. Each growth type has its own set of rules. Various scenarios can be generated for future growth.

2.2.4 Delta-tron Land Use/Land Cover Model (DLM)

The DLM model uses land use information in conjunction with the urbanization information to model and show how land use might transit from one land use category to another. The dynamics of the land cover change are understandable as a four-step process wherein they start with change initiation being the event when a new urbanization event occurs, then creating a change cluster whereby new delta-trons get created based on the probability of land use change followed by change propagation where the change is carried on to a few more delta-trons in the neighbourhood and finally the ageing of delta-trons in which case the repetitions over time lead to a new potential for delta-trons in the upcoming growth cycle. This model is iterative in nature.

2.2.5 Fuzzy Cellular Automata Urban Growth Model (FCAUGM)

Fuzzy logic when combined to CA greatly enhances its capabilities for expressing and mapping the urban growth. This model being based on fuzzy set theory rather than probability theory determines the transition potential of cells from one land use category to another. Like any other model, it too has got transition rules to dictate the transition on a cellular basis. These transition rules are constructed in two stages: a) by identifying spatial-based factors, b) by creating driving forces for urban growth.

Fuzzy Logic maintains that each variable has a certain degree of membership of its belongingness to a particular class and each fuzzy set is described by a linguistic variable. The knowledge base is represented as a linguistic "IF THEN" rules. The certainty factor in this case describes the level of certainty and uncertainty that a hypothesis under consideration would be favoured over others.

2.2.6 Agent Based Model (ABM)

The ABM can be used to overcome the limitations of existing models. CA, as have been described previously are used for spatial dynamics, ABM on the other hand are meant for aspatial phenomena. This model is a generalization of cellular automata model but with the exception that here agents are the mobile items in space. The agents have a unique identity and character associated with them. An agent is an object comparable to a computer software component or a robot or an actor which can perceive the things in its surroundings and can act autonomously based on the experiences it has. Agent-based models are useful in conceptualizing land use changes and urban growth.

2.2.7 Artificial Neural Network

A Neural Network is a massively parallel distribution processor which has the capability to be trained for some new pieces of information that can be retrieved at some later point of time when need be. The working is quite simple. The knowledge is acquired by the network through a learning process and the synaptic weights i.e. the inter-neuronal connections store the knowledge and impart it at suitable points of time (Aleksander and Morton 1990).

Unlike the more commonly used traditional analytical methods, ANN is neither dependent on the functional relationships between data nor makes any assumptions regarding the distributional properties of the data. This independence makes the Artificial Neural Networks (ANN) a potentially powerful modelling tool for exploring nonlinear complex problems like urban growth (Olden and Jackson, 2001). Artificial Neural Networks (ANN) based modelling is a type of regression modelling. Once the model knows how the spatial variables are functioning together in a systematic and coherent fashion, they are further utilizable for predicting the future conditions. Several authors including Pijanowski et al., 2000; Dougherty, 1995; Rodrique, 1997 have all studied urban growth by coupling ANN with GIS for the purpose of forecasting the change in land use.

2.3 Traditional Models of Urban Growth

Diverse models including CA based, Artificial Neural Networks, spatial-statistical, fuzzy logic based, agent based and several other techniques have been exploited to carry out the measure of urban growth as mentioned in the recent previous discussions. Urban growth is a spontaneous & a self-organising process (Wu, 1998). Spontaneous growth causes distributive sprawl which is random and lacks any form and spatial structure whereas self-organizing growth causes a unique spatial distribution pattern having a distinct form and structure (Cheng, 2003 a).

Several authors have addressed the complexity of the urban growth and how cities tend to spread, grow and age over time. Several ordered properties of cities have also been studies by various people including White & Engelen, 1994 & Brian Pijanowski, 2002a, to name a few.

So, now knowing that the cities are complex and that their pattern is something that plays a role in understanding their type and character and future growth possible, there are several questions that come up. First, can the patterns of the city be measured? Second, if the patterns of the city can be measured, is there any means to know how do they contribute to future urban growth? Answers to these questions help us know about the dynamics that are governing the growth.

The following five factors are identified as a measure of the city's pattern (Eastman et.al., 1993; Carver, 1991):

1. Environmental characteristics.
2. Local scale neighbourhood characteristics.
3. Spatial characteristics of the city.
4. Urban & regional planning policies.
5. Factors related to individual preferences.

The first part including the natural or geographical characteristics can be represented as constraints for growth like rivers, natural barriers, underlying landforms, slope etc. These have a direct impact on the urban growth. The second part is in accordance with Tobler's first law of geography stating that everything is related to every other thing but near things are more related than things that lie far away. We know that new residential areas usually grow near adjacent existing residential areas. Also as an example, industrial land use may be a repulsive factor for residential growth. Third are the spatial characteristics of the city. Distance from the city centre, accessibility, transport networks etc. influence the future growth. Planning policies help determining land use pattern, direction and dynamics of urban growth through land use zoning and regulations. The last set of factors relates to the individual preferences, socio-economic & political systems. They are complicated and reliant on human decisions and evolve with time being highly stochastic.

Modelling helps understand urban systems and their functions in a broader capacity. A model shall never be able to represent the real world the way it is but it helps provide valuable information on how things can be in the future with a fair degree of accuracy. Models serve as useful tools for:

1. Knowing the mechanisms underlying land use changes and their driving forces (Batty & Xie,1994)
2. Predicting potential future impacts of land use change (Alig,1986; Theobald,Miller & Hobbs,1997)

3. Influences of various policies on land use patterns (Constanza et al., 1997).

2.4 Cellular Automata for Urban Growth Modelling

CA was first developed in the late 1940s by S. Ulan and J. von Neumann. It was Wolfram (1984) who first demonstrated the capability of cellular automata for modelling complex natural phenomena and later laid the foundations of a Theory of Cellular Automata (Wolfram, 2002). CA simulation was soon applied to physical sciences, natural sciences and mathematics. Tobler (1979) was the first to propose the suitability of CA models to geographic modelling which were later followed by many (Batty and Xie, 1994; Couclelis, 1985; White and Engelen, 1994) for the simulation of urban expansion. When actually applying CA-based models to urban planning, the most difficult task is to choose a suitable model from among the many options available (Pinto and Antunes, 2007; Li and Yeh, 2002a). The next step is the application of a suitable theoretical framework for carrying out the simulation. Many different CA based models have been applied for urban applications.

CA based models are so efficient for urban studies that there are still many on-going research endeavours waiting for further exploration. The bottom-line is that dispersive/diffusive type of growth patterns are best performed using CA techniques as they are iterative localized neighbourhood based and are way more realistic than other techniques. This adequately shows that CA offers a flexible and advanced spatial modelling environment like no other.

2.5 Integration of GIS and CA for urban dynamics modelling

Many different authors have tried to couple Markov-CA models with GIS systems and they indicate that it delivers a better way to model the temporal and spatial change of land use (Myint and Wang, 2006). In the CA models, the Markov chain processes control the spatial and temporal change using the transition matrices whereas GIS can be used to define the initial conditions and to parameterize the model and lay down the neighbourhood rules (Batty et al., 1999; Weng, 2002; Aitkenhead and Aalders, 2008). These days, not only are the natural and socio-economic data being incorporated into the land use simulations but also other intricate data that characterize the city at various levels. Therefore, the integration of GIS and CA along with high-level city details still remains a major research challenge.

2.6 Summary

In the current chapter a detailed literature survey was conducted for various available urban growth modelling techniques that included spatial statistical models, agent based models, fractal based models, fuzzy models, ANN, etc. Various studies were surveyed and an observation was made that urban growth being dispersive /diffusive phenomena is best modelled using machine learning and CA coupled models.

CHAPTER 3: STUDY AREA & DATA LAYER GENERATION

3.1 General

The city of Jammu, also called the city of temples, is the winter capital of the state of Jammu and Kashmir. The legend says that Raja Jamboo Lochan originally founded the city in the 14th century. The name later distorted to that of Jammu as we know it today. The city actually took shape in 1962 when its extent was limited to just 16.87 sq. km. By 1994, the urban agglomeration had expanded much beyond its municipal limits to engulf a total area of around 143.52 sq. due to the mass exodus of Kashmiri Pundits and some families belonging to Sikh and Muslim communities since the 90's owing to the disturbed conditions existing in the Kashmir Valley. The present extent of the Jammu city is 167.38 sq. km while the planning area is 287.92 sq. km (Jammu Master Plan, 2021).

3.2 Study Area: Jammu City

3.2.1 Physical Setting

The study area consists of Jammu planning area as per Jammu Master Plan 2021. The city of Jammu is located at 74 degree 24' and 75 degree 18' East longitude and 32 degree 50' and 33 degree 30' North latitude. It falls in the sub-mountainous foothills of Himalayas and is situated on the banks of river Tawi. Jammu city is at an elevation of 1030 feet (327 m) above the sea level. It is located on the National Highway–1A. Because of its locational advantage, Jammu assumes importance as a linkage corridor to Rajouri, Poonch, Kishtwar, Doda and serves as the gateway to Kashmir Valley. The city has faced lateral expansion along the National Highway NH-1A towards south and along Akhnoor Road towards north. Rural areas especially towards the south have undergone extensive transformation from agricultural to urban use.

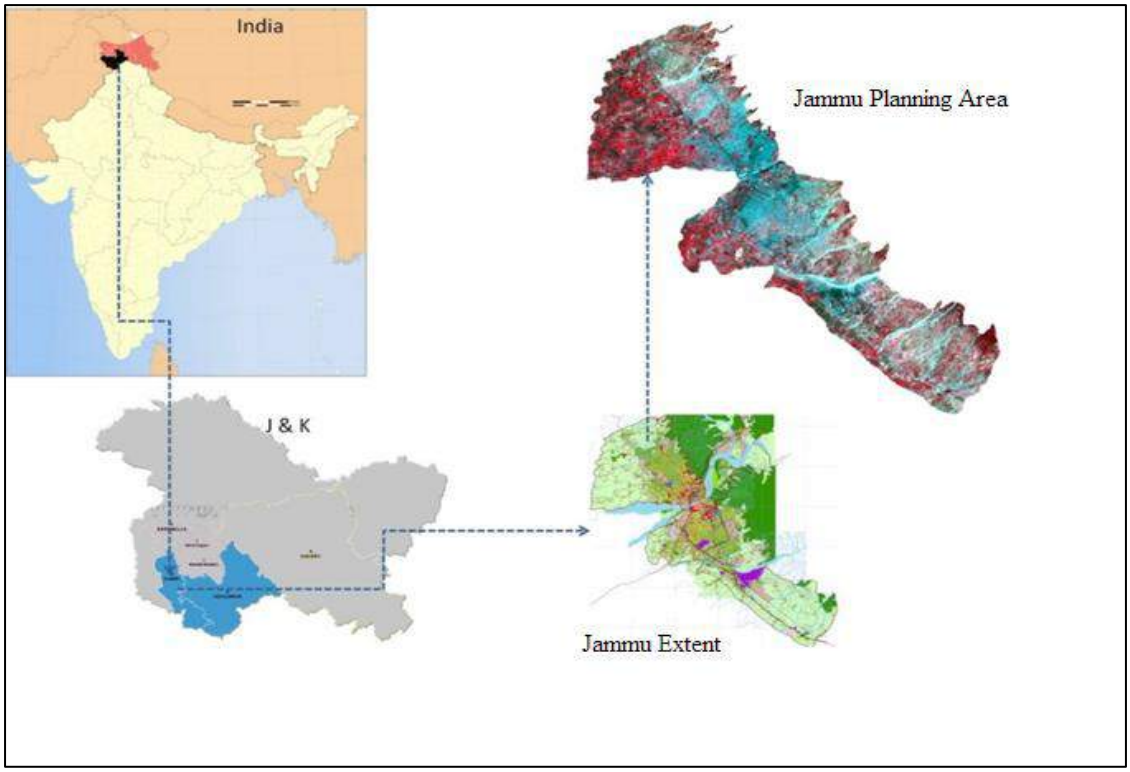


Figure 3: Locational Setting of the city of Jammu

3.2.2 Demography

The urban population of Jammu city as per the Census report 2011 is 503690 of which male and female are 265346 and 238344 respectively. Males constitute 52.7% of the population; females constitute 47.3% of the population. The sex ratio is 898 females per 1,000 males against a national average of 940.

3.2.3 Regional Connectivity

Jammu city is well connected to all parts within the State and outside through road, rail and air link. The city is approximately 600 km away from the National capital (Delhi) and about 290 km from summer capital (Srinagar) of the State. The city is accessible through all-weather roads and is frequented by state transport buses and private luxury coaches. Jammu is the northern-most railway head. Jammu-Tawi railway station is located at a distance of 2 km from the city centre. Close to the railway station is the bus stand, which offers bus services for various destinations.

3.2.4 Major Functions of the city

1) Administrative: Jammu city serves as the winter capital of Jammu & Kashmir state from November to April when all the offices move from Srinagar to Jammu due to the hostile weather conditions in Srinagar during the winter season. Jammu was a municipal committee in 2001 which got upgraded to the status of a municipal corporation on September 5th, 2003. Jammu city is the main cultural and economic centre of the administrative division of Jammu.

2) Industrial and Commercial: The city has a number of small industries. The industrial estates of Gangayal and Bari-Brahmana are the largest in the entire state. Jammu has a number of food-grain mills. Jammu also has the largest number of shopping complexes, cinemas, recreation centres in the state. Some major malls in Jammu are Wave Mall, City Square Mall, Kapsons Multiplex, Golden Palms to name a few.

3) Tourism: Tourism is the largest industry in Jammu as in the rest of the state. It is also a focal point for the pilgrims going to Vaishno Devi and Kashmir valley. More than a hundred million people visit Vaishno Devi shrine every year and a significant portion of it also visits Jammu, the city of temples. All the routes leading to Kashmir, Poonch, Doda and Laddakh emanate from Jammu city. So throughout the year, the city remains flooded with people from all the parts of India. Places of interest include old historic and heritage area like Mubarak Mandi, Purani Mandi, Rani Park, Amar Mahal, Bahu Fort, Raghunath Temple, Ranbireshwar Temple, Peer Meetha, fun parks, etc.

4) Educational and Institutional: Many important government engineering and medical colleges in the state are an attraction for a large share of students from all over India. Schools, general degree colleges and universities are still another point of interest. In the 2014-2015 General Budget of India, the Finance Minister of India has also proposed an Indian Institute of Technology and an Indian Institute of Management for Jammu.

5) Refugee Rehabilitation Centre: The annual rate of intra-regional migration is estimated to range from 29 to 35%. Being comparatively safe from terrorism, Jammu has become a hub of refugees. At present there are about 9-13 lakhs refugees living in and around Jammu in different relief camps and townships, example Jagti Township at Nagrota. These primarily include Kashmiri Pundits; partition-time refugees and refugees from Reasi, Doda and Kishtwar districts.

6) Defence: Being a border town, it has a lot of defence and security forces garrisoned in the Jammu city.

3.3 Generation of Spatial Database

For carrying out the process of generation of spatial database for Jammu city, the broad working methodology is described below. Here, the entire methodological frame-work entails a series of steps performed for predicting the future urban structure of the city of Jammu. It can be categorized into various phases. *Phase 1* describes the data generation of the three time period satellite data. *Phase 2* deals with the urban trend analyses between each pair years (2003-2008) and (2008-2014). *Phase 3* aims at applying various machine learning algorithms for comparative assessment and selecting the best one for future simulation. *Phase 4*, the last phase is all about using the best algorithmic approach selected above to perform future simulation for 2020 and generation of various urban growth scenarios.

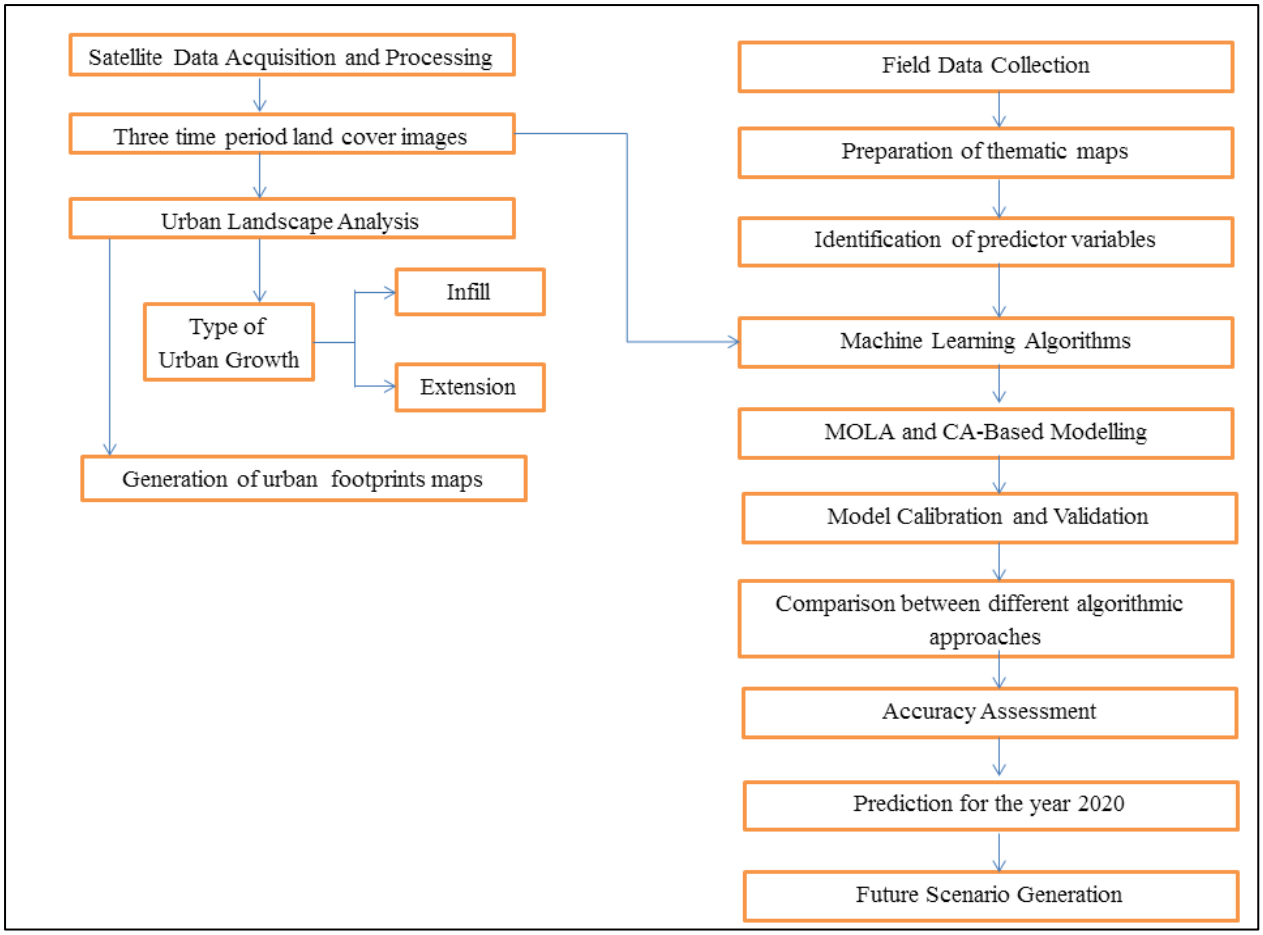


Figure 4: Broad Work-Flow Diagram

Phase 1

3.3.1 Software Used

The task of image correction, pre-processing and classification are done in ERDAS Imagine 14 software. Preparation of various data layers and their analyses are carried out in ArcMap 10.1. ULA (Urban Landscape Analysis) tool is downloaded and added at an extension to the ArcMap 10.1 for carrying out the urban trend analysis. All the simulations and algorithmic trainings are performed in IDRISI Selva 17.0.

3.3.2 Data Sources Used For Creating Spatial Data-Bases

The data for the three time periods (2003, 2008 and 2014) are made available by the website USGS Earth Explorer. Landsat 7 imagery for the year 2003 and 2008 with cloud cover approximately 0.04 % and 0.09 % ; and Landsat 8 imagery for the year 2014 with cloud cover approximately 0.7 % and data coordinates 33.17705^0 N and $74.42666\ ^0$ E are utilized as the data input sources. The same are mentioned below as:

- Landsat 7 (30 m resolution) acquisition date: 13 Apr, 2003

- Landsat 7 (30 m resolution) acquisition date: 19 Oct, 2008
- Landsat 8 (30 m resolution) acquisition date: 12 Oct, 2014
- Revised Jammu Master Plan-2021

The planning area boundary as per the Master Plan 2021 by the JDA (Jammu Development Authority) is used. The Jammu planning area boundary excluded the areas of Nagrota, Nandor, Chak Rakwalan and other small townships which are otherwise included under MP limit 2021. The afore-mentioned areas are excluded from the satellite imagery and are not included for growth analysis because most mathematical modelling techniques function optimally when the input data is enclosed as a contiguous piece of land. If dis-continuous i.e. in the form of small patches, the analysis quality suffers and the results become misleading. Keeping in view this working constraint imposed by the modelling software, those areas are ruled out of analysis. The final image boundary to work with is shown in figure below.

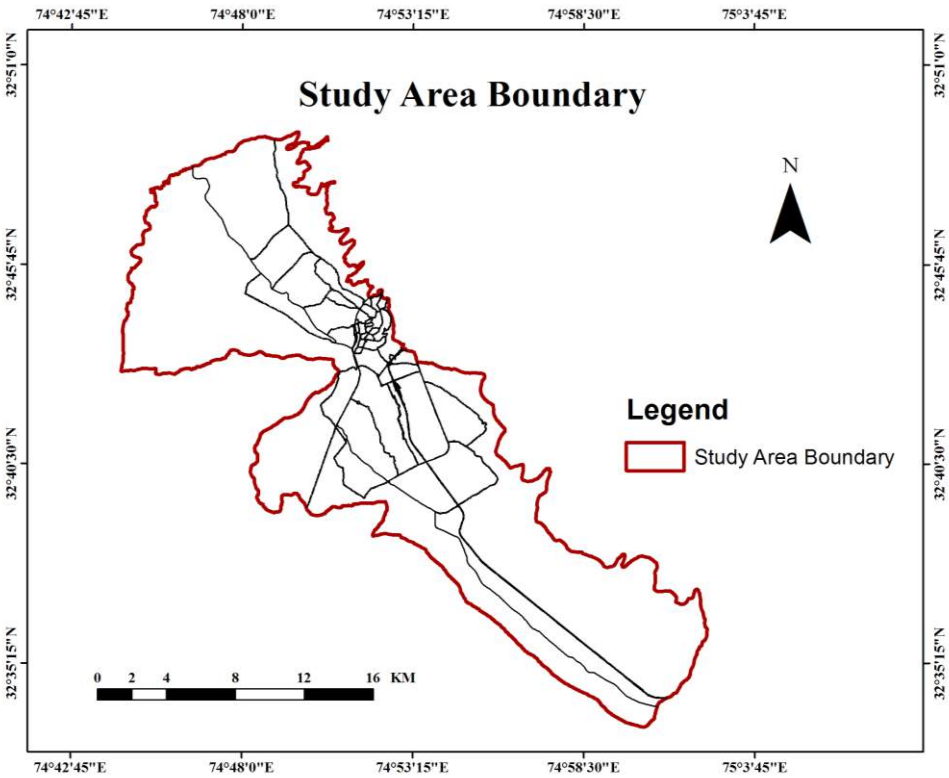


Figure 5: Delineated Study Area Boundary

3.3.3 Pre-processing of Remote Sensing Data

The major problem faced in this case is the data of Landsat 7 for the year 2008 as it suffered data-absence due to SLC off condition. All Landsat 7 images collected after May 31, 2003, when the Scan Line Corrector (SLC) failed have data gaps but are still useful and maintain the same radiometric and geometric corrections as the data collected prior to the SLC failure. A number of methods have been developed to fill the gaps of Landsat 7 data. In the present study, software ERDAS Imagine is used to

perform the task of data filling using the technique of focal analysis which computes the values of the neighbouring pixels and fills in the gaps based on those calculations for a single Landsat 7 scene. A total of 9 repetitions of Focal Analysis are performed to correct the image and fill the gaps. Figure 6 represents both the corrected as well as uncorrected images.

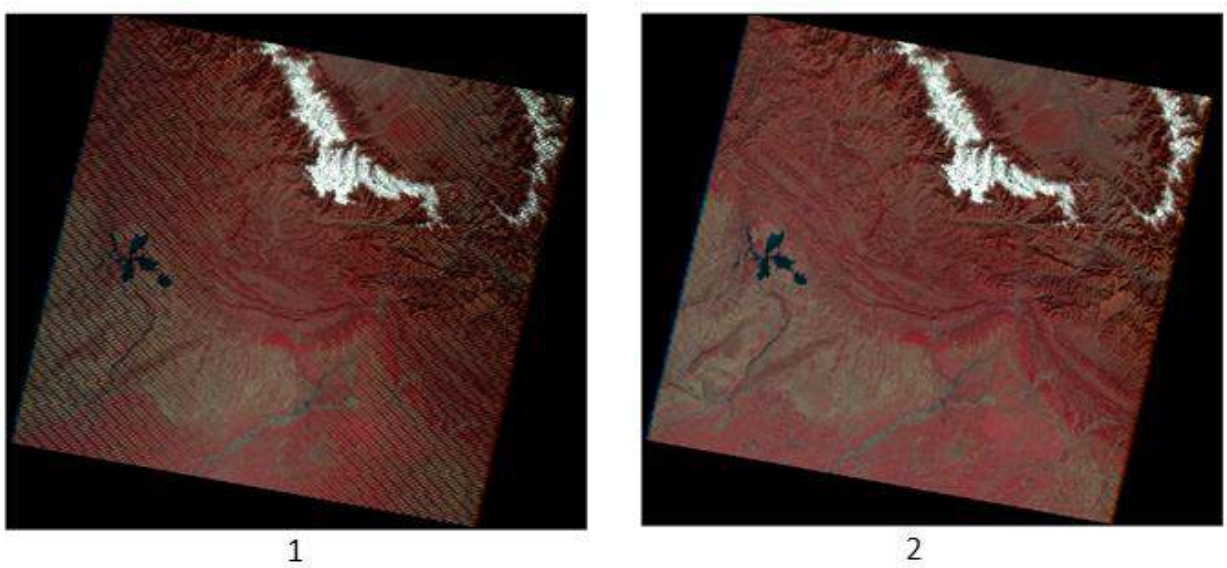


Figure 6: 1) Original imagery (SLC off with no gap-filling) 2) Corrected Imagery (SLC-off image filled after employing the Focal Analysis Model nine times)

The boundary of Jammu city as obtained from the Master Plan 2021 is cut out from the full satellite imagery to delineate the study area.

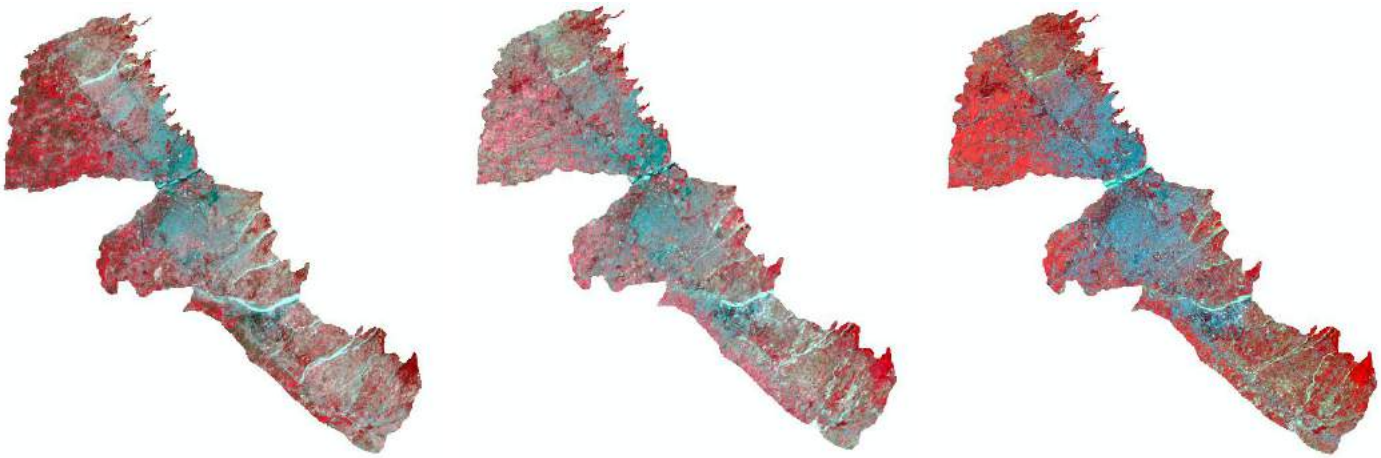


Figure 7: Landsat images for the years 2003, 2008 and 2014 from left to right

3.3.4 Generation of maps showing built up/non-built up areas

The images are geo-referenced having spatial reference WGS_1984_UTM_Zone_43N. All the three clipped images are then classified using MLC Classifier (Maximum Likelihood Classifier) which is a form of supervised classification technique performed using ERDAS Imagine software. The

classification resulted into 4 categories of land cover including Vegetation, Built Up, Cropland and Fallow Land. The classified images are again reclassified into built up and non-built up to ensure simplification as the domain of interest in this case was to map the non-urban to urban transitions in the due course of time series. Some areas such as Reserved Forests, River Drainage and Water bodies, Defence Lands are identified and masked out from the clipped images as they have no growth potential.

Figures 8, 9 and 10 that follow represent the classified land cover maps for the years 2003, 2008 and 2014 respectively after having performed MLC Supervised Classification Technique in ERDAS imagine software.

Figure 11, 12 and 13 again represent the simplified land cover maps for the years 2003, 2008 and 2014 respectively after reclassifying them into non-built up and built up categories.

Figure 14 points out at the exclusionary areas of Jammu with no potential of development. It includes Reserved Forests, Defence Areas and Jammu Airport.

