THESIS OF DOCTOR OF ENGINEERING

Evaluation of Urban Change Pattern and its Impact on Urban Development Plans – Case of Jaipur, India

(都市変遷パターンと都市開発計画効果の評価

–インド，ジャイプルをケースとして)

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August 2011

To my Mother and Father

&

To my Wife and Son

ABSTRACT

Urban growth is a spatial and dynamic process that tends to increase the priority of urban planning for developing cities with a fast growing population and economy. Urban growth and its spatial change patterns are of vital importance for budding towns and cities. Urban growth is one of the most important factors, which affects the requirement of the efficient and sustainable public transportation system for developing city. Unplanned and illegal urban growth is deteriorating the quality of the urban environment for city residents; therefore, adequate information and advanced technologies are required for better implementation of planning policies. The evaluation of historical remote sensing data has exceptional prospects for the geographical analysis of urban growth and for the future planning of a city. The integration of remote sensing and GIS is advantageous for mapping and monitoring urban growth at different temporal scale.

In the beginning of this study, the spatial and temporal urban changes of developing Jaipur city, is mapped over a period of 16 years (1989–2000 and 2000–2005) using Landsat satellite data. This study focuses on the classification of the urban area into different categories on the basis of density, use, and association using a rule-based classification system with remotely sensed data. The Markov model, geographic information systems (GIS), and remotely sensed data were integrated to quantify the urban expansion and the transition in the urban density of different categories. Statistical tests were used to establish the importance of the Markov model for land use change. The results reveal that urban land area in Jaipur is increased by 63% in 1989–2005 with an increase in density indicated by urban land use classes, while an increase in the suburban class implied growth in the urban areas along the city periphery. The transition of land use indicates that urban areas are rapidly expanding due to the conversion of agricultural and barren lands surrounding the cities into the urban areas. The scenario analysis quantified the increase in unplanned and informal urban growth in the future, which may have an impact on existing planning policies for the development of the city.

In the further step urban change dynamics are analyzed by integrating predictive variable those influence and control the urban change. To accomplish the urban change pattern dynamics modeling of Jaipur, an integrated modeling framework has been constructed. This consists of urban change estimation using multi-temporal remote sensing data (1975, 1989, 2000, 2002 and 2006), urban change simulation using a multi-layer perceptron-Markov method, and land suitability evaluation for assessment of change patterns using a multi-criteria evaluation method. Three scenarios are generated to assess the change patterns based on the proposed plan for 2025, using simulated data and landscape metrics. The simulation results using actual classified data of 2002 and 2006 imply higher accuracy in urban area prediction based on landscape metrics. Urban change patterns based on land suitability indicated the change in urban growth from very high suitable land area to high suitable land area during 2002–2006 in comparison with 1989–2000 and 2000–2002, reflecting urban expansion in suburban areas. The scenarios assessment has proved effectiveness in representing and understanding urban change patterns in the light of the policies planned for the development of the city. The analysis of scenarios indicated higher urban growth and increased density in residential, commercial, and industrial areas. Scenario-based analysis further implies that the time gap between proposing and implementing a plan may have a negative impact on urban development and the environment.

In the last step impact of rapid urban growth of Jaipur city are assessed on public transportation. Urban growth and its change patterns can be explained by urban form, and it is an essential aspect for the assessment. Especially in case, when lack of related research information then it is important criteria to study the travel demand of public transportation. In this study GIS based spatial analysis method is used to analyze the characteristics of urban form and its spatial difference. According to the characteristics of the travel demand, coverage area has been delineated using the road/street network based distance approach for public transportation stops. The coverage area is mapped and monitored to find out effectiveness of public transportation plan. To evaluate this demographic data and urban form indicator used in GIS environment. Three different scenarios are generated based on urban form to assess the impact of urban form indicator on public transportation plan. The scenarios, based on urban form indicate that the increase in compactness and land use mix will affect the trips. The public transportation trips are increasing with the change in urban form, and trips from private vehicles are also increasing at the same time. This indicated that in absence of adequate public transportation will lead to

increase in number of private vehicle users. This analysis has been performed for both current situation 2009 and future situation in 2031with proposed plan. The spatial statistical analysis methods have been used to study the influence of urban form on the trips of public transportation. The analysis results suggested that urban from have a definite impact on trips, and within the certain threshold. The statistical analysis implies that significant and positive values of spatial autoregressive coefficients indicated a positive spatial interaction between urban form indicators and trips.

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CHAPTER 1

INTRODUCTION

1.1 Background

Urban growth can be defined as the spread of new development of an urban area to the surrounding land. The urban growth plays an important role in urban ecosystem of the city. Urban growth is a major change taking place globally and responsible for the disorganized use of land resources and energy, and the large-scale intrusion onto agricultural lands. Over 70% of growth currently takes place outside the formal planning process, and 30% of the urban population in developing countries live in slums or illegal and unplanned settlements (UN-habitat, 2006).

In the last decade, more attention has been paid to urban change as the human behavior is affecting the urban ecosystems (Deal and Schunk 2004; Sudhira et al. 2004). Transformation of land caused by urban growth requires considerable attention and prioritization, especially in a developing country like India. In India, population growth coupled with unplanned development has led to unplanned urbanization (such as increase in slum area), which increases the demands made on infrastructure. Unplanned urban growth has been responsible for many problems such as poor quality of life, polluted drinking water, noise and air pollution, improper waste disposal, and traffic congestion. India has been called a country of villages, but its high economic and population growth, especially in the last decade, is converting India to an urban society. It is also estimated by UN, that percentage urban in India was 41% in 2007, that will reach to 51% in 2025 and in 2050 it will be 66% (UN-Habitat, 2006).

Jaipur, one of the rapidly developing cities of India, is also experiencing the same problems. Urban growths coupled with population growth issues have become a big challenge for the local authority as it deprive away the sustainable development of the city. Rapid urban growth of Jaipur city is characterized by the high population growth, haphazard growth, illegal developments and lack of open spaces. Urban growth of city coupled with illegal and haphazard development increasing slum area in the city. Instead of it illegal and unplanned development are also increasing and affecting the implementation of proposed plans.

In the first chapter, the orientation of the dissertation is described. It starts with the background to this topic, particularly the necessity to understand issues related to urban growth and its impact on development plans of Jaipur city. After summarizing the key points, the research motivation is raised to make the necessity of this study more apparent. The objectives and scope of this study are then described. Finally, the structure of the dissertation is provided at the end of this chapter.

1.1.1 Characteristics of Jaipur

Jaipur city is capital and administrative headquarter of the biggest state (Rajasthan) of India. Geographically it is well connected with other metro cities of India (such as Delhi, Mumbai, and Ahmedabad) by both rail and road. Jaipur city is facing high population growth especially in last three decades. Jaipur city population was 1.52 million in 1991 and this reached to 2.23 million in 2001, whereas population of Jaipur city was only 0.3 millions in 1951(Census, India, 2001). The annual average population growth rate from 1971 to 2001 was in the range of 4.1 to 4.7. The population growth rate was the highest in the year 1981 but declined sharply by 0.6 %in 1991 and in grew again by 0.2 % in 2001.

1.1.1.1 Current Urban Growth Issues

Jaipur city is one of the fastest growing mega cities of the India with an annual average growth rate of 5.3% twice that of the nation’s urban growth. With its current growth trend, it is likely to supersede many other cities. Over the last decade the city has experienced a growth in the range of 5-8% per annum (CMPJ, 2008). Urban growth of Jaipur city mapped using satellite data and found the same kind of trend. Urban area of city increased from 3,066.2 hectare in 1975 to 13,859.4 hectare in 2005(source: satellite data mapping).

According to city town planning department (CTP) study for urban growth development in Jaipur city, measured some weaknesses and threats, those are very important for planning and management of urban growth of Jaipur city (CTP, 2008).

Weakness

- Haphazard growth of the city.
- High rate of Unauthorized and illegal developments
- Lack of lung spaces/ open spaces.
- High rate of population growth and urbanization
- Inadequate number of vehicles for public transportation

Threats

- High population and urban growth can lead to create further pressure on the infrastructure sector in the future.
- Infrastructure provision in the slums is inadequate that can lead to very poor living conditions.

1.1.1.2 Planning Issues of Urban Growth

Jaipur city is facing many planning issues related to urban growth as reported in master development of 2011, prepared by Jaipur Development of Authority.

- Unplanned Growth
- Improper land management due to rapid urbanization
- Need of revised development control rules and regulations

- Speculation of land by co-operative societies, led to haphazard and illegal growth
- Illegal conversion of Land (agricultural land into non-agricultural land).
- Increase in slums area and 74% of slums located in environment sensitive areas

Another main important issue found, that urban growth is taking place in wrong places. Here wrong place defined as development of land not on proposed land, according to proposed master plan of Jaipur city. The local authority assessed the development on wrong place with the proposed land for different land use classes with actual urban development of 1991. Actual land use of 1991 is assessed with proposed land for master plan 1991 (Table 1.1) and found that 24% of urban development took place on wrong place. This information is alarming from planning point of view of city. It indicates the certainly there is gap between conceive a plan and implement a plan for Jaipur city.

Table 1.1 Master Plan Proposals 1991 V/S Actual Development 1991

Land use	**Total Development**	**Developed in proposed area**	**Developed in wrong place**	**% of Wrong Development**
Residential	6,427	4,862	1,565	24%
Commercial	384	277	108	28%
Industrial	1,008	715	293	29%
Government	158	116	42	26%
Public and Semi-Public	858	711	149	17%
Recreational	214	197	17	8%
Total	9,049	6,878	2,173	24%

(Source: Jaipur Development Authority-Master Development Plan Report 2011)

1.1.1.3 Urban Growth and Public Transportation System

The rapid pace of urbanization that Jaipur has witnessed will continue in future and as a consequence it is imperative that the transport system must support the Jaipur city and regional development. The existing infrastructures and facilities of transportation in the town will be inadequate to adequately meet the demands of the future growth by the horizon year. Integration of transport facilities with the economic activity areas must be a priority. The public transports that are available for the general public in the city are buses operated by Rajasthan State Road Transport Corporation (RSRTC), mini buses run by private operators, auto–rickshaws, and cycle rickshaws in the form of Intermediate Public Transport and personalized modes such as cars, two-wheelers and cycles. The bus routes mainly cater to the main arterial roads of the city. RSRTC buses do not have a good coverage while the Private buses do not run on time. The inadequate public transportation system is giving rise to private vehicles. In Jaipur city two-wheeler is the dominant vehicle mode as it constitutes 76% of registered vehicles. Car, van and jeep are the second highest (16%) registered vehicle. Bus has the lowest share as it constitutes only 1% of total registered vehicle of Jaipur city (CMPJ, 2008). Trip distribution by travel mode is shown in Table 1.2 of Jaipur of 2008.

