URBAN GROWTH MODELING USING CELLULAR AUTOMATA BASED MACHINE LEARNING TECHNIQUES

A Thesis submitted

in partial fulfilment for the award of the Degree of

Doctor of Philosophy

by

AARTHI AISHWARYA. D

DEPARTMENT OF EARTH AND SPACE SCIENCES

INDIAN INSTITUTE OF SPACE SCIENCE AND TECHNOLOGY

THIRUVANANTHAPURAM - 695547

MAY 2020

Dedicated to my beloved family members

CERTIFICATE

This is to certify that the thesis entitled **Urban Growth Modeling using Cellular Automata based Machine Learning Techniques** submitted by **Aarthi Aishwarya. D.,** to the Indian Institute of Space Science and Technology, Thiruvananthapuram, in partial fulfilment for the award of the degree of **Doctor of Philosophy** is a *bona fide* record of research work carried out by her under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institution or University for the award of any degree or diploma.

Dr. L. Gnanappazham
Supervisor
Associate Professor

Department of Earth and Space Sciences

डॉ. एल ज्ञानप्पऴम /Dr. Gnanappazham
सह आचार्य / Associate Professor
पृथ्वी एवं अंतरिक्ष विज्ञान विभाग
Department of Earth and Space Sciences
भारतीय अंतरिक्ष विज्ञान एवं प्रौद्योगिकी संस्थान
Indian Institute of Space Science and Technology
अंतरिक्ष विभाग, भारत सरकार
Dept. of Space, Govt. of India
तिरुवनंतपुरम / Thiruvananthapuram - 695 547

Thiruvananthapuram

May 2020

18/05/2020
Counter signature of HOD with seal

विभागाध्यक्ष / Head of the Department
पृथ्वी एवं अंतरिक्ष विज्ञान विभाग
Department of Earth and Space Sciences
भारतीय अंतरिक्ष विज्ञान एवं प्रौद्योगिकी संस्थान
Indian Institute of Space Science and Technology
अंतरिक्ष विभाग, भारत सरकार
Dept. of Space, Govt. of India
तिरुवनंतपुरम / Thiruvananthapuram

DECLARATION

I declare that this thesis entitled **Urban Growth Modeling using Cellular Automata based Machine Learning Techniques** submitted in partial fulfilment of the degree of **Doctor of Philosophy** is a record of original work carried out by me under the supervision of **Dr. L. Gnanappazham**, and has not formed the basis for the award of any other degree or diploma, in this or any other Institution or University. In keeping with the ethical practice in reporting scientific information, due acknowledgements have been made wherever the findings of others have been cited.

D. Aarthi Aishwarya

Aarthi Aishwarya. D. 18. 5. 2020

(SC14D001)

Thiruvananthapuram

May 2020

ACKNOWLEDGMENTS

Firstly, I would like to express my sincere gratitude to my advisor Dr. L. Gnanappazham for her continuous support to my research, for her patience, motivation, and immense knowledge. Her guidance helped me in all the time of my research and writing of this thesis. I could not have imagined having a better advisor and mentor for my PhD study. Besides my advisor, I would like to thank my doctoral committee members, Dr. Samir Mandal, Dr. A. Senthil Kumar, Dr. Thirumalaivasan, Dr. R. Krishnan, Dr. Rama Rao Nidamanuri, Dr. S. Sumitra, for their insightful comments and encouragement and also for their hard questions which motivated me to widen my research from various perspectives. I would like to thank Dr. Ramiya, for her guidance and support.

I am also thankful to Dr. Anandmayee Tej, my former doctoral committee member, for her support and motivation. I would like to acknowledge Dr. V. K. Dadhwal, the present Director and Dr. K. S. Dasgupta, the former Director of IIST, for providing me the research facilities and research fellowship.

My sincere thanks goes to Dr. Kanchanamala, Deputy Planner, Chennai Metropolitan Development Authority, Chennai, Dr. S. S. Ramakrishnan, Director, Institute of Remote Sensing, Chennai and Dr. Tune Usha, Scientist, National Centre for Coastal Research, Chennai whose expertises were invaluable for my research. I would also like to thank the staff members of Chennai Metropolitan Development Authority, Chennai Metropolitan Water Supply and Sewerage Board, Directorate of Technical Education, Chennai, Tamil Nadu Slum Clearance Board, Tamil Nadu Public Works Department for sharing with me their valuable information and dataset required for my research. Without all their precious support it would not have been possible to conduct this research.

My special thanks goes to my fellow research scholar, Dr. K. Arun Prasad, for the discussions I had with him, which were always so helpful and provided me assistance throughout my research. Also I thank my fellow lab mates, Dhanya. S. Pankaj, Gopakumar, Veena, Bharath Bhushan, Neeraj for their encouragement and support. I extent my heartfelt thanks to lab assistants Divya Mohan, Aswathy and office staffs, Celin and Shalini. My time at IIST was made enjoyable in large part due to my friends. I am grateful for the time spent with them.

Last but not the least, I would like to thank my parents, brother, husband, parents-in-law and sister-in-law who were a great source of support during my research. It was their unwavering support, continuous encouragement and wise counselling which helped me in the successful completion of my research.

Aarthi Aishwarya. D.

ABSTRACT

Rapid urbanization across the world is changing the landscape with significant deterioration to the environment affecting the quality of living of humans. It is estimated that currently, almost 55% of the world's population reside in urban areas, whereas in 1950 it was only 30%. It is expected that by 2050 about 68% of global population will be urbanized. Urbanization is one of the reasons for global warming throughout the world and has become very common in developing as well as developed countries. Urbanization is a gradual process, which is influenced by various economic, political and geographical factors. Urbanization refers to the growth of towns and cities as people move from rural areas to urban centres in search of better education, good health care, proper sanitation, comfortable housing, better business opportunities, transportation facilities and so on. In India, population, industrial and economic growth has resulted in rapid migration and urbanization in the country and thus the number of urban towns and cities has drastically increased and urban agglomeration is expected to continue in the years to come. Cities are rapidly expanding horizontally as well as vertically by utilizing all of the surrounding land to build residential areas and thus urban growth is happening in a haphazard and unplanned way. Urban growth has both positive and negative effects on the development of a city. Positive effects of urbanization includes better standards of livings as urbanization provides lots of employment opportunities, advancements in technology and infrastructure, improvements in transportation and communication, quality of educational and medical facilities and improved standards of living. On the other, the negative impacts of unplanned urbanization are numerous including overcrowding, housing problems, unemployment, under-employment, development of slums, water scarcity, sanitation problems leading to poor health issues, traffic congestion, air and water pollution, poor waste management, increase in crime and so on. Despite many challenges, governments are working hard to find out the solutions to minimize and resolve various problems pertaining to these consequences of unplanned urbanization. Sustainable development of a city depends mainly on successful management of environmental resources thereby leading to a better quality of living of mankind. Hence, efficient and appropriate urban development policies are needed to improve the lives of both urban and rural dwellers so as to avoid the adverse effects of urbanization.

Recently, urban growth models are developed and extensively used to study the urban sprawl of a city and its impact on the environment. These models can be employed in urban policy-making for the development of different urbanization scenarios to predict the future urban trends of the city. For the sustainable management of the natural resources and for the improvement of quality of living of humans, an efficient and appropriate urban growth models are indispensable, which is dependent on the simultaneous monitoring and modeling of urban land use. Remote sensing provides a useful tool for monitoring the land cover/land uses from local to global scale. Spatial models are increasingly employed as decision support tools in urban planning in order to inform planners

and decision makers. In the past two decades, several types of simulation and prediction models have been used within a GIS environment to determine a realistic future for urban growth patterns. These models include quantitative and spatio-temporal techniques that are implemented to monitor urban growth. The results derived through these techniques are used to create future policies that take into account sustainable development and the demands of future generations. Cellular automata based urban model has gained great attention from urban researchers in recent years. They have the potential to simulate the complex systems like cities. Cellular automata models are effective in simulating the urban growth dynamics and in projecting the future scenarios. In this research, the urbanization of Sriperumbudur Taluk, Kancheepuram district and Chennai Metropolitan Area, Tamil Nadu, India were modeled using Cellular Automata based machine learning techniques. Also the uncertainties arising from the model and input parameters were assessed through sensitivity analysis. The type and distribution of the urban sprawl of these study regions were analyzed through Shannon's entropy which would provide detailed information to the urban planners regarding the rapid urbanization occurring in these regions.

A pilot study on Sriperumbudur Taluk to assess the efficiencies of three Cellular Automata based urban models including Traditional Cellular Automata (TCA), Agents-based Cellular Automata (ACA) and Neural Network coupled Agents-based Cellular Automata (NNACA) models in capturing the urbanization of the taluk in 2016 was performed. The urban maps of the study region for the years 2009, 2013 and 2016 prepared from the satellite imageries, along with the agents of urbanization namely transportation, industries, elevation and also hotspot locations (future urban expansion based on the Government policy) were used in the modeling. Analytical Hierarchical Process technique was adopted to estimate the weights of the agents for suitability map preparation in ACA model. On validating the 2016 predicted outputs, NNACA model proved to be a better urban model (kappa coefficient - 0.72) when compared to the other models (kappa coefficient - 0.6 each). Further, the influence of agents of urbanization on the prediction output was assessed through 'sensitivity analysis' which revealed that all the 12 agents of urbanization selected based on the experts' opinions were equally important in determining the urban development of the taluk in 2016. To study the type and distribution of the urban sprawl, the study area was divided into 8 directional zones with the Sriperumbudur Head Quarters as centre and based on the urbanization in 2009, 2013 and 2016, Shannon's entropy for the study periods was measured. The results suggested that urban growth is dispersive in the taluk and higher urbanization is found towards the north-east direction of the taluk which is towards Chennai city. Further, the urban sprawl of the taluk was predicted using NNACA model for 2020 with an expansion of 157 km^2 from 113 km^2 of urban cover in 2016.

Based on the results from the pilot study, NNACA model proved to be efficient in capturing the urban growth of Sriperumbudur Taluk and thus the model was used to predict the urban growth of Chennai Metropolitan Area for the year 2017 based on 2010 and 2013 urban cover maps and hotspots region identified from the Chennai city master plan as. As per the experience from pilot study, 18 different agents of urbanization including transportation, hotspots, and industries were used in the prediction modeling. The prediction model was performed under two scenarios. One scenario included the hotspots based on the city's master plan into the urban map of 2013 and the other without the hotspots in the 2013 urban map. On validating the 2017 predicted outputs, the neural network model with hotspots proved to be better (urban hits: 498.52 km^2) than that of without hotspots (urban hits: 488.31 km^2). Out of the total 18 agents of urbanization, the most influencing agent of urbanization of 2017 was identified to be the 'Existing built-up of 2013' itself using 'sensitivity analysis' showing that the influence of agents unique for each study area. Further, the urban sprawl of the study region for 2010, 2013 and 2017 was measured through Shannon's entropy. The study area was divided into five directional and distance-based zones with the State Secretariat as the center. Entropy values suggest the need for more careful planning for further development in the southern region of CMA which has undergone congested urban growth while urbanization is dispersed in the northern part of the study region which can be thought for future urban developments. Though, NNACA models have proved to predict the urban growth more close to reality, recently, deep learning based techniques are being used for the prediction of urban growth to overcome the dimensionality issues arising from the neural network architecture. Hence, for Chennai Metropolitan Area, the urban growth of 2017 was performed using Deep-belief based Cellular Automata (DB-CA) model and the accuracies of the prediction outputs of these two models were compared. Upon validating, DB-CA model proved to be the better model, as it predicted 524.14 km^2 of the study area as urban with higher accuracy (kappa co-efficient: 0.73) when compared to NNACA model which predicted only 502.42 km^2 as urban (kappa co-efficient: 0.71), while the observed urban cover of Chennai Metropolitan Area in 2017 was 572.11 km^2. Analyzing the effects of different types of neighbourhood configurations (Rectangular: 3×3, 5×5, 7×7 and Circular: 3×3) on the prediction output based on DB-CA model was also performed and it was found that 3x3 rectangular neighbourhood configuration is the most appropriate one in predicting the urbanization of CMA in 2017. Further, Chennai Corporation (earlier Chennai city limit) was excluded from current limit of Chennai Metropolitan Area and neural network based prediction was implemented for the region beyond the Corporation limits, to check the influence of agents of Corporation beyond its boundary. Result suggested that the agents of urbanization of Chennai Corporation have lesser impact in the region beyond its boundary. Sensitivity analysis of the region beyond the corporation boundary suggested that all the 18 agents were appropriate to model the urbanization in 2017. Hence, urban prediction for 2020 for the region beyond the Corporation limits was done through neural network based Cellular Automata model with a future urban extent of 343.51 km^2 which would serve as a tool for urban planners and policy makers to take appropriate development plans to have sustained development of the study region.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

ACA	Agents-Based Cellular Automata
AHP	Analytical Hierarchical Process
ANN	Artificial Neural Network
CA	Cellular Automata
CI	Consistency Index
CMA	Chennai Metropolitan Area
CMDA	Chennai Metropolitan Development Authority
CR	Consistency Ratio
CRZ	Coastal Regulation Zone
CUF	California Urban Futures
DB-CA	Deep Belief based Cellular Automata
DBN	Deep Belief Network
DEM	Digital Elevation Model
DLM	Deltatron Land Use/Land Cover Model
DT	Decision Tree
FAST	Fourier Amplitude Sensitivity Test
GA	Genetic Algorithm
GIS	Geographic Information System
GND	Grama Niladari Division
IHS	Intensity-Hue-Saturation
LAC	Land Absorption Co-efficient
LCM	Land Change Modeler
LCR	Land Consumption Ratio
LR	Logistic Regression
MC	Markov Chain
MEPZ	Madras Export Processing Zone
ML	Machine Learning
MLC	Maximum Likelihood Classification
MLP	Multi-Layer Perceptron
NNACA	Neural Network coupled Agents-based Cellular Automata

O.A.	Overall Accuracy
OLI	Operational Land Imager
OMR	Old Mahabalipuram Road
PCM	Pairwise Comparison Matrix
PIS	Pollution Index Score
RBM	Restricted Boltzmann Machine
RI	Random Index
RMS	Root Mean Square
SI	Swarm-Intelligence
SIPCOT	State Industries Promotion Corporation of Tamil Nadu
SLEUTH	Slope, Land Use, Exclusion Layer, Urban extent, Transportation, Hillshade
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
TCA	Traditional Cellular Automata
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TPM	Transition Potential Matrix
TR	Transition Rule
UGM	Urban Growth Model

NOMENCLATURES

χ^2 – Chi-square value

V – Cramer's Value

k - kappa co-efficient

H_n – Normalized Entropy value

λ_{max} – Principal Eigen Value

CHAPTER 1

INTRODUCTION

1.1. Urbanization

Urbanization is defined as the migration of people in huge numbers from rural to urban areas and this process happens due to the concentration of resources and infrastructure facilities in towns and cities. Buhaug and Urdal (2013) characterized urbanization as the increase in population of cities, so that higher proportion of population lives in urban areas. In 1950, only 30% of the world population was urbanized, but since 2014 about 54% of the world population resides in urban areas (Department of Economic and Social Affairs, United Nations, 2018). Based on 2014 reports of United Nation, by 2050, about 66% of the world population is projected to live in urban areas. Increasing number of urban population has significantly increased the number of megacities in the world. There were only 10 megacities in 1990, which increased to 28 megacities in 2014. In 2018, there were 33 megacities and it is projected that there will be 41 urban agglomerations or megacities in 2030.

The urban population especially in Asian countries is growing faster than ever before and there will be more than 1.1 billion people living in urban areas in 2030 (Asian Development Bank, 2008). Rapid urbanization has been identified as the key driving factor for Asia's economic development. Urbanization and rapid urban development in several Asian countries are marked by increasing physical growth which extends beyond metropolitan and city boundaries (Hugo, 2007; McGee and Robinson, 1995). Urbanization is a process that will continue in the upcoming years, hence sustainable development challenges will be concentrated in cities, particularly in the developing countries which experiences rapid urbanization (United Nations, 2013) which attracts people to migrate for businesses, investments, infrastructure facilities and lifestyle betterments and so on.

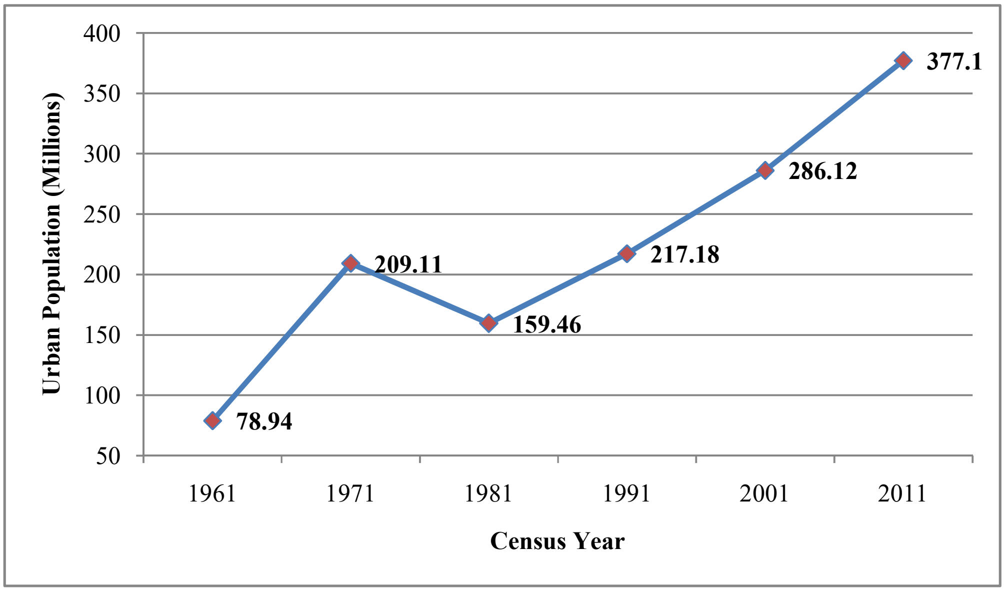


Figure 1.1. Urbanization trends of India between 1961 and 2011. Note: As 1981 Census was not conducted in Assam, and the 1991 Census was not held in Jammu and Kashmir, the population of India includes projected figures for these states in those periods (Bhagat, 2011).

The degree of urbanization in India has also increased significantly over the years (Elmqvist et al., 2013; Nagendra et al., 2013). The urbanization trends of India over the decades are shown in Fig.1.1. Such rapid urbanization in the country seems to have transformed the urban landscape leading to changes in land use and land cover considerably and causing severe pressure on various natural resources (Bhagat, 2011). It is projected that urban population of India will nearly double reaching 600 million by 2031 (World Urbanization Prospects, The 2011 Revision). It is expected that with this increasing urbanization, Indian cities will suffer from local environmental problems and unhealthy living conditions (Kantakumar et al., 2016; Mohan et al., 2011).

1.2. Need for Urban Growth Models

Sustainable development is possible only through the implementation of successful urban planning but a city can become gradually unsuitable for living if the urbanization process is unplanned and haphazard. Though the process of urbanization brings numerous benefits including monetary growth, expansion of business activities, social and cultural incorporation, as well as utilization of resources, there are certain serious issues due to rapid and unplanned urbanization (Chaudhuri, 2015). Effects of unplanned urbanization are the major concerns for planners and policy developers because it declines the quality of living for urban inhabitants. Due to unplanned urbanization, there is environmental degradation especially in the quality of water, air and noise. One of the main effects of rapid urbanization is the air pollution which has increased due to the emissions from motor vehicles, industries and use of fuel sources which harm the environment. The noise pollution is produced from various human actions which also degrade the environment and ultimately affect the human health. The growth of population has generated a very high quantity of solid waste and there is a pressure to provide a waste disposal place in the urban areas. With the influx of more people in cities, there is great demand of facilities such as housing, commercial complexes, education and health infrastructure etc. As the metropolis becomes a developed city, the land value will also increase. As such, there will be a problem in providing housing, especially for the middle and low class people. The maintenance of drains and debris collection is incompetent which can raise other serious problems such as flash floods and poor public health (Datta et al., 2017).

In developing countries, about one third of urban population lives in impoverished slums (Ooi and Phua, 2007). Slums are urban areas that are heavily populated and have sub-standard housing with very poor living conditions. The uncontrolled growth of urbanization is a major challenge for the local Government authorities as they need to deal with different goals and interests of different community groups to find solutions for different social issues. This makes the urban governance policies weak and incompetent. Thus, evaluating the urbanization process becomes crucial, as it is observed that the fast growth of urban population both naturally and through migration, has put immense pressure on both the environment and mankind.

1.3. Types of Urban Growth Models

Urban Growth Models (UGMs) have been developed and extensively adopted to study the urban expansion and its impact on the ambient environment. To better understand the urban growth patterns of a city, UGMs are necessary through which the urban growth can be quantified and its spatio-temporal dynamics can be assessed. These models can be employed in urban policy-making or analyses of different urban development scenarios. With the help of modeling and simulation, we can reduce the uncertainty and increase our understanding of the urban system. Urban modeling can facilitate scenario building and provide an important aid to future directed decision-making (Cheng, 2003). Urban models help planners and policy makers to analyze the past urban growth of a city thereby the current trends of urbanization can be assessed so that the future development scenario can be simulated. Several UGMs have been developed by urban planners, policy makers, geographers (Berling-Wolff and Wu, 2004). These models can be roughly grouped into three types: Rule based simulation model, Dynamic simulation model and Empirical estimation model (Zeng et al., 2008; Hu and Lo, 2007).

Dynamic simulation modeling is used for understanding complex phenomenon and problems through dynamic simulation. However, dynamic simulation models are very weak in representing the spatial patterns of land uses as it cannot deal with spatial data effectively (Guo et al., 2001). Empirical estimation models use statistical techniques to model the relationship between land use change and the drivers based on historical data. Major drawbacks of these two models are that they lack proper understanding on the simulation process that influence the land use process and they are unable to incorporate the temporal dynamics of the urban growth processes (Hu and Lo, 2007). Hence, rule based urban growth models are incorporated to handle the shortcomings in these two models.

Rule-based models include California Urban Futures (CUF) model, What-If? model, UPlan model and Cellular Automata (CA) model. CUF model is the first in a new generation of metropolitan simulation models which replicate realistic urban growth patterns and the impacts of development policy at various levels of government. The CUF model projects population growth at the city or subarea level, and then aggregates upwards. However, the model is limited to simulate only residential land consumption as CUF relies on specified land prices of the regions (Landis, 1994). What-If is a scenario-based deterministic planning support system that uses increasingly available GIS data to support community-based processes for conducting land suitability analysis, projecting future land-use demands, and allocating the projected demands to the most suitable locations. It is easy to use, can be customized to the user's database and policy issues, and provides outputs in easy to understand maps and reports (Klosterman and Pettit, 2005; Klosterman, 1999).UPlan is a simple rule based urban growth model intended for regional or county level modeling. The model was developed by researchers at the Information Center for the Environment (ICE) at the University of California, Davis, which spatially allocates new development for use in long-range land use planning and scenario testing and suitable for rapid scenario-based modeling (Walker et al., 2007). It has been used to model residential, commercial and industrial urban land-uses. The most widely used rule based prediction model is the CA model, which consists of lattice of discrete cells (Duwal, 2013). CA based models are inherently spatial and dynamic apart from highly adaptable (White and Engelen, 2000). CA based urban models are interactive, user friendly. The outputs from a CA model could be assessed both qualitatively and quantitatively and they have great affinity towards GIS and remote sensing based dataset. CA models have the ability to replicate complex urbanization patterns of a city through simple transition rules and they could be applied to any extent of geographical areas ranging from cities to continents. Thus, CA based UGMs can be effectively used for simulation as far as urbanization modeling processes are considered (Blecic et al., 2013; Santé et al., 2010; Oguz et al., 2007).

1.4. Role of GIS and Remote Sensing in Urban Growth Models

In India, the complexity of urban development of cities is very high that it requires immediate attention and appropriate planning policies (Sokhi and Rashid, 1999). New approaches, scientific technologies should be implemented to handle the current urban scenarios. Earlier, maps and land survey records from the 1960’s and 1970's were used for urban studies. Now-a-days, through remote sensing, digital, multispectral images acquired by satellites were used for gathering accurate information about the land use and land cover features. Remote sensing data is becoming an important source of spatial information for urban areas. Since remote sensing images alone may not provide all the information needed for a full-fledged assessment, many other spatial attributes from various sources are needed to be integrated with the remote sensing data. This integration of spatial data and their combined analysis is performed through GIS technique. The data can be derived from alternative sources such as survey data, geographical/topographical/aerial maps or archived data (Morgan et al., 2010).

Recent advancements in GIS help to analyze the urban growth and its direction and also to find the most suitable sites for further urban development. GIS, when integrated with remote sensing, can help to store, manipulate, and analyze physical, social, and economic data of a city. It is efficient in developing land use, land cover and environmental database. Planners can use the spatial query and mapping functions of GIS to understand the current scenario of the cities. Through map overlay analysis, GIS can help to identify the areas of conflict of land development with the environment by overlaying existing land development on land suitability maps (Ullah and Mansourian, 2014). Areas of environmental sensitivity analysis can then be used as decision support systems for the current and future city development planning. The simulation of different scenarios of urban development can help in developing planning options. GIS can also be used in the implementation of urban plans by carrying out environmental impact assessment of proposed projects to evaluate and minimize the impact of development on the environment. Following such work, remedial measures can be recommended to alleviate the impacts (Gunasekara, 2004).

One of the reasons why GIS is integrated with remote sensing technique is that it enables the urban planners to better understand the current needs for a city, and then design to fulfill those needs. By processing geospatial data obtained from satellite imaging, aerial photography and remote sensors, users gain a detailed perspective on land and its infrastructure. Thus, GIS technology integrated with remote sensing empowers urban planners with enhanced visibility into data.

1.5. Research Motivation

Urban growth monitoring is inevitable for the sustainable management of natural resources and for the betterment of humans. Thus, urban prediction models enable policy makers to plan the future urbanization of their cities (Hill and Lindner, 2010). However, based on the literature, in Indian context not much work has been reported in the field of urban growth modeling with the application of GIS technique. Also, a little concentration was given for implementing the urban modeling using machine learning techniques including neural networks and deep belief networks for Chennai, the capital city of Tamil Nadu. Chennai has the 4th highest population (Fig. 1.2) among the metro cities of India with higher literacy rate and sex ratio (Census of India, 2011).

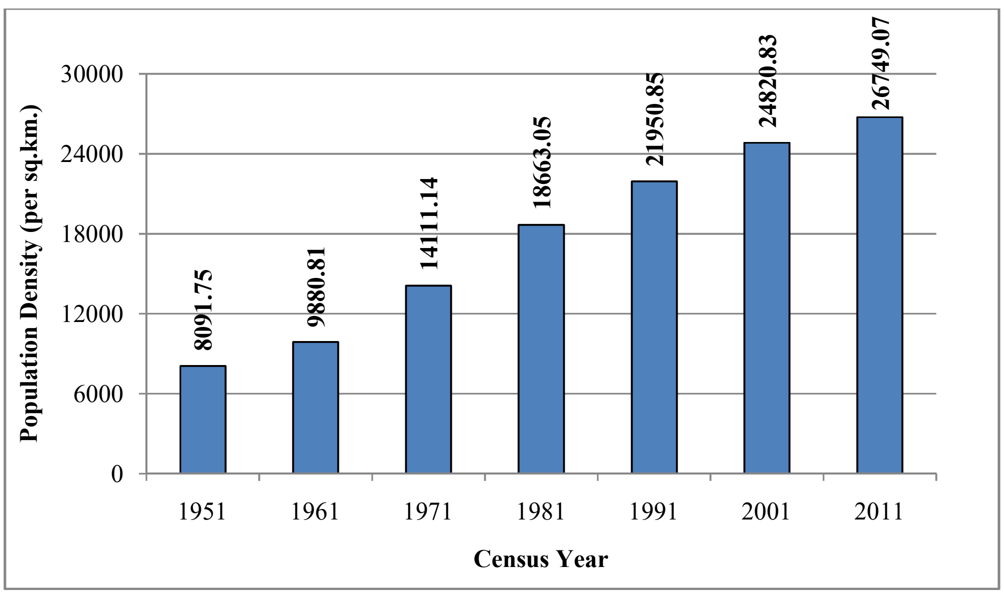


Figure 1.2. Population Density of Chennai city since 1951, after independence of the country

Urban growth of Kolkata Metropolitan area was predicted for the year 2025 by making use of the land use/land cover changes of the region of 1990, 1999, 2009 and 2017 using CA-MC model (Shafia et al., 2018). The model was developed to understand the changing dynamics of land use/land cover patterns of the study region. The model predicted that there would be increase in urbanization of 29% from 2017 to 2025 which is vital information for the urban planners and policy developers to devise efficient planning and management of natural resources and the city.

Siddiqui et al. (2018) used a hybrid model combining Logistic Regression, MC and CA to capture the urban growth of Lucknow, capital state of Uttar Pradesh. Landsat data of 1993, 2003 and 2013 along with agents of urbanization including population data, City master plan, DEM, road network and socio-economic factors like school, health facilities were used in the hybrid model. The model provided an insight on the pattern of urbanization in the capital city thereby highlighting the efficiency of implementing CA based hybrid models for modeling the urban growth.

Bharath et al., (2018) had predicted the urbanization of Indian mega cities including Delhi, Mumbai, Pune, Chennai and Coimbatore using Markov Chain (MC) based CA model. Apart from the landsat imageries of these regions, slope data was taken as the driving force or the agent of urbanization into the prediction modeling. In case of Chennai, the model predicted the urbanization of 2026 which forecasted increase in built-up by 2 folds with decrease in vegetation. The study showed that significant urbanization was found within the Chennai Metropolitan Area boundary and those regions closer to the boundary. The urban model further suggested that the urban growth was completely concentrated in the core area of CMA and spread beyond the boundary.

Aithal and Ramachandra (2016) predicted the urbanization of Chennai and the region surrounding it for a buffer of 10 km for the year 2026 using the landsat data of 1991, 2000 and Liss III data of 2012 through Agents-based CA (ACA) model. Apart from the satellite imageries used to detect the land use/land cover changes between 1991 and 2012, agents of urbanization including DEM and city development plans were included into the ACA model. The ACA model predicted that the vegetation category of the region would decrease from 70% to 48% and urbanization would increase from 1.46% to 18.5% in the study region by 2026. The study highlighted the need for a proper urban development policy with an emphasis on the sustainable utilization of the natural resources of the region.

Singh et al. (2015) implemented a Traditional CA (TCA) model to capture the urbanization of Allahabad city in 2010 which made use of only the land use/land cover changes between 1990 and 2000. Further the TCA model was used to predict the urbanization of the city in the future by 2020. The urbanization of Bangalore city was modeled using CA model by making use of landsat imageries of 1973, 1992 and 2006 by Kumar et al. (2014). Population density maps of 1973 and 1992 were also used to predict the urban growth of the city in 2006. The study showed how the developed CA based UGM was effective in capturing the urbanization of the study region.

However, not many researches had been reported on coupling machine learning techniques like neural network and deep belief network with ACA to model the urban growth of Chennai. Also, analyzing the effect of components of CA model on the prediction outputs and the uncertainty component arising from the choice of agents of urbanization and analyzing the type and distribution of the urban sprawl of the region had not been analyzed.

Chennai being the fourth largest metropolitan city in India, preparation of urban prediction model for the region becomes mandatory as the city faces severe urbanization in the last two decades due to increase in employment opportunities, availability of socio-economic facilities including hospitals, educational institutions and so on. Also, Chennai is the hub of many IT (Information Technology) parks which attracts many migrants to the city. Recently, the Housing and Urban Development Department of Tamil Nadu (2018) had proposed to extend the boundary of Chennai Metropolitan Area (CMA) from 1189 km^2 to 8878 km^2 including the entire districts of Thiruvallur, Kancheepuram and Arakkonam and Nemili Taluks in Vellore district for better administrative purposes and efficient urban development planning (In India, each state is divided hierarchically into number of districts, taluks and revenue villages for the purpose of administrative activities). Hence, urban planning for CMA becomes very essential as the region is already brimming with urban development and an appropriate planning tool could enable the city from getting congested anymore in the future.

1.6. Objectives of the research

Based on the research gaps identified in the section 1.5, the current research aims at achieving the following objectives which would be the first of its kind in urban growth prediction modeling. The research objectives for this research are as follows

1. To conduct a pilot study on Traditional Cellular Automata (TCA), Agents-based Cellular Automata (ACA) and Neural Network coupled Agents-based Cellular Automata (NNACA) based UGMs in 1:25000 scale for Sriperumbudur Taluk which is experiencing accelerated industrial growth adjoining to CMA to identify the most efficient urban growth model before working on CMA
2. To model the urban growth of CMA based on the identified model from the pilot study and to assess the uncertainty of input parameters of the model based on 'Sensitivity Analysis'
3. To model the urban growth of CMA based on NNACA and advanced machine learning algorithm, Deep Belief based Cellular Automata (DB-CA) model, using the most influencing agent of urbanization identified from objective 2 and to assess the uncertainty of model parameters on the prediction model
4. To evaluate the pattern and direction of maximum urban growth of CMA during the study period based on Entropy analysis

1.7. Organization of the thesis

Apart from this Introduction chapter, rest of the thesis is organized as follows:

- **Chapter 2** presents a detailed review on literature on the need for UGMs and types of urban growth prediction models in both global and Indian scenarios. It also presents literature on identifying the type of urban sprawl through entropy analysis. The chapter further describes the research gaps in this field and highlights the potential contribution made by this research to fill up the research gaps.

- **Chapter 3** discusses the preparation of time series land cover maps, the major inputs for the urban modeling. Since the study is taken up in 1: 25,000 scale and there is no other secondary source of open data available for Chennai city, the first activity of the study was preparing land cover maps. This chapter describes in detail the processes involved in the land cover maps preparation of Sriperumbudur Taluk and CMA using time series satellite remote sensing data. It further discusses the land cover changes observed in these two regions during the study periods.
- **Chapter 4** describes the pilot study on developing three types of CA based UGMs for Sriperumbudur Taluk of Kancheepuram district located in the southern extension of Chennai, Tamil Nadu, India. The urban sprawl analysis implemented through entropy analysis was also described.
- **Chapter 5** represents the implementation of urban growth prediction models for CMA. The influence of the model and input parameters on the prediction models assessed through Sensitivity Analysis were described in detail. Further, the type and distribution of urbanization of the area were also discussed in detail through entropy analysis.
- **Chapter 6** summarizes the research contributions made by this study. It also presents the future scope for research in the field of urban growth prediction modeling.

CHAPTER 2

REVIEW OF LITERATURE

2.1. Introduction

Most of the UGMs were carried out using CA models in various ways either using independent CA model alone or CA model coupled with other advanced algorithms. The thesis aims at developing CA based UGMs for Sriperumbudur Taluk and CMA, analyzing the uncertainties of the model and input parameters and to identify the pattern of urban sprawl of these two regions. In this chapter the previous research works done on urban growth modeling based on CA are discussed highlighting the urban growth prediction models in Indian scenario.

Urban development of cities and migration of people from rural to cities are an important phenomenon globally. The main factors for this urbanization are the job opportunities and the availability of social amenities in the cities. Recently, the settlements in urban areas are increasing at a rapid pace at the expense of agricultural lands, green space and natural resources which causes global climate change. Hence, urban growth developments need to be allowed to a certain extent that they do not pollute or deplete our natural resources and in this context, urban growth development models have become crucial and inevitable (Oğuz, 2004). Unplanned urbanization is resulting in urban sprawl with escalated vehicle and traffic density, impacts on the biodiversity, environment and ecosystem, land use fragmentation, human-animal conflicts and most importantly rapid changes in hydrological cycle with changing rainfall patterns and flooding. Hence, an understanding of spatial patterns of urbanization, quantification and visualization of urban growth are necessary for a sustainable management of both mankind and environment.

2.2. Urban Growth Modeling

2.2.1. Urban Growth Models

UGMs are crucial as they help in visualizing the growth of cities and could help urban planners and decision makers to understand the consequences of any unplanned urban development in a region. Indian cities have been experiencing a rapid urbanization consequent to globalization during the past three decades. This has posed challenges to the policy makers and necessitated appropriate urban policies to be taken into account. Urban modeling is a tool that can assist in analysis and prediction of urban growth dynamics (Silva and Clarke, 2002). UGMs provide an insight to policy makers and planners, who can use the model to anticipate and forecast future changes or trends of development, to understand the impacts of future development, and to explore the potential impacts of different policies (Verburg et al., 2002). Over the past few years, a number of urban growth models have been developed such as CA, agent based, spatial-statistics, artificial neural network, fractal models and so on (Barredo et al., 2004; Ward et al., 2000; Li and Yeh, 2000; Wu and Webster, 1998; White and Engelen, 1993, 1997; Wu, 1998a, 1998b, 1999, 2002). With the increased computational power and greater availability of the spatial data, agent based and CA models have shown great potential for representing and simulating the complexity of the dynamic process involved in urban growth and land use change (Dietzel and Clarke, 2006). Based on the review conducted by Triantakonstantis and Mountrakis (2012) on different types of urban growth models, CA remains the most popular modeling technique till now as far as urban growth modeling is considered and is shown in Fig. 2.1.

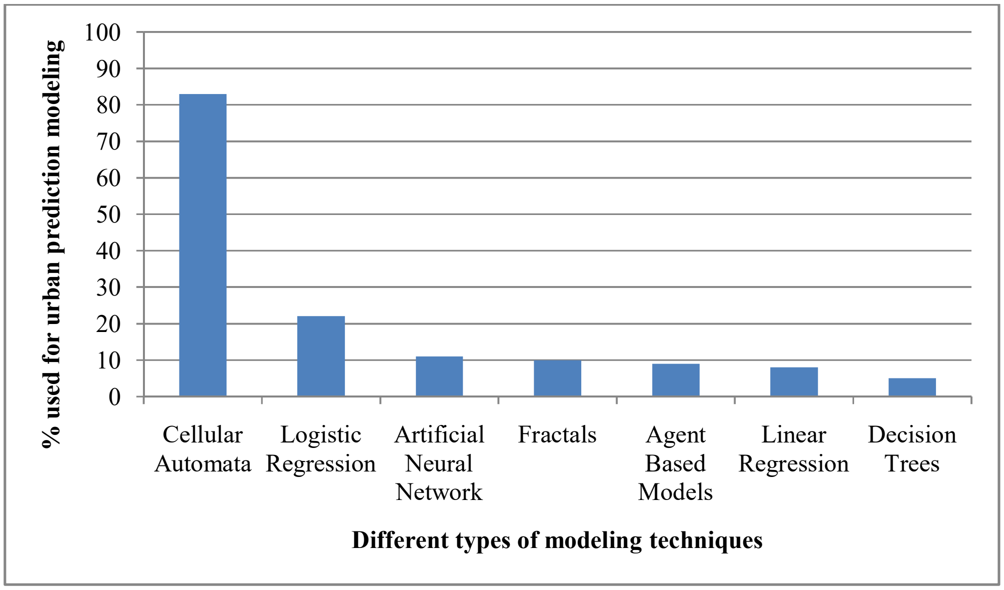


Figure 2.1. Different types of urban growth models based on their percentage of implementation (Triantakonstantis and Mountrakis, 2012)

2.2.2. Cellular Automata based Urban Growth Models

The study on urban sprawl is widely implemented in the developed countries (Basse et al., 2014; Epstein et al., 2002; Torrens and Alberti, 2000) and recently in developing countries such as China (Yang et al., 2017; Hua et al., 2014; Liu, 2008; Cheng and Masser, 2003) and India (Aithal et al., 2017; Kanchanamala, 2014; Sekar and Kanchanamala, 2011; Maithani, 2009; Sudhira et al., 2004; Lata et al., 2001; Jothimani, 1997). Many studies highlighted that the traditional mathematical based urban growth models are poor in handling the spatio-temporal data and they generalize data too much.

Von Neumann (1966) was one of the early pioneers of CA. He invented the idea of self-reproducing artificial structures and CA models are based on this self organization concept. Self organization refers to the tendency of a system to spontaneously develop ordered patterns, often on a large scale from local decision making processes (Torrens and Sullivan, 2001). In 1960s and 1970s for modeling urban land uses, CA models viewed space as a lattice of identical cells. CA models were improved once the concept of raster and regional modeling were incorporated in the 1970s and 1980s (Lee, 1973). Tobler (1979) was the first one to introduce the concept of CA in modeling geographical phenomena. In the 1980s CA were used to study ecology and environmental phenomena but then urban CA were developed towards the end of 1980s (Benenson and Torrens, 2004). In 1980, CA based UGMs were implemented as an alternative to the traditional mathematical models (Torrens, 2006). Sui and Zeng (2001) and Couclelis (1997) pointed out the natural affinity between CA and GIS in urban modeling and simulation. The integration of space, time and attributes in urban modeling was enhanced with the introduction of CA models (Berling-Wolff and Wu, 2004; Alberti and Waddel, 2000; Batty, 1998; Allen, 1997). Further, White and Engelen (1993) demonstrated that CA models can better understand spatial patterns and represent complex and realistic patterns.

2.2.3. Components of Cellular Automata

A typical CA is composed of five principal elements: Cell Space, Cell State, Cell Neighbourhood, Transition Rules and Time (Liu, 2008; Wolfram, 1984). **(i)** The space in which the automaton present is called cell space or lattice. Cell space can have n dimensions. In one-dimensional CA, the sites are single row of identical cells while two-dimensional CA is composed of matrix of identical cells arranged in rows and columns (Itami, 1994). One-dimensional CA is used to represent linear objects such as to model urban traffic (White and Engelen, 2000; DiGregorio et al., 1996). Two-dimensional CA is most commonly used in urban simulation (Liu, 2008). Most of the cell space is assumed to be homogeneous and different UGMs adopt different cell sizes (Barredo et al., 2003; Clarke et al., 1997; White and Engelen, 1993). **(ii)** Cell state represents any spatially distributed variable but in case of urban growth modeling, each cell state represents a particular land cover category (Parker et al., 2003; White and Engelen, 2000). Each cell in a CA model can occupy only one particular land use category at a particular given time.

(iii) Cell neighbourhood consists of surrounding or adjacent cells (Sipper, 1997). The two commonly used neighbourhoods are the Von Neumann and

Moore neighbourhoods. The neighbourhoods can also be extended from their 3x3 cells size to other larger odd numbered sizes (e.g. 5x5, 7x7, 9x9 and so on). The most commonly used neighbourhoods are the Von Neumann (4-cell) and the Moore (8-cell) neighbourhoods (White, 1998). Fig. 2.2 illustrates the types of neighbourhood configuration of a two-dimensional CA. There exist many neighbourhoods and the choice of neighbourhood depends on the user and on the region to be modeled. The urbanization of Dehradun city of India was modeled using CA model by Deep and Saklani (2014) by using different types of Moore neighbourhood configurations (3x3, 5x5, 7x7, 9x9, 11x11, 15x15 and 17x17) and their results suggested that the 17x17 was the most suitable configuration for their study area. Wu et al., (2012) implemented planar, linear and ribbon shaped neighbourhood configuration to model the urban land use of Wuhan, China. They suggested that the selection of appropriate neighbourhood configuration had greater impact on the accuracy of the prediction output and in their study planar neighbourhood type contributed to higher prediction accuracy. de Kok et al. (2001) adopted RaMCo (Rapid Assessment Model for Coastal Zone) model in which the cell neighbourhood is defined as a circular region around the centre cell up to a radius of 8 cells.

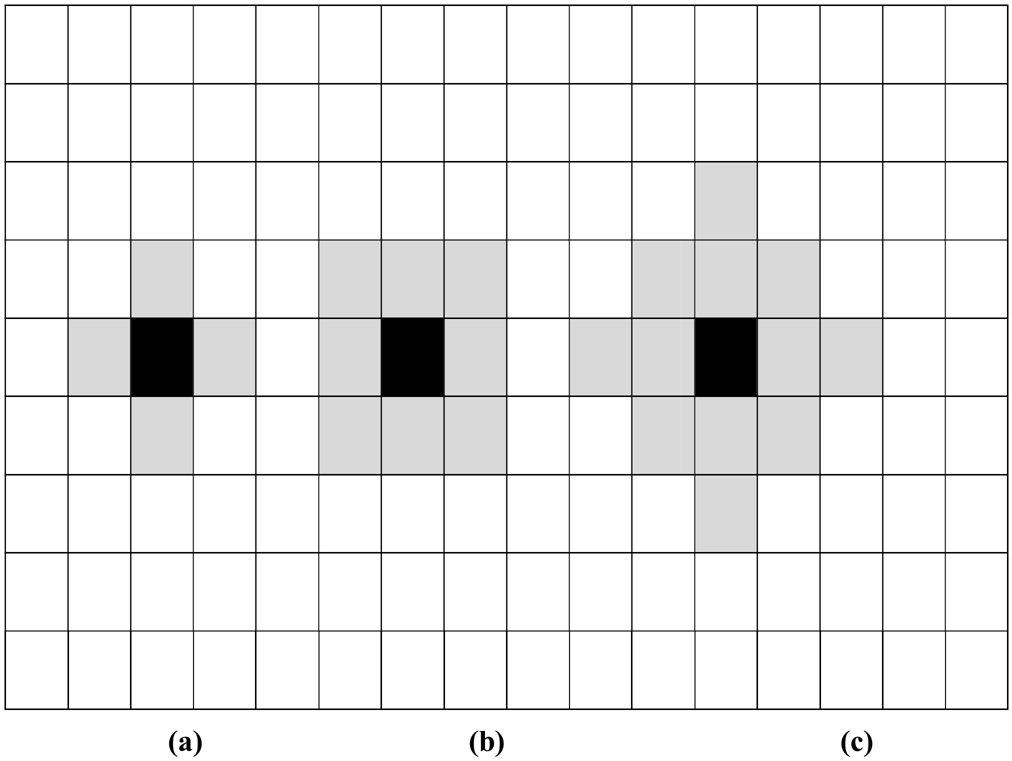


Figure 2.2. Neighbourhood configuration of two-dimensional CA. (a) 3 x 3 Von Neumann neighbourhood; (b) 3 x 3 Moore neighbourhood; (c) 5 x 5 Von Neumann neighbourhood (Benenson and Torrens, 2004)

(iv) Transition Rules (TRs), a set of IF-THEN rules, act as algorithm of CA models and define how one cell changes from one state to another based on its current state and state of its neighbouring cells. The state of future cells is determined by TRs in a discrete time frame. In a typical CA, the TRs are usually uniform and are applied synchronously to all cells within the system **(v)** Time is the temporal dimension in which CA is present and the states of all the cells are updated simultaneously at all iterations over time (Liu, 2008). For modeling urban land uses, yearly time steps are used in general. However for modeling traffic flow, time steps of seconds or minutes are considered (Mubea, 2014). In some cases, CA model had been implemented with different time steps within the same model. Uljee et al., (1996) used a model at different time steps for different cells which modeled low-lying areas on a monthly basis and the upland areas on a yearly basis.

CA models have the potential to replicate complex spatio-temporal dynamics at a global scale using local transition rules (García et al., 2012; White and Engelen, 2000). Numerous UGMs based on CA had produced accurate and satisfactory simulations of the real world (Arsanjani et al., 2013; Leao et al., 2004; Clarke et al., 1997). Thus CA models are considered as one of the best 'bottom-up' approaches in GIS based urban growth modeling as it has the potential to simulate urban processes at larger scales through local interactions.