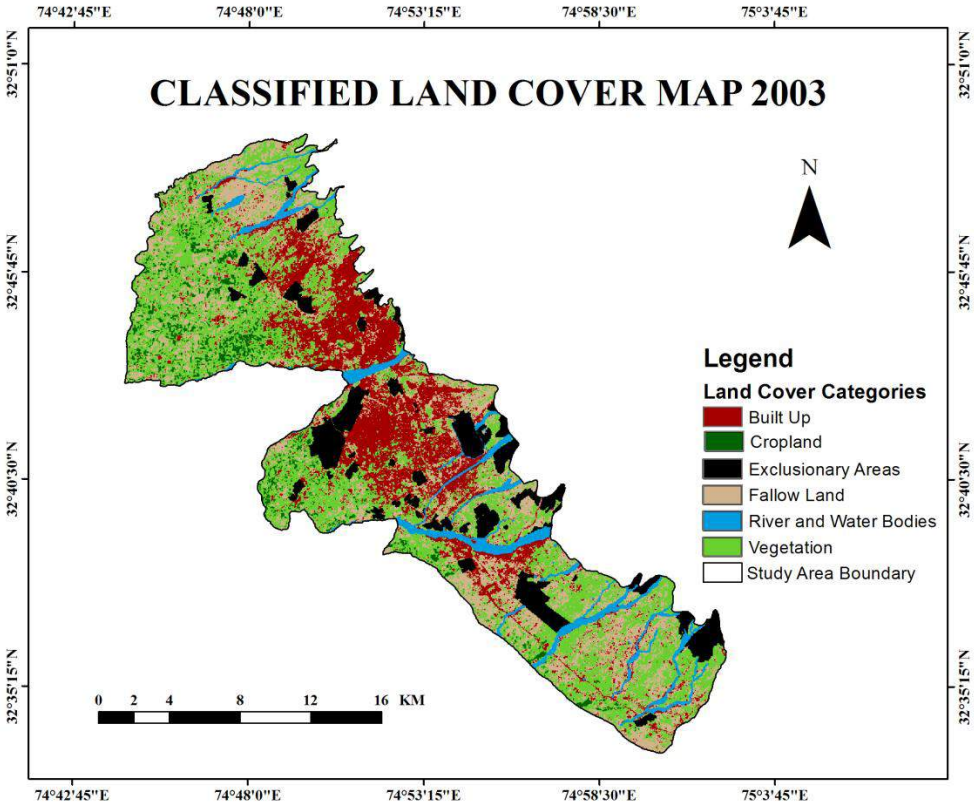


Figure 8: Classified Land Cover Map for the year 2003

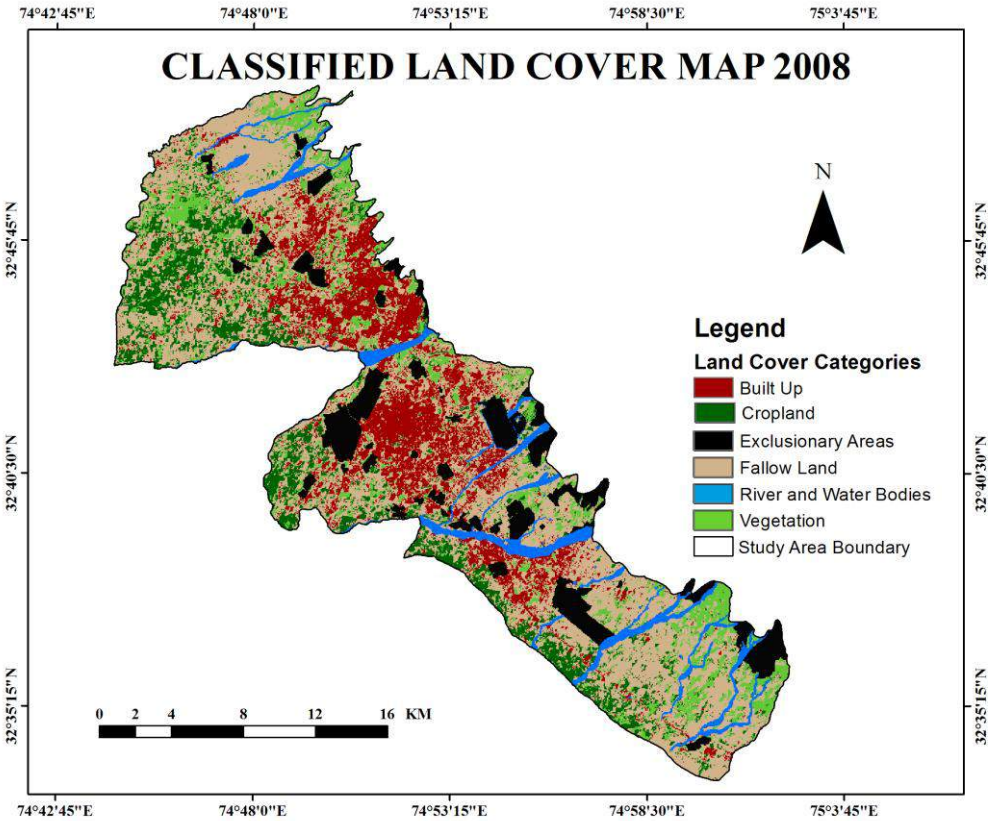


Figure 9: Classified Land Cover Map for the year 2008

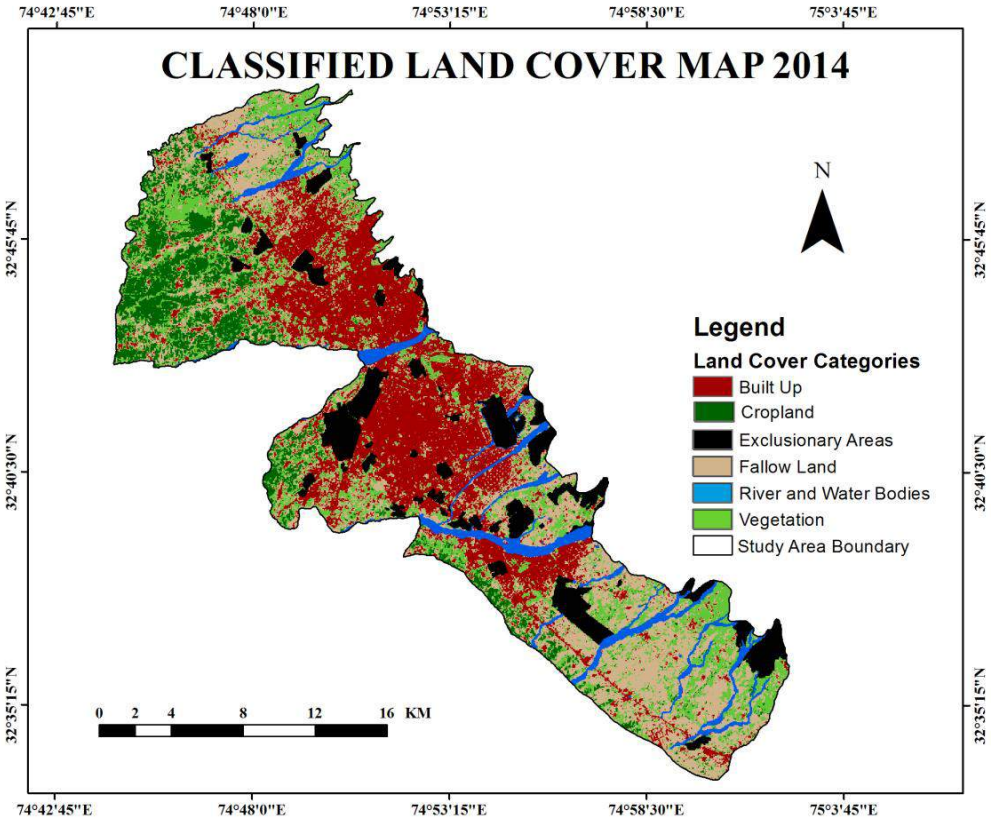


Figure 10: Classified Land Cover Map for the year 2014

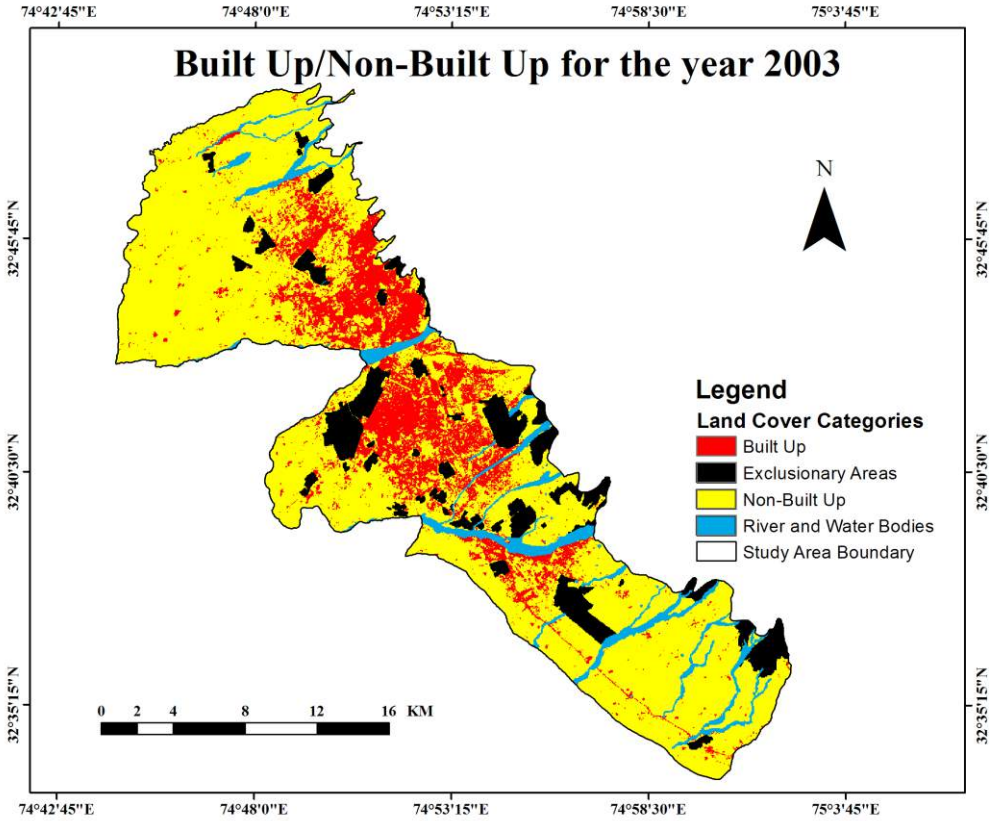


Figure 11: Built Up/Non-Built Up map for the year 2003

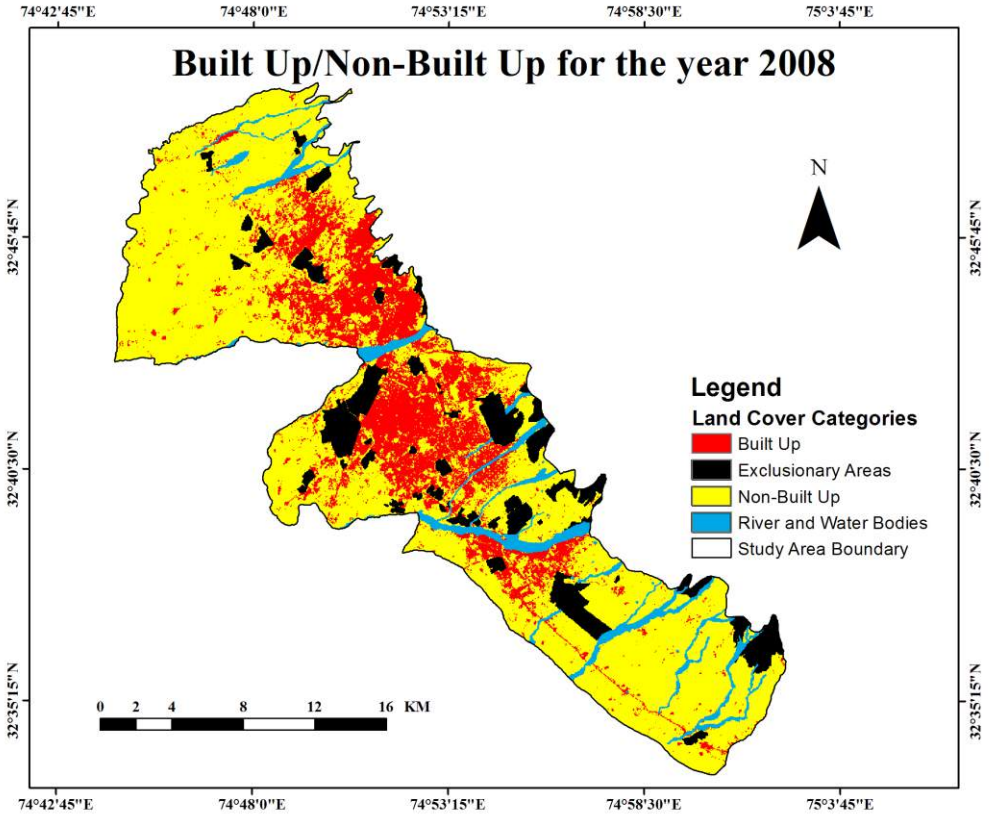


Figure 12: Built Up/Non-Built Up map for the year 2008

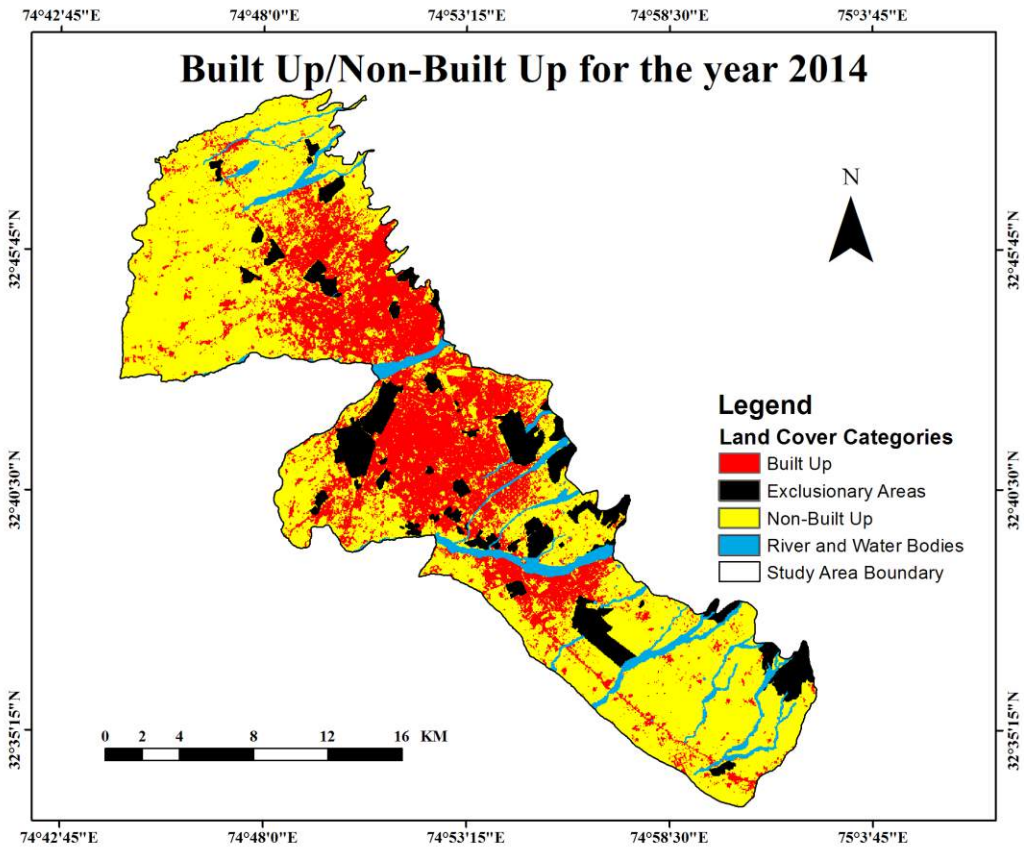


Figure 13: Built Up/Non-Built Up map for the year 2014

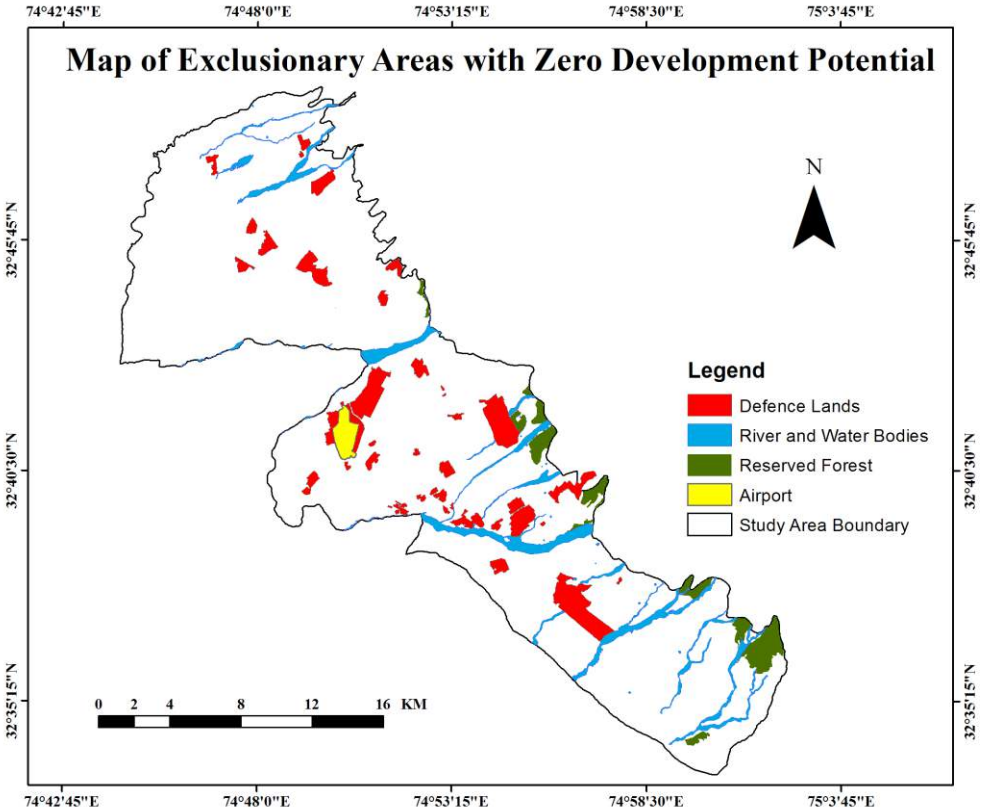


Figure 14: Map of Exclusionary Areas with zero potential of development

3.3.5 Generation of Various Thematic Maps

Road Map

Several layer maps are generated aided by primary data (Satellite imagery) and secondary data (Master Plan document) of the study area. According to PWD department, Jammu District has 79% road connectivity to habitations. The total numbers of habitations are 1269 out of which about 997 habitations have road connectivity (Jammu Master Plan 2021). Both major as well as secondary roads have been delineated in the study area.

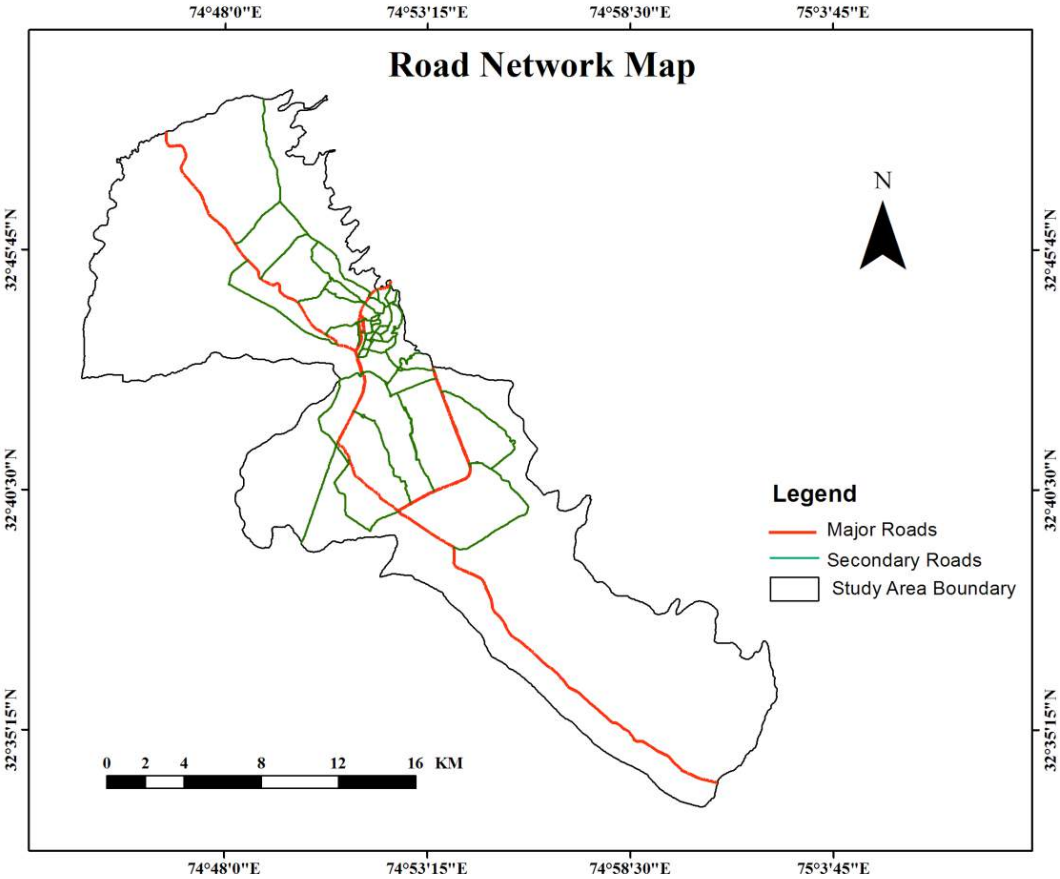


Figure 15: Road Network

Map of Major Transport Hubs

Jammu Civil Airport is located at a distance of 8 km. from the city. There are different flights which run through the airport covering different destinations. Jammu serves as the northern most railway head and the major centre for carriage of goods and passengers. Jammu-Tawi railway station is located at a distance of 2 km from city centre. Close to the railway station is the bus stand, which offers bus services for various destinations.

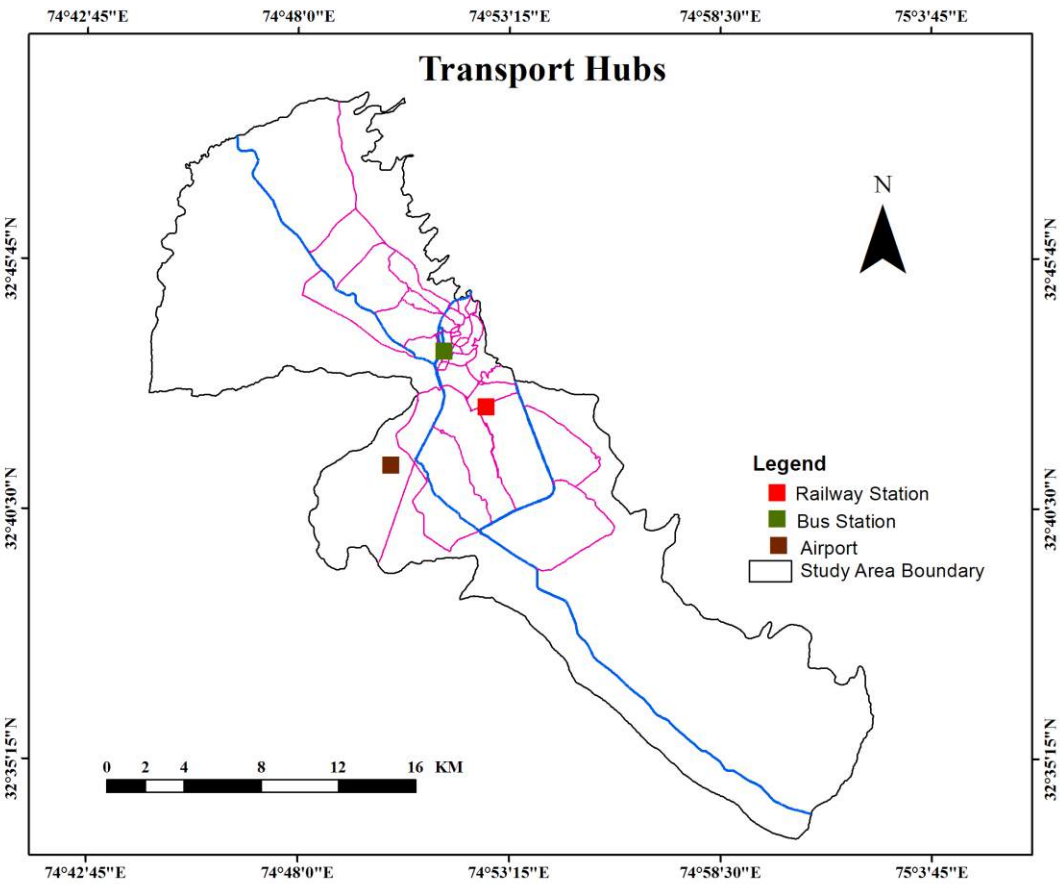


Figure 16: Location of Major Transport Hubs

City core (CBDs) and Other Business Districts (OBDs)

Mostly the central core of the city consists of the Old City of Jammu and New City extended along both sides of the river Tawi. The old city comprised of 23 wards and a total of 48 new wards are added to it. Jammu Municipal Corporation now comprises of a total of 71 wards. Some major areas from business stand-point have also been shown as they provide scope for further urban growth and development.

We can see most of the important business districts are around the city core as they act as critical points for the exchange of trade and commerce in and outside of the city of Jammu.

Figure 17 is depictive of the major Central and Other Business Districts (CBD's and OBD's) in the city.

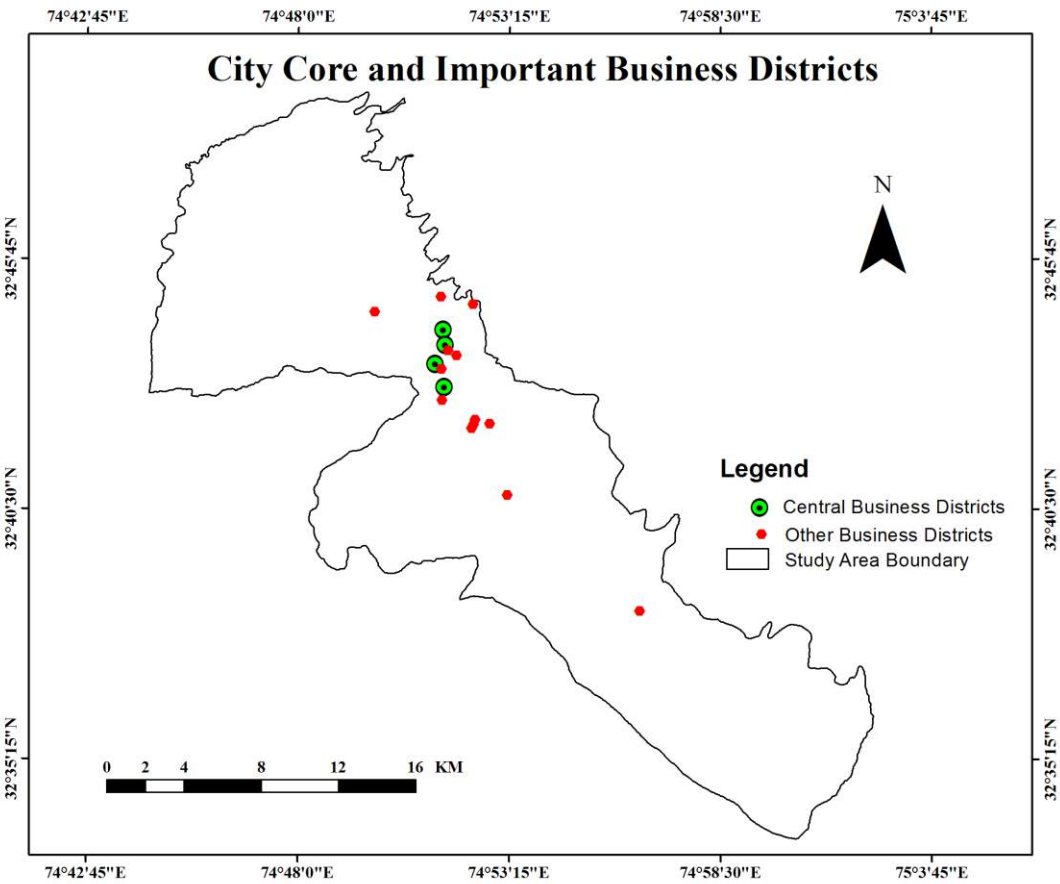


Figure 17: Delineation of City Core and other business districts

Educational Institutions

Many important government engineering and medical colleges in the state are an attraction for a large share of students from all over India. Schools, general degree colleges and universities are still another point of interest. Some of the predominant institutes include Govt. College of Engineering and Technology, Govt. Medical College and Hospital, GGM Science College, University of Jammu, Govt. Polytechnic College, MAM PG College, MIET, MBSCET, Central University of Jammu to name a few.

Industrial Area

The city has a number of small industries. The industrial estates of Gangayal and Bari-Brahmana are the largest in the entire state. Jammu has a number of food grain mills. Jammu also has the largest number of shopping complexes, cinemas, recreation centres in the state.

Figures 18 and 19 that follow point out at the major education institutions as well the industrial area of the city respectively.

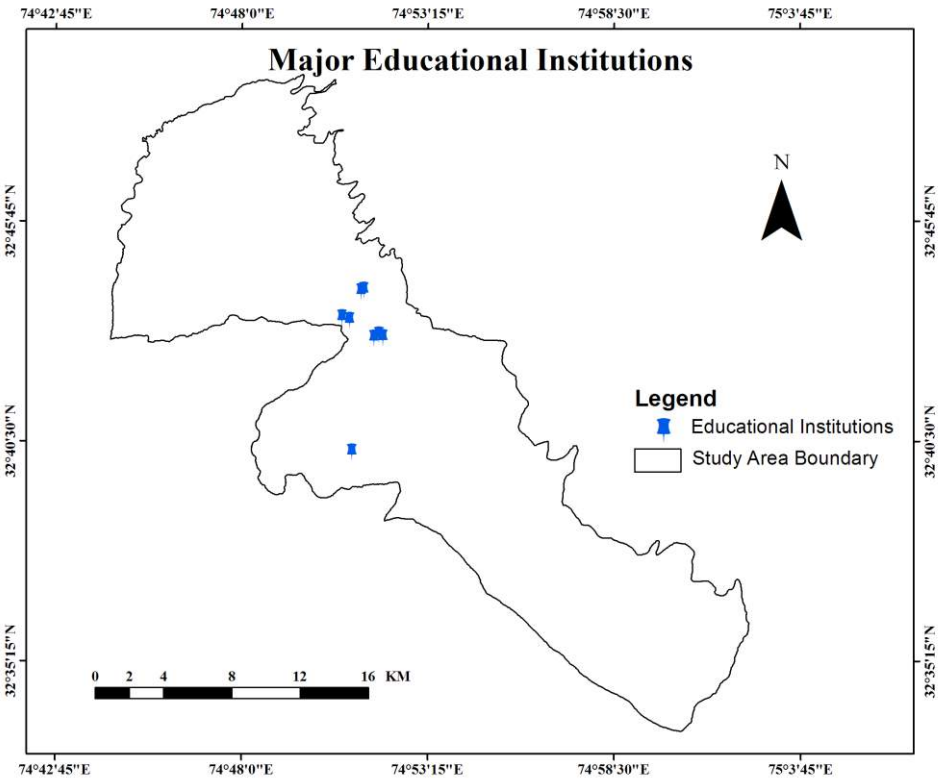


Figure 18: Major Educational Areas in the Study Area

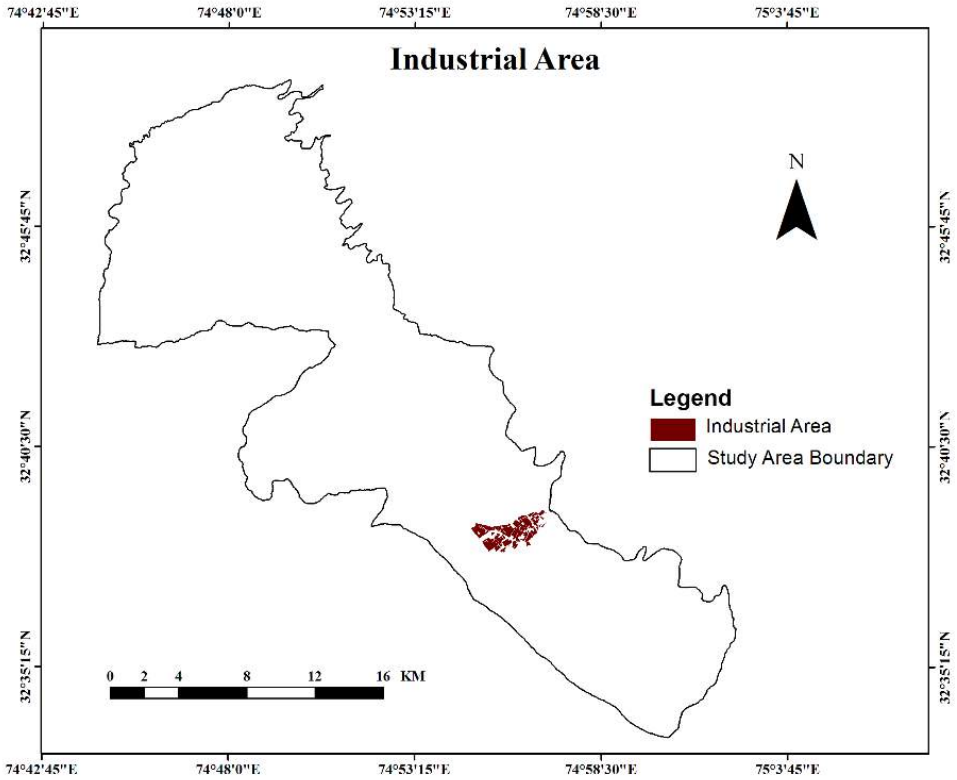


Figure 19: Industrial Area

Land Price Map

Based on the Land Price of each respective ward in the study area, a complete land price map for the entire study area is prepared. The areas of Gandhi Nagar, Trikuta Nagar and Nanak Nagar are ranked as the areas with the highest land prices, while the areas lying on the outskirts of the core city are ranked the least, moreover, the areas lying near the major roads assume higher land prices.

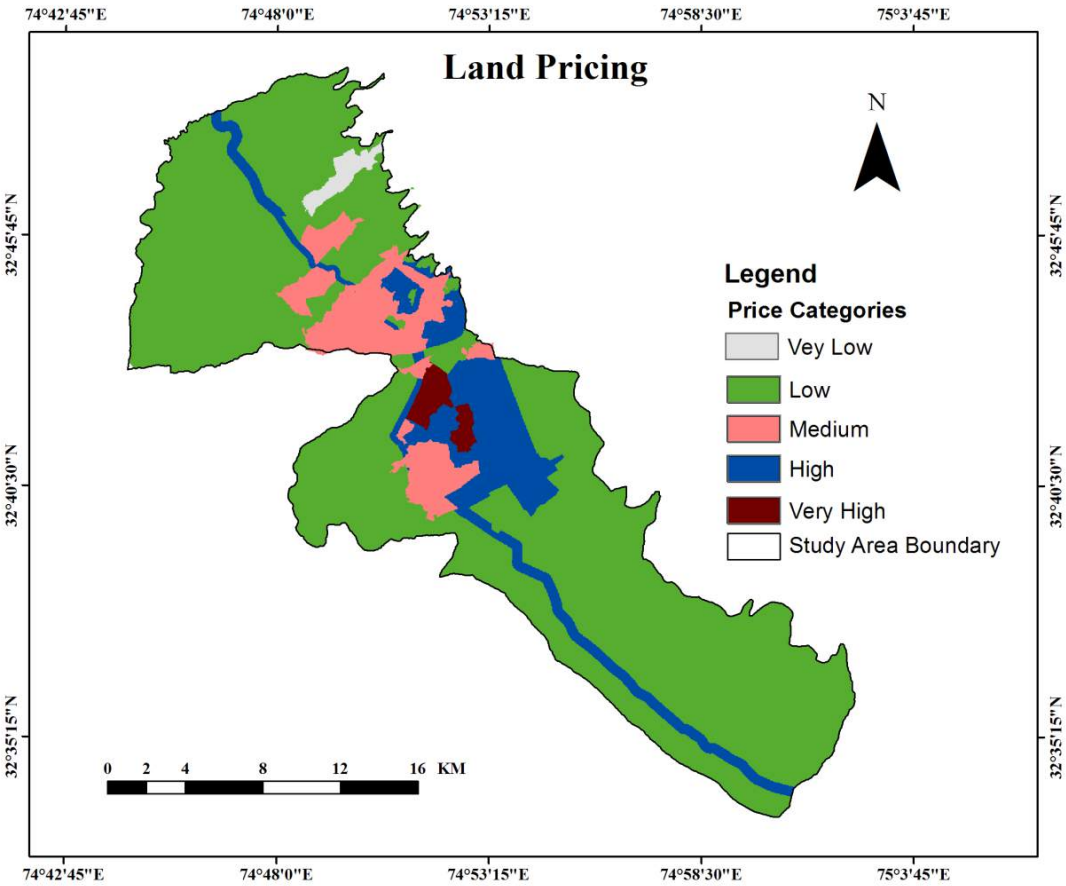


Figure 20: Land Price Map for the study Area

Neighbourhood Maps

The extent of built up cells in the surroundings of an already existing built up area is obtained by calculating the Euclidean distance from already existing built up with a circle of radius 500 m around it. This map is quite useful in understanding the neighbourhood around an existing built up land to see whether it is further liable for any urbanization or not. The task is performed for both the years 2003 and 2008 to see the maximum number of future urbanizable cells in the neighbourhoods for both the years. Figures 21 and 22 below represent the neighbourhood maps for the years 2003 and 2008 respectively.

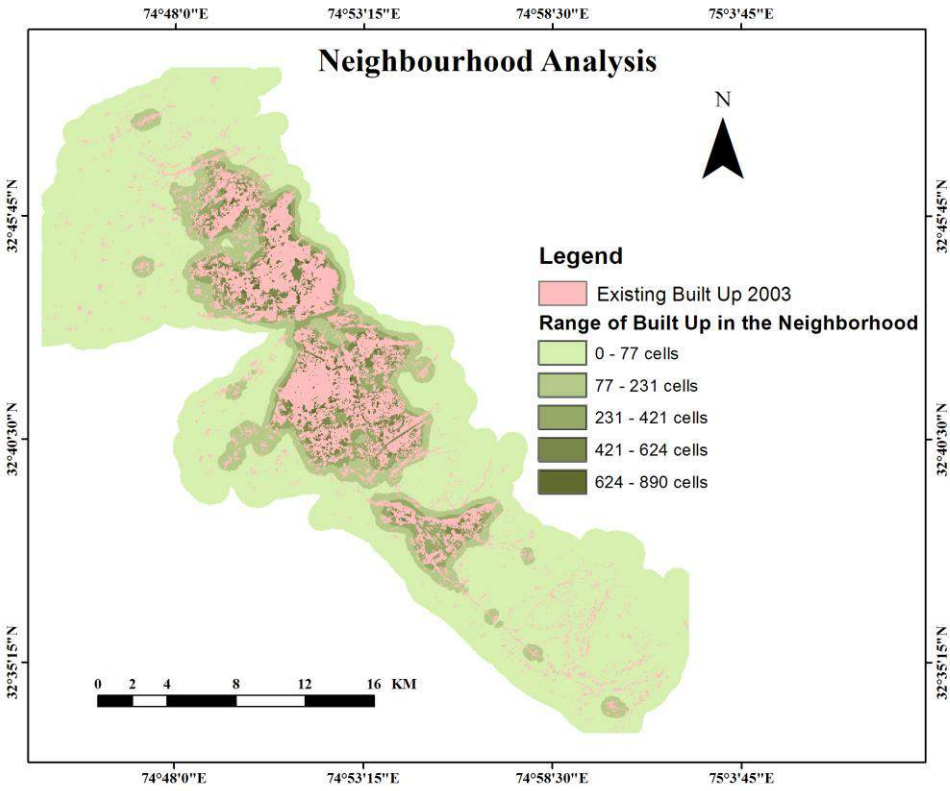


Figure 21: Neighbourhood Built Up analysis using 500 m buffer for 2003

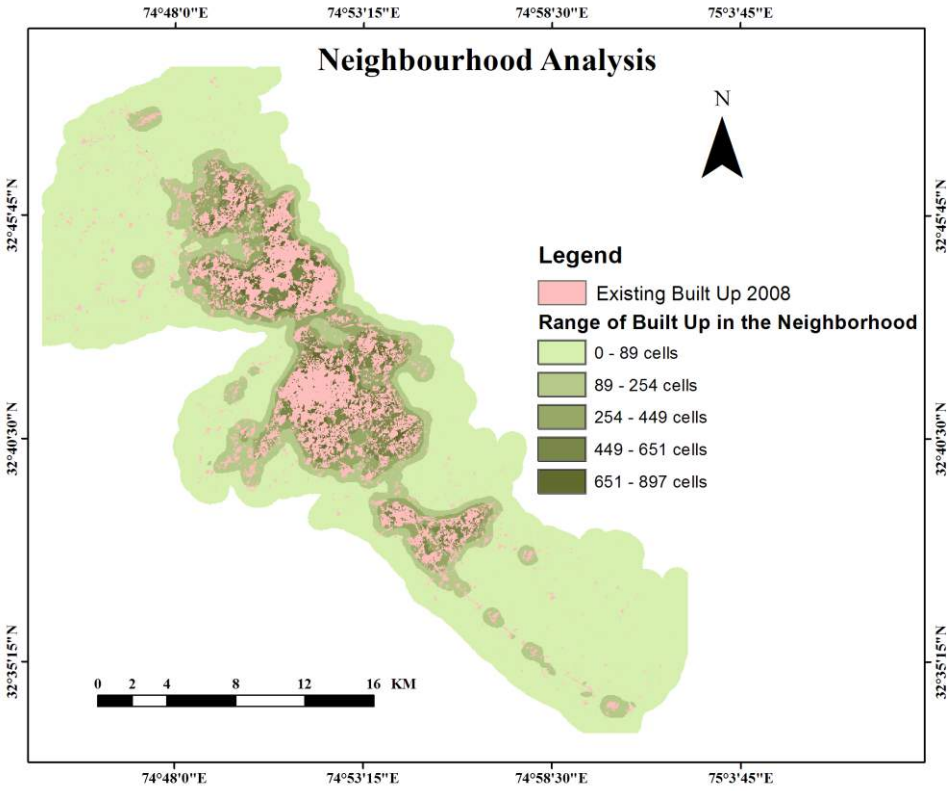


Figure 22: Neighbourhood Built Up analysis using 500 m buffer for 2008

Phase 2

3.4 Analysis of Urban Growth Trend in the Study Area

Urban Growth Trend for the study area is performed using cross-tabulation and image overlay techniques to see the actual amount of change from Non-Built Up to Built-Up categories respectively from the years 2003-2008, 2008-2014 and 2003-2014. This gives an overview of the growth trend in the study area.

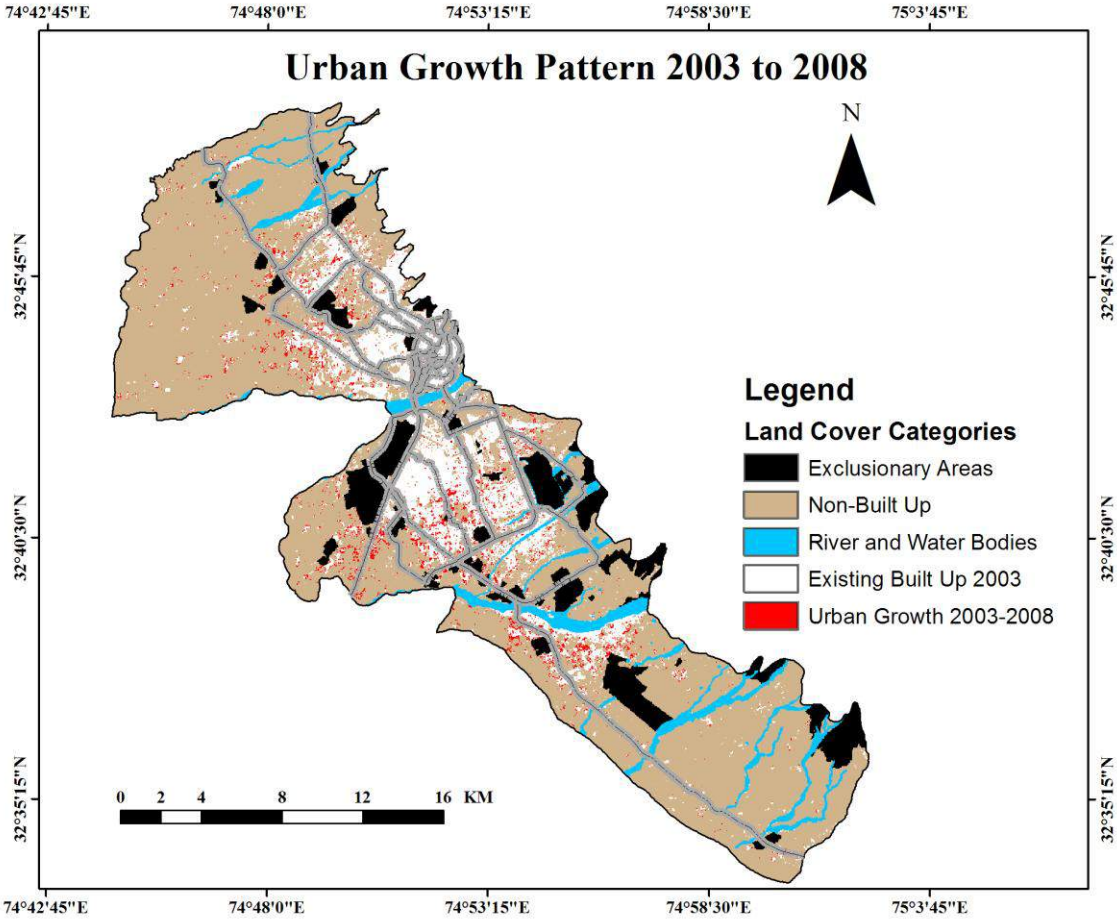


Figure 23: Actual Urban Growth from the year 2003 to 2008

The number of cells that actually transitioned from non-urban to urban category from the year 2003 to 2008 is 8694 cells. Figure 23 above shows the actual urban growth from the year 2003 to 2008.

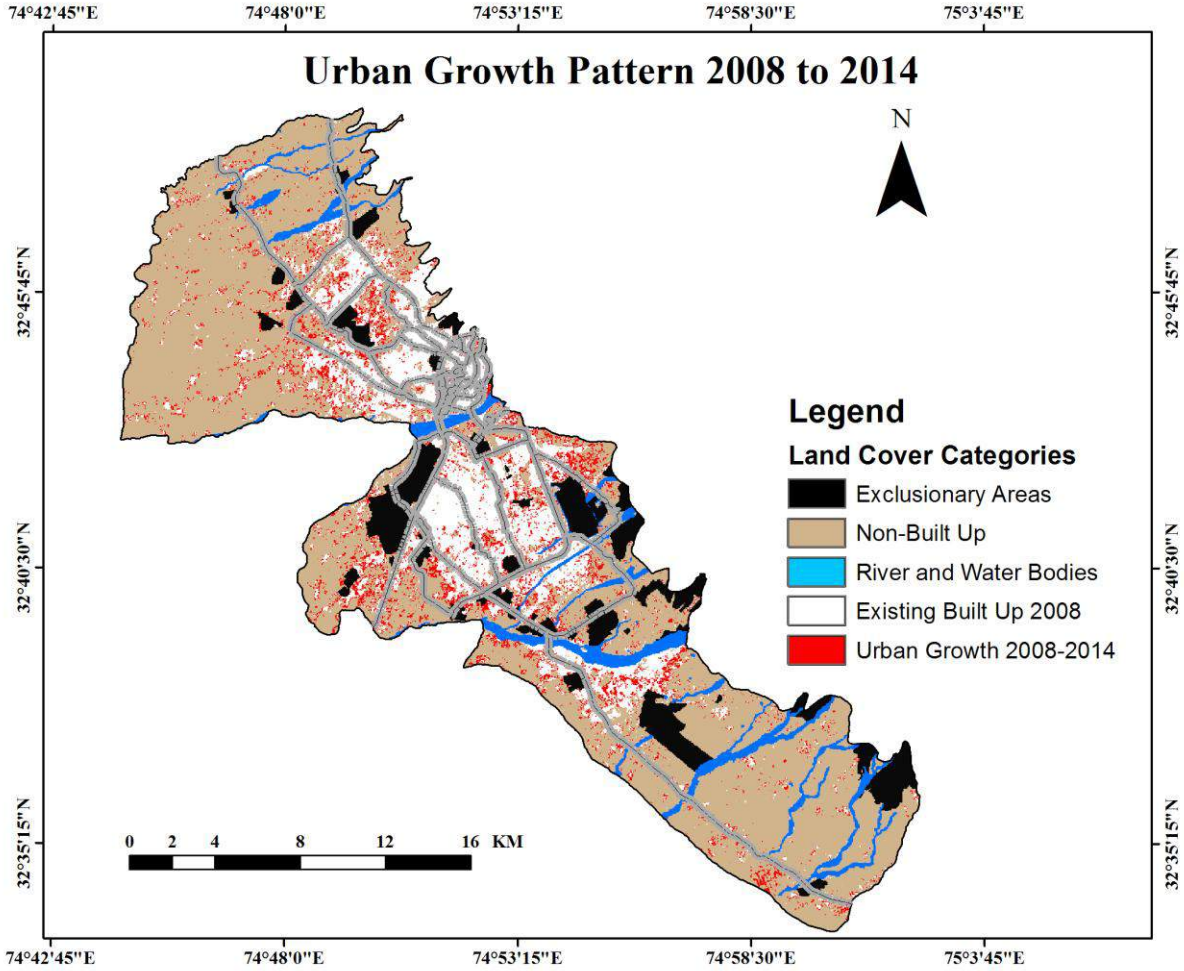


Figure 24: Actual Urban Growth from the year 2008 to 2014

The number of cells that actually transitioned from non-urban to urban category from the year 2008 to 2014 is 22634 cells.