Table 1.2 Trip based Travel Mode Data, Jaipur (2008)

Travel Mode	Percentage
Walk	33.90
Bicycle	3.80
Taxi	0.10
Auto	4.30
Two-wheeler	45.40
Car/Van	4.80
Bus	7.60
Cycle Rickshaw	0.10

(Source: Comprehensive Mobility Plan Jaipur, 2008)

1.2 Research Motivation and Methodology

Despite the apparent increase in knowledge of urbanization and understanding of factors responsible for urban growth, man's ability to conserve urban ecosystem is still considered rudimentary and far from being sufficient to arrest rapid urban sprawl. Particularly, in developing countries, the lack of readily available and directly accessible information hampers the urgent establishment of management mechanisms and activities crucial to the management of urban growth. In urban growth studies, there appears to be an imbalance between efforts devoted to either development plans or urban environment. It is very important to control and manage urban growth otherwise it leads to unplanned growth, and it can be in residential, commercial and industrial areas. In addition, it is essential to monitor and assess the proposed plan and policy for urban development with the time, especially for cities in developing countries. Most of the urban growth studies have focused on the physical (e.g. mapping urban growth and its dynamics) and prediction aspects of the connectivity without giving adequate attention to the gap between planning and implementation of plan and assess possible imbalance. This perceived informational gap and imbalance needs to be addressed to improve management efforts of urban ecosystems.

Considering the urban development of Jaipur city, the rapid urban growth and population growth, lead to severe problem on illegal encroachment and unplanned developments. Jaipur is a rapidly developing city with high population and economic growth. In current situation, absence of adequate public transportation system and private vehicle users are increasing with high growth rate for Jaipur city. The present serious problem of public transportation is that it does not have good network coverage in the city.

To overcome these problems, it is necessary to evaluate urban growth and its impact on urban development plans.

1.2.1 Land Use and Urban Change Perspective

For land use and urban change perspective, it is important to understand land use changes for better planning and management of policies. Therefore it is necessary to evaluate past changes in land use and also predict the future prospects of land use changes for Jaipur city. As land use changes provides the important information of conversion of different land use categories so this aspect is very important to study urban change.

Urban change mapping and monitoring is extremely important for development of plans for management of city urban ecosystem. Moreover, recent rapid increase in population and urban area should impose more impact on the planning and management issues of urban development of Jaipur city. Urban studies become more significant for management perspective, with detailed change pattern analysis of urban and also urban density change analysis. Therefore, it is required that an in depth analysis is conducted to understand the urban change pattern of Jaipur city. Urban area/built-up area delineation using remote sensing is very common approach and used by many researchers in their study. (for example, Li et al. 1999; Sudhira et al. 2004; Li et al. 2005; Xiao et al. 2006; Taubenböck et al. 2009; Kasimu et al. 2008; Bhatta et al. 2009;). However, there are very few studies in which urban area or built area is classified into sub-categories for analysis. In most of the research sub-categorization is based on land use such as residential, commercial and industrial, etc. using high resolution satellite data (For example, Bauer and Steinnocher, 2001; Van der Sande et al., 2003; Zha et al., 2003; Zhang and Wang, 2003). Lu and Weng (2005) classified built-up/urban area into five land-use classes (i.e., very-high-, high-, medium-, and low-intensity residential lands, and commercial/industrial/transportation lands) based on population density distribution. The urban growth is not yet studied based on sub-categorization of urban area based on density change in existing research. In this research urban area/built-up category of land use is classified into sub-categories on the basis of urban density, use, and association using a rule-based approach on remote sensing data.

1.2.2 Urban Change Simulation and Prediction Perspective

Urban change simulation and prediction is important from many perspectives, especially for urban planning and management. Artificial Neural Networks (ANNs) are a powerful tool for urban simulation studies, as it use a machine-learning approach to quantify and model complex behavior and patterns, and allow the integration of GIS tools and remote sensing data (Li and Yeh, 2002; Pijanowski et al., 2002). The multi-layer perceptron (MLP) network described by Rumelhart et al. (1986) is one of the most widely used ANNs. Theobald and Hobbs (1998) described two approaches to modeling spatial patterns and future development of urban area: one is a regression model and another is a spatial transition-based model. Pijanowski et al., (2002), Dai et al., (2005) and Aguayo et al. (2007) used Artificial Neural Networks (ANN) with regression for land use change and urban change analysis, whereas Li and Yeh (2002) used the spatial transition-based model with ANN-Cellular Automata for land use simulation. The spatial-transition-based model is rooted in a stochastic Markov-chain technique, requires less data with no restriction for spatial resolution, and is useful for descriptive and predictive modeling (Theobald and Hobbs 1998). Therefore, in this research, the spatial transition-based approach has been implemented for urban change simulation by integrating MLP with the Markov model. In simulation and prediction of urban change based on ANN approach always use predictive variables, which influence the urban change patterns, such as proximity to road, proximity to existing urban area, proximity to lake view etc. However, in this research proposed of master urban development plan of Jaipur city is included in simulation model (MLP–Markov method) to assess the change in urban change pattern of city.

The use of simulated urban data, for interpretation of conceived plan and policies is a real representation of city development prospects. However, this fact is poorly represented in the existing urban change studies. Therefore, it is important to conduct a thorough urban change study based on urban land suitability and also with urban development plans. In this research simulated urban change is assessed with land suitability and also with proposed land use plan of Jaipur city for 2011 and 2025 and revealed the gap between planning and implementation of a plan.

1.2.3 Urban Change Impact on Public Transportation System

Rapid urban change and rise in population influence the urban form and design. Urban form and design affect the access to transit service, such as core city, which usually has a grid street pattern and enhances access to transit service, where as the suburban area, limits access to transit service due to street network and neighborhood design (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008). There are several factors of urban form that influence the access to transit services such as urban density, population density, employment density, land use mix and compactness (Handy, 1996; Cervero and Kockelman, 1997; Hu and Huapu, 2007). Urban change pattern can be quantified by using urban form factors like compactness, land use mix and worker density. These factors are very significant for the assessment of public transportation system. But estimation of these factors is difficult when related data not available especially in developing cities. In this research urban form indicators are created at zone level, ward level and coverage area level for analysis of Jaipur city. The urban form based indicators also created for future to assess the impact on travel demand.

Coverage area of public transportation stops is describes that the proximity of demand (population and employment) to stops or stations on the network to a great extent explains its greater or lesser usage by potential users (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008; Biba et al. 2010). There are different method for estimation of coverage area such as straight line and road network method (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008). Most of the research, coverage area use to estimate population covered in that area. However, in this study urban form indicators are created also at coverage level and the impact of these indicators on travel demand in coverage area are evaluated. This coverage area also created for proposed public transportation plan of Jaipur city to assess the future scenario of city. In this research, urban form indicators are created at outside the coverage area and spatial statistical analysis is performed to assess the impact on travel demand in coverage area.

Spatial analysis using GIS helps us to capture important facets of the realities of spatial processes based on correlation or non-independence of spatial data and implies a focus on location, area, distance and interaction (Miller, 1999; Anderson and Gråsjö, 2005; Anselin, 1989). In this study different scenario has been created based on urban form and coverage area to assess the change in travel demand of Jaipur city at ward level using GIS based spatial analysis method for both current and future situations.

1.2.4 Remote Sensing and GIS Perspective

Remote sensing is a rich source of information for urban change management due to its synoptic and periodic observation capability. Over the years, images of the land use environment including urban change have accumulated, presenting an opportunity to understand change processes that have led to changes recorded by the imagery. Integration of GIS with remote sensing data is advantageous for urban change studies. It provides big scope for modeling urban growth and a platform to integrate models and policy to understand urban growth.

Complementary analysis methods need to be explored to extract other information potentially useful for urban growth management. In this study, remote sensing and GIS are used to generate data from the proposed plan for urban change pattern analysis of Jaipur city.

1.3 Overall Research Purpose and Objectives

The overall purpose of this research is to provide essential and adequate information for understanding urban change in developing city and analyze the impact on proposed plans for development of city. The main objective is to estimate and simulate urban change dynamics for Jaipur city, India by integrating remote sensing and GIS for better implementation of land use and public transport plans. Specific objectives chapter wise are:

Chapter 2

- Examination of spatio-temporal land use and urban density change analysis for assessment of urban growth.

Chapter 3

- Urban simulation to find out urban change dynamics by including variables and plans.

Chapter 4

- Assessment of urban land suitability to evaluate in urban change pattern.
- Evaluation of urban change pattern with different proposed plan scenario to assess the future urban prospects.

Chapter 5

Mapping and monitoring of urban form pattern to assess effectiveness of coverage area of public transportation plans in both current and future scenario. Spatial statistical analysis of urban form pattern to find out impact on the trips of public transportation (Bus).

1.4 Research Methodological Framework

The Figure 1.1 illustrates the general research flow and overall methodological framework utilized in this study focusing on assessing an impact of urban change on urban development plans of the city. Land cover extraction from multi-date satellite images is first conducted. The land use data are analyzed to examine changes over time and space. In the next stage urban cover change is analyzed by further categorized urban class in sub categorized based on density using rule based approach. Urban change is also simulated using multi-layer perceptron-Markov method for Jaipur city. This simulated data is assessed using land suitability and proposed land use plan for city. Urban land suitability is created using multi-criteria evaluation method. The proposed land use plans are analyzed using simulated data with GIS based spatial analysis and landscape metrics. Landscape metric analyzes the fragmentation patterns of urban change for different plan and policy.

GIS used to analyze the current and proposed plan for public transport system. In first step coverage area is delineated using road-network distance method using GIS for public transport stops. The impacts of urban form on public transport are assessed using spatial analysis and spatial statistical analysis. The simulated urban data is also used for generation of urban form parameters for future scenario. GIS is used to monitor the plan by comparing information among different year and assessment to check the performance of the plan as whole and to reveal possible imbalance operation efficiency at different ward level.