2.2.4. Cellular Automata based model - SLEUTH

SLEUTH model based on CA was developed by Clarke (1997) and integrates two tightly coupled models, the Urban Growth Model (UGM) and the Deltatron Land Use/Land Cover Model (DLM). The UGM is used to simulate the urban growth of an area and DLM is used to simulate land use change and land transitions. SLEUTH is an acronym for the spatial datasets required as inputs and they include Slope, Land use, Exclusion Layer, Urban extent, Transportation, and Hillshade. The model works based on five growth co-efficients (diffusion, spread, breed, slope resistant and road gravity) for determining four types of growth rules; spontaneous growth, new spreading growth, edge growth and road influenced growth (Silva and Clarke, 2002; Clarke and Gaydos, 1998). The advantages of SLEUTH based UGM are that it requires less input data and incorporates CA into the modeling process (Chaudhuri and Clarke, 2014; Bisht and Kothyari, 2001; White and Engelen, 2000; Wu, 1996; Batty and Xie, 1994). SLEUTH model was first applied to San Francisco Bay area (Clarke and Gaydos, 1998) and later had been used for the assessment and prediction of urban growth for many other urban areas in different countries. SLEUTH had been applied around the world especially in European countries where the urban sprawl is compact and in United States where the urbanization is distributed (Schneider and Woodcock, 2008; Ewing et al., 2003). Even though SLEUTH model is used to model the urbanization of developing countries like India, Iran, Malaysia and China, the model lacks in detecting the fragmented growth and small size built-up forms of these countries (Saxena and Jat, 2019).

Serasinghe Pathiranage et al., (2018) analyzed the land use/land cover trends in Matara City, Sri Lanka from 1980 to 2010 to assess the historic urban dynamics using SLEUTH based UGM. The study revealed that by 2030, 29 Grama Niladari Divisions (GNDs) out of 66 GNDs in the city will be totally converted into urban land. The study proved to be a useful planning tool to understand the near future urbanization of Sri Lankan cities. SLEUTH model was used to simulate and predict the urban growth and land use change for the Metropolitan City of Sana'a of Yemen for the period between 2004 and 2020 (Al-shalabi et al., 2013). The study found that the major urban growth occurred in agriculture areas and around unplanned areas outside township boundaries where no infrastructure facilities existed. This highlighted the lack of clear urban growth policy that could control and guides urban sprawl in the city.

2.2.5. Machine learning coupled Cellular Automata based models

Studying, understanding and modeling land use/land cover changes is important and can enable planners and policy-makers to manage the development and growth of a city in a sustainable way (Turner et al., 2007; Verburg et al., 2004; Agarwal et al., 2002). Land use/ land cover changes are influenced by many driving factors, including socioeconomic conditions, demography, landscape topography, physical infrastructure, and planning constraints and policies (Pijanowski et al., 2002; Dale et al., 1993). As a result, modeling the land use/ land cover process becomes challenging and can be expressed as being data-driven. In the last decade, advancements in data acquisition technologies and higher computation capacities have resulted in numerous research studies exploring data-driven approaches. Machine Learning (ML) is a data-driven approach that is successfully implemented in remote sensing (Friedl and Brodley, 1997; Bischof et al., 1992).

When CA based UGMs are used to model a complex geographical phenomenon like urban sprawl, it is important to define the transition rules of CA that determine the conversion of state of cells during the modeling processes (Liu, 2008). With many driving factors involved, there exists a non-linear relationship between driving factors and the prediction outputs, and it is difficult to obtain appropriate transition rules. A variety of mathematical methods were used to obtain the appropriate transition rules of CA. Although multi-criteria evaluation technique is used, it is still not efficient and reliable because the determination of parameters has certain subjectivity and introduces uncertainty into the UGM (Lai et al., 2013; Wu, 1998). Ou et al., (2019) highlighted that to overcome the uncertainties of CA, a series of ML algorithms have been proposed, such as Logistic Regression (LR), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Decision Trees (DTs), Random Forests (RFs), Genetic Algorithms (GAs) and Swarm-Intelligence (SI) algorithms.

Li and Yeh (2002) demonstrated that the ANN-based CA model can be successfully applied to land use change and urban expansion simulations, due to ANNs' strong self-adaptiveness, self-organization potential and ability to learn and replicate complex non-linear problems. In ANN, the basic processing elements are the neurons that are arranged in different layers and work in parallel to transform input data into output entities. The neurons in each layer are connected to the neurons in the next successive layer and each connection carries a weight (Atkinson and Tatnall, 1997). This arrangement of neurons in layers and the pattern of connection within and in between these layers are called ANN architecture. ANNs consist of layers and neurons which simulate the structure of human brains. The layers and neurons allow ANNs to have the learning and recall abilities like human, especially for non-linear mapping. ANNs can be well trained by using back-propagation learning algorithms (Mahajan and Venkatachalam, 2009). ANNs have been quite successfully employed to analyze and model geographical phenomena (Openshaw, 1998; Openshaw and Openshaw, 1997). Efforts have been made to integrate GIS and ANN with CA for minimizing the complexity of transition rules by providing linking among automatic transient neurons and parameter values generated automatically, which was rather difficult in traditional model (Guan et al., 2005; Pijanowski et al., 2002). However, the conventional ANNs are weak in global searching and fall more easily into local optima. Hence, improving conventional ANNs or developing a new tool to be coupled with the CA might offer better simulation precision (Zhou et al., 2017; Zhou and Civco, 1996; Wang, 1994).

In the past decade, deep learning has shown great success in image classification. ML based deep learning based methods attempt to model big data by using multiple processing layers, resulting in better representations from the input datasets (Ou et al., 2018). As one of the dominant methods of deep learning, Deep Belief Network (DBN) has excellent feature detection abilities. The DBN model was introduced by Hinton et al. (2006) for learning complex data patterns. It has become one of the extensively investigated and deployed deep learning architectures (Yu and Deng, 2011; Arel et al., 2010). DBN is a probabilistic multilayer neural network and is composed of several stacked Restricted Boltzmann Machines (RBMs) (Lopes and Ribeiro, 2015; Hinton et al., 2006). RBMs are used for the pre-train phase and then a feed-forward network for the fine-tune phase. DBNs are pre-trained using Greedy learning algorithm proposed by Geoffrey Hinton (2006) where each layer is trained at a time in an unsupervised manner. When compared to the conventional ANNs, DBN is more capable of interpreting complex structures, due to a number of hidden layers for the feature detection (Shen et al., 2015; Hinton, 2007). Furthermore, it is much easier to express the non-linear, complex structures of the data in deep hidden layers. Thus, the DBN overcomes ANN's local convergence problem effectively. DBN and ANN both employ ML approach, which is not dependent on fixed functional relationships and is able to handle complex non-linear functions without any a priori knowledge of variable relationships (Basse et al., 2014; Grekousis et al., 2013). DBN is a multilayer generative neural network along with a layer-wise learning algorithm, and it has been successfully implemented in dimensionality reduction (Hinton et al., 2006), time series forecasting (Chao et al., 2011) and digit recognition (Bengio et al., 2006). However, so far, only a few studies have been reported combining DBN with CA model to simulate land use change or urban growth.

The urban growth of Dongguan city, located in the Pearl river delta, South China was simulated using neural network coupled CA model for the year 2024 based on 2004, 2009 and 2014 datasets (Zhang, 2016). Socio-economic factors including distance to central city, distance to towns, distance to railway stations, distance to national road and distance to provisional roads were also taken into the modeling process. The study found that agricultural land and bare land were the main features converted to urban in the process of urban growth. The study further revealed that the new urbanization in the city will happen in the central and south-west area of the city owing to the convenient traffic and flat terrain. Neural network integrated CA model was used to simulate the urbanization of Athens metropolitan area between 1975 and 1991 (Grekousis et al., 2013). Urban growth boundary model combining ANN, GIS and remote sensing data was used to simulate the urban boundary of Tehran, Iran (Tayyebi et al., 2011). Several other datasets including distance to roads, built-up areas, service centres, green space, elevation and slope were also considered during simulation. The urban model was able to predict urban area with 80–84% accuracy. The model was used to predict urban growth of 2012 based on 1988 and 2000 historic datasets. These models can be used to assist planners in developing future urban growth boundaries. Li and Yeh (2002) demonstrated that neural networks can be conveniently integrated with CA for simulating multiple land use changes between 1988 and 2005 in Dongguan city, Pearl River Delta in southern China. The proposed method overcame some of the shortcomings of the currently used CA models in simulating complex urban systems and multiple land use changes by significantly reducing the tedious work in defining parameter values, transition rules and model structures.

Ou et al., (2018) explored the efficiency of implementing DBN to discover transitions rules of CA and the model was tested for Beijingtianjin-Hebei region, China, for the period 2005- 2015. The results indicate that the CA model based on DBN is a suitable tool for simulating multiple land use changes. DBN-based CA model was used to simulate the urban growth for Jiaxing City, Zhejiang Province, China, in 2000, 2008, 2015 and 2024 (Zhou et al., 2017). The study compared the prediction results with that of ANN-based CA and demonstrated the effective simulation ability of the DBN-CA for the study area.

2.3. Model Uncertainties

Accuracy of UGMs depends on the accuracy of input datasets and thus the uncertainties of UGM consist of four major components: uncertainty in model inputs, initial values, model structure, and uncertainty in the observations (Klepper, 1997). UGMs use remotely sensed data which contain uncertainty and error related to the sensor systems, processing, analysis and image processing software employed (Lunetta, et al., 1991). Also, the input data used in the prediction models contain positional errors and attribute errors (Yeh and Li, 2006). A huge volume of GIS data is usually used in urban growth models. Changes in scale, digitizing, conversion from raster to vector are possible sources of errors in model's input data. CA models, like other urban growth models are also subject to uncertainties due to limited human knowledge, complexity of urban environment and limitation of technology (Mustafa et al., 2015). Therefore, uncertainties are unavoidable and can affect the simulation accuracy of prediction outputs of CA (Yeh and Li, 2006). Models are representation of the real world and their structure can be source of uncertainty. Models calibrated for one region must be re-calibrated so as to be applied in other areas which would introduce further uncertainty into the prediction model. Figure 2.3 illustrates the propagation of possible errors from the initial stage of data input and how it gets propagated through the modeling process and its final impact on the prediction outputs.

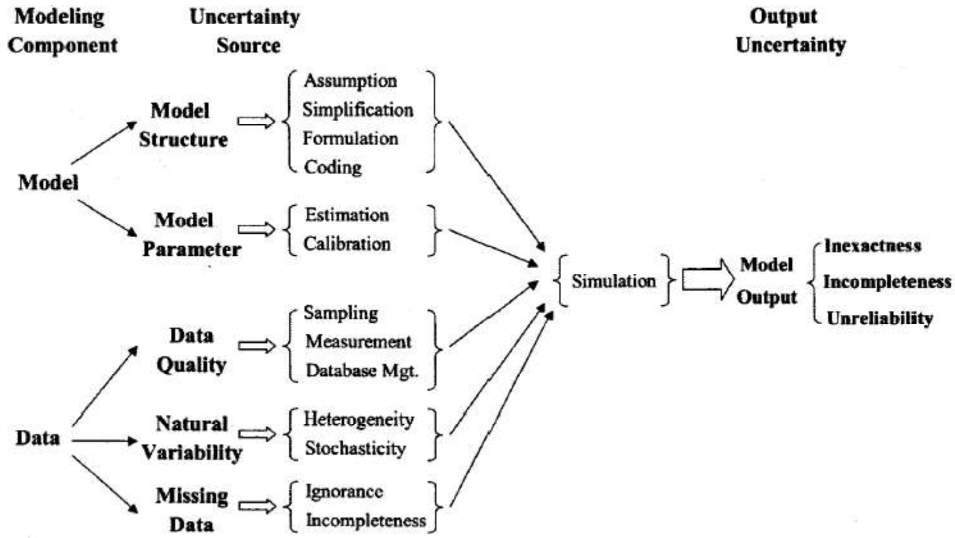


Figure 2.3. Sources of uncertainties in urban growth modeling (Wu and Li, 2006)

Understanding the impact of input parameter and model uncertainties on the prediction models is crucial for the successful use of any urban growth model (Ferchichi et al., 2018). Sensitivity analysis has been proved to be efficient and robust to find the most important sources of uncertainty on the prediction models output (Boulila et al., 2014). Screening method (Sánchez-Canales et al., 2012), differential analysis (Bettemier, 2010), variance-based methods (Ligmann-Zielinskaa and Sun, 2010), sampling-based methods (Helton et al., 2006) and a relative entropy-based method (Li et al., 2014) are some of the sensitivity analysis methods to quantify the uncertainties involved in the prediction models. Sampling based uncertainty analysis methods is one of the widely used methods that involve running the original model for a set of input and parameter combinations, and using the model outputs at those points to estimate model sensitivity (Pradhan and Kockelman, 2002). Such methods include the Monte Carlo and Latin Hypercube methods (Fishman, 1996), Fourier Amplitude Sensitivity Test (FAST) methods (McRae et al., 1982), reliability based methods (Bjerager, 1990), and response surface methods (Fedorov, 1983). Monte Carlo methods have been used in most cases for analysing uncertainty in complex urban systems. They involve random sampling from the distribution of inputs, and successive model runs until a statistically significant distribution of outputs is obtained (Pradhan and

Kockelman, 2002). Also, these methods are convenient to study error propagation when mathematical models are problematic to define (Yeh and Li, 2006).

2.4. Urban Growth modeling – Indian Scenario

Rapid urbanization is one of the most important factors for the loss of biodiversity after 1990 (Ramachandra et al., 2014; Sivaramakrishnan et al., 2005). Most of the rapid and uncontrolled urban growth occurs in less developed countries (Ginkel, 2008) and is particularly pronounced and more rapid than expected in India (Bhagat, 2011; Bhatta et al., 2010; Chakrabarti, 2001). This dynamically increasing urbanization has altered the natural landscape and has severe negative impacts on our environment and affect the standard of livings of humans (Mundia and Murayama, 2010; Berling-Wolff and Wu, 2004; Weber and Puissant, 2003; Pickett et al., 2001; Grimm et al., 2000). Poor environment, infrastructure and living conditions due to unplanned urbanization have been a major concern in metropolitan cities of India. Urban areas in India are relatively more heterogeneous due to the absence of proper land use planning, infrastructure development and proper funding. Availability of high resolution remote sensing data at regular intervals with the advancements in GIS based spatial analysis has proved to be highly efficient in identifying, measuring and quantifying spatio-temporal patterns of urban growth (Luo et al., 2008). Proper urban growth assessment and prediction can help policy planners in optimum land use planning, resource and fund allocation and optimum utilization of natural resources. However, monitoring urban land use change using the techniques of remote sensing and GIS and its subsequent modeling to arrive at a conventional approach is lacking in the context of India (Jat et al., 2008; Sudhira et al., 2003).

Tripathy and Kumar (2019) simulated the land use/land cover of Delhi between 1989 and 2014 based on CA model and the model predicted an increase in built-up area of 448 km^2 during the study periods. The land use/land cover change analysis based on satellite imageries during these periods exhibit 457 km^2 increase in urbanization in the city highlighting the efficiency of CA based urban growth models. Further, the CA model projected an increase in built-up area upto 708 km^2 in 2019 and 787 km^2 in 2024 in Delhi. The analysis shows that the rapid urban growth of the city has adverse effect on the habitat and may trigger critical risks to environment and ecosystem in Delhi. Hence, the study necessitates towards decentralization of urban functions and restoration of varied land use/land cover in order to regulate the future urban growth patterns for sustainable development.

Kumar et al., (2018) established a relationship between the urban sprawl of Pune city and its causative factors over a period of two decades using multivariate statistical technique. The results of their study show that built-up area of the city has increased from 43.22 km^2 in 1992 to 141.50 km^2 in 2011. The results of regression analysis depict that population density is the most significant variable for the urban growth pattern. It has also been found that the amount of built-up grew by 227.3% over the period of nearly 19 years and by 2051, the built-up area in the region would rise to 212.27 km^2, which would be nearly 50% more than the sprawl of 141.50 km^2 in 2011. Further, they highlighted that the growth pattern of the city would be influenced by other causal factors such as socio-economic change, future government investments corridors, development of small and medium towns around hinterland, industrialization, tourism initiatives, constrains of physical features, distances from major sites, etc.

The urbanization of two major IT and Tier I cities of India, Chennai and Hyderabad, was simulated using CA model integrated with fuzzy, Analytical Hierarchical Process (AHP) and Markov chain process during 1991-2013 (Bharath et al., 2017). The nature of urbanization was also assessed through the computation of Shannon's entropy. Results of analysis revealed an increase in urban area from 1.46% (1991) to 18.81% (2013) for Chennai region and 1.75% (1989) to 22.19% (2014) for Hyderabad region. The urban simulation model predicted urban growth of 36.6% and 51% in Chennai and Hyderabad in 2025 respectively. The spatial analysis revealed that the urbanization is fragmented or dispersed growth in the outskirts and compact in the core area. The study would aid policy makers in providing basic amenities and adequate infrastructure in rapidly urbanizing landscapes. Jat et al. (2017) predicted the urban growth of

Ajmer city of Rajasthan, using CA based SLEUTH model over 21 years from 1989 to 2009. The results showed that, the urban growth occurred rapidly in the north-east part of Ajmer. It further showed that the urban development in the city will be concentrated along the highways and the percentage of growth rate in terms of horizontal coverage would decrease through the year 2040 and the main reason could be the vertical growth in built-up activities like multi-storeyed housing in the city. Padmanaban et al. (2017) analyzed the land use/land cover changes of Chennai city, Tamil Nadu between 1991 and 2016 and implemented CA based model to simulate the urban growth of the city for 2027. The study found that urban growth in the outskirts of Chennai city is fragmented, with the transformation of vegetation cover and agriculture land into built-up settlements and reported that this alarming extent and level of urbanization will have adverse impacts on the natural resources and land of Chennai. The study also provides quantitative measures for urban planning and management authorities for mitigating social-ecological consequences of unplanned urban growth and preventing loss of urban ecosystem services.

Mishra and Rai (2016) integrated neural network with CA model to predict the urbanization of Patna district, Bihar in 2013 based on the land use/land cover maps of 1988, 2001. Based on the prediction results, the urban growth was simulated for the years 2038 and 2050 which revealed that the built-up areas in the region would decrease rapidly at the cost of agricultural lands. Mondal et al. (2016) implemented Markov chain based CA model to evaluate the fragmented uncontrolled urban expansion of Kolkata using 1990, 2001 and 2011 datasets to simulate the urban expansion of 2021. Landsat data of the study periods along with agents of urbanization including census data, socio-economic data including housing, employment data, land and house prices, development cost, transportation network, protected areas, river streams, and rail stations were also considered into the modeling process. Results provided evidences for the planning authorities to evaluate the effectiveness of spatial allocation and urban expansion trends and provide flexibility to modify the current allocation scenario.

Deep and Saklani (2014) used CA-Markov model to simulate the urban sprawl of Dehradun city between 2004 and 2014. The results suggest a continuous increase in urban settlement and a subsequent decrease in agriculture, forests and other natural vegetation covers. The study showed that there was an increase in the built-up area during 2009–2014 as compared to 2004–2009. The results clearly suggest that the mapping of urban sprawl can be an instrument of decision support system for policy makers to design urban expansion plans with an approach of sustainable habitat development. Mozumder and Tripathi (2014) developed an ANN based CA model to predict future impacts of urban and agricultural expansion on the uplands of Deepor Beel, a Ramsar wetland in the city area of Guwahati, Assam, India, for 2025 and 2035. The model outputs were compared with Guwahati Municipal Development Authority land demand as proposed for 2025 whereby the land demand as produced by the urban growth model was found to best match the projected demand. This study attempted to simulate the land use to explore the probable urban-agricultural growth, and its impact on the wetland. This study envisaged to support appropriate management strategies and policies for land use allocation around the periphery of the wetland, and utilization of the functionalities of a healthy ecosystem for the local population and possibly for ecotourism purposes.

Analysis of temporal and spatial changes of land use/land cover of Allahabad in 1990, 2000 and 2010 was carried out using agents-based CA model (Singh et al., 2015). DEM, drainage network and road networks were used in the modeling process. The Land Consumption Ratio (LCR) and Land Absorption Co-efficient (LAC) of the land use/land cover maps of the predicted land use/ land cover scenario for year 2020 provided useful inputs to the urban planners for effective management of the district and a direction for an effective land use policy making. Further suggestions for an effective policy making were also provided which could be used by government officials to protect the land resources. An integrated markov chains-CA model was used by Moghadam and Helbich (2015) to simulate the urban development of Mumbai during 2020-2030 based on the land use changes of the city between 1973 and 2010. Population, DEM and transportation network data were used as agents of urbanization of the city for the modeling process. The results of the analysis showed that the highest urban growth rates of 142% occurred between 1973 and 1990. The study further showed that areas most affected by this urbanization were open land and croplands and the urban growth model predicted that the increasing urban trend will continue upto 26% by 2020 and 12% by 2030.

Maithani (2009) demonstrated that the subjectivity in urban growth modeling and the calibration time can be reduced by using objective techniques like ANN. He implemented an ANN-based CA model to simulate the urban growth of Saharanpur city in Uttar Pradesh. Different feed forward ANN architectures were evaluated in this study and finally the most optimum ANN architecture was selected for future growth simulation.

Sudhira et al., (2004) studied the urban sprawl along the Mangalore, Udupi highway during 1971-1999 to identify and quantify the sprawl of the region using linear regression analysis model. It was found that the percentage change in built-up over the period of nearly thirty years was 145.68% and by 2050, the built-up area in the region would rise to 127.7 km^2, which would be nearly 106% growth in the change in built-up area to the current sprawl of 61.77 km^2.

2.5. Type and Distribution of urban sprawl

Understanding and analyzing the pattern of urbanization are useful for determining the current and future urban development pattern of a region (Ozturk, 2017). Urban sprawl is a complex phenomenon, which not only has environmental impacts, but also social impacts (Barnes et al., 2001). Due to its complexity, there is no specific, measurable and generally accepted definition of urban sprawl (Sutton, 2003). Also, the determination of degree and form of urban sprawl and understanding the reasons for urbanization are very important for the sustainable development of a city (Hassan and Lee, 2015; Jaeger and Schwick, 2014; Feng and Li, 2012; Marsousi and Lajevardi, 2011; Jat et al., 2008a). Hence, many attempts have been made to measure urban sprawl (Sudhira et al., 2004; Yeh and Li, 2001; Ewing, 1997) and many techniques have been used for measuring and mapping urban morphology and urban sprawl, including shape index, contagion index, Shannon's entropy, fractal analysis and Moran's I (Zeng et al., 2014; Bhatta, 2012). Shannon's entropy and fractal analysis are widely used in urban growth analysis models which use GIS and remote sensing data (Dewan and Corner, 2014). Shannon's entropy originated from information theory (Bailey, 2009; Jat et al., 2008) and can be used to measure the degree of spatial concentration and dispersion exhibited by geographical variable (Thomas, 1981; Theil, 1967). It is one of the most commonly used and one of the most reliable techniques for the determination of urban sprawl due to its robustness and easy application (Sarvestani et al., 2011; Verzosa and Gonzalez, 2010). Shannon's Entropy, when integrated with GIS, has proved to be a simple but efficient approach for the measurement of urban sprawl (Shekhar, 2004). A detailed insight on the calculation of entropy for identification of the type of urban sprawl is given by Cabral et al. (2013).

Shannon's entropy values characterize the pattern of built-up over time that can help officials to identify which area is being used inefficiently (Yeh and Li, 2001). It is an index that determines the distribution of built-up as a function of the area of built-up among 'n' spatial zones (Jat et al., 2008a). There are several spatial zone division approaches to calculate the entropy values. The most common are administrative boundaries (Li, 2012; Bhatta, 2009; Sudhira et al., 2003, 2004), circular buffer zones around the center (Hsieh, 2013; Sarvestani et al., 2011; Sun et al., 2007), pie sections (Bhatta et al., 2010) and a combination of circular buffers and pie sections (Alsharif et al., 2015; Ramachandra et al., 2012).

Shannon's entropy was used to quantify the degree of dispersion or concentration of built-up areas in the mountainous city of Baguio in northern Philippines (Verzosa and Gonzalez, 2010) and Calgary city of Alberta, Canada (Sun et al., 2007) together with remote sensing, GIS and photogrammetric techniques. These types of studies assist in monitoring the growth of built-up areas and in drafting measures and policies to address effect of urban sprawl. In Indian context, the type and distribution of urban sprawl using Shannon's entropy was implemented to study the urban sprawl of Tiruchirappalli city of Tamil Nadu (Rastogi and Jain, 2018), Rohtak city, Haryana (Singh, 2014), Gurgaon region, Haryana (Rajeev, 2016), Jorhat district of Assam (Deka et al., 2012), Hyderabad (Lata et al., 2001).

2.6. Conclusion

In this chapter, several literatures on urban growth models using CA had been reviewed in both global and Indian context. It could be seen that only a very few research works had been concentrated on developing machine learning based CA models for Indian cities especially for the capital city of Tamil Nadu, Chennai, India. In developing countries like India, there is an urgent need for sustainable urban development due to the alarming increase in urbanization. CA models can be used as a planning tool for developing alternative scenarios and the urban planner can take more rational and scientific decisions by looking at the various scenarios generated, thus providing a scientific basis for decision making and implementation. Machine learning technique based urban growth models has the potential to overcome the uncertainties present in the CA based models including transition rule determination, multi-criteria based suitability map preparation and difficulty in handling non-linear, huge voluminous dataset. These were the major motivations behind the research to develop machine learning based CA model for a pilot study on Sriperumbudur Taluk, Tamil Nadu and Chennai Metropolitan Area (CMA) to predict the urban development and to identify the nature of the urban sprawl. The present study also analyses the uncertainties of the model and input parameters which would be discussed in detail in the forthcoming chapters.

CHAPTER 3

MONITORING LAND COVER CHANGES

3.1. Introduction

Studies on urban growth prediction are gaining importance among the policy makers and urban planners as the urbanization of the cities are increasing at an alarming rate globally (Bhatt et al., 2017; Cohen, 2006). Total urban population of the state of Tamil Nadu has increased exponentially from 27.48 million (2001) to 34.92 million (2011) as per the Census of India (http://www.censusindia.gov.in/). Hence there arises a need to model the urban growth as any urbanization if unplanned would cause severe degradation to both humans and environment. To develop an urban growth model of a city, it becomes mandatory to understand the urban development pattern of the region which could be derived from time series land use/ land cover maps. The primary objective of this research is to model the urban growth of Sriperumbudur Taluk and Chennai Metropolitan Area and thus urban maps of these regions are used in the prediction modeling. In the absence of secondary data on periodic urban maps of the study areas at a relatively large scale like 1:25000, primary data generation on land cover maps with first level land cover classification specific for the current study became essential. The land use/land cover maps could be extracted from the remote sensing dataset which provide information regarding the evolution of the city both at spatial and temporal scales (Xia et al., 2019; Jat et al., 2008; Herold et al., 2002). In this context, the preparation of land cover maps becomes mandatory by making use of the high resolution temporal satellite data along with the sophisticated GIS based spatial analysis tools.

3.1.1. Use of GIS and Remote Sensing data in monitoring land cover/land use changes

In recent days, high resolution temporal dataset are available due to the advancements in the field of remote sensing. Remote sensing images are becoming an important source of spatial information for the study of urban areas. They help to detect the land use changes of a region (Serasinghe Pathiranage et al., 2018; Xiao et al., 2006; Ridd, 1995). The application of remote sensing includes resource mapping, land use change detection and analysis, urban planning and so on. In the case of urban planning, remote sensing data forms the major source of input for analyzing the urban sprawl of a region because based on the high resolution temporal dataset, land cover/land use maps can be generated which play a vital role in determining the urban characteristics (Thunig et al., 2011; Lo´pez et al., 2001). These remote sensing data can also be used in assessing the urban heat islands, air and water pollution and traffic congestion in an urbanized area. The field of remote sensing is ever developing that recently high resolution multi-spectral and hyper-spectral data, LiDAR (Light Detection And Ranging) have been developed which makes the urban prediction outputs more accurate (Dawood et al., 2017).

GIS has become an important component in urban planning as an analytical and modeling tool. It is useful in handling remote sensing dataset integrated with other secondary data to perceive detailed information regarding the land and its infrastructure. This information could be useful in monitoring an area to conduct the feasibility study for future urban development. The use of GIS in environmental planning is increasing as they help planners in visualization, analysis and modeling of the spatial data (Dhiman et al., 2018; Cetin, 2015). GIS could store, manipulate and analyze socio-economic data of a city which makes urban planning more feasible. The quantitative analysis and statistics of the existing land use of an area could be analyzed through the spatial analysis tools thereby the urban growth and its direction of expansion could be estimated and the historical development of the city can be studied (Alghais and Pullar, 2015). In India, the urban development is so complex that it demands immediate attention and planning (Sokhi and Rashid, 1999). Therefore, it is necessary for policy makers to integrate remote sensing with GIS based tools for urban planning and management.

Landsat imageries of moderate resolution are most widely used for the preparation of land use/land cover map of any region at large scale with its continued availability as free data (Hu et al., 2016; Tan et al., 2010; Yuan et al., 2005; Aniello et al., 1995). Landsat Thematic Mapper (TM) was launched on 1st March 1984 and is used for observing climate changes, agricultural practices, development and urbanization of cities, ecosystem evolution and increasing demand for natural resources (https://eos.com/landsat-5-tm/). Landsat TM consists of 6 spectral bands with spatial resolution of 30 meters for bands 1 – 5 and 7 and one thermal band (band 6). Landsat 8 is the eighth satellite in the series and was launched on 11th February 2013 with two main sensors: the Operational Land Imager (OLI) and TIRS (Thermal Infrared Sensor) with spatial resolution of 30 meters (OLI multispectral bands (bands 1 – 7, 9)), 15 meters (OLI panchromatic – band 8) and TIRS bands (bands 10, 11) collected at 100 meters resolution. The spectral bands of the OLI sensor was enhanced from the previous landsat instruments with the inclusion of two additional spectral bands, a deep blue visible channel (band 1) for water resources and coastal zone investigation and shortwave infrared channel (band 9) for the detection of cirrus clouds (https://landsat.gsfc.nasa.gov/landsat-data-continuity-mission/).

3.1.2. Image Classification techniques

Image classification is the process of assigning predefined land cover categories to satellite imageries. Typically, remote sensing based image classification techniques can be broadly classified into

1. Unsupervised image classification
2. Supervised image classification

Unsupervised classification finds the spectral classes or clusters in a multi-spectral image without user intervention. It is the most basic technique to classify an image as it does not require training samples to be generated for the classification process. The final classification image is the result of groupings of pixels with common characteristics based on the analysis of the image. In unsupervised classification, the algorithm first groups the pixels into 'clusters' based on their spectral properties and assigns classes to each of those clusters. The algorithm uses techniques to group the related pixels into clusters depending on the user defined number the classes the classified image should contain (Tzotsos and Argialas, 2008). However, it is important for the user to have knowledge of the area being classified when the algorithm groups pixels with common characteristics. K-means, ISODATA clustering algorithms are widely used to classify the remote sensing images using unsupervised classification.

In supervised classification, the user selects the representative samples for each pre-defined land cover/land use categories. Supervised classification uses the spectral signatures obtained from training samples to classify an image. The algorithm then uses these 'training sites' and applies them to the entire image. Supervised classification uses the spectral signature defined in the training set (Keuchel et al., 2003). For example, it determines each class on what it resembles most in the training set. Supervised classification is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites are selected based on the knowledge of the user. The common supervised classification algorithms used to classify remote sensing data are minimum-distance to mean, maximum likelihood and Mahanabolis distance and recently developed algorithms including Artificial Neural Network, Support Vector Machine (SVM), Decision Tree classifiers etc. In this current research, the land cover maps of the study regions from the remote sensing datasets are classified using SVM algorithm of supervised classification technique.

The main objectives of this chapter are

- Using multi-temporal Landsat imageries of Sriperumbudur Taluk (for the pilot study) and Chennai Metropolitan Area (the main study area of this research) to prepare the land cover maps, which form the main inputs for the urban prediction modeling

- To quantitatively assess the changes of land cover categories of these two regions during the study periods

3.2. Study Area and Dataset Used

3.2.1. Sriperumbudur Taluk

In India, each state is divided hierarchically into number of districts, taluks and revenue villages for the purpose of administrative activities. In this research, Sriperumbudur Taluk (Fig. 3.1) was chosen for the pilot study to predict the urban growth of CMA which would be discussed in the following chapters. The main objective of this research (as discussed in Chapter 1) was to develop an appropriate UGM for CMA. Since, Sriperumbudur taluk lies in close proximity to Chennai district, the taluk was selected for the pilot study. Also, the taluk is nested with many automobile based industries which provide employment opportunities both to the residents of the taluk and the Chennai district. Hence, it was appropriate to choose Sriperumbudur taluk for the pilot study as urbanization of Chennai is influenced by the urban development of this taluk also. The taluk is located in the Kancheepuram district of southern state of Tamil Nadu. Geographically, the taluk extends to an area of 645 km^2 and lies between 12° 58' 25.6080" N latitude and 79° 56' 28.7880" E longitude. As per the 2011 census, the taluk had a population of 4,86,000. In the year 1999, Hyundai Motor Company commenced the automotive industries in Sriperumbudur and since then the taluk has seen tremendous industrial growth. The accelerated growth in industries is mainly due to the fact that the taluk lies in the neighbourhood, approximately 40 km from Chennai.

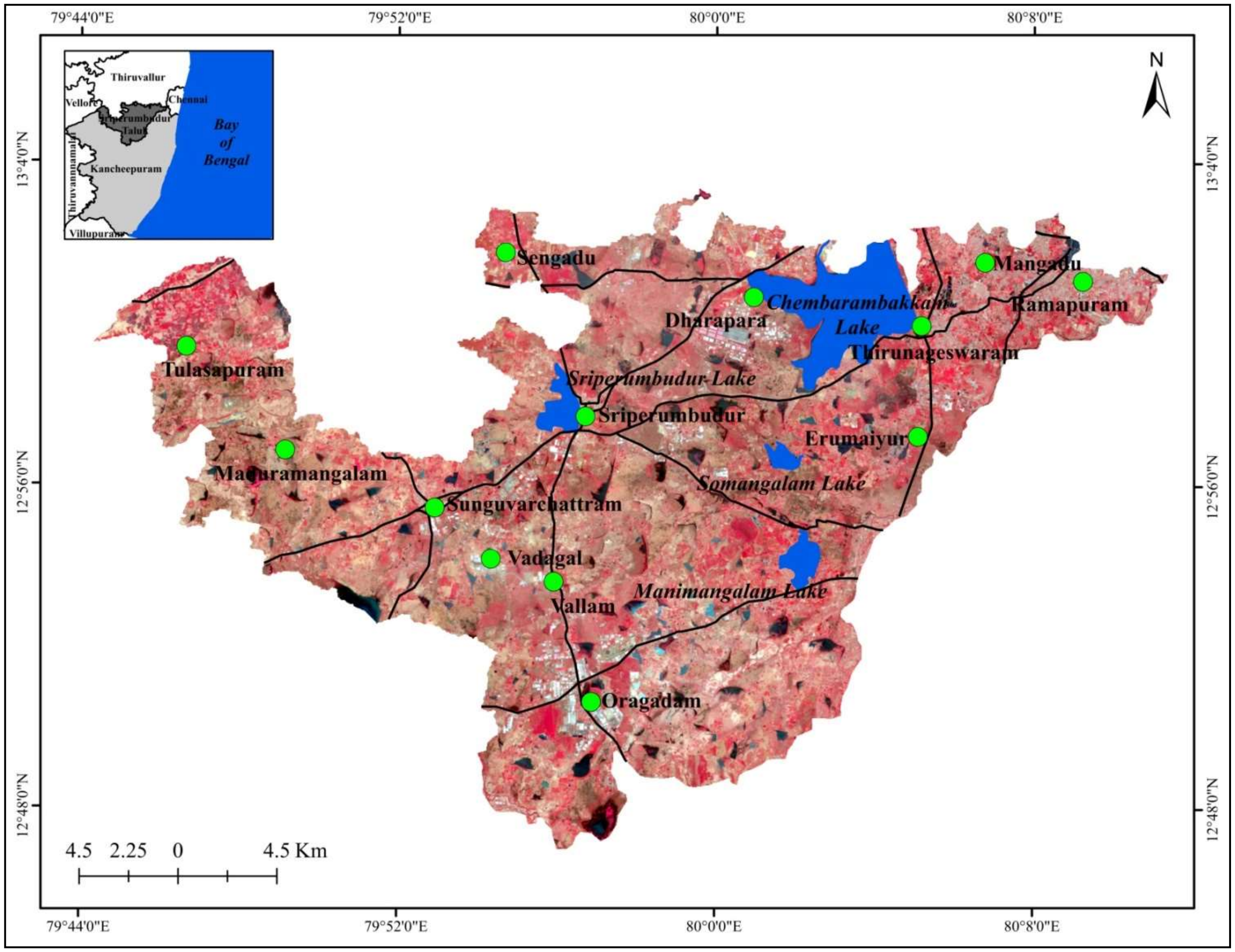


Figure 3.1. Map of Sriperumbudur Taluk

Apart from the industrial development, the location of the taluk on the Chennai-Bengaluru highway, establishment of Information Technology (IT) centres had also led to the fast development of the study region (The Growth story of Sriperumbudur Real Estate, 2013). Agriculture is the main occupation of the residents of the taluk and due to the recent industrial developmental activities in the study region, the agricultural lands had been converted into openland suitable for residential or industrial activities. Chembarambakkam Lake, the main source of water to the residents of Chennai city and Sriperumbudur, Manimangalam and Somangalam lakes are located in the taluk.

Kancheepuram district is also referred to as 'Temple Town' and Sriperumbudur is believed to be the birthplace of Saint Ramanuja and many pilgrimages are located in the study region which attracts thousands of pilgrims from the state as well as from other parts of the country and the taluk serves as a tourist spot also. Apart from the Sriperumbudur Taluk Headquarters, the major locations in the taluk include Oragadam, Mangadu, Ramapuram where settlements are increasing at a rapid pace due to the employment opportunities available in the taluk. Further the proposal made by the Government of Tamil Nadu for the Greenfield airport in Sriperumbudur by the year 2027 will further accelerate the growth of the taluk in the upcoming years (https://centreforaviation.com/data/profiles/newairports/new-chennai-sriperumbudur-airport).

To model the urban growth of the taluk, the following spatial parameters were used considering the nature of urban development in the area.

1. Urban maps of 2009, 2013 and 2016 were derived using satellite images of Landsat 5 TM of 6th May 2009 and Landsat 8 data of 17th May 2013 and 23rd April 2016 (https://earthexplorer.usgs.gov/).
2. Transportation data including road networks and major road junctions of the taluk available from the Openstreet data (http://www.openstreetmap.org/) were updated using Google Earth and used in the prediction modeling

3. SRTM (Shuttle Radar Topography Mission) DEM (Digital Elevation Model) of 1 arc-second (~30 m) resolution
4. Categories of industries were obtained from Government of India MEPZ (Madras Export Processing Zone) Special Economic Zone (http://www.mepz.gov.in/Directory_SEZ.php?page=18&District=&Entity=&SEZ=&Unit=)

3.2.2. Chennai Metropolitan Area

Chennai, the capital state of Tamil Nadu, is India's fourth largest metropolitan cities after Mumbai, New Delhi and Kolkata. CMA falls under three districts including Chennai and parts of Thiruvallur and Kancheepuram districts and is located on the Coromandel Coast (Fig. 3.2). It extends over an area of 1189 km^2. As per Chennai Metropolitan Development Authority (CMDA), 176 km^2 area of Chennai district, 637 km^2 of Thiruvallur district including Ambattur, Thiruvallur, Ponneri and Poonamallee taluks and 376 km^2 of Kancheepuram district comprising Tambaram, Sriperumbudur and Chengalpattu taluks constitute CMA (http://www.cmdachennai.gov.in/index.html). Chennai is the most densely populated city in Tamil Nadu, with a density of 26,553 people per km^2. Chennai is the largest commercial and industrial centers of South India as well as a cultural, economic, educational and IT centres attracting large number of migrants to the city. After 2010, due to rapid growth of industrialization, especially textiles and tanneries industries, the rate of migration toward Chennai city had increased to multiple folds. Majority of Chennai's economy is based on the automobile sector, software services, hardware manufacturing, healthcare and financial services. It is also known as 'Detroit of India' with thriving automotive industries.

Chennai district has a coastal length of 19 km and CMA has a total coastal length of 46 km. Famous beaches in Chennai are Marina, Elliot's or Besant Nagar, Thiruvanmiyur beaches of which Marina beach is the world's second longest beach and it attracts number of tourists every year. Chennai is well connected to other cities through its developed transportation networks. Chennai central is the main terminus railway station and is adjacent to Chennai Egmore, another major railway junction. One of the fastest growing railway hubs is

Tambaram railway station and is located in the southern region of the study area. In addition, the city has also recently commenced its metro rail service, a rapid transit system, in 2015. The city has an international airport located at Meenambakkam about 14 km from the Chennai city center. Three major rivers namely Kosasthalaiyar, Cooum and Adyar pass through CMA and major lakes including Sholavaram Lake, Puzhal Lake and Chembarambakkam Lake are situated within the CMA which serve as the major source of drinking water.

Due to the boom in industrial, automobile, electronic and entertainment sectors, the study region has experienced rapid urbanization over the past two decades (Second Master Plan for Chennai Metropolitan Area, 2008). For better administrative purposes and efficient urban development planning, Housing and Urban development department of Tamil Nadu (2018), had planned to extent the area of CMA to 8878 km^2 including the entire districts of Thiruvallur, Kancheepuram and Arakkonam and Nemili Taluks in Vellore district. Following datasets were used in the urban modeling of CMA.

1. Urban maps of 2010, 2013 and 2017 were derived using 15 meters resolution (Multispectral PAN merged) satellite images of Landsat 7 ETM of 2nd June 2010, Landsat 8 OLI of 17th May 2013 and 25th March 2017 respectively (https://earthexplorer.usgs.gov/). The panchromatic band (band 8) of 15 meters is merged with the 30 meters multi-spectral bands to generate the pan sharpened images of CMA. Pan sharpening is an image processing technique where higher resolution panchromatic image is merged with lower resolution multi-spectral imagery to obtain a single higher resolution image. Pan sharpening refers to increasing the spatial resolution of the multi-spectral image for a better visualization. Various image processing algorithms are available to pan sharpen the multi-spectral data including Brovey, Intensity-Hue-Saturation (IHS), Esri, Gram-Schmidt transformations (Rahaman et al., 2017)
2. Locations of industries within the study area were obtained from Government of India MEPZ (Madras Export Processing Zone) Special Economic Zone

(http://www.mepz.gov.in/Directory_SEZ.php?page=2&District=Chennai&Entity=SEZ%20Unit&SEZ=&Unit=)

3. Places of public interests, public utility centers, road and railway networks and road junctions derived from (http://www.openstreetmap.org/) were updated using Google Earth
4. Population data for each revenue villages within CMA were obtained from Directorate of Census Operations, Government of Tamil Nadu (http://www.census.tn.nic.in/)
5. Land values were obtained from Guideline Value and Property Valuation of the Registration Department, Government of Tamil Nadu (http://www.tnreginet.net/guideline_value.asp)
6. Apart from the field knowledge about the study area, Google Earth was used for the validation of urban maps of CMA during the study periods

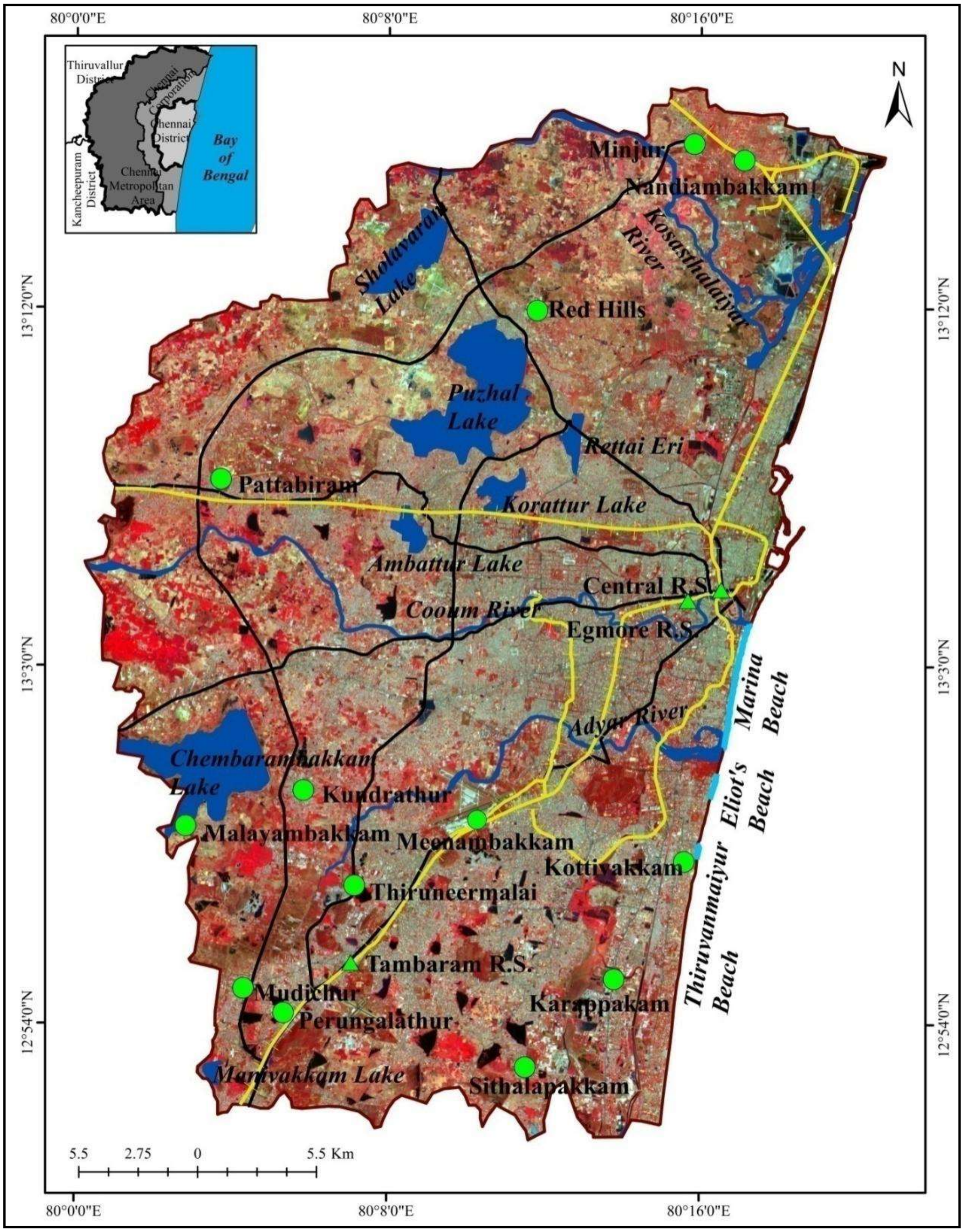


Figure 3.2. Map of Chennai Metropolitan Area

3.3. Land Cover Mapping and Monitoring

Support Vector Machine (SVM) technique is a supervised classification technique used in the preparation of land use/land cover maps from the remote sensing images (Pal and Mather, 2003; Huang et al, 2002). They are based on Statistical Learning Theory and are widely used in the image processing field because they are robust, accurate and are effective even when using a small training sample. SVMs function by nonlinearly projecting the training data in the input space to a feature space of higher (infinite) dimension by use of a kernel function. This results in a linearly separable dataset that can be separated by a linear classifier. This process enables the classification of remote sensing datasets which are usually non-linearly separable in the input space. In many instances, classification in high dimension feature spaces results in over-fitting in the input space, however, in SVMs over-fitting is controlled through the principle of structural risk minimization (Cortes and Vapnik, 1995). The risk of misclassification in SVM is minimized by maximizing the margin between the data points and the decision boundary (Mashao, 2004). The functions used to project the data from input space to feature space are sometimes called kernels (or kernel machines), examples of which include polynomial, Gaussian (more commonly referred to as radial basis functions) and quadratic functions. Each function has unique parameters which have to be determined prior to classification and they are also usually determined through a cross validation process. Detailed reviews on SVMs are given by Christianini and Schölkopf (2002), Campbell (2000).