Figure 24 represents the actual urban growth from the year 2008 to 2014. The growth trend maps are clear indications to the directions toward which the urban growth is more likely in the future. It also throws light on the pattern of urbanization. From what is seen in the maps depicting the actual growth in the study area, the fact that growth of Jammu city is more diffusive in nature than compact and centralised is emphasized and appreciated.

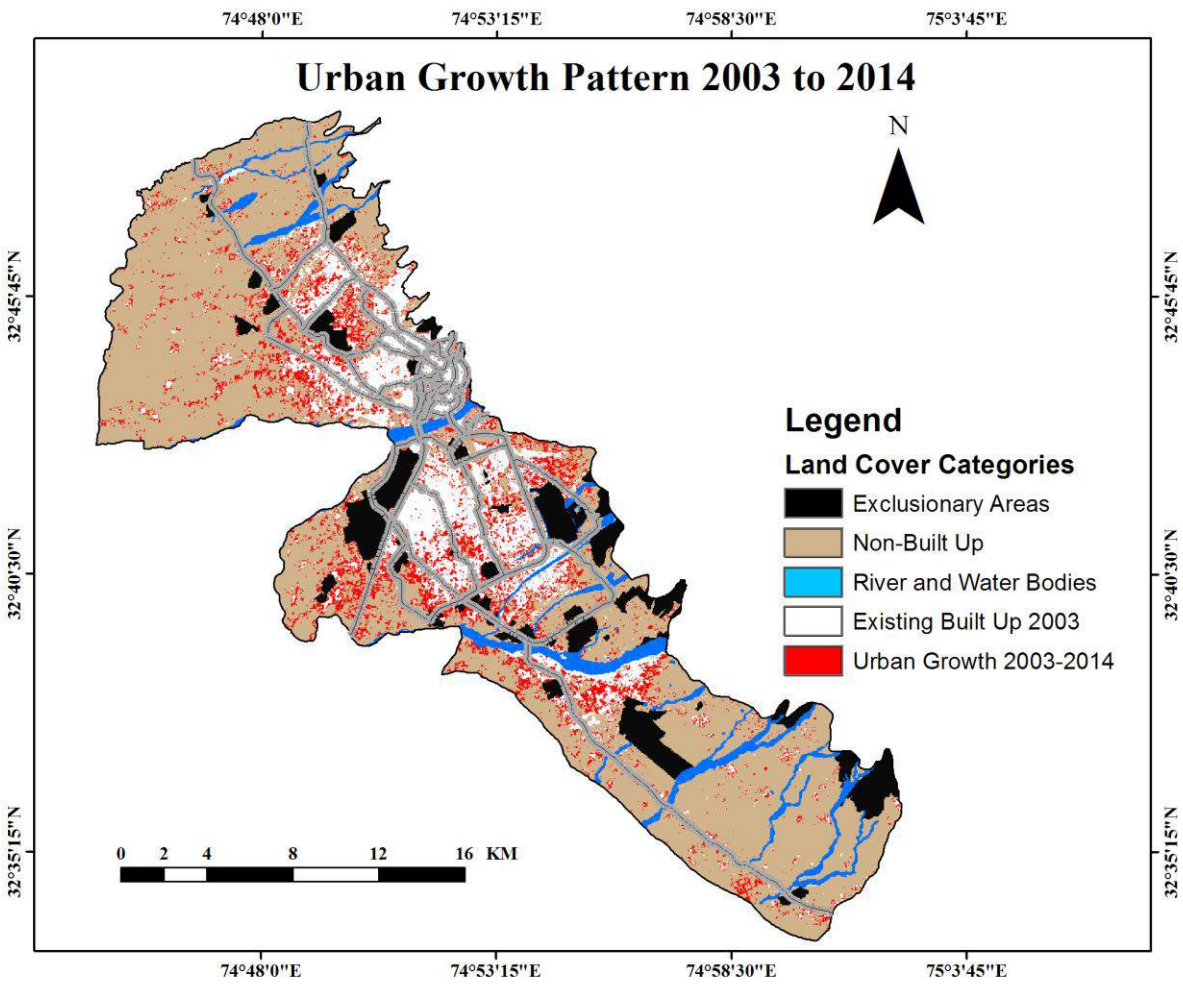


Figure 25: Actual Urban Growth from the year 2003 to 2014

Figure 25 represents the overall actual growth from the year 2003 to 2014.

The number of cells that actually transitioned from non-urban to urban category from the year 2003 to 2014 is 31328 cells.

The growth trends obtained from cross-tabulation techniques surely provide insight into the pattern and direction of urban growth but no clue as to which land use densification class is more likely to sprawl and which type of growth will take place. A tool is downloaded and utilized to perform the same task.

After the temporal datasets are reclassified again into two categories of built up and non-built up, they are made Urban Landscape Analysis (ULA) - compatible by reclassifying them into four code categories:

- 0 - No Data
- 1 – Others
- 2 – Water

- 3 - Urban Area (Impervious Surface).

The pixels that are left unclassified are coded as 0 and are called No Data; 1 represents others which included exclusionary areas and non-built up areas, 2 refers to river and water bodies and 3 shows urban areas.

This tool by the name ULA, developed by Jason Parent, is freely downloadable and is intended to assist in the analyses of urban spatial patterns in a city over multiple time periods. The maps generated by the tool can help identify areas where developed areas infringe on open lands and consequently have a negative impact on the environmental conditions. ULA is intended to classify developed areas of different densities (low, medium and high) as well as identify undeveloped lands that are likely to be degraded by close proximity to the development. In addition, the tool classifies the type of development (infill and extension) that occurs between two consecutive time periods, based on its proximity to previously existing development.

The ULA model is run for the three time data and several maps are generated which showed the Urban Footprints for the three time periods as well as the new developments from 2003 to 2008 and from 2008 to 2014 respectively which throws lights on the urban trends and patterns of development over the given time scales in a much broader capacity. This serves as a very necessary input towards understanding the direction and magnitude of urban growth between two time periods as well as the major causative factors responsible for urbanization in the study area. This finally leads to the confirmation of predictor variables about which the subsequent machine learning algorithms could be trained for future prediction and evaluations.

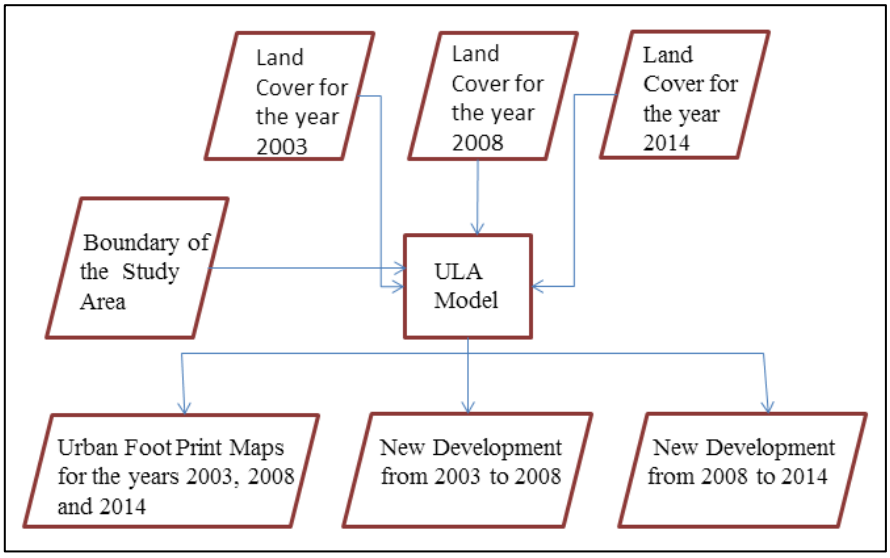


Figure 26: ULA Tool for urban Trend Analyses

ULA tool is used to develop land cover maps of the study area for the year 2003, 2008 and 2014 which are displayed in figures 27-29. The generated maps have the following mentioned land use

classes: 1) Urban Built-Up; 2) Sub Urban Built-Up; 3) Rural Built-Up; 4) Open Spaces; 5) Agricultural Land and 6) Water.

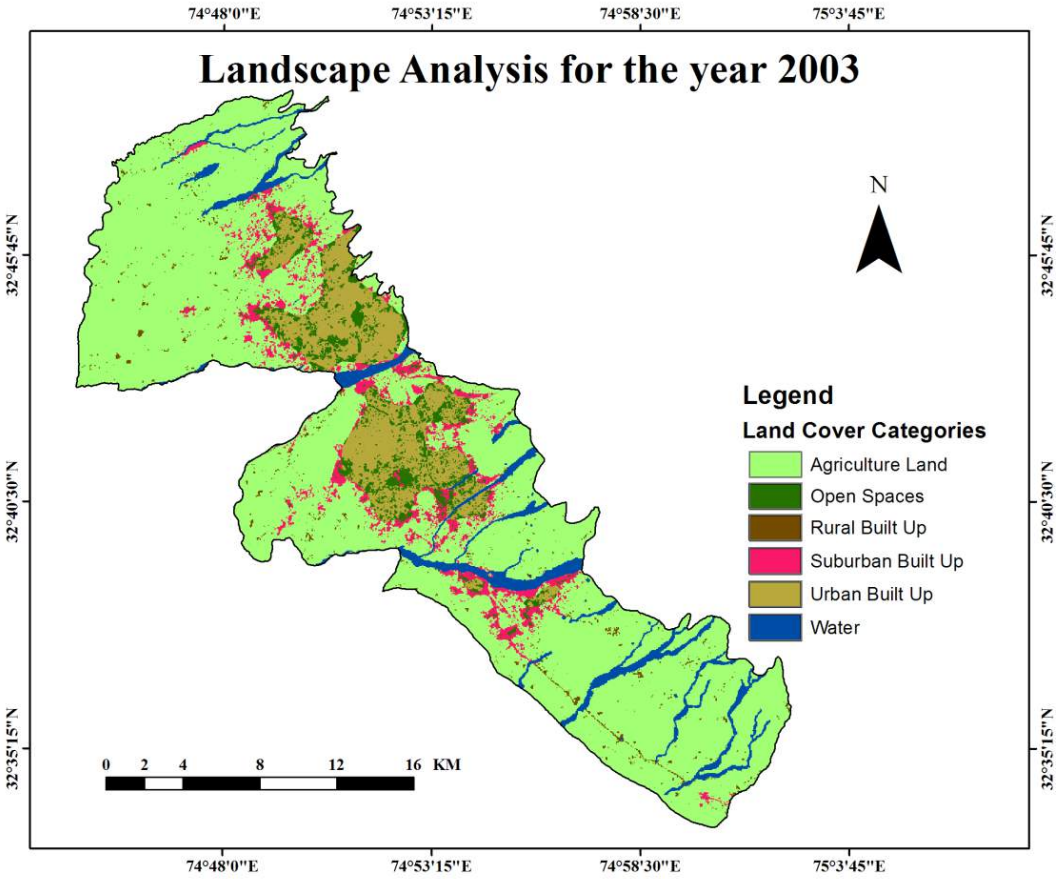


Figure 27: Landscape Analyses for the year 2003

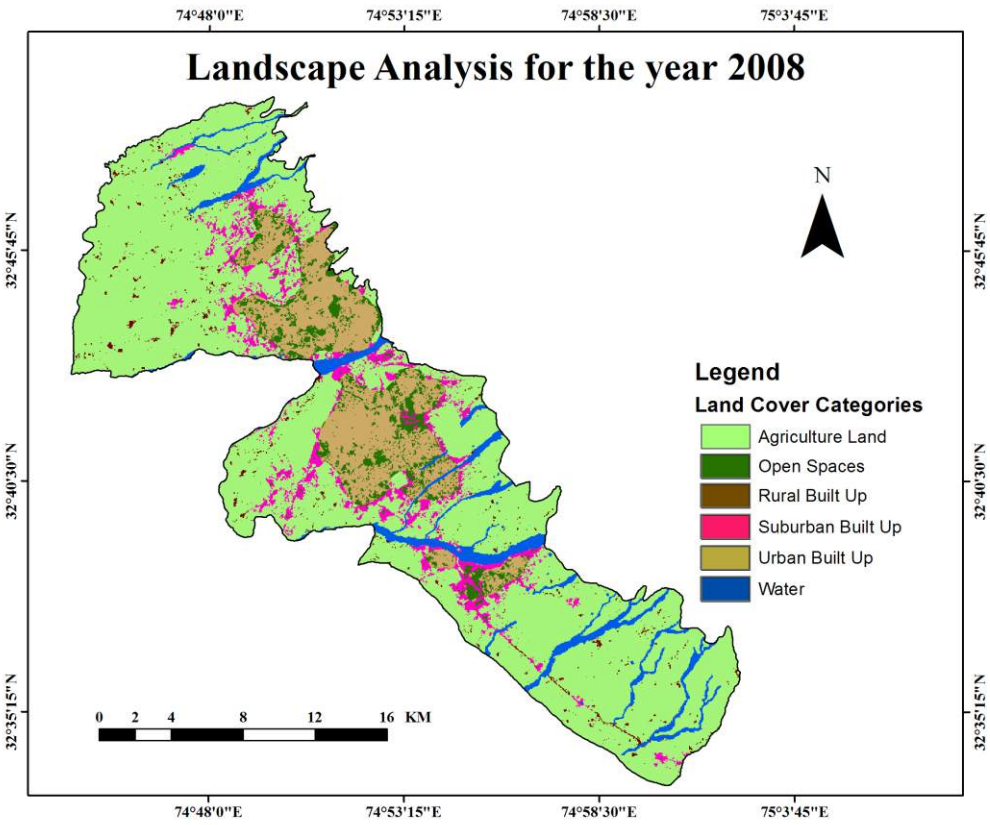


Figure 28: Landscape Analyses for the year 2008

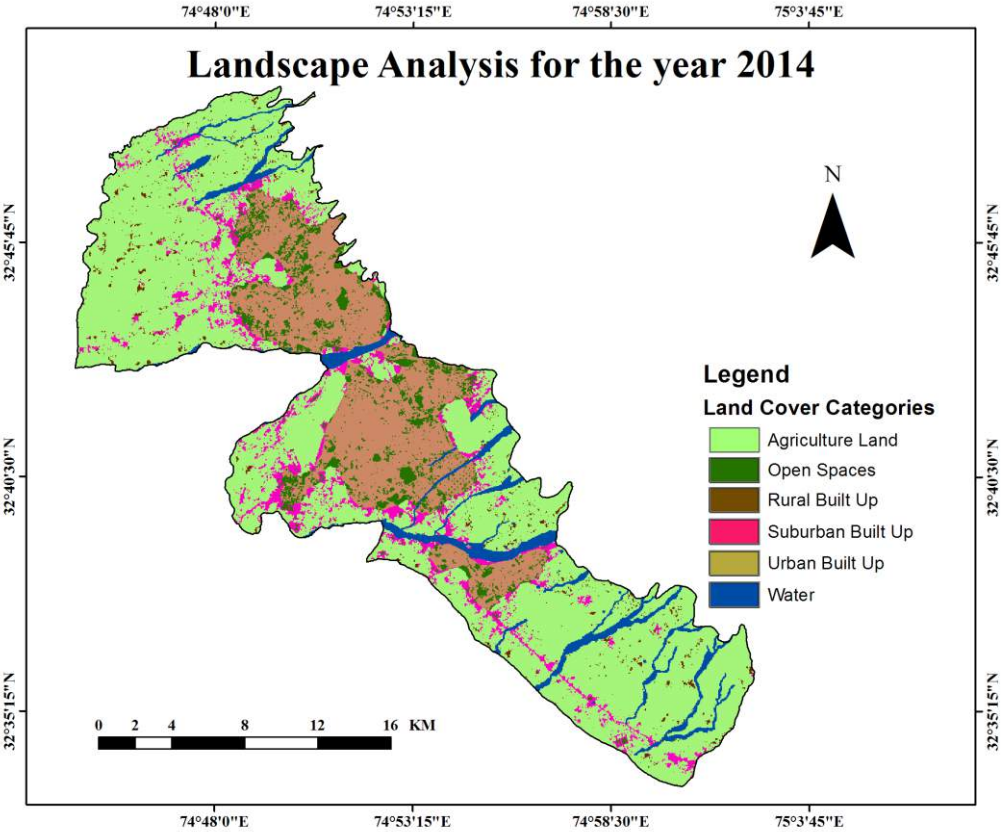


Figure 29: Landscape Analyses for the year 2014

It is always easy to find out the growth in the urban area taking place over different time periods but to categorise the urban growth type in the form of Infill Growth, Extension Growth is some great added advantage of using this tool. We can not only know the spatial distribution of growth but also the type. Infill growth refers to the new development occurring within the spaces inside the city core i.e. when the urbanized open spaces get converted to built-up. It increases the contiguity of the built-up area by filling in the urbanized space. Extension growth on the other hand extends directly from the previous development. The new growth is thus contiguous to the already existing built-up area and could be extended linearly or in patches from the previous development.

Figure 30 and Figure 31 represent the different types of urban growth occurring between the years 2003-2008 and 2008-2014 respectively.

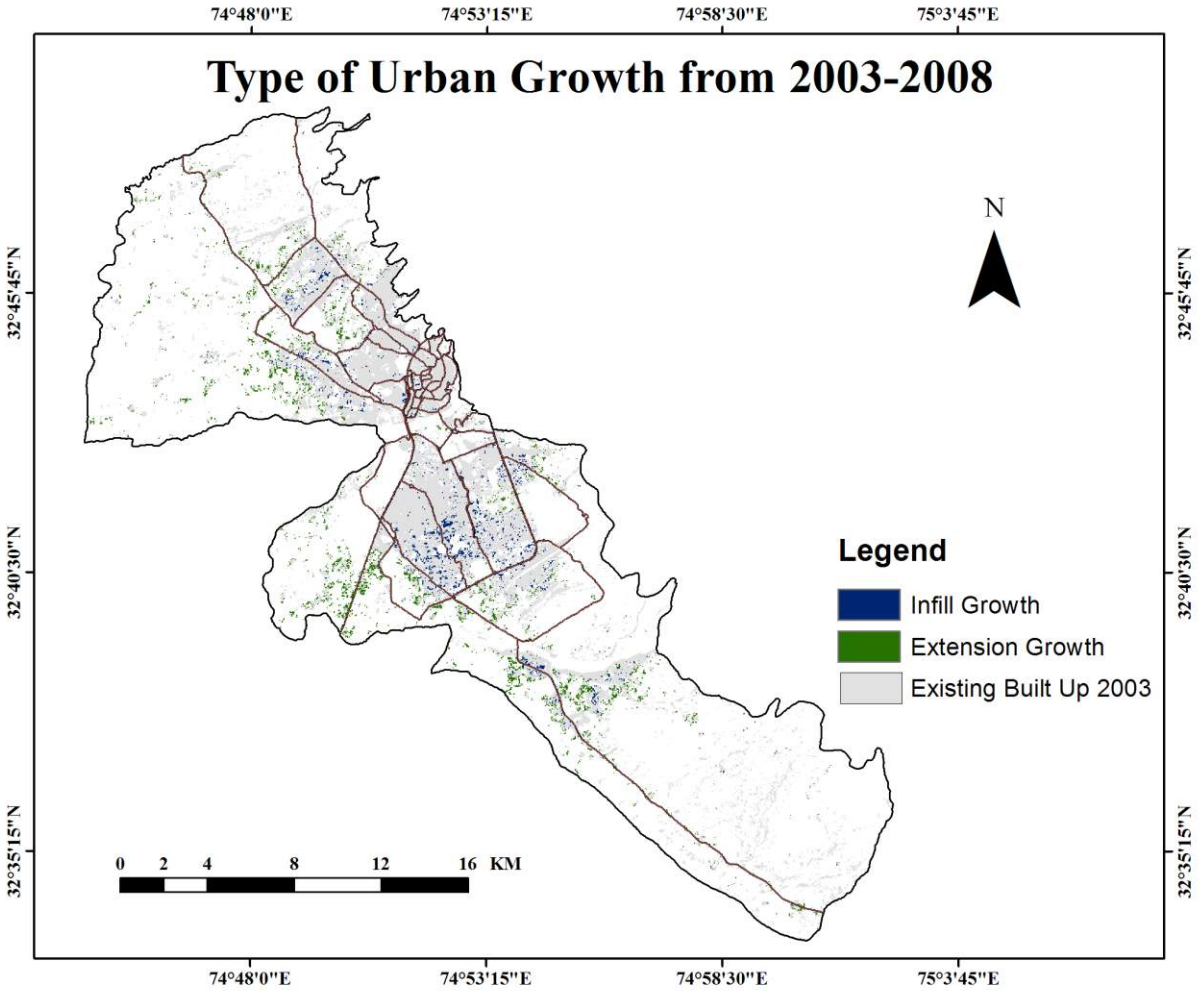


Figure 30: Type of Urban Growth from 2003 to 2008

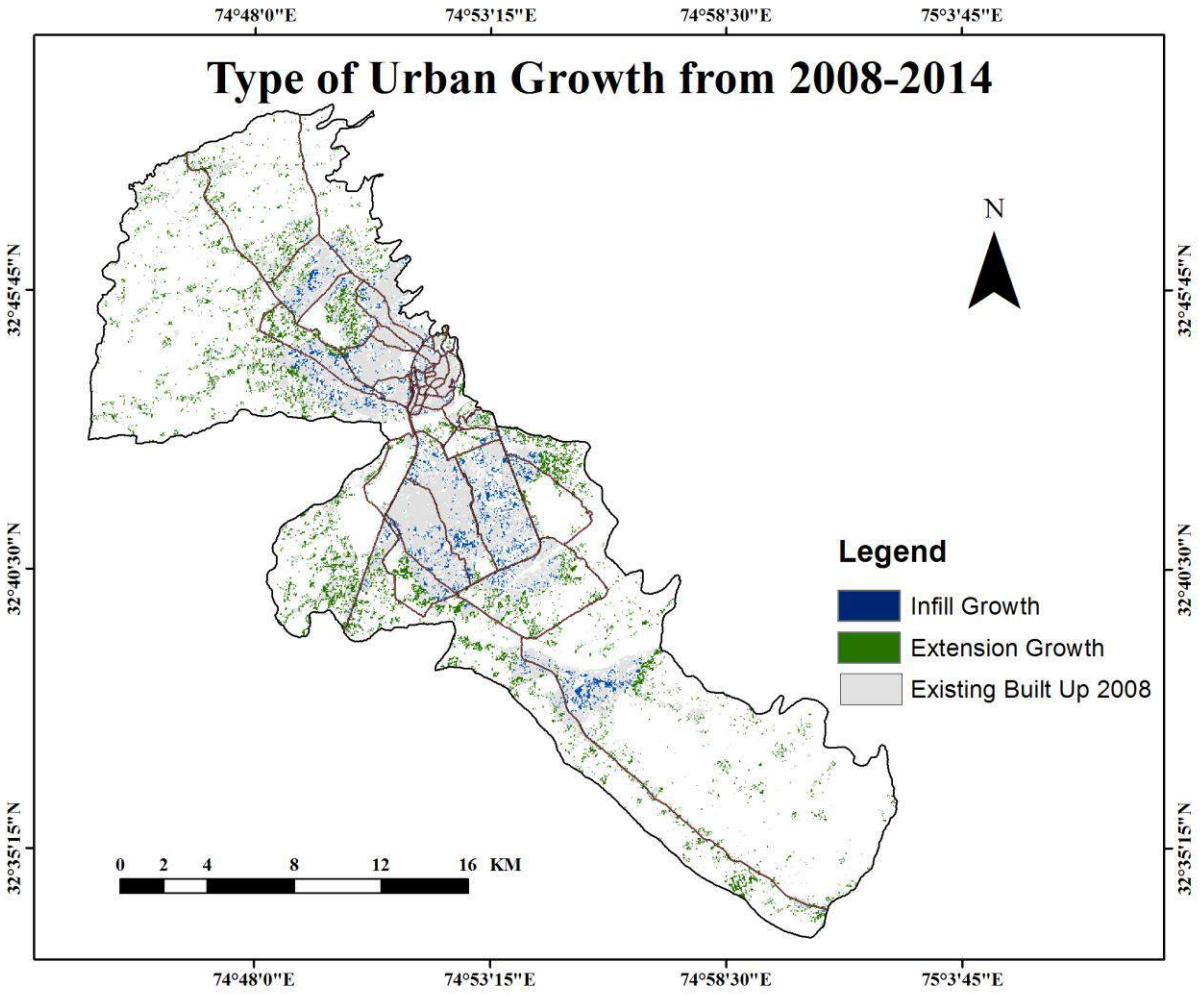


Figure 31: Type of Urban Growth from 2008 to 2014

3.5 Factors driving the Urban Growth

There are various factors that induce urban growth. The factors responsible for urbanization can be obtained by carrying out the systematic study of the city and performing historic trend analysis which is essentially statistical in nature. Also from the trend analysis carried out in the previous step, the variables responsible for urbanization in the study area are isolated and arranged as a sequence.

Some of the key factors identified for urban growth models are:

1. Accessibility - Road Structure (Major, Minor)
2. Distance from higher level facility - Central Business Districts (CBDs) and OBDs (Other Business Districts)
3. Mobility Services -Transport Hubs, Railways, Airports etc.
4. Social Infrastructure - Educational Institutions
5. Employment - Industrial Area
6. Local facilities - Neighbourhood Analysis

A means to measure all these factors is to obtain Euclidean Maps corresponding to each factor in the study area. Based on that, the following 10 Euclidean Raster maps are prepared:

- Euclidean Distance from airport
- Euclidean Distance from bus station
- Euclidean Distance from CBD's (Central Business Districts)
- Euclidean Distance from major educational institutions
- Euclidean Distance from the industrial area
- Neighbourhood raster map (500 m) from existing Built-Up
- Euclidean Distance from major roads
- Euclidean Distance from OBD's (Other Business Districts)
- Euclidean Distance from railway station
- Euclidean Distance from secondary roads

The above mentioned Euclidean distance maps and neighbourhood focal maps are displayed below in the Figure 32 - Figure 37.

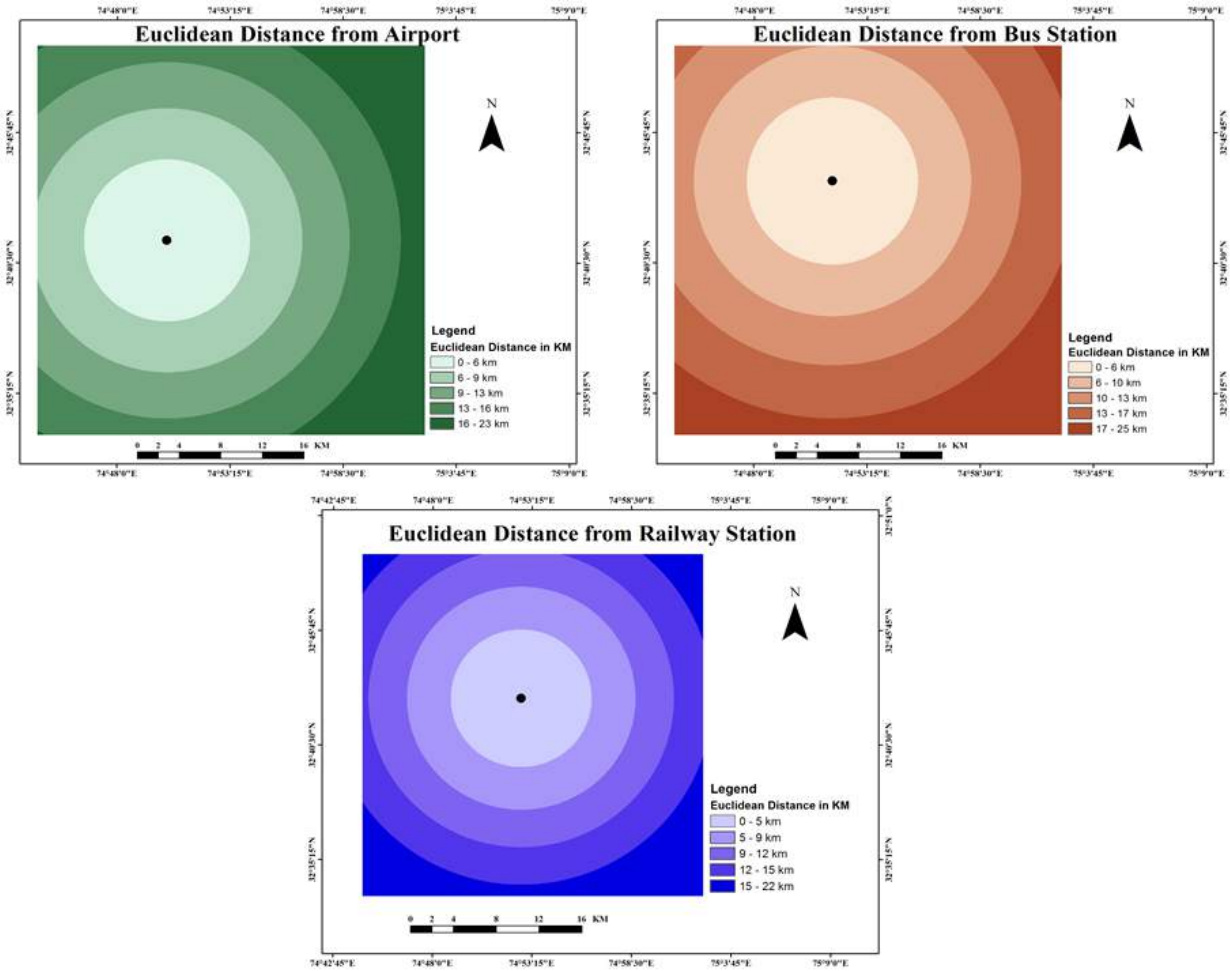


Figure 32: Distance from Mobility Services

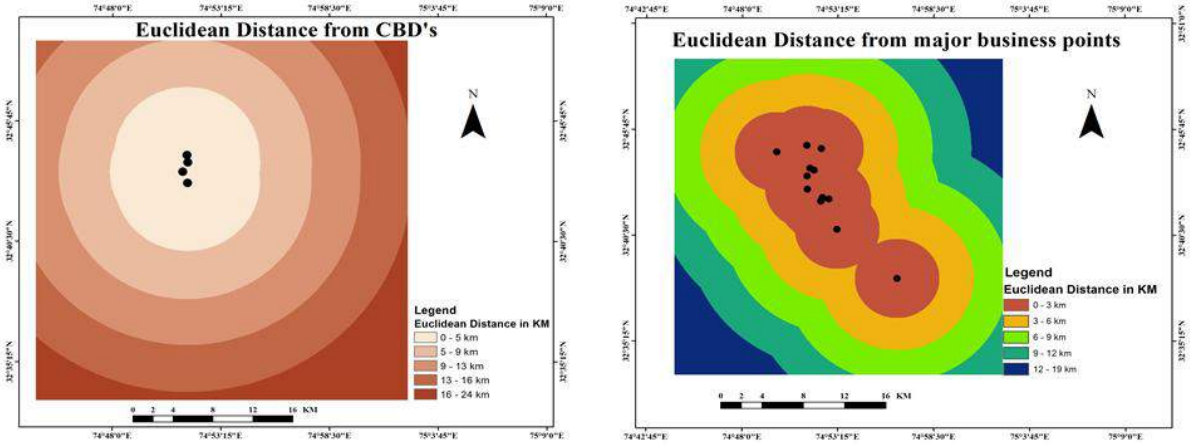


Figure 33: Distance from higher level facilities

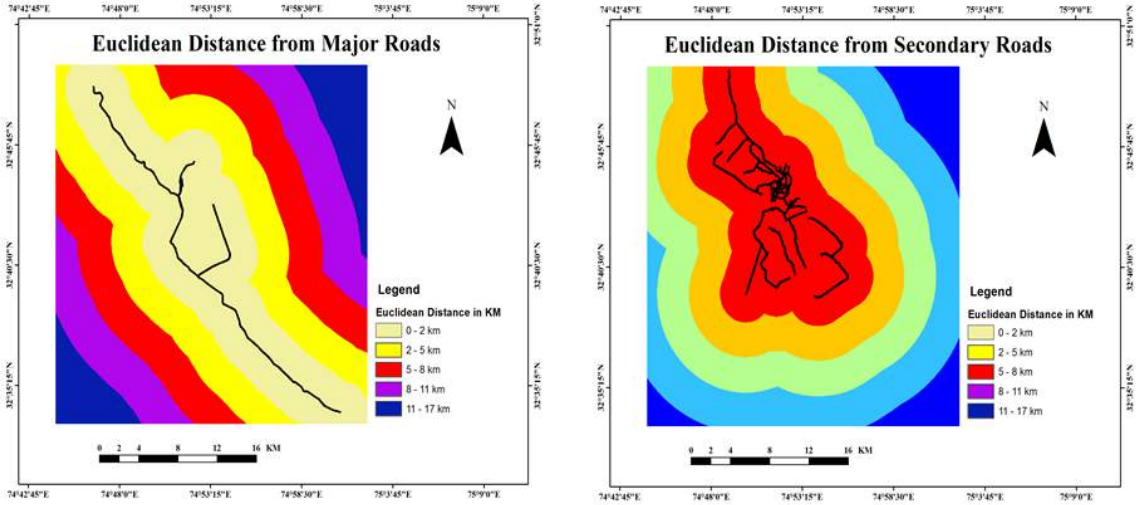


Figure 34: Accessibility

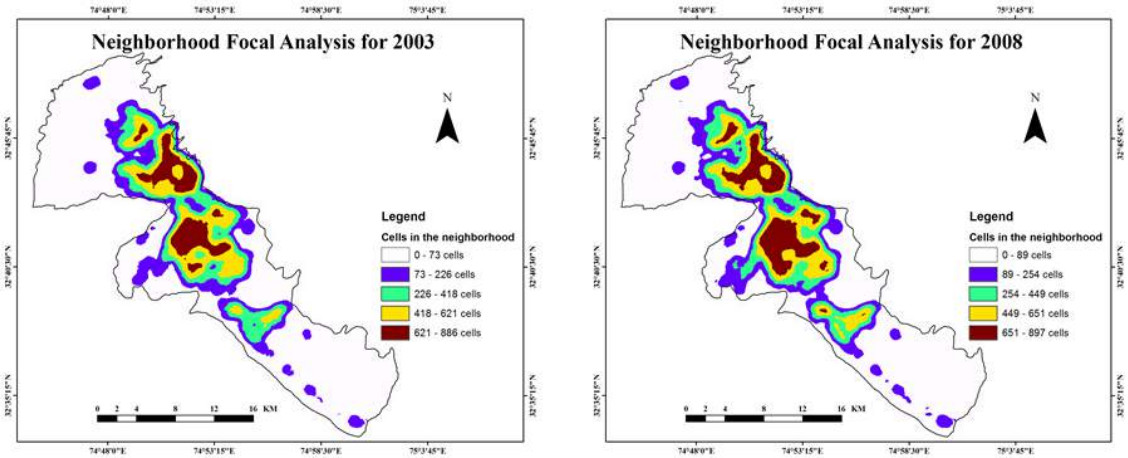


Figure 35: Local Facilities

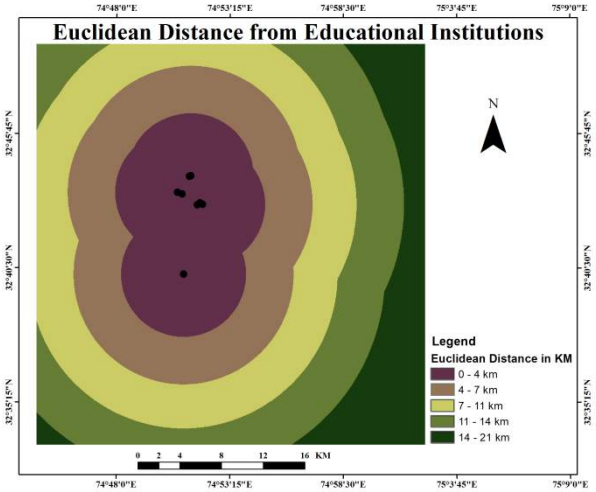


Figure 36: Social Infrastructure

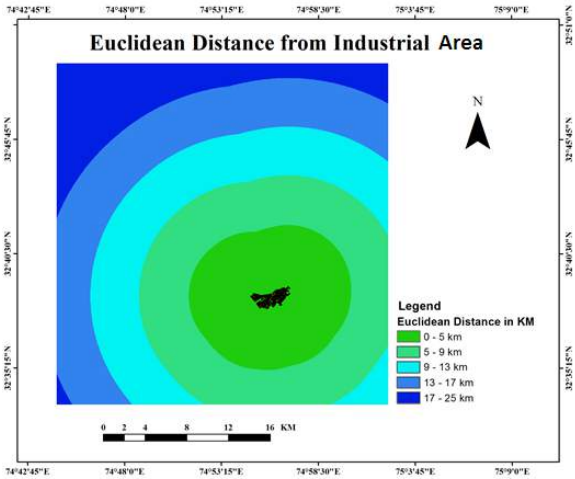


Figure 37: Employment

3.6 Summary

The chapter envisaged a general discussion about the study area showing its location, demographics and the existent urban trends in the different time periods. The major functions of the city were also listed. The important task of spatial database generation is discussed along with the various sources from where the data was acquired. Several layer maps / thematic maps were generated. The factors responsible for urbanization were identified and they serve as necessary inputs to the subsequent urban growth modelling.

CHAPTER 4: ANN- BASED CA MODELS

4.1 Introduction

As discussed in the literature survey, a cellular automaton (CA) is a discrete dynamic system divided into regular spatial cells and the time in which case progresses in steps. Each cell is characterized by a particular state in which it resides. It is actually a function of the current state as well the neighbourhood influences. Local rules operate over the current states of the cells and bring out up-gradation in its characteristics over a span of time (Wolfram 1984).

The five basic elements of cellular automata are: a) *the cell*, which is the elementary spatial unit. Cells in a cellular automaton are arranged in a spatial tessellation forming a pattern cluster. A two-dimensional grid of cells is the most commonly used form of a cellular automaton in case of modelling urban growth and land-use change; b) *the state*, which defines the attributes/properties of the system. At any point of time, each single cell has a single state. We can think of a state as a numeric number associated with a cell; c) *the neighbourhood*, which is a set of cells surrounding any given cell in consideration. We are mostly involved with two basic types of neighbourhoods: the von Neumann Neighbourhood consisting of four cells in the North, South, East, and West directions corresponding to a given cell; and the Moore Neighbourhood consisting of eight cells which includes the cells already defined in the von Neumann neighbourhood as well as cells in the North-west, North-east, South-east, and South-west directions; d) *the transition rule*, being the set of rules that define the transition of one state to another of any given cell at any point of time. This is the key component of cellular automata as they are essential for successful modelling practice because they help define the way how changes will take place over time; and e) *the time*, which specifies the temporal dimension of a CA. All the changes that take place in a CA get manipulated as the time component passes. CA is an iterative model.