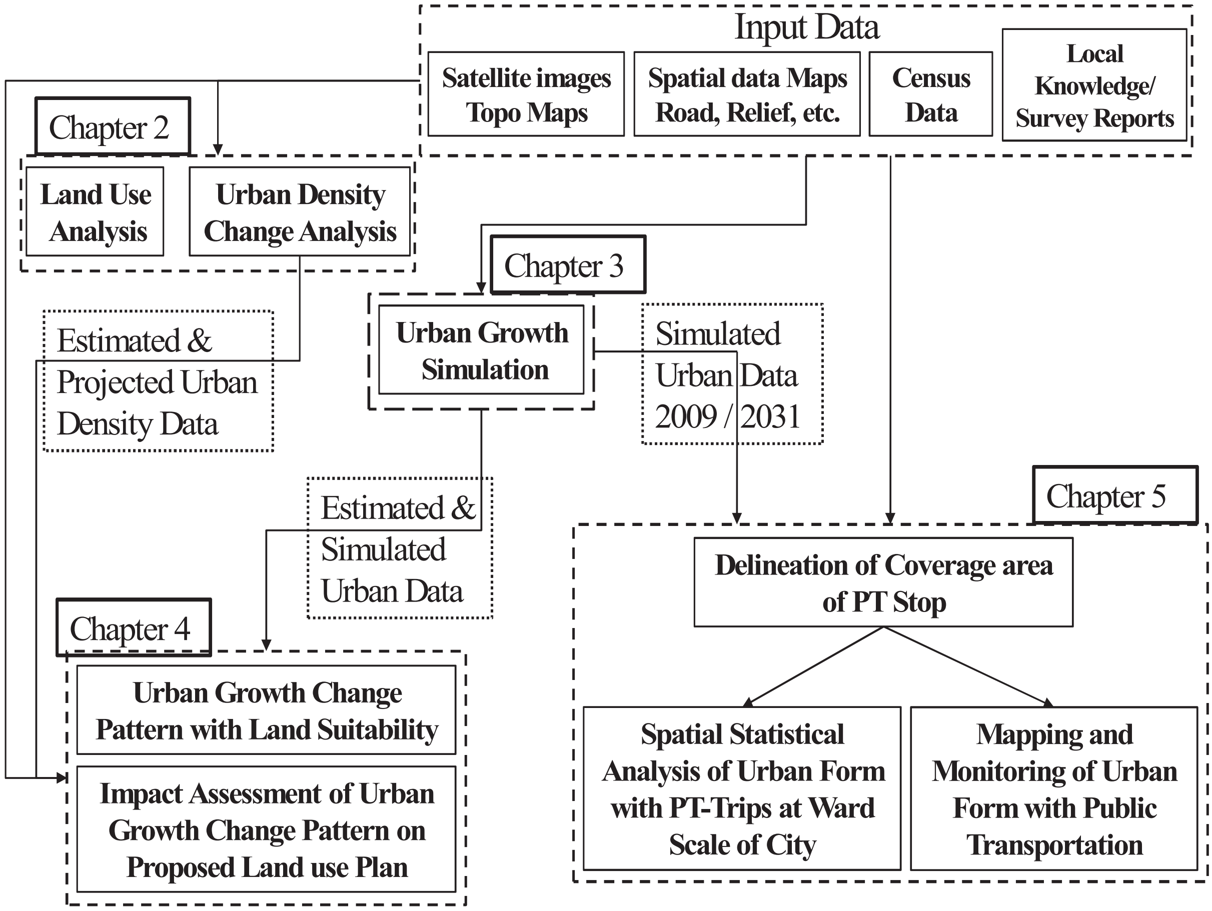

Figure 1.1 Overall Methodology Flow

1.5 Organization and Overview of Chapters

The chapters are organized by presenting first the historical and present condition of the urban change inferred through remote sensing analysis coupled with GIS approach and spatial analysis, and through urban density change analysis. Succeeding chapters then focuses on integrating model for simulation of urban change and computation of impact of urban change on urban development plans and policies.

Chapter 2 assesses long-term land use changes over a 30-year period and explored the future changes in land use. Essentially, this chapter brings urban density change analysis. Urban density is created using by classifying urban in sub categorizes based on density using rule based method. This density change is also predicted using Markov method. This change analysis reveals interaction of different land use type as well as urban change of Jaipur city.

Chapter 3 presents urban simulation. The urban change is simulated using multi layer perceptron–Markov method. This multi-layer perceptron method is allowed to used variables or factors, those not only influence but also control urban growth. The variables used for the analysis are created using GIS, and distance based method. The simulated urban change is verified by using GIS with actual urban data of 2002 and 2005.

Chapter 4 investigates the urban change patterns with land suitability and proposed land use plan for Jaipur city. Land suitability is analyzed using multi–criteria analysis and assessed the urban change pattern based on suitability. The proposed plans and policies are analyzed using spatial analysis and landscape metrics.

Chapter 5 explores the influence of urban growth patterns on a public transport system. To explore this, coverage area is delineated for public transport stop (both current and proposed). Urban form at ward level as well as for zone level for Jaipur city is used for assessment of a public transport system efficiency using spatial analysis and spatial statistical analysis. In the last part of this chapter GIS analysis presents the monitoring efficiency of public transport and reveals possible imbalance at ward level.

The last chapter, Chapter 6, summarizes and integrates the findings of the previous chapters and suggests future research topics.

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CHAPTER 2

SPATIO-TEMPORAL MAPPING AND PREDICTION OF LAND USE

2.1 Introduction

In recent period, study of land use has become very important factor for global change, as land use change has direct impacts on environment. Transformation of land use always requires high attention and priority. From the last decade, more attention has been paid to land use change because human activities are affecting the urban ecosystems as population is growing very rapidly. Urban change is important aspect for land use change studies. Urban change can be defined as the spread of new development of an urban area to the surrounding land. Transformation of land caused by urban change requires considerable attention and prioritization, especially in a developing country like India. Urban change is responsible for the disorganized use of land resources and energy, and the large-scale intrusion onto agricultural lands. In the last decade, more attention has been paid to urban change as the impact of human behavior is affecting the urban ecosystems (Deal and Schunk 2004; Sudhira et al. 2004). Over 70% of growth currently takes place outside the formal planning process, and 30% of the urban population in developing countries live in slums or illegal and unplanned settlements (UN-Habitat, 2006). In India, population growth coupled with unplanned development has led to urbanization, which increases the demands made on infrastructure. Unplanned urban change has been responsible for many problems such as poor quality of life, polluted drinking water, noise and air pollution, improper waste disposal, and traffic congestion. To avoid urban environment degradation and improve living conditions in and around cities, it is necessary to adopt a technological perspective. This will lead to efficient and effective development for the deprived populations.

The conventional surveying and mapping techniques are time consuming and costly. Mapping from remote sensing techniques have very much advantage because it is synoptic, repetitive and multi temporal. Remote sensing technique is cost effective and a versatile tool for mapping and monitoring of natural features and as well as manmade features (Sudhira, et al., 2004; Bhatt et al., 2006; Martinuzzi, et. al., 2007; Jat, et.al., 2008). The availability of spatial data and advanced evaluation techniques offers a significant improvement for analysis, ascertaining, depiction, and modeling of urban dynamics. The combination of spatial data and analytical methods should provide support to city planners, economists, ecologists, and resource managers in their planning and decision making (Herold et al. 2003). Dynamic spatial urban models provide an enhanced capability for evaluating future development and generating planning scenarios; these models also allow the exploration of the impacts of different urban planning and management policy implementations. The technology of remote sensing includes both aerial and satellite-based observations with high resolution and high temporal frequency. This method, along with geographic information systems (GIS), facilitates spatial data analysis and offers a platform to produce various options for modeling and planning process.

Planning is a widely established approach for managing resource allocation and decision making. It includes the use of collective intelligence and knowledge of future requirements and the need to improve the environment in which people live work, and spend their leisure time. Local authority requirements become essential to provide more efficient and specific direction for better planning. Hence, this emphasizes the need for adequate information for planning and developmental activities for urban change. In recent times, research on urban change has become a very important factor for the elucidation of global environmental change as it has direct impacts on the local environment and the economy.

Economic growth and urbanization are linked with each other (Irwin, et al, 2004). Economic growth often guides the conversion into urban land from rural land (Henderson, et al., 2003). Economic growth of any area depends on availability of resources. Economy of India is mainly based on agriculture and in that good mineral resources are enhancing the development. The more industrialization matured, the more opportunities were created for work and investment, and this brought more people to cities as consumers and as workers. Minerals are good source for industrialization and play an important role in the economy. Availability of mineral resources increases the industrial activities. Industrial development activities facilitate urban to grow (Joshi, et al. 2009). Urbanization is the social process whereby cities grow and societies become more urban. Urbanization is significant all over the world and there are many factors which influence the urbanization like population growth, good prospects for livelihood and good availability of facilities (Sudhira, et al. 2004; Martinuzzi, et al. 2007; Jat, et al. 2008). In India 25.73% of the population lives in the urban area and it will increase to 33% in the next fifteen years (Census of India).

In this chapter, in first step we have analyzed and predicted land use changes of Jaipur district (Capital of Rajasthan state, India) by combined use of remote sensing, GIS and Markov model. In second step, an attempt has been made to ascertain the spatiotemporal urban change dynamics using the Markov model on rule-based classified remote sensing data. In this study, urban area is further classified into sub-categories on the basis of density, use, and association using a rule-based approach in remote sensing and this kind of categorization has not been done for any city before. In the last step of the chapter, finds out the impact of economic natural resources on urban change. The main objective of this analysis is to assess the changes in urban area during 30years due to increase in marble mines of Makrana city by applying remote sensing. This information is used to establish a harmonic relationship in mining and urbanization.

2.2 Literature Review

The land use change can be mapped and monitored using satellite data (Joshi and Suthar, 2002; Ayad, 2005; Bothale and Sharma, 2007; Kent and Gullari, 2007; Taubenböck, et al., 2008) systematically and efficiently. Mapping and monitoring of land use includes information on change pattern, dimension and transformation in between the different categories of land. Remote sensing is a good tool for identifying threats generated by land use change to the different environmental and natural resources.

The combination of remote sensing and geographical information system (GIS) is an effective and powerful tool for analyzing the land cover data (Li and Yeh, 2004; Li, et al., 2005). In recent years, remote sensing and GIS has been widely used for studying the spatial and temporal transformation of land cover (Sudhira, et al., 2004; Bhatt et al., 2006; Shlomo, et al., 2007; Huang et al., 2008; Kasimu, et al., 2008).

Remote sensing is a vital tool in mapping as it avoids the necessity of conducting tedious field surveys: it provides data sets for large areas with high resolution and high temporal frequency. Remote sensing using GIS is an effective and powerful combination for analyzing land cover data and displaying digital data for change detection and database development. Urban change can be systematically and efficiently mapped and monitored using satellite data (Li et al. 1999; Sudhira et al. 2004; Li et al. 2005; Xiao et al. 2006; Taubenböck et al. 2008; Kasimu et al. 2008; Bhatta et al. 2009; Zhang et al. 2011). Taubenböck et al. (2008) spatiotemporally analyzed the urban change of 12 Indian cities using remote sensing data. The results indicated that the urban change of some cities was influenced by coastal or hilly orography, and the built-up density clearly showed similar trends for majority of the urban centers of the 12 large Indian urban agglomerations. However, the shape complexity of urban agglomerations like Jaipur showed high complexity at the peripheries, indicating uncontrolled and complex growth. Sudhira et al. (2004) used GIS and remote sensing data to ascertain the urban growth of Udupi city in Karnataka in southern India. The results revealed that the percentage of changes in built-up regions over a period of nearly 30 years was 145.68%, and that the rate of land development in Udupi outstripped the rate of population growth. Bhatta et al. (2009) used remote sensing data from two different time spans, 1975–1990 and 1990–2005, to determine the urban sprawl pattern of Kolkata city, India. They found that different zones have a different level of compactness leading to different patterns of growth; therefore, applying single policy for the entire city will not be equally effective in all areas.