Jiménez et al. (2018) assessed the performances of SVM, Maximum Likelihood Classification (MLC) and Artificial Neural Networks (ANNs) in classifying the land cover/land use of the metropolitan area of Tepic-Xalisco, located in the central part of the state of Nayarit, Mexico. The results suggested that the SVM based classification offered greater certainty on the distribution and quantification of the different land covers of the study region. The land cover of Gwinnett County, a suburban county at north-eastern Atlanta metropolitan area, Georgia, USA was classified through SVM technique (Shi and Yang, 2015). The study highlighted the efficiency of SVM technique and suggested that the accuracy of land use/land cover maps improve significantly especially for spectrally and spatially complex land cover categories. Bahari et al. (2014) classified the land covers over Klang valley, Malaysia using SVM technique and it was able to perform the land cover classification with high accuracy without any pixel being unclassified indicating that image classification based on SVM is a promising and reliable tool.

3.3.1. Sriperumbudur Taluk

The land cover maps of Sriperumbudur Taluk during 2009, 2013 and 2016 were prepared using SVM classification technique (Huang et al., 2002) with four land cover categories including built-up, vegetation, water body and openland (Fig. 3.3). The classification accuracies of land cover maps prepared using SVM technique were given in Fig. 3.4. Fig. 3.5 shows that the built-up areas were increasing in the taluk since 2009. The urbanization of 2009 almost quadrupled in the year 2016. Since the objective of the research focuses on modeling only the urban growth of the region, the contribution of other land cover categories to the built-up category in 2016 was analyzed (Fig. 3.6). Based on the land cover maps of the region, it is revealed that 28.99 km^2 of built-up observed in 2009 continued to be in the built-up category in the upcoming years 2013 and 2016.

The major contribution of urbanization in 2016 comes from the openland category of 2009. Around 34.87 km^2 area of openland of 2009 had been urbanized in 2013 itself and it remained urban in 2016. It could be seen that the openland around the already urbanized regions of 2009 were urbanized in the year 2013. Due to the industrial development, regions around Oragadam, Sriperumbudur were urbanized since 2013 in the region. Ramapuram, Mangadu located in close proximity to Chennai city also experienced rapid urbanization in the taluk.

Table 3.1. Change detection of land cover categories during the study periods in Sriperumbudur Taluk

Land Cover Categories	Area (sq.km.) in			Change in area (sq.km.) between		
	2009	2013	2016	2009 and 2013	2013 and 2016	2009 and 2016
Vegetation	105.63	109.19	252.18	+ 3.56	+ 142.99	+ 146.55
Waterbody	41.34	27.84	62.92	- 13.50	+ 35.08	+ 21.58
Openland	469.45	433.91	217.16	- 35.54	- 216.75	- 252.29

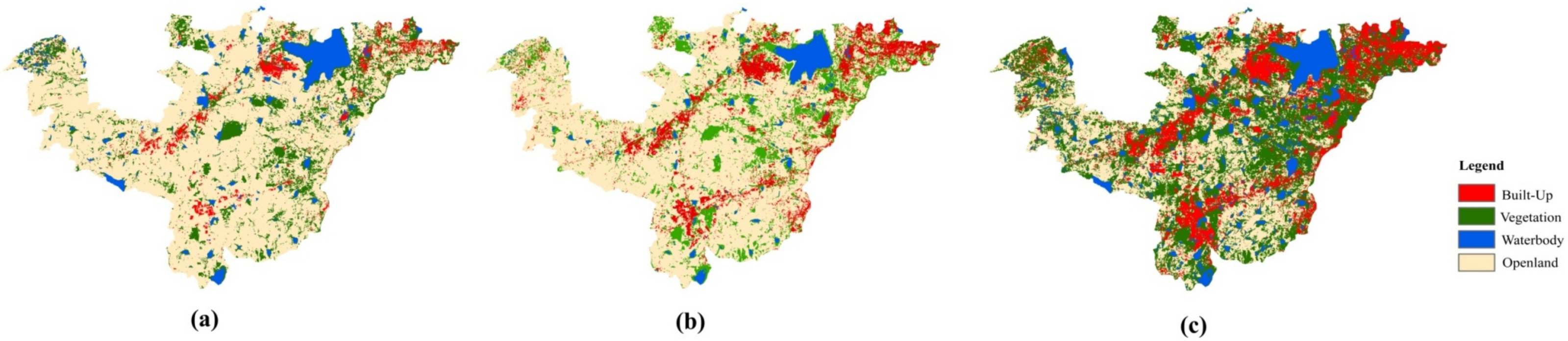


Figure 3.3. Land Cover Maps of Sriperumbudur Taluk during the study periods. (a) May 2009; (b) May 2013; (c) April 2016 (Increased vegetation observed in 2016 was mainly due to the occurrence of flood in December 2015).

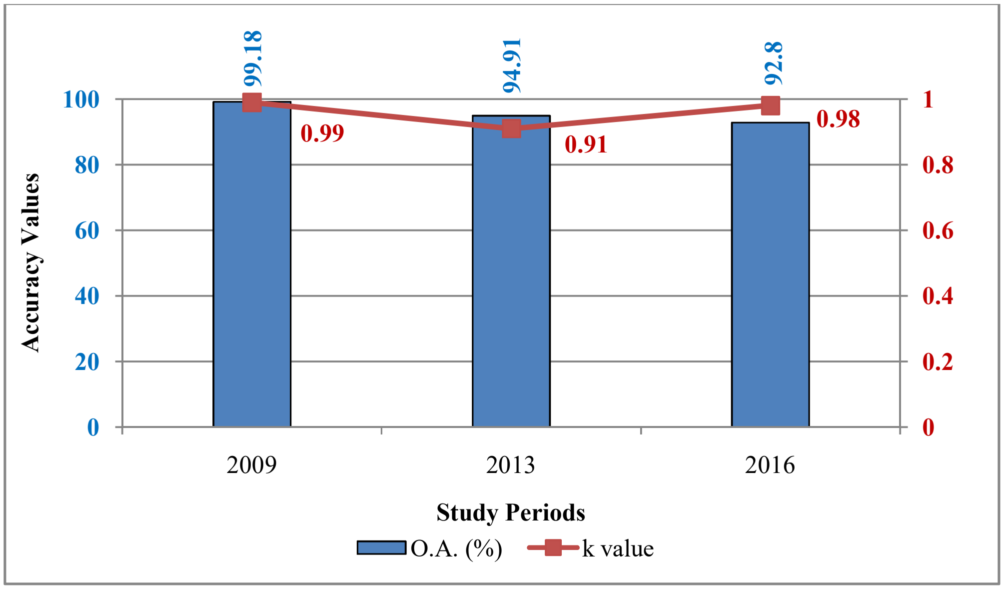


Figure 3.4. Accuracies of land cover maps of Sriperumbudur Taluk based on SVM technique

The second major contribution to the urban development of 2016 was from the vegetation category of the region. It is important to note here that the vegetation land cover category in this analysis includes agricultural lands, farmlands, cultivated and vegetated areas. In 2009, 105.63 km^2 of area was mapped as vegetation in Sriperumbudur Taluk which increased to 109.19 km^2 in 2013 and 252.18 km^2 in 2016 (Table 3.1). This sudden increase in the vegetation category in the year 2016 could be attributed to the massive flood occurred in Chennai between 8th November and 14th December 2015 (Seenirajan et al., 2017). Kancheepuram district, where Sriperumbudur taluk is located, received heavy rainfall during the flood and in addition to that, the excess water released from Chembarambakkam lake, one of the main sources of water supply, resulted in severe inundation. Hence, it could be the reason for the sudden increase of vegetation in 2016 (252.18 km^2) and also for the steady increase of water body from 41.34 km^2 in 2009 to 62.92 km^2 in 2016. In Sriperumbudur Taluk, many agricultural lands, farmlands, openland were urbanized due to rapid urbanization. Around 4.09 km^2 area of openland in 2009 were classified as vegetation in 2013 which further became urbanized in the year 2016 and 2.97 km^2 area of vegetation of 2013 became urbanized in 2016.

The urban growth of the taluk was mapped to be 28.99 km^2, 74.48 km^2 and 113.16 km^2 in 2009, 2013 and 2016 respectively. Between 2009 and 2016, the region experienced increased urbanization of 84.17 km^2 area within 7 years. The urban growth in 2016 was contributed mainly from the openland category (51.61%) of 2009 and 48.39% of urbanization was attributed from the vegetation land cover category of 2009. Further the analysis reveals that 200.89 km^2 area remained openland since 2009 and around 45.66 km^2 area continued to be in the vegetation category during the entire study periods. The prediction of urbanization of Sriperumbudur Taluk in 2016 was carried out in two scenarios: one scenario included hotspots in the urban map of 2013 and the other without hotspots in the urban map of 2013 which would be discussed in detail in Chapter 4.

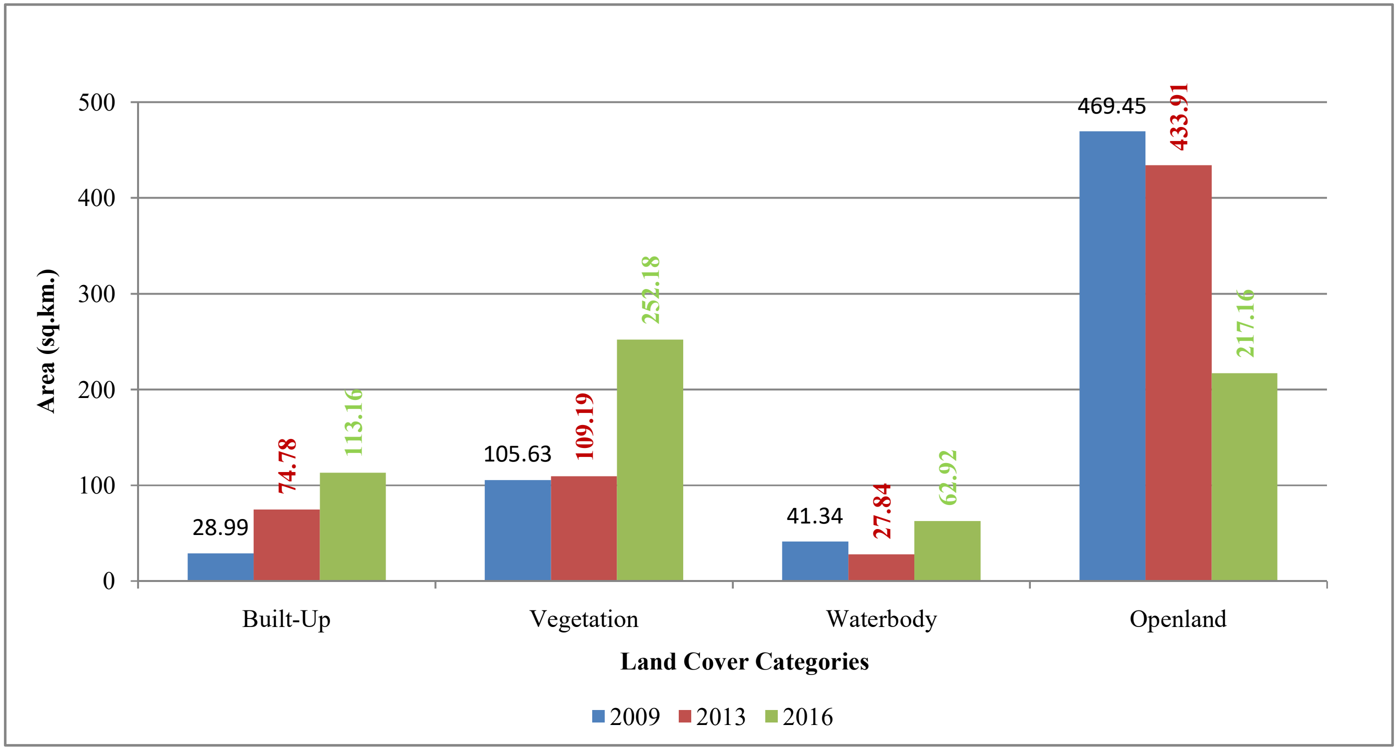


Figure 3.5. Estimates of land cover categories of Sriperumbudur Taluk during the study periods

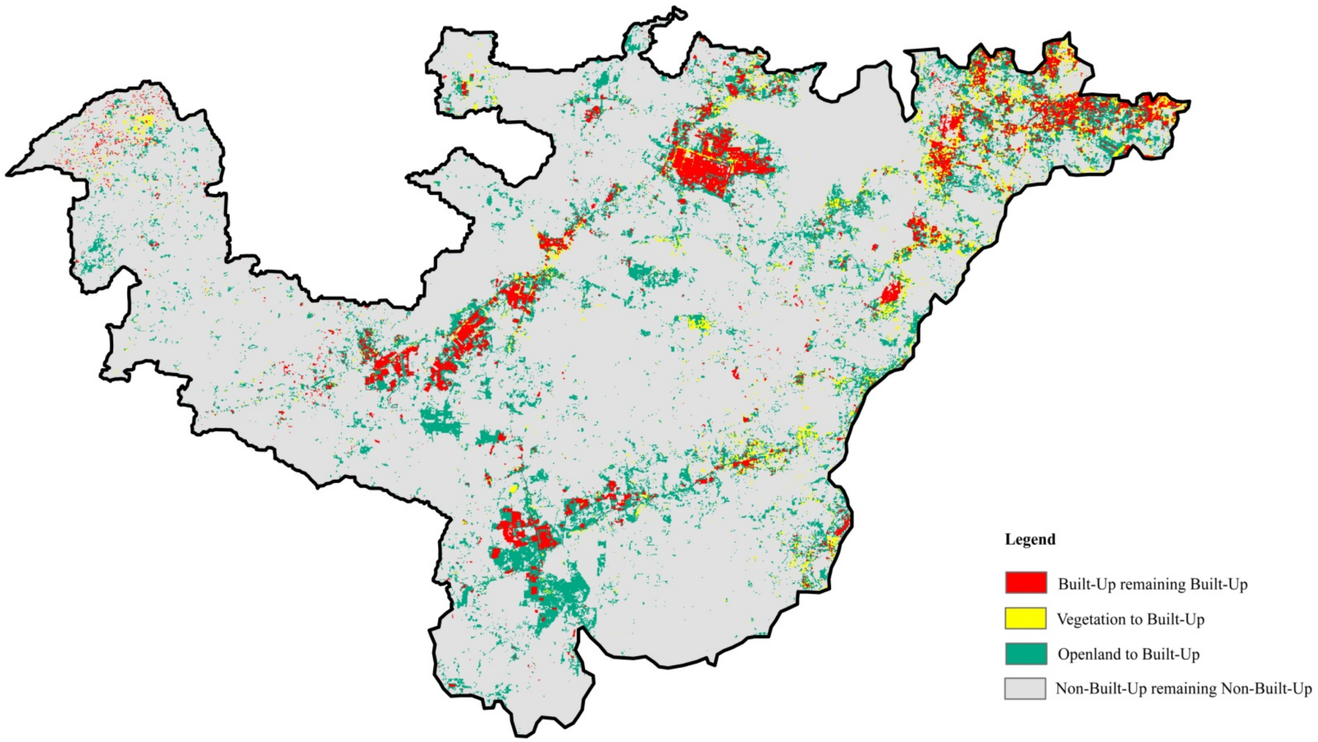


Figure 3.6. Non-Built-Up land cover categories of 2009 and 2013 contributing to urbanization of Sriperumbudur Taluk in 2016

3.3.2. Chennai Metropolitan Area

The land cover maps of CMA for the years 2010, 2013 and 2017 prepared using SVM technique (Fig. 3.7) show that the urbanization of 2010 had doubled in 2017. Fig. 3.8 shows the classification accuracies of the land cover maps prepared using SVM technique. The urban growth of the study region was increasing since 2010 (Fig. 3.9). Migration of people to the city in search of employment and educational opportunities, lifestyle changes had made CMA the fourth most populous metropolitan city in India after Delhi, Mumbai and Kolkatta (Sekar and Kanchanamala, 2011) which is evident from the increase in the land prices since 2010 as per the Guideline Value and Property Valuation of the Registration department of Tamil Nadu (http://www.tnreginet.net/guideline_value.asp). Rapid urbanization, establishment of IT centres, availability of socio-economic amenities including hospitals, educational institutions, recreational centres, religious centres and so on had made the city brimming with urban growth (Bhatta, 2010). The urbanization in 2010 (237.41 km^2) remained built-up in 2013 and 2017 also. The openland of 2010 (97.21 km^2) contributes mostly to the urbanization in 2017. Since CMA experiences rapid urban growth, the available openland are utilized for human settlements. Areas outside Chennai Corporation including Pattabiram, Sithalapakkam, Kottivakkam are undergoing rapid urbanization in CMA. Fig. 3.10 shows vegetation, waterbody and openland land cover categories of 2010 and 2013 converted to the built-up in 2017.

Table 3.2. Change detection of land cover categories during the study periods in CMA

Land Cover Categories	Area (sq.km.) in			Change in area (sq.km.) between		
	2010	2013	2017	2010 and 2013	2013 and 2017	2010 and 2017
Built-Up	237.41	400.57	572.11	+ 163.16	+ 171.54	+ 334.70
Vegetation	370.56	375.62	170.71	+ 5.06	- 204.91	- 199.85
Waterbody	97.85	71.88	69.14	- 25.97	- 2.74	- 28.71
Openland	480.70	338.45	374.57	- 142.25	+ 36.12	- 106.13

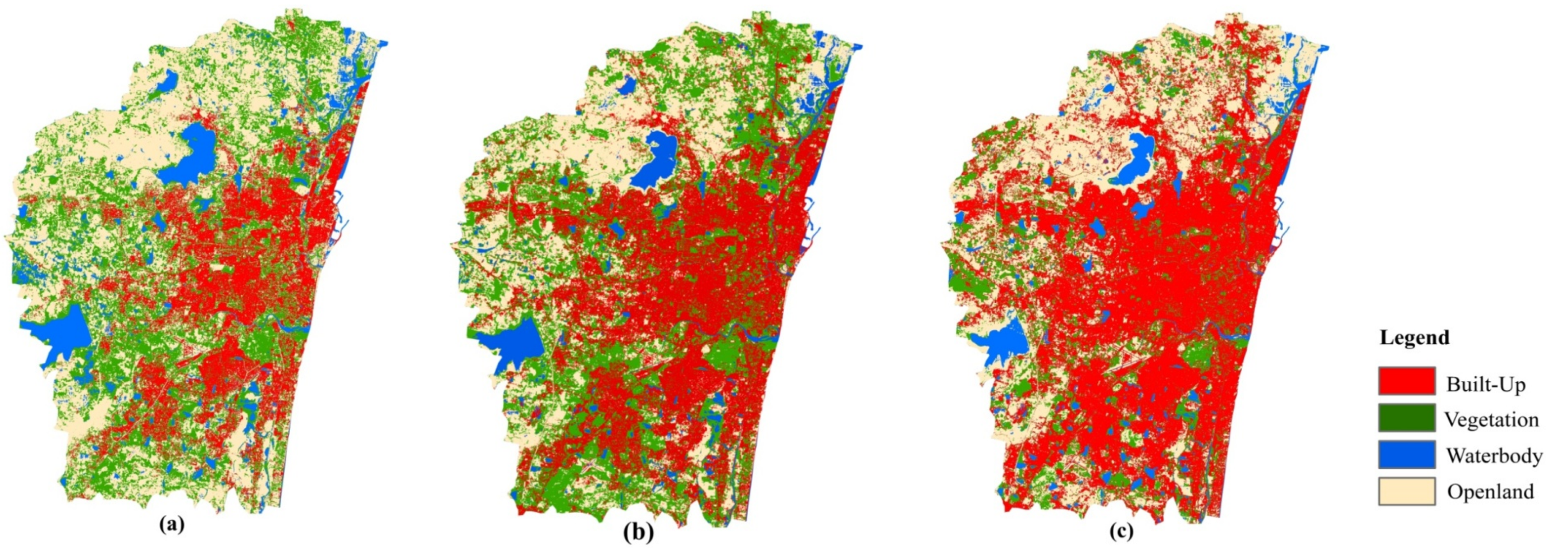


Figure 3.7. Land Cover Maps of Chennai Metropolitan Area during the study periods. (a) June 2010; (b) May 2013; (c) March 2017

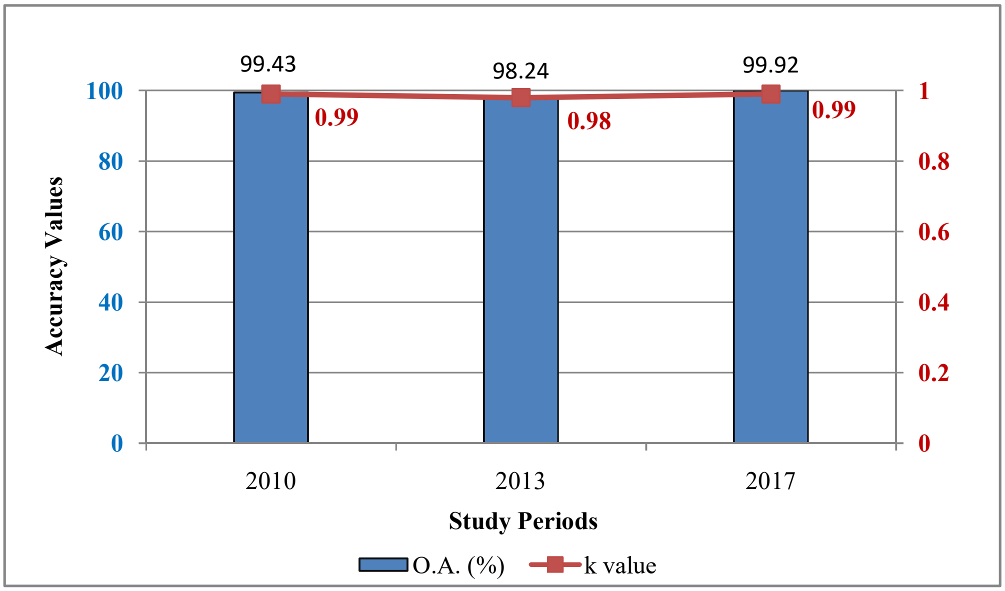


Figure 3.8. Accuracies of land cover maps of Chennai Metropolitan Area based on SVM technique

Area of 81.21 km^2 remained under vegetation category in 2010 and 2013 were urbanized in 2017. Of which, about 66.7 km^2 of vegetation of 2010 were converted to urban in the year 2013 itself. Vegetation land cover mostly found associated with the built-up areas in Perungalathur, Red hills, Karapakkam were urbanized in 2017. Most of the agricultural lands were converted to built-up regions to accommodate the rise in population of the study region. Similarly openland of 2010 accounting to 38.64 km^2 of area was converted to vegetation in 2013. This in turn was occupied by settlements in 2017. About 10.11 km^2 of vegetation in 2010 were converted to openland in 2013. One of the reasons could be the clearance of agricultural/ vegetated lands for future built-up activities. These land cover categories were urbanized in 2017.

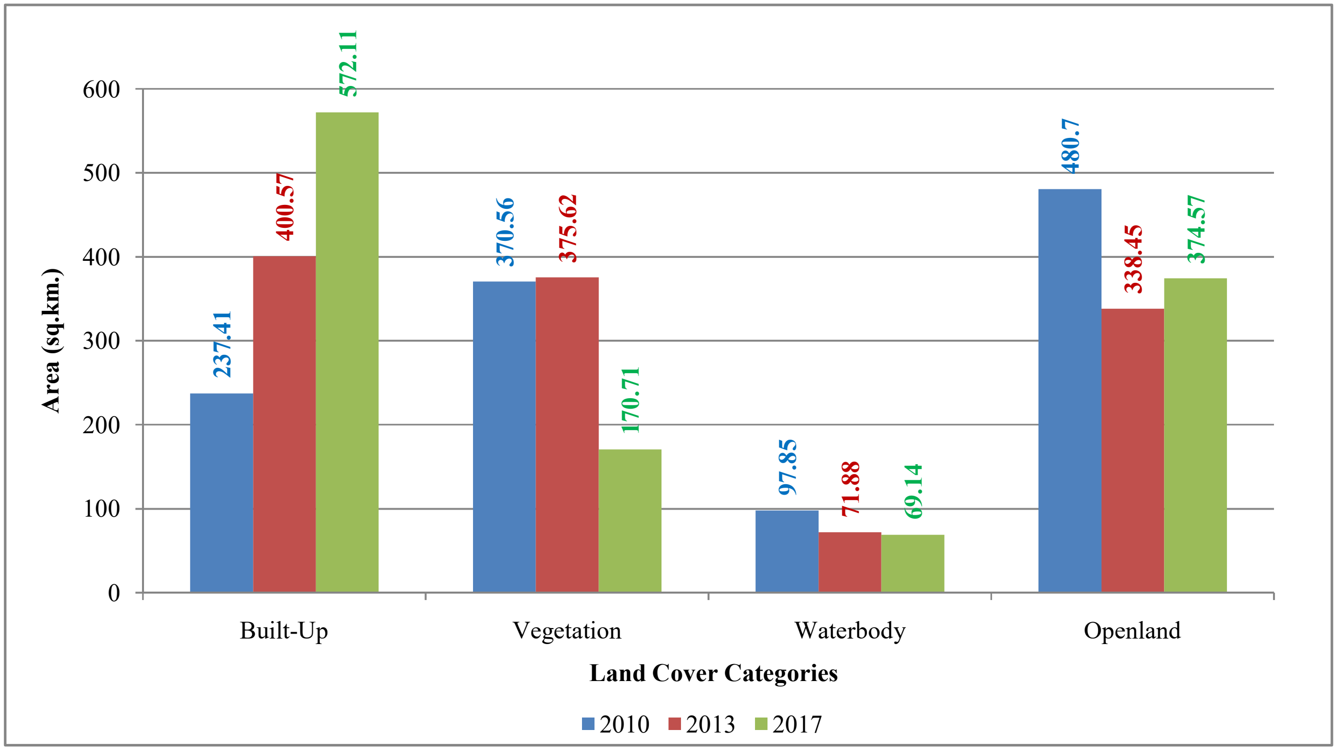


Figure 3.9. Estimates of land cover categories of Chennai Metropolitan Area during the study periods

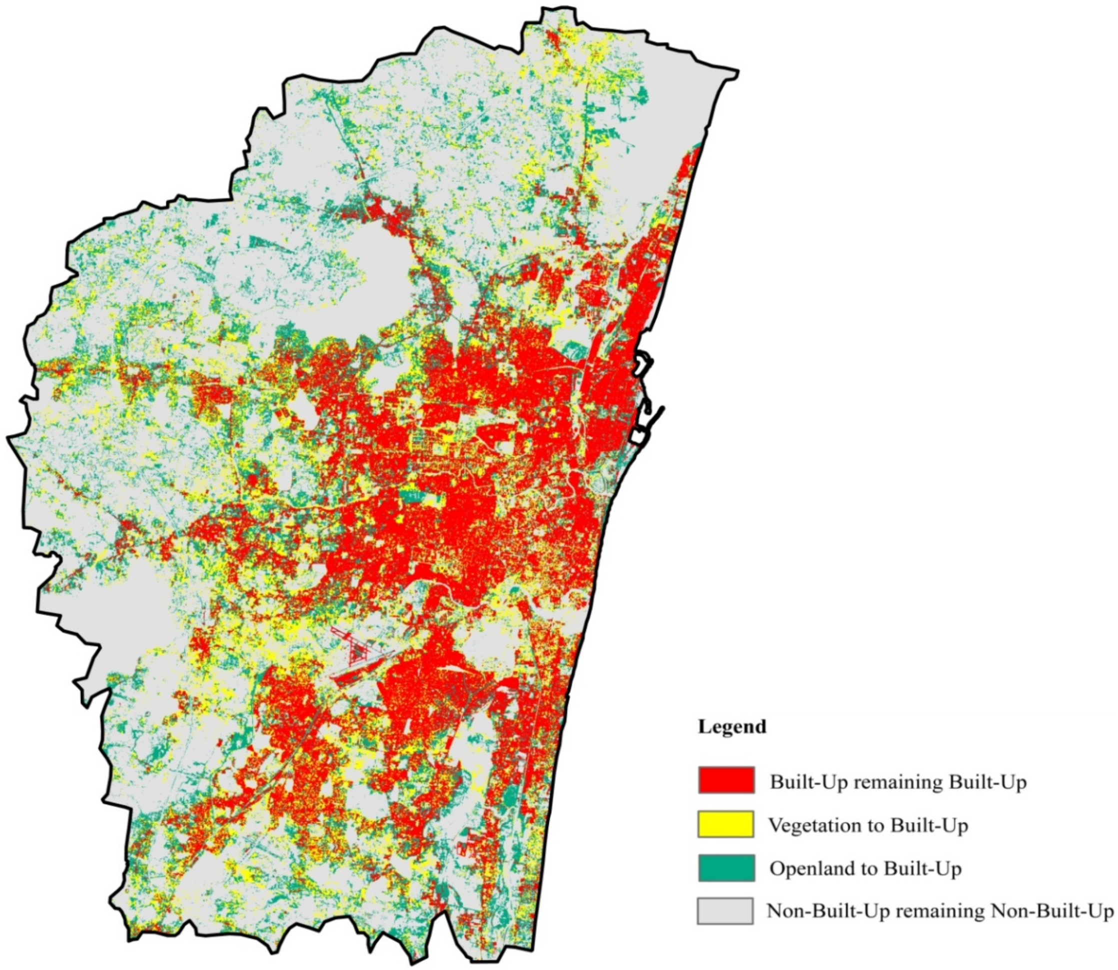


Figure 3.10. Non-Built-Up land cover categories of 2010 and 2013 contributing to urbanization of 2017 in Chennai Metropolitan Area

The urbanization of CMA in 2017 was mapped to 572.11 km^2 of which 237.41 km^2 of built-up of 2010 remained built-up in 2017. The further increase of urbanization accounting to 334.7 km^2 occurred within a span of 7 years from 2010 to 2017. Of which around 56% of urban growth was associated with the openland of 2010 and 44% of the vegetation category got converted to built-up areas in 2017. This highlights the fact that openland followed by vegetation category especially around the already urbanized areas including Minjur, Thiruneermalai are favourable locations for future urbanization in CMA. From this analysis it is also estimated that 199.89 km^2 and 101.35 km^2 areas remain as openland and vegetation respectively in this region and thus a total of 301.24 km^2 areas including Malayambakkam, Nandiambakkam, Mudichur would be probable areas of future urbanization in CMA.

Based on the land cover maps prepared, urbanization of CMA for 2010, 2013 and 2017 occupies 237.41 km^2, 400.57 km^2 and 572.11 km^2 respectively. For the prediction of urbanization of CMA in 2017 two scenarios were considered: one included urban maps of 2010 and 2013 without hotspots and the other scenario made use of urban maps of 2010 and 2013 with hotspot for the prediction modeling which would be discussed in Chapter 5.

3.4. Conclusion

The objectives of this chapter were to prepare the land cover maps of Sriperumbudur Taluk and CMA and to monitor the changes in the land cover categories especially the built-up category during the study periods. The main outcomes of this chapter are

- In Sriperumbudur Taluk, urbanization had increased during the study periods 2009, 2013 and 2016 with a noticeable increase of 113.16 km^2 (2016) from 28.99 km^2 (2009) within a period of 7 years.
- This increase in the urban growth in the Taluk could be mainly attributed to the fact that the taluk lies in close proximity to the capital city of Tamil

Nadu, Chennai. Also, the availability of transportation facilities linking the region to various major cities including Bengaluru, Chennai makes Sriperumbudur a favourable location for various industrial developments which further increases the urbanization of the region.

- In CMA, the urban growth in 2010 was mapped to be 237.41 km^2 which increased up to 572.11 km^2 in 2017.
- Since 2010, CMA experiences industrial growth providing employment opportunities to people in other sectors including textiles, tanning, financial, manufacturing, computer based, entertainment and so on. Being the capital city, people prefer to settle down in the city due to the availability of socio-economic amenities and betterment of lifestyle. This explains the increase in urbanization of 334.7 km^2 of area from 2010 to 2017.
- The outputs obtained from this chapter, i.e., the land cover maps, would be utilized further in the modeling process which would be discussed in Chapters 4 and 5.

CHAPTER 4

URBAN GROWTH PREDICTION OF SRIPERUMBUDUR TALUK – A PILOT STUDY

4.1. Introduction

Cities expand because of increase in population and migration of people from rural places to cities. Unplanned urbanization degrades the natural resources and affects the quality of life of the humans. Urban prediction models will help decision makers to plan the growth of their cities in the future (Hill and Lindner, 2010). In recent days, the availability of high-resolution temporal satellite data and different types of GIS-based modeling tools help in the handling of spatial data and its analyses, making urban growth models (UGMs) more realistic. CA models are widely used among all developed UGMs as they are found to perform well in predicting urban development more close to the reality than conventional mathematical models (Mubea, 2014; Divigalpitiya et al., 2007). The main objectives of this chapter are

- To implement a pilot study on Sriperumbudur Taluk, the south-west extension of Chennai, Capital city of Tamil Nadu, India to analyze the performances of three CA based UGMs including Traditional Cellular Automata (TCA), Agents-based Cellular Automata (ACA) and Neural Network based Agents-based Cellular Automata (NNACA) in assessing the urban growth of the taluk in 2016 using 2009 and 2013 dataset
- Using 2013 and 2016 data, to model the future urban growth of the taluk in 2020 using the most efficient CA based UGM
- To identify the most influencing agent of urbanization for the urban growth in 2016 through 'Sensitivity Analysis'
- To identify the pattern and distribution of urban sprawl in the taluk during the study periods through Shannon's entropy

4.2. Materials used in the prediction model

4.2.1. Urban Cover Maps

Sriperumbudur Taluk (Fig. 4.1) was chosen for the pilot study on assessing the efficiencies of different types of CA based UGMs before analyzing the urbanization CMA as discussed in Chapter 1. In a CA based urban prediction models, the future urbanization of a city is based on the current urban scenario and thus in the current study, the urbanization of Sriperumbudur Taluk in 2016 is dependent on the developmental activities of the years 2009 and 2013. The land cover features of the region mapped include Built-Up, Vegetation, Water Body and Openland (as discussed in Chapter 3). Since the present study focuses on predicting only the urbanization of Sriperumbudur Taluk, Vegetation, Water body and Openland were combined into one category as 'Non-Built-Up'. Thus from the land cover maps, urban maps of the study region of 2009, 2013 and 2016 were prepared which contain only binary categories namely 'Built-Up' and 'Non-Built-Up' which would be further used in the modeling processes (Fig. 4.2).

4.2.2. Agents of Urbanization

Apart from the urban maps, certain agents of urbanization, i.e., factors influencing the process of urban growth are crucial in urban growth models to predict the real world scenario with higher accuracy. In the current study, to predict the urban development of the study region, along with the 2009 and 2013 urban maps, spatial data of agents of urbanization including transportation networks like road, railway and major road junctions, DEM and industrial data of 2013 were also considered. These agents of urbanization are unique to a given study region and thus the choice of appropriate agents of urbanization for a region is always uncertain. In this study, based on the experts' opinions from CMDA (Chennai Metropolitan Development Authority), urban planning departments and academicians, 12 agents were identified for Sriperumbudur Taluk including (i) Hotspots; (ii) Existing Built-Up; (iii) Built-Up Neighbours; (iv) High Preference

Roads; (v) Medium Preference Roads; (vi) Least Preference Roads; (vii) Road Junctions; (viii) Red Category Industries; (ix) Orange Category Industries; (x) Green Category Industries; (xi) White Category Industries and (xii) Slope, which would be discussed in the following sections.

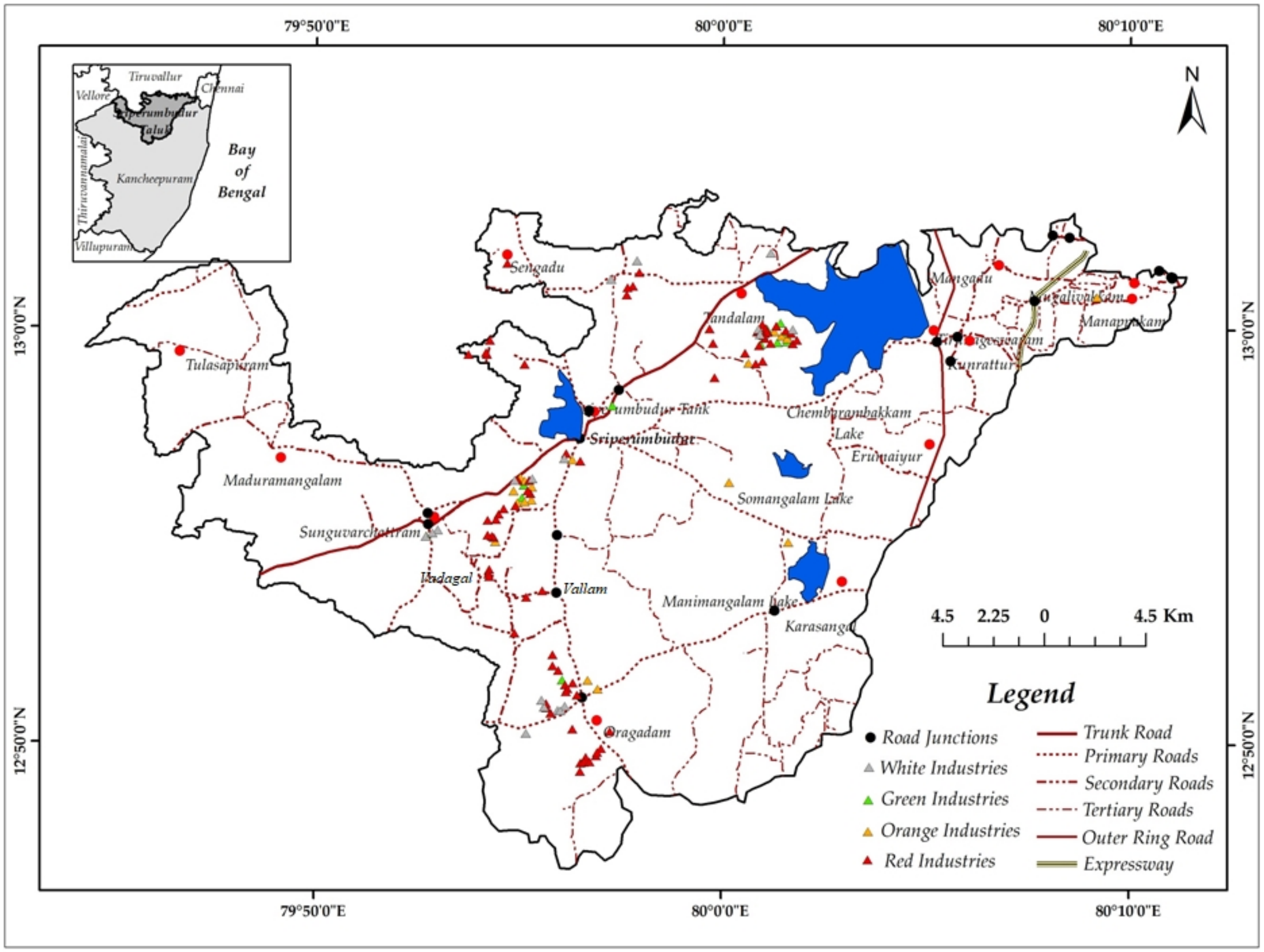


Figure 4.1. Map of Sriperumbudur Taluk depicting the agents of urbanization selected for modeling

4.3. Methodology

4.3.1. Urban Built-up maps - Identification of Hotspots

In a CA based prediction model, the state of a cell at a given time is dependent on its own state at the previous time step and also on the state of the neighbouring cells in the previous time step (Wolfram, 1984). It could be seen from the urban map of 2016 that at the locations of Vallam and Vadagal villages there was a sudden spurt of urbanization, which was not observed in both 2009 and 2013 urban maps (Fig. 4.2(a) and Fig. 4.2(b)). This sudden emergence of development in 2016 is because of the establishment of new SIPCOT (State Industries Promotion Corporation of Tamil Nadu) Industrial park over 4.64 km^2 in these two villages based on the Government development policy (Government of Tamil Nadu, Ministry for Industries Policy Note 2014 – 2015, (2014)).

In a completely non-built area a minimum number of built-up cells are necessary to trigger the process of urbanization based on CA model. Hence, built-up cells of area 3.65 km^2 at Vadagal and 0.99 km^2 at Vallam villages in the taluk were introduced as hotspots into the 2013 urban map (Fig.4.2(c)) for the prediction of urbanization in 2016. The study on hotspots reveals the significance of Government policy on the city development plan and the importance of including them into the modeling process to make the prediction outputs more close to the reality. Thus in the current study on predicting the urbanization of Sriperumbudur Taluk in 2016 urban maps of 2009 and 2013 were used under two scenarios. One scenario contains 2013 urban map including the hotspots (IHS) and the other scenario excluding the hotspots (EHS).

4.3.2. Development of Spatial Data of Agents and Proximity maps

Since the prediction modeling is based on CA, existing built-up and the built-up neighbours were also chosen as agents of urbanization. As far as the transportation data is considered, based on the experts' knowledge about the study region, trunk roads, primary roads and residential roads were categorized as ‘High Preference Roads’, secondary and tertiary roads were categorized as ‘Medium Preference Roads’ and ‘Least Preference Roads’ included outer ring road and expressway. The categorization was based on the recent developmental activities occurred along these road networks in the study region. Since Sriperumbudur Taluk is endowed with numerous industries, locations of industries were also identified as one of the major agents and were grouped into four categories based on their Pollution Index Score (PIS) (Ministry of Environment, Forests and Climate change, 2016). Accordingly, industries with PIS >= 60, 41 - 59, 21 - 40 and <=20 are categorized as ‘Red’, ‘Orange’, ‘Green’ and ‘White’ category industries respectively.

Proximity maps play major role in ACA and NNACA modeling. While, proximity maps were used as such in NNACA model for the prediction, they were used to prepare suitability maps for urbanization in ACA model. Proximity maps were derived for each of the identified 12 agents of urbanization and they were reclassified into 5 classes. For the prediction modeling based on ACA, weighted overlay analysis of all these reclassified maps of the agents was carried out to obtain the suitability maps of urbanization of the study region (Pramanik, 2016).

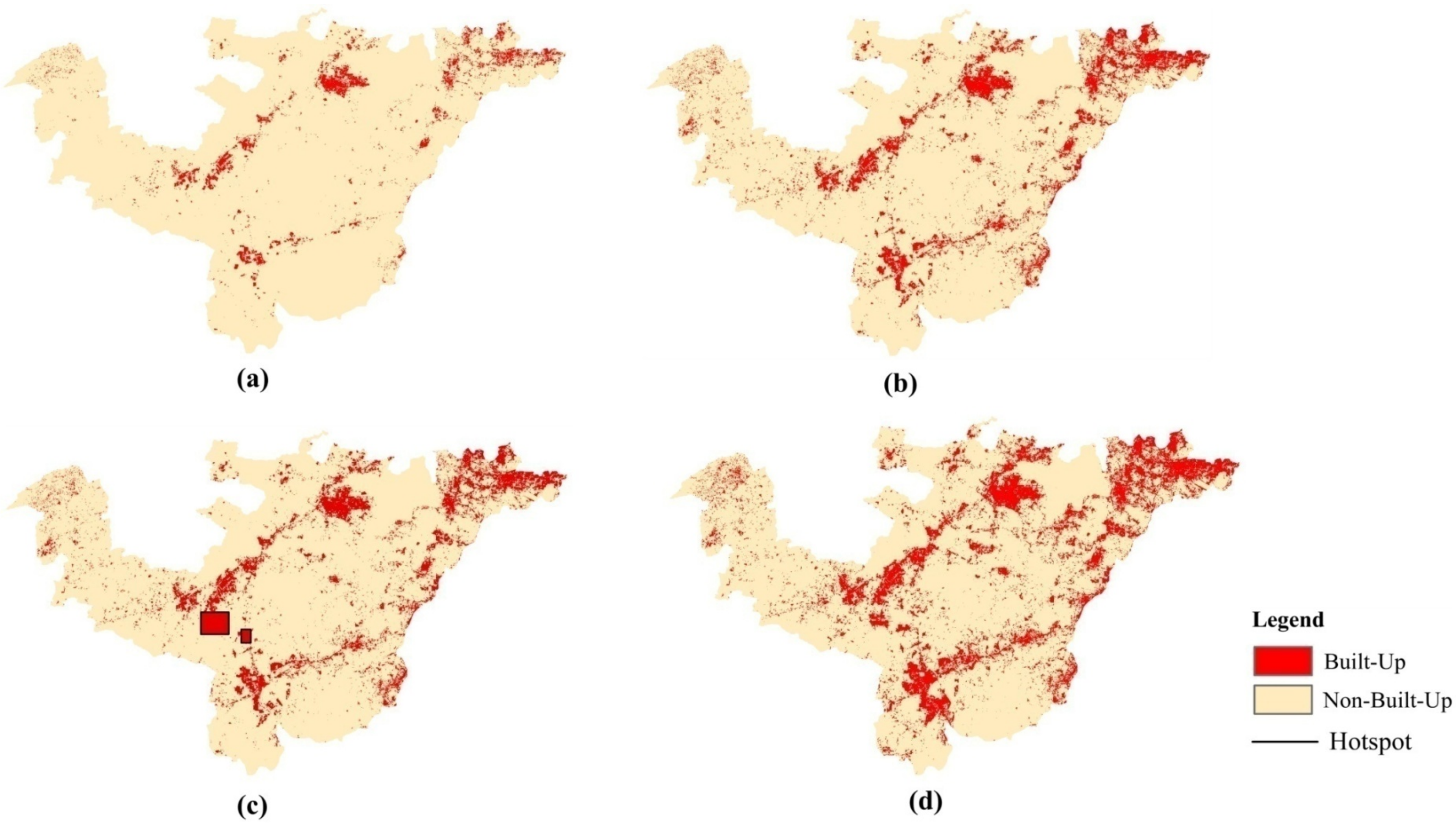


Figure 4.2. Urban Maps of Sriperumbudur Taluk. (a) 2009; (b) 2013 (EHS); (c) 2013 (IHS); (d) 2016

4.3.3. Suitability mapping of Urbanization

Suitability map of urbanization is used only in the urban prediction based on ACA model. Preparation of suitability map based on overlay analysis involves assigning weights to each of the agents which involves uncertainty. This requires experts' opinions, their knowledge about the study region and the past urban development pattern of the region. Analytical Hierarchical Process (AHP) technique is used in the current study to prepare the suitability map.

AHP developed in 1970s (Saaty, 1977) is a mathematical method which is widely used in multi-criteria decision making processes (Parry et al., 2018). AHP is a relative measurement methodology and is best suitable in solving multi-criteria evaluation technique where selecting the best alternative among several others become difficult due to the cognitive limits of the decision makers and the difficulty in effectively comparing several alternatives at the same time (Brunelli, 2015).