The capabilities of CA to represent the urban growth phenomena have already been discussed emphasizing that CA make a really good choice for the depiction of non-linear, spatial stochastic phenomena. Many works have already demonstrated greatly the CA model's capability in such scenarios. The time-space relationship underlying the basic functioning of a CA plays a vital role in order in understanding the dynamic processes comprising complex non-linear interaction between several components, i.e., topography, land use, transportation, population, economy, and growth policies. Such non-linear relationships between land change and the various driving factors can be addressed smoothly by coupling CA with artificial neural network (ANN) modelling framework as evidenced by various authors and as also mentioned in the Chapter 2 (Literature Survey).

4.2 Concept of ANN

Neural Networks are like distributed parallel massive networks simulating the characteristics of a human brain. These methods are fast and robust in the approximation of real valued, discrete-valued,

and vector-valued functions. Complex real-world problems including dealing with training data from sensors like cameras and microphones etc. are best solvable through ANNs. ANN and decision tree learning techniques often produce results of comparable accuracy. The Back Propagation algorithm is the most commonly used learning technique for ANN. The major attractions of an ANN lie in its independence from the statistical distribution pattern of the data and no requirement for specific statistical variables. Therefore, the integration of remote sensing data or GIS data is convenient. Additionally, accurate analysis is possible even with a few training area datasets.

ANN is a mathematical model essentially based on biological concept of brain and neurons. Conceptually, it is an interconnected group of artificial neurons. The neurons are the store-house of the knowledge that is acquired by the system by proper stimulatory techniques like excitation and inhibition, the knowledge is then rendered available for further use. A neural network usually comprises one input layer, one output layer, and one or more hidden layers in between. These layers are connected to each other and lead to proper relay of message or communication from one level to another. The connections are responsible for passing of information throughout the network, and they are characterized by weights. Weights can be artificially set initially in a random way and can be positive or negative. A training process is employed to automatically generate the series of parameters that would be required to train the data-sets. Such trained data, having learned a particular pattern can then be imported into the cellular automata model to simulate the land change process.

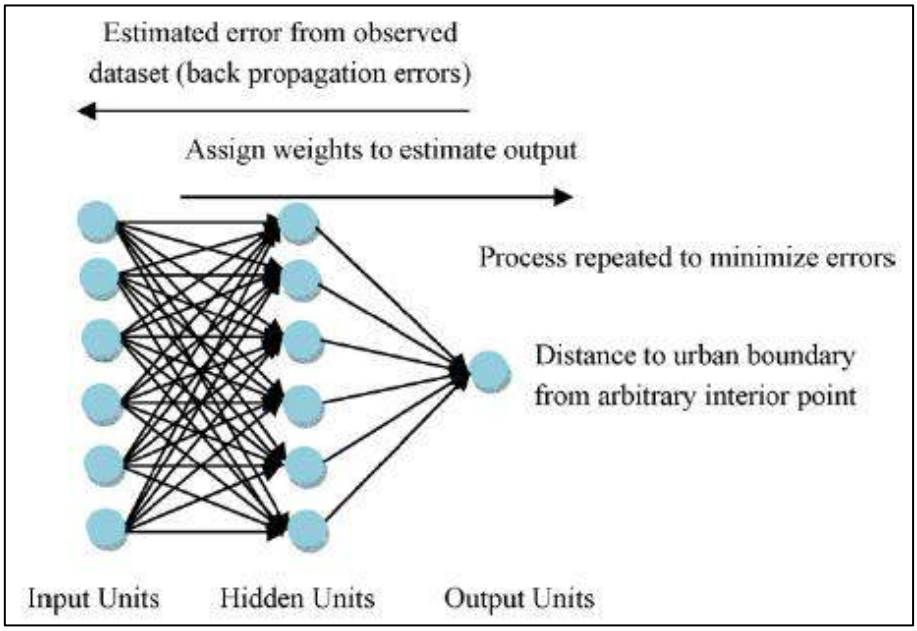


Figure 38: A typical Architecture of a Feed-Forward ANN

4.2.1 ANN Architectures

There are several different forms of machine learning neural network architectures. They are essentially different in the way they are being trained for learning some patterns. The accuracies also

vary from architecture to architecture. A simple perceptron network is the basic form of an ANN.A perceptron is a basic element of a neural network which perceives it surroundings and is able to learn from its own experiences. Basically the number of hidden layers, learning rates, momentum term and other features help formulate different architectures. The predominant ANN architecture is an MLP (Multi-Layer Perceptron). Several other neural networks are used for training the data-sets which are discussed under the current header.

4.2.1.1 MLP: Multi-Layer Perceptron:

MLP consists of a number of perceptron nodes connected together and is majorly used for the classification of remotely sensed imagery using the back propagation algorithm. The calculation relies upon the information obtained from training sites. Training sites are the small cut-out portions of the imagery which are used to train the algorithm for a specific class. For example, using a supervised classification technique, certain portions of the imagery are categorized as class 1 and they are distinguishable from other classes. Once all the different classes are obtained, the algorithm tries to categories the entire satellite imagery into various classes as per the training sites.

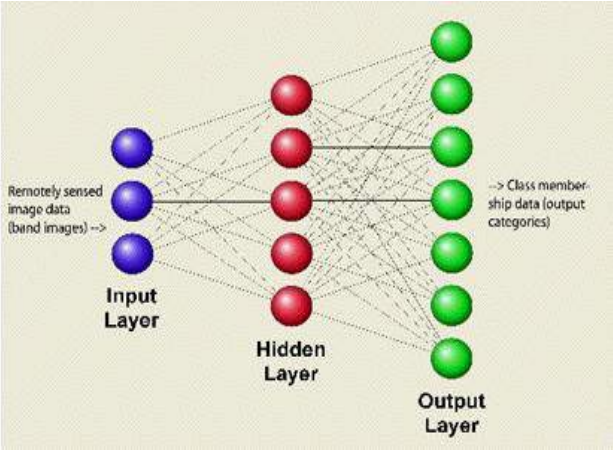


Figure 39: Structure of an MLP

Back propagation involves forward and backward propagation of different land-use categories to attain the modification of the neural state. The more number of times the process is repeated, the lesser is the error encountered. During training, a sample is fed into the input layer and the hidden node sums the weighted signals from which it is connected in the preceding layer. The hidden layer comprises of nodes to perform the mathematical mapping of the input layer information to trap the specific structure of learning.

It is basically a sigmoidal function which applies the weighted sum of inputs before it passes onto the output layer. Once the forward pass is completed, the output nodes are activated and their responses are compared with the previous responses. A desired level of accuracy which is pre-set governs how

many times the same action would be performed. Each node in the output layer is associated with a class. When a particular pattern is presented to the network, the output nodes generate a set of values indicating their similarity between the input pattern and the corresponding class. The to and fro mechanism of the forward and the backward passes continue till the network gets trained in the desired characteristics of the classes. As we know that the weights are the placeholders of the actual knowledge content, the main task here is to get the network trained so that they assume the desired ranges of weights for the classification of the unknown pixels. The input pattern is thus classified into a class that is associated with the highest activation level of any specific node at any point of time.

4.2.1.1.1 Training Parameters:

Automatic training and dynamic learning rate are the two essential parameters to capture a particular learning exercise. When there is a great leap (also called oscillation) in the learning rate, it is assumed that either the network is under-trained or over-trained. Such a condition is avoided by automatically restarting the learning process. In such a case, one of the following things happens:

a) The starting weights (those available before the learning initiates) are re-randomized and the learning rate is halved.

b) When the training restarts automatically the weights are re-randomized and again the learning rate is halved so as to smoothen the error surface gradient.

c) In case of dynamic learning, the learning rate is progressively decreased based on the number of iterations specified and the start and end learning rates. The start and the end learning rates are subject to the choice of the training network or can be controlled by an outsider agent.

The number of training samples can greatly affect the accuracy of the result. Very few as well as larger number of samples are both unsuited as they cannot either represent the population of each category or lead to improper generalization of the network. The hidden layer nodes play an important role in defining the power of the neural network model to delineate the underlying relationships and structures inherent in a dataset. Networks that are too small cannot identify the internal structure of the data (under-fitting) and therefore produce lower classification accuracies. Networks that are too big become over-specific to the training data. They result in low classification accuracies and longer training times and poor generalizability. The acceptable error rate is considered 0.01, beyond that the network efficiency can no longer be improvised.

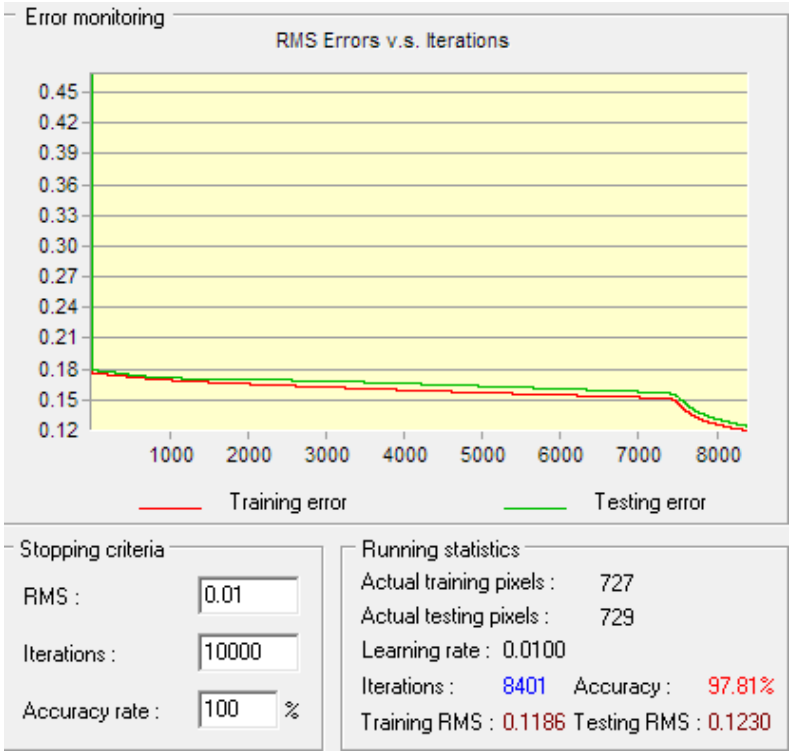


Figure 40: Illustrating the training of an MLP Neural Network (The closer the two RMSs' and the lesser their numeric values, the greater is the accuracy level of an MLP)

4.2.1.2. SOM: Self Organising Maps:

A self-organizing map (SOM) or self-organizing feature map (SOFM) is another type of ANN that is trained using both unsupervised as well as supervised learning to produce a discrete low-dimensionality representation of the inputs fed into them. The output of a SOM is termed a map. SOMs are different from other ANNs in that they maintain the topological properties of the input. For this, a neighbourhood function is used. The working is based on Kohonen's neural network technique.

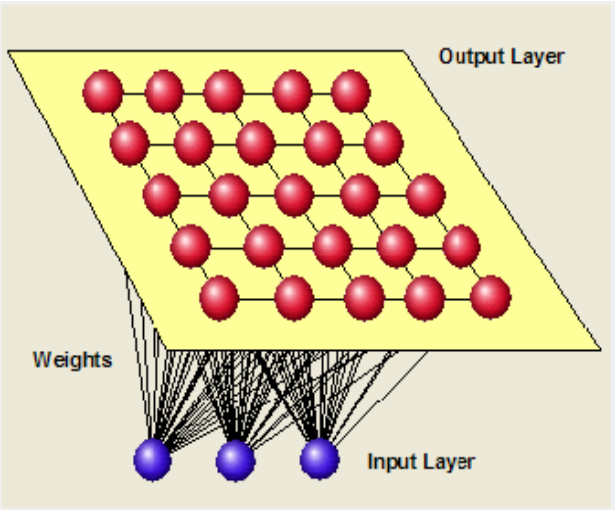


Figure 41: Example of the architecture of a SOM with an input layer (made up of three neurons) and an output layer (made up of 5 by 5 neurons equally spaced).

Figure 41 illustrates the basic architecture of a SOM. The input layer represents the input feature vector which implies a different neuron for each reflectance band of the satellite imagery. Weights store the information as in the general case of an ANN. The output layer here is a sequential 2D array of neurons. Output layer is connected to the input layer by means by of weights. Labelling and fine tuning techniques are utilized to reform the learning experience in this type of an ANN. The description is given below.

4.2.1.2.1 Labelling and Fine Tuning

Labelling is performed so as to facilitate the association of the training datasets to each unique class category. When a neuron is most frequently assigned to a particular training site class, it becomes its own unique label. As the name suggests, the task of fine tuning is performed to re-define the decision boundaries between the various classes corresponding to the training datasets. Fine tuning is obtained by using LVQ (Learning Vector Quantization) technique (Ji 2000; Tso and Mather 2001). It stabilizes the structure of learning and weights are determined in a better way.

4.2.1.3 Fuzzy ART-Map:

A mixture of fuzzy set theory and Adaptive Resonance Theory (ART), this technique performs both the supervised and unsupervised classification of remotely sensed imagery. Adaptive Resonance Theory (ART) based neural network was developed by Grossberg and Carpenter in 1991. An ARTMAP essentially comprises of two modules to perform the mapping of input-output relations. Fuzzy ART is a clustering algorithm that operates on vectors with fuzzy analogue input space. It applies an incremental learning approach. Incremental learning approach is a technique which allows a system to rapidly and continuously learn new things by retaining the already learnt information. It's like learning in steps where new learning does not lead to loosing away the already learned concepts.

As is apparent from figure 42, a fuzzy ARTMAP has two layers, F1 (input layer) and F2 (category layer). The F1 layer represents the input features in the form of a continuous vector and has neurons for each measurement dimension. F2 layer is the category layer comprising the class categories as the training site samples get trained. The number of neurons in the F2 layer is automatically determined. It first begins with a single neuron and dynamically grows in number with each respective incremental learning approach implemented.

Fuzzy ARTMAP can have two additional layers i) the map field layer and ii) output layer. These two layers make up the ART b model. Otherwise, F1 and F2 layers represent the conventional ART a model. The output and map field layers consist of same number of neurons, each of which is equal to the output class dimension.

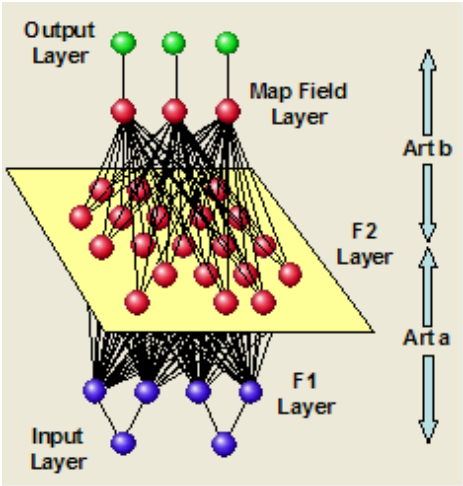


Figure 42: A Fuzzy-ART Map based Neural Network Model

4.2.1.3.1 Parameterization:

The degree of belongingness to a particular class is measured in terms of its tightness to a specific cluster. The vigilance parameter governs the "tightness" of a cluster. A small vigilance parameter value causes more patterns to be associated with the same neuron in F2 thereby resulting in a loose clustering while a high value causes the network system to perform only exemplar learning.

4.2.1.4 CTA: Classification Tree Analysis:

CTA is the most conventional technique ever used without any depreciation in its value as a means to data classification. Classification Tree Analysis is non-parametric in nature. The underlying principle is simple. We simply go on splitting the data into homogenous subsets as per the decision rules to finally arrive at a hierarchical tree structure. There are a couple of splitting algorithms out there to help split the data including gain ratio, entropy, and Gini. Manual and auto-pruning techniques also help in regulating the output.

A typical decision tree is composed of a root which marks the starting point of the tree, an internode which connects the root and all other internodes and the leaves, which are simply a collection of pixels belonging to the same category class.

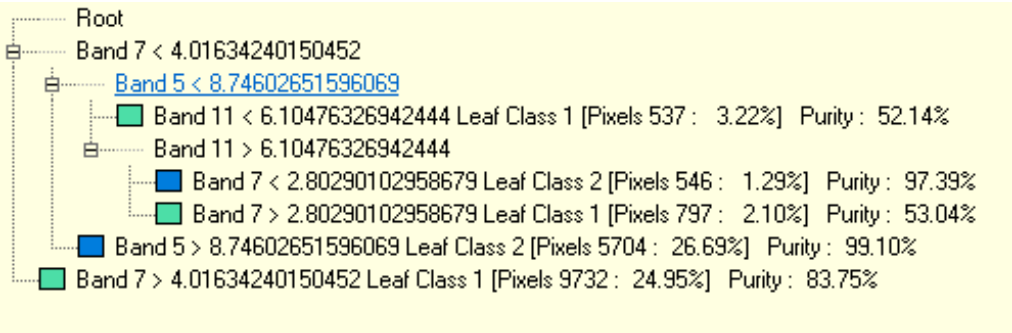


Figure 43: CTA for the 11 input layers

Phase 3

4.3 Training the neural networks and generation of transition potential files using different algorithms.

A representation of how the different machine learning algorithms are applied to train the networks for the production of several hard and soft output maps indicating the growth potential is depicted in the form of a flowchart below:

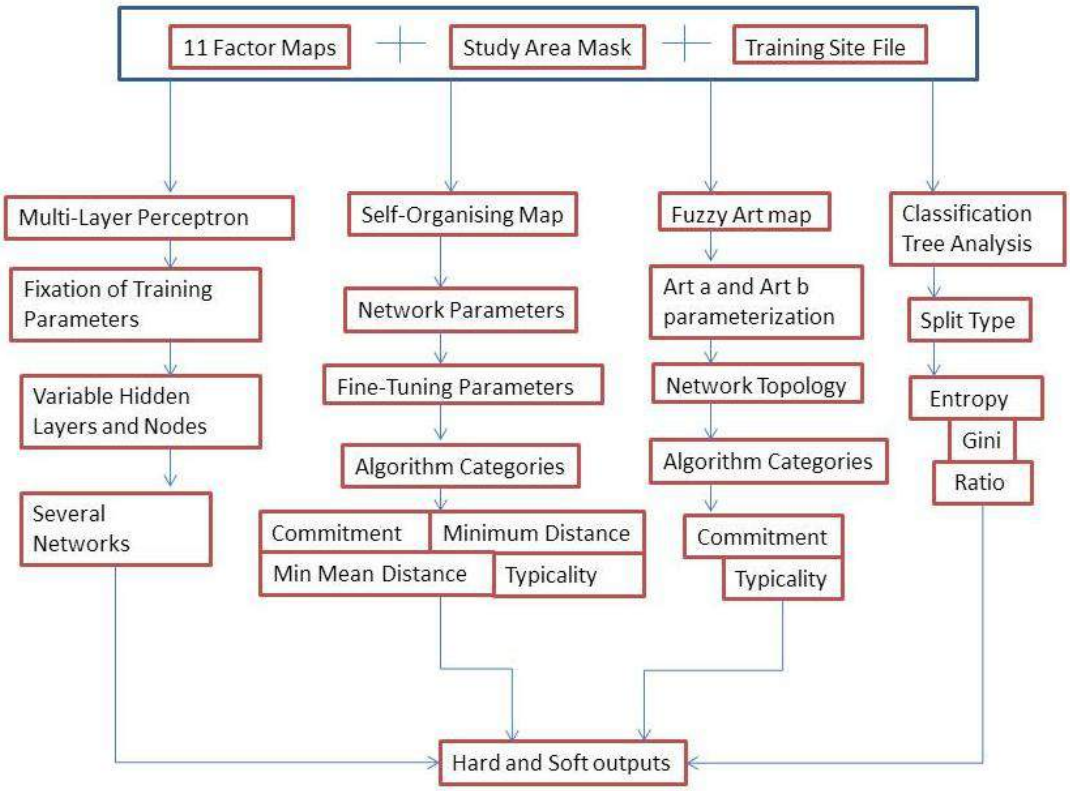


Figure 44: Training several machine learning algorithms

What goes as input to the algorithms are the 3 data layers namely, factor map raster group file, training site file and the study area mask file. These datasets are supplied as input layers to several algorithms which give hard as well as soft outputs describing the potential of transitions from a scale of 0 to 1 (on a cellular basis) from non-urban to urban.

The generation of transition potential files can be done by setting the training parameters of each algorithm category, all of which are mentioned below as a sequence.

For MLP:

Input Layer nodes = 11, Output layer nodes = 2, Hidden layers = 1 and 2 with variable number of nodes to be trained, Automatic training and dynamic learning rate being put ON, momentum factor = 0.5, sigmoid constant (a) = 1.0

For SOM:

Input Layer neuron = 11, Output Layer neuron = 225, Initial neighbourhood radius = 22.21, minimum learning rate = 0.5, maximum learning rate = 1, minimum gain term = 0.0001, maximum gain term = 0.0005, fine tuning rule = LVQ2, fine tuning epochs = 50

For Fuzzy ART Map:

F1 Layer neurons = 22, F2 Layer neurons = 0, Map Field Layer neurons = 2, ART a choice parameter = 0.01, ART a learning rate = 1.0, ART a vigilance parameter = 0.98, ART b learning rate = 1.0, ART b vigilance parameter = 1.0

For CTA:

Auto-pruning ON, Leaves with proportion = 1.0% with full-leaf details.

The output of all these schematics results in various transition potential files, both hard and soft classified. The several different neural networks give rise to a series of transition potential files (files describing about the transition potential from non-urban category to urban category of land use change). The transition potential files resulting out of the different algorithms described above are further utilizable into the CA-Markov model as they help estimate the future urbanizable areas.

4.4 Testing the Selected Driving Variables

Each spatial variable has its unique effect that it brings out on the LULC transition that is possible from one land use category to another. Some methods to measure the impact of spatial variables are Cramer's V, Contingency Coefficient and the Joint Information Uncertainty (Sallis and Nti 2014). Cramer's V is based on chi-square technique and is considered to be one the best measure of association between two categorical maps (Rees, 2008). The value of Cramer's V coefficient ranges from 0 to 1. The values higher than 0.15 can be considered useful and values higher than 0.4 are considered good to evaluate the driving variables. A high value of Cramer's V coefficient accounts for high potential of usefulness of a particular variable in the modeling technique applied however, a variable can be discarded if the Cramer's V is low.

The variables selected for modelling can be checked for their suitability.

Table 1: Testing Suitability of driving factors

S.No.	Name of the driver variable	Value of Cramer's V
1.	Distance from airport	0.3362
2.	Distance from bus station	0.3136

3.	Distance from railway station	0.4550
4.	Distance from major roads	0.3152
5.	Distance from secondary roads	0.4157
6.	Distance from CBD	0.4048
7.	Distance from OBD	0.4588
8.	Distance from Industrial Area	0.3764
9.	Distance from Educational Institutions	0.3793
10.	Land Price	0.4125
11.	Neighbourhood Focal Analysis	0.4854

All the variables selected are marked significant for the functioning of the neural networks as depicted from their high values of Cramer's V coefficient as shown in the table above.

4.5 Selection of the optimal neural network

The different parameters of the algorithms were changed in order to bring out different results. The accuracy obviously varies from architecture to architecture. In case of SOM, CTA and Fuzzy ART Map techniques, there is no direct way to measure the level of accuracies of the transition potential files obtained. However, in case of an MLP, we can determine the accuracies of several architectures by comparing the training and testing RMS error as well as the overall accuracy and Kappa Coefficient.

The number of inputs to a given ANN defines the level of complexity of a given problem. The number of output nodes determines the number of feature classes desired in the output. How these two layers (input and output layers) are mapped together is performed by the underlying mathematical formulation of hidden layer. The accuracy of the models is highly dependent upon the number of hidden layers chosen and the number of nodes in each respective hidden layer. Several strategies and heuristics are suggested to estimate the optimum number of hidden layer nodes (Kavzoglu and Mather 1999).

Table 2: Heuristics proposed to compute the optimum number of hidden layer nodes.

Name of the Heuristic	Source	Optimum nodes for the datasets
$2N_i$ or $3N_i$	Kanellopoulos and Wilkinson (1997)	22 or 33
$3N_i$	Hush (1989)	33
$2N_i + 1$	Hecht-Nielsen (1987)	23
$2N_i/3$	Wang (1994 b)	7
$(N_i + N_o)/2$	Ripley (1993)	6
$N_p/[r(N_i + N_o)]$	Garson (1998)	61-123
$[2 + N_o.N_i + ½ N_o (N_i^2 + N_i)-3]/ (N_i + N_o)$	Poala (1994)	11

In the table 2 shown above, the number of input and output layer nodes are represented by N_i and N_o (in this case, the number of input nodes were 11 as there were 11 factor maps as discussed previously and the number of output nodes were 2 as the output needed is to be classed as either built-up or non-built up) respectively, and the number of training samples is represented by N_p (In the present context, it was 8000 samples). The symbol r used in Grason's (1998) formulation is a constant which is a representation of the level of noise in the data. It ranges from 5 to 10.

It is to be emphasized that both the single layer and double hidden layered networks are formulated by arbitrarily taking any number of nodes respectively to specify the input output mapping. The number of nodes in a given layer was taken to be a number ranging from 4 and going up randomly seeing the reported performance and stopping at some larger number beyond which there is no significant change in the RMS error (training and testing).

Table 3: Error Report of a single hidden layer MLP architecture.

Name	Training RMS	Testing RMS	Overall Accuracy	Kappa
n_11_4_2	0.3799	0.3864	80.44	0.5907
n_11_5_2	0.3863	0.3883	80.12	0.5932
n_11_6_2	0.3869	0.3891	80.12	0.593
n_11_8_2	0.3804	0.3793	80.68	0.5955
n_11_10_2	0.3976	0.3905	80.08	0.5932
n_11_15_2	0.3832	0.3874	80.06	0.5924
n_11_20_2	0.3999	0.4007	77.69	0.5948

The ones marked in yellow are favourable over others as the level of RMS accuracies and Kappa are relatively higher, so they make a suitable candidate for future urbanization estimation. Similarly, several permutations and combinations of SOM, Fuzzy ART and CTA with different set of parameters are performed to identify the best level of output.

Table 4: Error Report of double hidden layer MLP architecture.

Name	Training RMS	Testing RMS	Overall Accuracy	Kappa
n_11_5_5_2	0.3828	0.381	79.9	0.5992
n_11_5_8_2	0.3749	0.3862	80.06	0.5928
n_11_5_10_2	0.3956	0.3886	79.88	0.5919
n_11_5_15_2	0.3919	0.3883	79.7	0.5862
n_11_5_20_2	0.3987	0.3957	79.75	0.5905
n_11_10_10_2	0.3794	0.3681	82.21	0.5919
n_11_10_15_2	0.4239	0.4264	79.82	0.5896
n_11_10_20_2	0.4297	0.4241	80.25	0.5884

4.6 Masking of Exclusionary Areas

Some areas such as reserved forests, water bodies, river, defence lands etc. are known to be non-urbanizable, in such a case, the transition potential files which are produced from the application of various algorithms should be erased for any such areas with no transition for development. This is performed by extracting the areas with no development potential. The requirement is that the urban growth should be shown only in areas that are urbanizable and not just anywhere in the study area. This called for the masking of such exclusionary sites.

4.7 Estimation of future urbanizable areas

This can be performed on the basis of the two time-period land cover maps for the earlier and the later years for the categories of built up and non-built up and feeding them into the Markov Chain process. A change matrix is formed which precisely points at the number of cells expected to change from non-urban to urban. By controlling and regulating the change matrix, we can have a fair estimate of the future urbanizable areas. The Markov chain process performs an analysis of a pair of land cover images and outputs a transition probability matrix, a transition areas matrix, and a set of conditional probability images.

The transition probability matrix is a text file that records the probability that each land cover category will change to every other category. The transition areas matrix is a text file that records the number of pixels that are expected to change from each land cover type to another over the specified number of time units.

4.8 Spatial Allocation of Urban Growth Cells

Once the number of cells that are expected to change from one category to another are known, the second important task of allocating the urban growth cells spatially comes into picture. This can be performed by using two methods:

1. MOLA (Multi-Objective Land Allocation) in a single step :

MOLA provides a procedure for solving multi-objective land allocation problems. It is especially useful in cases where conflicting objectives prevail over a finite set of pixels that are to be allocated. The working of MOLA technique is quite simple in understanding. It derives information from suitability maps generated for each objective, assigns requisite weight vectors to each objective, calculates the area required to be allocated to each category and tries to find out a compromising solution that maximizes the suitability to a particular objective.

This is a single step procedure in which a background running algorithm selectively takes the pixels to be allocated spatially to different land use classes in a single go. Say we have 10,000 pixels which are to be assigned spatial locations; this technique will allocate them in a single step.

2. Iterative CA-Markov method:

CA-MARKOV is a combined Cellular Automata / Markov Chain / Multi-Criteria Evaluation (MCE) land cover prediction procedure that is stochastic and iterative and depends upon the user as an external intervention to help redefine places and areas where pixels should be allocated as against MOLA in a single step. It adds an element of spatial contiguity and also implies upon the knowledge of the likely spatial distribution of transitions. The algorithm works as follows: The transition areas file is generated based on two prior land use maps which helps quantify the expected land cover change from each existing category to another. Suitability maps determine the suitability of a set of pixels to belong to a particular class. The number of iterations control in discrete time steps, the allocation of pixels to different spatial locations.

This method provides for a better distribution of pixels in the spatial domain. This method is favorable over single step distributive techniques as urban phenomena being a dispersed/diffusive are usually best captured by iterative processes.

4.9 Evaluation of simulation results

We already have a number of changed pixels and the spatial location of the areas where we expect urbanization. The only thing left to compare is the accuracies of each different algorithm type. The model results can be validated by comparing the actual image with the one obtained by running the model. Predictions can be performed for the future patterns only by comparing the simulation results of the calibrated model.

Also, we have a number of spatial metrics to evaluate the accuracy of the simulation. The analysis separates the components of agreement and disagreement between the two images by finding the degree of agreement and disagreement between two maps by chance, by quantity and by location respectively. These metrics guide us how well given pair of maps agree in terms of quantity as well as location of pixels in each category.

Table 5: Components of agreement and disagreement in case of all algorithmic results

1	Name of the algorithm	AgreementChance	AgreementQuantity	AgreementStrata	AgreementGridcell	DisagreeGridcell	DisagreeStrata	DisagreeQuantity
2	CTAGINI	0.5	0.2282	0	0.0756	0.1962	0	0
3	CTAENTROPY	0.5	0.2282	0	0.0756	0.1962	0	0
4	CTARATIO	0.5	0.2282	0	0.0756	0.1962	0	0
5	FUZZYCOM	0.5	0.2282	0	0.1165	0.1152	0	0
6	FUZZYTYP	0.5	0.2282	0	0.599	0.2119	0	0
7	N_11_4_2	0.5	0.2282	0	0.1156	0.1562	0	0
8	N_11_5_5_2	0.5	0.2282	0	0.1167	0.155	0	0
9	N_11_5_8_2	0.5	0.2282	0	0.114	0.1578	0	0
10	N_11_8_2	0.5	0.2282	0	0.1148	0.157	0	0
11	N_11_10_10_2	0.5	0.2282	0	0.1139	0.1579	0	0
12	N_11_20_2	0.5	0.2282	0	0.1145	0.1572	0	0
13	SOMCOM	0.5	0.2282	0	0.1121	0.1597	0	0
14	SOMMINDIST	0.5	0.1939	0	0	0.3061	0	0
15	SOMMINMEAN	0.5	0.2282	0	0.0247	0.2471	0	0
16	SOMTYP	0.5	0.2282	0	0.0929	0.1789	0	0

From the table above, it is evident that some algorithmic approaches are favourable over the other by looking at the level of agreement by chance, quantity, grid cell and so on.

To assess the validity of the models in the study, different indices like kappa for no information (Kno), kappa for grid-cell level location (Klocation), and kappa for stratum level location (KlocationStrata) are also used in addition to kappa standard (Kstandard). Kstandard is alone not appropriate for evaluating the accuracy of both quantity and location. Kno has no regards for the location and is a measure of proportion classified correctly relative to the expected proportion classified correctly by a simulation without the ability to accurately specify the quantity of location. Klocation defines the success of a simulation to specify the actual locations where the pixels are allocated and KlocationStrata is the measure of the accuracy associated with the correct assignment within a predefined strata. Using all these techniques together allows us to determine the overall success rate of each respective algorithmic approach, the end result being the discretion in the choice of algorithms over which to base the final simulation.

Table 6: Comparing the simulation results for model validation

S.No.	Name of the Algorithm	Kno	Klocation	KlocationStrata	Kstandard
1	CTAGINI	0.6076	0.2781	0.2781	0.2781
2	CTAENTROPY	0.6076	0.2781	0.2781	0.2781
3	CTARATIO	0.6076	0.2781	0.2781	0.2781
4	FUZZYCOM	0.6895	0.4288	0.4288	0.4288
5	FUZZYTYP	0.5762	0.2203	0.2203	0.2203
6	N_11_4_2	0.6877	0.4253	0.4253	0.4253
7	N_11_5_5_2	0.69	0.4296	0.4296	0.4296
8	N_11_5_8_2	0.6844	0.4194	0.4194	0.4193
9	N_11_8_2	0.686	0.4223	0.4223	0.4223
10	N_11_10_10_2	0.6842	0.4191	0.4191	0.419
11	N_11_20_2	0.6855	0.4213	0.4213	0.4213
12	SOMCOM	0.6806	0.4124	0.4124	0.4123
13	SOMMINDIST	0.3877	-0.1265	-0.1265	-0.1265
14	SOMMINMEAN	0.5058	0.0908	0.0908	0.0907
15	SOMTYP	0.6422	0.3418	0.3418	0.3418

As is seen from the table 6, we can straight come to the conclusion regarding making choices for the final algorithm selection for prediction. Those marked in yellow are good enough as they produce a good quality simulation that matches very much closely to the actual form of urban growth.

Phase 4

4.10 Future Urban growth simulations

The accuracy assessment performed in the previous step is workable for helping short-list the best algorithms to carry out the simulation task for some future time. The algorithms obtained as the best candidates for future urbanization are further utilizable in the iterative 3 by 3 CA-Markov model to generate the growth pattern for the future. Maps are prepared for the same.

4.11 Scenario generation

It is not enough that we simulate the urban growth pattern for the future year, what is more important that we know how the growth will take place under certain conditions. For accomplishment of the afore-mentioned fact, we have taken three growth scenarios:

4.11.1 Business as Usual

Here, we let the same results for some future simulation and assume that under no external constraints or conditions, the growth would be just same as the mathematical model depicted i.e. same number of pixels transitioned and same spatial allocation of change pixels.

4.11.2 Compact Development

In this scenario, we assume that the urban development would be compact, that is, vertical growth/extension of urban areas will exceed that of horizontal development. So, here, we assume that only 70% of the total pixels predicted by the model will actually change on ground.

4.11.3 Hazard-free development

In the last scenario, we have taken into consideration that rivers and other floodable areas should not be the sites where future urbanization has to occur. So, we simply mask the river buffers from the transition potential files and then produce the simulation.

4.12 Summary

In the nut shell, in this section we discussed about the basic concepts of machine based learning techniques and how they were utilized in training the diverse networks and how they helped in the generation of potential maps indicating the potential of transition from non-urban to urban. We also came to know that different methods have their own merits and demerits and they can be compared using spatial matrices to help short-list the very best algorithms which are actually then utilized to produce simulations for some future time period.

CHAPTER 5: RESULTS AND DISCUSSIONS

5.1 Image Classification and preparation of land cover maps

Land cover maps for the three time periods of 2003, 2008 and 2014 were prepared after the images were classified using the Maximum Likelihood Classifier (MLC). The overall classification accuracies for the years 2003, 2008 and 2014 were 88.67%, 85.33% and 91.02% respectively and the overall Kappa statistics as 0.8490, 0.8044 and 0.8802 for each respective year.

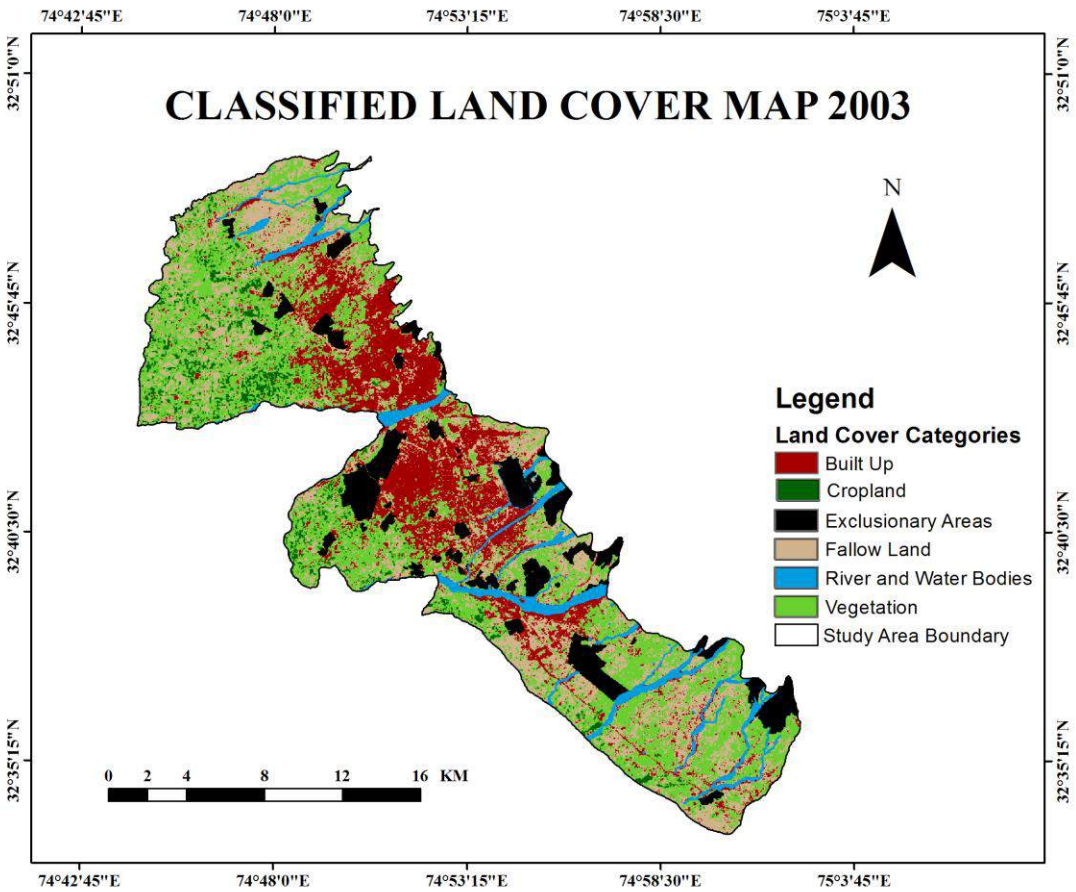


Figure 45: Land Cover Map for the year 2003

Figure 45 illustrates the result of classification for the year 2003. It shows the categories namely, Built-Up, Cropland, Exclusionary Areas (defence lands, reserved forests and airport), Fallow Land, River and Water Bodies and Vegetation.