Incorporation of GIS information and knowledge base (expert system) for digital image processing has been recognized as a necessary tool for improving remote sensing image analysis. An expert system technique has been used in collaboration with other data sources for classification or post classification (Treitz 1992; Harris and Ventura 1995). Harris and Ventura (1995) used zoning and housing density data for post classification of the urban area of Beaver Dam, Wisconsin.

To understand the stochastic nature and the stability of the land use, Markov model is very useful. Markov model is frequently used to simulate landscape change (Baker, 1989; Muller and Middleton, 1994), analyze land use types, trends and dimension of changes (Weng, 2002; Huang et al., 2008). Due to advancement in GIS technology and its interconnectivity with remote sensing Markov model has become more popular (Bell, 1974; Weng, 2002; Huang et al., 2008). The Markov model has been used to examine the stochastic nature of land use change and to project the stability of land development for the future. The Markov model is one of the models that allow for the study of land use change (see Baker (1989) for details). The Markov model is frequently used to simulate landscape change and analyze land use types, trends, and dimension of changes (for example, Bell 1974; Muller and Middleton 1994; López et al. 2001; Weng 2002; Li et al. 2005; Coppedge et al. 2007; Huang et al. 2008). The Markov model has gained popularity due to advancements in GIS technology and its interconnectivity with remote sensing. Zhang et al. (2011) used a Markov chain and a cellular automata model to understand the dynamics of Shanghai's urban growth.

2.3 Land Use Change Detection of Jaipur District

2.3.1 Study Area and Data Used

Jaipur district is located approximately between Lat. 27.88 N, Long 74.88 E / Lat 26.42N Long 76.29 E (Degree Decimal). Jaipur, the pink city was founded in 1727 by Maharaja Sawai Jai Singh II at that time total area was approx. 4.80 km sq. Jaipur is the one of the first planned city of India. It has an average elevation of 431.91 meter. The city is situated in the eastern part of Rajasthan. The city is surrounded by Jhalana hills in the east. Banas and Banganga are major rivers passing through the district. The drought is rare, but poor water management and exploitation of groundwater with extensive tube-well systems threatens agriculture in some areas of Jaipur district.

The climate of Jaipur is semi-arid. The annual rain fall is over 50 cm (20 inches) and the rainfall is concentrated in the monsoon months between June and September. Temperatures remain relatively high throughout the year, with the summer months of April to early July having average daily temperatures of around 35^0C. During the monsoon months heavy rains are frequent, and thunderstorms, but flooding is not common. The winter months of November to February are good and pleasant, temperatures varies between 10-15^{0}C during this period little and no humidity. There are however occasional cold waves that lead to temperatures near freezing (JDA, Master plan report, 2009).

Landsat data of March 1975 with spatial resolution of 60 meter, October 1989 and April 2002 with 30 meter spatial resolution have been used for land use map preparation. Losses and gains in area from 1975 to 2002 have been calculated for each category using GIS, and transition matrix has been prepared for land use change. This land use change matrix helps to understand the major changes and future development in land use.

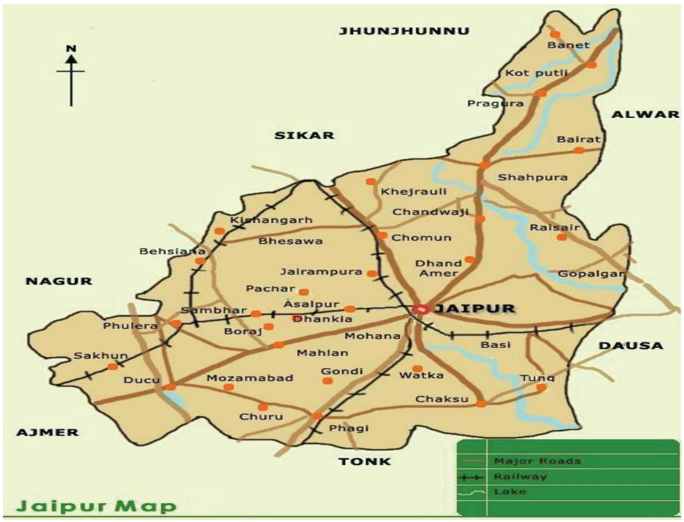

Figure 2.1 District map of Jaipur (Source: www.maps-india.com)

2.3.2 Classification of Satellite Data for Land Use Analysis

Landsat data of March 1975 with spatial resolution of 60 meter, October 1989 and April 2002 with 30 meter spatial resolution have been used for land use map preparation. Losses and gains in area from 1975 to 2002 have been calculated for each category using GIS, and transition matrix has been prepared for land use change. This land use change matrix helps to understand the major changes and future development in land use.

Land use change patterns of the city were mapped using Landsat data. In this study modified classification scheme is adopted for the different categories of land use. These categories are: 1. Built-up, 2. Crop Land, 3.Fallow Land, 4. Forest, 5. Barren Land and 6. Water body. Landsat images are rectified using 1:50k topographic maps and then reprojected to UTM projection system. The satellite image of 1975 was re-sampled using nearest neighbor algorithm to the same resolution as rest of two satellite data. This study is based on detection of changes of surface reflectance of object so for this relative radiometric correction has been done with image regression (Jensen 1996) over all images. Brightness value of pixels of all bands of all the three satellite data were calibrated by using linear regression equation for better interpretation. For classification, first training sites have been defined for crop land, fallow land, forest, barren land and water body. Then these classes have been classified using supervised approach of classification. Manual editing has been used to remove mixing of pixel between different classes and addition of missing pixels in the classified data. Built up area is captured first by visual interpretation using aoi tool of Erdas. For capturing of built up area, ancillary data like village points and Google Earth has been used. Spectral reflectance value of built up surface have been used to identify the built up area and then unsupervised classification procedure applied for built up data classification.

2.3.3 Markov's Model for Land Use Analysis

In this study, it is assumed that the land use data are compatible with the Markov process, the land use changes as a stochastic process, and the different categories of land use are the chain states (Stewart 1994; Weng 2002).

The conditional probability distribution of the process at time n + 1, X_{n+1} depends only upon the value of X_n and not on all the other previous values $X_{n-1}, X_{n-2} \ldots\ldots X_0$.

It can be explained as

$$P\,[X_{n+1} = x_{n+1} |\, X_n = x_n \ldots X_0 = x_0]$$

$$= P\,[Xn + 1 = xn + 1 |\, Xn = xn] \qquad (2\text{-}1)$$

This can also be expressed as

$$P_{ij} = P\,[X_{n+1} = j|\, X_n = i] \tag{2-2}$$

$$i\,j = 0,1,2,\ldots\ldots\ldots$$

Here, P_{ij} is the transition probability of one step and can be analyzed as the conditional probability at time n when the process is in state i and at time n + 1 when the process is in state j.

The two-step transition probability is defined as a generalization of the Chapman-Kolmogorov equation.

$$P_{ij}^{(2)} = P\,[X_{n+2} = j \mid X_n = i]$$

$$= \sum P\,[X_{n+2} = j \mid X_{n+1} = k]\; P\,[X_n = k \mid X_n = i] \tag{2-3}$$

This is equivalent to

$$(P)_{m+n} = (P)_n * (P)_m \tag{2-4}$$

2.3.3.1 Statistical Test of Independence

The hypothesis of statistical independence was tested by comparing the actual values of land use categories with the expected values. Under this hypothesis there are 11 land use categories in this study; so, $(11\text{-}1)^2$ degrees of freedom are used for the computation of Karl Pearson's χ^2,

$$\chi^2 = \sum_i \sum_k (A_{ik} - E_{ik})^2 / E_{ik} \tag{2-5}$$

where

A_{ik} = Actual value of land use data from category i in 1989 to category k in 2005

E_{ik} = Expected value of land use data under the Markov hypothesis.

If the computed value χ^2 is lower than the value at the critical region 0.05 with (degree of freedom – 1)^2, then the data are compatible with the hypothesis of independence. The expected value in Equation (5) is calculated using the Chapman-Kolmogorov equation (Stewart 1994; Weng 2002). The expected value of the transition matrix for the period of 1989–2005 is computed by multiplying the matrix of 1989–2000 with that of 2000–2005. The following equation is used to calculate the expected value in Equation (6):

$$E_{ik} = \sum_{j} (E_{ij})(E_{jk}) / E_{j} \qquad (2\text{-}6)$$

where

E_{ij} = the amount of transition from category i to j during the period 1989–2000

E_{jk} = the amount of transition from category j to k during the period 2000–2005

E_{j} = the amount of hectare cells in category j in 2000.

2.3.3.2 Goodness-of-Fit Test

The chi-square goodness-of-fit has been used to test first order Markovian dependence. This test effectively defines the distribution of the observations. The test is performed by comparing the observed transition probabilities with the expected transition probabilities for the observation. This relationship is shown in Equation (7):

$$\chi_{c}^{2} = \sum_{i} \sum_{k} (O_{ik} - E_{ik})^{2} / E_{ik} \qquad (2\text{-}7)$$

where O_{ik} = Observed transition probability data for 1989–2005

E_{ik} = Expected transition probability for 1989–2005 under the Markov distribution.

The advantage of the Markov process is that it can project future land changes on the basis of the current transition of land, using steady state probabilities. The steady state for the 1989–2000 periods can be used to predict the changes for the different land use categories for 2011, 2022, and so on. Similarly, by following the steady state of 2000–2005, it is possible to predict the changes in land use for 2010, 2015, and so on. This stationary information points out the tendencies of the urban expansion process (Weng 2002).

2.3.4 Results of Land Use Change Analysis at District Level of Jaipur

The graphical representation of land use and land cover is shown in Figure 2.2. From the graph it is clearly visible that there is decrease in barren land and water body and increase in built up and agricultural area (inclusion of fallow land). Land use maps displayed in Figures 2.3, 2.4 and 2.5 were prepared using Landsat data of 1975, 1989 and 2002 respectively. Accuracy of classified data is checked using 400 random samples. The accuracy for 1975, 1989 and 2002 is 89.00%, 95.00, and 93.00% respectively. The overall Kappa indices for 1975, 1989 and 2002 land use data were 0.91, 0.94, and 0.93 respectively.