Table. 4.1. The comparison table in AHP (Saaty, 1980)

Intensity of Importance	Definition	Explanation
1	Equal importance of *i* and *j*	Two activities contribute equally to the objective
3	Moderate importance of *i* over *j*	Experience and judgment slightly favour one activity
5	Strong importance of *i* over *j*	Experience and judgment strongly favour one activity
7	Very strong or Demonstrated importance of *i* over *j*	An activity is strongly favoured and its dominance is demonstrated in practice
9	Extreme importance of *i* over *j*	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals of above non zero	If activity *i* has one of the above nonzero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	A comparison mandated by choosing the smaller element as the unit to estimate the larger one as a multiple of that unit

In this context, AHP introduces an effective way to overcome this difficulty by using a 9 point scale measurement (Table 4.1) to express the individual preferences in the form of a Pairwise Comparison Matrix (PCM). PCM allows the decision makers to consider and compare only two alternatives at a time and thus making the complex decision making simpler and easier. Ideally, if there are n numbers of alternatives to be compared, the dimension of the PCM would be In the present study, 12 agents of urbanization were used in the prediction modeling and thus the PCM contains comparisons between 66 number of agents pairs.

Let a PCM, A = $[a_{ij}]_{n\times n}$ be given as

$$A = \begin{bmatrix} a_{11} & a_{12} \cdots\cdots & a_{1n} \\ a_{21} & a_{22} \cdots\cdots & a_{2n} \\ \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix} \tag{4.1}$$

where, a_{ii} = 1 and $a_{ij} = \frac{1}{a_{ji}}$

From the PCM, the normalised Eigen vector of the matrix, i.e., the priority vectors (**V**: V_1, $V_2 \ldots V_n$) of the matrix are calculated based on equation (4.2) which provide the relative weights of the agents of urbanization.

$$\mathbf{V} = \frac{1}{n} \begin{bmatrix} \frac{a_{11}}{a_{11}+a_{21}+..+a_{n1}} & \frac{a_{12}}{a_{12}+a_{22}+..+a_{n2}} \cdots\cdots & \frac{a_{1n}}{a_{1n}+a_{2n}+..+a_{nn}} \\ \frac{a_{21}}{a_{11}+a_{21}+..+a_{n1}} & \frac{a_{22}}{a_{12}+a_{22}+..+a_{n2}} \cdots\cdots & \frac{a_{2n}}{a_{1n}+a_{2n}+..+a_{nn}} \\ \vdots & & \\ \frac{a_{n1}}{a_{11}+a_{21}+..+a_{n1}} & \frac{a_{n2}}{a_{12}+a_{22}+..+a_{n2}} \cdots\cdots & \frac{a_{nn}}{a_{1n}+a_{2n}+..+a_{nn}} \end{bmatrix} \tag{4.2}$$

For each of the agents, the relative weights are obtained, the summation of which is one. AHP also provides a mathematical measure to determine the consistency of the weights generated through the calculation of Consistency Ratio (CR) through Consistency Index (CI) based on equations (4.3), (4.4) and (4.5) (Saaty, 1980).

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{4.3}$$

$$\mathrm{CI} = \frac{\lambda_{max-1}}{n-1} \tag{4.4}$$

where, λ_{max} is the principal Eigen value of the PCM which can be obtained from equation (4.5).

$$\lambda_{max} = \frac{1}{a_{11}}(\mathrm{V}_1) + \frac{1}{a_{22}}(\mathrm{V}_2) + \ldots.. + \frac{1}{a_{nn}}(\mathrm{V}_n) \tag{4.5}$$

RI is the Random Index provided by Saaty and the RI values for different numbers of n are shown in Table 4.2.

If CR <= 0.10, then the PCM has acceptable consistency and the relative weights generated can be used to prepare the suitability maps. If CR value >= 0.10 then the weights are considered to be inconsistent and the elements of the PCM has to be re-examined and re-assigned till the CR value reaches the threshold. In the present study, a CR value of 0.073 was obtained and hence the weights generated could be considered consistent. Based on these weights, the suitability map for the urbanization of Sriperumbudur Taluk was prepared for two scenarios (EHS and IHS) for further modeling.

Table 4.2. Random Index (RI) Table (Saaty, 1980)

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.58

4.4. Urban Growth Prediction

4.4.1. TCA and ACA Models

In case of urban growth prediction based on TCA model, only the historical time series maps of the study region were used based on the Transition Potential Matrix (TPM). In the current study, for predicting the urban growth of Sriperumbudur Taluk in 2016, urban maps of 2009 (t_1) and 2013 (t_2) (EHS and IHS) only were used to create the TPM (X_n) based on equation (4.6).

$$X_n = \begin{bmatrix} p_{b-b} & p_{b-nb} \\ p_{nb-b} & p_{nb-nb} \end{bmatrix} \quad (4.6)$$

where, p: Probability of change for n time steps = $\frac{N_C}{N_T}$ (N_C: number of pixels in each category; N_T: Total number of pixels). b: State of Built-up; nb: state of non-built-up. In this present study, to determine the TPM for one time step, elements of equation (4.6) were divided by the number of time steps between the transition periods (Here, n = 4) with the following consideration (Chung, 1960).

i. Sum of row elements of TPM = 1
ii. Diagonal elements are changed to satisfy above condition (i)
iii. $p_{b-nb} = 0$ (Assumption). It is assumed that once a cell is built-up in time t_1, it will not become non-built-up in the further time periods
iv. Hence, $p_{b-b} = 1$. A built-up cell at a previous time step will remain built-up only in all the further time periods

Based on the above assumptions, the TPM for one time step (X_1) is given as

$$X_1 = \begin{bmatrix} 1 & 0 \\ p_{1_{nb-b}} & 1 - p_{1_{nb-b}} \end{bmatrix} \quad (4.7)$$

Hence, TPM between 2013 and 2016 is given by equation (4.8).

$$X_{n+1} = X_n(X1)^m \tag{4.8}$$

where, X_{n+1} is the projected TPM between t_2 and t_3; m: number of time steps between t_2 and t_3 (here, m = 3).

Urban modeling based on TCA and ACA makes prediction based on the assumption that the number of cells that would convert from non-built-up to built-up from t_2 to t_3 is based on the number of cells that had transitioned from non-built-up to built-up from t_1 to t_2. Cell neighborhood plays a major role in CA based urban modeling. In the present study a 3x3 cell neighbourhood was used.

In a 3x3 cell neighbourhood each cell has 8 neighbours and thus the TR adopted in TCA model was to 'find all non-built-up cells with urban neighbours >=3'. ACA based model also makes the prediction similar to TCA model based on TPM but ACA included the suitability maps prepared through AHP technique into the prediction model along with the urban maps of 2009 and 2013. The TR adopted in ACA model was to 'find all non-built-up cells with urban neighbours >=3 AND Suitability Index (SI) >= twice the minimum SI, which is the threshold for SI derived from suitability analysis. In case of both the TCA and ACA models, the iteration was carried out in ArcGIS environment with major water bodies as constraints till the expected number of cells based on the TPM became urbanized in 2016 (Fig.4.3).

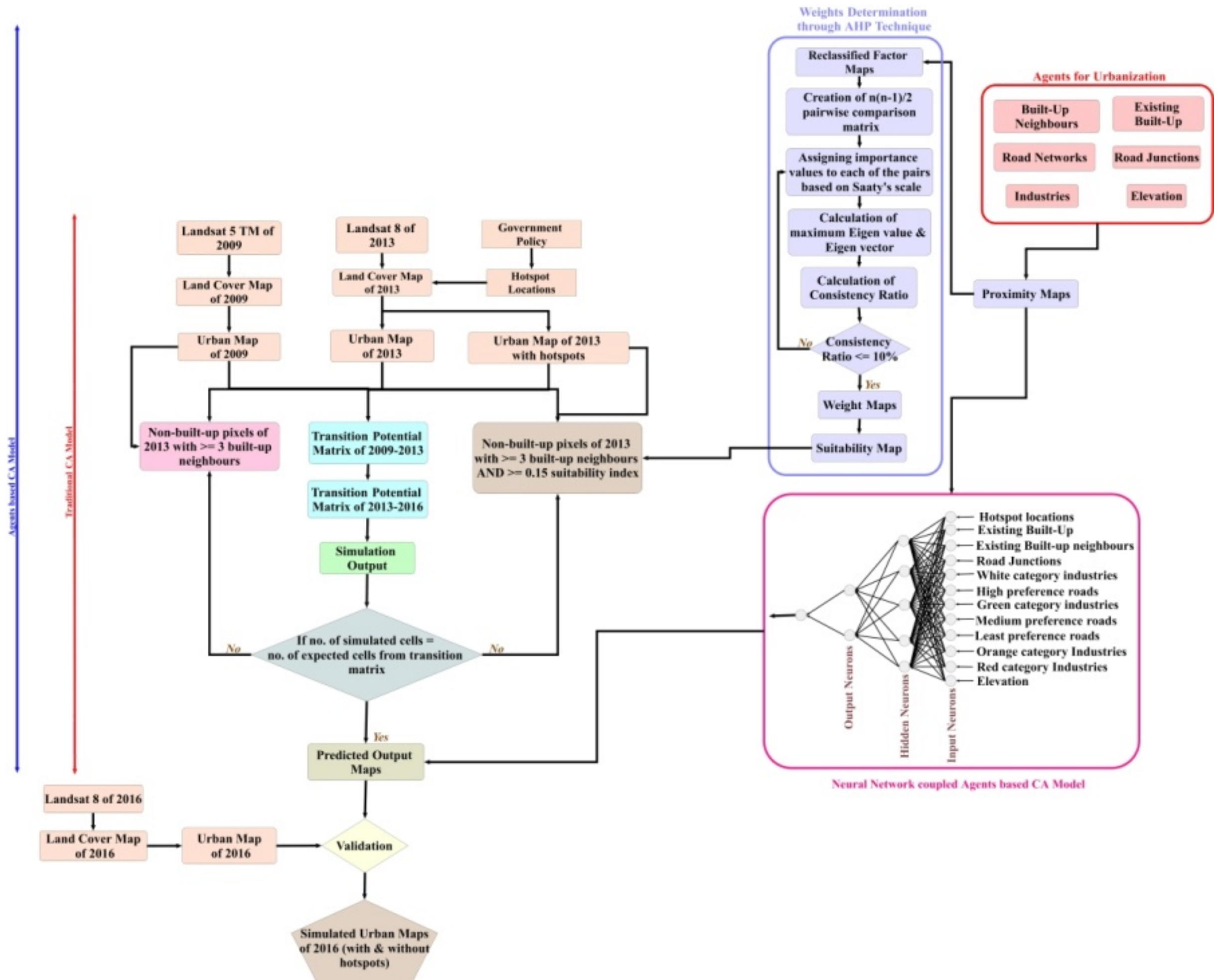


Figure 4.3. Methodology adopted in the study for the prediction of urban areas using TCA, ACA and NNACA models.

4.4.2. NNACA Model

NNACA model makes use of urban maps of 2009 and 2013 along with the proximity maps of agents of urbanization implemented through the Multi-Layer Perceptron (MLP) neural network of LCM (Land Change Modeler) (https://clarklabs.org/terrset/land-change-modeler/), Terrset with major water bodies as constraints for the prediction of urban growth in 2016 (Fig. 4.3). A typical MLP consists of an input layer, one or more hidden layers and an output layer. In the present study, let K be the input neurons to the NNACA model. K: $[k_1, k_2, \ldots, k_{12}]$, where k_1 to k_{12} represent the proximity maps of all the agents of urbanization. number of hidden neurons are appropriate in modeling the complex scenarios like urban prediction (Yeh and Li, 2002), where n is the number of input neurons (Here, n = 12). In the current study, 8 hidden neurons were used to predict the urbanization of the study region. To each of these 8 hidden neurons, input was assigned based on equation (4.9).

$$H_I = \sum_{0}^{8} (w_k \text{ x } I_k) \tag{4.9}$$

where, H_I is the input to the hidden neurons; I_K is the input neurons representing the proximity maps of all the agents; w is the weights assigned randomly by the neural network ranging between -1 and +1. The output from the hidden neurons (H_O) is given by

$$H_O = \frac{1}{1 + e^{-H_I}} \tag{4.10}$$

Sigmoidal functions are often used in artificial neural networks as an activation function to introduce nonlinearity in the model (Bishop, 1995). The outputs from the hidden neurons are fed into the output neurons as input (O_I).

$$O_I = \sum_{h=1}^{8} (w_h \text{ x } H_O) \tag{4.11}$$

$$\mathrm{O_o} = \frac{1}{1 + e^{-\mathrm{O_I}}} \tag{4.12}$$

where, h: number of hidden neurons; O_o: Outputs from the output neurons.

Each of the two output neurons in the model gets a value ranging between 0 and 1. These 'model outputs' obtained from the NNACA model along with the 'true outputs' also known as 'targets', obtained from the historical datasets, were used to assess the accuracy of the prediction modeling through root-mean-square (RMS) error calculation. Thus, for each of the pixel in the study area, the NNACA estimates the RMS error based on equation (4.13).

$$\mathrm{E_{Total}} = \sum \frac{1}{2}(\text{target} - \text{model output})^2 \tag{4.13}$$

where, $E_{Total} = E_{O1} + E_{O2}$; E_{O1} and $E_{O2}$are the errors from the output neurons 1 and 2 respectively. MLP with back propagation algorithm is widely used in urban prediction modeling, as with every iteration, the weights in the network gets updated such that the model outputs come closer to the target outputs, thereby minimizing the RMS error for each of the output neurons and thereby for the entire network, and the entire process is continued till the RMS error reaches the minimum. An accuracy rate of 80% is considered to be acceptable (Eastman, 2012) and it can be considered that the model has learnt well based on the input datasets and model parameters.

4.5. Validation

Validation is an important process which enables the users to understand the accuracy of the prediction model. The most widely adopted accuracy assessment technique is 'Error Matrix' through which Overall Accuracy (O.A) and Kappa co-efficient (k) are derived (Conglaton, 1991).

4.6. Sensitivity Analysis

For an efficient urban prediction model, apart from the time series urban maps, various agents of urbanization are also essential. However, the choice of appropriate number of agents remains very crucial as the agents vary from region to region and it requires experts' knowledge about the historic urban development of the region. Sensitivity analysis is usually carried out to identify the influence of agents of urbanization on the prediction outputs (Al-Ahmadi et al., 2013). Based on this analysis, initially, the prediction model was run with each of the agents individually and the effects of the agents were assessed based on their prediction accuracies (Luo et al., 2019). Further, based on 'leave-one out' technique each one of the agents was excluded from the UGM and the model was run with the rest of the input variables and the efficiency of the prediction model was assessed (Sanchez et al., 2018).

Then the efficiency of the each of the agents of urbanization on the prediction outputs was assessed through Cramer's (V) value which is based on Chi-squared statistics (Gingrich, 1992). Once the sensitivity analysis was performed, each of the output obtained were validated against the observed urban map of 2016. Based on the validation outputs, V values were calculated as given in Equation (4.14).

$$\mathrm{V} = \sqrt{\frac{\chi^2}{\mathrm{N} * (\min\,(\mathrm{r}-1, \mathrm{c}-1))}} \tag{4.14}$$

where, N: Total number of pixels in the study area

r and c: Number of rows and columns respectively in the error matrix

(Here, r = c = 2)

χ^2 is the Chi-square statistics value which can be obtained from Equation (4.15)

$$\chi^2 = \sum \frac{(\mathrm{O_i} - \mathrm{E_i})^2}{\mathrm{E_i}} \tag{4.15}$$

where, O_i and E_i are observed and expected numbers of urban pixels respectively. V ranges between 0 and 1 and the influence of each of the agent of urbanization on the prediction output could be interpreted based on these values as given in Table 4.3.

Table 4.3. Interpretation of influence of agents of urbanization on the prediction outputs based on Cramer's Value

Cramer's V	**Influence of agents on the prediction outputs**
0	No influence
Less than 0.25	Weak
Between 0.25 and 0.75	Moderate
Greater than 0.75	Strong
1	Highly influential

4.7. Assessment of Urban Sprawl using Shannon's Entropy

When modeling the urban development of a city, analyzing the direction and type of distribution of urbanization also becomes essential. Because based on that information, policy makers will have an in insight on the pattern of urbanization of that region. In this study, quantifying the direction and distribution of urban sprawl was done through Shannon's Entropy by making use of the observed urban maps of 2009, 2013 and 2016 and the projected urban map of 2020 (Mosammam et al., 2017). In the present study, the study area was divided into 8 directional zones with the Sriperumbudur Taluk Headquarters as the centre including North-North East (N-NE), North East-East (NE-E), East-South East (E-SE), South East-

South (SE-S), South-South West (S-SW), South West-West (SW-W), West-North West (W-NW) and North West-North (NW-N). Based on the urbanization in each of these zones normalized entropy (H_N) was calculated as given by equation (4.16).

$$H_N = \frac{1}{n}\sum_{i=1}^{n} p(x_i)\log\left\{\frac{1}{p(x_i)}\right\} \tag{4.16}$$

where, n: Number of zones (n = 8); p(x): Probability of built-up in each zone; H_n values range from 0 to log (n). Values closer to 0 indicate a compact distribution of urbanization and values closer to $\log_e(n)$ indicates that the urban distribution is dispersed.

4.8. Results and Discussions

4.8.1. Urban cover map and Hotspots

Based on the land cover maps of the study region prepared in the Chapter 3, urban maps of the taluk were obtained (Fig. 4.2) which revealed that urbanization in the taluk in 2009, 2013 and 2016 to be 28.99 km^2, 74.48 km^2 and 113.16 km^2 respectively and the urban growth during the study periods was concentrated mainly along the road networks leading towards Chennai. Also, based on the land cover change analysis, it was reported that an area of 246.55 km^2 remains available for further urbanization in the study region. To make the prediction outputs more realistic urban hotspots were introduced in Vallam and Vadagal villages of the taluk over an area of 4.64 km^2 based on the Government policy. The hotspots were introduced as rectangular and square shaped (Fig.4.2(c)) as in the development regulation policy only the extent of the industrial development in these villages was proposed but not the shape of the urbanization.

4.8.2. Agents of Urbanization and Suitability map

UGM based only on the previous urban maps of a region does not replicate the real world phenomena. Hence, 12 different agents of urbanization based on experts' opinions were identified for this study region. Relative weights were assigned to these agents based on AHP technique (Table 4.4; Fig. 4.4). It could be noted that a maximum weight of 0.24 was assigned to the agent, hotspot. This is because hotspots are the most probable locations in the study region where urbanization is most likely to happen and hence the maximum weight was assigned to it. Since the study region experiences a gentle slope, a least weight of 0.01 was assigned to slope as its influence on the prediction modeling is comparatively very low (Table 4.4). Based on these weights, suitability maps of urbanization were prepared (EHS and IHS) (Fig. 4.5). These suitability maps had indices ranging between 0.07 and 0.42. The threshold for SI chosen in this study was 0.15, which is twice the minimum value 0.07. The highest SI was observed in the north-eastern part of the study region including Kundrathur, Mangadu, Moulivakkam indicating that the areas in close proximity to Chennai district is most favourable for urbanization due to the higher employment opportunities and socio-economic facilities including transportation facilities, educational institutions, hospitals, religious and recreational centres and so on than the rest of the study region.

Table 4.4.Weights generated through AHP technique for the agents of urbanization for Sriperumbudur Taluk

Factors of Urbanization	Weights of Criteria	Alternatives and its weights				
Hotspots	0.2430	**0-1 km**	**1-2 km**	**2-3 km**	**3-4 km**	**>4 km**
		0.4630	0.2560	0.1490	0.0860	0.0460
Existing Built-Up	0.1860	**0-0.25 km**	**0.25-0.5 km**	**0.5-1 km**	**1-2 km**	**2-3 km**
		0.4481	0.2607	0.1517	0.0882	0.0513
No. of Existing Built-Up Neighbours	0.1420	**0**	**1-2**	**3-4**	**5-6**	**7-8**
		0.0392	0.0824	0.1443	0.2633	0.4708
Road Junctions	0.1100	**0-1 km**	**1-2 km**	**2-3 km**	**3-4 km**	**>4 km**
		0.3500	0.2195	0.1830	0.1818	0.0657
White Category Industries	0.0850	0.5615	0.1802	0.1454	0.0748	0.0381
High Preference Roads	0.0650	0.5713	0.1441	0.1097	0.0645	0.1104
Green Category Industries	0.0500	0.5683	0.1420	0.1291	0.1818	0.0657
Medium Category Industries	0.0380	0.4675	0.2054	0.0898	0.0578	0.1795
Least Preference Roads	0.0290	0.0804	0.0603	0.0653	0.0503	0.7437
Orange Category Industries	0.0230	0.1371	0.1560	0.1817	0.1841	0.3411
Red Category Industries	0.017	0.0466	0.0628	0.0667	0.2761	0.5478
Slope	0.0130	1°-3°	3°-10°	10°-20°	20°-32°	0°
		0.5160	0.2939	0.1033	0.0554	0.0314

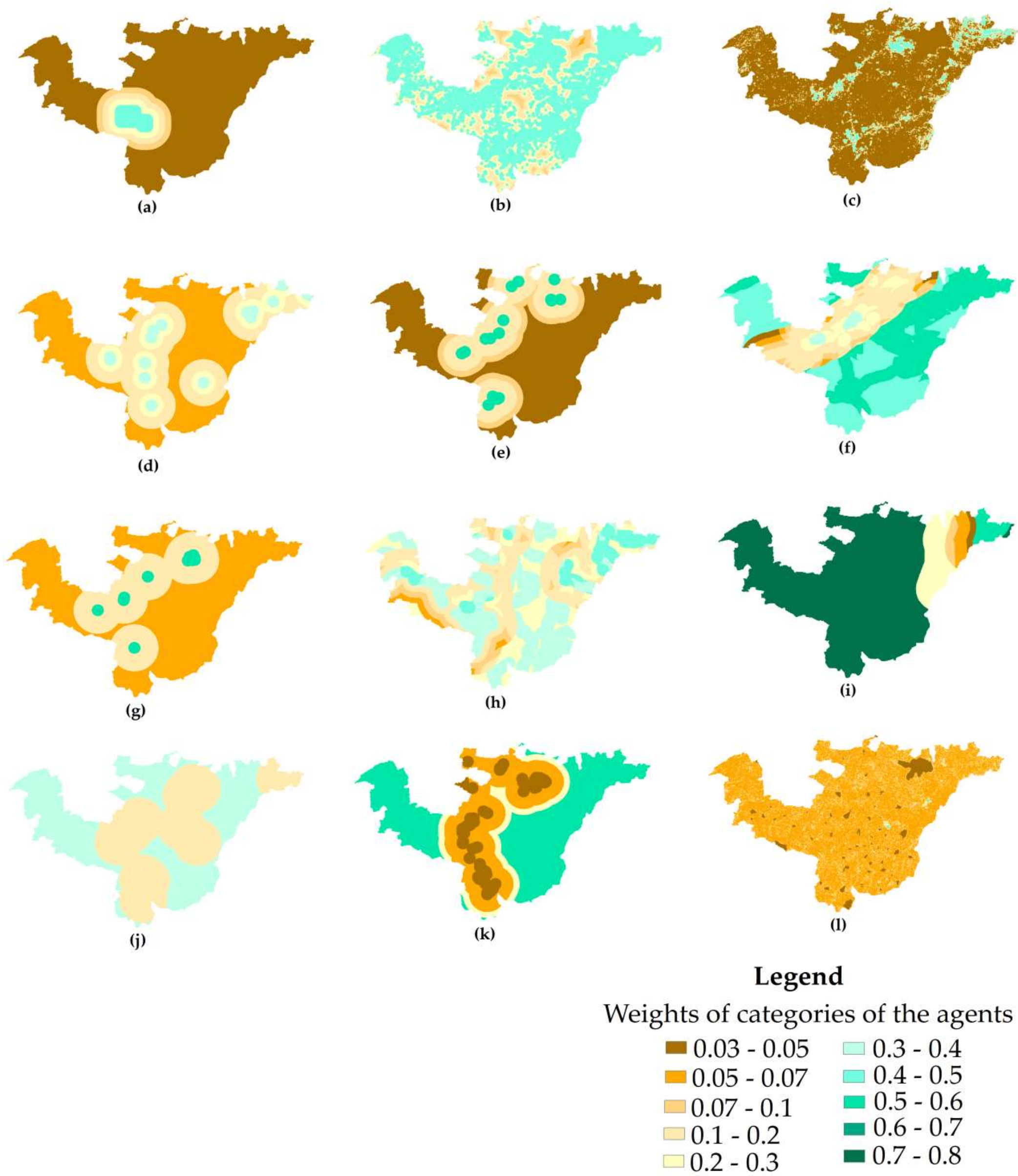


Figure 4.4. Weighted Maps of the agents of urbanization used for the prediction of urbanization in 2016. (a) Hotspots; (b) Existing Built-Up; (c) Built-Up Neighbours; (d) Road Junctions; (e) White Category Industries; (f) High Preference Roads; (g) Green Category Industries; (h) Medium Category Industries; (i) Least Preference Roads; (j) Orange Category Industries; (k) Red Category Industries; (l) Slope

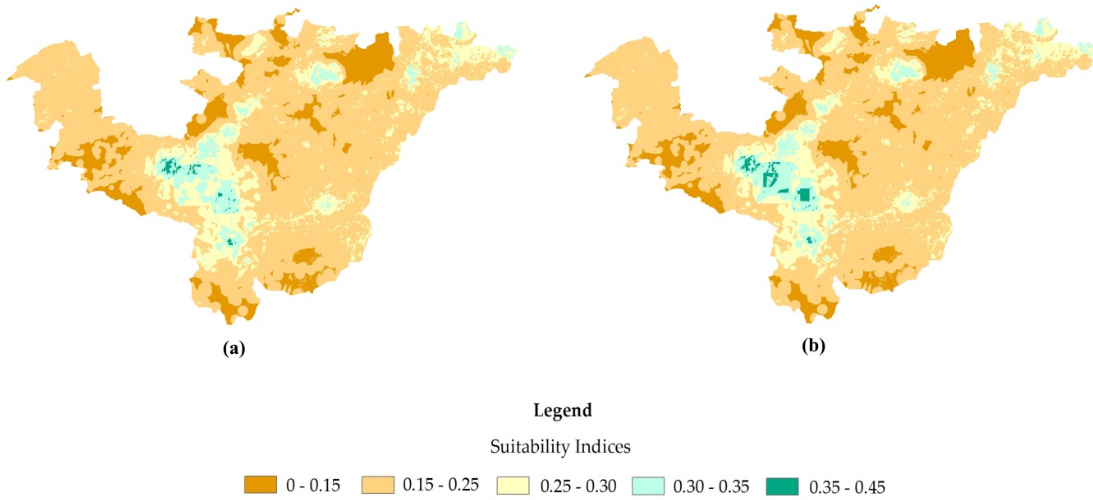


Figure 4.5. Suitability Maps of urbanization of the study region. (a) EHS; (b) IHS

4.8.3. Model outputs of TCA, ACA and NNACA

The observed urbanization in the year 2016 was mapped as 113.16 km^2. Both TCA and ACA (EHS) models based on TPM (Table 4.5) predicted 145.39 km^2 of built-up which is an over-prediction of the reality (Fig. 4.6). In case of IHS model, the prediction was still higher at 158.48 km^2. It could be seen that in both the TCA and ACA models, the urbanization was accumulating near the already built-up cells because these models are based on the transition potential between the previous time steps. Even after the inclusion of agents in ACA model, the prediction outputs remained the same as TCA because ACA also employed the similar transition potential concept into the prediction modeling. Hence the prediction output did not improve even after the inclusion of suitability maps based on the weights of the agents of urbanization. Whereas in the case of NNACA model, the EHS and IHS models predicted 106.12 km^2 and 107.13 km^2 of urbanization in 2016 respectively, which could be seen as an under-prediction of the observed urbanization of 2016. NNACA model made use of MLP based back propagation technique and in the current study, an accuracy of 90% was reported while training the NNACA model and it could be understood that the model had learnt well based on the input dataset. NNACA does not involve the uncertainty associated with the assignment of weights for the agents as NNACA makes use of only the proximity maps of the agents. This reduces the uncertainty in the input dataset into the prediction modeling. Also, the prediction modeling is not based only on the TPM of the previous time step which is unrealistic and the selection of TRs remain another uncertainty in the prediction modeling based on TCA and ACA models.

The accuracies of the prediction models are given in Table 4.6. NNACA (IHS) model predicted the outputs with higher O.A. and k value implying the efficiency of NNACA model over the other two models. It is known that for a prediction model to be more accurate, apart from having higher O.A. it should also have lesser number of misses and false alarms. Hits correspond to the areas that are correctly predicted as urban by the prediction model. Misses correspond to under-prediction and over-prediction causes false alarms in the prediction outputs. From Table 4.7 it is evident that though TCA and ACA models have maximum urban hits, the false alarms associated with them were very high whereas in the case of NNACA (IHS) model, 87.05 km^2 was predicted as urban with only 20.08 km^2 identified as false alarms (Fig. 4.7).

Table 4.5. Observed and simulated Transition Probability Matrix between 2009 and 2013, 2013 and 2016 and its corresponding areas.

	Observed transition probability between 2009 and 2013		Projected transition probability between 2013 and 2016	
	Built-Up	Non-Built-Up	Built-Up	Non-Built-Up
Built-Up	1 (28.98 km^2)	0	1 (74.78 km^2)	0
Non-Built-Up	0.0738 (45.50 km^2)	0.9262 (570.93 km^2)	0.1242 (70.91 km^2)	0.8758 (499.72 km^2)

The occurrence of false alarms was mainly because of the proposed area of 4.64 km^2 of hotspots in the Vallam and Vadagal villages in the urban map of 2013. The proposed hotspot areas had included non-built-up region also whereas urban cover map of 2016 for validation prepared using remote sensing data included only built-up area. Overall, it could be understood that apart from introducing agents of urbanization into the prediction model when neural network is also coupled with ACA model, then the prediction model would produce more realistic output. Hence in the present study, it could be taken that NNACA model is the most efficient one in predicting the urbanization of Sriperumbudur Taluk in 2016. The efficiency of NNACA (IHS) model was further proved from Table 4.7 which shows higher Cramer's value for NNACA (IHS) model (0.7477) when compared to other models. Thus the urbanization of 2020 for the study region was predicted using NNACA model which predicted 157.46 km^2 of built-up in 2020, i.e., from 2016 within a span of 4 years urbanization was predicted to increase around 44.3 km^2. This would enable the policy makers and decision planners to take appropriate development actions to regulate the growth of urbanization in the region and provide better developmental infrastructure facilities.

Table 4.6. Accuracies of different types of CA models used in Sriperumbudur Taluk

	EHS			**IHS**		
	TCA	ACA	NNACA	TCA	ACA	NNACA
O.A. (%)	87.91	87.78	92.21	88.20	88.08	92.22
k value	0.6242	0.6201	0.7240	0.6331	0.6294	0.7267

Table 4.7. Validation of prediction outputs and Cramer's values for estimating the efficiency of different types of CA models

UGM with all 12 agents of urbanization		**Validation Outputs (km^2)**			**Cramer's Value**
		Urban Hits	Misses	False Alarms	
EHS	TCA Model	90.34	22.82	55.05	0.6325
	ACA Model	92.92	22.84	55.06	0.6323
	NNACA Model	90.32	29.13	22.10	0.7191
IHS	TCA Model	92.29	20.23	65.56	0.6167
	ACA Model	84.02	20.87	66.20	0.6106
	NNACA Model	87.05	26.10	20.08	0.7477

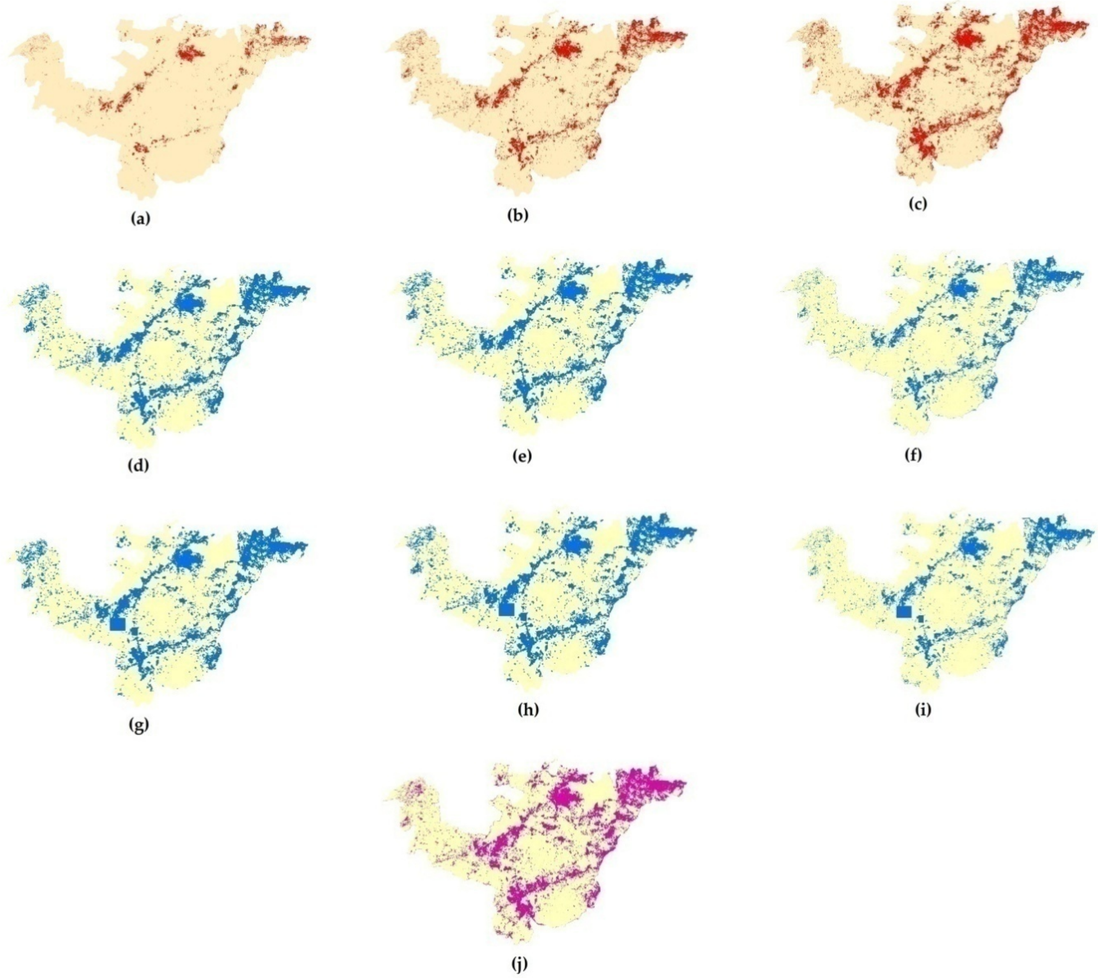


Figure 4.6. Predicted Urban in 2016 and 2020 using TCA, ACA and NNACA Models. (a)–(c) Observed Urban Cover in 2009, 2013 and 2016 respectively; (d)–(f) Predicted Urban Cover of 2016 using TCA, ACA and NNACA (EHS) models; (g)–(i) Predicted Urban Cover of 2016 using TCA, ACA and NNACA (IHS) models; (j) Predicted Urban Cover of 2020 using NNACA model.

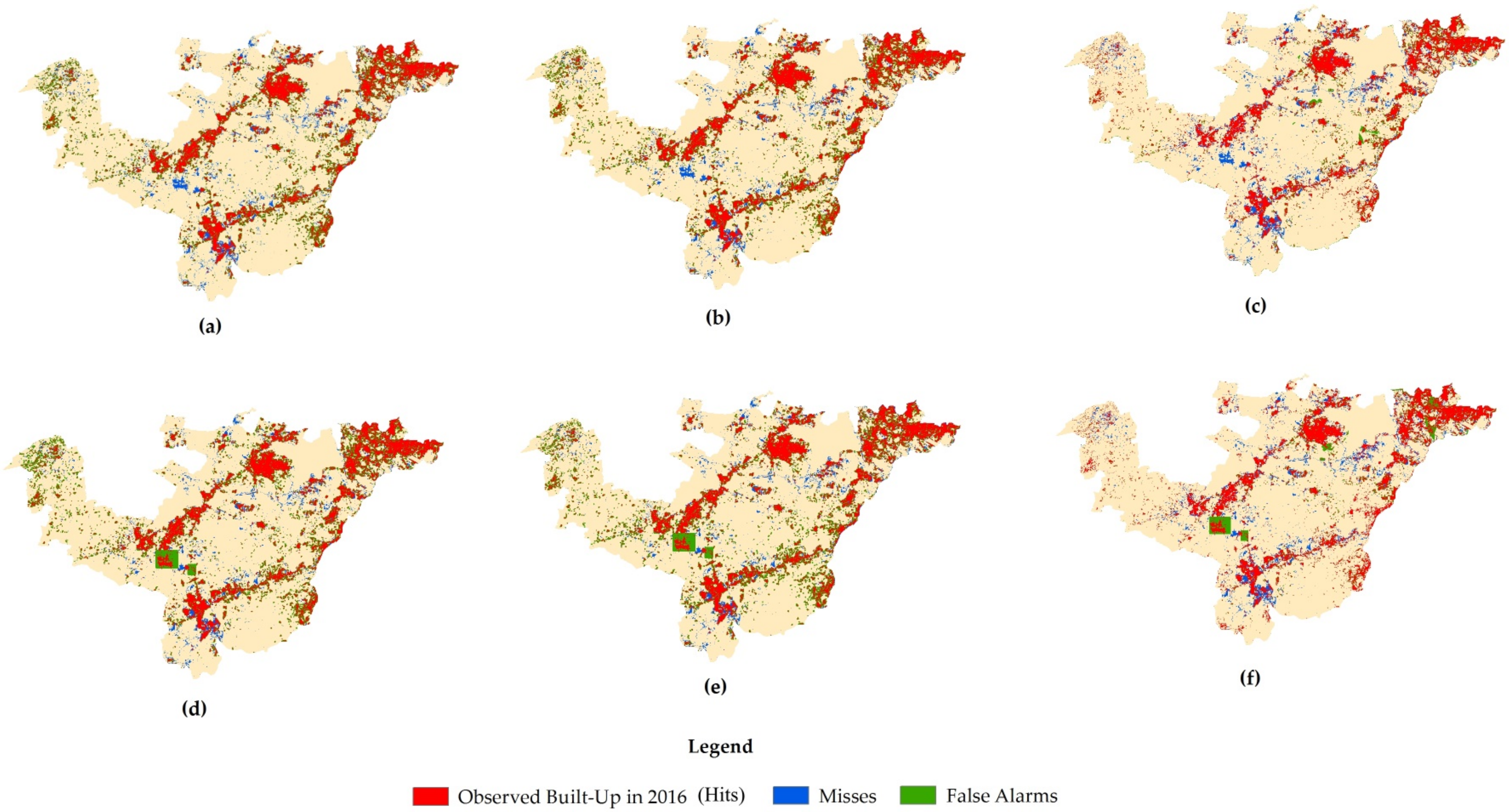


Figure 4.7. Validation of predicted urban with observed urban in 2016 (a)–(c) Using TCA, ACA and NNACA (EHS) models; (d)–(f) Using TCA, ACA and NNACA (IHS) models.

4.8.4. Influence of analysis of agents of urbanization on the prediction outputs

To analyze the influence of each of the agents of urbanization on NNACA (IHS) model, the model was run with individual agents of urbanization and their efficiency was reported. Further, the prediction model was run with all the agents of urbanization leaving each one agent of urbanization and their accuracies and Cramer's values were reported (Table 4.8). The results of the validation outputs along with the Cramer's values of the sensitivity analysis based on running NNACA (IHS) model with each individual agents were reported in Table 4.8 (**(a) - (k)).** The results of sensitivity analysis based on leave-one out technique were given in Table 4.8 (**(l) – (v)).** It could be seen that when individual agents of urbanization were used to run the NNACA model, almost all the agents produced similar areas of hits (~87 km^2). However, NNACA model with all the 12 agents of urbanization together produced 87.05 km^2 areas of hits (Table 4.7). This indicates that for Sriperumbudur Taluk, all the chosen 12 agents of urbanization were essential in determining the urban growth of the taluk in 2016. However, it is evident that when hotspots were excluded from the NNACA (IHS) model, the area of hits decreased to 84.75 km^2 and the corresponding Cramer's value also reduced (0.6851) indicating that hotspots are crucial and should be included in predicting the urbanization of the taluk in 2016. This substantiates the results obtained from Table 4.7 which also highlights that inclusion of hotspots improves the accuracy of the prediction outputs. Also, Table 4.8 shows that the exclusion of remaining agents of urbanization produced similar areas of hits (~87 km^2) with Cramer's value of 0.71. Thus, it could be inferred that NNACA (IHS) model with all the 12 agents of urbanization which produced an urban hits of 87.05 km^2 and Cramer's value of 0.7477 could be considered the most appropriate UGM to predict the urban growth of the taluk in 2016.

Table 4.8. Results of validation outputs and Cramer’s values of sensitivity analysis based on NNACA (IHS) model

Urban Growth Models		**Validation Outputs (km^2)**			**Cramer’s Value**
		Urban Hits	Misses	False Alarms	
NNACA (IHS) model only with	**(a)** Existing Built-Up	86.89	26.27	28.74	0.7078
	(b) Hotspots	78.32	34.84	37.31	0.6168
	(c) High Preference Roads	86.83	26.32	28.80	0.7072
	(d) Medium Preference Roads	87.11	26.05	28.52	0.7102
	(e) Least Preference Roads	86.83	26.32	28.80	0.7072
	(f) Road Junctions	86.83	26.32	28.80	0.7072
	(g) Red Category Industries	86.83	26.32	28.80	0.7072
	(h) Orange Category Industries	86.83	26.32	28.80	0.7072

	(i) Green Category Industries	86.83	26.32	28.80	0.7072
	(j) White Category Industries	86.83	26.32	28.80	0.7072
	(k) Slope	86.09	27.07	28.54	0.7100
NNACA (IHS) model excluding	**(l)** Existing Built-Up	86.81	26.34	28.81	0.7071
	(m) Hotspots	84.75	28.41	30.88	0.6851
	(n) High Preference Roads	85.49	27.67	30.14	0.6929
	(o) Medium Preference Roads	85.49	27.67	30.14	0.6930
	(p) Least Preference Roads	86.75	26.41	28.88	0.7064
	(q) Road Junctions	86.90	26.25	28.72	0.7080
	(r) Red Category Industries	86.84	26.31	28.78	0.7074

	(s) Orange Category Industries	85.49	27.66	30.14	0.6930
	(t) Green Category Industries	86.90	26.25	28.72	0.7080
	(u) White Category Industries	87.09	26.06	28.54	0.7100
	(v) Slope	86.83	26.32	28.79	0.7073

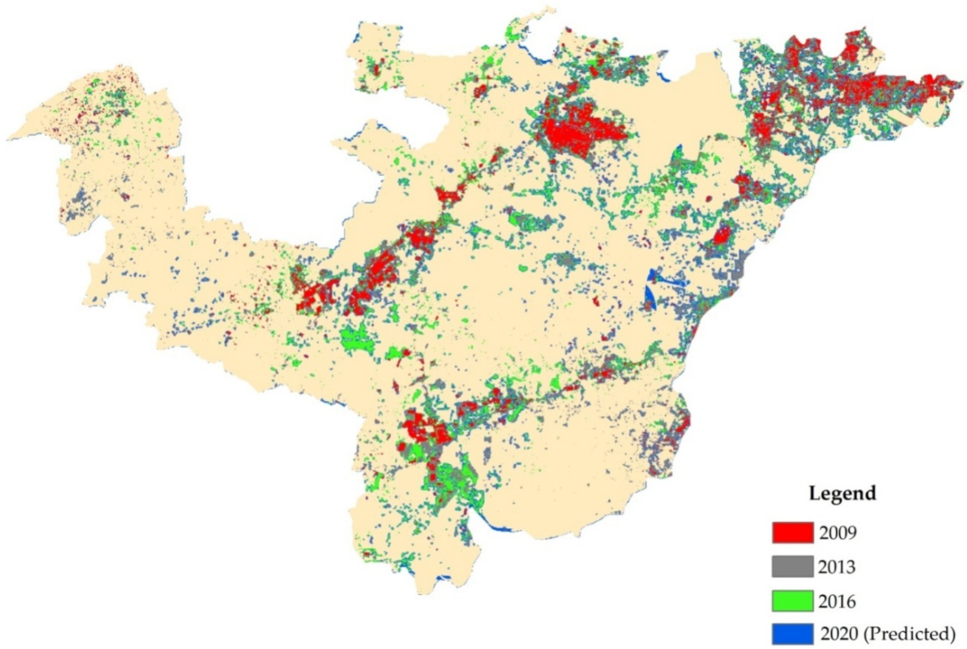


Figure 4.8. Urban Sprawl of observed 2009, 2013 and 2016 and predicted 2020 of the study region

4.8.5. Urban Sprawl analysis

The extent of the built-up in the study area kept sprawling from 2009 to 2020 (with the inclusion of predicted urbanization) (Fig. 4.8) and the entropy values of observed urbanization of 2009, 2013,2016 and predicted 2020 were found to be 0.4107, 0.7812, 1.0172 and 1.1556 respectively based on Shannon's Entropy technique. The maximum entropy value with eight zones is 2.0794 ($\log_e 8$). It could be seen that the entropy values of urbanization in all the study periods were increasing. Also, the entropy values of all eight zones of the taluk kept increasing from 2009 to 2020 and were getting closer to the maximum entropy value. This clearly indicates that the urban development is dispersive in nature. This dispersive nature of the urbanization could be the reason for TCA and ACA models not able to provide a realistic prediction outputs because they were able to predict the urbanization in cells which is in proximity to already built-up cells and thus failed to capture the dispersive nature of urbanization of the region.

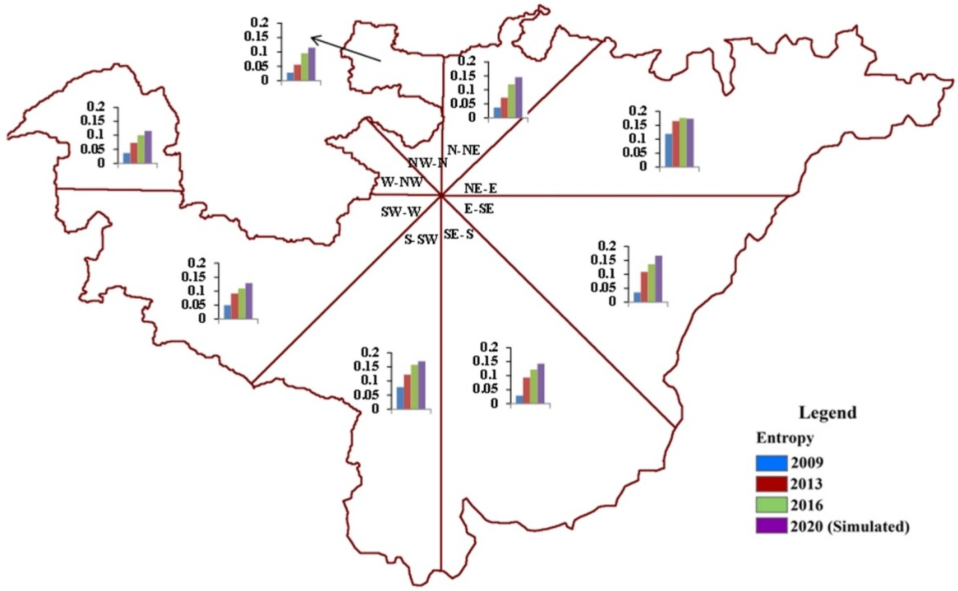


Figure 4.9. Entropy values of urbanization observed in 2009, 2013, 2016 and predicted in 2020

Further, this dispersive nature of urbanization of the taluk could be the reason that all the chosen agents of urbanization were crucial in predicting the urbanization of the region (Table 4.8). During the years of 2009, 2013, 2016 and 2020, NE-E direction of the study region had the maximum entropy values followed by E-SE and then by N-NE (Fig. 4.9). All these three directions lie in close proximity to Chennai district and also had high suitability index justifying the higher migration of people to these regions.