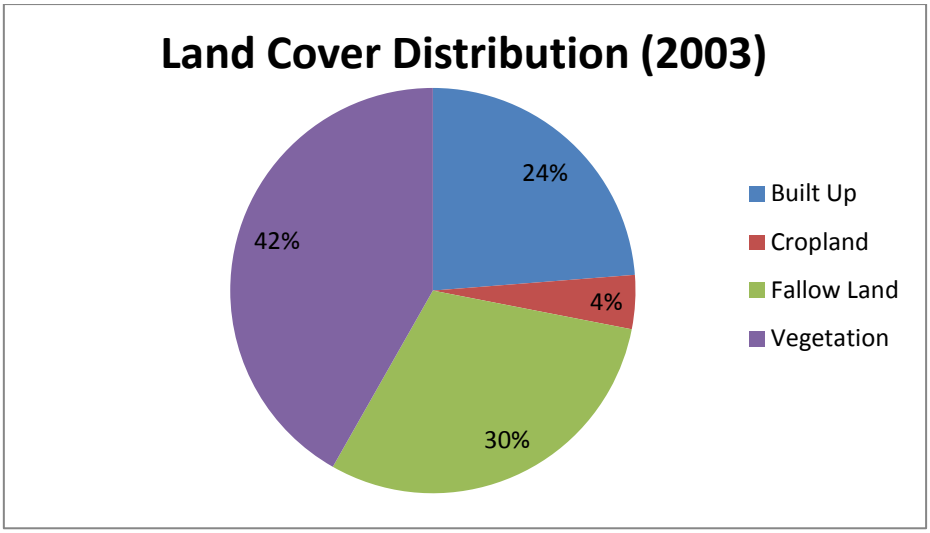


Figure 46: Land Cover Distribution for the year 2003

As can be seen from the pie-chart above, in the year 2003, out of the total area of 21870 hectares, 5196 hectares which is 24% of the total area is the Built-Up area whereas a major share of the total area, 42% which is 9138 hectares is covered by vegetation; and a land area of 940 and 6596 hectares which is 4% and 30% respectively belongs to the categories of cropland and fallow land categories.

Figure 47 represents the classified land cover map for the year 2008.

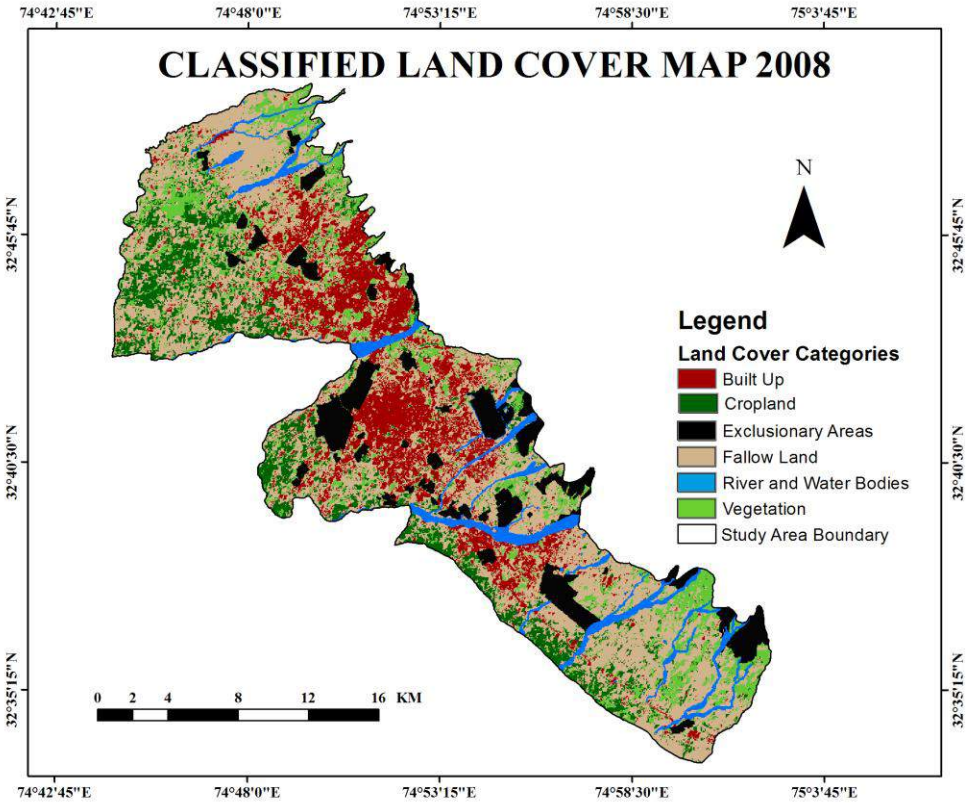


Figure 47: Land Cover Map for the year 2008

Again, the land cover distributions for each category are found out for the year 2008 and 2014 respectively. A pie showing the distribution of various categories for the year 2008 is given below:

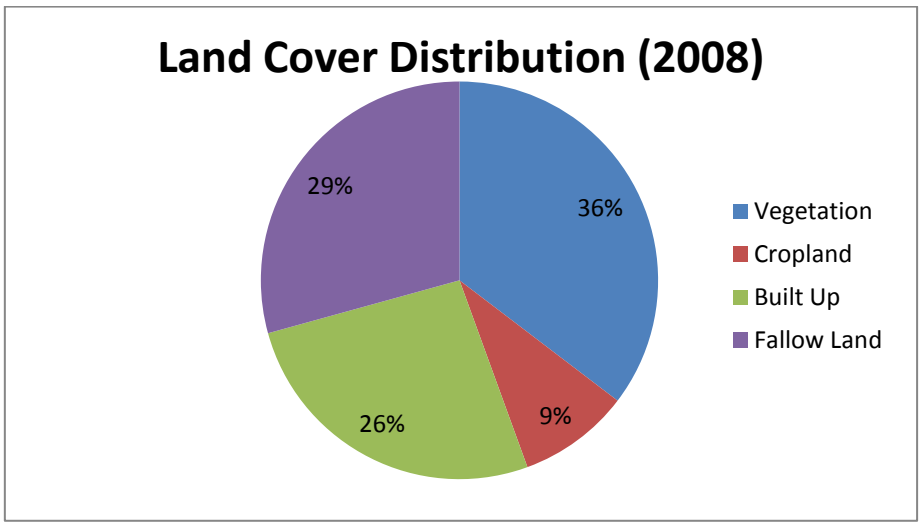


Figure 48: Land Cover Distribution for the year 2008

From the pie diagram for the year 2008, it is quite evident that there was a total increase of 2% in the built area from 2003 to 2008. The percentage of built-up rose from 24% in 2003 to 26% in 2008. A substantial area, 36% still belonged to the vegetation class. An increase can be seen in the cropland compared to the one in 2003 because of the practice of extensive wheat and rice cultivation during the month when the imagery was acquired (October, 2008). The percentage of land cover classed as fallow remained more or less the same.

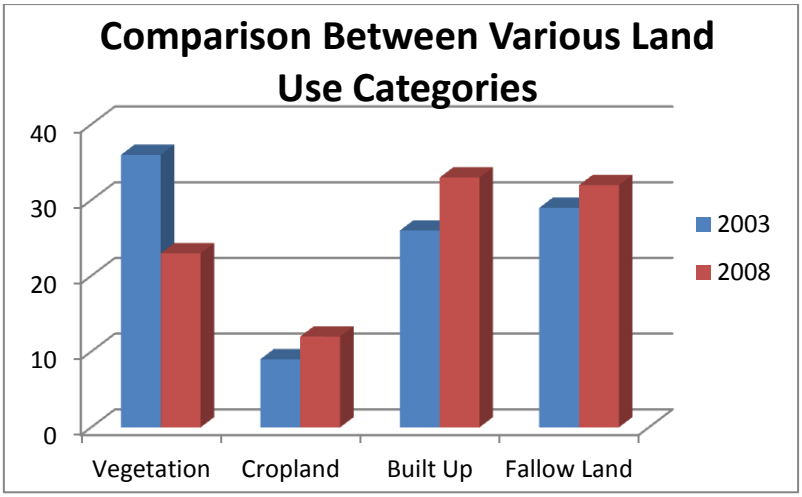


Figure 49: Percentage Change in Land Use Categories from 2003-2008

Figure 49 gives a piece-wise comparison between the various land use classes for the two time periods of 2003 to 2008 where one can visually find out the changes in each land cover categories

between the two time periods. The horizontal axis represents the land cover classes and the vertical axis defines the proportion of each land cover class (in percentage) with respect to the total area under consideration and how it varies between the two time periods of 2003 to 2008.

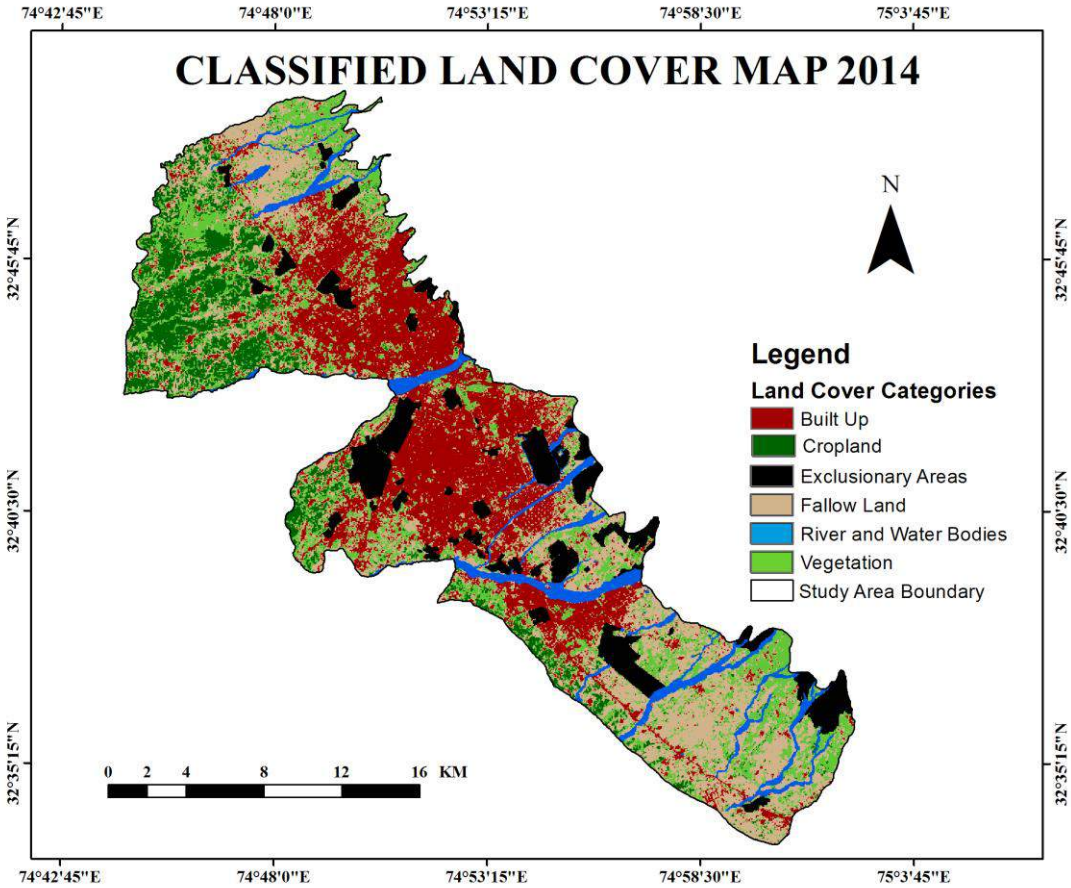


Figure 50: Land Cover Map for the year 2014

The land cover map for the year 2014 as shown in the figure 50 clearly indicates substantial growth in the built-up area with respect to the previous years' land cover counterparts. The rapid urbanization in the latest time period is attributed to the increasing availability of higher level facilities, better employability, infrastructure and industrialization.

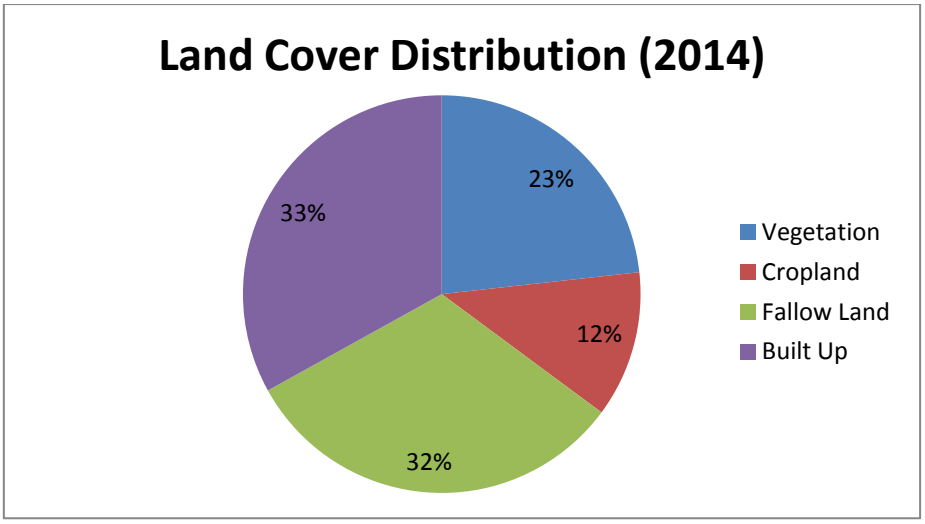


Figure 51: Land Cover Distribution for the year 2014

As is evident from the land cover map of figure 50 and the pie chart of figure 51 above, the year of 2014 shows a marked increase in the area under built-up. A total area of 7229 hectares out of a total of 21870 hectares which account for more than 30% of the study area is urban. The fallow-land which is 32% of the total area also assumes an important part in the land cover categories for the year 2014. A great proportion of the area under vegetation has decreased from 2003 to 2014 (42% in 2003 to 23% in 2014) which means a loss of 4056 hectares.

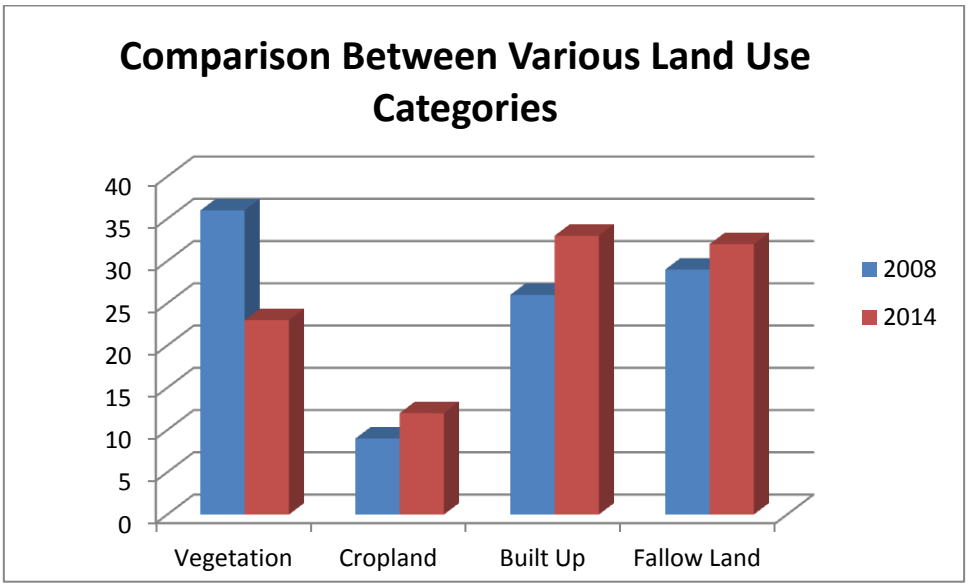


Figure 52: Percentage Change in Land Use Categories from 2008-2014

Figure 52 gives a piece-wise comparison between the various land use classes for the two time periods of 2008 to 2014 where one can visually find out the changes in each land cover categories between the two time periods. The horizontal axis represents the land cover classes and the vertical axis defines the proportion of each land cover class (in percentage) with respect to the total area under consideration and how it varies between the two time periods of 2008 to 2014.

These classified land cover maps for the three time periods were then required to be reclassified into built up and non-built up for further analysis as in the current research, we were more interested in finding out the transformation from non-urban to urban land cover categories. Non-Built up in the reclassified image thus included vegetation, fallow land and cropland and built up remained the same as in the previous land cover images.

Figures 53 to 55 illustrate the re-classified images showing the built up and the non-built up for the years 2003, 2008 and 2014 respectively.

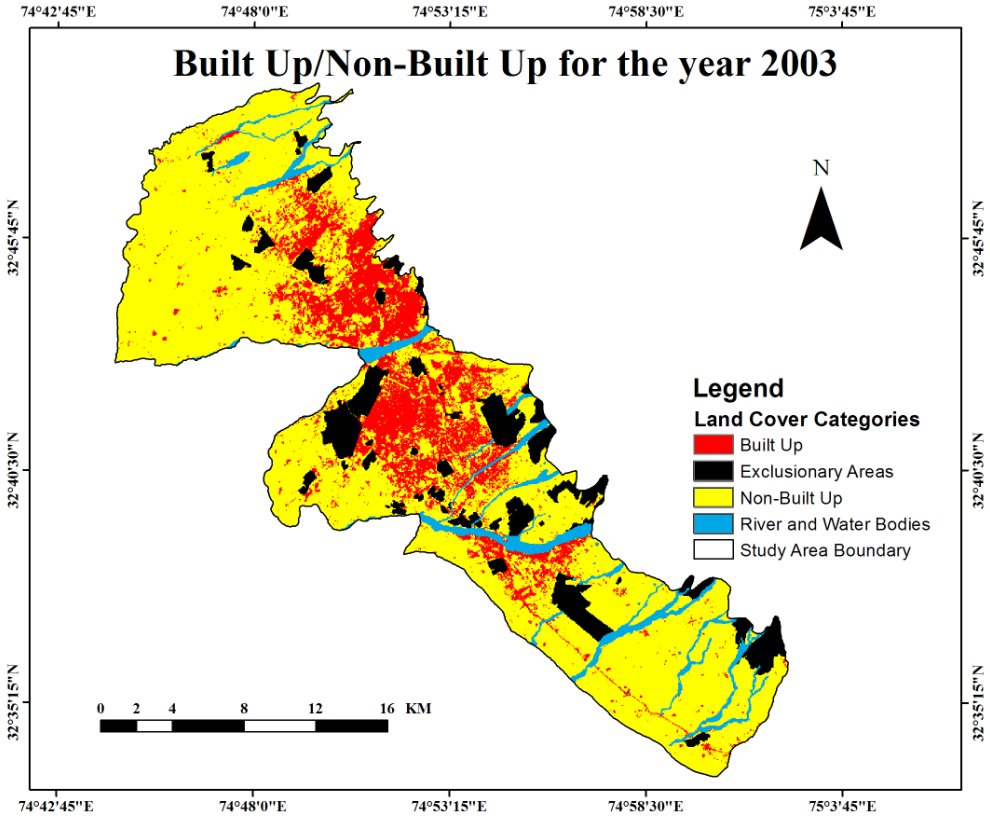


Figure 53: Simplified Land Cover Map for the year 2003

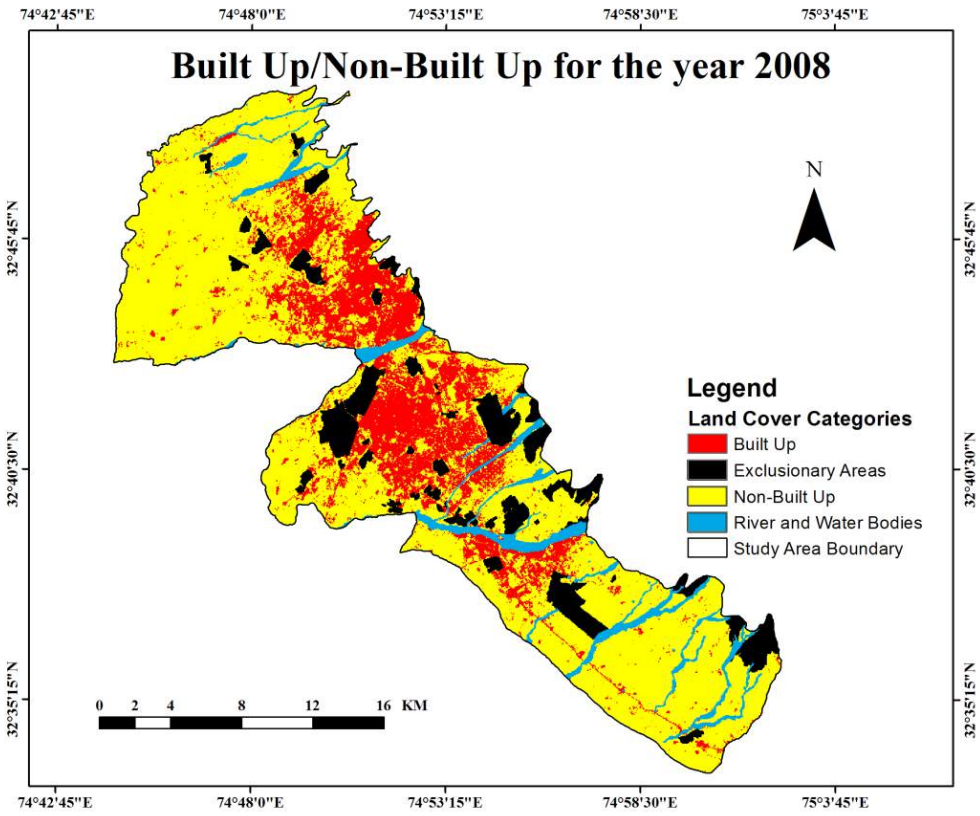


Figure 54: Simplified Land Cover Map for the year 2008

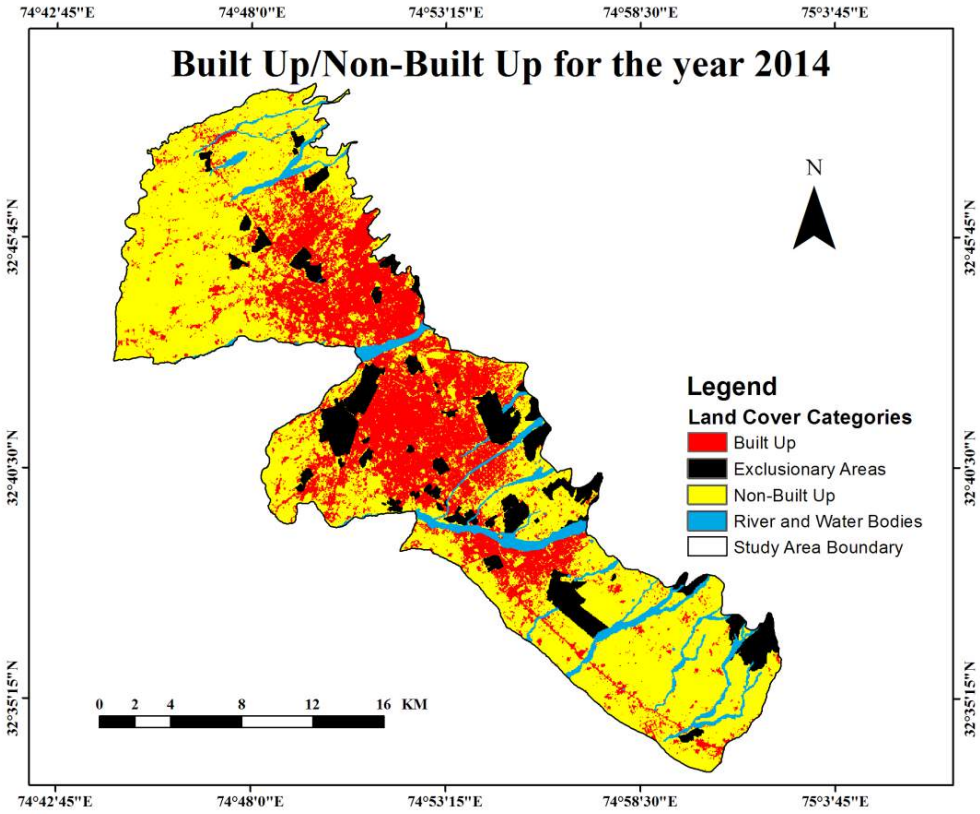


Figure 55: Simplified Land Cover Map for the year 2014

5.2 Generation of several thematic (layer) maps

Several layer maps were generated aided by primary data (Satellite Imagery) and secondary data (Master Plan document) of the study area. For that purpose, the image file as given in the Master Plan was geo-referenced with the actual satellite imagery. Then the roads, educational institutes, industries and other areas of importance were marked directly over the geo-referenced image of the Master Plan also in conjunction with what was being observed in the imagery. This exercise led to the development of several data layer maps. The different layer maps generated are as follows: Road Maps (Major roads and Secondary roads), Transport Hubs within the city structure, core city area and other important business districts, major educational institutions and the industrial area.

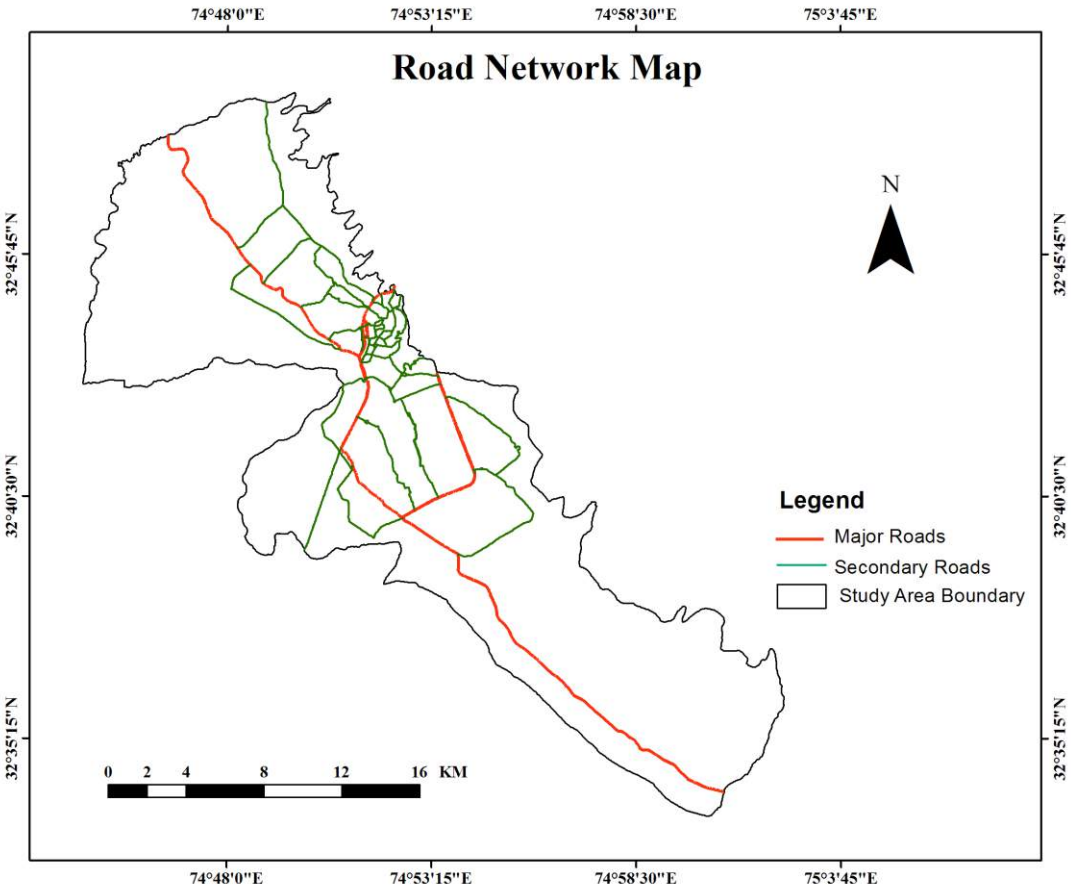


Figure 56: Road Network

Figure 56 represents the major as well as the secondary roads of Jammu. NH-1A and Akhnoor Road provide wide road connectivity in the region. Various other secondary (minor) roads provide for the overall local connectivity within the region.

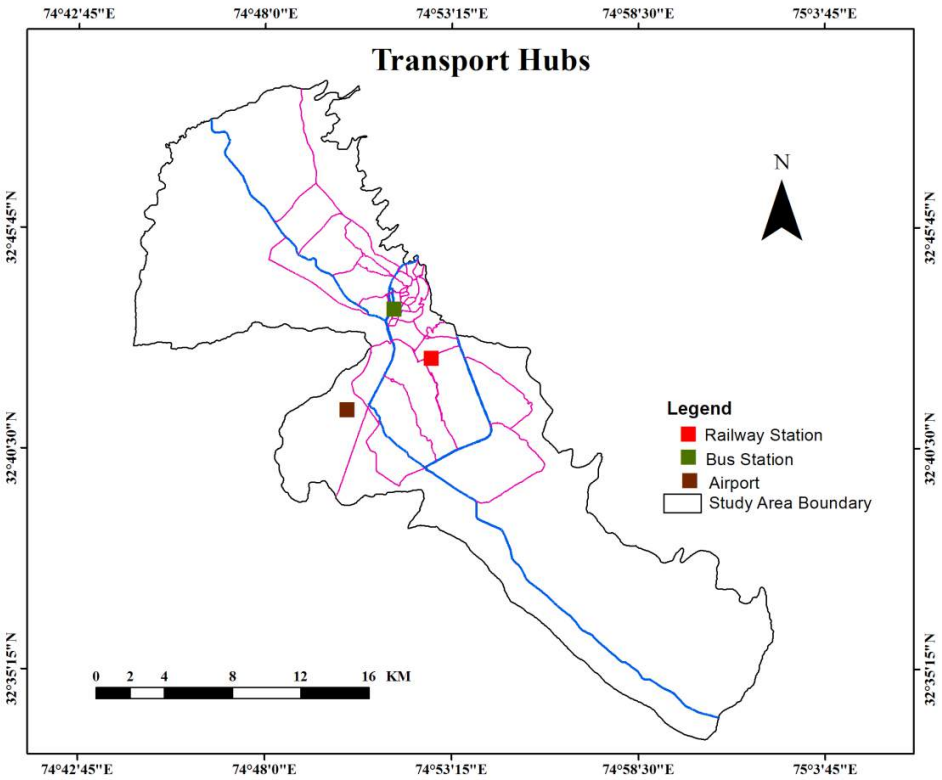


Figure 57: Location of Major Transport Hubs

Figure 57 shows the geographical location of the major transport hubs in the study area. Three different colour squares are representative of the location of Railway Station, Bus Station and Airport.

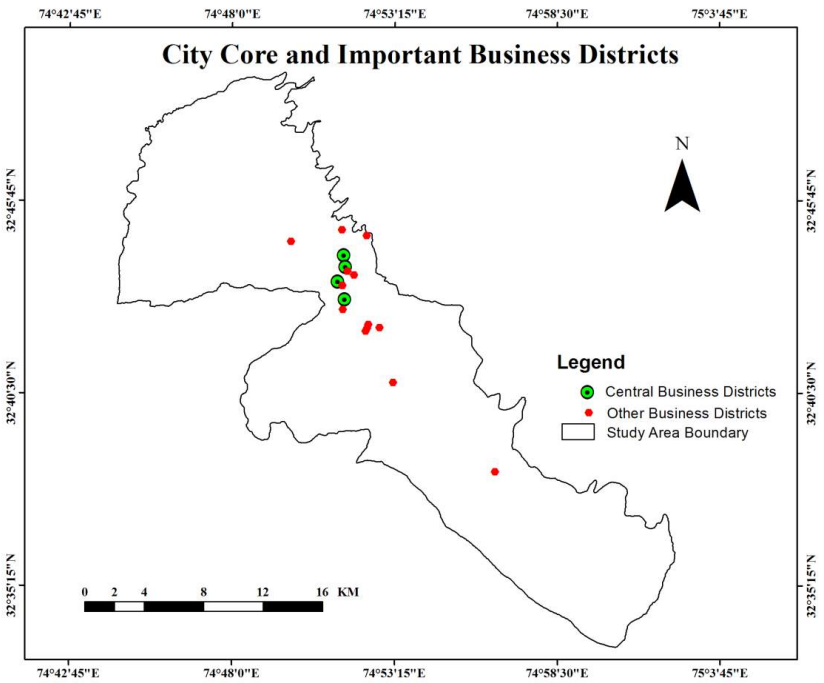


Figure 58: Delineation of city core and other business districts

Figure 58 shows the location of the core city centre. Some other chief business district points can also be seen surrounding the city core. These are the points where trade and commerce takes place for the most part.

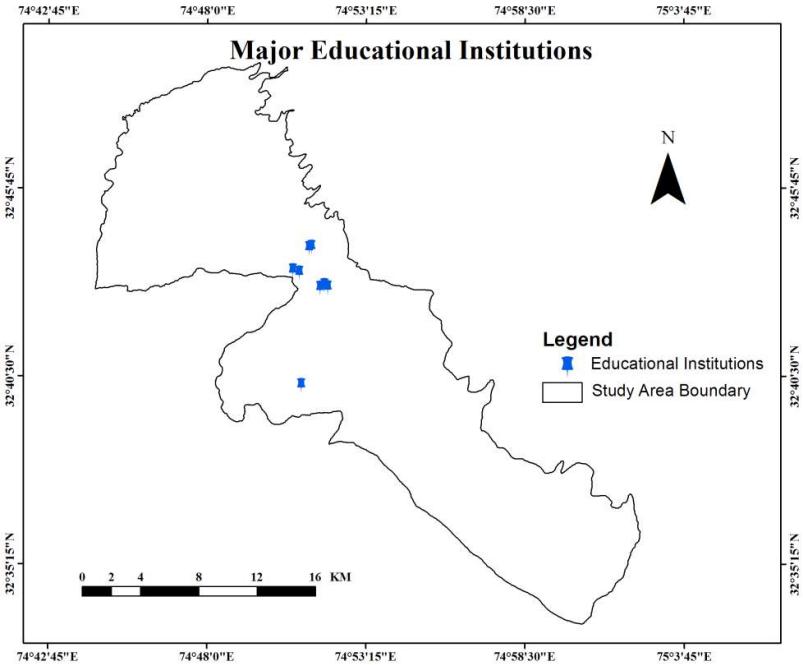


Figure 59: Major educational areas

Figure 59 is indicative of the major educational points in the study area. These educational institutes include medical colleges, engineering and technological institutions, schools, general degree colleges and universities.

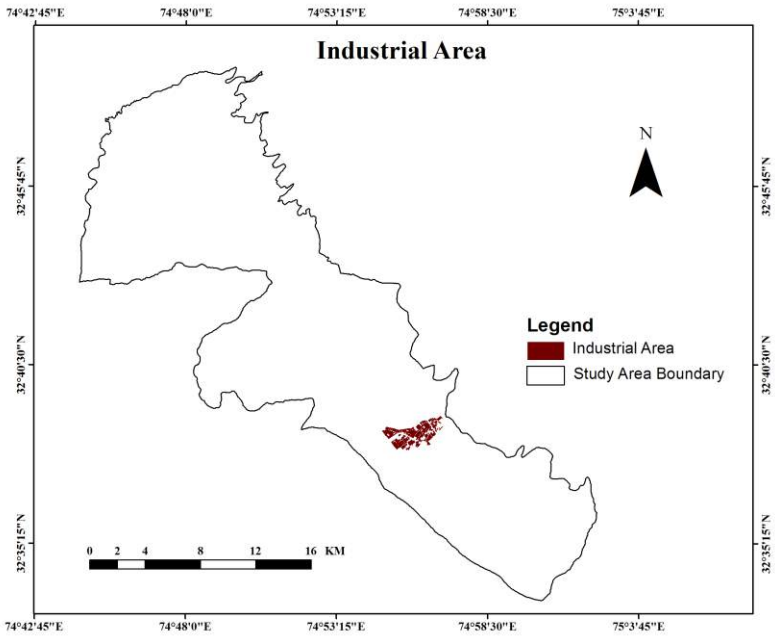


Figure 60: Industrial Area

Figure 60 represents the geographical location of the Industrial Area in Jammu. It is known by the name Bari Brahmana Industrial area.

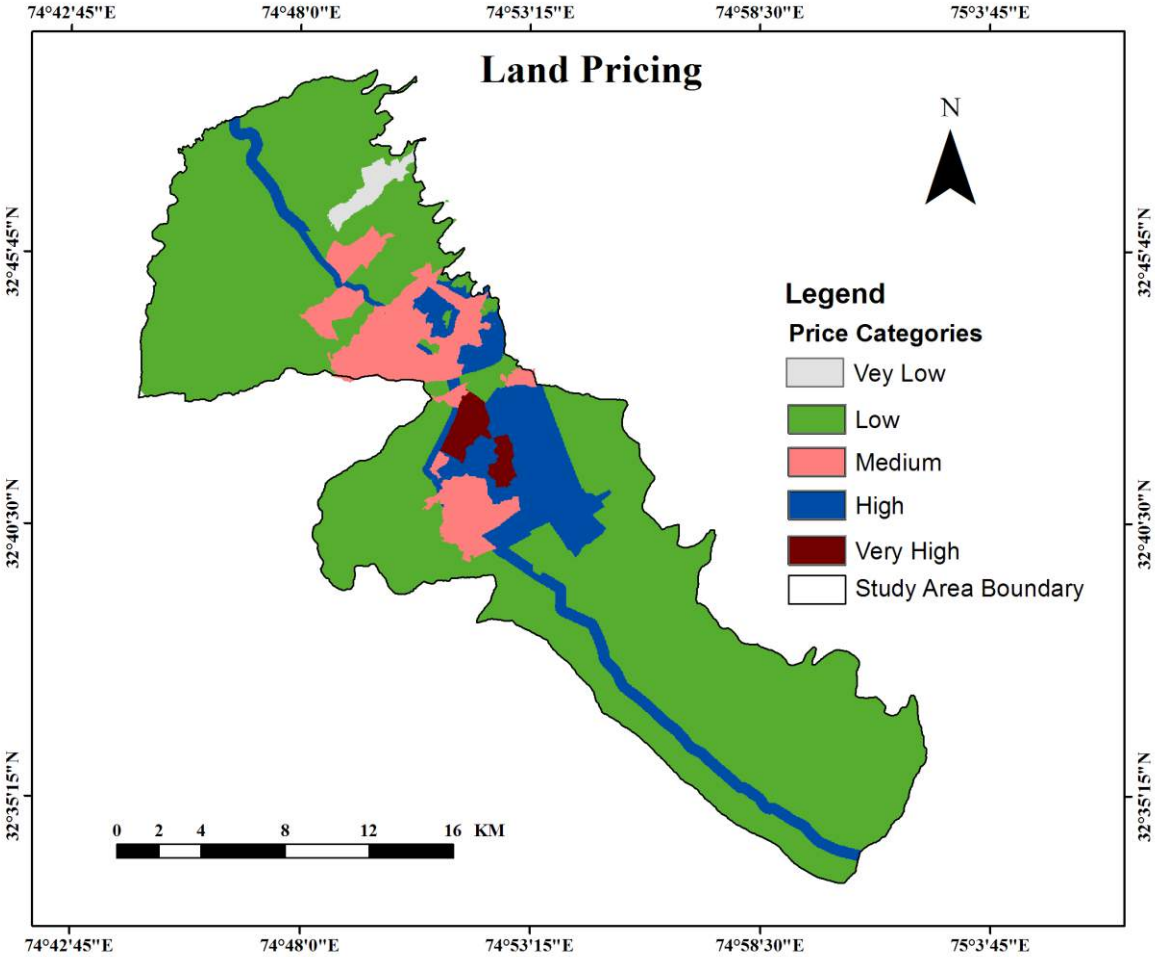


Figure 61: Land Price Map

Figure 61 depicts the land pricing. The map was based on the land price information at ward level. The ward map of the study area along with the land prices was used to prepare this map. Apart from this, a buffer of 200 meter from the major roads was also marked as the areas of high land price. Other remaining areas were given low land price.