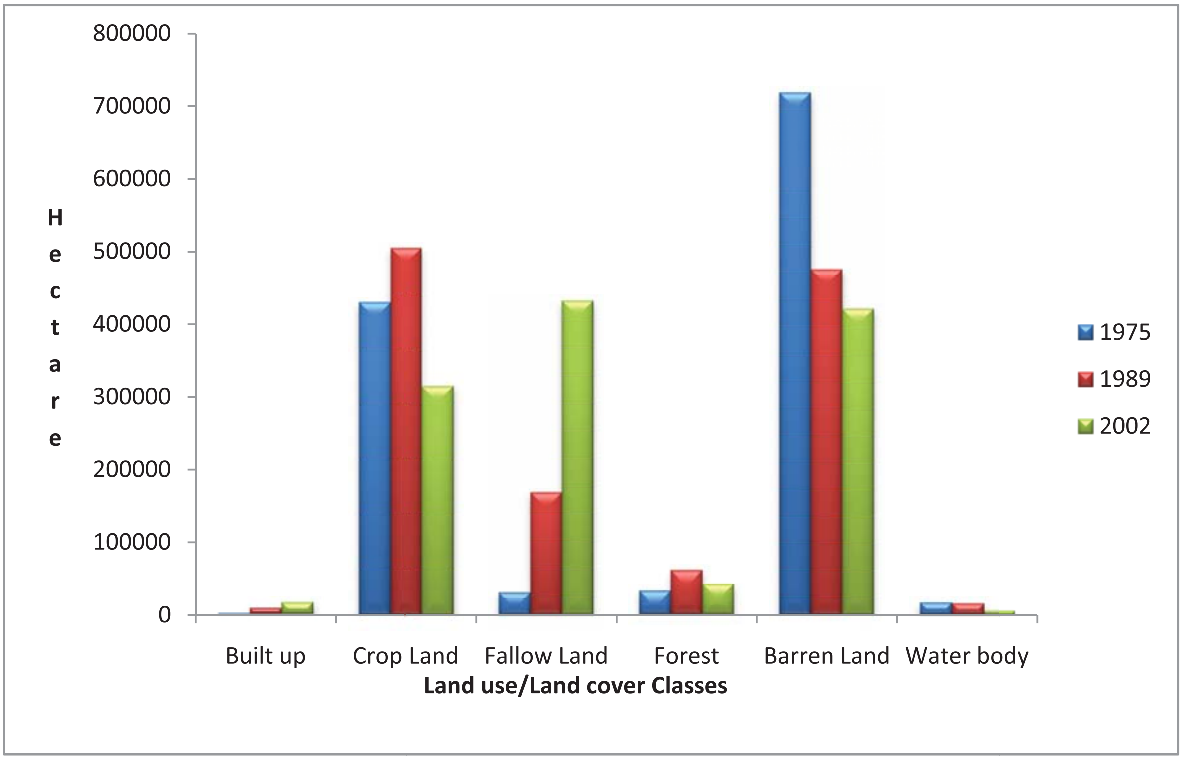

Figure 2.2 Graphical Representation of Land Use Change from 1975-2002

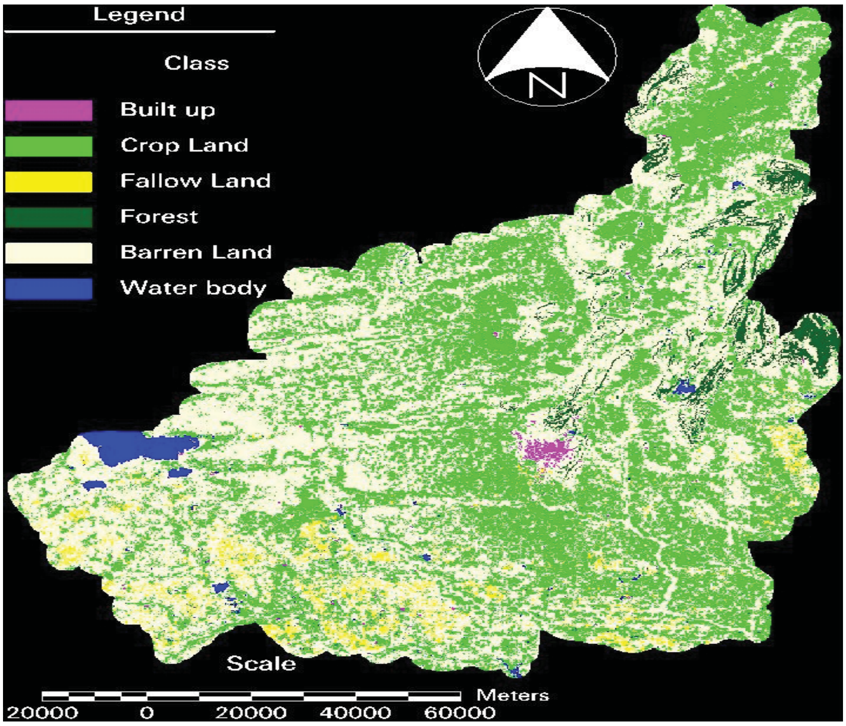

Figure 2.3 Land Use Map of Jaipur District of 1975

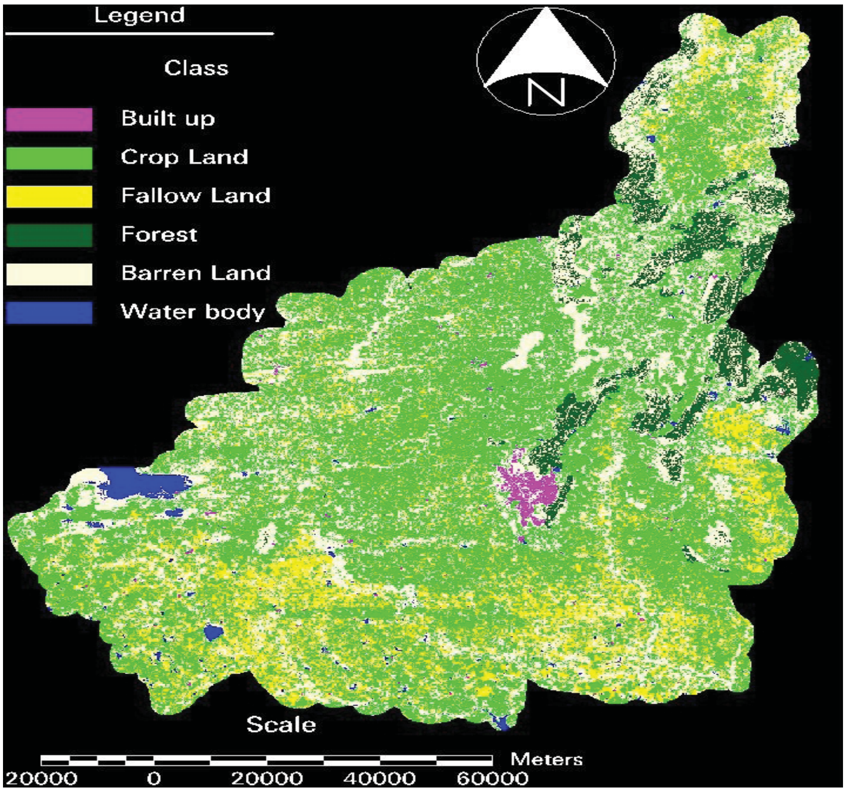

Figure 2.4 Land Use Map of Jaipur District of 1989

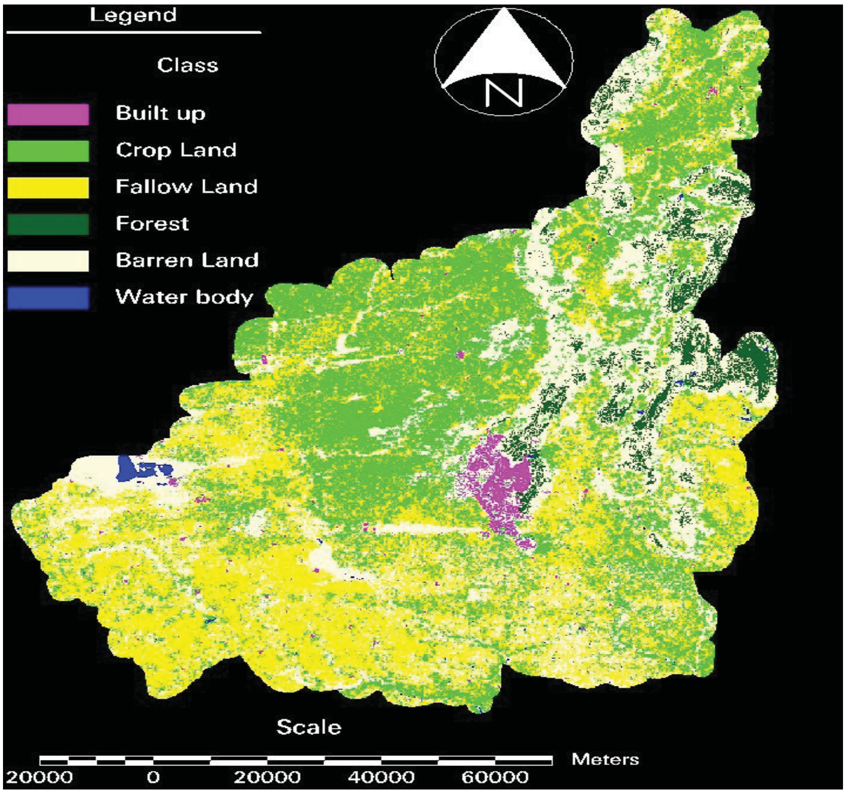

Figure 2.5 Land Use Map of Jaipur District of 2002

Table 2.1 Land Use Transition Matrix from 1975-2002 (Unit- Hectare)

1975	2002						
	Built up	Crop Land	Fallow Land	Forest	Barren Land	Water body	Total
Built up	3296.07	414.18	309.06	45.99	1028.25	7.56	5101.11
Crop Land	5081.40	176463.36	141011.46	2665.44	103748.40	311.40	429281.46
Fallow Land	564.03	1116.72	23484.96	29.97	5988.33	112.23	31296.24
Forest	10.17	171.99	83.61	15009.93	17357.04	63.99	32696.73
Barren Land	8183.52	135931.32	265938.93	24253.74	282469.68	967.68	717744.87
Water body	57.87	1014.48	1558.44	27.27	10235.70	3979.53	16873.29
Total	17193.06	315112.05	432386.46	42032.34	420827.40	5442.39	
Change Rate (%)	237.05	-26.60	1281.59	28.55	-41.37	-67.75	

Table 2.1 contains land use transition matrix from 1975 to 2002. From this Table we can say that there is an enormous change in land use in 27 years. Built up area is increased from 5101.11 ha.

in 1975 to 17193.06 ha. in 2002. Agricultural area with fallow land also increased during 1975 - 2002. Forest is also increased during 1975-2002 from 32696.73 ha. to 42032.34 ha. Barren land is decreased from 717744.9 ha. in 1975 to 420827.4 ha. in 2002. Water bodies are also decreased from 16873.29 ha. in 1975 to 5442.39 ha. in 2002.