4.9. Conclusion

The objectives of this chapter were to conduct a pilot study to analyze the effects of TCA, ACA and NNACA based urban prediction modeling for Sriperumbudur Taluk by considering 12 different agents of urbanization based on the experts' opinions and choose the best model to predict the urbanization of the taluk in 2020. The main outcomes of this study include

- The urbanization of the taluk kept increasing during the study periods and an area of 246.55 km^2 are available for further urbanization. This provides an insight for urban planners and policy makers to take appropriate planning decisions for the sustainable management of the land cover features of the taluk
- NNACA (IHS) model is a better modeling tool for predicting the urbanization of Sriperumbudur Taluk in 2016 rather than TCA and ACA models and inclusion of hotspots into the NNACA model improved the prediction accuracy significantly. NNACA model was able to handle the model uncertainties including TR determination present in both the TCA and ACA models and determination of weights of agents which were present in the ACA models which required experts' knowledge
- TCA and ACA models were based only on the transition potential between the previous time series urban maps and thus their modeling outputs became unrealistic as the pattern and distribution of urban development change from time to time
- The appropriate choice and number of agents of urbanization are very crucial in a prediction model and selecting more number of agents than the required number of agents causes dimensionality issues in a neural network based UGM. Also choosing less number of agents would make the model unrealistic. Hence, a sensitivity analysis was implemented to analyze the effect of each of the agents of urbanization on the prediction output and choose only those agents which had maximum influence on the outputs.
- In this study, the analysis suggested that all the chosen 12 agents of urbanization were essential for the prediction of urban growth in the region and especially the agent, hotspot, is very crucial and should be included into the modeling technique for a realistic prediction output.
- Entropy analysis suggested that the taluk is experiencing distributed growth during the study periods and the growth is higher towards the Chennai city. This distributed type of urban growth could be the reason

that all the selected 12 agents of urbanization being crucial to model the urbanization of the taluk in 2016.

- Further, this dispersive nature of the urbanization of Sriperumbudur Taluk could be one of the reasons for the inability of TCA and ACA models to capture the urbanization effectively

Further, the choice of the neighbourhood cells i.e., whether to choose 3x3, 5x5, 7x7 or rectangular, circular or hexagonal have a major impact on the prediction outputs since neighbourhood configuration is the main component of a CA model. All these lessons learnt from the pilot study would be taken into account and a more customized and robust NNACA based model would be considered while modeling the urbanization of the main study area, CMA which would be discussed in the next chapter.

CHAPTER 5

URBAN GROWTH PREDICTION OF CHENNAI METROPOLITAN AREA

5.1. Introduction

Urbanization occurs due to migration of people from rural areas to cities and increase in population. Migration to cities happens in search of employment opportunities, better infrastructure facilities, lifestyle changes and so on. Unplanned urbanization leads to uneven distribution of natural resources, thereby affecting the quality of human lifestyle. Thus, UGMs are getting popular to predict future urban growth pattern based on the past and current scenarios, which is widely known as Markov Chain principle (Jafari et al., 2016; Iannone et al., 2011; Hill and Linder, 2010). UGMs based on CA are found to be most efficient than any other mathematical models such as regression (Mubea 2014; Triantakonstantis and Mountrakis 2012; Batty and Xie 1994). Sante´ et al. (2010) had given a detailed review of CA-based urban prediction models. As discussed in earlier chapter, there are many developments made on traditional CA model like ACA and NNACA aiming to achieve better prediction output. Recently, Deep belief or Belief theory implemented in CA (DB-CA) model is being used for the urban prediction. Unlike, neural networks, DB-CA models calculate the conditional dependencies between the input dataset, i.e., t_1 and t_2 urban or land cover maps (Fenton and Neil, 2018; He et al., 2018; Mohamed et al., 2011). In NNACA model, data sampling is required for training and testing the model based on the input data and also the choice of the activation function for the model involve user's intervention (Karlik and Vehbi, 2011). However, in DB-CA model, the priori data is used as such for the prediction modeling which gives more accurate results. For example, DB-CA model showed better efficiency (*k*: 0.77) for predicting the urban growth of Jiaxing City in 2015 over NN-CA model (*k*:

0.63) (Zhou et al., 2017). Similarly, Ou et al. (2018) found out that DB-CA model yielded better accuracy (*k:* 0.83) than logistic regression based CA (*k*: 0.81) while predicting the urban growth of Beijing, Tianjin and Hebei regions of China.

Following the outcomes of the pilot study (as discussed in Chapter 4) on developing urban model for Sriperumbudur Taluk, located at the fringe of Chennai Metropolitan Area (CMA), the main study area of this research, urban growth modeling was implemented using Neural Network coupled Agents-based Cellular Automata (NNACA) based model. With the recent developments in deep learning based CA model, urban prediction was done based on Deep belief network based CA (DB-CA) model also and the prediction accuracies of NNACA and DB-CA models were compared. Thus the main objectives of this chapter are

- To model the urban growth of CMA in 2017 using NNACA model by making use of 2010 and 2013 datasets
- To assess the influence of agents of urbanization (input parameters) on the accuracies of the prediction outputs based on 'Sensitivity Analysis'
- To analyze the influence of CA model parameters (neighbourhood configuration, hotspots modifications) on the prediction outputs
- To identify the type and distribution of urban sprawl (directional and distance based) of CMA during the study periods using 'Shannon's entropy'
- To compare the efficiencies of the prediction accuracies of NNACA and DB-CA models in capturing the urbanization of the study region in 2017

5.2. Materials used in the prediction model

5.2.1. Urban Cover Maps

Developing an appropriate UGM for CMA (Fig. 5.1) is the main objective of this research. Similar to the pilot study on Sriperumbudur Taluk discussed in Chapter 4, the land cover maps were prepared using the Landsat imageries of 2010, 2013 and 2017 (discussed in Chapter 3) and they contained four land cover categories including Built-Up, Vegetation, Waterbody and Openland. Since the research focuses on predicting only the urbanization of CMA, Vegetation, Water body and Openland were combined into one category as ‘Non-Built-Up’. Thus from the land cover maps, urban maps of the study region of 2010, 2013 and 2017 were prepared which contain only binary categories namely ‘Built-Up’ and ‘Non-Built-Up’ which would be further used in the modeling processes (Fig. 5.2).

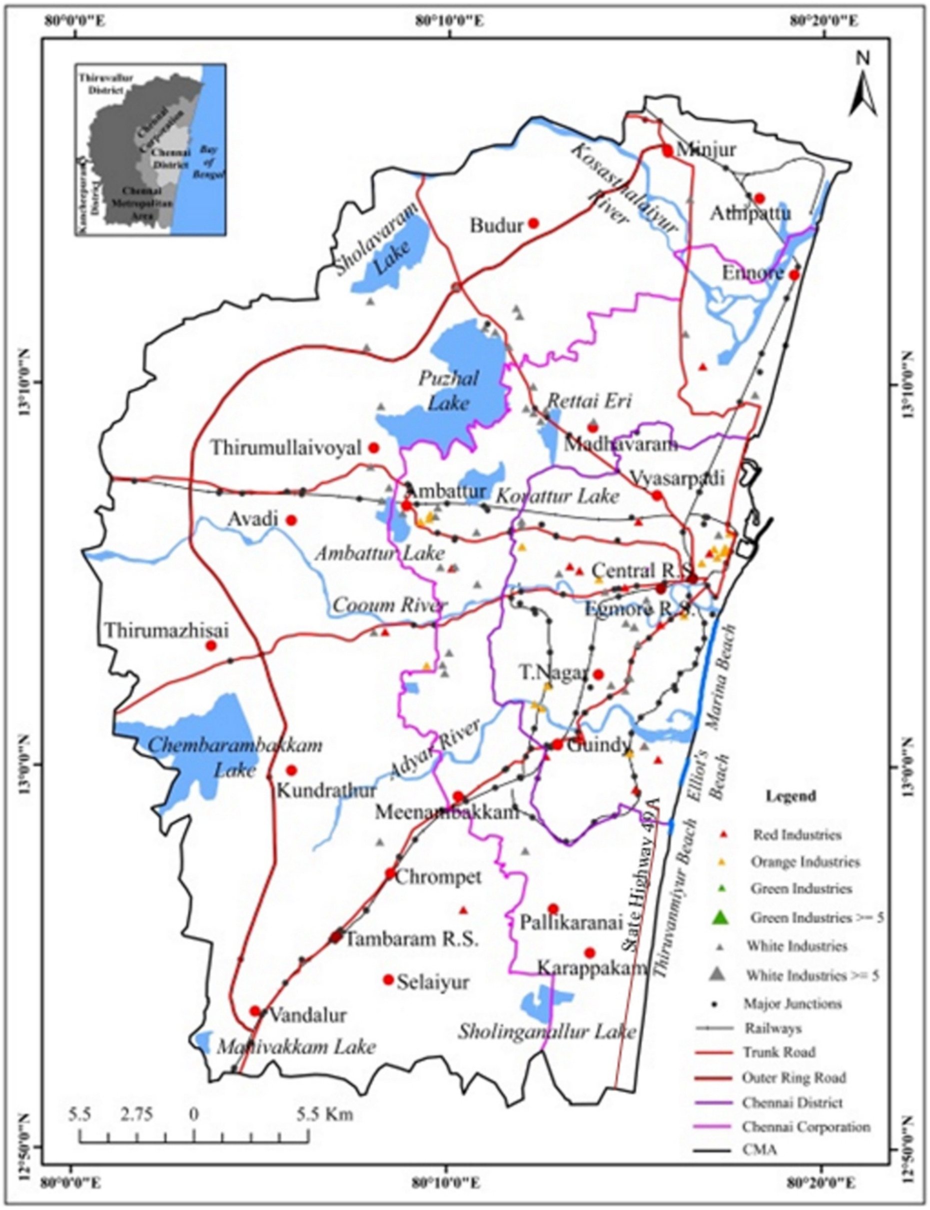


Figure 5.1. Study Area Map showing the expanded administrative boundaries of Chennai City.

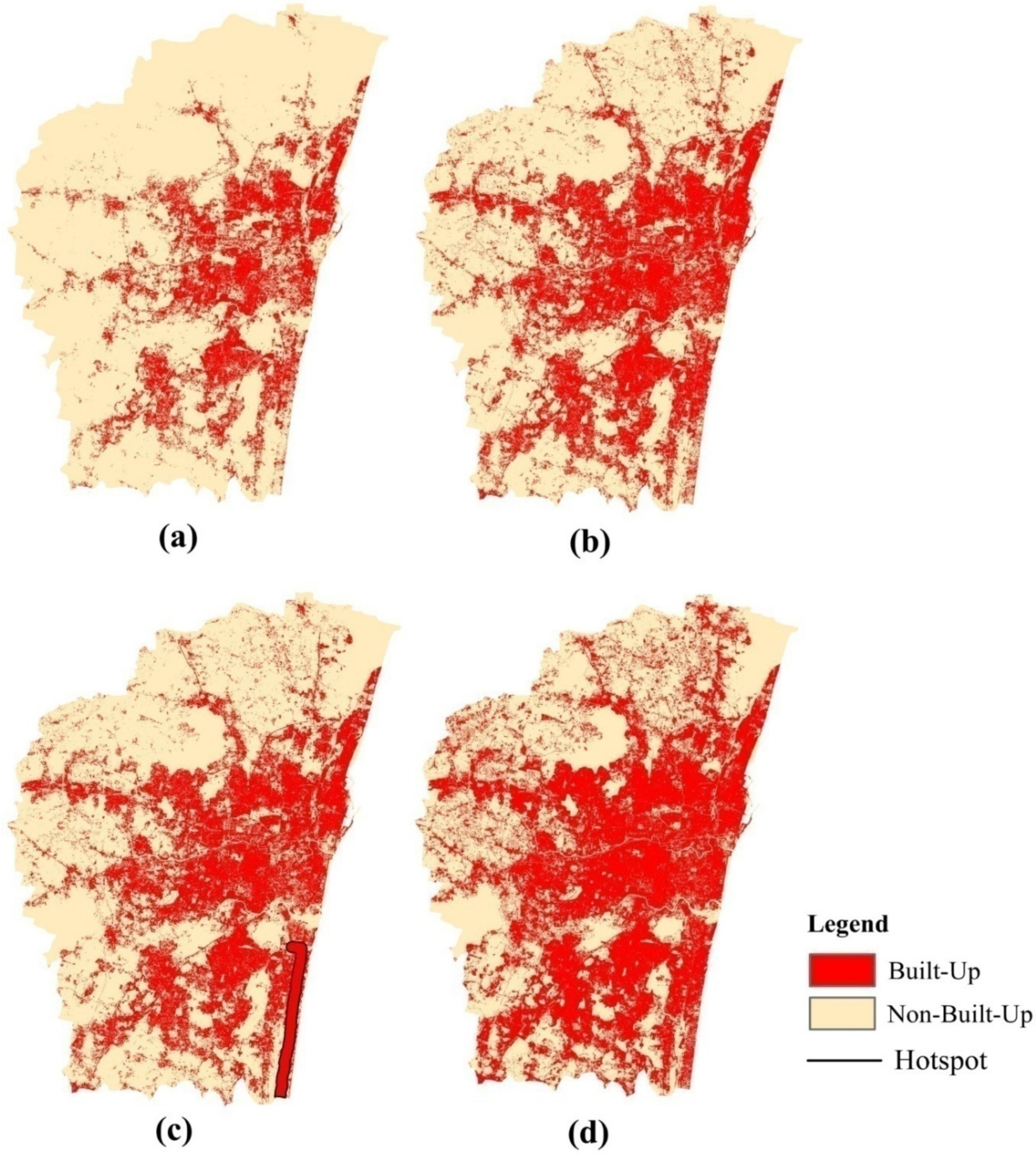


Figure 5.2. Urban Maps of Chennai Metropolitan Area. (a) 2010; (b) 2013 (EHS); (c) 2013 (IHS); (d) 2017

5.2.2. Agents of Urbanization

As discussed in section 4.2.2 of Chapter 4, agents of urbanization along with the urban maps are essential for predicting the urbanization of a region. The choice of appropriate agents of urbanization depends on the knowledge of the study region and experts' opinion. Based on experts of CMDA, academicians,18 different agents of urbanization were identified for CMA which includes (i) Existing Built-up of 2013, (ii) Hotspots, (iii) Commutation, (iv) High Preference Roads (including Trunk, Primary and Residential Roads), (v) Medium Preference Roads (including Secondary and Tertiary Roads), (vi) Least Preference Roads (Expressways and Outer Ring Road), (vii) Railway Networks. Industries were categorized into four based on their PIS (as discussed in Chapter 4): (viii) Red, (ix) Orange, (x) Green and (xi) White Industries. Monetary value of land plays a major role in determining the rate of urbanization in that region. Hence, in this study, land values at village level were taken into account and they were categorized into three: (xii) High land Prices (> 1500 INR); (xiii) Medium land prices (>500 AND <=1500 INR); (xiv) Low land prices (<=500 INR). (xv) Places of public interests including educational institutions, hospitals, recreational centres, religious centres, (xvi) Public Utility centres including banks, Government offices and (xvii) Population density map of the study area at revenue village level was prepared based on the census data. Since the prediction model is based on CA, (xviii) 3x3 urban neighbourhood is also taken as one of the agents of urbanization for predicting the urban growth of CMA in 2017. The urban maps of 2010, 2013 and 2017 along with the proximity maps of these 18 agents were used in the prediction of urbanization of CMA based on NNACA and DB-CA models.

5.3. Methodology

5.3.1. Identification of Hotspots and Constraints

In our pilot study on the prediction of urban growth of Sriperumbudur Taluk, inclusion of hotspots improved the accuracy of prediction model. The development activity of a city is unique and a sudden emergence of growth may be observed in areas where there is no urban development earlier also. For instance, construction of recreation centres or establishment of any IT centres may spark urbanization in a completely non-urbanized areas. Hence, inclusion of hotspots based on Government's development policy becomes mandatory in the prediction model. Based on the Second Master Plan for Chennai Metropolitan Area (2008a) area of 500 m on either side of the State Highway 49A, also known as Old Mahabalipuram Road (OMR) were identified for IT development in the year 2014 and considered as the potential hotspot for further urbanization in CMA. Hence, a buffer zone of 500 m around OMR is included in the urban map of 2013 as hotspot for predicting the urbanization of 2017 (Fig. 5.2(c)).

In an urban growth prediction model, apart from the identification of potential hotspots, identifying the areas where growth is prohibited is also important. These areas are termed as 'Constraints' in which any urban developmental activity is restricted and hence our prediction model should not make any urban predictions in those regions. For predicting the urbanization of CMA, the following 6 layers of constraints were considered: (i) Coastal Regulation Zone (CRZ) – I, (ii) major water bodies within the study region, (iii) areas around airport at Meenambakkam, (iv) areas of 100 m around the boundary of Indian Air Force station near Tambaram, (v) Pallikaranai swamp area and (vi) green belt areas of 15 m along Poonamallee and Red Hills bye pass roads and these areas were considered as non-built-up during the entire urban modeling process.

5.4. Urban Growth Prediction

5.4.1. NNACA Model

MLP of LCM, Terrset, (Fig. 5.3) was used for the prediction of urban growth based on NNACA for CMA in 2017. A typical MLP architecture includes one input layer, one or more hidden layers and an output layer. 2n/3 number of hidden layers is most appropriate in modeling complex scenarios (Yeh and Li, 2002) (n: number of input layers). Here, n = 18 and thus 12 hidden layers were used in the modeling. The urban maps of 2010, 2013 along with the proximity map of existing built-up of 2013 along with 3 × 3 neighbourhood map were fed into the NNACA model and it was run for 10,000 iterations with dynamic learning rate (Aarthi and Gnanappazham, 2018). An accuracy rate of 80% is considered to be accepted and it can be understood that the model has learnt well based on the input datasets (Eastman, 2012).

5.4.2. DB-CA Model

UGMs based on NNACA have proved to be efficient in predicting the urbanization of a region. However, there are certain uncertainties in NNACA model regarding the determination of transition rule, neighbourhood configuration. Hence, DB-CA model is implemented in this chapter to overcome the difficulties of NNACA model. DB-CA model is based on Bayes' theorem, a mathematical equation used in probability and statistics to calculate conditional probability. In other words, it is used to calculate the probability of an event based on its association with another event. The theorem is also known as Bayes' law or Bayes' rule (Stone, 2013). Bayes' theorem is named after English minister and statistician Reverend Thomas Bayes of 18th century. The rule provides us a way to update the probabilities of hypotheses given evidence through conditional probability. Conditional probability is the probability of an event happening, given that it has some relationship to one or more events. Given a hypothesis A and evidence B, Bayes rule is given as $P(A \mid B) = \frac{P(B \mid A)\,P(A)}{P(B)}$. Bayes rule is implemented recently in the urban prediction studies since they consider the probability of the previous urbanization of the study region and also the experts' knowledge about the region (Ouyang et al., 2019).

In this chapter, the prediction of urban growth in 2017 (t_3) based on the urbanization of 2013 (t_2) and 2010 (t_1) was implemented using DB-CA model (Fig. 5.3). Conditional probability of finding urban pixels in t_3 given urban neighbours greater than or equal to 3 in t_2, $P(U_{t3} \mid N_{t2})$ is given by

$$P(U_{t_3} \mid N_{t_2}) = P(U_{t_2}) * \frac{P(N_{t_1} \mid U_{t_2})}{P(N_{t_2})} \tag{5.1}$$

Probability of urban pixels in t_2, $P(U_{t_2})$ is calculated as

$$P(U_{t_2}) = \frac{N_{U_{t2}}}{N_T} \tag{5.2}$$

Conditional probability of urban neighbours >=3 in t_1 given urban pixels in t_2, $P(N_{t_1} \mid U_{t_2})$ is given by

$$P(N_{t_1} \mid U_{t_2}) = \frac{N_{n_{t_1}}}{N_{U_{t_2}}} \tag{5.3}$$

Probability of urban neighbours >= 3 in t_2, $P(N_{t_2})$ is calculated as

$$P(N_{t_2}) = \frac{N_{n_{t2}}}{N_T} \tag{5.4}$$

where,

$N_{n_{t_1}}$: Number of urban neighbours >= 3 in t_1

$N_{U_{t_2}}$: Number of urban pixels in t_2

$N_{n_{t_2}}$: Number of urban neighbours >=3 in t_2

N_T: Total number of pixels in the study region

DB-CA model predicts the posterior probability $P(U_{t_3} \mid N_{t_2})$ based on the prior probability $P(U_{t_2})$ and the likelihood $\frac{P(N_{t_1} \mid U_{t_2})}{P(N_{t_2})}$

In this model, it is assumed that probability of built-up at time t_1 getting converted to non-built-up at time t_2 remains zero. Hence, it is assumed that the number of built-up pixels of 2013 remain built-up in the year 2017 also. Based on the DB-CA model, the expected number of non-built-up pixels to be converted to built-up in 2017 was calculated based on equation 5.1. The model was run in ArcGIS environment till the expected number of non-built-up pixels are converted to built-up in 2017.

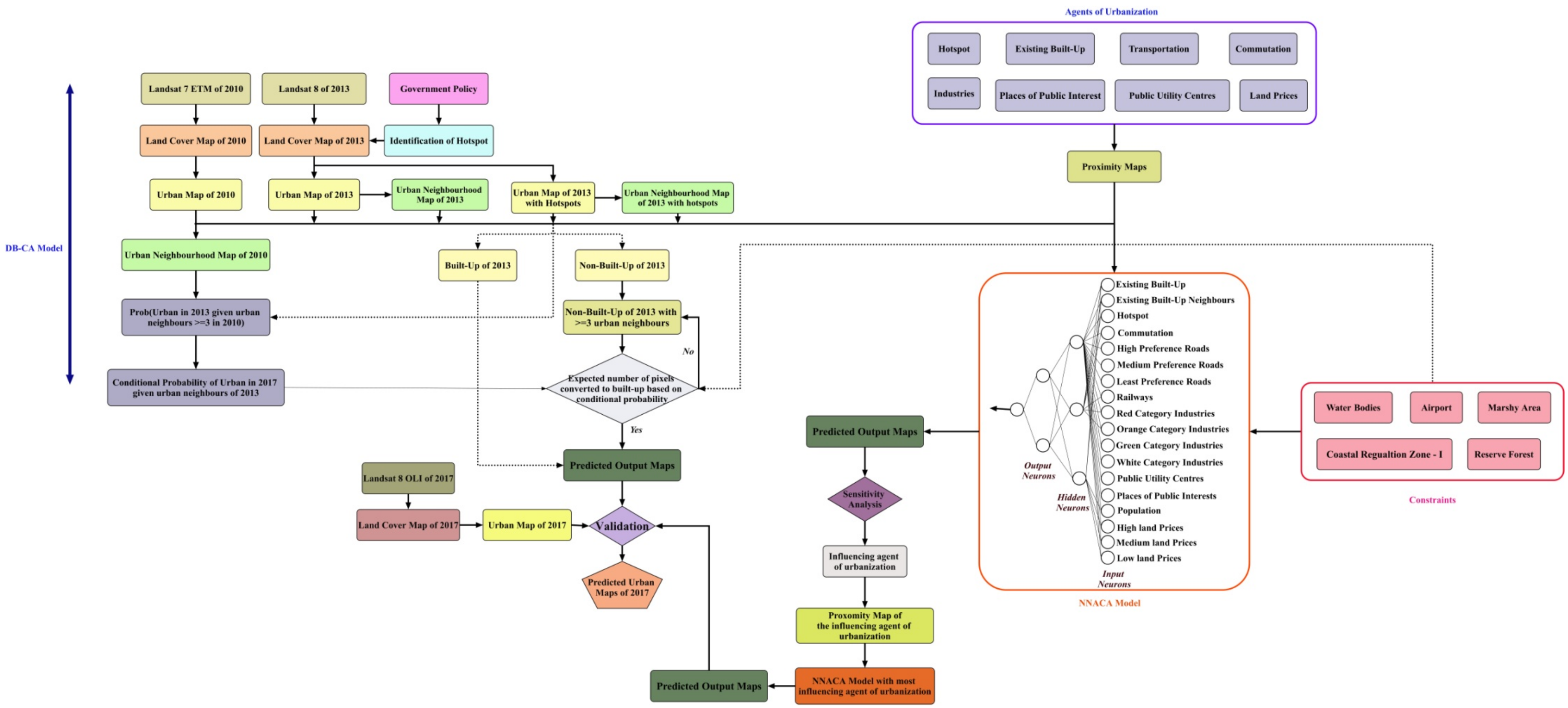
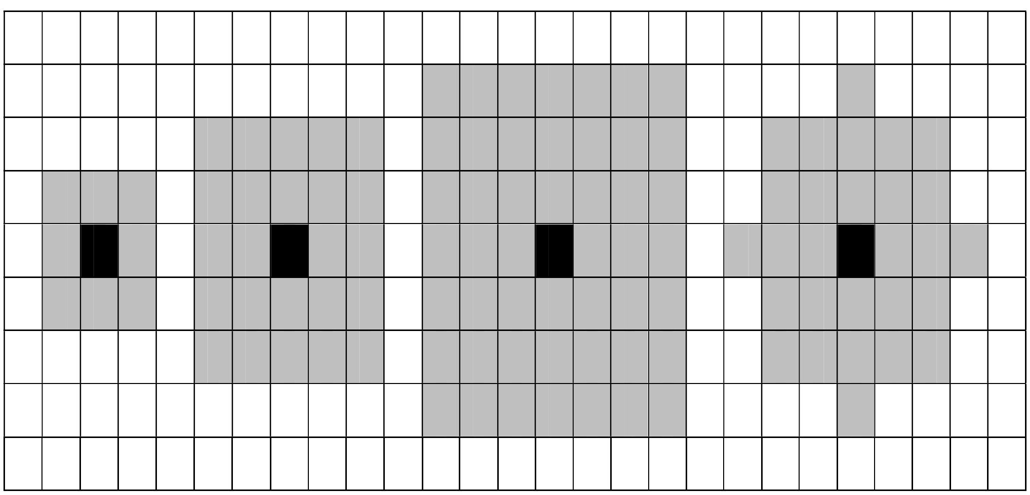


Figure 5.3. Methodology adopted in the study for the prediction of urban growth in CMA using NNACA and DB-CA models

5.5. Influence of neighbourhood configuration on the prediction outputs

In an urban model based on CA, neighbourhood configuration, one of the main components of CA model, plays a vital role in predicting the urbanization of a study region. Because, based on the neighbourhood configuration the state of a cell gets converted to built-up in the next time step during the prediction process. However, the choice of appropriate neighbourhood configuration depends on the experts' knowledge about the study region. The most commonly used neighbourhoods are Von Neumann (4-cell) and Moore (8-cell) (White, 1998). Mostly rectangular 3x3 neighbourhoods are used in the urban prediction models (Mubea, 2014). However, circular, hexagonal neighbourhoods with 5x5, 7x7, 9x9 and so on are used in the modeling. In this study, 3 x3, 5 x 5 and 7 x 7 rectangular and 3 x 3 circular neighbourhood configurations (Fig. 5.4) were used in DB-CA modeling to find the most suitable one based on their prediction accuracies.



(a) **(b)** **(c)** **(d)**

Figure 5.4. Types of neighbourhood configuration used in DB-CA model to predict the urbanization of CMA in 2017. Rectangular (a) 3x3; (b) 5x5; (c) 7x7; (d) Circular 3x3

5.6. Assessing the type of Urban Growth based on Shannon's Entropy

To assess the direction and distribution of urban sprawl during 2010, 2013 and 2017, normalized Shannon's entropy was calculated (as discussed in Chapter 4). In this chapter for assessing the type and distribution of urban sprawl of CMA, urban maps of the years 2010, 2013 and 2017 were used to assess the (i) direction and (ii) distance-based entropy values of CMA. The study area was divided into eight directional zones [North–North East (N–NE), North West–North (NW–N), West–North West (W–NW), South West–West (SW-W), South–South West (S–SW), South East–South (SE–S), East–South East (E–SE) and North East–East (NE–E)] with the State Secretariat as the center. Since the study area lies on the east coast, the directional zones with insignificant areas were merged with the neighbouring zones, i.e., NE–E is merged with N–NE zone and E–SE and SE–S were merged with S–SW zone resulting in five zones (N–NE, NW–N, W–NW, SW–W and S–SW). Further, the study area is divided into five buffer zones of each 7 km based on the distance from the State Secretariat and entropy values for each of these zones were calculated to measure the urban sprawl of CMA during the study periods.

5.7. Results and Discussions

5.7.1. Temporal Urban cover maps and Hotspots

Urban maps of CMA (Fig. 5.2) reveal that the built-up area was increasing from 2010 to 2017. The study area occupies 1189 km^2 of area of which built-up of 2010, 2013 and 2017 occupied 237.41 km^2, 400.57 km^2 and 572.11 km^2 respectively. The land cover change analysis (discussed in Chapter 3) reported that an area of 356.18 km^2 remains available for further urbanization in CMA. In our pilot study on Sriperumbudur Taluk the inclusion of hotspots increased the area of hits and decreased the area of misses thus improving the accuracy of the prediction outputs. Similarly in this current chapter, to make the urban prediction maps more accurate and realistic, urban hotspot as linear feature of 500m buffer around OMR was introduced in the urban map of 2013 (Fig. 5.2**(c)**). Areas around OMR is a hub of many IT centres and the establishment of these IT centres had been the main reason for the development of areas in this buffer zone. In this study, urban prediction of 2017 was carried out with the proximity maps of 18 agents of urbanization (Fig. 5.5**(a)**-**(r)**) along with the urban maps of 2010 and 2013 using NNACA model (EHS and IHS) along with the constraints (Fig. 5.5**(s)**).

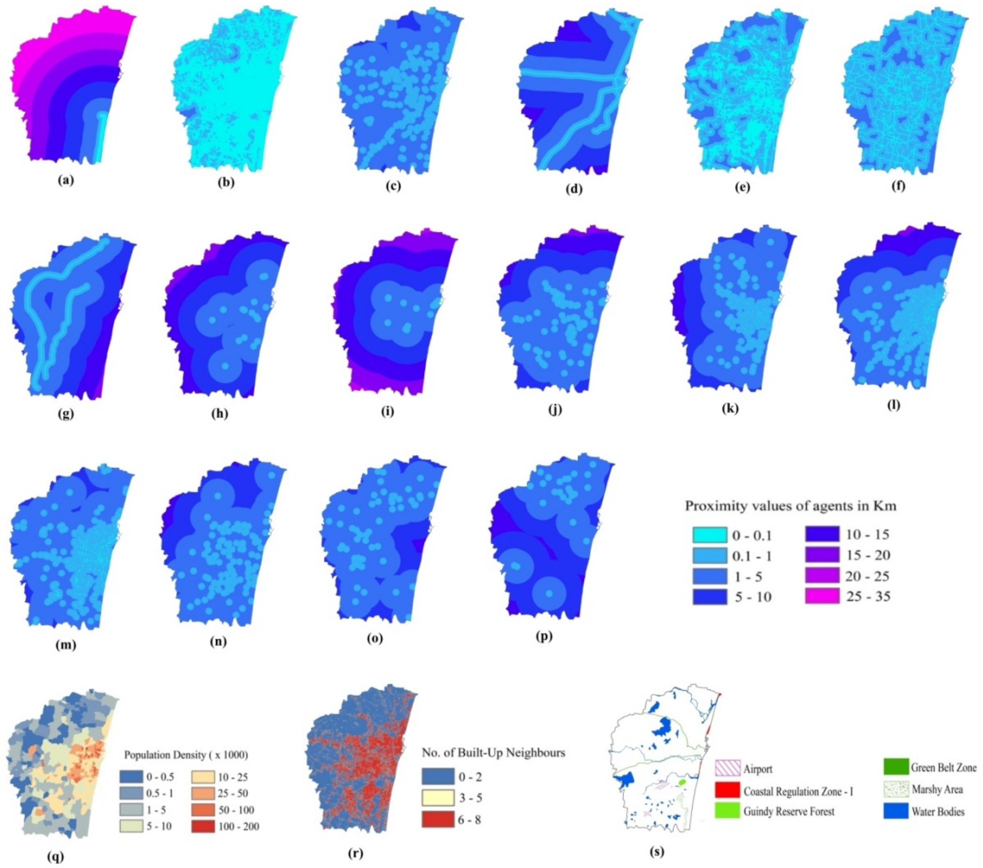


Figure 5.5. Inputs of NNACA model for the urban growth prediction for CMA. Proximity maps of (a) hotspots; (b) existing built-up; (c) commutation; (d) railways; (e) high preference roads; (f) medium preference roads; (g) least preference roads; (h) red category industries; (i) orange category industries; (j) green category industries; (k) white category industries; (l) places of public interests; (m) public utility centers; (n) high land prices; (o) medium land prices; (p) low land prices; (q) population density map; (r) urban neighbourhood map; (s) constraints

5.7.2. Model outputs of NNACA

The observed urbanization of CMA in 2017 was mapped to be 572.11 km^2. The urbanization predicted by IHS model was 606.35 km^2 whereas EHS model predicted 576.92 km^2 of urban development in 2017 (Fig. 5.6). However, the accuracy of the prediction output of IHS was higher (OA: 85.51%; *k:* 0.71) than EHS model (OA: 84.82%; *k*: 0.6966) (Fig. 5.5). For an efficient model, apart from the higher OA (higher areas of hits), it is also important to have lesser areas of false alarms and misses, as given by k values (Shafizadeh-Moghadam et al., 2017). Also, when the predicted outputs were validated against the observed urban map of 2017 the areas of hits were highest in the IHS model (498.52 km^2) when compared to 488.31 km^2 in EHS model. Hence, the rate of under-prediction (misses) was lesser in IHS model corresponding to only 73.59 km^2 whereas the area of misses of EHS is found to occupy 83.8 km^2 of CMA. Since, the higher areas of hits were found associated with IHS model the rate of over-prediction (false alarms) were also higher with this model. IHS with all the 18 agents of urbanization produced 106.57 km^2 false alarm while EHS resulted in 88.57 km^2 of false alarm in the predicted urban growth of CMA in 2017 (Fig. 5.6).

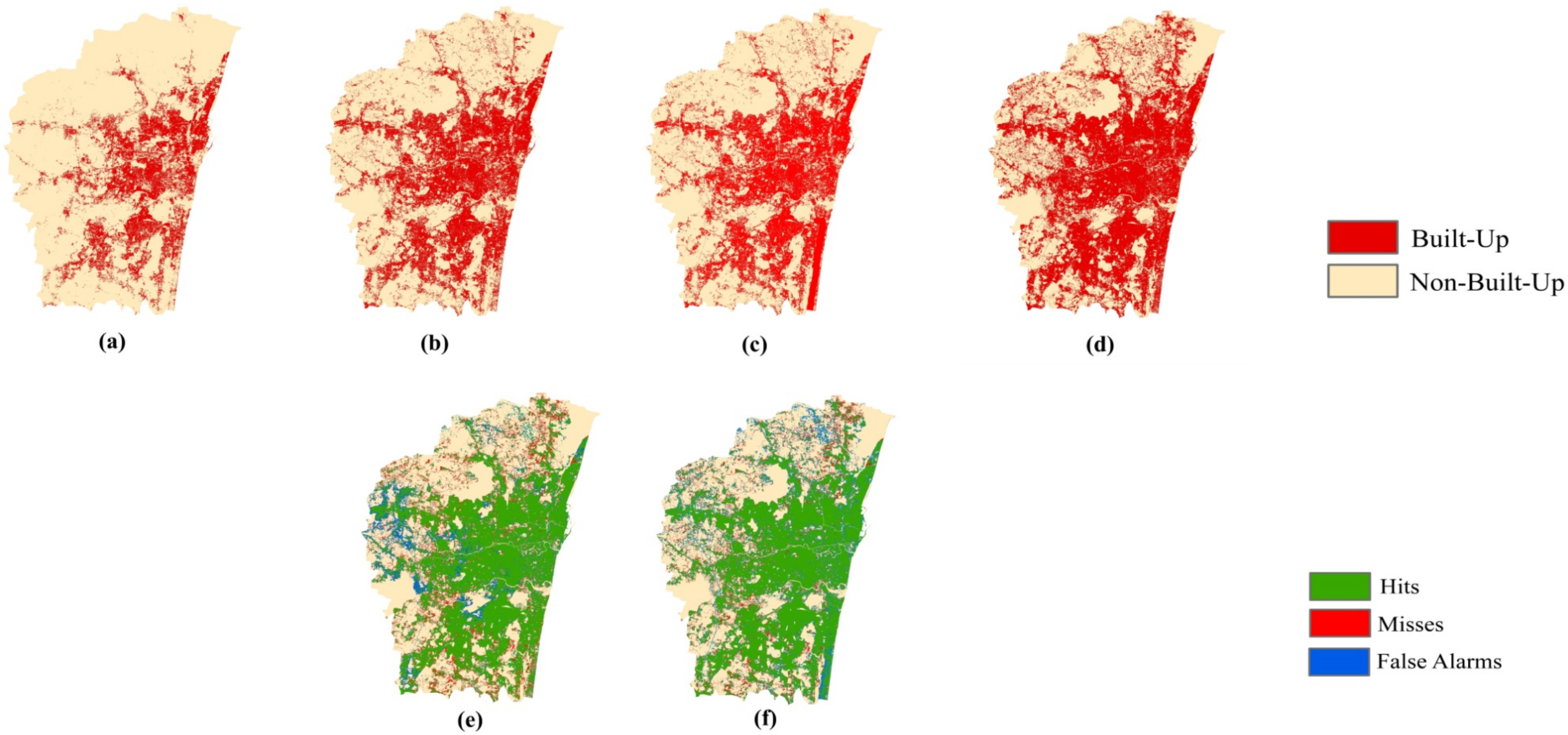


Figure 5.6. Observed and Predicted Urban Maps using NNACA model of CMA. Observed Urban Map of (a) 2010; (b) 2013; (c) 2013 with hotspot; (d) 2017; Validation outputs of (e) EHS model with all the 18 agents of urbanization; (f) IHS model with all the 18 agents of urbanization

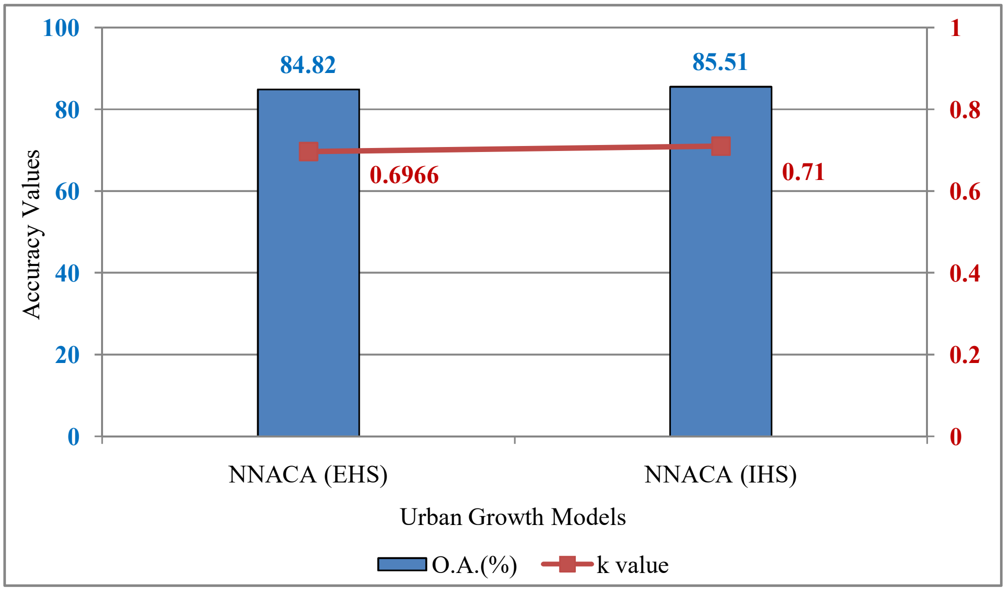


Figure 5.7. Accuracies of the prediction outputs based on NNACA model to model the urbanization of CMA in 2017

5.7.3. Sensitivity analysis - Influence of input parameters on the prediction outputs

The choice of appropriate agents of urbanization for the prediction model is uncertain and it involves experts' knowledge about the study region and also on the knowledge about the past historic urban development of the region. In this study, based on the experts' opinions 18 agents of urbanization were chosen for the prediction modeling. However, to check the influence of each of these agents of urbanization on the prediction output, sensitivity analysis was performed (Table 5.1). In this regard, each of the agents along with the urban neighbourhood map was implemented using IHS model (Table 5.1 **(i) - (xvii)**) and their prediction accuracies were reported. Since IHS model is based on CA, urban neighbourhood map along with each one agent is used to run the prediction model. This analysis was carried out mainly because of the fact that making use of more number of required agents of urbanization in the prediction model would make the IHS model output less realistic. On the other, a lesser number of agents of urbanization would not reflect the real world phenomena and would make the prediction output with less accuracy. In our pilot study discussed in chapter 4, the agent 'slope' was allotted the least weight in the suitability map preparation based on AHP technique implying that that the particular agent has almost null or less influence on the prediction output. Making use of agents which has least or almost no influence on the prediction outputs into the NNACA model would introduce 'dimensionality' issue into the network (Bach, 2017). Hence to avoid these, sensitivity analysis was performed to find the appropriate agent of urbanization among the 18 agents and use only the most influencing one in the prediction model. The result reveal that 'Existing Built-Up of 2013' produced the maximum area of hits (502.42 km^2) with lesser misses (69.7 km^2) and higher false alarm (102.69 km^2) with higher Cramer's value (0.7107) when compared to the IHS model. The higher the Cramer's value, higher is the influence of the agent of urbanization on the prediction model.

Based on the 'leave-one out' technique, the sensitivity analysis was again implemented based on IHS model (Table 5.1 **(xviii)** – **(xxxii)**). It is found that when the 'Existing Built-up of 2013' was excluded from the prediction model, the accuracy of the output decreased (Hits: 489 km^2; Misses: 82.64 km^2; False Alarms: 115.52 km^2) with least Cramer's value (0.6672) which substantiates the fact that it is the most influencing agent in the study region. Thus, the results of sensitivity analysis suggest that existing built-up of 2013 alone was sufficient to predict the urbanization of CMA in 2017.

Table 5.1. Validation outputs and Cramer's values of sensitivity analysis of agents of urbanization using IHS model for the prediction of urban cover of CMA in 2017

Urban Growth Models		Area (km^2) of validation outputs			Cramer's Value
		Hits	Misses	False Alarms	
NNACA (IHS) only with	**(i)** Existing Built-Up	502.42	69.7	102.69	0.7107
	(ii) High Preference Roads	495.18	76.93	109.91	0.6664
	(iii) Public Utility Centres	491.59	80.52	113.52	0.6407
	(iv) Population	491.56	80.55	113.53	0.6863
	(v) Green Category Industries	491.51	80.6	113.54	0.6732
	(vi) Places of public interests	491.37	80.74	113.74	0.6584

	(vii) Medium Preference Roads	491.28	80.83	113.79	0.6572
	(viii) High land prices	490.65	81.46	114.46	0.6294
	(ix) Hotspots	489.27	82.84	115.84	0.6469
	(x) White Category Industries	489.26	82.86	115.84	0.6740
	(xi) Least Preference Roads	486.89	85.23	118.18	0.6664
	(xii) Railways	486.52	85.59	118.51	0.6710
	(xiii) Medium land prices	484.67	87.44	120.43	0.6508
	(xiv) Low land prices	484.62	87.49	120.44	0.6509
	(xv) Orange Category Industries	483.52	88.59	121.64	0.6734

	(xvi) Commutation	481.64	90.48	123.43	0.6742
	(xvii) Red Category Industries	480.58	91.53	124.41	0.6741
NNACA (IHS) excluding	**(xviii)** Existing Built-Up	489.48	82.64	115.52	0.6672
	(xix) Places of Public Interests	494.70	77.41	110.37	0.6848
	(xx) White Category Industries	494.84	77.27	110.27	0.6852
	(xxi) Population	495.19	76.92	109.86	0.6864
	(xxii) Low land prices	495.52	76.59	109.53	0.6876
	(xxiii) Medium land prices	495.95	76.16	109.13	0.6890

	(xxiv) Public Utility Centres	496.23	75.88	108.84	0.6899
	(xxv) Green Category Industries	496.42	75.69	108.66	0.6906
	(xxvi) High land prices	496.49	75.62	108.58	0.6908
	(xxvii) Medium Preference Roads	496.87	75.24	108.19	0.6921
	(xxviii) Red Category Industries	496.98	75.13	108.07	0.6925
	(xxix) Orange Category Industries	497.16	74.95	107.92	0.6930
	(xxx) Hotspots	497.30	74.81	107.77	0.6935
	(xxxi) Railways	498.40	73.71	106.67	0.6972

	(xxxii) High Preference Roads	498.56	73.55	106.49	0.6978
	(xxxiii) Least Preference Roads	498.67	73.44	106.41	0.6981
	(xxxiv) Commutation	498.97	73.14	106.15	0.6991

5.7.4. Prediction output based on DB-CA model

It could be understood that NNACA (IHS) model is better than EHS model for predicting the urbanization of CMA in 2017. Further, it was also identified through sensitivity analysis that, IHS model performed much better with just one identified influencing agent of urbanization i.e., 'Existing built-up of 2013' along with the urban maps of 2010 and 2013 in predicting the urbanization of CMA in 2017. However, using DB-CA model, the urbanization of CMA was predicted to be 665.09 km^2 for 2017 using the urban maps of 2010 and 2013 and existing built-up of 2013 as the agent of urbanization with 3x3 urban neighbourhood configuration with higher accuracy (OA: 86.08%; *k*: 0.73) (Fig. 5.8) than NNACA-IHS model. Validation of the predicted output of DB-CA model (Fig. 5.9) reveal that the areas of hits (524.14 km^2) produced was higher than that of IHS model with the influencing agent of urbanization. Areas of misses were lesser in DB-CA model accounting to 47.97 km^2. However, the false alarm was higher (140.95 km^2). This is because when an urban prediction model predicts higher areas of hits, the false alarm rate will also be higher (Feng et al., 2016). Thus, the areas of hits and false alarms are higher and misses are lesser in DB-CA model when compared to those of NNACA model.