Figure 62 and 63 is a pictorial representation of the neighbourhood around the already existent built up for the year 2003 and 2008 respectively. This map is actually a 500 meter focal Euclidean Distance map which demonstrates the number of built up cells in a neighbourhood of 500 m from the already existing built up cells for the two years. As we can see from the map, the number of built up cells inside the buffer rises to 890 inside the city core for the year 2003. As we can see from the map, the number of built up cells inside the buffer rises to 897 inside the city core for the year 2008. The farther one moves from the city core, the number of built up cells in the 500 m neighbourhood

decreases to 0. The outermost regions with very less number of built up cells show very little potential for development as a city tends to grow faster in areas that lie near the already existing built up.

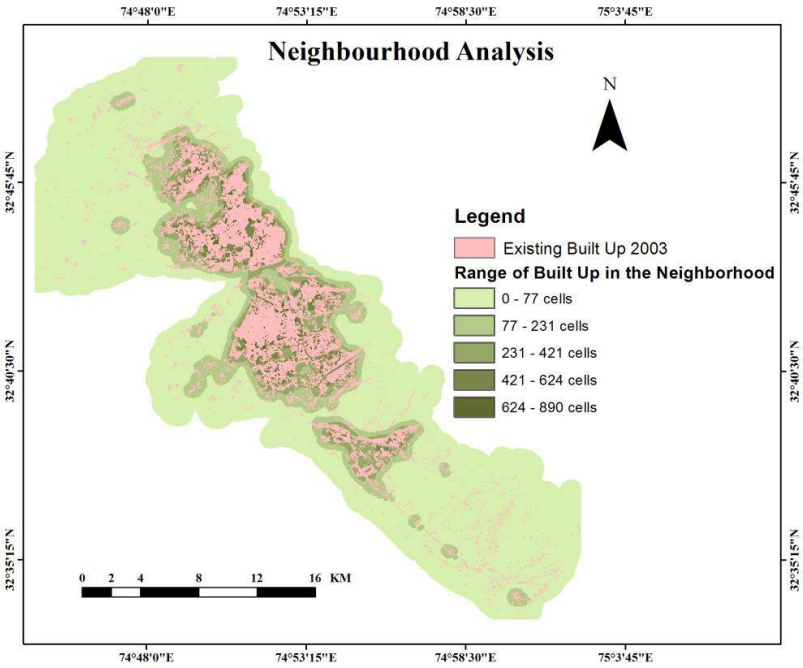


Figure 62: Neighbourhood Built Up for 2003

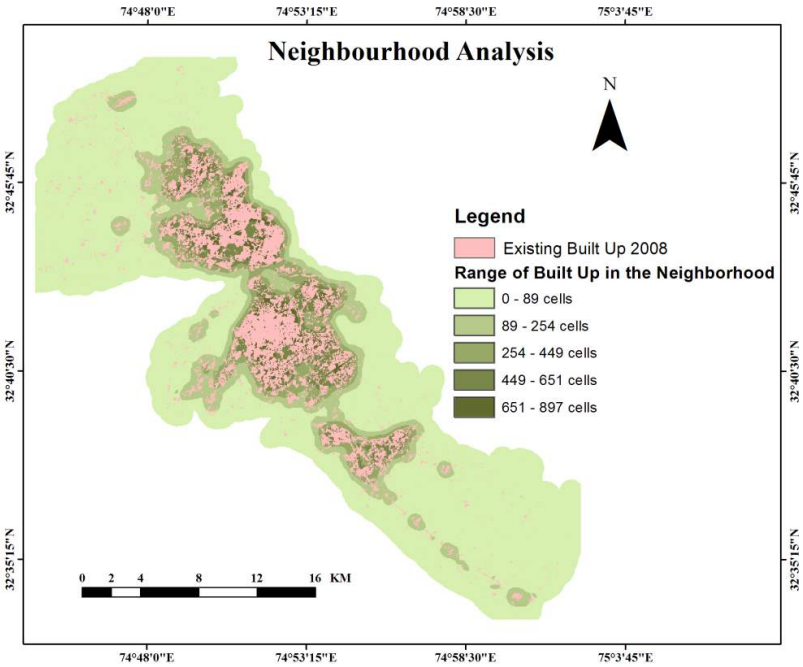


Figure 63: Neighbourhood Built Up for 2008

5.3 Urban Trend Analyses

Urban Growth Trend for the study area was performed using cross-tabulation and image overlay techniques to see the actual amount of change from Non-Built Up to Built-Up categories respectively from the years 2003-2008, 2008-2014 and 2003-2014. This gave an overview of the growth trend in the study area.

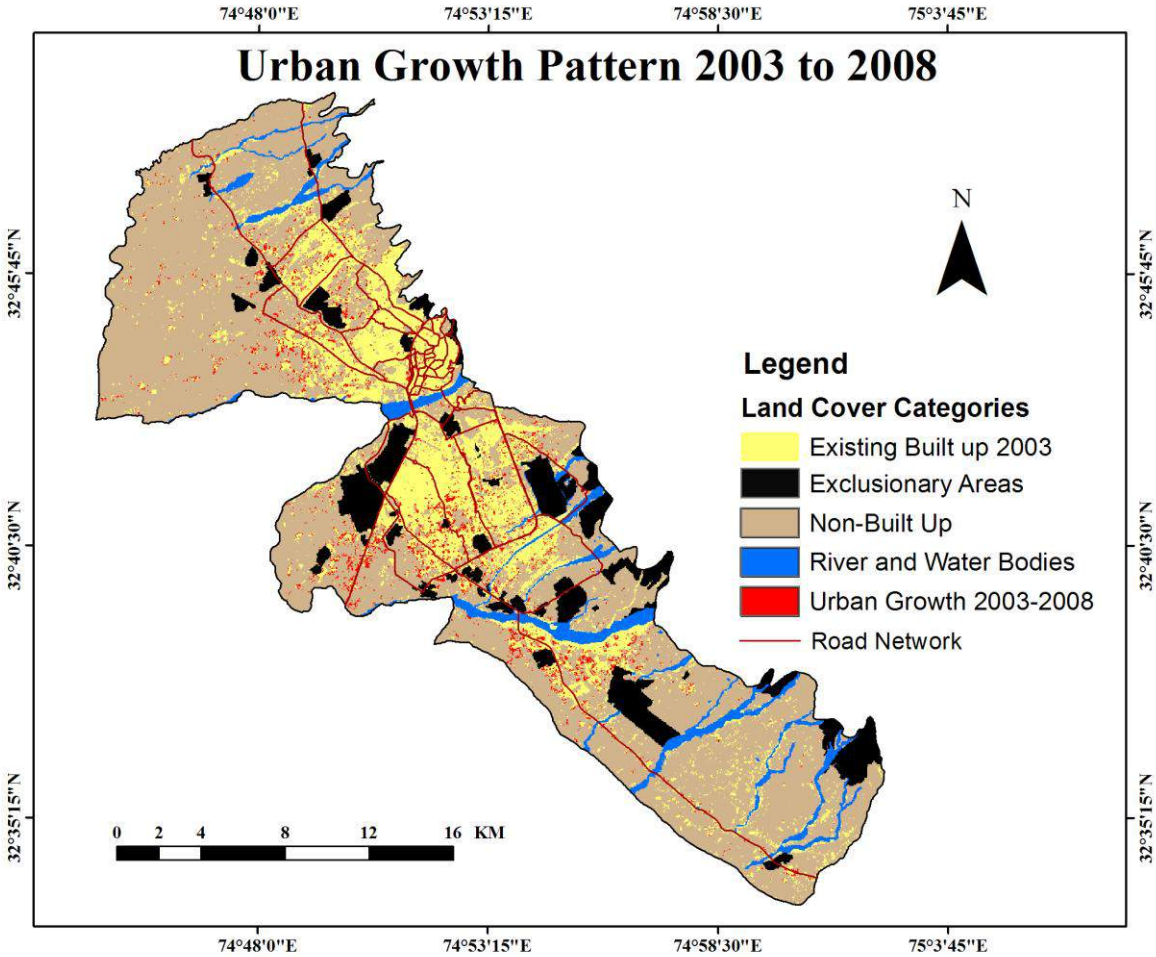


Figure 64: Actual Urban Growth from the year 2003-2008

Figure 64 above shows the actual urban growth taking place from the year 2003 to the year 2008. It was obtained by cross-tabulation between the actual land covers of the years 2003 and 2008. We can see very dispersed form of urban growth occurring within the two time-periods, mostly scattered around the national highways and close to the already existent built up (shown as red on the map). One of the results of cross-tabulation technique was also that the number of pixels which transitioned from non-built up to built-up was also known. The actual number of cells transitioned is 8694 from 2003 to 2008 which amounts to total change of 782.46 hectares.

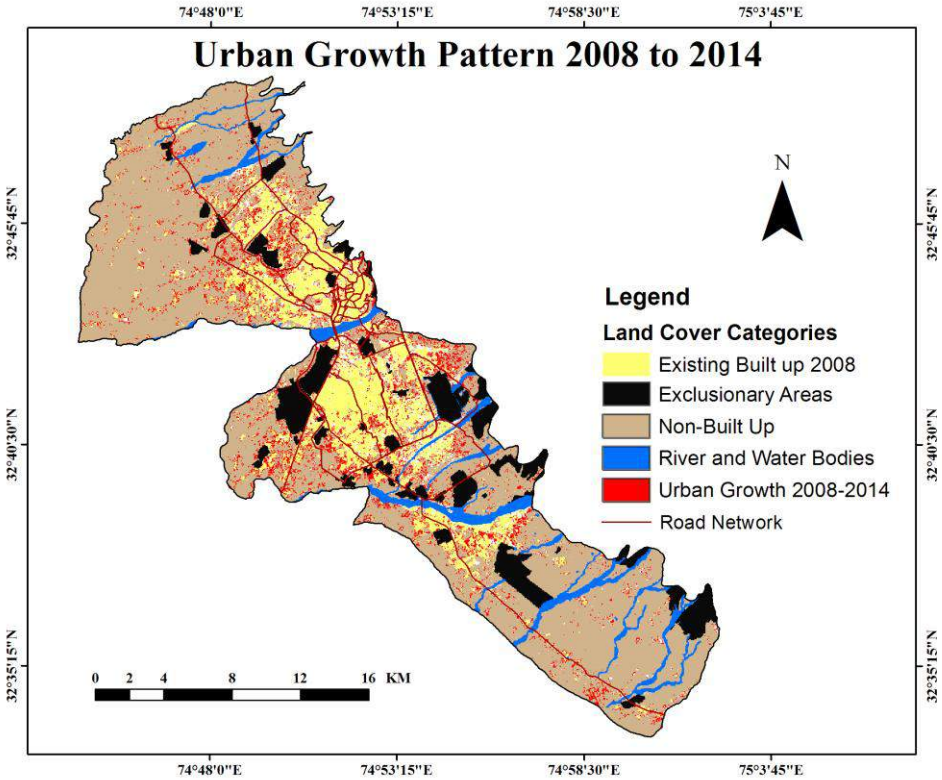


Figure 65: Actual Urban growth from the year 2008-2014

Figure 65 above shows the actual urban growth taking place from the year 2008 to the year 2014. It was again obtained by cross-tabulation between the actual land covers of the years 2008 and 2014. We can see a relatively condensed form of urban growth occurring within the two time-periods, mostly growing as an extension to the previous growth for the year 2003-2008 (shown as red on the map). The city expanded towards south-east and north-west predominantly and also in small patches around the NH-1A national highway. The actual number of cells transitioned is 22634 from 2008 to 2014 which amounts to total change of 2037.06 hectares.

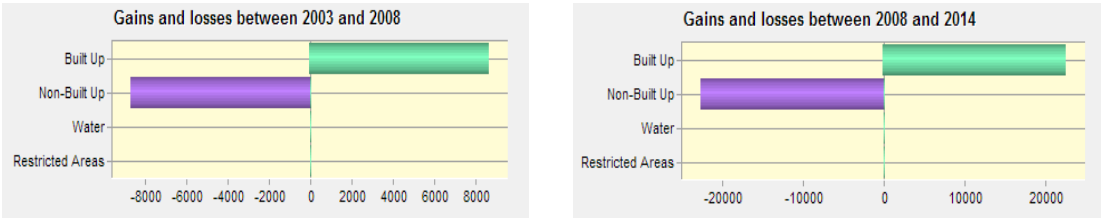


Figure 66: Comparison between urban growth from 2003-2008 and 2008-2014 in terms of pixel changes.

In addition to the image-overlaying techniques, a tool named ULA was used to perform the trend analyses in a much better way. The tool could analyse the land cover data for multiple time periods

for a given city. In this case, three land cover maps for the years 2003, 2008 and 2014 were used as inputs to the model which generated several maps showing Urban Footprints for the three time periods as well as the new developments from 2003-2008 and from 2008-2014 respectively which threw lights on the urban trends and patterns of development over the given time scales in a much broader capacity.

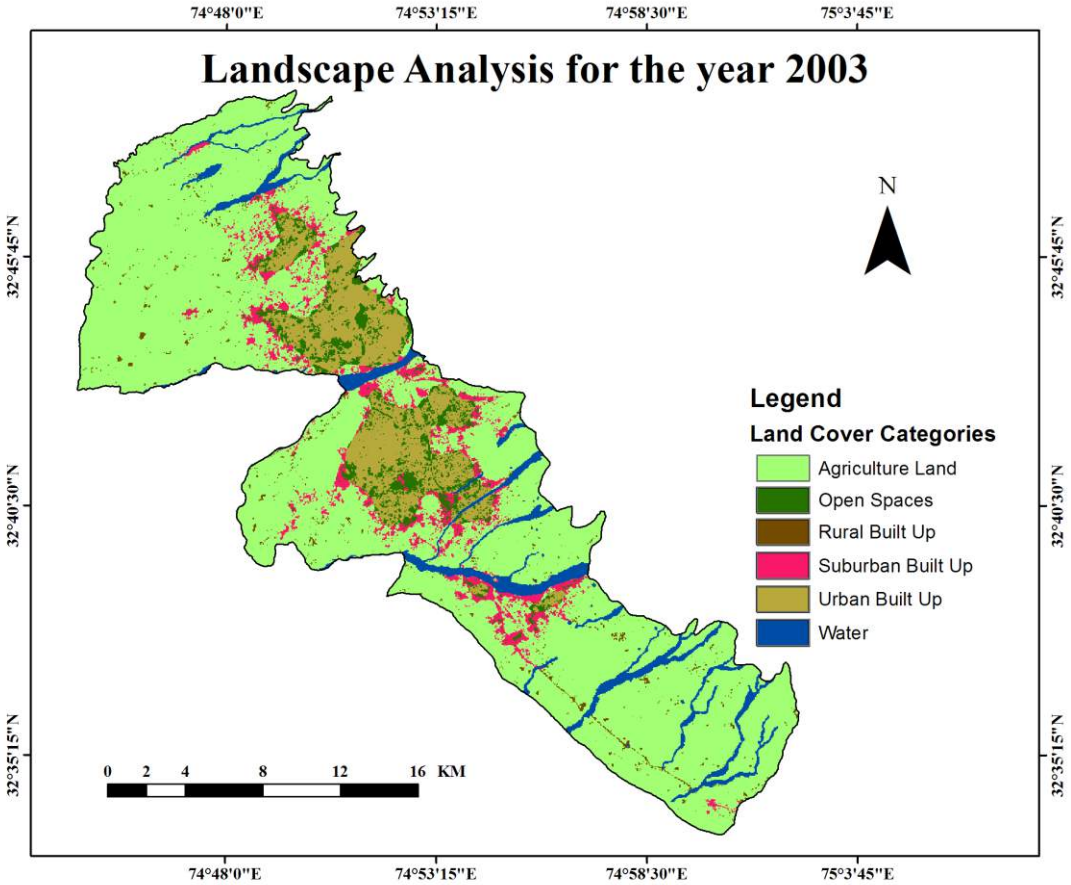


Figure 67: Landscape analysis using ULA for the year 2003

The growth trends obtained from cross-tabulation techniques surely provide insight into the pattern and direction of urban growth but no clue as to which land use densification class is more likely to sprawl and which type of growth will take place.

Figures 67 to 69 represent the land use categories obtained after the ULA tool was applied to the three time land cover images (the images had to be converted to the ULA compatible form as described in the previous section to be fed as input to the tool).

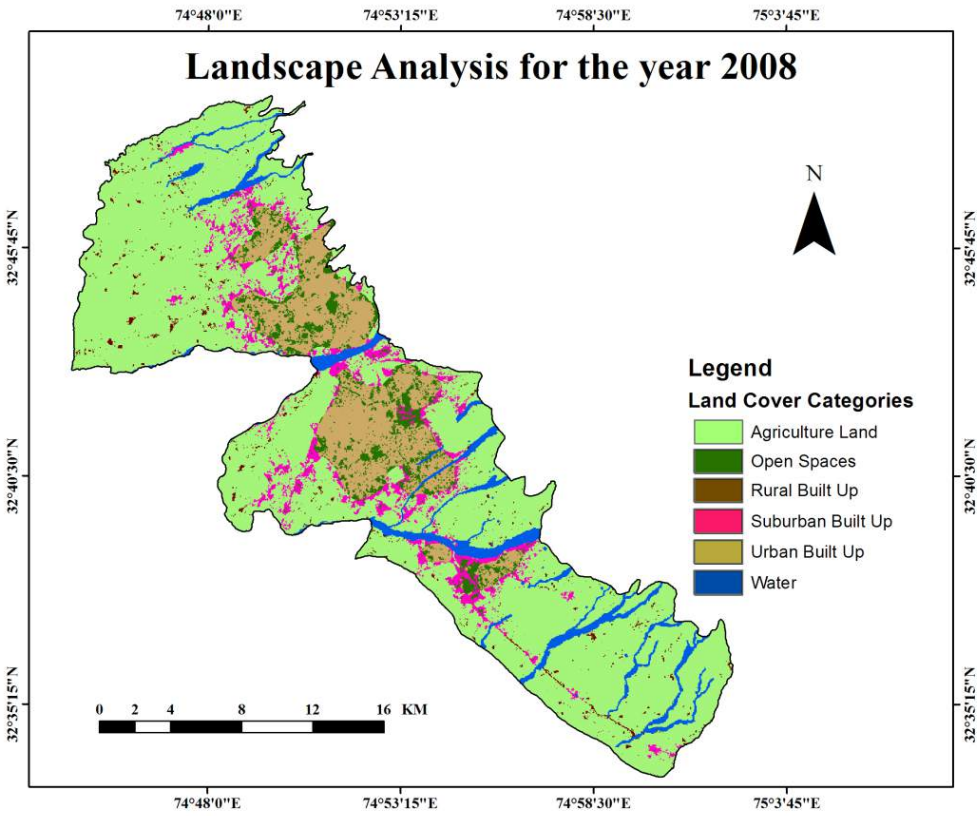


Figure 68: Landscape analysis using ULA for the year 2008

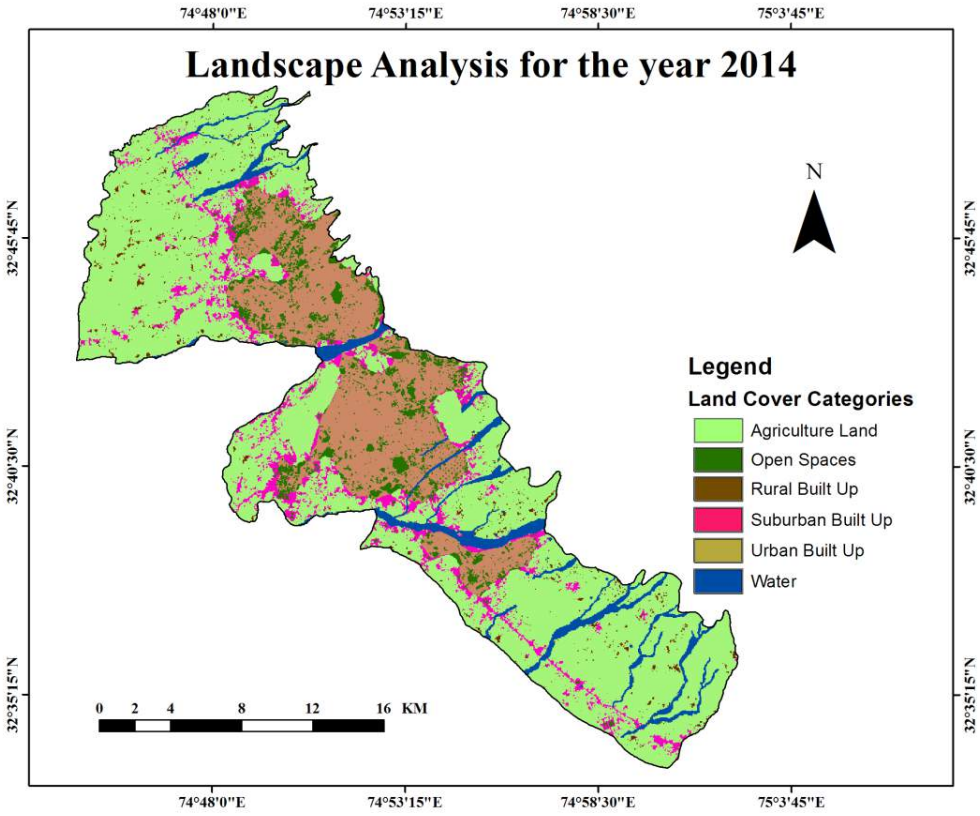


Figure 69: Landscape analysis using ULA for the year 2014

Table 7: Landscape Analysis result for the year 2003

S.No.	Name of the Category	No. of Pixel Counts	Area in Hectares
1	Urban Built Up	29721	2674.89
2	Suburban Built Up	16675	1500.75
3	Rural Built Up	3444	309.96
4	Open Spaces	13190	1187.1
5	Agricultural Land	208467	18762.03
6	Water	16571	1491.39

Table 8: Landscape Analysis result for the year 2008

S.No.	Name of the Category	No. of Pixel Counts	Area in Hectares
1	Urban Built Up	37115	3340.35
2	Suburban Built Up	17638	1587.42
3	Rural Built Up	3781	340.29
4	Open Spaces	14308	1287.72
5	Agricultural Land	198655	17878.95
6	Water	16571	1491.39

Table 9: Landscape Analysis result for the year 2014

S.No.	Name of the Category	No. of Pixel Counts	Area in Hectares
1	Urban Built Up	56962	5126.58
2	Suburban Built Up	20286	1825.74
3	Rural Built Up	3920	352.8
4	Open Spaces	17209	1548.81
5	Agricultural Land	173120	15580.8
6	Water	16571	1491.39

In tables 7-9, the area under different land uses is listed. It was observed that for the Urban Built Up class there was 24.87% increase for the year 2003-2008 and 53.47% for the year 2008-2014. This land use class showed the most variation for the years the analysis was done. Agricultural class however suffered a depreciation of 4.70% in the years 2003-2008 and 12.85% for the years 2008-2014. The

increase in the area under remaining land use classes ranged between 10% for the years 2003-2008 and20% for the years 2008-2014.

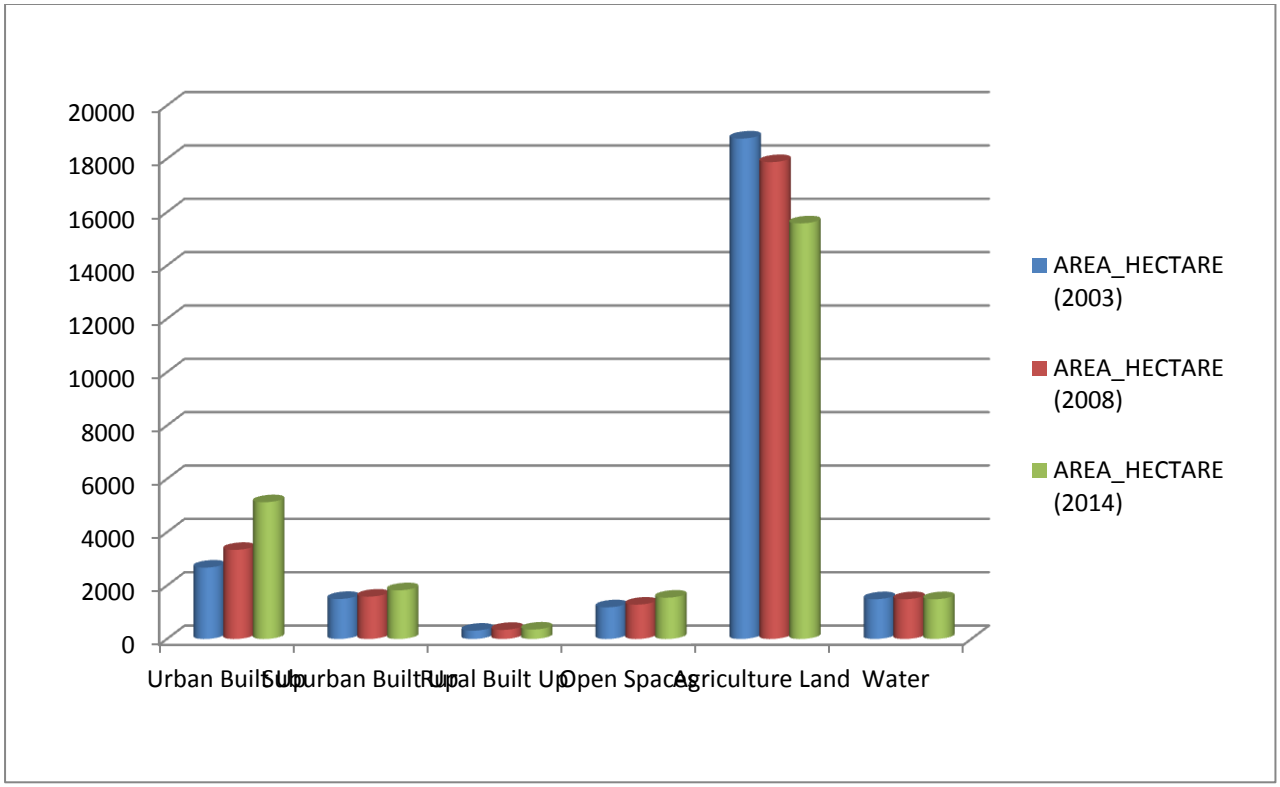


Figure 70: Areas under different land use categories in hectares

From what is evident from the bar diagram above is that agricultural land has continually decreased from 18762.03 to 15880.8 hectares from 2003 to 2014. Also, the urban built up has rose to a fair extent from 2674.89 hectares in 2003 to 5126.58 hectares in 2014. Sub-urban and rural built-up did rise, though not in great magnitude.

It is always easy to find out the growth in the urban area taking place over different time periods but to categorise the urban growth type in the form of Infill Growth, Extension Growth is some great added advantage of using this tool. We could not only know about the spatial distribution of growth but also the type of growth.

Infill growth refers to the new development occurring within the spaces inside the city core i.e. when the urbanized open spaces get converted to built-up. It increases the contiguity of the built-up area by filling in the urbanized space.

Extension growth on the other hand extends directly from the previous development. The new growth is thus contiguous to the already existing built-up area and could be extended linearly or in patches from the previous development.

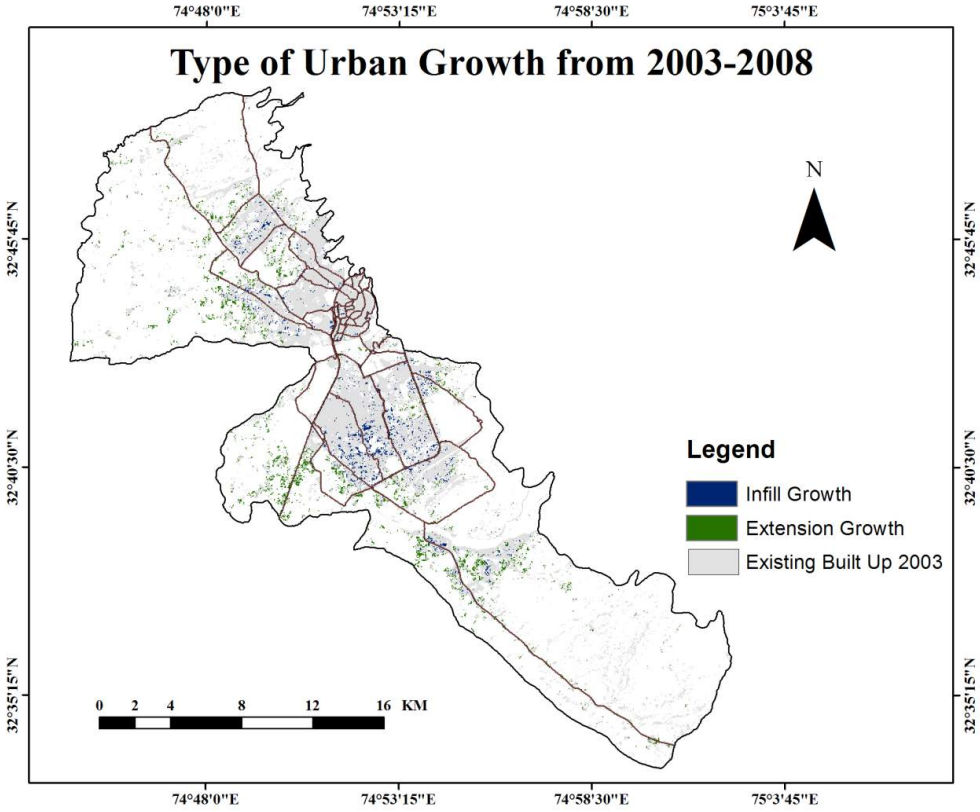


Figure 71: Type of urban growth from 2003 to 2008

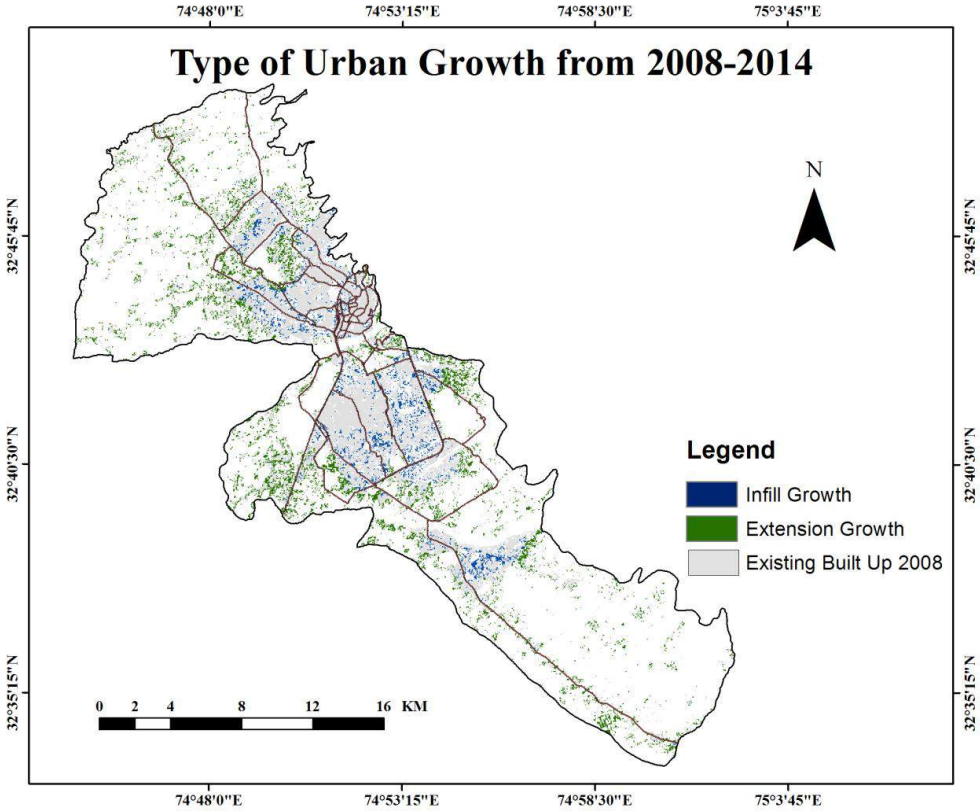


Figure 72: Type of urban growth from 2008 to 2014

It can be seen from figures 71 and 72 above that infill growth within the city core is much lesser in comparison to the lateral city expansion in both the temporal data images.

Table 10: Comparison between growth types for the two time periods (2003 to 2008 and 2008 to 2014)

	Type of Urban Growth		Total Growth in hectares
Year Span	Infill Growth	Extension Growth	
2003-2008	267.12 hectares	515.34 hectares	782.46
2008-2014	565.65 hectares	1471.41 hectares	2037.06

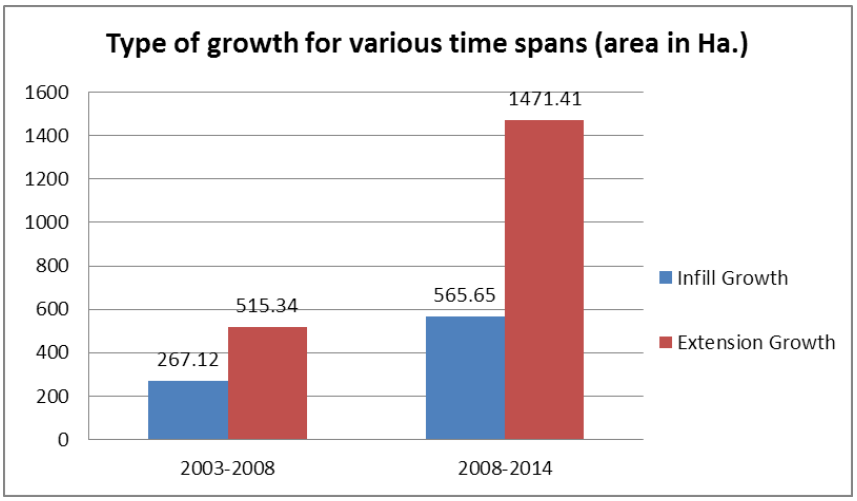


Figure 73: Comparison of growth types from 2003-2008 and 2008-2014

Figure 73 compares the two types of growths along with the area they cover. In the year 2003-2008, the infill growth was almost half of the extension growth whereas for the year 2008-2014, extension could be seen three times the infill growth explaining the fast sprawl taking place in the study area. Fringe regions are more liable for development in each category.

5.4 Factors inducing urban growth in the study area

There are various factors that induce urban growth. The factors responsible for urbanization were obtained by carrying out the systematic study of the city and performing historic trend analysis which was essentially statistical in nature. Also from the trend analysis carried out in the previous step, the variables responsible for urbanization in the study area were isolated and arranged as a sequence. The factors included accessibility, distance from higher level facilities, mobility services, social infrastructure, employment and local facilities; a measure of which was made possible by generating Euclidean maps corresponding to each factor. In addition to the Euclidean Maps, the neighbourhood analysis for the year 2003 and 2008 also played a significant role in defining the future level of

urbanization expected. So, these maps were also considered necessary inputs to the algorithms to perform the training task.

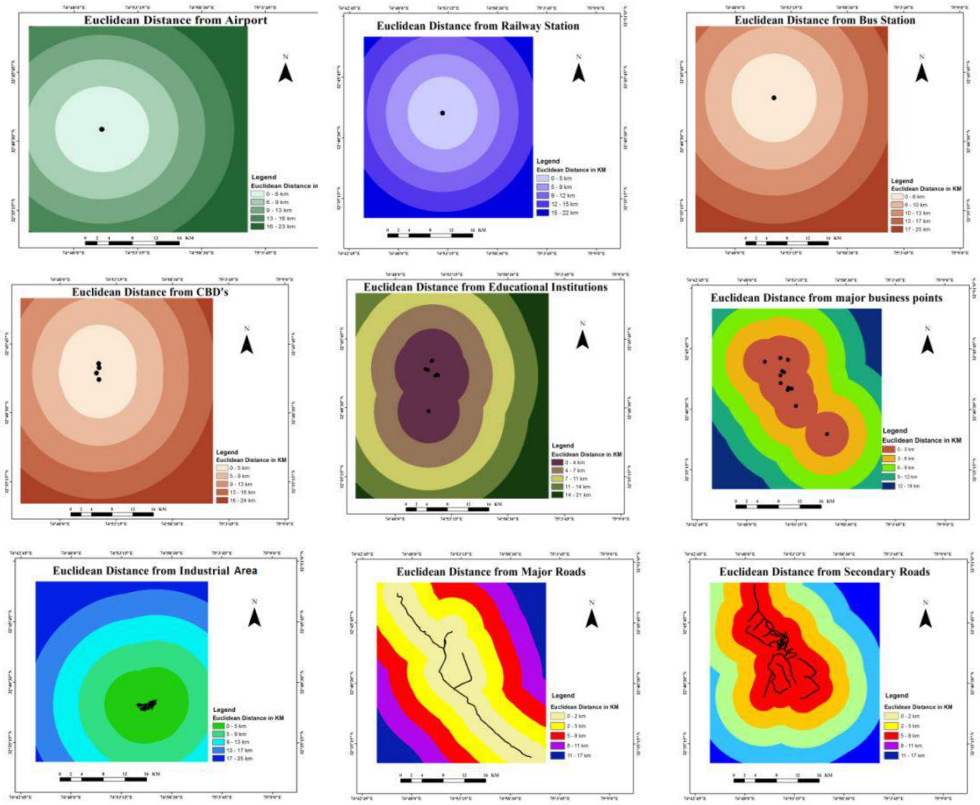


Figure 74: Euclidean Distance Maps

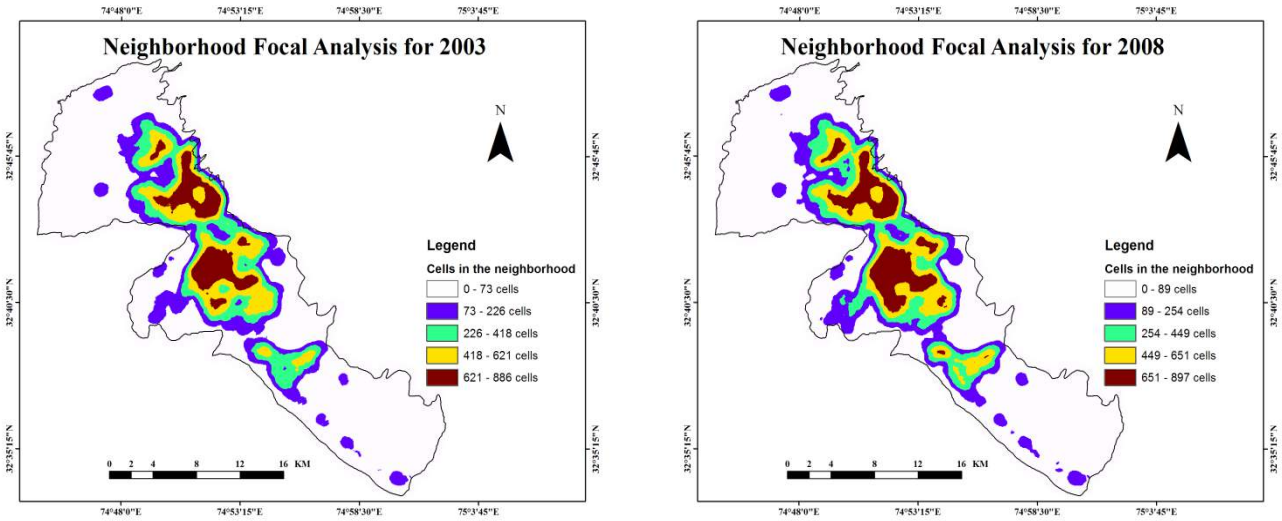


Figure 75: Neighbourhood analyses for the two years 2003 and 2008

Figures74 represents the collection of Euclidean Distance maps whereas figure 75 represents the focal neighbourhood for the years 2003 and 2008 as described in the preceding paragraphs.