The transition probability has been calculated for the period of 1975-2002, 1975-1989, and 1989-2002. In Table 2.2 probability of Transition of land use from 1975-2002 is displayed. The transition probabilities of Table 2.2 are calculated for land use data of Jaipur district. Results indicate that most of the contribution to built up category came from agricultural area and some part also from barren Land. Transition probability in Table 2.2 such as 0.01140, 0.18939, 0.37052 and 0.03379 respectively for built up, crop land, fallow land and forest, and this came from barren land area.

Table 2.2 Transition Probability of Prepared Land Use Data for 1975-2002

1975	2002					
	Built up	Crop Land	Fallow Land	Forest	Barren Land	Water body
Built up	0.646	0.081	0.061	0.009	0.202	0.001
Crop Land	0.012	0.411	0.328	0.006	0.242	0.001
Fallow Land	0.018	0.036	0.750	0.001	0.191	0.004
Forest	0.000	0.005	0.003	0.459	0.531	0.002
Barren Land	0.011	0.189	0.371	0.034	0.394	0.001
Water body	0.003	0.060	0.092	0.002	0.607	0.236

Table 2.3 consist expected transitional probabilities, for calculation of these value Chapman-Kolmogorov equation is used. These expected values are calculated by multiplying the probabilities of 1975-1989 and 1989-2002 matrices. By looking on data from Table 2.3 it is found that from barren land 0.01321, 0.25486, 0.34418 and 0.03697 would go respectively to built-up, crop land, fallow land and forest respectively of land use categories.

Table 2.3 Transition Probability of Land Use Change Matrix from 1975 to 2002 under Markov Hypothesis

1975	2002					
	Built up	Crop Land	Fallow Land	Forest	Barren Land	Water body
Built up	0.409	0.159	0.172	0.012	0.245	0.002
Crop Land	0.011	0.271	0.379	0.017	0.320	0.002
Fallow Land	0.013	0.260	0.416	0.008	0.295	0.006
Forest	0.007	0.133	0.155	0.234	0.469	0.002
Barren Land	0.013	0.255	0.344	0.037	0.349	0.002
Water body	0.008	0.135	0.214	0.014	0.451	0.178

The statistical of independence is used to understand the changes in land use are dependent or not. For this statistical test of independence (χ^2) is performed on land use data. The result of χ^2 is 5.2078 $*10^9$ which is more than the significance 37.7 on the critical region 0.05 with degree of freedom $(6-1)^2$. So the hypothesis of statistical independence is rejected. Therefore the changes in land use are dependent. One can say that the land use change trends are dependent on previous development of land.

The markovian suitability has been checked by using hypothesis of goodness of fit. In this test actual change in land use from 1975 to 2002 has been compared with expected data which were calculated using markov model. This hypothesis is accepted for these data. The calculated value of χ_c^2 is 1.591 and it is very less then significance 11.1 on critical region 0.05 with 5 degree of freedom. With acceptance of the hypothesis one can say that actual transition probability of matrix from 1975-2002 is fitted with expected transition probability prepared using markov method.

Land use change will show stability in future or not this is a critical issue for Land use development policies. For this steady state probability is calculated for three periods 1975-1989, 1989-2002 and 1975-2002. Table 2.4 show values of the steady state for each category of land. By viewing Steady state values one can say that all the values for all the three periods are not similar to each other. It has discrepancy in values. Instead of this discrepancy in values of Table 2.4, few classes have somehow similarity in steady state. The values of 1975-1989 can be distinguish easily and but some categories are bit similar to rest of two steady state. The value of built up during 1975-1989 is very distinct from the 1975-2002 and 1989-2002. If transitions of land continue according to this steady state for these periods, one can predict change of Land use for different categories for future. So from Table 2.4, 4 % will be for built up, 12.3% for crop land, 55.6% fallow land, 1.9% for forest, 25.8% for barren land and 0.3% for water body in the coming future through the steady state of 1975-2002. But the value of 1989-2002 is showing more stable information as compare to rest of two periods.

Table 2.4 Steady State Probabilities

	Built up	Crop Land	Fallow Land	Forest	Barren Land	Water body
1975-2002	0.041	0.123	0.556	0.019	0.258	0.003
1975-1989	0.013	0.4	0.175	0.049	0.346	0.016
1989-2002	0.024	0.24	0.406	0.017	0.312	0.001

In this study Remote Sensing, GIS and Markov method are used for land use change analysis of the Jaipur district for the period 1975-2002. Landsat data is used to explore the change in land use. The remotely sensed classified information is combined with GIS and became a good combination for interpretation. This interpretation provides information of direction, nature, rate and location of new development of land use change. The use of Markov model has shown good capabilities for predicting land use changes (Muller and Middleton, 1994; Li, et al., 2005). This is also useful for the predicting direction and magnitude of change in future.

It is found in this study that built up, crop land, fallow land and forest have increased but barren land and water body have decreased during this period. Built up area is increased by 200% during this period. There is 28% increment in forest area during this period. Water bodies have decreased during 1975-2002 by 67%. By looking at graph in figure 2 it shows that there is increase in crop land and decrease in barren land in 1989 and in 2002 there is decrease in crop land and increase in fallow land.

In the land use conversion most of the land converts from barren land area and followed by crop land. During this period agricultural area is increased by 286959.74 ha. during 1975-2002. But it does not show that there is no impact of built up on agriculture area. From Table 1 it is showing that approx 5081 ha. of agriculture land is used for built up development.

This analysis of land use data can provide indication of direction and magnitude of change for the future and quantitative change in the past (Xiao, et al., 2006; Kasimu, et al., 2008; Weng, 2002). The Jaipur city is increasing in all direction and also especially city is expanding along the highways and major roads. Industrial development is also affecting the expansion of city. Land use change mainly caused by population growth and economic growth (Taubenböck, et al., 2008; Sudhira, et al., 2004; Bhatt et al., 2006).

2.4 Spatio-Temporal Urban Density Change Analysis of Jaipur City

2.4.1 Study Area and Data Used

The Landsat Program is a series of earth-observing satellite missions jointly managed by NASA and the U.S. Geological Survey. Since 1972, Landsat satellites have collected information about the earth from space. The first Landsat satellite was launched in 1972, and the most recent one, Landsat 7, was launched on April 15, 1999. Data from Landsat 7 has eight spectral bands with spatial resolutions ranging from 15 to 60 m; the temporal resolution is 16 days. The Landsat satellite data of 1989, 2000, and 2005 have been used in this study with a spatial resolution of 30 m.

2.4.2 Classification of Satellite Data for Urban Density Change Analysis

Basic image processing methods, such as image extraction, rectification, restoration, and classification, have been used for the analysis of the satellite data. The image data were atmospherically corrected to bring all the images to a common spectral reflectance using the Fast Line-of-Site Atmospheric Analysis of Spectral Hypercube (FLAASH) atmospheric correction module from the ENVI image processing software package. FLAASH incorporates the MODTRAN4 radiative transfer code.

The satellite data were checked thoroughly before classification into land use groups and their respective range of reflectance values. Spectral signature charts were prepared to distinguish and find out the differences in pixel values of different land use classes in different bands. Primary land use classes were defined, such as urban, forest, agricultural, barren land, and water, as shown in Table 2.5. At first, the maximum likelihood algorithm of supervised classification was used for forest, agricultural, barren land, and water classes. For this, the algorithm was trained by training samples to perform the supervised classification. Each training sample consisted of at least 90 image pixels to satisfy the 10n criterion. The parameter n refers to the number of bands used for classification (Congalton 1991; Jat et al. 2008). The land use classes are defined in Table 2.5.

Table 2.5 Land Use Class Definition

	Land Use Class Name	**Definition of Land use Classes**
1	High-Density Urban	Areas within urban perimeters. Inner city, central business district, very little or no vegetation High density of building.
2	Medium-Density Urban	Areas within urban perimeters, moderate open space in-between buildings, less vegetation, middle density of buildings. Small pedestrian zones and streets are visible.
3	Low-Density Urban	Low density of buildings with some vegetation or sparse built up inside city with more of vegetation or open areas in between.
4	Suburban	Urban areas those are scattered, Generally outskirts of any city, small cluster of buildings.
5	Villages	Low density of built-up generally surrounded by farmlands/agricultural fields, far from urban/suburban areas.
6	Industrial	Factory, Warehouse, Garage, Shipyards Mostly situated outside the main city.
7	Forest	All kinds of forested areas, high-density tall trees etc.
8	Agriculture	Cultivated areas, Crop lands, Grass lands etc.
9	Barren Land	This contains open lands mostly barren but also Scattered Vegetation, Trees along the roadside and scrub vegetation.
10	Water	All the water within land mainly lakes, ponds, static water bodies, river are included within this class.
11	Airport	Airstrips and associated terminal buildings.

2.4.3 Rule based Classification System for Urban Density

The Erdas Imagine software was used for the classification of the satellite data. The classification of an urban area started with capturing the area by using the area of interest (AOI) tool of the Erdas module. Different enhancement techniques such as the edge, Gaussian, and linear methods were applied to the satellite data during the capturing of the urban area to identify and differentiate it from the non-urban area land use class. The satellite data were then masked using these captured AOI of the urban area. These masked satellite data were classified using a maximum likelihood classifier of a supervised method by creating training samples (Jensen 1996; Stuckens et al. 2000). These classified outputs of urban areas were thoroughly checked by overlaying on satellite data. Wrongly classified and missing pixels of urban areas were updated using the unsupervised K-means clustering classification method.

This urban layer was further categorized into different land use classes such as high-density urban, medium-density urban, low-density urban, suburban, and industrial. A visual interpretation was used for this sub categorization of urban areas. Primary to higher order image elements were implemented for visual interpretation, such as tone, shape, texture, pattern, site, and association; ancillary data such as road network data were also used. The density of the urban pixels in the classified output and in the original satellite data, and their mixing with other land use classes between the urban areas, such as barren land pixels, were used for sub categorization of urban into high-density urban areas, etc. The industrial class is differentiated from the residential one by using linear enhancement, its association, and Google Earth as references. For differentiating between the urban density of pixel convolution filtering and texture analysis, we used the original satellite data with a kernel size of 3 × 3. For this, a different enhancement filter such as edge detection and edge enhancements were used on the masked urban area of the satellite data for the creation of the urban sub class.