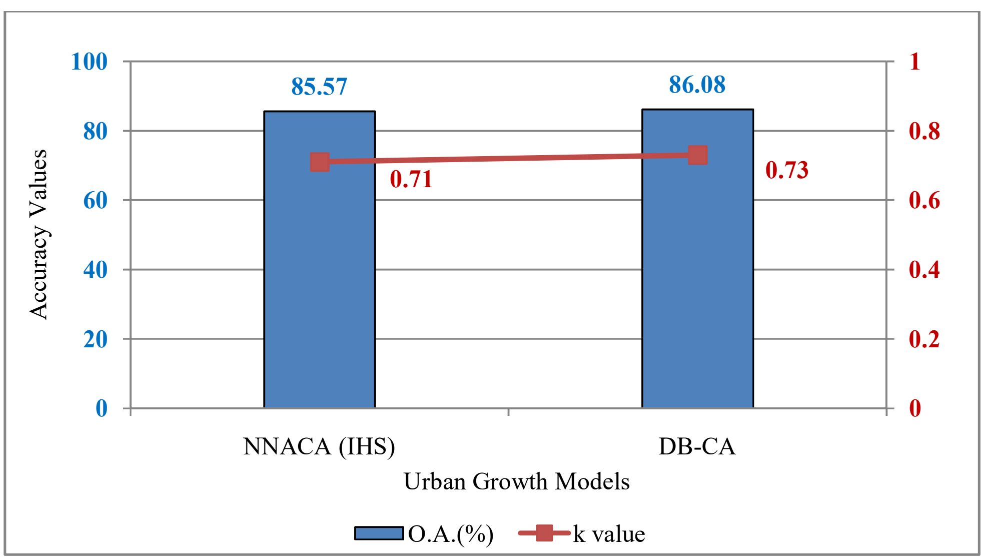


Figure 5.8. Accuracies of the prediction outputs based on NNACA and DB-CA models to model the urbanization of CMA in 2017

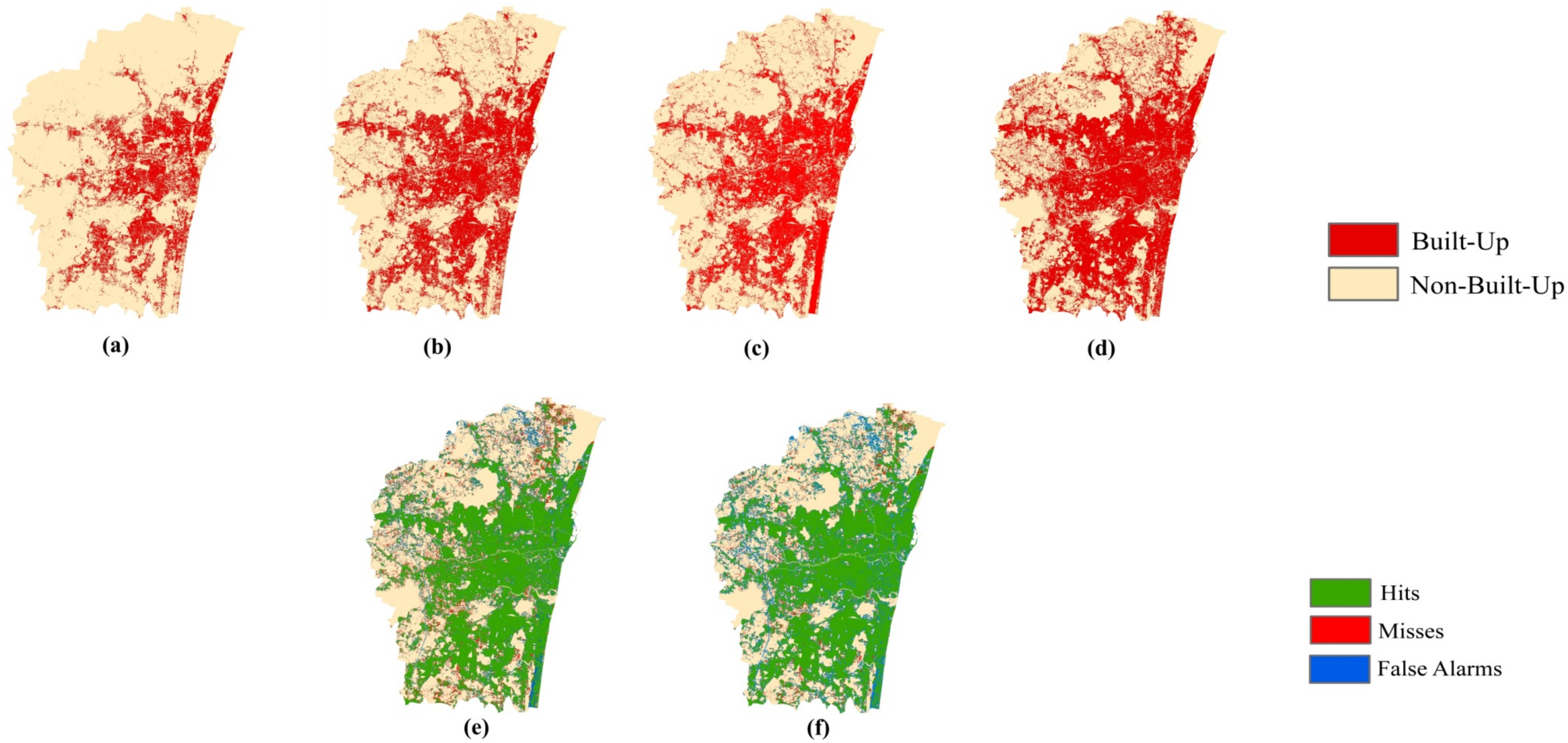


Figure 5.9. Observed and Predicted Urban Maps using NNACA (IHS) and DB-CA models with only existing built-up of 2013 as agent of urbanization. Observed Urban Map of (a) 2010; (b) 2013; (c) 2013 with hotspot; (d) 2017; Validation outputs of (e) IHS model; (f) DB-CA model

5.7.5. Sensitivity analysis – Influence of model parameters on the prediction outputs

Neighbourhood configurations

Since DB-CA model predicted the urbanization with higher hits, the same model was used to assess the influence of neighbourhood configuration on the prediction output. Rectangular (3x3, 5x5 and 7x7) and Circular (3x3) different types of configurations were used to predict the urbanization based on DB-CA model. Results proved that rectangular 3x3 configuration produced the maximum hits (524.14 km^2) with lesser misses (47.97 km^2) (Table 5.2). Hence, it could be understood that 3x3 rectangular neighbourhood configuration is best suitable to predict the urbanization of CMA in 2017.

Table 5.2. Validation of prediction outputs based on DB-CA model to predict the urbanization of CMA in 2017 with different neighbourhood configurations

Neighbourhood Configurations		**Accuracies**		**Area (km^2) of validation outputs**			**Cramer's Value**
		O.A. (%)	*k* value	Hits	Misses	False Alarms	
Rectangular	3x3	84.81	0.6970	524.14	47.97	140.95	0.7080
	5x5	83.11	0.6903	518.94	53.17	123.52	0.7052
	7x7	83.05	0.6902	512.89	59.22	118.15	0.6914
Circular	3x3	83.07	0.6902	518.97	53.17	124.43	0.7067

Modification of hotspot area in the urban map of 2013

It is to be noted that the hotspot was introduced into the urban map of 2013 to predict the urbanization of 2017. Though, DB-CA model predicted higher areas of hits when compared to NNACA model, the areas of false alarms were higher. Hence, an attempt was made to check if there was any influence on the prediction output and thereby on the false alarm rate by modifying the areas of hotspot. In other words, in our prediction model, all the non-built-up pixels falling within the 500 m buffer zone around OMR were considered as built-up and were introduced into the 2013 urban map which was further used to predict the urbanization in 2017. Here, modifying the area of urban pixels within the hotspot was used to check how it affected the accuracy of the prediction outputs. Thus, in this context, non-built-up pixels falling within the hotspot were randomly selected and converted as built-up and introduced into the urban map of 2013. Thus, in this study, random value of 80% and 60% of non-built-up pixels within the hotspots were converted to built-up and introduced into the urban map of 2013 to predict the urbanization of CMA in 2017. The results obtained are shown in Table 5.3. It could be seen that 80% and 60% modification of hotspot produced the same outputs. When all the non-built-up pixels within the hotspot buffer zone were considered as built-up, the prediction output produced maximum hits (524.14 km^2). Hence, in our study, all the pixels within the linear buffer of hotspot around OMR were considered as built-up and included as hotspot in the urban map of 2013 in the prediction modeling process using NNACA (IHS) model.

Table 5.3. Validation outputs of DB-CA model based on modified hotspots using 3x3 rectangular neighbourhood to predict the urban growth of CMA in 2017

% of non-built-up pixels within the hotspot considered as built-up and included in the urban map of 2013	**Accuracies**		**Area (km^2) of validation output**			**Cramer's Value**
	O.A. (%)	*k* value	Hits	Misses	False Alarms	
100	84.81	0.6970	524.14	47.97	140.95	0.7080
80	84.08	0.6830	519.72	52.39	127.94	0.7053
60	84.08	0.6830	519.72	52.39	127.95	0.7053

5.7.6. Entropy analysis: Distribution of urban growth

It is to be noted that the urbanization of the study region was increasing from 2010 to 2017 (Fig. 5.10). The entropy values of urbanization of 2010, 2013 and 2017 were found to be 0.981, 1.114, and 1.0845, respectively showing that the urban sprawl was distributed till 2013 and after the year 2013 congested or concentrated type of urban growth was observed in CMA. The maximum entropy value with five zones is 1.6094 ($\log_e 5$). To assess the direction and distribution of the urban growth of CMA, entropy analysis was carried out by dividing the study area into 5 direction based zones (S-SW, SW-W, W-NW, NW-N and N-NE) and 5 distance based zones (7, 14, 21, 28 and 35 km) from the State Secretariat.

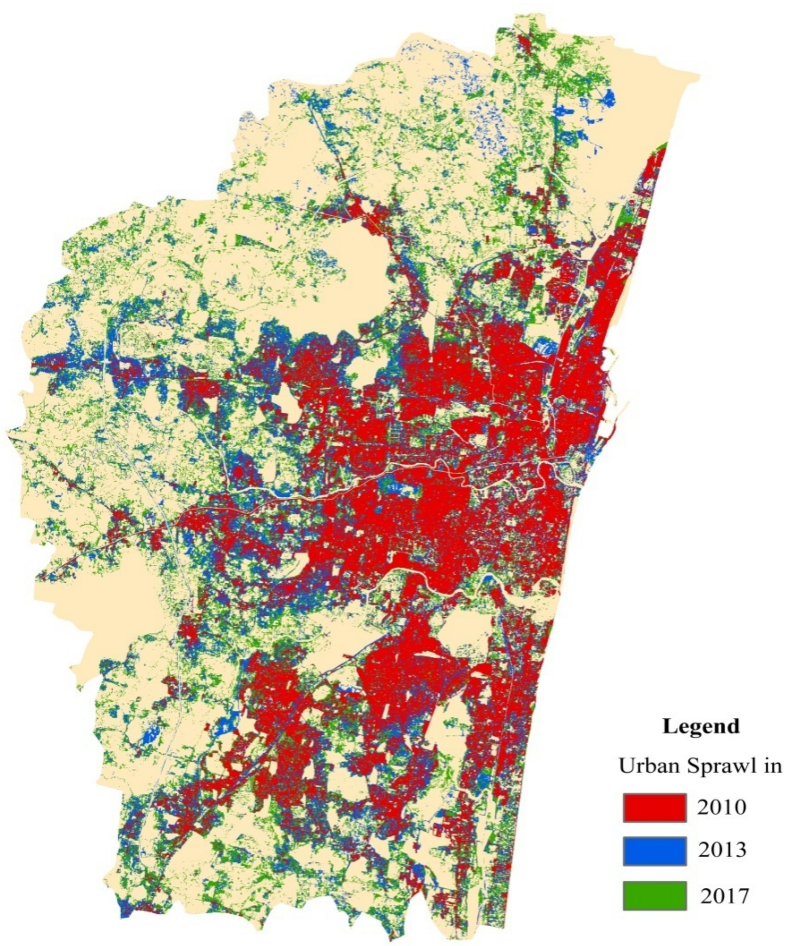


Figure. 5.10. Urban Sprawl of CMA during 2010, 2013 and 2017

Directional based entropy analysis

In the directional based entropy analysis, the urbanization of CMA in each of the 5 zones was calculated based on Shannon's entropy value for the study periods. It can be noted that the southern part of CMA experiences higher growth than the northern region, maybe because the southern region falls within the State boundary (Fig. 5.11 **(a)**). Urbanization is lesser in the northern zones (N–NE, NW–N) as they are lie at the cross-state boundary. From the direction based analysis we could infer the following:

- In 2017, concentrated type of urban growth was observed in S–SW, SW–W directions. Because of the availability of employment opportunities and socio-economic amenities, southern CMA was highly urbanized than the north and settlements occurred mainly in the southern region and thus urbanization in south got congested. N–NE, NW–N and W–NW zones experienced distributed growth in 2017
- Maximum urbanization (192.03 km^2) occurred in SW–W zone which included T.Nagar, Thirumazhisai. Location of commercial industries, amenities including hospitals, educational institutions, and religious centers are higher, and also the accessibility to transportation network is much higher in this zone. Hence, this zone experienced highest urban growth in CMA
- The S–SW zone is the second most urbanized (139.79 km^2), and the major locations within this zone include Adyar, Perungudi. Location of IT centers and industries mainly caused the urbanization in this zone (https://www.sipcot.com/industrial_complex.html).
- The third most urbanized in CMA is the W–NW zone (134.87 km^2) including Anna Nagar, Avadi and location of SIPCOT (State Industries Promotion Corporation of Tamil Nadu) Industrial Estates drove the urbanization in this zone
- Vyasarpadi and Minjur are located within the NW–N zone, the fourth urbanized in CMA (83.16 km^2), in which automobile and petro-chemical-based industries are situated.

- The least urbanization is found in the N–NE zone (22.88 km^2) which comprises Tondiarpet, Ennore. Urbanization occurred in this zone mainly due to the industries related to coastal activities.

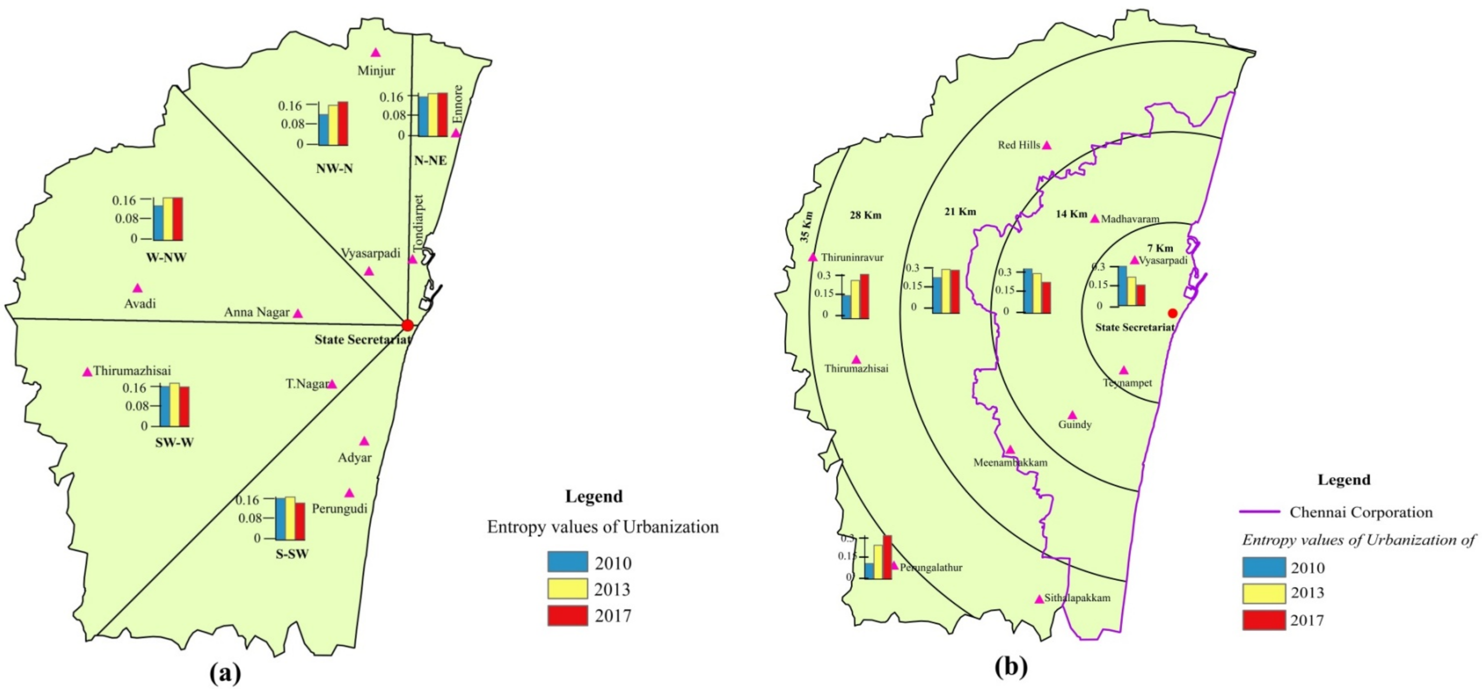


Figure 5.11. Entropy values of urbanization of CMA during the study periods. (a) Entropy values of urbanization of study region for five direction based zones based on the State Secretariat; (b) Entropy values of urbanization of the study region for five distance based buffer zones from the State Secretariat.

Distance based entropy analysis

In the analysis of urbanization based on distance from the State Secretariat, the rate of urban growth is higher within the 7 km from the State Secretariat followed by the 14 km, 21 km, 28 km and 35 km zones, respectively (Fig. 5.11 **(b)**).

- It is important to note that the entropy values of urbanization of the 7 and 14 km zones kept decreasing from 2010 to 2017. These two zones fall within the Chennai Corporation limits. Thus, it is implied that the Chennai Corporation had begun to experience congested type of urban growth since 2010 itself. Teynampet, Vyasarpadi, Guindy, Madhavaram are some of the locations within these zones where the employment opportunities, accessibility to transportation and availability of socio-economic factors including hospitals, schools, recreation center, etc., are higher (Sekar and Kanchanamala, 2011).
- The third highest urbanized zone (21 km zone) had started to experience congested urban growth after 2013. Major locations within this zone are Meenambakkam, Red Hills. Since the Chennai Corporation had already become saturated with urbanization, further urban growth had started to occur in the fringes of the Corporation boundary.
- The 28 km and 35 km zones including Thiruninravur, Thirumazhisai, Sithalapakkam, Perungalathur experience distributed type of urban sprawl and show an increase in urbanization in 2017.
- Based on the urbanization in each of these zones, it is seen that 7 km zone is the most urbanized, i.e. , 81.1% of the zone area is urbanized in 2017, followed by 14 km, 21 km, 28 km and 35 km zones which has 69%, 46.4%, 34.1% and 29.4% of urban cover in 2017.
- The 7 km and 14 km zones alone have an urbanization of 232.75 km^2 whereas the urbanization of the study area in 2017 is 572.11 km^2. This shows that almost 40% of the urban growth of CMA happens within the Corporation extent (http://www.tn.gov.in/cma/). This further emphasises the fact that the Corporation boundary and its periphery (7 km, 14 km and 21 km) experiences compact type of urbanization whereas urbanization is

distributed in the 28 km and 35 km zones which had started to experience urbanization since 2013.

CMDA (Housing And Urban Development Department, Chennai Metropolitan Area 2018) had announced the expansion of CMA from 1189 km^2 to an area of 8878 km^2 including the entire Chennai, Kancheepuram, Thiruvallur districts and Arakkonam and Nemili taluks of Vellore district. The need for expansion was mainly due to the rapid urbanization in Sriperumbudur, Thiruvallur, Ambattur, Sholinganallur. Thus, this analysis clearly highlights the importance of the Government's decision in the expansion of CMA for effective urban planning policies.

5.7.7. Comparison of prediction efficiencies of DB-CA and NNACA (IHS) models

The efficiencies of NNACA (IHS) and DB-CA models in predicting the urbanization of CMA in 2017 were compared based on their prediction outputs in each of the 5 distance based zones from the State Secretariat. Based on their results, the following considerations were drawn:

- Both the models predicted the urbanization with almost similar areas of hits in the congested zones (7 km and 14 km zones), whereas DB-CA model performed efficiently better than NNACA (IHS) model in 21 km, 28 km and 35 km zones where urban growth is dispersive in nature
- Within 7 km from the Secretariat, the observed area of urbanization in 2017 is 68.46 km^2. DB-CA and NNACA models predicted 67.93 km^2 and 67.26 km^2 as built-up in 2017. Misses were reported to be lesser in DB-CA model (0.54 km^2) than that of NNACA model (1.2 km^2). In this zone, both the models were able to capture the urbanization almost close to the reality. However, DB-CA model predicted with better accuracy than NNACA model with misses almost less than 1 km^2 area

- In the 14 km buffer zone, where the observed urban growth in 2017 is 164.29 km^2, DB-CA model predicted 157.82 km^2 and NNACA predicted 154.62 km^2 area of urban growth. Misses were lesser in DB-CA model (6.47 km^2) than that of NNACA model (9.67 km^2). These two zones fall within the Corporation boundary and DB-CA model reported only 7.01 km^2 area of misses and 225.75 km^2 as hits whereas NNACA model had misses of 10.87 km^2area and hits of 221.88 km^2
- Urbanization in the 21 km buffer zone which lies at the periphery of the Corporation boundary was 184.37 km^2 in 2017. DB-CA model had hits of 166.73 km^2 while NNACA had only 158.94 km^2area of hits. DB-CA model had lesser areas of misses (17.64 km^2) than NNACA model (25.42 km^2)
- In the 28 km and 35 km zones, where the urbanization is distributed, observed urbanization in 2017 was 155.15 km^2. DB-CA model produced hits of 131.85 km^2 with misses of 23.3 km^2 area. NNACA model reported hits of 121.75 km^2 and misses corresponds to 33.4 km^2 (Fig. 5.12)

In a region where urban growth is congested, for a given pixel, the number of urban neighbours is comparatively higher than in a region where urbanization is dispersed (Kanchanamala, 2014). Hence an efficient UGM should not only be able to capture the urban growth in a congested region but also in a region where urban development is dispersive in nature for a realistic representation of urbanization of the city.

- In our study, DB-CA model predicted the urban growth with lesser areas of misses than NNACA (IHS) model not only in the congested zones (7 km, 14 km and 21 km) but also in the zones where the urban sprawl is distributed (28 km and 35 km)
- The area of misses reported within the Corporation boundary based on DB-CA model (7.01 km^2) was much lesser than that of NNACA model (10.87 km^2)
- The comparison study on the prediction outputs of DB-CA and NNACA (IHS) models revealed that DB-CA model has the potential to predict the

urbanization of the study region better than NNACA (IHS) model. While, DB-CA model showed better prediction accuracy in the congested zones, the efficiency of the DB-CA model was more profound in the dispersed zones where NNACA (IHS) model had comparatively higher areas of misses

5.7.8. Comparison of DB-CA with NNACA (IHS) based on number of urban neighbours

To further assess the prediction outputs of NNACA and DB-CA models, the validation outputs of these models associated with the urban neighbours were analysed based on the 5 distance based zones. Results obtained (Table 5.4) and (Fig. 5.13, Fig. 5.14, Fig. 5.15) include the following:

- The observed urbanization of CMA in 2017 was 572.11 km^2. Of this, the 7 km zone had urbanization of 68.41 km^2. The 14 km, 21 km, 28 km and 35 km zones had urban growth of 164.12 km^2, 184.26 km^2, 129.75 km^2 and 25.42 km^2 in 2017 respectively.
- Based on the observed urban map of 2017, within the 7 km zone, maximum urban growth of 42.32 km^2 was observed in areas which had 8 urban neighbours and urban development of 2.57 km^2 area was observed in areas where there were no urban neighbours also. The total urbanization observed in this zone was 68.41 km^2. Of which, DB-CA model predicted 67.88 km^2 of urban hits when compared to NNACA (IHS) model which predicted 67.21 km^2 of urbanization. It could be seen that DB-CA model failed to predict only 0.53 km^2 of urban growth in this zone. The reason could be due to the fact that those areas had no urban neighbours and hence the model was unable to capture the urbanization in those meager areas. But, NNACA (IHS) model missed 1.21 km^2 in the prediction output in this zone. However, the false alarm associated with DB-CA model (10.66 km^2) is higher than that of NNACA model (8.9 km^2).

- In the 14 km zone, DB-CA model predicted 157.65 km^2 of urban hits with lesser misses (6.47 km^2) than that of NNACA model (hits: 154.45 km^2; misses: 9.64 km^2), whereas the observed urban growth of this zone was reported to be 164.12 km^2.
- Similarly in the rest of the 3 zones, DB-CA model produced the maximum hits with lesser misses than the NNACA model (Table 5.6).
- In all the 5 zones, total area of misses (47.95 km^2) of DB-CA model occurred due to the fact that there were no urban neighbours in those regions and the model failed to capture the urban development in those areas. However, the area of misses associated with NNACA (IHS) was higher (69.71 km^2).
- It is worthwhile to note that in DB-CA model, misses occurred only in regions where there were null or zero urban neighbours. However, NNACA (IHS) model produced misses even when there were 7 urban neighbours. This highlights the fact that DB-CA model is much better than NNACA model in predicting the urban growth of CMA in 2017

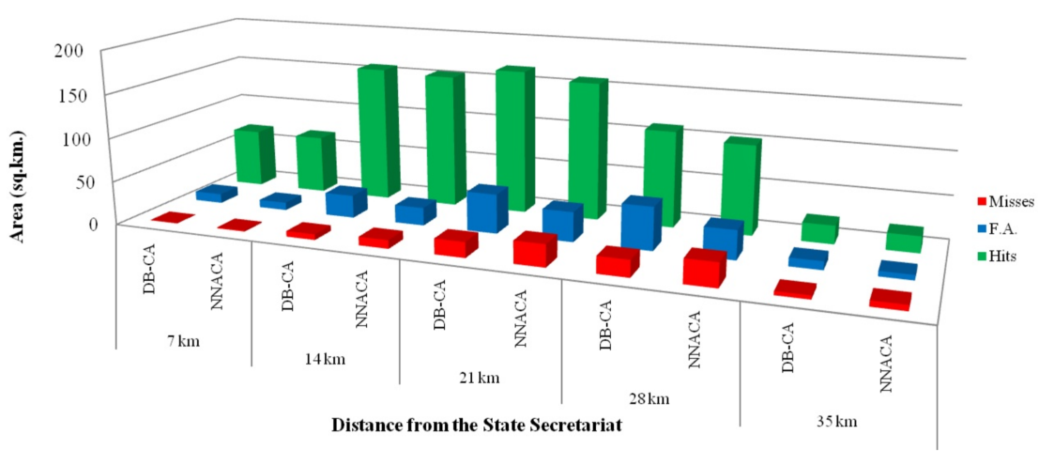


Figure 5.12. Zone wise analysis of the validation outputs of DB-CA and NNACA models

Results highlight the fact that when the urban neighbours were greater than or equal to 2, both the DB-CA and NNACA models, produced almost similar areas of hits in all the 5 zones. The difference in the areas of hits produced by these two models were noticeable when there was only one urban neighbour and was more profound when there was no urban neighbour (0 urban neighbour) at all (Fig. 5.15). This suggests that NNACA model was unable to capture the urbanization effectively when there are least or no urban neighbours when compared to DB-CA model and this could be due to the fact that DB-CA model makes use of the conditional probability between 2010 and 2013 and makes the prediction unlike the IHS model which assigns weights to each of the neurons in the network.

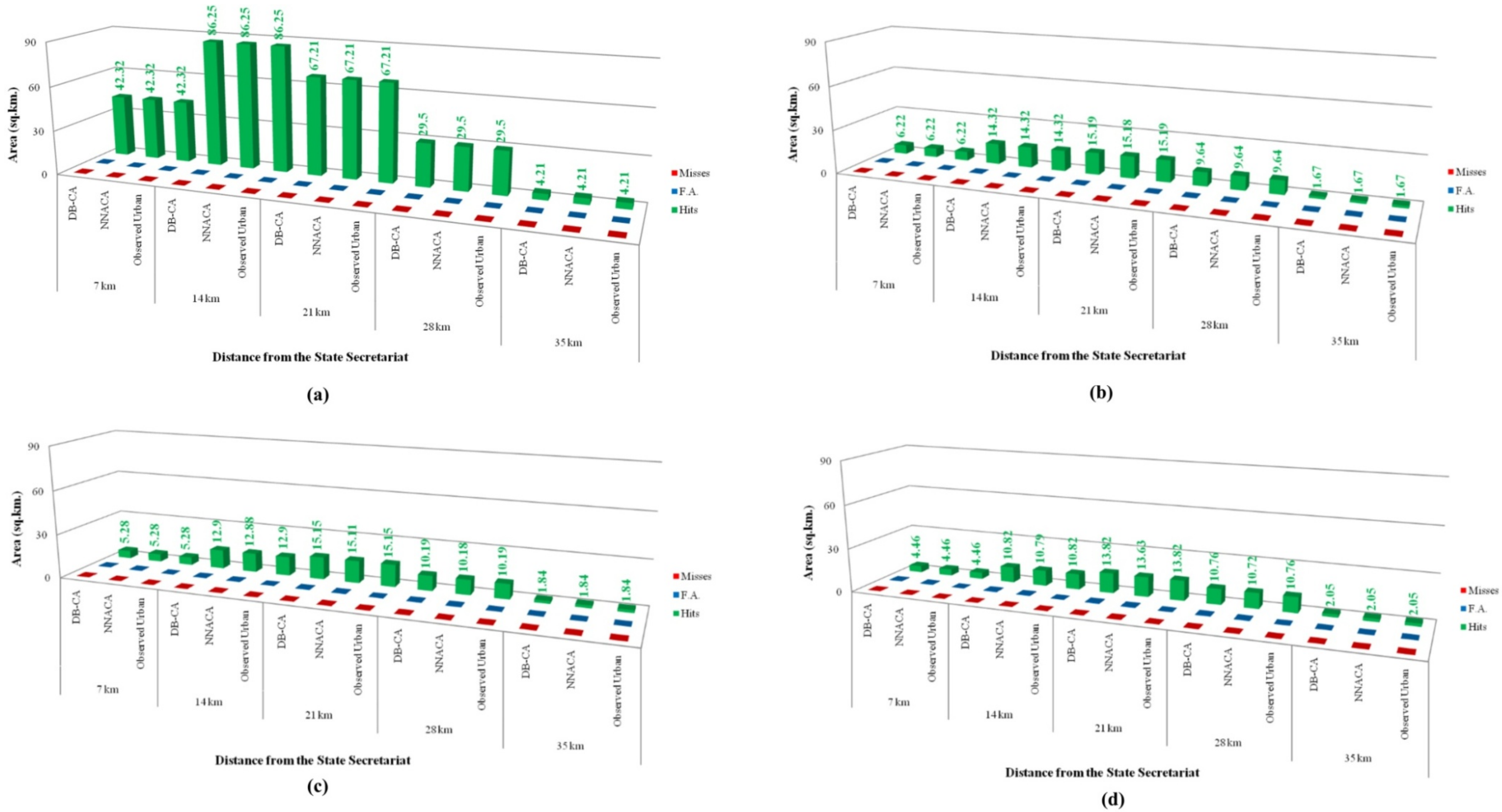


Figure 5.13. Zone wise analysis of validation outputs of DB-CA and NNACA (IHS) models based on neighbourhood. (a) At 8 urban neighbours; (b) At 7 urban neighbours; (c) At 6 urban neighbours; (d) At 5 urban neighbours

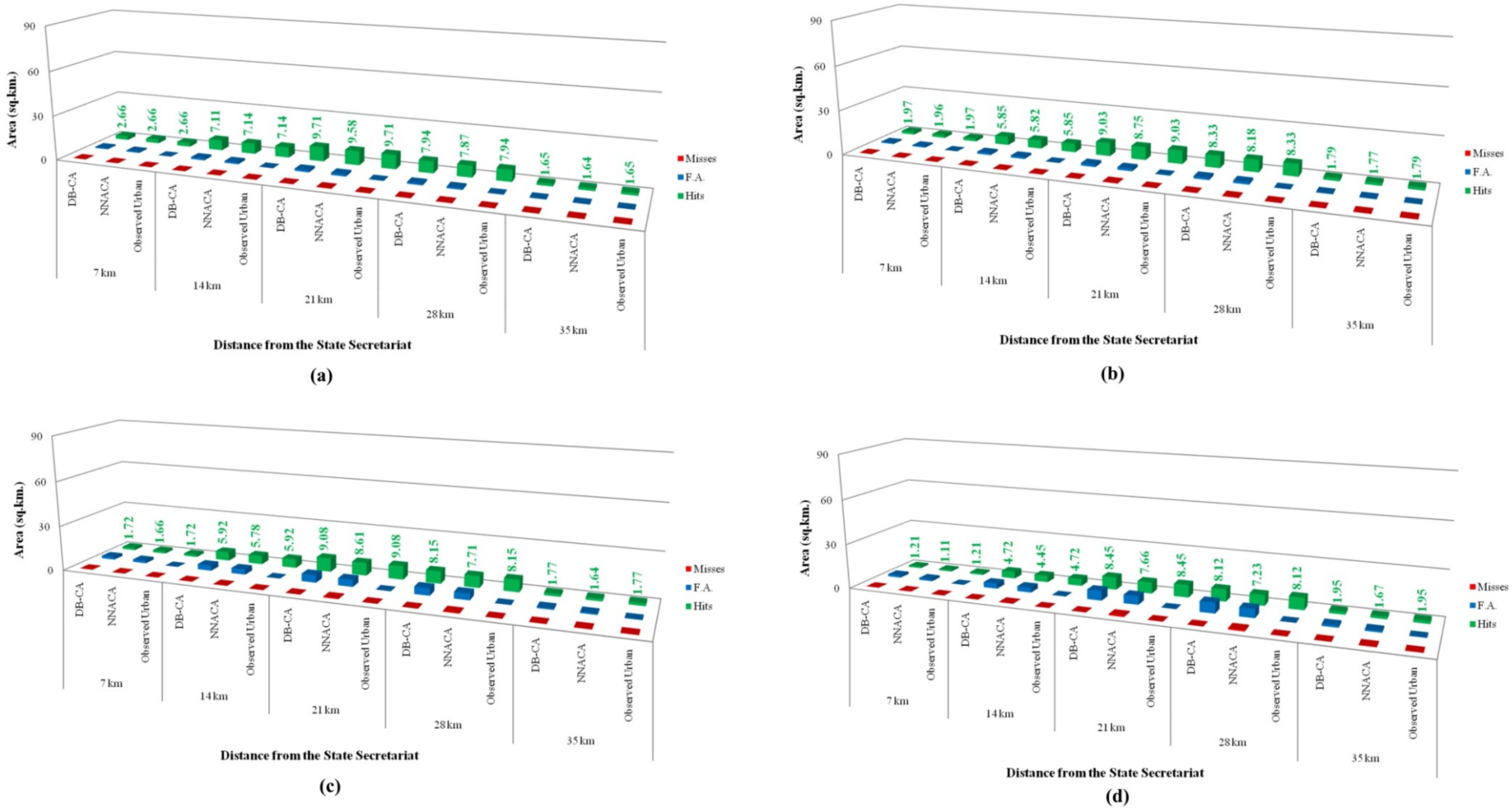


Figure 5.14. Zone wise analysis of validation output of DB-CA and NNACA (IHS) models based on neighbourhood. (a) At 4 urban neighbours; (b) At 3 urban neighbours; (c) At 2 urban neighbours; (d) At 1 urban neighbour

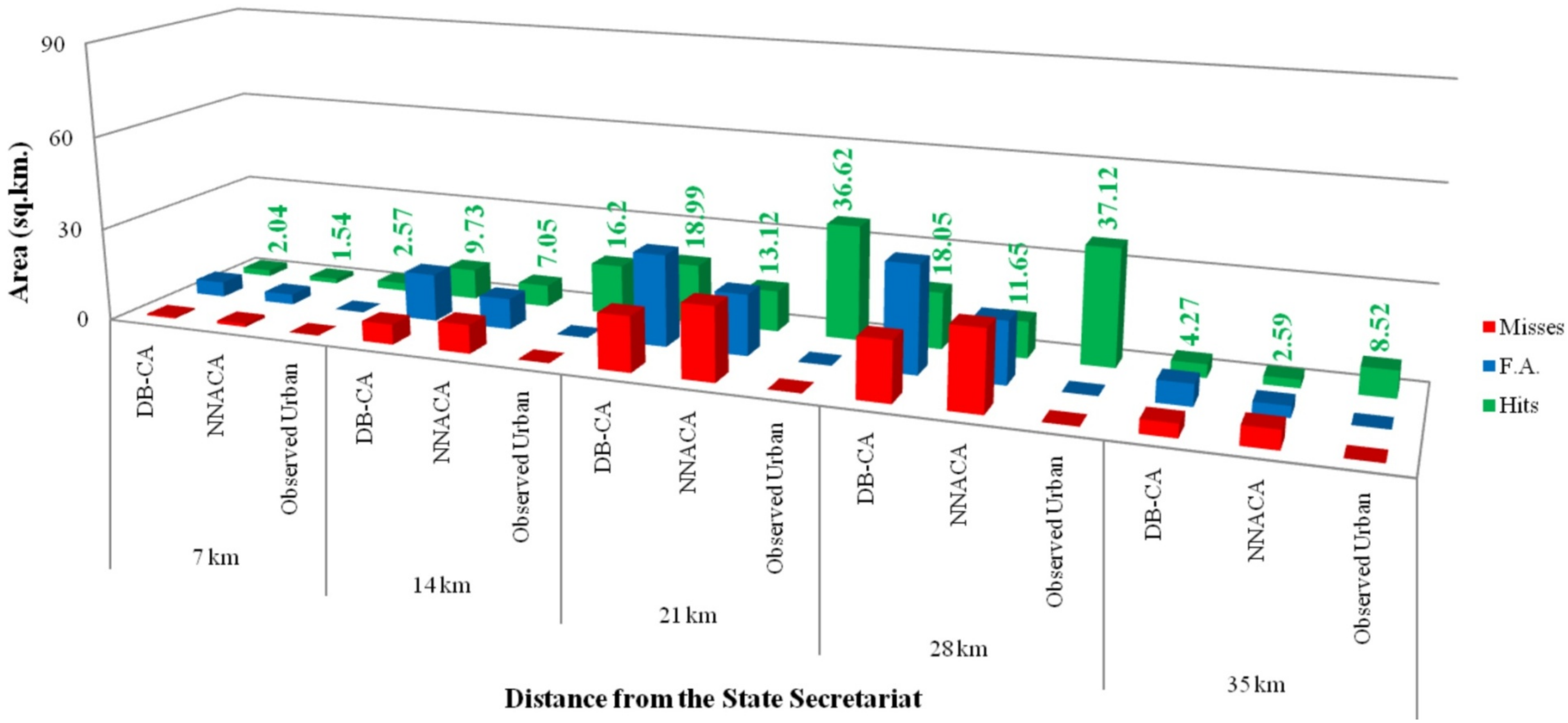


Figure 5.15. Zone wise analysis of validation output of DB-CA and NNACA models at 0 urban neighbour

Table 5.4. Validation outputs of DB-CA and NNACA (IHS) models in 5 distance based zones with their corresponding urban neighbours

Distance from the Secretariat	**No. of Urban Neighbours**	**Area (km^2) of observed urban in 2017**	**Area (km^2) of validation outputs**					
			DB-CA Model			NNACA Model		
			Hits	Misses	False Alarms	Hits	Misses	False Alarms
7 km	8	42.32	42.32	0	0	42.32	0	0
	7	6.22	6.22	0	0.14	6.22	0	0.14
	6	5.28	5.28	0	0.24	5.28	0.0002	0.24
	5	4.46	4.46	0	0.31	4.46	0.0002	0.31
	4	2.66	2.66	0	0.85	2.66	0.01	0.84
	3	1.97	1.97	0	0.82	1.96	0.02	0.83
	2	1.72	1.72	0	1.87	1.66	0.06	1.79
	1	1.21	1.21	0	1.57	1.11	0.09	1.44
	0	2.57	2.04	0.53	4.86	1.54	1.03	3.31
	SUM	**68.41**	**67.88**	**0.53**	**10.66**	**67.21**	**1.21**	**8.9**
14 km	8	86.25	86.25	0	0	86.25	0	0
	7	14.32	14.32	0	0.17	14.32	0	0.17

	6	12.9	12.9	0	0.29	12.88	0.01	0.29
	5	10.82	10.82	0	0.44	10.79	0.03	0.44
	4	7.14	7.14	0	1.33	7.11	0.02	1.33
	3	5.85	5.85	0	1.37	5.82	0.03	1.43
	2	5.92	5.92	0	3.61	5.78	0.14	3.57
	1	4.72	4.72	0	3.65	4.45	0.26	3.41
	0	16.2	9.73	6.47	15.27	7.05	9.15	9.91
	SUM	**164.12**	**157.65**	**6.47**	**26.13**	**154.45**	**9.64**	**20.55**
21 km	8	67.21	67.21	0	0	67.21	0	0
	7	15.19	15.19	0	0.14	15.18	0.01	0.14
	6	15.15	15.15	0	0.29	15.11	0.05	0.29
	5	13.82	13.82	0	0.47	13.63	0.19	0.47
	4	9.71	9.71	0	1.47	9.58	0.13	1.45
	3	9.03	9.03	0	1.72	8.75	0.28	1.72
	2	9.08	9.08	0	5.07	8.61	0.47	4.78
	1	8.45	8.45	0	6.52	7.66	0.8	5.76

	0	36.62	18.99	17.63	29.37	13.12	23.5	19.52
	SUM	**184.26**	**166.63**	**17.63**	**45.05**	**158.85**	**25.43**	**34.13**
28 km	8	29.5	29.5	0	0	29.5	0	0
	7	9.64	9.64	0	0.09	9.64	0	0.09
	6	10.19	10.19	0	0.2	10.18	0.01	0.2
	5	10.76	10.76	0	0.32	10.72	0.04	0.33
	4	7.94	7.94	0	1.1	7.87	0.07	1.08
	3	8.33	8.33	0	1.5	8.18	0.15	1.47
	2	8.15	8.15	0	4.79	7.71	0.43	4.34
	1	8.12	8.12	0	7.08	7.23	0.9	5.9
	0	37.12	18.05	19.07	34.13	11.65	25.47	19.76
	SUM	**129.75**	**110.68**	**19.07**	**49.21**	**102.68**	**27.07**	**33.17**
35 km	8	4.21	4.21	0	0	4.21	0	0
	7	1.67	1.67	0	0.01	1.67	0	0.01
	6	1.84	1.84	0	0.03	1.84	0	0.03
	5	2.05	2.05	0	0.05	2.05	0	0.05

	4	1.65	1.65	0	0.18	1.64	0.006	0.17
	3	1.79	1.79	0	0.27	1.77	0.02	0.27
	2	1.77	1.77	0	0.85	1.64	0.13	0.73
	1	1.95	1.95	0	1.4	1.67	0.28	1.1
	0	8.52	4.27	4.25	6.86	2.59	5.92	3.56
	SUM	**25.45**	**21.2**	**4.25**	**9.65**	**19.08**	**6.36**	**5.92**
Total Sum		571.99	524.04	47.95	140.7	502.27	69.71	102.67

5.7.9. Influence of agents of urbanization of CMA beyond Corporation limits

Further to assess the influence of agents of urbanization of Chennai Corporation over the entire study region, the corporation boundary was excluded from CMA and urban prediction in 2017 for the excluded region was implemented. Since hotspot does not fall into this excluded boundary, urban growth prediction was carried out using EHS model. The area excluding Chennai Corporation from CMA extends up to 752.56 km^2 in which observed area of built-up in this region in 2017 was 271.7 km^2. EHS model was implemented with all the agents of entire CMA which resulted in 206.73 km^2 area of built-up (Fig. 5.16). However, when the agents of CMA excluding Chennai Corporation were used, the EHS model predicted 210.94 km^2 area of built-up in 2017 with improvement in the accuracy from 0.63 to 0.65 and decrease in areas of misses and improvement in Cramer's value (Table 5.5). This further emphasizes the fact that the effects of agents of urbanization vary from region to region and in the current study the agents of urbanization of Chennai Corporation could have comparatively lesser impact in the region away from the corporation boundary. Also, urban growth for this region was predicted for the year 2020 using the urban maps of 2013 and 2017 and agents of CMA excluding Chennai Corporation of 2017. The NNACA model predicted 343.51 km^2 to be urbanized within a span of 3 years.

Table 5.5. Accuracy and validation of predicted urban in 2017 in the region excluding Chennai Corporation from CMA using NNACA model

	Accuracy Values		**Area (km^2) of validation outputs**			**Cramer's Value**
	O.A. (%)	*k* value	Hits	Misses	False Alarms	
With agents of CMA excluding Chennai Corporation	84.01	0.6533	210.94	60.74	59.52	0.6531
With agents of entire CMA	83.80	0.6268	206.73	64.97	56.87	0.6468

Also, sensitivity analysis was implemented for this excluded region and the results of the analysis were shown in Table 5.6. It was clear that the maximum area of hits (209.80 km^2) was obtained when a high preference road alone was used to predict the urbanization of the region. However, EHS model with all the 18 agents of urbanization produced 210.94 km^2 area of hits with higher Cramer's value (0.6531) indicating that the EHS model has better influence on the prediction output rather than using a single agent of urbanization. Further, when leave-one out based sensitivity analysis was run using EHS model, almost all the models returned areas of hits ranging between 203 km^2 and 206 km^2 none exceeding 210.94 km^2 obtained using all the 18 agents of urbanization. This implies that in this excluded region, all the selected 18 agents of urbanization were appropriate in determining the urban growth in 2017. This could be due to the fact that the region away from Chennai Corporation experiences distributed urban growth and thus all the agents were responsible for the urbanization of the region. The similar effect was observed in the pilot study on Sriperumbudur Taluk, which also experiences distributed urban growth based on the entropy values and all the selected agents of urbanization were found to be influencing the urban development of the taluk in 2016. However, the sensitivity analysis results of CMA suggest that only existing built-up of 2013 was the most influencing agent of urbanization, i.e., the agent alone was sufficient to predict the future urbanization of the region. Thus, from this study, we could infer that when a study region experiences congested type of urban growth, existing built-up alone could be sufficient to predict the urbanization in the future and when a region shows distributed type of urban sprawl, various agents of urbanization would be necessary to develop a most appropriate UGM. The results of this analysis could suggest urban model developers to study the urban development pattern and distribution of their cities initially and based on the results the agents of urbanization could be selected which would avoid the uncertainty in selecting the appropriate agents and also avoid the tedious time involved in the choice of selection of agents.