5.5 Generation of transition potential maps using different algorithms

All the factor maps (Euclidean Distance and Neighbourhood Maps) along with the training site files were fed as input to the different algorithmic approaches so as to produce the transition potential files. The transition potential files represented the potential of cell transition from non-urban to urban on a numeric base scale of 0 to 1. The more the numeric value closer to 1, the greater is its potential to get converted from non-urban class to urban class. Various algorithms by the name, SOM, Fuzzy ART Map, CTA and MLP were applied to the factor maps and trained against training data-set, producing different sets of transition potential files.

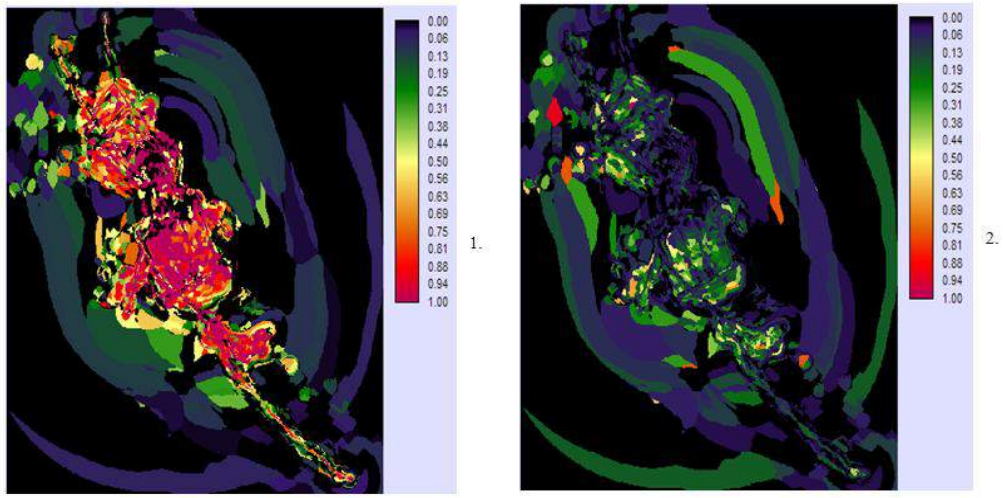


Figure 77: Transition Potential Files after applying Fuzzy ART Map algorithm (1: Commitment, 2: Typicality)

From the figure above, we can see the areas with maximum transition potential marked as pink and least transition potential marked as purple blue in the image numbered 1. Similarly in image 2, orange red areas represent maximum transition potential and blue the least. The two different algorithmic approaches of commitment and typicality produced these results. We can see here that the area lying adjacent to previously existing built up and also the fringes have maximum potential for development as per the Fuzzy ART Map Neural Network.

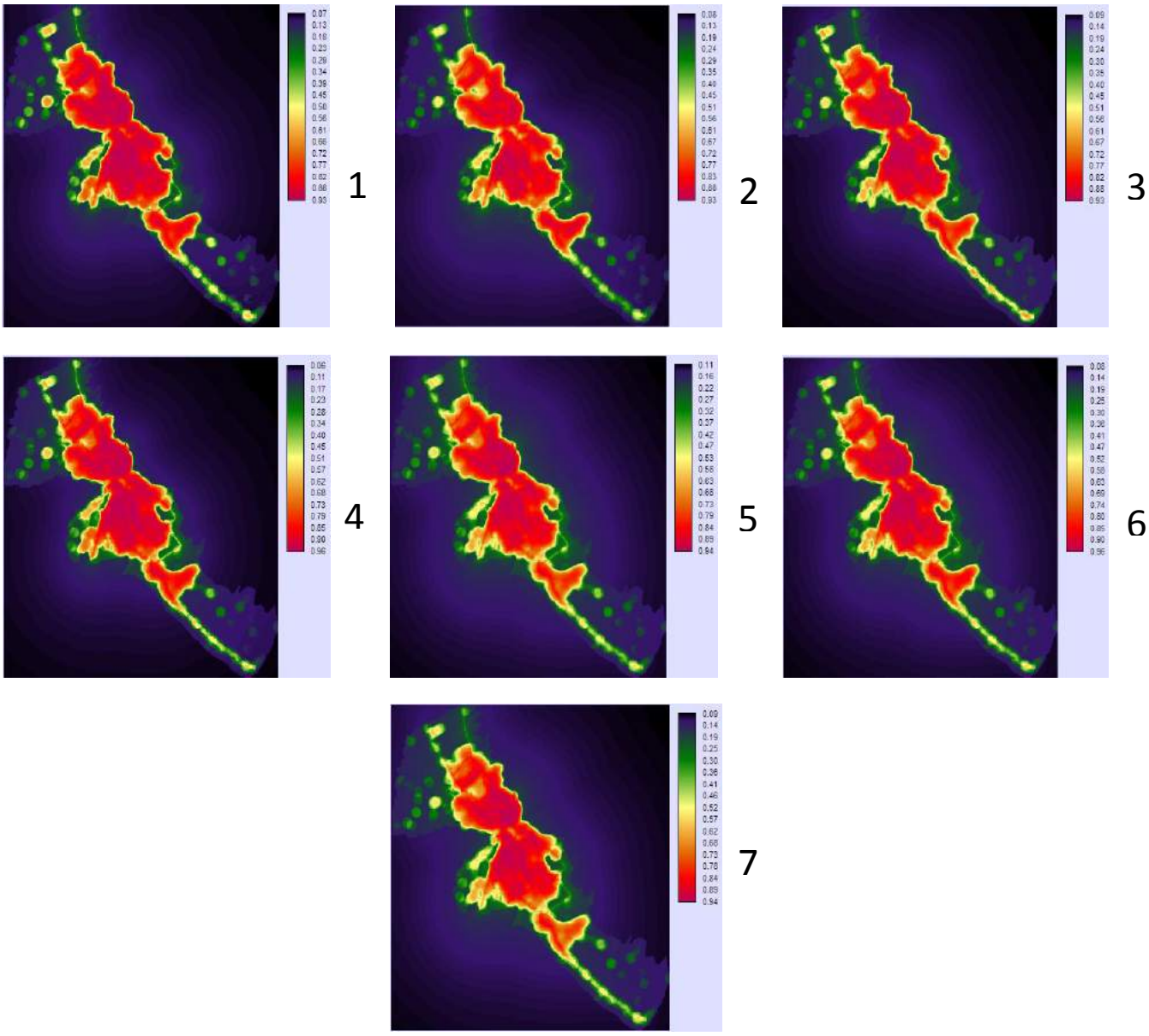


Figure 79: Transition potential files for hidden layer 1

Figure 79 represents the series of transition potential files after training the MLP BP algorithm with variable number of nodes in the hidden layers. In the present figure, the hidden layer was fixated at one and the numbers of nodes were kept variable ranging from 4 to 20.

The areas in orange red tinge show maximum potential for development. Those in greenish yellow and blue show the areas having least potential for future development.

The same task was then performed by fixating the hidden layers as two and then varying the number of nodes ranging from 5 nodes in each layer to 10-15 nodes and the results are shown in figure 80 below.

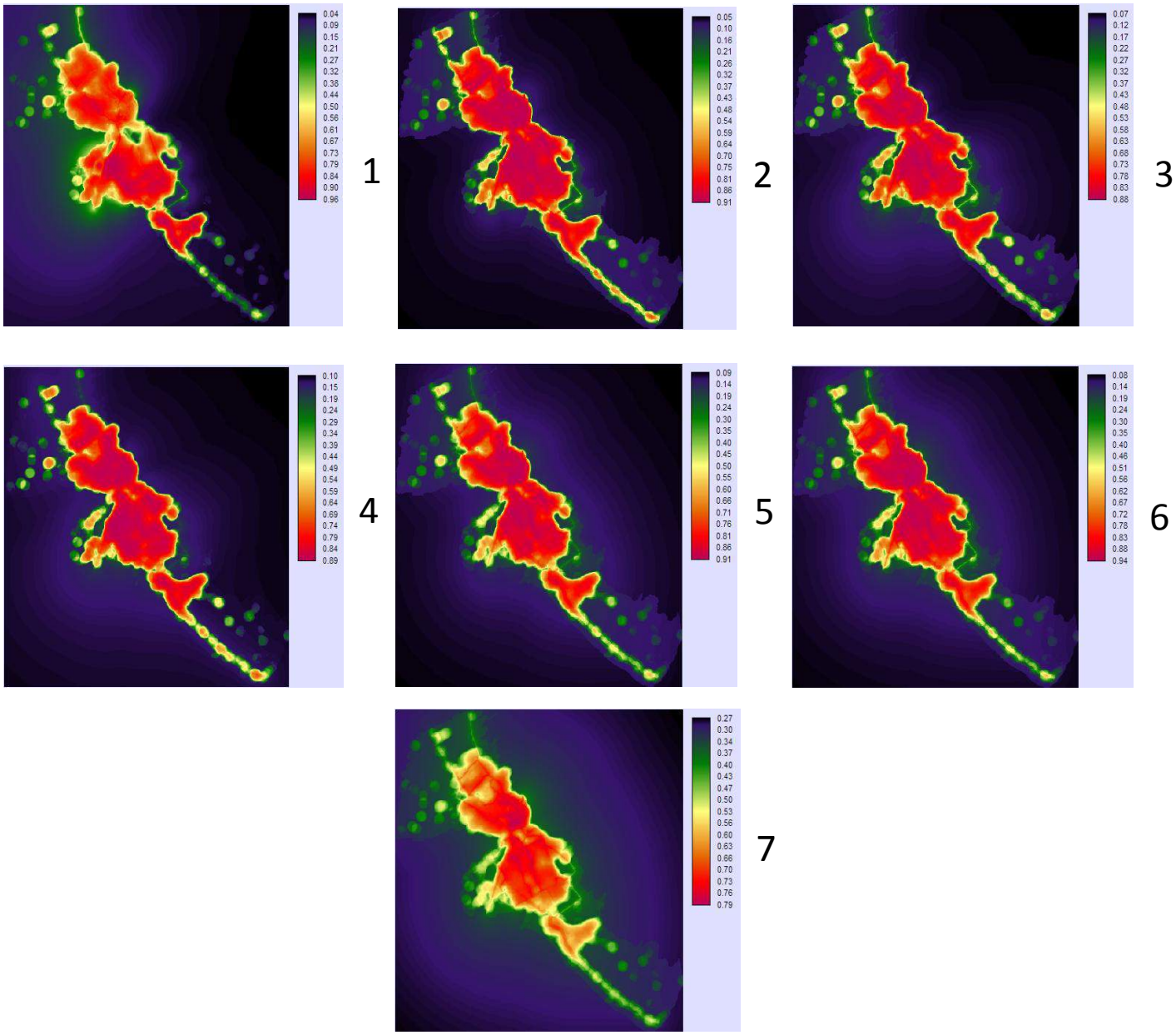


Figure 80: Transition potential files for hidden layers 2

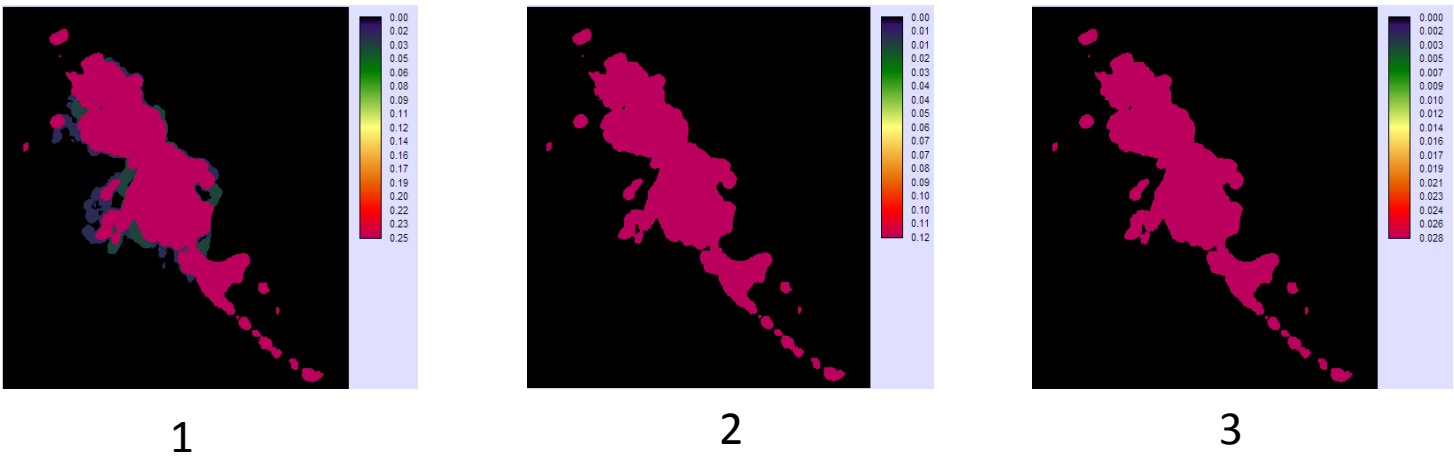


Figure 81: Transition Potential Files after applying CTA algorithm types (1: Entropy, 2: Gini and 3: Ratio)

Figure 81 shows the results obtained by applying the Classification Tree Analysis using Entropy, Gini and Ratio methods. Areas in pink show the maximum potential for development and the rest show very little potential. The results produced in the three methods are almost the same.

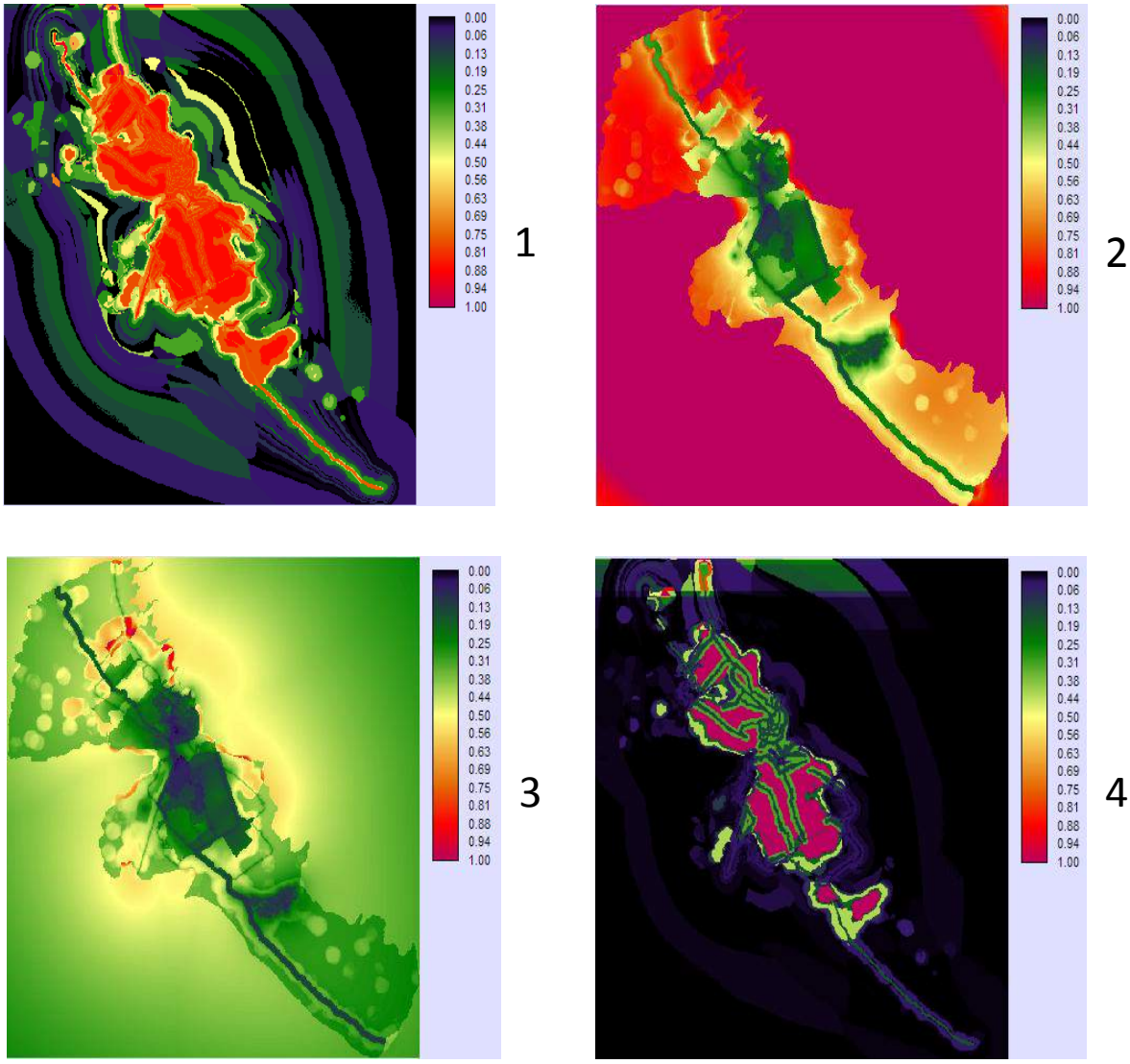


Figure 82: Transition Potential Files after applying SOM algorithm (1: Commitment, 2: Minimum distance, 3: Minimum mean, 4: Typicality)

Figure 82 shows the results produced after applying SOM algorithm techniques being Commitment, Minimum Distance, Minimum Mean and Typicality respectively. The colour pinkish red again represents the areas with maximum potential for cell transition from non-urban to urban whereas bluish green show the least.

All these development potential files were then used for predicting the urban growths at various time periods by putting them into CA-Markov Model as well as using MOLA Techniques.

5.6 Evaluation of several machine learning algorithms

The choice of the best machine learning algorithms from amongst the several neural architectures was performed based on several indices like KNo, KLoc, Kappa modified and so on. The difference between the maps with actual growth from 2003 to 2008 and that from the year 2008 to 2014 were compared against the ones produced by the model for the same set of years for performing what is called model validation. It was observed that some few of the algorithmic approaches were valuable as they produced results with a relatively much higher level of accuracy.

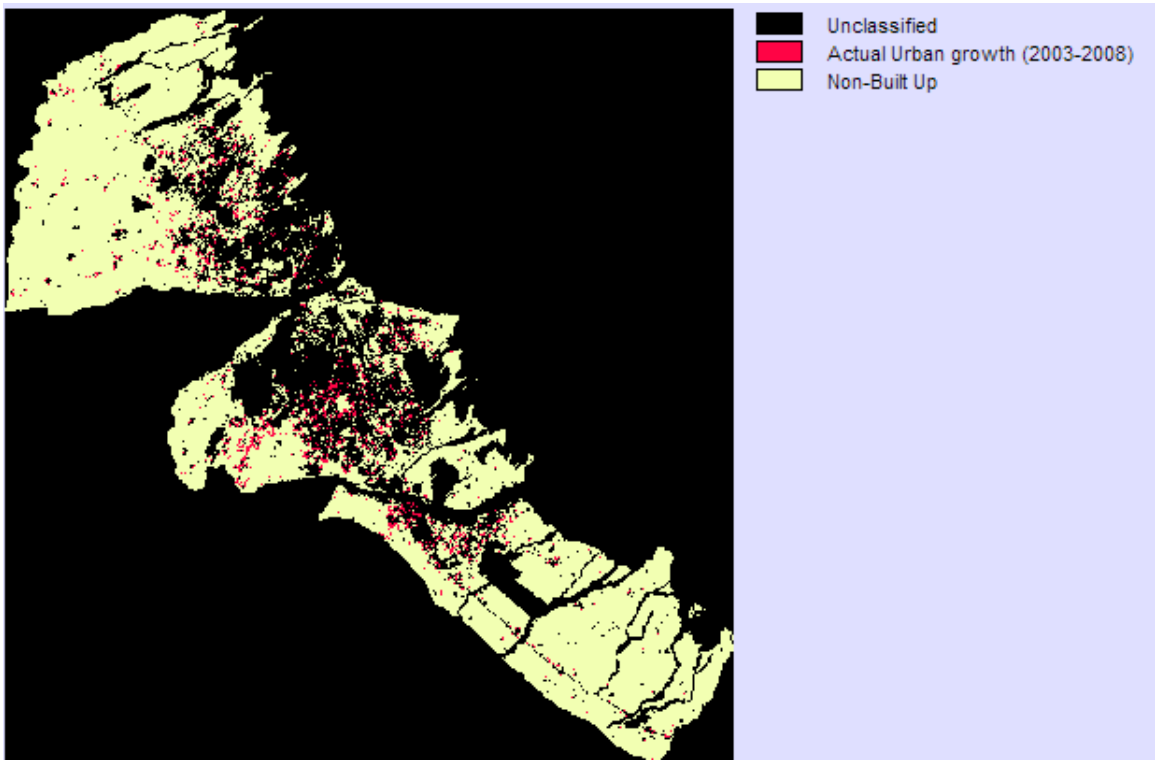


Figure 83: Actual Urban Growth from the year 2003 to 2008

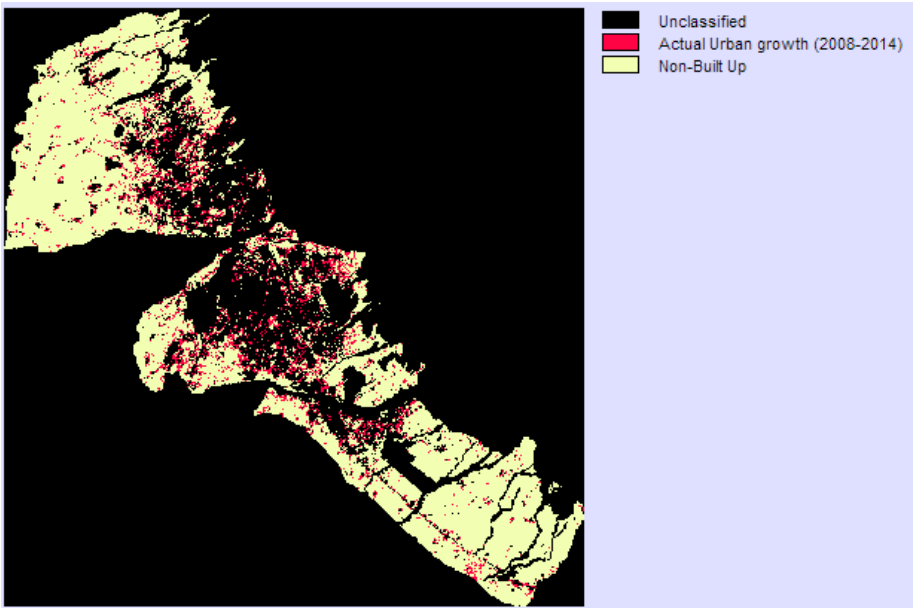


Figure 84: Actual Urban Growth from the year 2008 to 2014

Figures 83 and 84 represent the actual urban growths in the year spans 2003-2008 and 2008-2014 which were then compared against the growths suggested by the CA-Markov model in the same time periods to compare the accuracy level. Results showing the urban growth as per the simulation are shown in the form of map diagrams below.

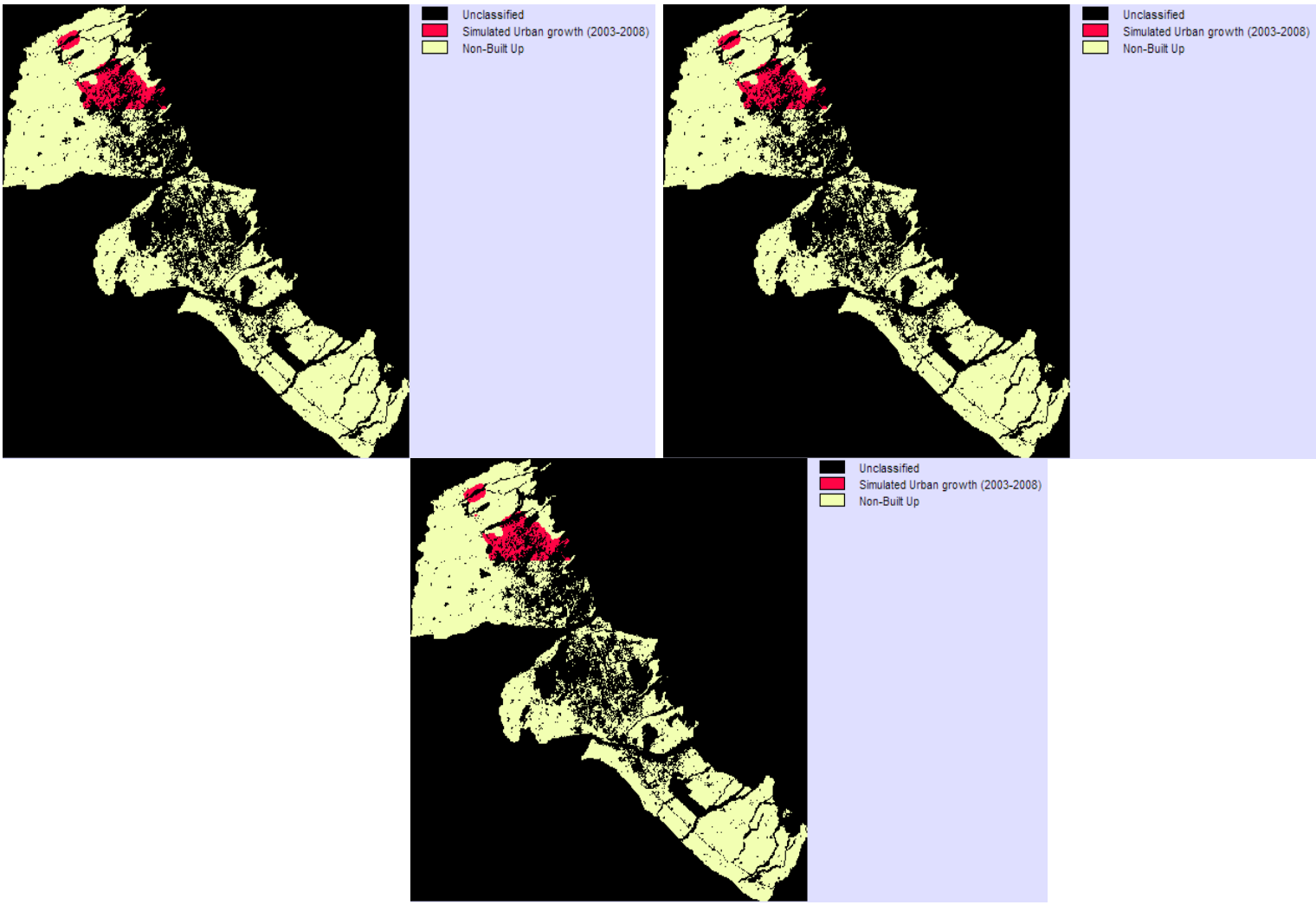
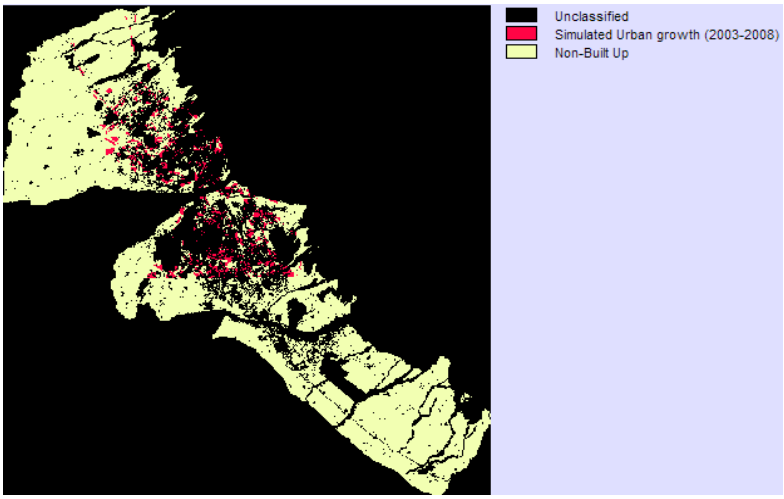


Figure 85: Predicted Urban Growth from 2003-2008 as per CTA algorithm (entropy, gini and ratio)

We can see here from the Figure 85 above that the results of the simulation are not good as the urban growth projected as per the CTA (Entropy, Gini and Ratio) algorithm is basically clustered at the topmost part of the study area whereas the actual growth from 2003 to 2008 is quite dispersed. Thus, we can conclude that CTA method is more suitable for areas where compact form is growth is expected rather than dispersed. We carried out the analyses with the other sets of algorithms to compare and evaluate the prediction results.



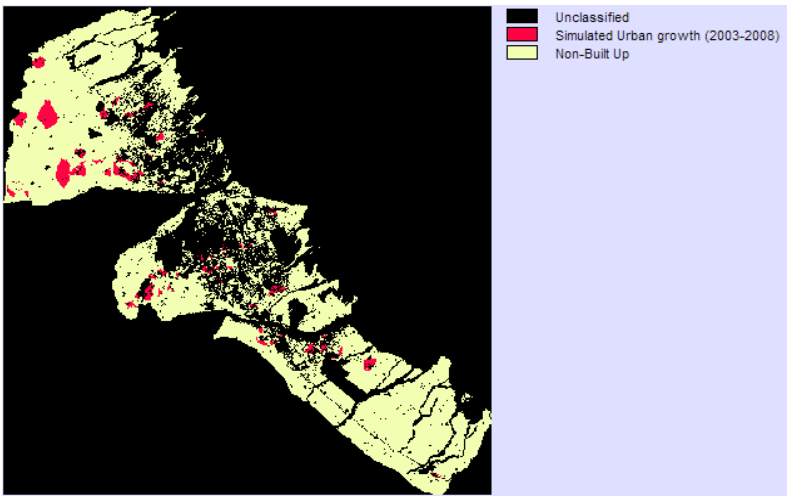


Figure 86: Predicted Urban Growth from 2003-2008 as per Fuzzy Art Map algorithm (commitment and typicality)

Again from the figure 86, we can see that fuzzy ART Map algorithm is quite better suited as the simulation quality is better as the growth pattern given by the algorithm is dispersed and very much like the actual growth pattern. Specially, a form of Fuzzy Art Map named Fuzzy Commitment algorithm is more useful in this case.

We can also compare from the two images above that the Fuzzy ART algorithm makes a better candidate for urban growth modelling in areas where growth pattern is expected to be more of a dispersed form rather than compact. Both of the algorithm categories, Commitment and typicality are

good in capturing the dispersion of growth pattern. Commitment produces results with lesser dispersion whereas typicality produces a typical growth pattern which is excessively loosely coupled with the already existent built-up which hinders the applicability of Typicality in the most general cases of urban growth and development.

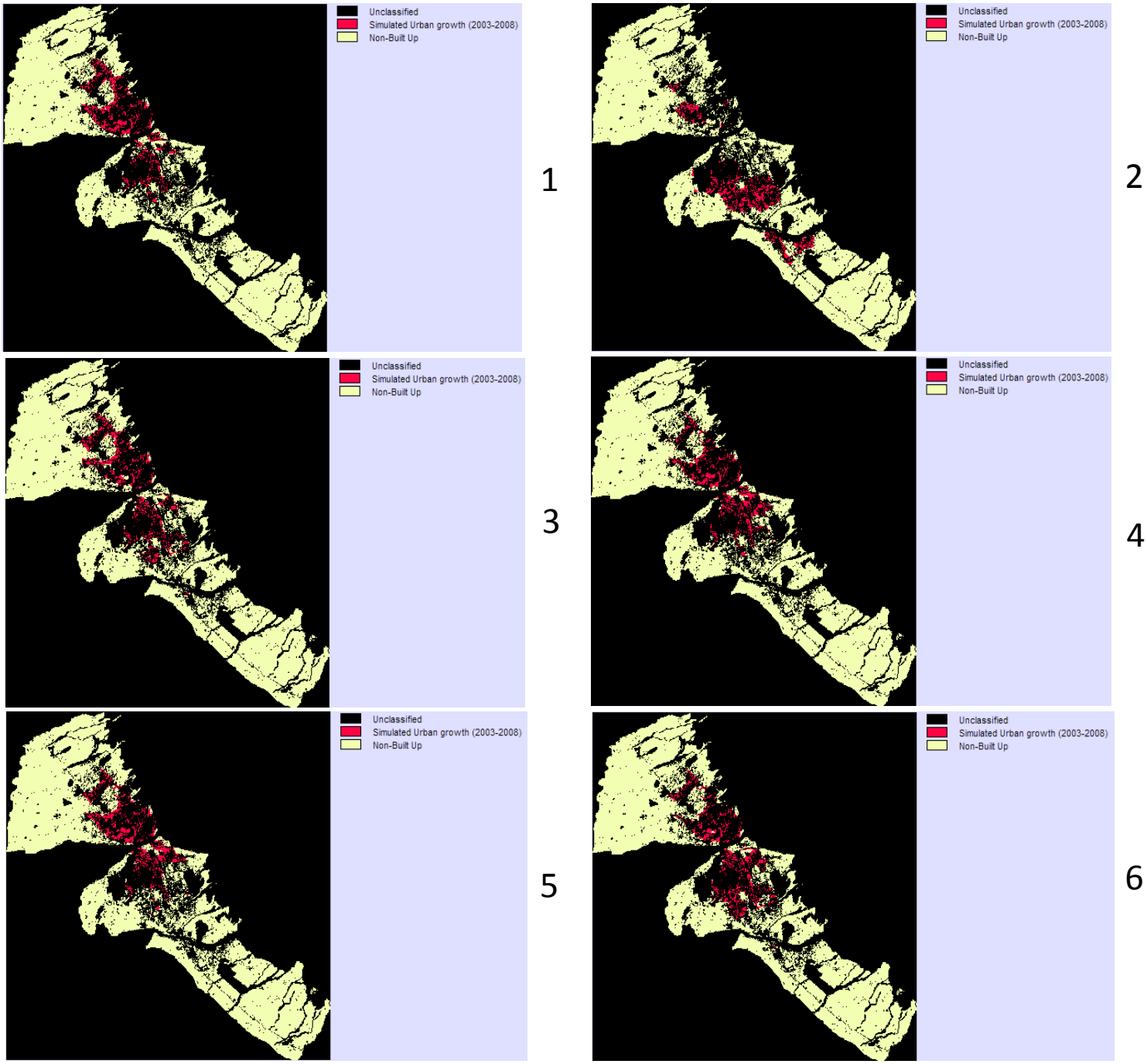


Figure 87: Predicted Urban Growth from 2003-2008 as per MLP BP-algorithm (networks: 11-4-2, 11-5-5-2, 11-5-8-2, 11-8-2. 11-10-10-2, 11-20-2 as per the number sequence from 1 to 6)

As per the figure 87 above, the MLP – BP algorithm also gave a fairly good accuracy and the simulation quality is significantly better. Special point here is that the number of hidden layers in the MLP network structure played a chief role in the efficiency of simulation results. One hidden-layered network tended to skew the growth pattern to one side whereas the double hidden-layered network produced much better results.

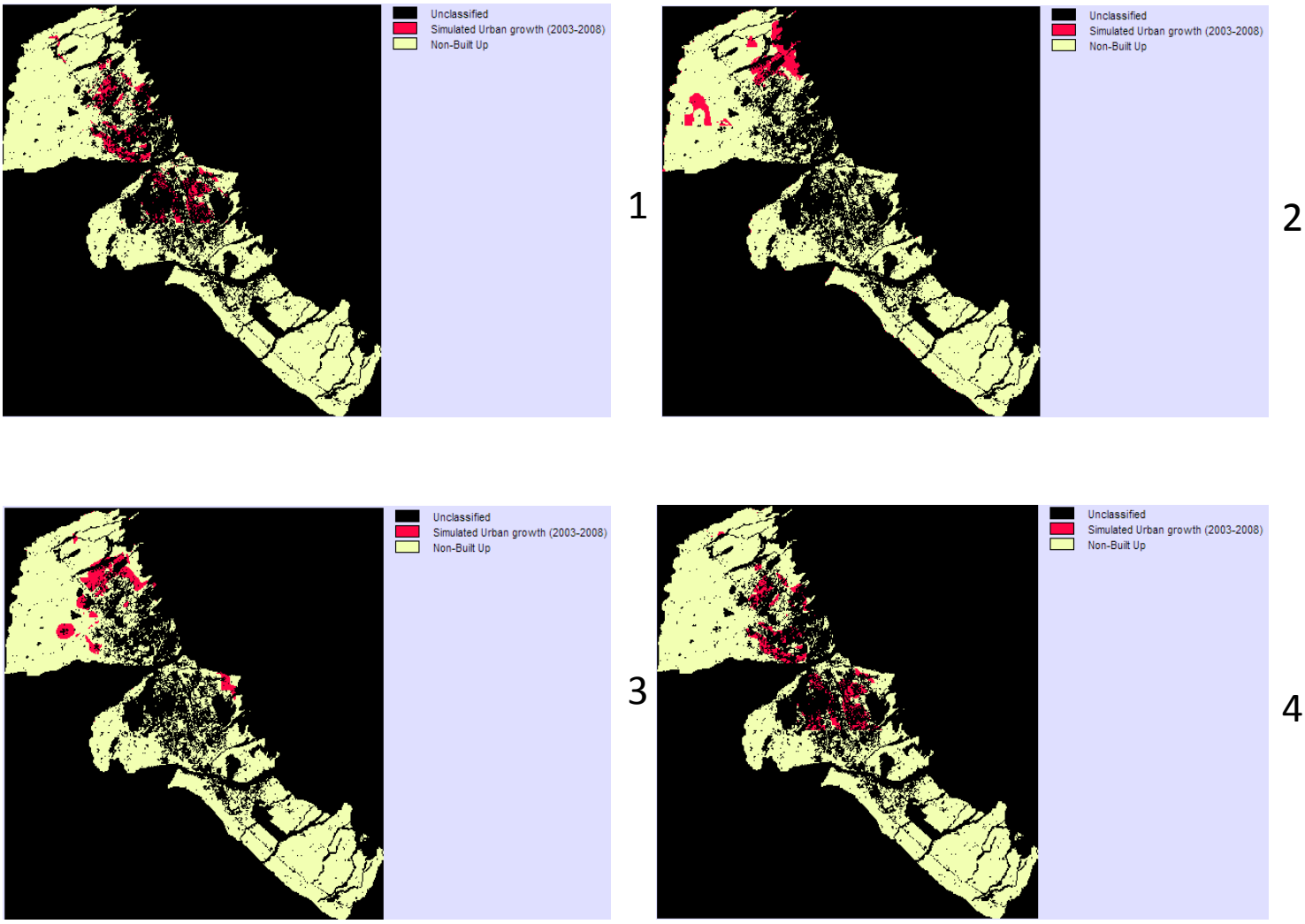


Figure 88: Predicted Urban Growth from 2003-2008 as per SOM algorithm (Commitment, Minimum distance, minimum mean, typicality as per the sequence of numbers from 1 to 4)

Also, from the figure 88, we see that SOM Commitment and SOM Typicality algorithm produced far better results than their other counterparts.

From the pictorial analyses and well as with the use of several spatial matrices which have been described in the previous section, of the projected urban growth from the year 2003-2008 and the actual growth from 2003-2008, we came to the conclusion that a few algorithmic approaches viz.

fuzzy commitment, different MLP architectures and SOM commitment were the best as far as the results of the simulations are concerned.

5.7 Preparation of future simulation 2020 using the best algorithms

Since the best algorithms were sort-listed in the previous stages, we were already set as to which schematic is better and which not. Based on this, we generated the maps for future projected urban growth by 2020.