A rule-based expert system was used for the post classification update. This system was applied to the output of land use cover for each year. The rule-based expert classification system was created using Erdas Imagine image processing software. The purpose of implementing this expert system was to evaluate the sub categorization of the urban class, to improve the quality of urban classification, and to reduce errors in classification. The rule-based system was created on the basis of the continuity of urban pixels and its intermingling with non-urban pixels such as agricultural land and barren land.

The procedure of using the rule-based expert system for classification of remote sensing images incorporates GIS data, training data, hypothesis creation, and the generation of rules. The results of this procedure create the rule base, which is used in the rule base classifier module of Erdas to perform the final image classification.

In the first step, the classified data was prepared using satellite images by generating a classification scheme and integrating it with GIS for ancillary data preparation and the creation of attributes. In the next step, a knowledge engineer was used for hypothesis creation, variable input, and production of the rule base. The rule-based classification was determined by creating a hypothetical framework for the pixels. A typical hypothesis would stipulate that a given pixel is surrounded by the same class or other classes and that the other class is an urban or non-urban class. This hypothesis is considered true only if a number of conditional statements are true. For example, if any pixel initially classified as high-density urban is surrounded by only high-density urban class pixels, and is located within a 3 km radius from the central business district, and the pixel has a smooth to fine texture value of less than 10, then the pixel is classified as high-density urban. The same approach is used to reclassify pixels to improve the classification.

A production of the rule can be defined as follows:

$$C_1\ldots\ldots, C_n \quad \rightarrow \quad A_{1\ldots\ldots}, A_n \qquad (2\text{-}8)$$

Equation (8) indicates that if conditions C_1 …, C_n are true, then perform actions A_1 …., A_n. All the rules were created in accordance with this concept. All the rules are mutually exclusive and comprehensive. To avoid duplicity and conflicts, the rules are ordered according to the class of land use data. To assess the quality of the rules, error rates are predicted by applying the rules to a test data set and after evaluation, using them in a rule base classifier.

2.4.4 Results of Urban Density Change Analysis of Jaipur City

2.4.4.1 Urban Change Analysis

Land use maps, shown in Figures 2.6, 2.7, and 2.8 were prepared using Landsat data. The accuracy of these classified maps was checked using the Erdas accuracy tool. The accuracy for 1989, 2000, and 2005 are 92%, 90%, and 89%, respectively, and the overall kappa indices are 0.91, 0.89, and 0.88, respectively.

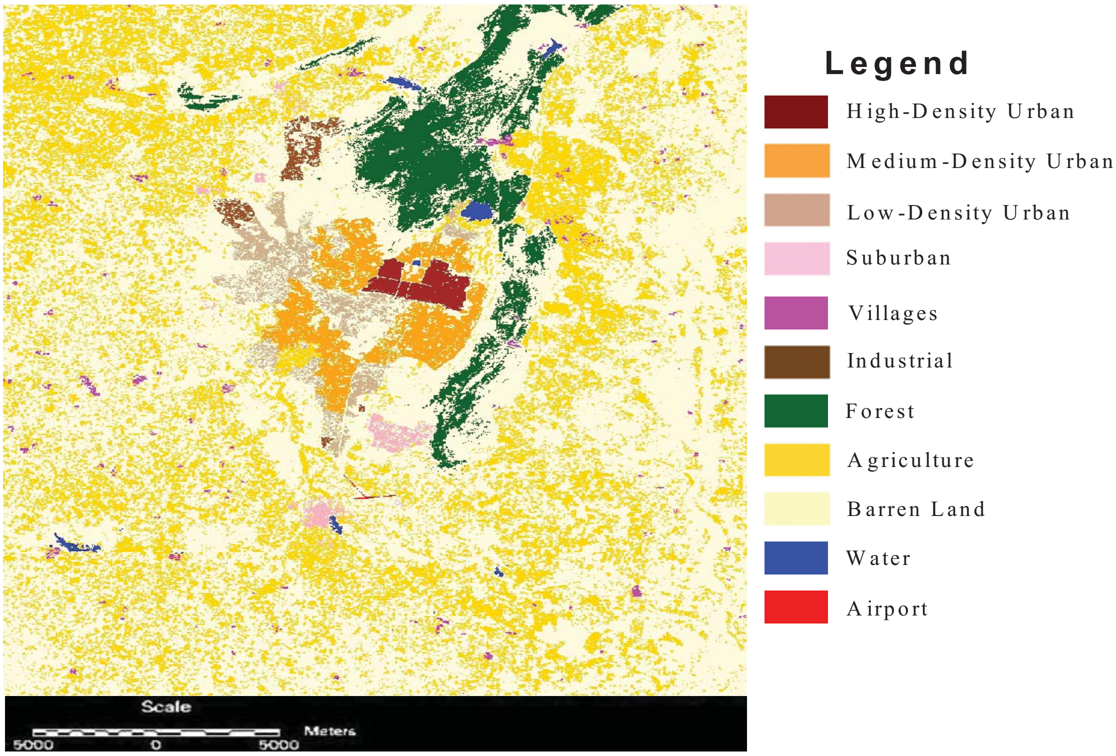

Figure 2.6 Land Use Map of Jaipur City 1989

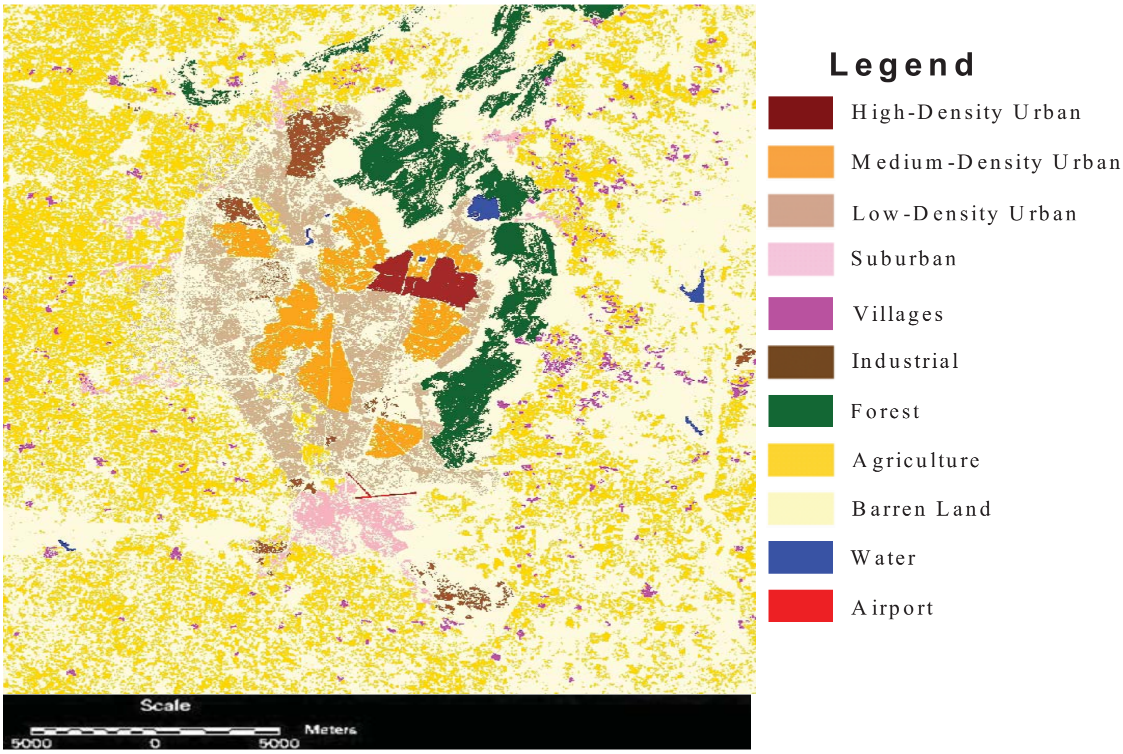

Figure 2.7 Land Use Map of Jaipur City 2000

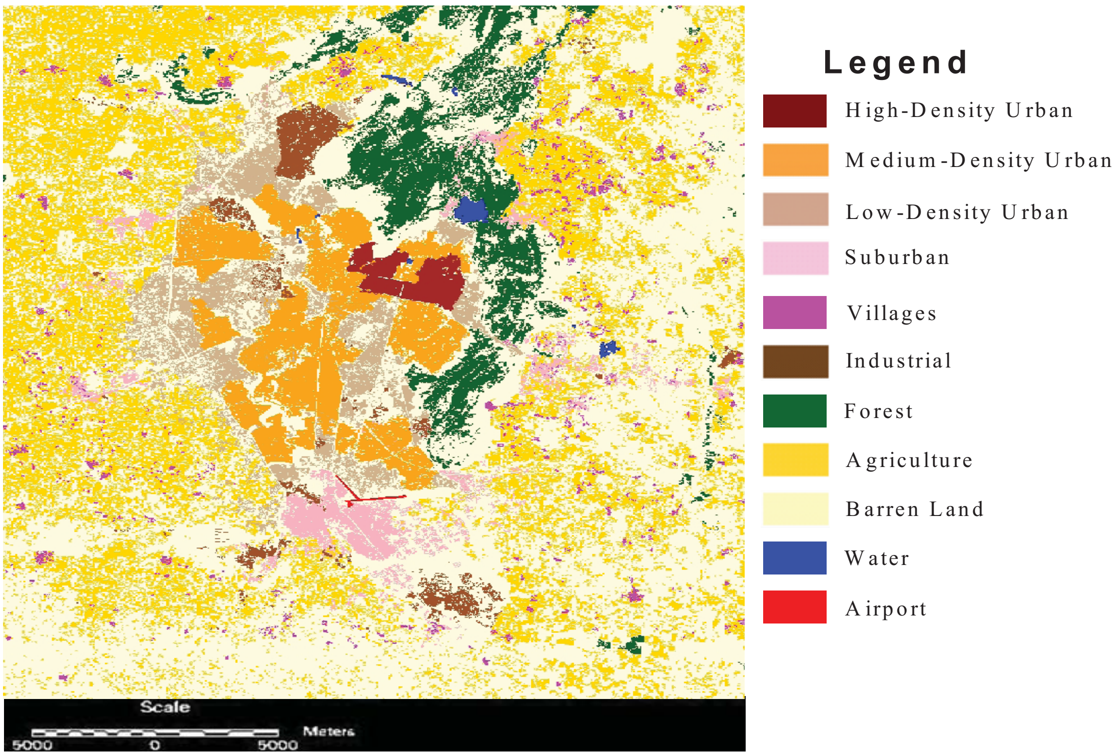

Figure 2.8 Land Use Map of Jaipur City 2005

There is a huge change in land use during this period, as shown in the graphical representation of the data in Figure 2.9. This graph implies that all the classes of land use increase during this period, occupying barren land and water. The reduction in water area is very critical for this area. All the urban categories increased continuously during this period, with the urban land area increased by 11,276 hectare. During the same time, the barren land area decreased by 13,700 hectare.