Table 5.6.Validation results and Cramer's values of NNACA model for region excluding Chennai Corporation from CMA for urban growth prediction in 2017

Urban Growth Models		**Area (km^2) of validation output**			**Cramer's Value**
		Hits	Misses	False Alarms	
NNACA model with only	**(i)** Existing Built-Up	203.11	68.58	60.48	0.6259
	(ii) Places of Public Interests	202.31	69.38	61.28	0.6212
	(iii) White Category Industries	201.95	69.75	61.65	0.6191
	(iv) Population	202.96	68.73	60.63	0.6250
	(v) Low land prices	203.32	68.38	60.28	0.6271
	(vi) Medium land prices	202.94	68.76	60.66	0.6248
	(vii) Public Utility Centres	204.01	67.68	59.58	0.6311
	(viii) Green Category Industries	202.49	69.21	61.11	0.6222
	(ix) High land prices	202.45	69.25	61.15	0.6220
	(x) Medium Preference Roads	207.66	64.04	55.94	0.6522
	(xi) Red Category Industries	208.47	63.23	55.13	0.6569
	(xii) Orange Category Industries	203.78	67.92	59.82	0.6297
	(xiii) Hotspots	202.24	69.45	61.35	0.6208
	(xiv) Railways	204.44	67.26	59.16	0.6336
	(xv) High Preference Roads	209.80	61.90	53.80	0.6647
	(xvi) Least Preference Roads	204.13	67.56	59.46	0.6318
	(xvii) Commutation	206.72	64.98	56.87	0.6468
NNACA Model excluding	**(xviii)** Existing Built-Up	206.39	65.30	57.20	0.6449
	(xix) Places of Public Interests	206.58	65.12	57.02	0.6460
	(xx) White Category Industries	205.94	65.76	57.66	0.6423
	(xxi) Population	206.02	65.68	57.58	0.6427
	(xxii) Low land prices	204.72	66.98	58.88	0.6352
	(xxiii) Medium land prices	204.67	67.03	58.93	0.6349
	(xxiv) Public Utility Centres	203.56	68.14	60.04	0.6285

	(xxv) Green Category Industries	205.48	66.22	58.12	0.6396
	(xxvi) High land prices	203.27	68.42	60.32	0.6268
	(xxvii) Medium Preference Roads	205.88	65.82	57.72	0.6419
	(xxviii) Red Category Industries	204.03	67.67	59.56	0.6312
	(xxix) Orange Category Industries	206.26	65.43	57.34	0.6441
	(xxx) Hotspots	206.05	65.65	57.55	0.6429
	(xxxi) Railways	205.93	65.77	57.67	0.6422
	(xxxii) High Preference Roads	205.82	65.88	57.78	0.6416
	(xxxiii) Least Preference Roads	203.62	68.07	59.97	0.6288
	(xxxiv) Commutation	205.98	65.72	57.62	0.6425

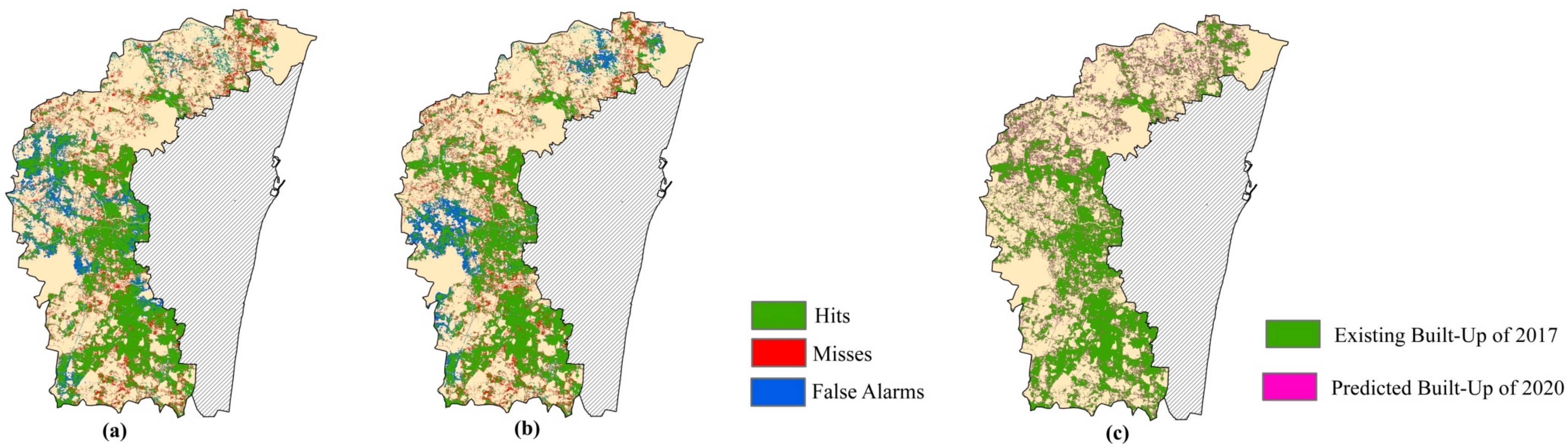


Figure 5.16. Validation outputs of NNACA model for the region excluding Chennai Corporation from CMA. (a) With agents of CMA excluding Chennai Corporation; (b) With agents of entire CMA; (c) Urban Prediction for 2020 with agents of CMA excluding Chennai Corporation (which gave more accurate results for 2017, i.e., based on (a))

5.8. Conclusion

The main objective of this chapter was to model the urban growth of CMA in 2017 using DB-CA and NNACA models and compare their prediction accuracies. The chapter also aimed at assessing the model and input parameters uncertainties through sensitivity analysis. The major outcomes of this study are

- Similar to our pilot study on Sriperumbudur Taluk, inclusion of hotspots into the NNACA model improved the accuracy of urban prediction of CMA significantly
- Sensitivity analysis suggested that only the existing built-up of 2013 was sufficient to model the urban growth of the region in 2017
- However, advanced machine learning technique, DB-CA model with only the influencing agent was able to perform the urban prediction of CMA in 2017 with higher accuracy than NNACA
- In predicting the urban growth of CMA in 2017 using DB-CA model, rectangular 3x3 neighbourhood configuration was found to be the most appropriate one
- Inclusion of all the non-built-up pixels within the hotspot boundary produced higher hits rather than including only 60% and 80% of non-built-up pixels as built-up in the urban map of 2013 for prediction
- Assessment of urban sprawl through Shannon's entropy revealed that the urban development of the study region was getting congested during the study periods.
- Directional based entropy analysis suggest that urbanization is more congested in the southern region and northern CMA experienced distributed urban growth in 2017
- Distance based analysis of urban sprawl revealed that within the Corporation boundary the urban growth was congested while beyond the corporation boundary distributed urbanization was observed
- Comparison of prediction efficiencies of DB-CA and NNACA models was further assessed based on the urban neighbours. It was found out that DB-CA model was able to capture the urbanization even when there were

least or 0 urban neighbours implying that DB-CA model is a better modeling tool for predicting urbanization of CMA in 2017

- Further, the urban growth of the region excluding Chennai Corporation from CMA was modeled using NNACA model to check if the agents of CMA have any influence on this excluded region. Results suggest that the agents of urbanization of CMA have less influence on the region excluding Corporation limits from CMA. Sensitivity analysis of the region suggest that all the 18 agents of urbanization are appropriate in predicting the urban growth of the region in 2017 as the region experiences distributed urban growth unlike CMA which shows congested urban development where only existing built-up of 2013 was found sufficient to model the urban development.
- The results further suggested that Chennai Corporation had already become saturated with urban growth whereas in the periphery of the Corporation boundary, the urbanization has begun to get congested. Areas away from the Corporation experience distributed urban growth in 2017
- Also, the urban growth for the year 2020 was predicted for the region excluding Chennai Corporation from CMA using NNACA model which would enable the urban policy makers to take appropriate development actions for a sustainable allocation and urbanization of the study area

Based on the outcomes of this chapter, it could be said that it is the crucial moment to develop the city plan with due care for further development activities of CMA especially in the southern and south-west region which has undergone congested urban growth, whereas urbanization is dispersed in the northern part of the study region which can be thought for future urban developments. This chapter further highlights the importance of the Government's decision in expanding the area of CMA as it will enable the urban planners and policy makers to devise appropriate planning actions so that the study area does not get congested anymore at least within the Chennai Corporation as it is already brimming with urban growth.

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE

To avoid the adverse effects of urbanization, developing UGMs to analyze the current urban trends and predict the future scenario is one of the major goals of city planners and policy developers. In this thesis, urban growth of CMA was analyzed and an appropriate UGM was developed to predict the urbanization in 2017 based on the pilot study on Sriperumbudur Taluk. Based on the literature reviews discussed in detail in Chapter 2, it is evident that CA based urban prediction models perform significantly well when compared to other traditional mathematical models. Further, only a very few UGMs based on machine learning techniques had been developed especially in Indian context. For CMA, one of the metropolitan cities of India, studies on urban prediction based on machine learning techniques had not been reported so far. Also, the uncertainty of the model and the input parameters had not yet been reported. The following are the significant contributions made by this research:

- Compared the efficiency of machine-learning techniques including Neural Network and Deep learning based UGMs with the traditional and agents-based CA models for urban prediction
- Emphasized the importance of including Government policies into the prediction modeling process
- Analyzed the uncertainties of input and model parameters on the prediction outputs through sensitivity analysis
- Revealed how the study on urban sprawl pattern of a region could help urban model developers to choose the most efficient agent of urbanization

The main objectives of Chapter 3 were to prepare land cover maps of Sriperumbudur Taluk and CMA and to assess the land cover changes in these regions during the study periods. The results obtained from this chapter include

- Multi-temporal landsat imageries of Sriperumbudur Taluk and CMA were used to quantify the land cover changes in the study regions through the implementation of SVM based supervised classification technique
- The land cover maps contained four categories: Built-up, Vegetation, Waterbody and Openland
- Land cover statistics of the study regions reveal that urbanization in these regions are occurring at an alarming rate and majority of open lands and vegetation land cover categories were getting cleared up to accommodate the increasing urban population.

Chapter 4 discussed in detail about the pilot study on developing UGM Sriperumbudur Taluk in 2016 using Traditional CA (TCA), Agents-based CA (ACA) and Neural Network coupled Agents-based CA models (NNACA). Following results are inferred from this chapter

- NNACA model was most appropriate in modeling the urban growth of the taluk in 2016 when compared to other two models
- The study highlighted the significance of including City development plans based on Government's development policies to have a realistic urban model of the region
- Sensitivity analysis was performed to find the most influencing agent of urbanization and the result suggests that all the selected 12 agents of urbanization had almost equal influence on the prediction output implying that all these agents were appropriate in determining the urban growth of the taluk in 2016
- The distribution of urban sprawl was analyzed through Shannon's entropy which revealed that the taluk experienced distributed or scattered urban growth during the study periods and the growth was much higher in the north-eastern region, i.e., towards the Chennai city. This dispersive nature of urban sprawl of the taluk could be the reason that all the selected agents of urbanization had equal importance on the NNACA based prediction output.

- Based on NNACA model, urban prediction of the taluk in 2020 was implemented which would serve as a tool for the urban planners and policy developers to plan the urbanization of the study region in an efficient manner for the sustainable management of natural resources and for the betterment of humans

Based on the results of the pilot study, the urban growth of CMA was modeled using NNACA and further using advance machine learning technique including DB-CA model. The main outcomes of this chapter are listed below:

- DB-CA model was found to perform much better than NNACA model in predicting the urbanization of CMA in 2017
- Out of the 18 agents of urbanization selected based on the experts' opinions for CMA, 'existing built-up of 2013' alone was found to be the most influencing agent based on the sensitivity analysis
- The influence of neighbourhood configuration was assessed and it was revealed that 3x3 rectangular was the most appropriate neighbourhood configuration to predict the urban growth of CMA in 2017
- Directional and distance based urban sprawl analysis of CMA during the study periods was performed through Shannon's entropy. The direction based results revealed that southern CMA experienced congested growth while northern CMA faced distributed urban growth in 2017
- Distance based entropy analysis revealed that within the Corporation boundary the urban growth was congested while scattered growth was observed outside the Corporation boundary in 2017
- The congested urban growth pattern of CMA could be the reason for only the existing built-up of 2013 being the most influencing agent of urbanization of CMA in 2017
- The prediction efficiencies of DB-CA and NNACA models were further compared based on the urban neighbours. It was found out that DB-CA model performed better than NNACA especially where there were 0 urban neighbours implying that DB-CA model could capture urbanization in a much realistic manner than NNACA model

- Further, the influence of agents of CMA beyond the Corporation limits was assessed based on sensitivity analysis. Results suggested that the agents of CMA had comparatively lesser influence in the region away from Chennai Corporation. In the region beyond Chennai Corporation, all the 18 agents were found to be crucial in the urban development. This could be due to the fact that beyond Corporation limits, the urban sprawl was dispersive in nature and thus all the agents became crucial in determining the urbanization in 2017
- Further, the urban growth for the year 2020 was predicted for the region excluding Chennai Corporation from CMA using NNACA model which would enable the urban policy makers to take appropriate development actions for the sustainable allocation and urbanization of CMA

The research highlighted the efficiency of CA model in modeling urbanization of CMA and Sriperumbudur Taluk under different scenarios. This could help city planners and policy makers to take appropriate and effective steps to manage the resources efficiently and sustainably. Also the research highlighted the importance of the Government's decision in expanding the area of CMA as it will enable the urban planners and policy makers to devise appropriate planning actions so that the study area does not get congested anymore at least within the Chennai Corporation as it is already brimming with urban growth. UGMs would be more appropriate and efficient if improvements in algorithms which would enable the users to determine the most appropriate neighbourhood configuration, agent of urbanization and time step based on their input datasets.

The future scope of the research includes the following:

- A 2-dimensional cell state is considered in the urban modeling based on Cellular Automata model in the current research. When heights of the buildings are also taken into consideration, a 3-dimensional urban model could be developed which would represent the real world scenario
- Time-step is one of the most important components of Cellular Automata based urban models. Hence, the effect of different sets of temporal satellite

dataset for the preparation of land cover maps has to be assessed since the choice of appropriate temporal dataset depends on the landscape and its urban pattern.

- Comparing the efficiency of Machine Learning coupled CA based UGMs with high resolution and medium resolution satellite imageries.
- Development of genetic algorithms which would enable the users to select the appropriate neighbourhood configurations and agents of urbanization would make the Cellular Automata based urban models more robust.
- Further, modeling the uncertainties of the UGM will make the decision making process still much more efficient.

REFERENCES

1. Aarthi, A. D. and Gnanappazham, L. (2018). Urban growth prediction using neural network coupled agents-based cellular automata model for Sriperumbudur Taluk, Tamil Nadu, India. *The Egyptian Journal of Remote Sensing and Space Science*, 21(3): 353–362. 10.1016/j.ejrs.2017.12.004.

2. Agarwal, C., Green, G. M., Grove, J. M., Evans, T. P. and Schweik, C. M. (2002). A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice, General Technical Report NE-297, United States Department of Agriculture.

3. Aithal, B. H. and Ramachandra, T. V. (2016). Visualization of Urban Growth Pattern in Chennai Using Geoinformatics and Spatial Metrics. *Journal of the Indian Society of Remote Sensing*, 44(4): 617-633. 10.1007/s12524-015-0482-0.

4. Aithal, B. H., Shivamurthy, V. and Ramachandra, T. V. (2017). Characterization and Visualization of Spatial Patterns of Urbanisation and Sprawl through Metrics and Modeling. *Cities and the Environment (CATE),* 10(1):1-31.

5. Al-Ahmadi, K., See, L. and Heppenstall, A. (2013). Validating spatial patterns of urban growth from a cellular automata model. In A.Salcido (Ed.), Emerging applications of cellular automata (pp.26). London: InTechOpen.

6. Alberti, M. and Waddell, P. (2000). An integrated urban development and ecological simulation model. *Integrated Assessment,* 1(3):215-227. 10.1023/A:1019140101212.

7. Alghais, N. and Pullar, D. (2015). Modelling the impacts of current patterns of urban form expansion in Kuwait with the use of ABM and GIS. In *21st International Congress on Modelling and Simulation*, Gold Coast, Australia. November 29 – December 4, 2015.

8. Allen, P. M. (1997). Cities and Regions as Evolutionary Complex Systems. *Journal of Geographical Systems*, 4(1):103-130.

9. Al-shalabi, M., Billa, L., Pradhan, B., Mansor, S. and Al-Sharif, A. A. A. (2013). Modelling urban growth evolution and land-use changes using GIS based cellular automata and SLEUTH models:

the case of Sana’a metropolitan city, Yemen. *Environmental Earth Sciences*, 70(1):425-437. 10.1007/s12665-012-2137-6.

10. Alsharif, A. A. A., Pradhan, B., Mansor, S. and Shafri, H. Z. M. (2015). Urban expansion assessment by using remotely sensed data and the relative Shannon entropy model in GIS: a case study of Tripoli, Libya. *Theoretical and Empirical Researches in Urban* Management, 10(1): 55–71.

11. Aniello, C., Morgan, K., Busbey, A. and Newland, L. (1995). Mapping micro-urban heat islands using LANDSAT TM and a GIS. *Computers & Geosciences,* 21(8): 965-967, 969.10.1016/0098-3004(95)00033-5.

12. Arel, I., Rose, D. C. and Karnowski, T. P. (2010). Deep Machine Learning - A New Frontier in Artificial Intelligence Research. *IEEE Computational Intelligence Magazine,* 5(4):13-18. 10.1109/MCI.2010.938364.

13. Arsanjani, J. J., Helbich, M. and Vaz, E. N. (2013). Spatiotemporal simulation of urban growth patterns using agent-based modeling: The case of Tehran. *Cities*, 32: 33-42. 10.1016/j.cities.2013.01.005.

14. Atkinson, P. M. and Tatnall, A. R. L. (1997). Introduction Neural networks in remote sensing. *International Journal of Remote Sensing,* 18(4):699-709. 10.1080/014311697218700.

15. Bach, F. (2017). Breaking the Curse of Dimensionality with Convex Neural Networks. *The Journal of Machine Learning Research,* 18(19):1-53.

16. Bahari, N. I. S., Ahmad, A. and Aboobaider, B. M. (2014). Application of support vector machine for classification of multispectral data. In *7th IGRSM International Remote Sensing & GIS Conference and Exhibition. IOP Conf. Series: Earth and Environmental Science,* Kuala Lumpur, Malaysia. April 22-23, 2014. 10.1088/1755-1315/20/1/012038.

17. Bailey, K. D. (2009). *Entropy systems theory. Systems Science and Cybernetics*. Eolss Publishers: Oxford, UK.

18. Barnes, K. B., Morgan III, J. M. M., Roberge, M. C. and Lowe, S. (2001). Sprawl Development: Its Patterns, Consequences, and Measurement, Towson University, Maryland. Retrieved from https://tigerweb.towson.edu/morgan/files/sprawl_development.pdf.

19. Barredo, J. I., Demicheli, L., Lavalle, C., Kasanko, M. and McCormick, N. (2004). Modelling Future Urban Scenarios in Developing Countries: An Application Case Study in Lagos, Nigeria. *Environment and Planning B: Urban Analytics and City Science*, 31(1):65-84. 10.1068/b29103.

20. Barredo, J. I., Kasanko, M., Mccormick, N. and Lavalle, C. (2003). Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. *Landscape and Urban Planning,* 64(3):145-160. 10.1016/S0169-2046(02)00218-9.

21. Basse, R. M., Omrani, H., Charif, O., Gerber, P. and Bódis, K. (2014). Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale. *Applied Geography,* 53:160-171. 10.1016/j.apgeog.2014.06.016.

22. Batty, M. (1998). Urban Evolution on the Desktop: Simulation with the Use of Extended Cellular Automata. *Environment and Planning A: Economy and Space,* 30(11):1943–1967. 10.1068/a301943.

23. Batty, M. and Xie, Y. (1994). From Cells to Cities. *Environment and Planning B: Planning and Design,* 21(7): S31-S48. 10.1068/b21S031.

24. Benenson, I. and Torrens, P. M. (2004). *Geosimulation: Automata-Based Modeling of Urban Phenomena.* John Wiley & Sons, Ltd: England.

25. Bengio, Y., Lamblin, P., Popovici, D. and Larochelle, H. (2006). Greedy Layer-Wise Training of Deep Networks. In *Proc. NIPS'06 Proceedings of the 19th International Conference on Neural Information Processing Systems,* 2006, pp. 153-160.

26. Berling-Wolff, S. and Wu, J. (2004). Modeling urban landscape dynamics: A case study in Phoenix, USA. *Urban Ecosystems* 7(3):215-240. 10.1023/B:UECO.0000044037.23965.45.

27. Bettemier, Ö.H. (2010). Error estimation of orthorectification of small satellite images by differential sensitivity analysis. *Journal of Aeronautics and Space Technologies*, 4(4):65–74.

28. Bhagat, R. B. (2011). Emerging Pattern of Urbanisation in India. *Economic and Political Weekly,* 56(34):10-12.

29. Bharath, H. A., Chandan, M. C., Vinay, S. and Ramachandra, T. V. (2018). Modelling urban dynamics in rapidly urbanising Indian cities. *The Egyptian Journal of Remote Sensing and Space Science,* 21(3):201-210. 10.1016/j.ejrs.2017.08.002.

30. Bharath, H. A., Chandan, M. C., Vinay, S. and Ramachandra, T. V. (2017). Modelling the growth of two rapidly urbanizing Indian cities. *Journal of Geomatics,* 11(2):149-166.

31. Bhatt, U. S., Walker, D. A., Raynolds, M. K., Bieniek, P. A., Epstein, H. E., Comiso, J. C., Pinzon, J. E., Tucker, C. J., Steele, M., Ermold, W. and Zhang, J. (2017). Changing seasonality of panarctic tundra vegetation in relationship to climatic variables. *Environmental Research Letters,* 12(055003). 10.1088/1748-9326/aa6b0b.

32. Bhatta, B. (2009). Analysis of urban growth pattern using remote sensing and GIS: a case study of Kolkata, India, *International Journal of Remote Sensing,* 30(18): 4733–4746. 10.1080/01431160802651967.

33. Bhatta, B. (2010). Causes and Consequences of Urban Growth and Sprawl. In *Analysis of Urban Growth and Sprawl from Remote Sensing Data*. *Advances in Geographic Information Science* (pp. 17-36). Berlin, Heidelberg: Springer. 10.1007/978-3-642-05299-6_2.

34. Bhatta, B. (2012). *Urban Growth Analysis and Remote Sensing. A Case Study of Kolkata, India 1980 – 2010.* Springer Briefs in Geography. 10.1007/978-94-007-4698- 5_2.

35. Bhatta, B., Saraswati, S. and Bandyopadhyay, D. (2010). Urban sprawl measurement from remote sensing data. *Applied Geography,* 30(4):731-740. 10.1016/j.apgeog.2010.02.002.

36. Bischof, H., Scheider, W. and Pinz, A. J. (1992). Multispectral classification of Landsat-images using neural networks. *IEEE Transactions on Geoscience and Remote Sensing*, 30(3):482-490. 10.1109/36.142926.

37. Bishop, C. M. (1995). *Neural networks for pattern recognition*. Oxford University Press: New York.

38. Bisht B.S. and Kothyari B.P. (2001). Land-Cover change analysis of garur Ganga Watershed using GIS/ Remote Sensing technique. *Journal of the Indian Society of Remote Sensing,* 29(3):137-141. 10.1007/BF02989925.

39. Bjerager, P. (1990). On computational methods for structural reliability analysis. *Structural Safety,* 9(2):79–96. 10.1016/0167-4730(90)90001-6.

40. Blecic, I., Cecchini, A. and Trunfio, G. A. (2013). Cellular automata simulation of urban dynamics through GPGPU. *The Journal of Supercomputing*, 65(2):614-629. 10.1007/s11227-013-0913-z.

41. Boulila, W., Amine, B. and Farah, I.R. (2014). A Probabilistic Collocation Method for the imperfection Propagation: Application to Land Cover Change Prediction. *Journal of Multimedia Processing and Technologies,* 2(3):127–139.

42. Brunelli, M. (2015). *Introduction to the Analytic Hierarchy Process.* Springer, Cham. 10.1007/978-3-319-12502-2.

43. Buhaug, H. and Urdal, H. (2013). An urbanization bomb? Population growth and social disorder in cities. *Global Environmental Change,* 23(1):1-10. 10.1016/j.gloenvcha.2012.10.016.

44. Cabral, P., Augusto, G., Tewolde, M. and Araya, Y. (2013). Entropy in Urban Systems. *Entropy,* 15(12):5223-5236. 10.3390/e15125223.

45. Campbell, C. (2000). An Introduction to Kernel Methods. In R. J. Howlett & L. C. Jain (Eds.), *Radial Basis Function Networks 1*: *recent developments in theory and applications.* Physica Verlag Rudolf Liebing KG: Vienna, Austria.

46. Census of India, (2011). District Census Handbook, Chennai. Directorate of Census Operations, Tamil Nadu. Retrieved from http://censusindia.gov.in/2011census/dchb/3302_PART_B_DCHB_CHENNAI.pdf.

47. Cetin, M. (2015). Using GIS analysis to assess urban green space in terms of accessibility: case study in Kutahya. *International Journal of Sustainable Development & World Ecology,* 22(5):420-424. 10.1080/13504509.2015.1061066.

48. Chakrabarti, P. G. D. (2001). Urban crisis in India: New initiatives for sustainable cities. *Development in Practice*, 11(2-3):260-272. 10.1080/09614520120056397.

49. Chao, J., Shen, F. and Zhao, J. (2011). Forecasting exchange rate with deep belief networks. In *The 2011 International Joint*

Conference on Neural Networks, San Jose, USA. July 31 – August 5, 2011. 10.1109/IJCNN.2011.6033368.

50. Chaudhuri, G. and Clarke, K. (2014). Temporal Accuracy in Urban Growth Forecasting: A Study Using the SLEUTH Model. *Transactions in GIS,* 18(2). 302-320. 10.1111/tgis.12047.

51. Chaudhuri, S. (2015). Urban poor, economic opportunities and sustainable development through traditional knowledge and practices. *Global Bioethics,* 26(2):86-93. 10.1080/11287462.2015.1037141.

52. Cheng, J. (2003). "Modelling Spatial & Temporal Urban Growth" Ph.D.Thesis, Utrecht University, The Netherlands.

53. Cheng, J. and Masser, I. (2003). Urban growth pattern modelling: a case study of Wuhan City, P.R. China. *Landscape and urban planning,* 62(4)*:*199-217. 10.1016/S0169-2046(02)00150-0.

54. Christianini, N. and Schölkopf, B. (2002). Support Vector Machines and Kernel Methods: The New Generation of Learning Machines. *AI Magazine,* 23(3):31-42. 10.1609/aimag.v23i3.1655.

55. Chung, K.L. (1960). Transition probabilities. In: Grammel, R., Hirzebruch, F., Hopf, E., Hopf, E., Maak, H., Magnus, W., Schmidt, F.K., Stein, K., van der Waerden, B.L.(Eds.), Markov Chains with Stationary Transition Probabilities. Springer, Berlin, Heidelberg, pp. 5–11. 10.1007/978-3-642-49686-8_2.

56. Clarke , K. and Gaydos, L. J. (1998). Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science, 12*(7), 699-714. 10.1080/136588198241617.

57. Clarke, K., Hoppen, S. and Gaydos, L. (1997). A Self-Modifying Cellular Automaton Model of Historical Urbanization in the San Francisco Bay Area. *Environment and Planning B: Planning and Design, 24*(2), 247-261. 10.1068/b240247.

58. Cohen, B. (2006). Urbanization in developing countries: Current trends, future projections, and key challenges for sustainability. *Technology in Society,* 28(1-2):63-80. 10.1016/j.techsoc.2005.10.005.

59. Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment,* 37(1):35-46. 10.1016/0034-4257(91)90048-B.

60. Cortes, C. and Vapnik, V. (1995). Support-Vector Networks. *Machine Learning,* 20(3):273-297. 10.1023/A:1022627411411.

61. Couclelis, H. (1997). From Cellular Automata to Urban Models: New Principles for Model Development and Implementation. *Environment and Planning B: Planning and Design,* 24(2):165-174. 10.1068/b240165.

62. Dale, V. H., O'Neill, R. V., Pedlowski, M. and Southworth, F. (1993). Causes and Effects of Land Use Change in Central Rondonia, Brazil. *Photogrammetric Engineering and Remote Sensing*, 59(6):997-1005.

63. Datta, R. K., Alam, O. and Hossain, M. M. (2017). Current status of urban drainage system and its problem in Netrokona Municipal, Dhaka. *Journal of Institute of Science and Technology,* 22(1):165-178.

64. Dawood, N., Dawood, H., Rodriguez-Trejo, S. and Crilly, M. (2017). Visualising urban energy use: the use of LiDAR and remote sensing data in urban energy planning. *Visualization in Engineering,* 5(22):1-13. 10.1186/s40327-017-0060-3.

65. de Kok, J. L., Engelen, G., White, R. and Wind, H. G. (2001). Modeling Land-Use Change in a Decision-Support System for Coastal-Zone Management. *Environmental Modeling & Assessment, 6*(2):123-132. 10.1023/A:1011587222253.

66. Deep, S. and Saklani, A. (2014). Urban sprawl modeling using cellular automata. *The Egyptian Journal of Remote Sensing and Space Science,* 17(2):179-187. 10.1016/j.ejrs.2014.07.001.

67. Deka, J., Tripathi, O. P. and Khan, M. L. (2012). Urban growth trend analysis using Shannon Entropy approach – A case study in North-East India. *International Journal of Geomatics and Geosciences,* 2(4):1062-1068.

68. Dewan, A.M. and Corner, R.J. (2014). Spatiotemporal Analysis of Urban Growth, Sprawl and Structure. In A. Dewan, R. Corner (Eds.), *Dhaka Megacity* (pp.99-121). Dordrecht: Springer. 10.1007/978-94-007-6735-5_6.

69. Dhiman, R., Kalbar, P. and Inamdar, A. (2018). GIS coupled multiple criteria decision making approach for classifying urban coastal areas in India. *Habitat International,* 71:125-134. 10.1016/j.habitatint.2017.12.002.

70. Dietzel, C. and Clarke, K. (2006). The effect of disaggregating land use categories in cellular automata during model calibration and forecasting. *Computers, Environment and Urban Systems,* 30(1):78–101. 10.1016/j.compenvurbsys.2005.04.001.

71. DiGregorio. S., Festa. D., Gattuso. D., Rongo. R., Spataro. W., Spezzano. G. and Vitetta, A. (1996). Cellular automata for freeway traffic simulation. In E. Besussi & A. Cecchini (Eds.), *Artificial worlds and urban studies* (pp.365-392). Venice: DAEST.

72. Divigalpitiya, P., Ohgai, A., Tani, T., Watanabe, K. and Gohnai, Y. (2007). Modeling Land Conversion in the Colombo Metropolitan Area Using Cellular Automata. *Journal of Asian Architecture and Building Engineering,* 6(2):291-298.10.3130/jaabe.6.291.

73. Duwal, S. (2013). "Modelling Urban Growth in Kathmandu Valley" M.S. Thesis, University of Twente, The Netherlands.

74. Eastman, J. R. (2012). IDRISI selva tutorial, manual version 17. Retrieved from http://uhulag.mendelu.cz/files/pagesdata/eng/gis/idrisi_selva_tutorial.pdf.

75. Elmqvist, Th., Fragkias, M., Goodness, J., Güneralp, B., Marcotullio, P. J., McDonald, R. I., Parnell, S., Schewenius, M., Sendstad, M., Seto, K. C. and Wilkinson, C. (Eds.). (2013). *Urbanization, Biodiversity and Ecosystem Services: Challenges and Opportunities, A Global Assessment.* New York, USA: Springer.

76. Epstein, J., Payne, K. and Kramer, E. (2002). Techniques for Mapping Suburban Sprawl. *Photogrammetric Engineering & Remote Sensing,* 63(9):913–918.

77. Ewing, R. (1997). Is Los Angeles-Style Sprawl Desirable?. *Journal of the American Planning Association,* 63(1):107-126. 10.1080/01944369708975728.

78. Ewing, R., Pendall, R. and Chen, D. (2003). Measuring Sprawl and Its Transportation Impacts. *Transportation Research Record: Journal of the Transportation Research Board,* 1831(1):175-183.10.3141/1831-20.

79. Fedorov, V. V. (1983). Analysis and Design of Simulation Experiments for the Approximation of Models, *IIASA, WP-83-071,* International Institute for Applied Systems Analysis, Austria.

80. Feng, L. and Li, H. (2012). Spatial Pattern Analysis of Urban Sprawl: Case Study of Jiangning, Nanjing, China. *Journal of Urban Planning and Development*, 138(3):263-269. 10.1061/(ASCE)UP.1943-5444.0000119.

81. Feng, Y., Liu, Y. and Batty, M. (2016). Modeling urban growth with GIS based cellular automata and least squares SVM rules: a case study in Qingpu-Songjiang area of Shanghai, China. *Stochastic Environmental Research and Risk Assessment,* 30(5): 1387-1400. 10.1007/s00477-015-1128-z.

82. Fenton, N. and Neil, M. (2018) *Risk Assessment and Decision Analysis with Bayesian Networks* (2nd Edition). CRC Press: London. 10.1201/b21982.

83. Ferchichi, A., Boulila, W. and Farah, I. R. (2018). Reducing uncertainties in land cover change models using sensitivity analysis. *Knowledge and Information Systems,* 55(3):719-740. 10.1007/s10115-017-1102-9.

84. Fishman, G.S. (1996). *Monte Carlo: Concepts, Algorithms, and Applications*. Springer-Verlag: New York.

85. Friedl, M. A. and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment,* 61(3):399-409. 10.1016/S0034-4257(97)00049-7.

86. García, A. M., Santé, I., Boullón, M. and Crecente, R. (2012). A comparative analysis of cellular automata models for simulation of small urban areas in Galicia, NW Spain. *Computers, Environment and Urban Systems, 36*(4), 291-301. 10.1016/j.compenvurbsys.2012.01.001.

87. Gingrich, P. (1992). *Introductory Statistics for the Social Sciences*. Regina: Canada.

88. Ginkel, H. V. (2008). Urban Future. *Nature,* 456:32-33.

89. Government of Tamil Nadu, Ministry for Industries Policy Note 2014–2015, (2014). Technical Report. Retrieved from: http://cms.tn.gov.in/sites/default/files/documents/industries_pn_e_2014.

90. Grekousis, G., Manetos, P. and Photis, Y. N. (2013). Modeling urban evolution using neural networks, fuzzy logic and GIS: The case of the Athens metropolitan area. *Cities,* 30:193-203. 10.1016/j.cities.2012.03.006.

91. Grimm, N. B., Grove, J. G., Pickett, S. T. A. and Redman, C. L. (2000). Integrated Approaches to Long-Term Studies of Urban Ecological Systems: Urban ecological systems present multiple challenges to ecologists—pervasive human impact and extreme heterogeneity of cities, and the need to integrate social and ecological approaches, concepts, and theory. *BioScience,* 50(7):571-584. 10.1641/0006-3568(2000)050[0571:IATLTO]2.0.CO;2.

92. Guan, Q., Wang, L. and Clarke, K. C. (2005). An Artificial-Neural-Network-based, Constrained CA Model for Simulating Urban Growth. *Cartography and Geographic Information Science,* 32(4):369-380. 10.1559/152304005775194746.

93. Gunasekera, R. (2004). Use of GIS for environmental impact assessment: an interdisciplinary approach. *Interdisciplinary Science Reviews,* 29(1):37-48. 10.1179/030801804225012473.

94. Guo, H. C, Liu, L., Huang, G. H., Fuller, G. A., Zou, R. and Yin, Y. Y. (2001). A system dynamics approach for regional environmental planning and management: a study for the Lake Erhai Basin. *Journal of Environmental Management,* 61(1), 93–111. 10.1006/jema.2000.0400.

95. Hassan, A. M. and Lee, H. (2015). Toward the sustainable development of urban areas: An overview of global trends in trials and policies. *Land Use Policy*, 48:199–212. 10.1016/j.landusepol.2015.04.029.

96. He, H., Chen, M., Chen, T. and Li, D. (2018). Matching of Remote Sensing Images with Complex Background Variations via Siamese Convolutional Neural Network. *Remote Sensing,* 10(2), 355. 10.3390/rs10020355.

97. Helton, J. C., Johnson, J. D., Sallaberry, C. J. and Storlie, C. B. (2006). Survey of sampling-based methods for uncertainty and sensitivity analysis. *Reliability Engineering & System Safety*, 91(10-11):1175-1209. 10.1016/j.ress.2005.11.017.

98. Herold, M., Scepan, J. and Clarke, K. C. (2002). The Use of Remote Sensing and Landscape Metrics to Describe Structures and Changes

in Urban Land uses. *Environment and Planning A: Economy and Space*, 34(8):1443–1458. 10.1068/a3496.

99. Hill, A. and Lindner, C. (2010). "Modelling informal urban growth under rapid urbanisation - A CA-based land-use simulation model for the city of Dar es Salaam, Tanzania" Ph.D. Thesis, Technical University of Dortmund, Germany.

100. Hinton, G. E. (2007). Learning multiple layers of representation. *Trends in Cognitive Sciences,* 11(10):428-434. 10.1016/j.tics.2007.09.004.

101. Hinton, G. E., Osindero, S. and Teh, Y. W. (2006). A Fast Learning Algorithm for Deep Belief Nets. *Neural Computation*, 18(7):1527–1554. 10.1162/neco.2006.18.7.1527.

102. Housing and Urban Development Department of Tamil Nadu (2018). Chennai Metropolitan Development Authority, Government of Tamil Nadu. Retrieved from http://www.cmdachennai.gov.in/pdfs/go/2018/go13.pdf.

103. Hsieh, S.-C. (2013). Analyzing urban population data using generalized gamma model and wave-spectrum relation: A case study of Kaohsiung. *Computers, Environment and Urban Systems,* 41:332–341. 10.1016/j.compenvurbsys.2012.07.005.

104. Hu, T., Yang, J., Li, X. and Gong, P. (2016). Mapping Urban Land Use by Using Landsat Images and Open Social Data. *Remote Sensing*, 8(2), 151. 10.3390/rs8020151.

105. Hu, Z. and Lo, C. P. (2007). Modeling urban growth in Atlanta using logistic regression. *Computers Environment and Urban Systems,* 31(6):667-688. 10.1016/j.compenvurbsys.2006.11.001.

106. Hua, L., Tang, L. Cui, S. and Yin, K. (2014). Simulating Urban Growth Using the SLEUTH Model in a Coastal Peri-Urban District in China. *Sustainability*, 6(6):3899-3914. 10.3390/su6063899.

107. Huang, C., Davis, L. S. and Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, 23(4):725-749. 10.1080/01431160110040323.

108. Hugo, G. (2007). Population geography. *Progress in Human Geography*, 31(1):77-88. 10.1177/0309132507073538.

109. Iannone, G., Troisi, A., Guarnaccia, C., D'Agostino, P. P. and Quartieri, J. (2011). An Urban Growth Model Based on a Cellular Automata Phenomenological Framework. *International Journal of Modern Physics C,* 22(5):543-561. 10.1142/S0129183111016427.

110. Itami, R. M. (1994). Simulating spatial dynamics: cellular automata theory. *Landscape and Urban Planning,* 30(1-2):27-47. 10.1016/0169-2046(94)90065-5.

111. Jaeger, J. A. G. and Schwick, C. (2014). Improving the measurement of urban sprawl: Weighted Urban Proliferation (WUP) and its application to Switzerland. *Ecological Indicators,* 38:294-308. 10.1016/j.ecolind.2013.11.022.

112. Jafari, M., Majedi, H., Monavari, S. M., Alesheikh, A. A. and Zarkesh, M. K. (2016). Dynamic simulation of urban expansion through a CA-Markov model Case study: Hyrcanian region, Gilan, Iran. *European Journal of Remote Sensing,* 49(1):513-529. 10.5721/EuJRS20164927.

113. Jat, M. K., Choudhary, M. and Saxena, A. (2017). Application of geo-spatial techniques and cellular automata for modelling urban growth of a heterogeneous urban fringe. *The Egyptian Journal of Remote Sensing and Space Science*, 20(2):223-241. 10.1016/j.ejrs.2017.02.002.

114. Jat, M. K., Garg, P. K. and Khare, D. (2008). Monitoring and modelling of urban sprawl using remote sensing and GIS techniques. *International Journal of Applied Earth Observation and Geoinformation,* 10(1):26-43. 10.1016/j.jag.2007.04.002.

115. Jat, M. K., Garg, P.K. and Khare, D. (2008a). Modeling of urban growth using spatial analysis techniques: a case study of Ajmer city (India). *International Journal of Remote Sensing*, 29(2): 543-567. 10.1080/01431160701280983.

116. Jiménez, A. A., Vilchez, F. F., González, O. N. and Flores, S. M. (2018). Analysis of the Land Use and Cover Changes in the Metropolitan Area of Tepic-Xalisco (1973–2015) through Landsat Images. *Sustainability*, 10(6):1860. 10.3390/su10061860.

117. Jothimani, P. (1997). Operational urban sprawl monitoring using satellite remote sensing: Excerpts from the studies of Ahmedabad, Vadodara and Surat, India. In *18th Asian Conference on Remote Sensing,* Malaysia. October 20–24, 1997.

118. Kanchanamala, S. (2014). "Cellular Automata Based Simulation Model of Land Use for Metropolitan Suburban Area. A Case Study of Chennai Metropolitan Area" Ph.D. Thesis, Anna University, Chennai.

119. Kantakumar, L. N., Kumar, S. and Schneider, K. (2016). Spatiotemporal urban expansion in Pune metropolis, India using remote sensing. *Habitat International*, 51:11–22. 10.1016/j.habitatint.2015.10.007.

120. Karlik, B. and Vehbi, A. (2011). Performance Analysis of Various Activation Functions in Generalized MLP Architectures of Neural Networks. *International Journal of Artificial Intelligence and Expert Systems,* 1(4):111-122.

121. Keuchel, J., Naumann, S., Heiler, M. and Siegmund, A. (2003). Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data. *Remote Sensing of Environment,* 86(4):530-541. 10.1016/S0034-4257(03)00130-5.

122. Klepper, O. (1997). Multivariate aspects of model uncertainty analysis: tools for sensitivity analysis and calibration. *Ecological Modelling*, 101(1):1-13. 10.1016/S0304-3800(96)01922-9.

123. Klosterman, R. E. (1999). New Perspectives on Planning Support Systems. *Environment and Planning B: Planning and Design*, 26(3):317-320. 10.1068/b260317.

124. Klosterman, R. E. and Pettit, C. J. (2005). An Update on Planning Support Systems. *Environment and Planning B: Planning and Design,* 32(4): 477-484. 10.1068/b3204ed.

125. Kumar, M., Singh, R. B., Pravesh, R., Kumar, P., Tripathi, D. K. and Sahu, N. (2018). Urban growth dynamics and modelling using remote sensing data and multivariate statistical techniques. *Current Science,* 114(10):2080-2091.

126. Kumar, U., Mukhopadhyay, C. and Ramachandra, T. V. (2014). Cellular Automata Calibration Model to Capture Urban Growth. *Boletín Geológico y Minero,* 125(3):285-299.

127. Lai, T., Dragićević, S. and Schmidt, M. (2013). Integration of multicriteria evaluation and cellular automata methods for landslide simulation modelling. *Geomatics, Natural Hazards and Risk,* 4(4):355-375. 10.1080/19475705.2012.746243.

128. Landis, J. D. (1994). The California Urban Futures Model: A New Generation of Metropolitan Simulation Models. *Environment and Planning B: Planning and Design,* 21(4):399-420. 10.1068/b210399.

129. Lata K. M., Sankar Rao C. H., Krishna Prasad V., Badrinath K. V. S., Raghavaswamy (2001). Measuring urban sprawl: A case study of Hyderabad. *GISdevelopment*, 5(12):8-13.

130. Leao, S., Bishop, I. D. and Evans, D. (2004). Simulating Urban Growth in a Developing Nation's Region Using a Cellular Automata-Based Model. *Journal of Urban Planning and Development*, 130(3):145-158. 10.1061/(ASCE)0733-9488(2004)130:3(145).

131. Lee, C. (1973). *Models in Urban Planning*. Pergamon Press: New York.

132. Li, F. (2012). "Investigation of urban sprawl on the basis of remote sensing data - A case study in Jiangning, Nanjing City, China" Ph.D. Thesis, University of Stuttgart, Germany.

133. Li, J., Yan, J., Liu, X. and Ouyang, G. (2014). Using Permutation Entropy to Measure the Changes in EEG Signals During Absence Seizures. *Entropy,* 16(6):3049-3061. 10.3390/e16063049.

134. Li, X. and Yeh, A. G. O. (2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science,* 16(4):323-343. 10.1080/13658810210137004.

135. Li, X. and Yeh, A.G.O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science*, 14(2):131-152. 10.1080/136588100240886.

136. Ligmann-Zielinska, A. and Sun, L. (2010). Applying time-dependent variance-based global sensitivity analysis to represent the dynamics of an agent-based model of land use change. *International Journal of Geographical Information Science,* 24(12):1829-1850. 10.1080/13658816.2010.490533.

137. Liu, Y. (2008). *Modelling Urban Development with Geographical Information Systems and Cellular Automata*. CRC Press. Taylor & Francis Group: Boca Raton.

138. Lo´pez, E., Bocco, G., Mendoza, M. and Duhau, E. (2001). Predicting land-cover and land-use change in the urban fringe. A

case in Morelia City, Mexico. *Landscape and Urban Planning*, 55(4):271-285. 10.1016/S0169-2046(01)00160-8.

139. Lopes N. and Ribeiro B. (2015). Deep Belief Networks (DBNs). In *Machine Learning for Adaptive Many-Core Machines - A Practical Approach* (pp.155-186). Cham: Springer. 10.1007/978-3-319-06938-8_8.

140. Lunetta, R.S., Congalton R. G., Fenstermaker, L.K., Jensen J. R., McGwire, K. C. and Tinney, L.R. (1991). Remote Sensing and Geographic Information System Data Integration: Error Sources and Research Issues. *Photogrammetric Engineering & Remote Sensing,* 57(6):677–687.

141. Luo, J., Yu, D. and Xin, M. (2008). Modeling Urban Growth Using GIS and Remote Sensing. *GIScience & Remote Sensing*, 45(4):426-442. 10.2747/1548-1603.45.4.426.

142. Luo, P., Li, Y., Tian, L. P. and Wu, F. X. (2019). Enhancing the prediction of disease–gene associations with multimodal deep learning. *Bioinformatics*, 35(19):3735-3742. 10.1093/bioinformatics/btz155.

143. Mahajan, Y. and Venkatachalam, P. (2009). Neural Network Based Cellular Automata Model for Dynamic Spatial Modeling in GIS. In *International Conference on Computational Science and Its Applications,* Seoul, Korea. June 29-July 2, 2009, pp.341-352.

144. Maithani, S. (2009). A neural network based urban growth model of an Indian city. *Journal of the Indian Society of Remote Sensing*, 37(3):363-376. 10.1007/s12524-009-0041-7.

145. Marsousi, N. and Lajevardi, A. R. (2011). The Evaluation of Ecological Sustainable Development Capacities in Kashan: An Historic City of Iran. *Sustainable Development and Planning V*, 150:371-380. 10.2495/SDP110311.

146. Mashao, D. (2004). Comparing SVM and GMM on parametric feature-sets. In *Proceedings of the 15th Annual Symposium of the Pattern Recognition*, *Association of South Africa,* Cape Town, South Africa. 2004.

147. McGee, T and Robinson, I. (Eds.). (1995). *The Mega-Urban Regions of Southeast Asia.* Vancouver, Canada: UBC Press.

148. McRae G. J., Tilden J. W. and Seinfeld J. H. (1982). Global sensitivity analysis - a computational implementation of the Fourier

amplitude sensitivity test (FAST). *Computers & Chemical Engineering*, 6(1):15–25. 10.1016/0098-1354(82)80003-3.

149. Mishra, V. N. and Rai, P. K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arabian Journal of Geosciences,* 9(4):1-18. 10.1007/s12517-015-2138-3.

150. Moghadam, H. S. and Helbich, M. (2015). Spatiotemporal variability of urban growth factors: A global and local perspective on the megacity of Mumbai. *International Journal of Applied Earth Observation and Geoinformation,* 35(Part B), 187-198. 10.1016/j.jag.2014.08.013.

151. Mohamed, A., Sainath, T. N., Dahl, G., Ramabhadran, B., Hinton, G. E. and Picheny, M. A. (2011). Deep Belief Networks using discriminative features for phone recognition. *In Proc. 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* 2011. 10.1109/ICASSP.2011.5947494.