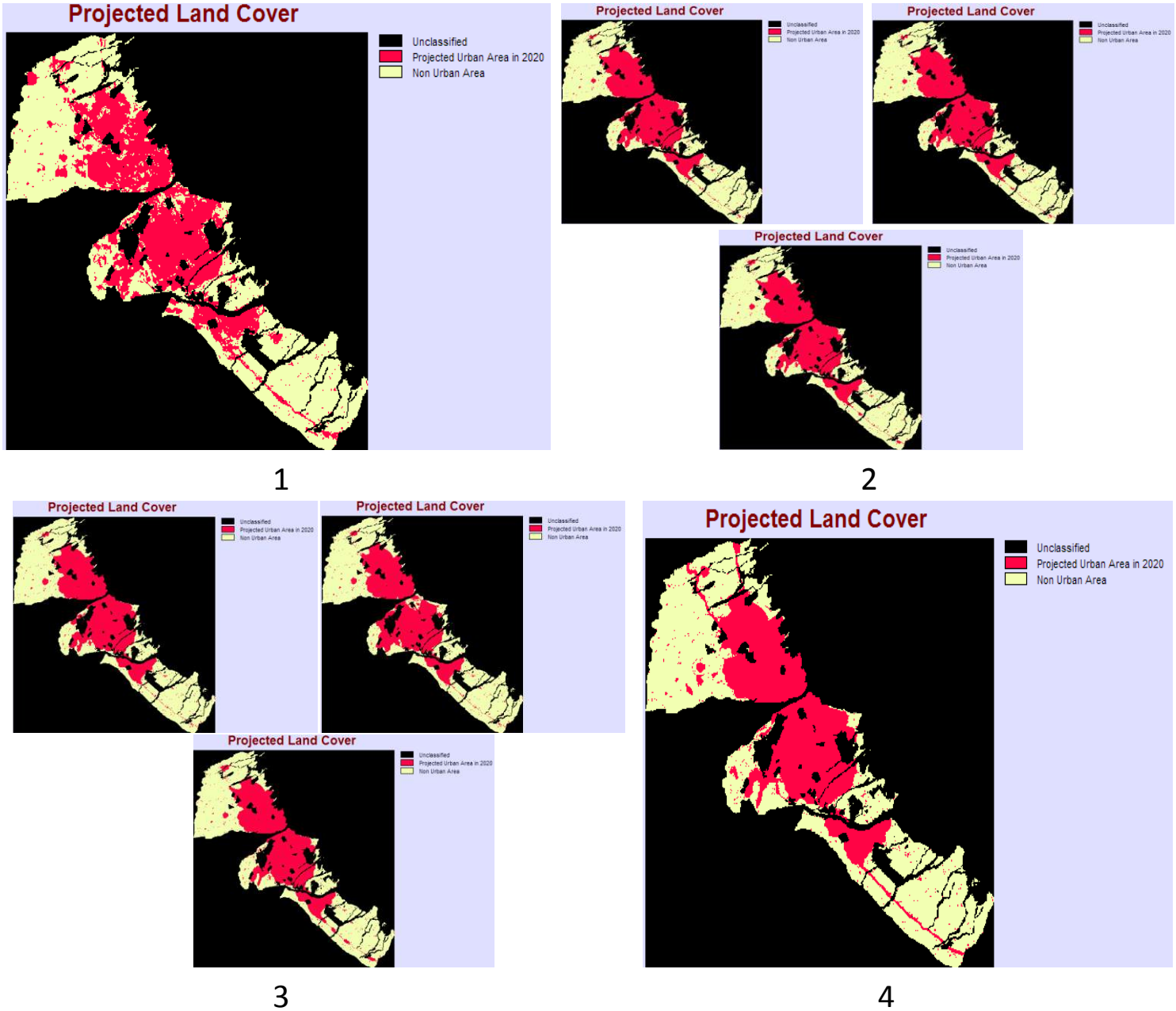


Figure 89: Figure showing the projected land cover for the year 2020 using various algorithms (1-Fuzzy ART Map Commitment, 2 & 3 – MLP BP algorithm with different hidden layers and nodes and 4-SOM Commitment).

Figure 89 compares and contrasts the different results produced by the application of various algorithm types. Each category of algorithm produces a total projected built-up of 8661.6 hectares in 2020 as against 7305.12 hectares in 2014 which means a total increase of 1356.48 hectares over the upcoming 6 years from 2014 to 2020.

Not only these maps are enough, we needed to be able to generate future scenarios for the year 2020 depicting different growth scenarios using the three selected algorithm categories as they gave the best simulation results. The scenarios were: Business As Usual Development, Compact Development and Hazard-Free Development which are presented below.

5.8 Generation of Future Urban Growth Scenarios

1. Business as Usual growth scenario

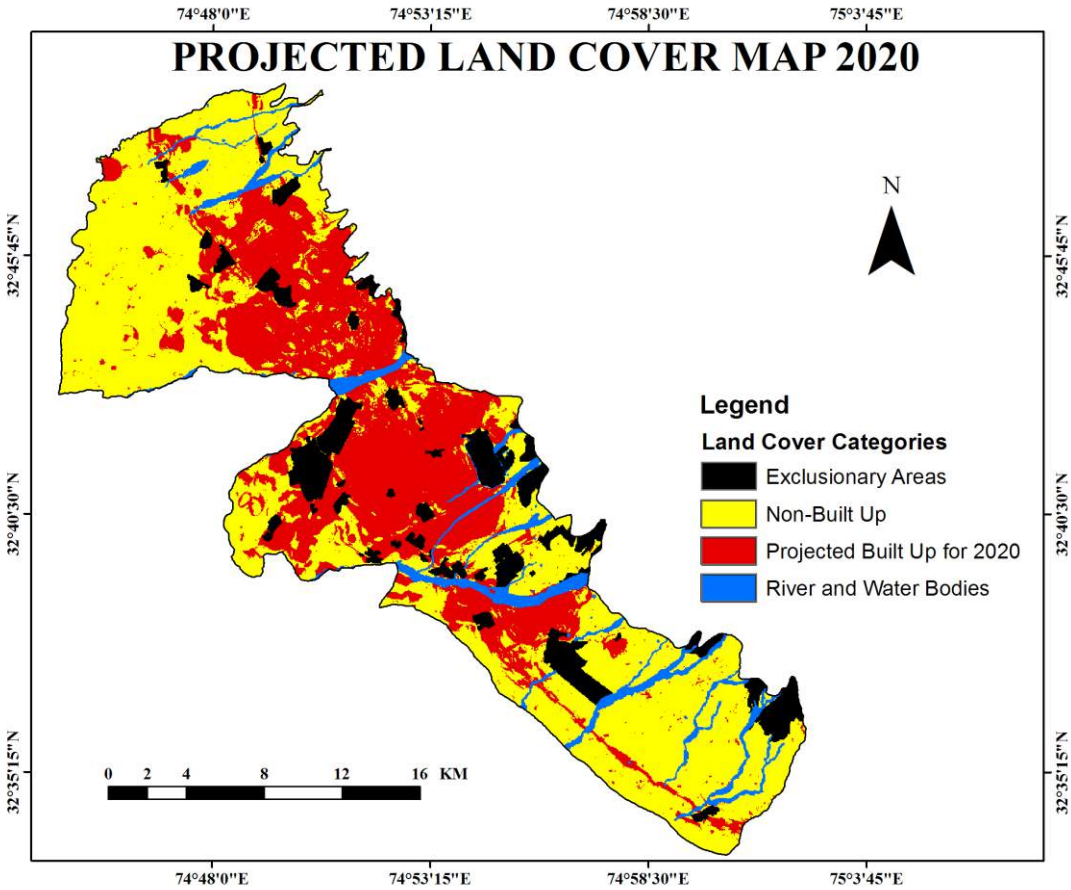


Figure 90: Projected Land Cover for 2020 using Fuzzy Commitment algorithm

Figure 90 represents the projected built-up for the year 2020 using Fuzzy Commitment algorithm. As can be seen from the figure above, most of the development is bound to occur near the city core, mostly extending toward the South East and North West direction and also along the national highway NH-1A which provides connectivity to the other cities within and outside the state of Jammu and Kashmir.

The name Business as usual indicates that under the conditions of no change, we let the same results for the simulation 2020 as directly produced by the model and assume that growth will be just the same as the mathematical model depicted i.e. same number of pixels transitioned and same spatial allocation of change pixels under no external constraints or conditions.

The number of pixels changing from non-urban to urban from 2014 to 2020 in this case was 15072 pixels adding to a built up area of 1356.48 hectares.

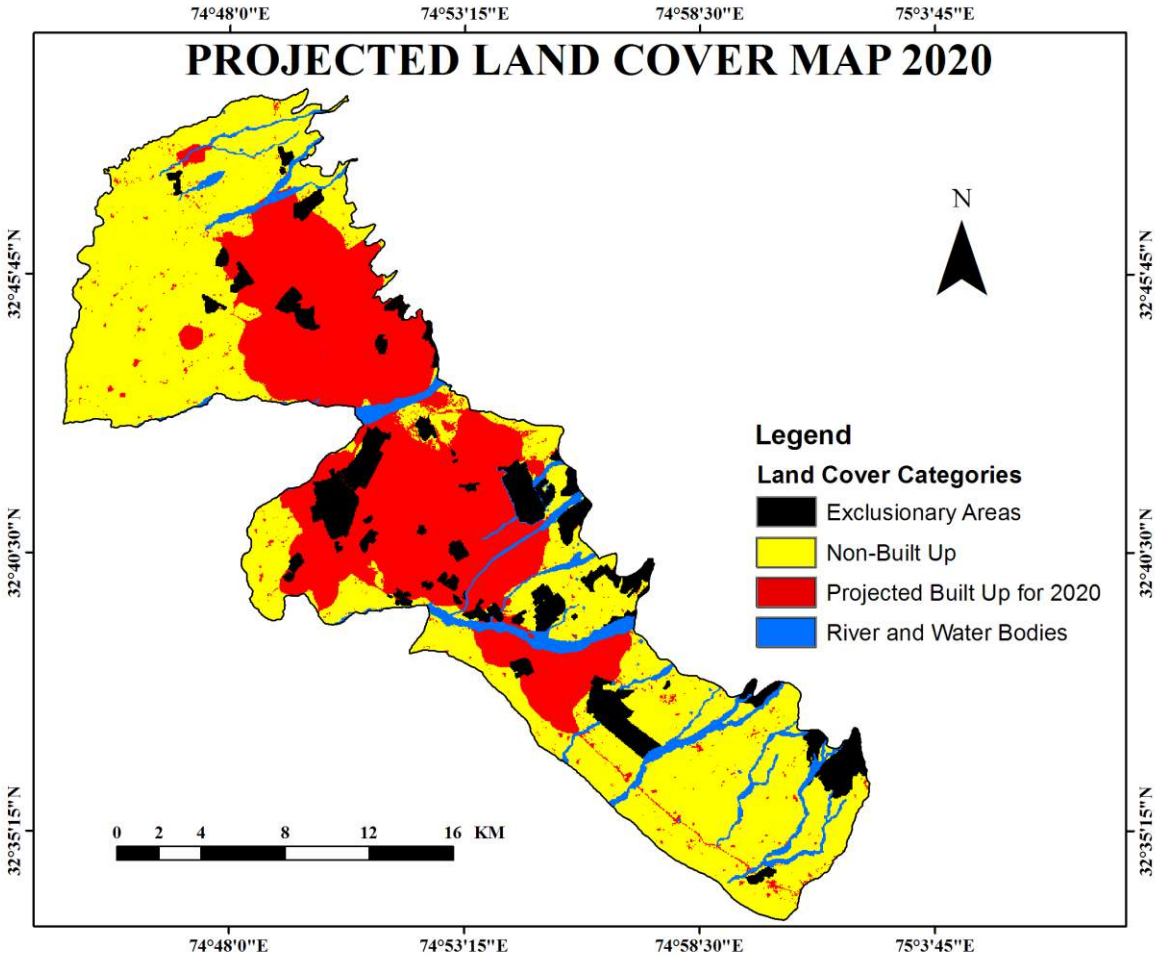


Figure 91: Projected Land Cover for 2020 using MLP-BP algorithm.

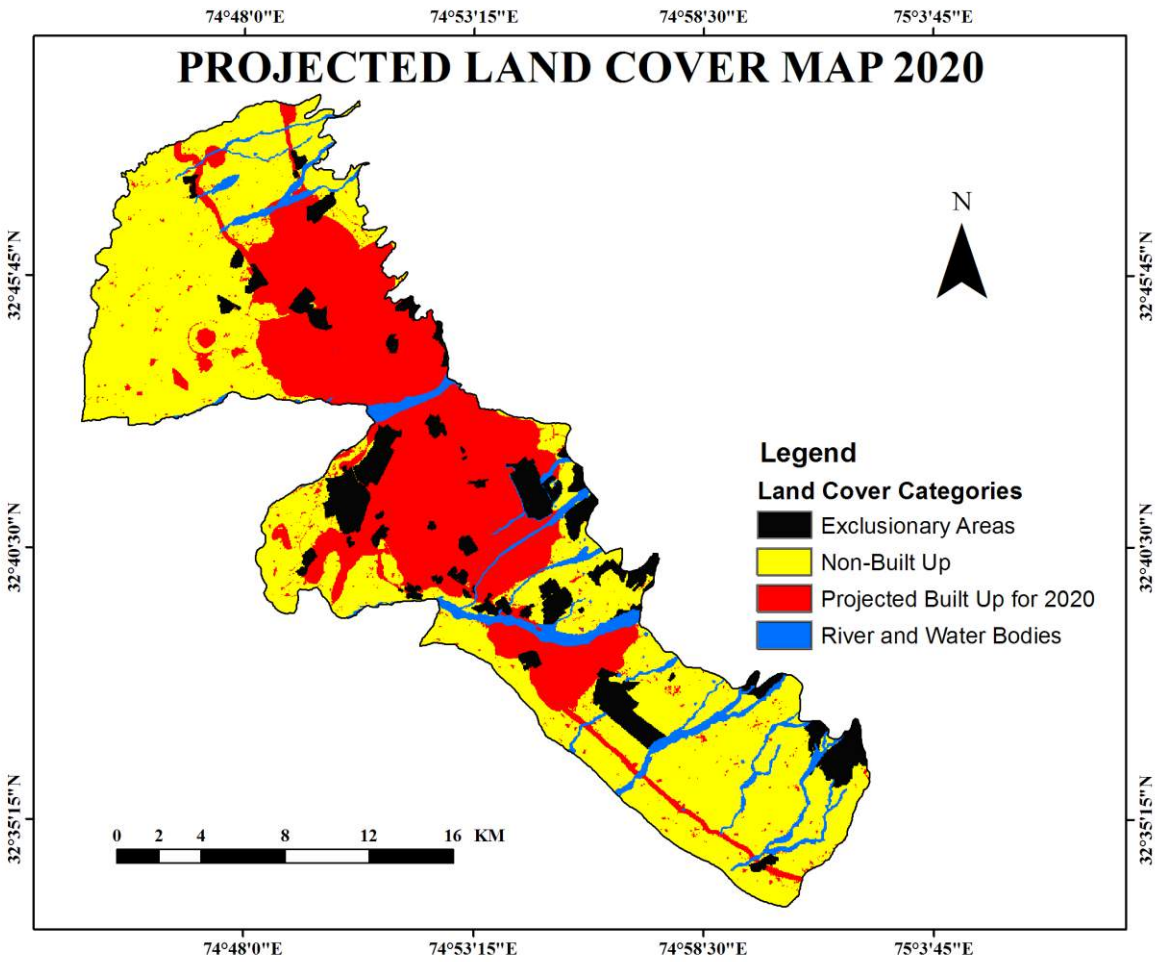


Figure 92: Projected Land Cover for 2020 using SOM Commitment algorithm

Figures 91 and 92 show the same Business as Usual type of urban growth but using MLP-BP and SOM Commitment algorithms. Growth pattern as suggested by the MLP-BP and SOM Commitment algorithms are more compact and continuous whereas it is not so in the case of Fuzzy ART Commitment.

2. Compact Growth Scenario

In this scenario, we assume that the urban development would be compact, that is, the vertical growth/extension of urban areas will exceed that of horizontal development. Thus, the buildings/urban area will increase in heights increasing the space use than the ground usage. In this scenario, we assume that only 70% of the total pixels predicted by the model will actually change on ground.

The number of pixels that would undergo a change in the category from non-urban to urban as suggested by the model is 15072 pixels but for the current case, we have assumed 70% of this change to actually occur on ground, thereby reducing the number of pixels to be transitioned from 15072 to a total of 10550 pixels. This surely causes compaction of built-up in the study area.

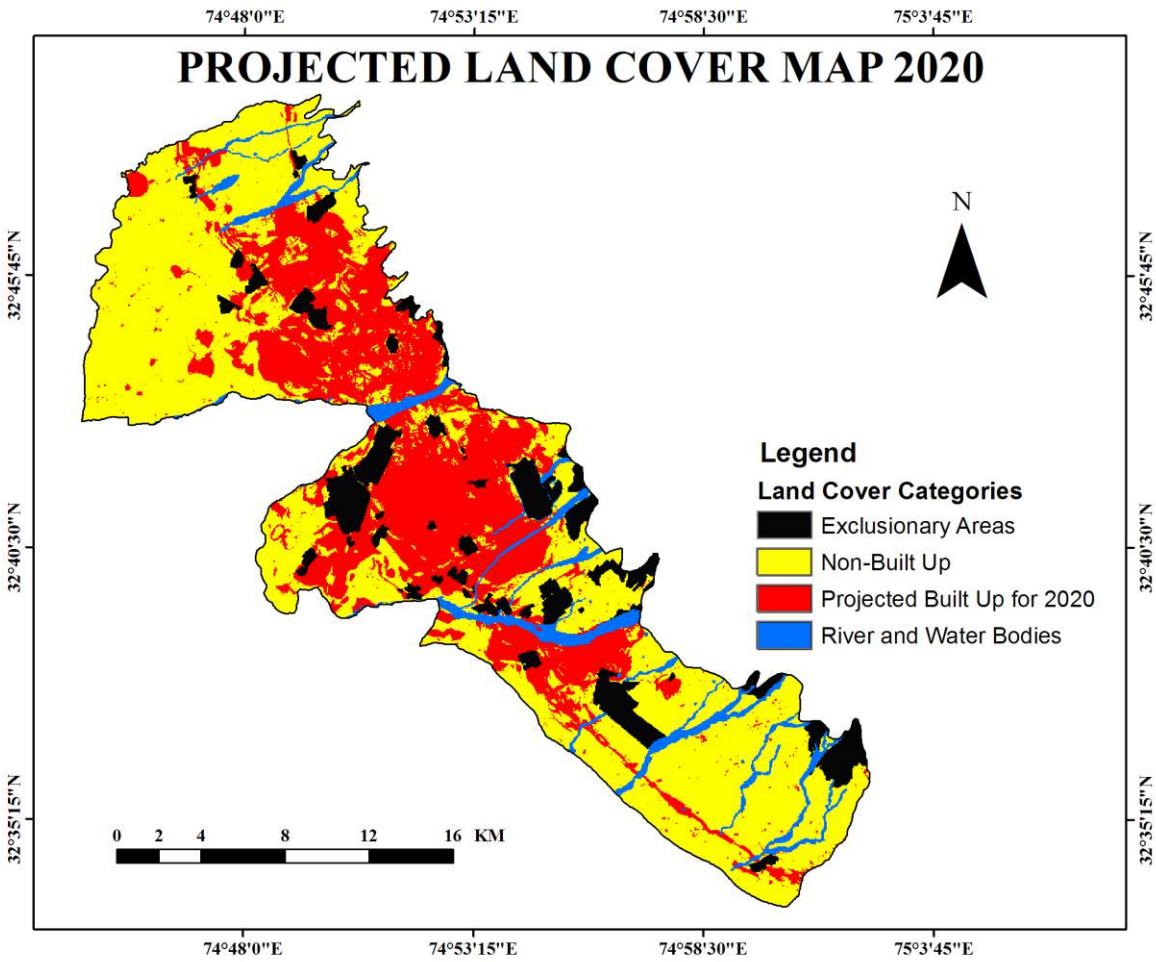


Figure 93: Projected Land Cover for 2020 using Fuzzy ART Commitment algorithm

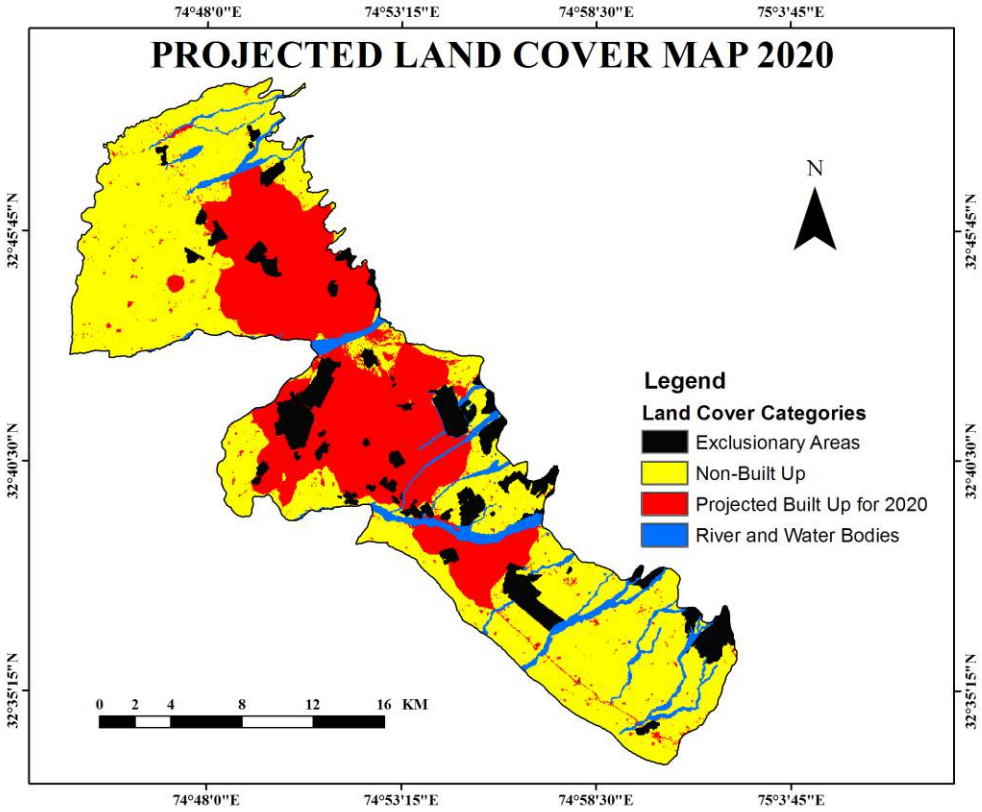


Figure 94: Projected Land Cover for 2020 using MLP-BP algorithm

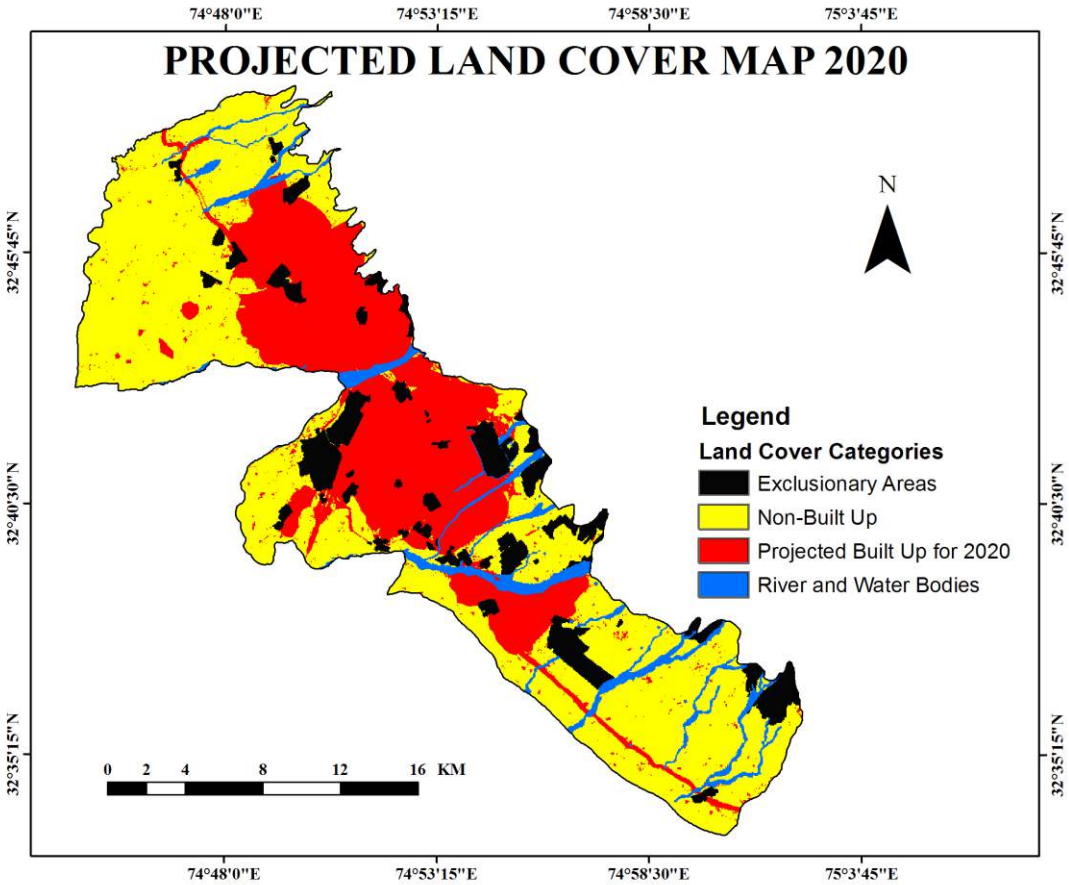


Figure 95: Projected Land Cover for 2020 using SOM Commitment

Figures 93 through 95 represent the Compact Urban Growth scenario using the three algorithms. We can see the effect of pixel reduction. Compaction can be seen from the images mentioned above.

3. Hazard-free development:

In the last scenario, we have taken into consideration that rivers and other floodable areas should not be the sites where future urbanization has to occur. So, we simply mask the river buffers from the transition potential and then produce the simulation.

Tawi River flowing through the middle of the study area (appearing as the neck of the image) is prone to flooding. The city has witnessed recent episodes of floods in September 2014 which caused break down of a bridge system built on the river. Keeping in view the chances of any upcoming hazards, a buffer zone of 200 meter was marked around Tawi River and it was masked out of the transition potential files thereby preventing the algorithms to allocate the urban growth pixels in the buffer zone around the river.

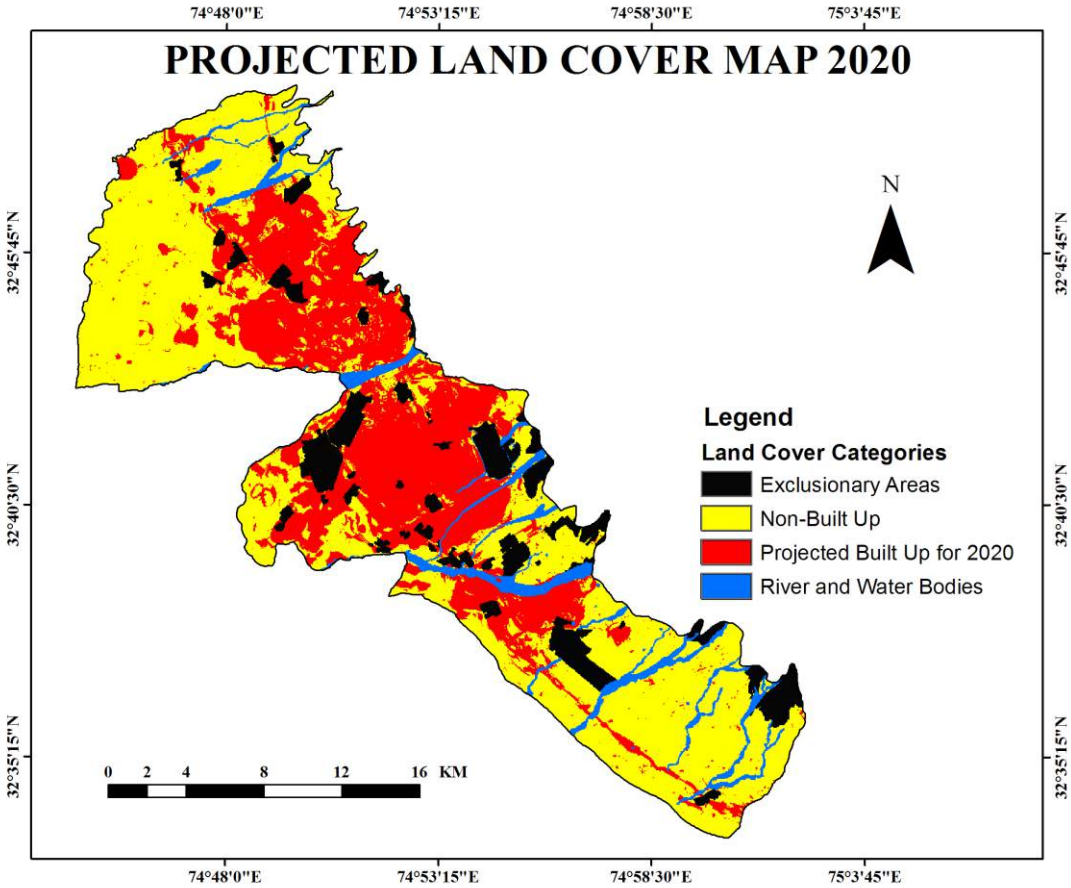


Figure 96: Projected Land Cover for 2020 using Fuzzy ART Commitment algorithm

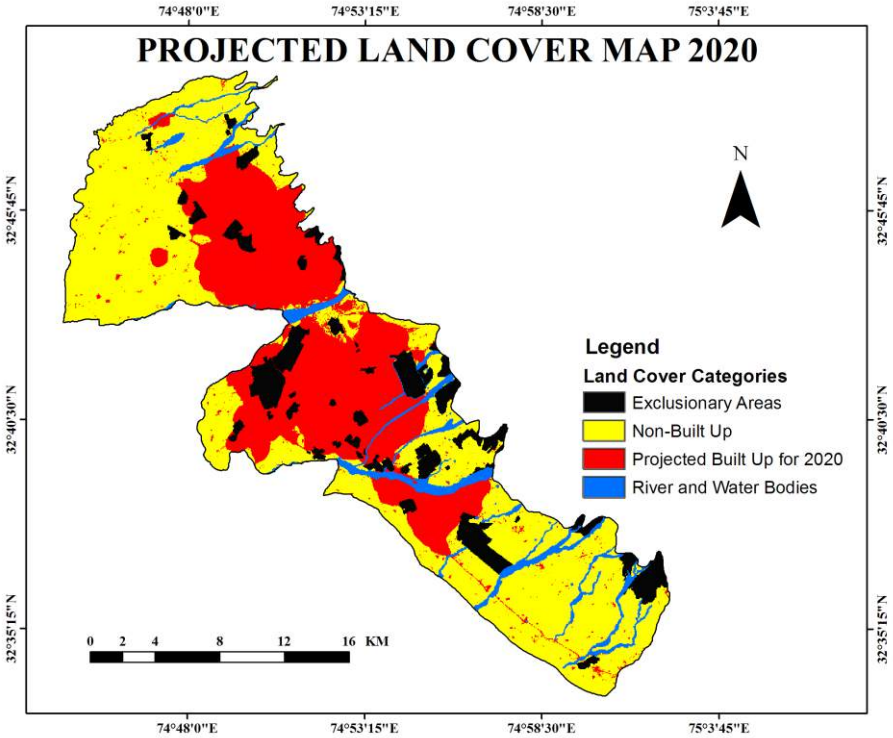


Figure 97: Projected Land Cover for 2020 using MLP-BP algorithm

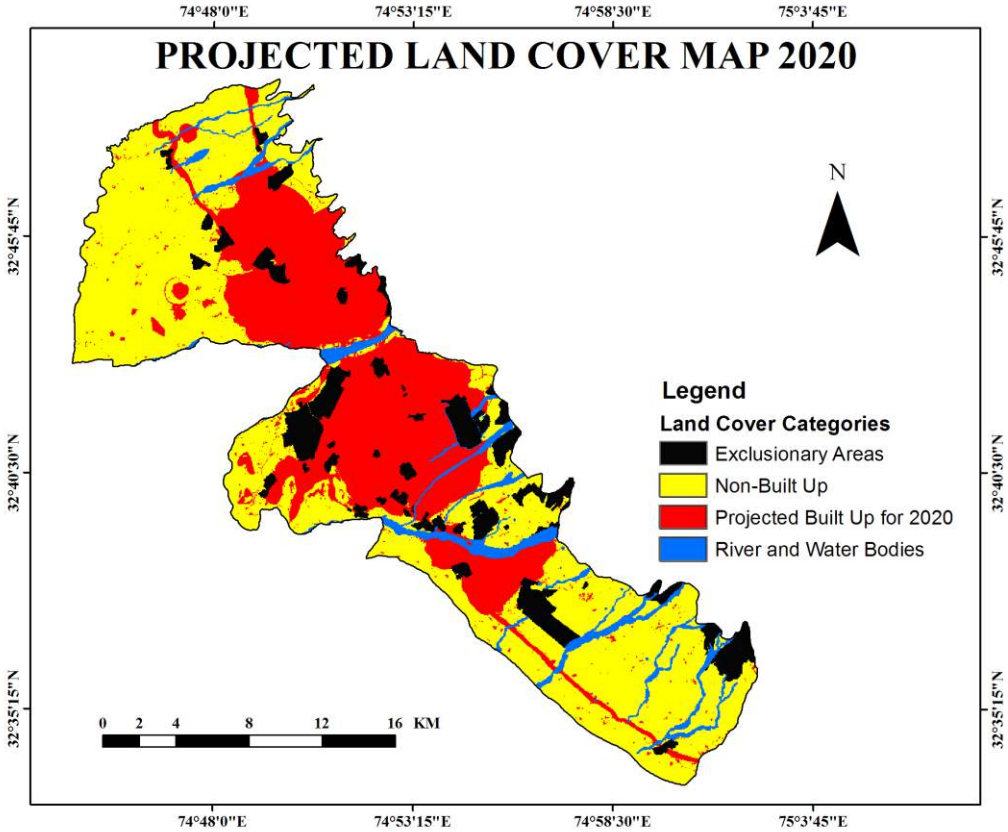


Figure 98: Projected Land Cover for 2020 using SOM Commitment

Figures 96 through 98 depict this type of growth scenario using the different algorithms. It can be seen from the maps that urban growth pixels (15072 in number) have been allocated elsewhere but not within a range of 200 meter from the river Tawi, thus allowing for hazard-free development in the study area.

5.9 Summary

In the present section, we described all the maps produced at different stages of the research work. Starting from how the satellite imagery was classified and into how many categories to the urban trend analysis followed by the training of different algorithms based on input factor files and others to the evaluation of results and using the best algorithms for predicting the future simulation for the year 2020 and then concluding at the generation of several future scenarios for the year 2020.

CHAPTER 6: CONCLUSIONS AND FURTHER RESEARCH

6.1 Introduction

The developing world is associated with many problems if its growth is unchecked and uncontrolled. For this reason, determining the current spatial use and urban growth dynamics of cities and knowing the factors that fuel this growth are among the top-marked issues in modern urban research. The city of Jammu has experienced rapid urbanization in the recent years. As a result of this rapid urbanization, Jammu is faced with several problems like destruction of natural resources, population expansion, ineffective utilization of space and resources, haphazard growth which have severe consequences not only for the city from the stand-point of its economic condition but also for the state and the country as a whole. When large numbers of cities are growing this way, unchecked and improper haphazard development could take tolls and bring barriers to the overall nation.

6.2 Overview of Methodology

The current study was focused to determine the future urban growth potential of the city of Jammu signifying the areas which are at risk due to urbanization so that better decision-making and planning policies could be realized and well-informed decisions could be formulated for the same. In this study, GIS and remote sensing played a pivotal role by providing three-time satellite data and the simulation models were combined to understand the dynamics of changes in the urban patterns of Jammu and to examine the growth trends that might be encountered by the year 2020. Several models as proposed by different authors to explain the urban spatial growth in terms of various variables were studied. Most of the modelling techniques assume inherent subjectivity which is ruled out by the application of neural network techniques for model development. In the present work in addition to using the conventional Back Propagation algorithm (MLP – BP), various advanced machine learning algorithms like Classification Tree Analysis (CTA using Entropy, Gini and Ratio techniques), Fuzzy ART Map (a variant of ART technique which couples Fuzzy set theory and ART) and Self Organising Maps (SOM) were used to perform the simulation. The simulation results were evaluated using advanced metrics showing components of agreement and disagreement based on Kno, Klocation, KlocationStrata and Kstandard and the best algorithms were finalized on which to base the future prediction for the year 2020. The values of the metrics were calculated for the simulated and the actual urban growth map and three algorithmic approaches were short-listed as a result (Fuzzy Commitment, MLP-BP with two hidden layers and 5, 5 as the number of nodes in each hidden layer and SOM Commitment). For spatial allocation of urban growth cells as predicted by the algorithms, MOLA as well as CA-Markov techniques were applied. It came to the conclusion that CA-Markov being iterative in nature produced better simulation results as the growth pattern in the study was dispersed, MOLA being a single shot process does the random spatial allocation and thus is incompetent to truly capture the pattern of growth.

6.3 Conclusions

According to the simulation results, an increase in the built up area by 1356.48 hectares from 2014 to 2020 is expected. Jammu city has a dispersed growth and not a city centric growth pattern. This means that city is not necessarily developing depending upon the proximity to the city centre which is generally the case. As opposed to this, the city expands along the National Highway and also grows near fringe areas in the south-east and north-west directions. The result of this study will be considered by city planners, managers and all organizations involved in the decision-making process regarding the land use and creation of prospective land use policies for environmental sustainability, protection of natural resources and preparation of city plans.

The present study also suggested the applicability and adequacy of one algorithmic approach over the other for generating the transition potential maps. Here, it suggested that CTA is incompetent for generating transition potential files for areas showing dispersed growth pattern. Fuzzy ART and SOM are better suited in addition to MLP Back Propagation techniques for simulation. It also affirms the usefulness of CA-Markov for urban growth modelling suggesting that iterative models are better than single-go methods.

This study showed that simulation approaches integrated with remote sensing data and a GIS environment can be used effectively to predict the future changes in LU/LC and to analyse the direction, rate and spatial distribution of possible changes.

6.4 Further Research

As is the case with any other study, recommendations and further research were furnished as mentioned below:

1. The number of variables which could explain any city's pattern of growth are generally not finite but are constrained due to the working of mathematical models. Greater number of variables impose greater complications in the smooth working of a model. In this study, only a few identifiable variables were employed to build the predictive model. There is a great scope to include some more variables like water supply, sewer, and socio-economic variables and likewise. Making the model more realistic by incorporating the stochastic perturbations induced by human decision, social and economic variables can be done. Planning constraints could also be applied to bring out diverse scenarios.
2. There is a further scope of developing new models by integrating more machine learning algorithms for urban growth modelling. New approaches for boundary modelling are also a current research interest.
3. Use of high resolution remote sensing datasets is a boon as sub-metric level availability of data can help model multiple land use categories change predictions with greater ease.

4. In this study, three time periods were taken into consideration. A better illustration can be drawn with the inclusion of repetitive analysis over time as it truly reveals the intricate character of a city in a greater comic detail.
5. Integration of 3D data with the current study could yield more realistic results because not only will the urban growth be modelled in the form of maps but also in the form of 3d model which can represent the space use. Space use gives a practical and a much more realistic touch to the model as that is something much more useful in terms of its display and analytical capabilities.

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