152. Mohan, M., Pathan, S. K., Narendrareddy, K., Kandya, A. and Pandey, S. (2011). Dynamics of Urbanization and Its Impact on Land-Use/Land-Cover: A Case Study of Megacity Delhi. *Journal of Environmental Protection*, 2(9):1274-1283. 10.4236/jep.2011.29147.

153. Mondal, B., Das, D. N. and Bhatta, B. (2016). Integrating cellular automata and Markov techniques to generate urban development potential surface: a study on Kolkata agglomeration. *Geocarto International,* 32(4):401-419. 10.1080/10106049.2016.1155656.

154. Morgan, J. L., Gergel, S. E. and Coops, N. C. (2010). Aerial Photography: A Rapidly Evolving Tool for Ecological Management. *BioScience*, 60(1):47-59. 10.1525/bio.2010.60.1.9.

155. Mosammam, H. M., Nia, J. T., Khani, H., Teymouri, A. and Kazemi, M. (2017). Monitoring land use change and measuring urban sprawl based on its spatial forms. The case of Qom city. *The Egyptian Journal of Remote Sensing and Space Science*, 20(1):103–116. 10.1016/j.ejrs.2016.08.002.

156. Mozumder, C. and Tripathi, N. K. (2014). Geospatial scenario based modelling of urban and agricultural intrusions in Ramsar wetland Deepor Beel in Northeast India using a multi-layer perceptron neural network. *International Journal of Applied Earth Observation and Geoinformation,* 32(1):92-104. 10.1016/j.jag.2014.03.002.

157. Mubea, K.W. (2014). "Scenarios of Urban Growth in Kenya Using Regionalised Cellular Automata based on Multi temporal Landsat Satellite Data" Ph.D. Thesis, University of Bonn, Germany.

158. Mundia, C. N. and Murayama, Y. (2010). Modeling Spatial Processes of Urban Growth in African cities: A Case Study of Nairobi City. *Urban Geography*, 31(2):259-272. 10.2747/0272-3638.31.2.259.

159. Mustafa, A., Saadi, I., Cools, M. and Teller, J. (2015). Modelling Uncertainties in Long-Term Predictions of Urban Growth: A Coupled Cellular Automata and Agent-Based Approach. In *14th International Conference on Computers in Urban Planning and Urban Management*, Cambridge, USA. July 7-10, 2015.

160. Nagendra H., Sudhira H.S., Katti M., Schewenius M. (2013). Sub-regional Assessment of India: Effects of Urbanization on Land Use, Biodiversity and Ecosystem Services. In: Elmqvist T. et al. (Eds.), *Urbanization, Biodiversity and Ecosystem Services: Challenges and Opportunities* (pp. 65-74). Dordrecht: Springer.

161. Oğuz, H. (2004). "Modeling Urban Growth and Land Use/Land Cover Change in the Houston Metropolitan Area from 2002 – 2030" Ph.D. Thesis, Texas A&M University, USA.

162. Oğuz, H., Klein, A. G., and Srinivasan, R. (2007). Using the Sleuth Urban Growth Model to Simulate the Impacts of Future Policy Scenarios on Urban Land Use in the Houston-Galveston-Brazoria CMSA. *Research Journal of Social Sciences,* 2:72- 82.

163. Ooi, G. L. and Phua, K. H. (2007). Urbanization and Slum Formation. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, 84(1):i27 – i34. 10.1007/s11524-007-9167-5.

164. Openshaw, S. (1998). Neural Network, Genetic, and Fuzzy Logic Models of Spatial Interaction. *Environment and Planning A: Economy and Space,* 30(10):1857-1872. 10.1068/a301857.

165. Openshaw, S. and Openshaw, C. (1997). *Artificial Intelligence in Geography* (1st edition). John Wiley & Sons, Inc: New York.

166. Ou, C., Yang, J., Du, Z., Li, P. and Zhu, D. (2018). Simulating Multiple Land Use Changes by Incorporating Deep Belief Network into Cellular Automata: A Case Study in BEIJING-TIANJINHEBEI Region, China. In *21st Conference on Geo-information science, AGILE,* Lund. June 12-15, 2018.

167. Ou, C., Yang, J., Du, Z., Zhang, X. and Zhu, D. (2019). Integrating Cellular Automata with Unsupervised Deep-Learning Algorithms: A Case Study of Urban-Sprawl Simulation in the Jingjintang Urban Agglomeration, China. *Sustainability,* 11, 2464. 10.3390/su11092464.

168. Ou, Y., Yi, L., Zou, B. and Pei, Z. (2018). The linguistic intuitionistic fuzzy set TOPSIS method for linguistic multi-criteria decision makings. *International Journal of Computational Intelligence Systems*, 11(1):120-132.

169. Ouyang, Z., Fan, P., Chen, J., Lafortezza, R., Messina, J. P., Giannico, V. and John, R. (2019). A Bayesian approach to mapping the uncertainties of global urban lands. *Landscape and Urban Planning,* 187:210-218. 10.1016/j.landurbplan.2018.07.016.

170. Ozturk, D. (2017). Assessment of urban sprawl using Shannon's entropy and fractal Analysis: a case Study of Atakum, Ilkadim and Canik (Samsun, Turkey). *Journal of Environmental Engineering and Landscape Management,* 25(3):264-276. 10.3846/16486897.2016.1233881.

171. Padmanaban, R., Bhowmik, A. K., Cabral, P., Zamyatin, A., Almegdadi, O. and Wang, S. (2017). Modelling Urban Sprawl Using Remotely Sensed Data: A Case Study of Chennai City, Tamilnadu. *Entropy,* 19(4), 163. 10.3390/e19040163.

172. Pal, M. and Mather, P. M. (2003). An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment,* 86(4):554-565. 10.1016/S0034-4257(03)00132-9.

173. Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J. and Deadman, P. (2003). Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. *Annals of the Association of American Geographers,* 93(2):314-337. 10.1111/1467-8306.9302004.

174. Parry, J. A., Ganaie, S. A. and Bhat, M. S. (2018). GIS based land suitability analysis using AHP model for urban services planning in Srinagar and Jammu urban centers of J&K, India. *Journal of Urban Management,* 7(2):46-56. 10.1016/j.jum.2018.05.002.

175. Pickett, S. T. A., Cadenasso, M. L, Grove, J. M., Nilon, C. H., Pouyat, R. V., Zipperer, W. C. and Costanza, R. (2001). Urban Ecological Systems: Linking Terrestrial Ecological, Physical, and Socioeconomic Components of Metropolitan Areas. *Annual Review*

of Ecology and Systematics, 32(1):127-157. 10.1146/annurev.ecolsys.32.081501.114012.

176. Pijanowski, B. C., Brown, D. G., Shelito, B. A. and Manik, G. A. (2002). Using neural networks and GIS to forecast land use changes: a Land Transformation Model. *Computers, Environment and Urban Systems*, 26(6):553-575. 10.1016/S0198-9715(01)00015-1.

177. Pradhan, A. and Kockelman, K. M. (2002). Uncertainty Propagation in an Integrated Land Use-Transportation Modeling Framework: Output Variation via UrbanSim. *Transportation Research Record: Journal of the Transportation Research Board*, 1805(1), 128-135. 10.3141/1805-15.

178. Pramanik, M. K. (2016). Site suitability analysis for agricultural land use of Darjeeling district using AHP and GIS techniques. *Modeling Earth Systems and Environment,* 2:56. 10.1007/s40808-016-0116-8.

179. Rahaman, K. R., Hassan, Q. K. And Ahmed, M. R. (2017). Pan-Sharpening of Landsat-8 Images and Its Application in Calculating Vegetation Greenness and Canopy Water Contents. *ISPRS International Journal of Geo-Information,* 6(6), 168. 10.3390/ijgi6060168.

180. Rajeev. (2016). Measuring Urban Sprawl through Shannon's Entropy – An Approach using Remote Sensing and GIS. *International Journal of Science, Engineering and Technology,* 5(1):24-30.

181. Ramachandra, T. V., Aithal, B. H. and Sanna, D. D. (2012). Insights to urban dynamics through landscape spatial pattern analysis. *International Journal of Applied Earth Observation and Geoinformation,* 18:329–343. 10.1016/j.jag.2012.03.005.

182. Ramachandra, T. V., Bharath, A. H. and Sowmyashree, M. V. (2014). Monitoring urbanization and its implications in a mega city from space: spatiotemporal patterns and its indicators. *Journal of Environmental Management,* 148:67-81. 10.1016/j.jenvman.2014.02.015.

183. Rastogi, K. and Jain, G. V. (2018). Urban Sprawl Analysis using Shannon's Entropy and Fractal Analysis: A Case Study on Tiruchirappalli City, India. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-5, ISPRS TC V Mid-term Symposium "Geospatial Technology – Pixel to People,* Dehradun, India. November 20–23, 2018, pp. 761-766. 10.5194/isprs-archives-XLII-5-761-2018.

184. Ridd, M. K. (1995). Exploring a V-I-S (vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities. *International Journal of Remote Sensing,* 16(12):2165-2185. 10.1080/01431169508954549.

185. Saaty, T.L. (1977). A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology,* 15(3):234-281. 10.1016/0022-2496(77)90033-5.

186. Saaty, T.L. (1980). *The Analytic Hierarchy Process*. McGraw-Hill: New York.

187. Sanchez, M., Ambros, A., Milà, C., Salmon, M., Balakrishnan, K., Sambandam, S. Sreekanth, V., Marshall, J. D. and Tonne, C. (2018). Development of land-use regression models for fine particles and black carbon in peri-urban South India. *Science of the Total Environment*, 634:77-86. 10.1016/j.scitotenv.2018.03.308.

188. Sánchez-Canales, M., Benito, A. L., Passuello, A., Terrado, M., Ziv, G., Acuña, V, Schuhmacher, M and Elorza, F. J. (2012). Sensitivity analysis of ecosystem service valuation in a Mediterranean watershed. *Science of the Total Environment,* 440(1):140-153. 10.1016/j.scitotenv.2012.07.071.

189. Santé, I., García, A. M., Miranda, D., and Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning,* 96(2):108-122. 10.1016/j.landurbplan.2010.03.001.

190. Sarvestani, M. S., Ibrahim, A. L. and Kanaroglou, P. (2011). Three decades of urban growth in the city of Shiraz, Iran: A remote sensing and geographic information systems application. *Cities*, 28(4):320-329. 10.1016/j.cities.2011.03.002.

191. Saxena, A. and Jat, M. K. (2019). Capturing heterogeneous urban growth using SLEUTH model. *Remote Sensing Applications: Society and Environment*, 13:426-434. 10.1016/j.rsase.2018.12.012.

192. Schneider, A. and Woodcock, C. E. (2008). Compact, Dispersed, Fragmented, Extensive? A Comparison of Urban Growth in Twenty-five Global Cities using Remotely Sensed Data, Pattern Metrics and Census Information. *Urban Studies*, 45(3):659-692. 10.1177/0042098007087340.

193. Second Master Plan for Chennai Metropolitan Area, (2008). Volume I: Vision, Strategies and Action Plans, Chennai Metropolitan

Development Authority, Government of Tamil Nadu. Retrieved from http://www.cmdachennai.gov.in/Volume1_English_PDF/Vol1_Chapter00_Introduction.pdf.

194. Second Master Plan for Chennai Metropolitan Area. (2008a). Volume II: Development Regulations, Chennai Metropolitan Development Authority, Government of Tamil Nadu. Retrieved from http://www.cmdachennai.gov.in/Volume2_English_PDF/DR-English.pdf.

195. Seenirajan, M., Natarajan, M., Thangaraj, R. and Bagyaraj, M. (2017). Study and Analysis of Chennai Flood 2015 Using GIS and Multicriteria Technique. *Journal of Geographic Information System*, 9(2):126-140. 10.4236/jgis.2017.92009.

196. Sekar, S. P. and Kanchanamala, S. (2011). An Analysis of Growth Dynamics in Chennai Metropolitan Area. *Institute of Town Planners,* 8(4), 31-57.

197. Serasinghe Pathiranage, I. S., Kantakumar, L. N. and Sundaramoorthy, S. (2018). Remote Sensing Data and SLEUTH Urban Growth Model: As Decision Support Tools for Urban Planning. *Chinese Geographical Science*, 28(2):274-286. 10.1007/s11769-018-0946-6.

198. Shafia, A., Gaurav, S. and Bharath, H. A. (2018). Urban growth modelling using Cellular Automata coupled with land cover indices for Kolkata Metropolitan region. *IOP Conference Series: Earth and Environmental Science,* 169 (012090). 10.1088/1755-1315/169/1/012090.

199. Shafizadeh-Moghadam, H., Asghari, A., Tayyebi, A. and Taleai, M. (2017). Coupling machine learning, tree-based and statistical models with cellular automata to simulate urban growth. *Computers Environment and Urban Systems,* 64:297–308. 10.1016/j.compenvurbsys.2017.04.002.

200. Shekhar, S. (2004). Urban sprawl assessment Entropy approach. *GIS Development*, 8(5), 43-48.

201. Shen, F., Chao, J. and Zhao, J. (2015). Forecasting exchange rate using deep belief networks and conjugate gradient method. *Neurocomputing*, 167:243-253. 10.1016/j.neucom.2015.04.071.

202. Shi, D. and Yang, X. (2015). Support Vector Machines for Land Cover Mapping from Remote Sensor Imagery. In J. Li & X. Yang

(Eds.), *Monitoring and Modeling of Global Changes: A Geomatics Perspective* (pp. 265-279). Springer: Dordrecht. 10.1007/978-94-017-9813-6_13.

203. Siddiqui, A., Siddiqui, A., Maithani, S., Jha, A. K., Kumar, P. and Srivastav. S. K. (2018). Urban growth dynamics of an Indian metropolitan using CA Markov and Logistic Regression. *The Egyptian Journal of Remote Sensing and Space Science,* 21(3):229-236. 10.1016/j.ejrs.2017.11.006.

204. Silva, E. A. and Clarke, K. C. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems,* 26(6):525-552. 10.1016/S0198-9715(01)00014-X.

205. Singh, B. (2014). Urban Growth Using Shannon's Entropy: a Case Study of Rohtak City. *International Journal of Advanced Remote Sensing and GIS,* 3(1):544-552.

206. Singh, S. K., Mustak, Sk., Srivastava, P. K., Szabó, S. and Islam, T. (2015). Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information. *Environmental Processes*, 2(1):61-78. 10.1007/s40710-015-0062-x.

207. Sipper, M. (1997). *Evolution of Parallel Cellular Machines: The Cellular Programming Approach*. Springer: Berlin.

208. Sivaramakrishnan, K. C., Kundu, A. and Singh, B. N. (2005). *Handbook of Urbanization in India.* Oxford University Press: New Delhi, India.

209. Sokhi, B.S. and Rashid, S.M. (1999). *Remote sensing of urban environment.* Manak Publications: New Delhi, India.

210. Stone, J. V. (2013). *Bayes' Rule: A Tutorial Introduction to Bayesian Analysis*. Sebtel Press: London. 10.13140/2.1.1371.6801.

211. Sudhira, H. S., Ramachandra, T. V. and Jagadish, K. S. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation*, 5(1):29-39.10.1016/j.jag.2003.08.002.

212. Sudhira, H. S., Ramachandra, T. V., Raj, K. S. and Jagadish, K. S. (2003). Urban growth analysis using spatial and temporal data. *Journal of the Indian Society of Remote Sensing*, 31(4):299– 311. 10.1007/BF03007350.

213. Sui, D.Z. and Zeng, H. (2001). Modeling the dynamics of landscape structure in Asia's emerging desakota regions: a case study in Shenzhen. *Landscape and Urban Planning,* 53(1-4):37-52. 10.1016/S0169-2046(00)00136-5.

214. Sun, H., Forsythe, W. and Waters, N. (2007). Modeling Urban Land Use Change and Urban Sprawl: Calgary, Alberta, Canada. *Networks and Spatial Economics*, 7(4):353–376. 10.1007/s11067-007-9030-y.

215. Sutton, P. C. (2003). A scale-Adjusted measure of "Urban sprawl" using nighttime satellite imagery. *Remote Sensing of Environment*, 86(3):353-369. 10.1016/S0034-4257(03)00078-6.

216. Tan, K. C., Lim, H. S., Jafri, M. Z. M. and Abdullah, K. (2010). Landsat data to evaluate urban expansion and determine land use/land cover changes in Penang Island, Malaysia. *Environmental Earth Sciences*, 60(7):1509-1521. 10.1007/s12665-009-0286-z.

217. Tayyebi, A., Pijanowski, B. C. and Tayyebi, A. H. (2011). An urban growth boundary model using neural networks, GIS and radial parameterization: An application to Tehran, Iran. *Landscape and Urban Planning,* 100(1-2):35-44. 10.1016/j.landurbplan.2010.10.007.

218. The Growth Story of Sriperumbudur Real Estate (2013). Government of Tamil Nadu. Retrieved from: http://www.etastar.com/The-Growth-Story-Sriperumbudur-Real-Estate

219. Theil, H. (1967). *Economics and Information Theory.* North-Holland Publishing Company: Amsterdam.

220. Thomas, R.W. (1981). *Information Statistics in Geography.* Headey Brothers Ltd, The Invicta Press: Ashford, Kent, UK.

221. Thunig, H., Wolf, N., Naumann, S., Siegmund, A., Jürgens, C., Uysal, C. and Maktav, D. (2011). Land use/land cover classification for applied urban planning - The challenge of automation. In *2011 Joint Urban Remote Sensing Event*, Munich. April 11-13, 2011, pp. 229-232. 10.1109/JURSE.2011.5764762.

222. Torrens, P. M. and M. Alberti (2000). Measuring sprawl. In *Association of Collegiate Schools in Planning Conference,* Atlanta. November, 2000.

223. Torrens, P. M. and O'Sullivan, D. (2001). Cellular Automata and Urban Simulation: Where Do We Go from Here?. *Environment and Planning B: Planning and Design*, 28(2):163–168. 10.1068/b2802ed.

224. Torrens, P.M. (2006). Geosimulation and its Application to Urban Growth Modeling. In J. Portugali (Eds.), *Complex Artificial Environments* (pp.119-136). Berlin, Heidelberg: Springer. 10.1007/3-540-29710-3_8.

225. Triantakonstantis, D. and Mountrakis, G. (2012). Urban Growth Prediction: A Review of Computational Models and Human Perceptions. *Journal of Geographic Information System,* 4(6):555–587. 10.4236/jgis.2012.46060.

226. Tripathy, P. and Kumar, A. (2019). Monitoring and modelling spatio-temporal urban growth of Delhi using Cellular Automata and geoinformatics. *Cities,* 90:52-63. 10.1016/j.cities.2019.01.021.

227. Turner, B. L., Lambin, E. F. and Reenberg, A. (2007). Land Change Science Special Feature: The Emergence of Land Change Science for Global Environmental Change and Sustainability. *Proceedings of the National Academy of Sciences of the United States of America,* 105(7):20666–20671. 10.1073pnas.0704119104.

228. Tzotsos, A. and Argialas, D. (2008). Support Vector Machine Classification for Object-Based Image Analysis. In T. Blaschke, S. Lang, G. J. Hay (Eds.), Lecture Notes in Geoinformation and Cartography (pp.663-677). Heidelberg, Berlin: Springer. 10.1007/978-3-540-77058-9_36.

229. Uljee, I., Engelen, G. and White, R. (1996). Ramco Demo Guide, *Work document CZMOC 96.08*, National Institute for Coastal and Marine, The Hague.

230. Ullah, K. M. and Mansourian, A. (2014). Evaluation of Land Suitability for Urban Land-Use Planning: Case Study Dhaka City. *Transactions in GIS*, 20(1):20-37. 10.1111/tgis.12137.

231. Verburg, P. H., Schot, P. P., Dijst, M. J. and Veldkamp, A. (2004). Land use change modelling: current practice and research priorities. *GeoJournal,* 61(4):309-324. 10.1007/s10708-004-4946-y.

232. Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V. and Mastura, S. S. A. (2002). Modeling the Spatial Dynamics of Regional Land Use: The CLUE-S Model.

Environmental Management, 30(3): 391-405. 10.1007/s00267-002-2630-x.

233. Verzosa, L. C. O. and Gonzalez, R. (2010). Remote sensing, geographic information systems and Shannon's entropy: Measuring urban sprawl in a mountainous environment. In *ISPRS TC VII Symposium – 100 Years ISPRS*, Vienna, Austria. July 5–7, 2010, pp. 269-274.

234. Walker W. T., Gao S. and Johnston R. A. (2007). UPlan: Geographic Information System as Framework for Integrated Land Use Planning Model. *Transportation Research Record: Journal of the Transportation Research Board*, 1994(1):117-127. 10.3141/1994-16.

235. Wang, F. (1994). The use of artificial neural networks in a geographical information system for agricultural land-suitability assessment. *Environment and Planning A*, 26:265–284.

236. Ward, D. P., Murray, A. T. and Phinn, S. R. (2000). A Stochastically Constrained Cellular Model of Urban Growth. *Computers, Environment and Urban Systems*, 24(6):539-558. 10.1016/S0198-9715(00)00008-9.

237. Weber, C. and Puissant, A. (2003). Urbanization pressure and modeling of urban growth: example of the Tunis Metropolitan Area. *Remote Sensing of Environment,* 86(3):341-352. 10.1016/S0034-4257(03)00077-4.

238. White, R. (1998). Cities and cellular automata. *Discrete Dynamics in Nature and Society*, 2(2):111-125. 10.1155/S1026022698000090.

239. White, R. and Engelen, G. (1993). Cellular Automata and Fractal Urban Form: A Cellular Modelling Approach to the Evolution of Urban Land-Use Patterns. *Environment and Planning A: Economy and Space,* 25(8):1175-1199. 10.1068/a251175.

240. White, R. and Engelen, G. (1997). Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning B: Planning and Design,* 24:235-246.

241. White, R. and Engelen, G. (2000). High-resolution integrated modelling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems*, 24(5):383-400. 10.1016/S0198-9715(00)00012-0.

242. Wolfram, S. (1984). Cellular automata as models of complexity. *Nature*, 311, 419–424. 10.1038/311419a0.

243. World Urbanization Prospects, The 2011 Revision (2012). Department of Economic and Social Affairs, Population Division. United Nations, New York. Retrieved from https://www.un.org/en/development/desa/population/publications/pdf/urbanization/WUP2011_Report.pdf.

244. Wu, F. (1996). A linguistic cellular automata simulation approach for sustainable land development in a fast growing region. *Computers, Environment and Urban Systems*, 20(6):367–387. 10.1016/S0198-9715(97)00003-3.

245. Wu, F. (1998). SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. *International Journal of Geographical Information Science*, 12(1):63–82. 10.1080/136588198242012.

246. Wu, F. (1998a). An Experiment on the Generic Polycentricity of Urban Growth in a Cellular Automatic City. *Environment and Planning B: Planning and Design,* 25(5):731-752. 10.1068/b250731.

247. Wu, F. (1998b). Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a geographical information system. *Journal of Environmental Management,* 53(4):293-308. 0.1006/jema.1998.0195.

248. Wu, F. (1999). GIS-based simulation as an exploratory analysis for space-time processes. *Journal of Geographical Systems*, 1(3):199–218. 10.1007/s101090050012.

249. Wu, F. (2002). Calibration of stochastic cellular automata: the application to rural-urban land conversions. *International Journal of Geographical Information Science,* 16(8):795–818. 10.1080/13658810210157769.

250. Wu, F. and Webster, C. J. (1998). Simulation of Land Development through the Integration of Cellular Automata and Multicriteria Evaluation. *Environment and Planning B: Urban Analytics and City Science*, 25(1):103-126. 10.1068/b250103.

251. Wu, H., Zhou, L., Chi, X., Li, Y. and Sun, Y. (2012). Quantifying and analyzing neighborhood configuration characteristics to cellular automata for land use simulation considering data source error. *Earth Science Informatics*, 5(2):77-86. 10.1007/s12145-012-0097-8.

252. Wu, J. and Li, H. (2006). Perspectives and Methods of Scaling. In J. Wu, K. B. Jones, H. Li & O. L. Loucks (Eds.), *Scaling and Uncertainty Analysis in Ecology: Methods and Applications* (pp.17-44). The Netherlands: Springer.

253. Xia, N., Cheng, L. and Li, M. (2019). Mapping Urban Areas Using a Combination of Remote Sensing and Geolocation Data. *Remote Sensing,* 11, 1470. 10.3390/rs11121470.

254. Xiao, J., Shen, Y., Ge, J., Tateishi, R., Tang, C., Liang, Y. and Huang, Z. (2006). Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing. *Landscape and Urban Planning*, 75(1-2):69-80. 10.1016/j.landurbplan.2004.12.005.

255. Yang, X., Leung, L. R., Zhao, N., Zhao, C., Qian, Y., Hu, K., Liu, X. and Chen, B. (2017). Contribution of urbanization to the increase of extreme heat events in an urban agglomeration in east China. *Geophysical Research Letters*, 44(13):6940-6950. 10.1002/2017GL074084.

256. Yeh, A.G.O. and Li, X. (2002). Urban Simulation Using Neural Networks and Cellular Automata for Land Use Planning. In D.E. Richardson & P. van Oosterom (Eds.), *Advances in Spatial Data Handling* (pp.451-464). Heidelberg, Berlin: Springer.

257. Yeh, A.G.O. and Li, X. (2001). Measurement and Monitoring of Urban Sprawl in a Rapidly Growing Region Using Entropy. *Photogrammetric Engineering & Remote Sensing,* 67(1):83-90.

258. Yeh, A.G.O. and Li, X. (2006). Errors and uncertainties in urban cellular automata. *Computers, Environment and Urban Systems*, 30(1):10–28. 10.1016/j.compenvurbsys.2004.05.007.

259. Yu, D. and Deng, L. (2011). Deep Learning and Its Applications to Signal and Information Processing [Exploratory DSP]. *IEEE Signal Processing Magazine*, 28(1):145–154. 10.1109/MSP.2010.939038.

260. Yuan, F., Sawaya, K. E., Loeffelholz, B. C. and Bauer, M. E. (2005). Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. *Remote Sensing of Environment,* 98(2-3):317-328. 10.1016/j.rse.2005.08.006.

261. Zeng, C., He, S., and Cui, J. (2014). A Multi-Level and Multi-Dimensional Measuring on Urban Sprawl: A Case Study in Wuhan

Metropolitan Area, Central China. *Sustainability,* 6(6):3571– 3598. 10.3390/su6063571.

262. Zeng, Y., Wu, G., Zhan, F. B. and Zhang, H. H. (2008). Modeling spatial land use pattern using auto logistic regression. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37(B2):115-118.

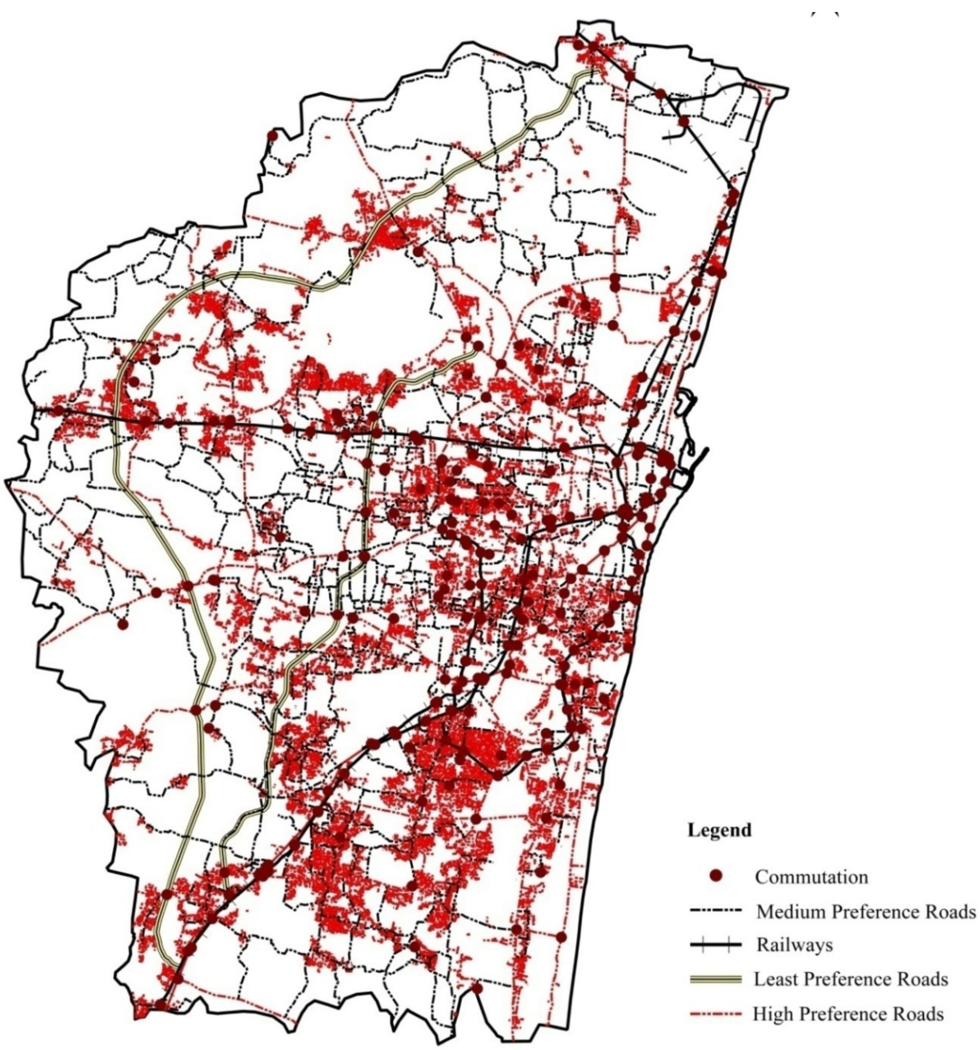
263. Zhang, X. (2016). Urban Growth Modeling Using Neural Network Simulation: A Case Study of Dongguan City, China. *Journal of Geographic Information System,* 8(3):317-328. 10.4236/jgis.2016.83027.

264. Zhou, J. and Civco, D. L. (1996). Using Genetic Learning Neural Networks for Spatial Decision Making in GIS. *Photogrammetric Engineering & Remote Sensing*, 62(11):1287–1295.

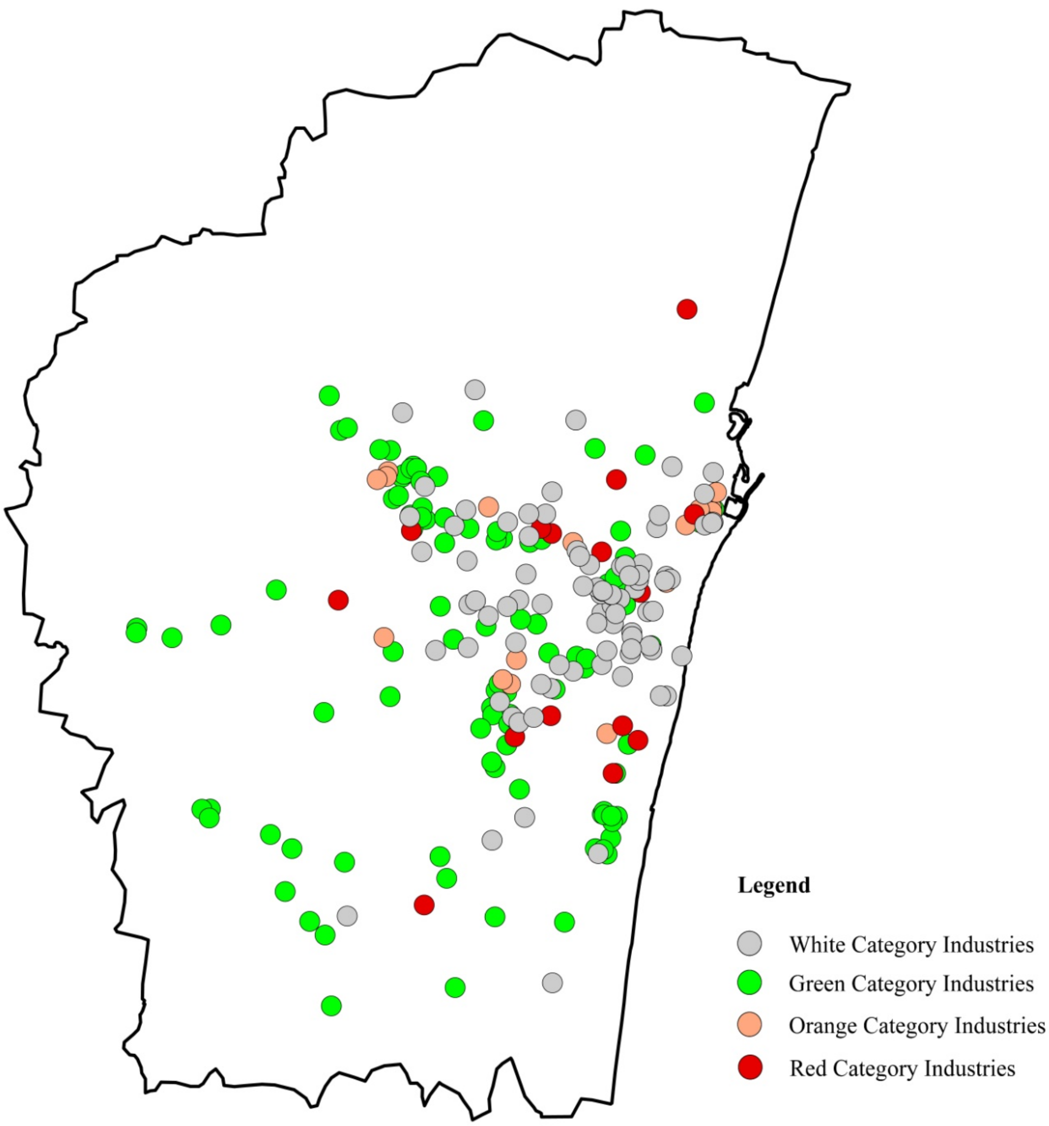
265. Zhou, Y., Zhang, F., Du, Z., Ye, X. and Liu, R. (2017). Integrating Cellular Automata with the Deep Belief Network for Simulating Urban Growth. *Sustainability,* 9(1786):1-19. 10.3390/su9101786.

APPENDICES

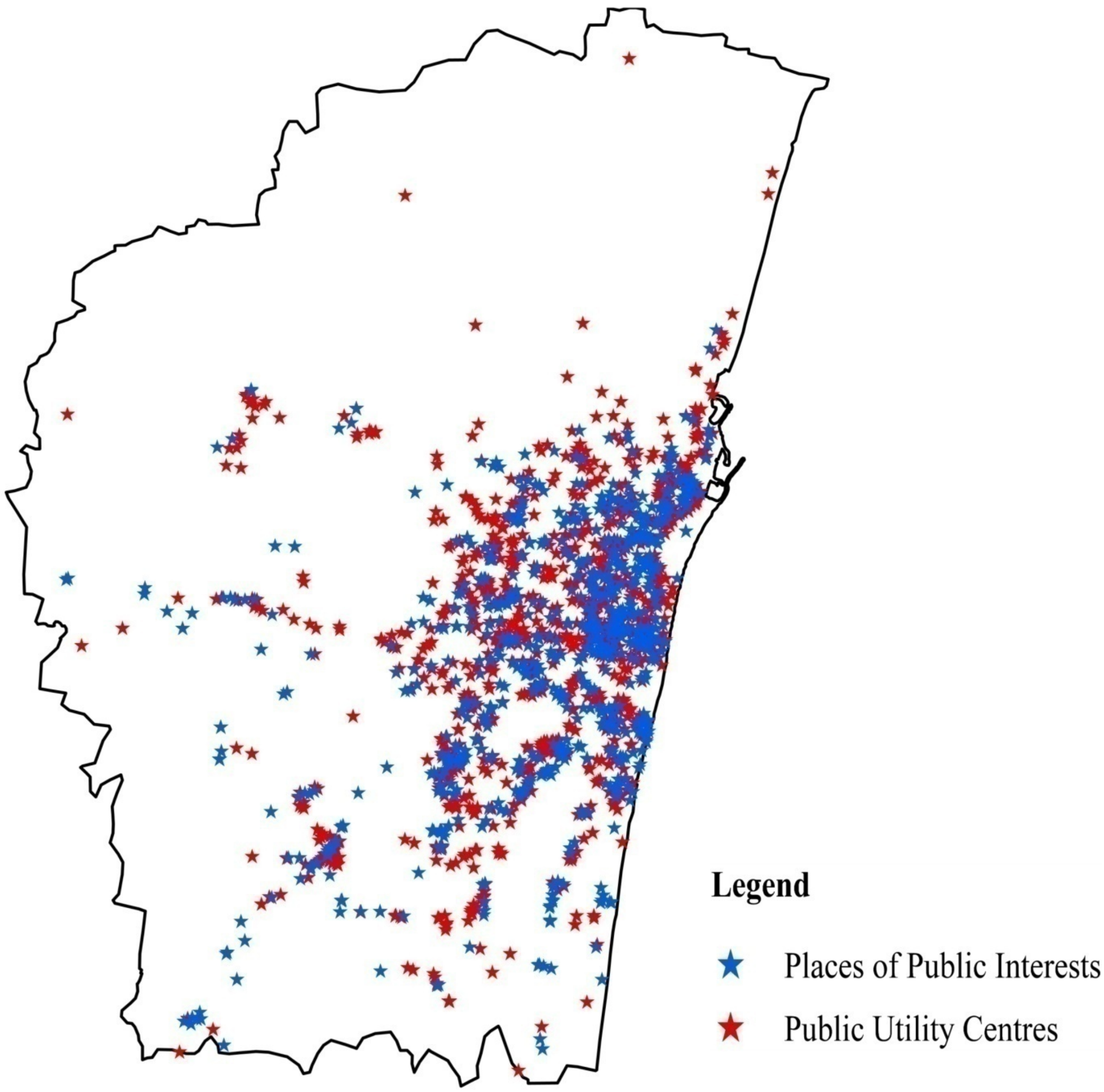
Appendix 1: Transportation Network Map of Chennai Metropolitan Area



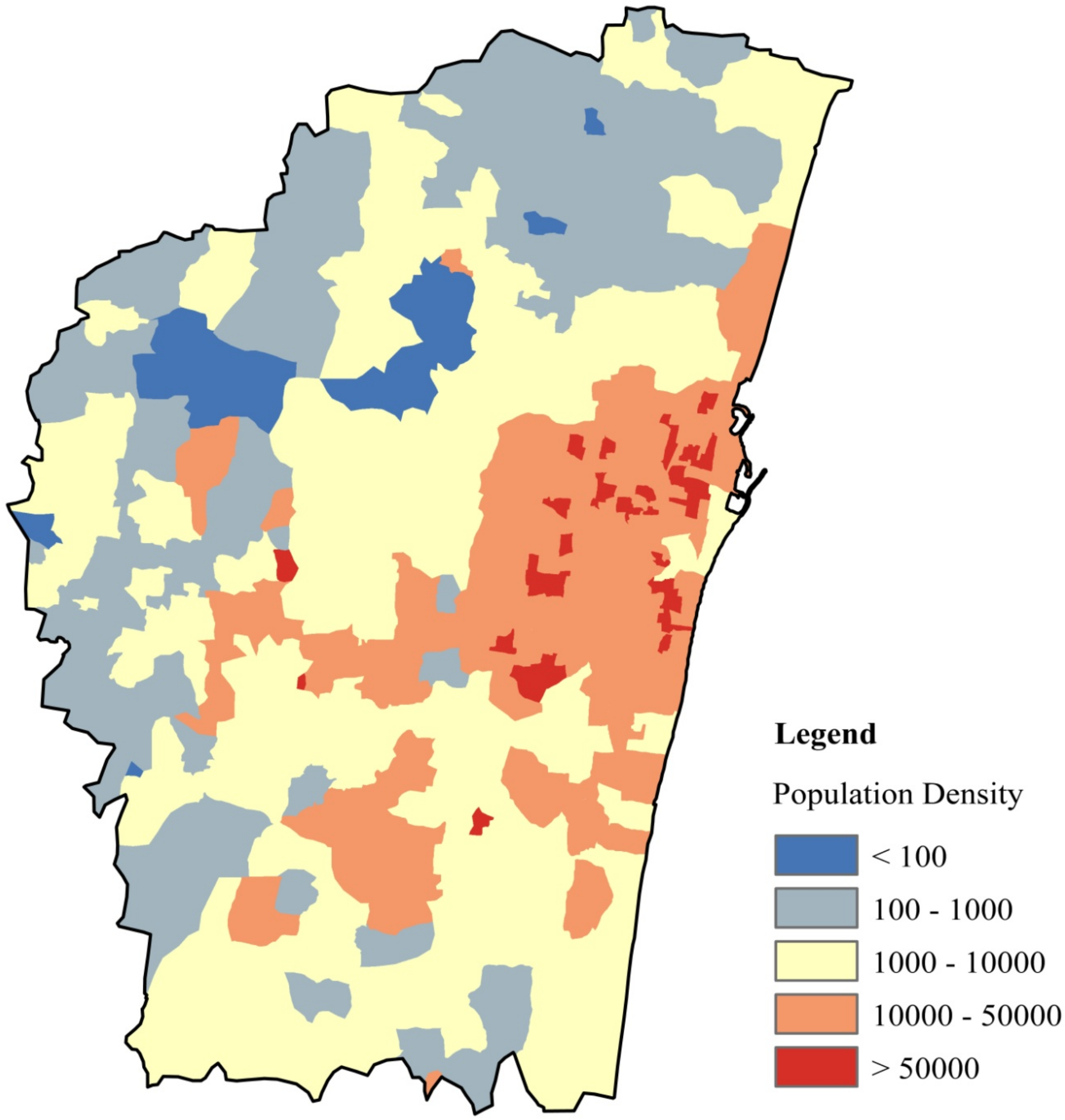
Appendix 2: Industrial Location Map of Chennai Metropolitan Area



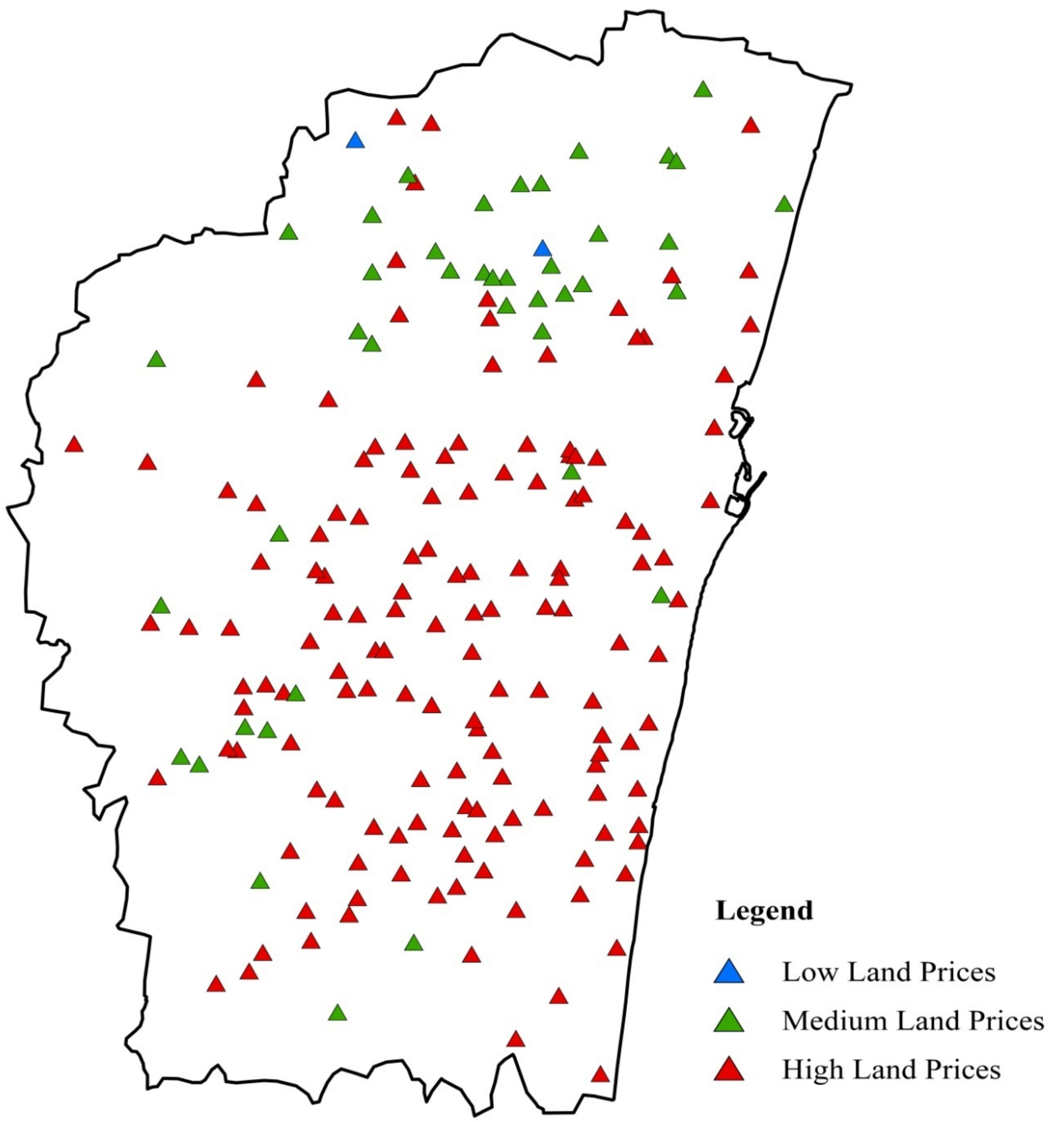
Appendix 3: Socio-economic Factor Map of Chennai Metropolitan Area



Appendix 4: Population Density Map of Chennai Metropolitan Area



Appendix 5: Land Prices Map of Chennai Metropolitan Area



LIST OF PUBLICATIONS

Refereed Journals

1. Devendran, A. A. and Lakshmanan, G. (2019). Analysis and Prediction of Urban Growth Using Neural-Network-Coupled Agent-Based Cellular Automata Model for Chennai Metropolitan Area, Tamil Nadu, India. *Journal of the Indian Society of Remote Sensing,* 47(9):1515- 1526. 10.1007/s12524-019-01003-8.
2. Aarthi, A. D. and Gnanappazham, L. (2019). Comparison of Urban Growth Modeling Using Deep Belief and Neural Network Based Cellular Automata Model-A Case Study of Chennai Metropolitan Area, Tamil Nadu, India. *Journal of Geographic Information System,* 11(1):1-16. 10.4236/jgis.2019.111001.
3. Aarthi, A. D. and Gnanappazham, L. (2018). Urban growth prediction using neural network coupled agents-based Cellular Automata model for Sriperumbudur Taluk, Tamil Nadu, India. *The Egyptian Journal of Remote Sensing and Space Science,* 21:353-362. 10.1016/j.ejrs.2017.12.004.

Refereed Conferences

1. Devendran, A. A. and Lakshmanan, G. (2015). A Review on Artificial Neural Network Coupled Agent Based Cellular Automata Model for Urban Growth Simulation. In *The National Symposium on Geomatics for Digital India*, Jaipur, India. December 16-18, 2015.
2. Devendran, A. A. and Lakshmanan, G. (2014). A Review On Accuracy and Uncertainty of Spatial Data and Analyses with Special Reference to Urban and Hydrological Modelling. In *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences,*

ISPRS Technical Commission VIII Symposium, Hyderabad, India. December 9 – 12, 2014. 10.5194/isprsannals-II-8-171-2014.