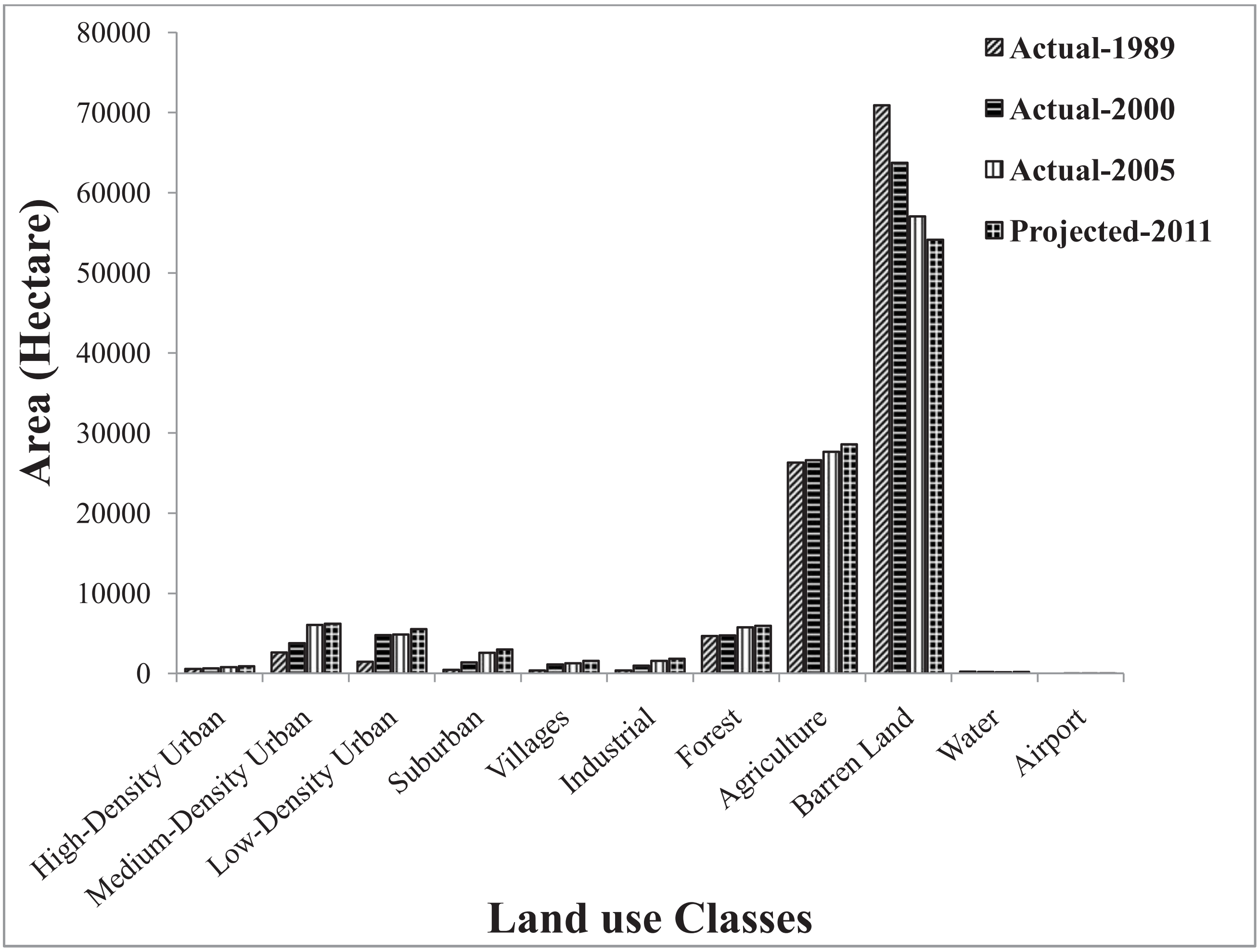

Figure 2.9 Change in different Land Use Classes from 1989-2011

The land use transition during the 1989–2005 periods is displayed in Table 2.6. Barren land was the highest contributor to urban change, and it decreased by 19.4% (70,771.12 to 57,068.5) during this period in the study area. The water area is decreased by 27.4% (253.53 to 184.1). In contrast, all the other classes, particularly the urban, showed high increases. The transition of barren land into forest land was also significant, and this forest land lies in the reserved forest area. The total mapped urban land area, which includes all four urban categories, increased by 9,215.3 (64%) hectare from 1989 to 2005, and the barren land area contributed 87% to this urban expansion. During the study period (1989–2005), the urban land area increased from 5.5% to 16% of the total land in the study area and at the same time the population for this urban area increased by 45%. Among the urban categories, the increases in land area were 41% for the high-density urban land area, 130% for the medium-density urban area, 230% for the low-density urban area, 460% for the suburban land area, and 284% for the industrial land area. The increase in high-density urban area and medium-density urban area indicates an increase in the density of the urban area.

Table 2.6 Land Use Transition Matrix form 1989-2005 (Unit- Hectare)

1989	2005											
	High-Density Urban	Medium-Density Urban	Low-Density Urban	Sub urban	Villages	Industrial	Forest	Agriculture	Barren Land	Water	Airport	Total
High-Density Urban	556.2	9.54	6.57	0	0	0	0	0	9.54	0	0	581.85
Medium-Density Urban	169.65	2303.01	103.32	0	0	12.78	0	0	53.46	0	0	2642.22
Low-Density Urban	0.81	487.8	852.84	14.67	0	41.85	0	0	81.72	0	0	1479.69
Suburban	0	151.74	45.99	216.13	0	16.65	0.72	3.96	27.68	0	0	462.87
Villages	0	1.35	14.94	55.08	268.73	1.62	0.99	15.63	24.52	0	0	382.86
Industrial	0	7.74	13.86	0	0	378.68	0	0	8.23	0	0	408.51
Forest	0	2.25	4.32	27.81	6.3	4.77	3150.72	108.27	1393.47	6.12	0	4704.03
Agriculture	0.09	271.98	648.72	595.53	351.09	249.84	285.84	11171.55	12716.37	2.13	6.21	26299.35
Barren Land	93.06	2847.78	3193.29	1674.9	653.94	866.07	2328.93	16378.38	42653.88	58.32	22.5	70771.05
Water	0	1.98	0	8.91	0.18	0.18	7.38	17.73	99.63	117.54	0	253.53
Airport	0	0	0	0	0	0	0	0	0	0	14.04	14.04
Total	819.81	6085.17	4883.85	2593.03	1280.24	1572.44	5774.58	27695.52	57068.50	184.11	42.75	
Change Rate %	40.89	130.31	230.06	460.21	234.38	284.92	22.75	5.31	-19.36	-27.38	204.48	

2.4.4.2 Urban Expansion

Remotely sensed data combined with GIS for interpretation turned out to be an advantage for land use change analysis, so Landsat data were used in this study to determine the change in the urban area during 1989–2005. This analysis provides the direction, magnitude, and trend of land use and also the future prospects for urban development. The integration of remotely sensed data with the Markov model is beneficial for determining the tendency of land use and projecting land use change.

The urban area of the city expanded from 5,958.3 hectare in 1989 to 12,811.5 hectare in 2000 at an average of 623 hectare/year, whereas the total urban area increased from 12,811.9 in 2000 to 17,234.5 in 2005, with an annual growth of 884.6 hectare/year. The urban expansion from 1989 to 2005 was 704.8 hectare/year with an average annual growth rate of 11.8%. The urban area increased by 11,276 hectare from 1989 to 2005. The high-density urban area increased by 238 hectare, and the medium-density urban area increased by 3,442.9 hectare. The growth in the low-density urban area and the suburban area was 3,404.2 and 2,130.2 hectare, respectively, while the industrial land area increased by 1,163.9 hectare increased during the study period.

Most of the new high-density urban area was converted from medium-density urban areas, and most of the new medium-density urban area came from barren land and also from low-density urban areas. Of the low-density urban growth, 3,193.3 hectare came from barren land and some part from agricultural and suburban land. Most of the suburban change was on the outskirts of the city and near the highways and industrial areas. Most of the industrial development was in the government planned areas for industrial growth, all on the outskirts of the city. The transition of land during this period is very well understood, especially for the different urban categories, as this transition between urban categories shows a trend of urban expansion and also an increase in the density of the urban area. Implementation of the Markov model for further findings in the field of urban transitions is constantly providing more information on urban change as this change depends on the past land development plan of the city.

The urban density also shows an increasing trend during the study period when interpreted using Table 2.6. This is indicated by the increase in high-density urban and medium-density urban areas. During 1989-2005, 21% of medium-density urban land was converted to high-density urban land, while 9% of the low-density urban area was converted to medium-density urban land. The overall high- and medium-density urban area increased by 40% and 130% in 1989 and 2005, respectively, indicating an increase in urban density. The transitions among the different urban classes indicate the changes in the level of density in the urban area. Barren land is the highest contributing land use class for the density increase of the urban area.

In this urban expansion of the city, most of the land area came from barren land. Agricultural land areas were also encroached on in favor of urban expansion. The conversion of non-urban land into urban land is shown in Table 2.6, which indicates that more than 2,100 hectares of agricultural land is converted into urban land during this period. Agricultural land contributed 17.4% of the total urban expansion during 1989–2005. For the expansion of these urban categories, 82% of the total urban area came from barren land. The conversion from forest land to urban land is negligible because most of the forest area in the study area comprises reserved land.

The urban expansion of the city is also measured along the highways and major roads. This buffer of 1 km along the highways and major roads was created to determine the changes in the urban area in 1989, 2000, and 2005 (shown in Table 2.7). The impact of roads on the urban expansion was greatest in the low-density urban and suburban areas of the city. The low-density urban area increased from 22% to 38% during this period, whereas the suburban land area increased from 4.5% to 18%.

Table 2.7 Change in Urban Classes along Highways and Major Roads of Jaipur City

Urban Category	**% Change 1989**	**% Change 2000**	**% Change 2005**
High-Density Urban	0.005	0.010	0.053
Medium-Density Urban	21.253	23.564	28.879
Low-Density Urban	22.756	37.154	38.386
Suburban	4.547	15.675	18.904
Industrial	4.980	7.165	8.165

2.4.4.3 Markov Chain for Transition Probability and Stability of Urban Expansion

The transition probabilities were calculated for the prepared land use data of 1989–2000, 2000–2005 and 1989–2005, and transition probability of 1989-2005 as shown in Table 2.8. The calculation of these transition probabilities is based on the actual value of change in land use during the study period. The transition probability from barren land to low-density urban land is highest, followed by the transition to medium-density urban land and then to suburban land. It shows that in 1989, the lands converted from barren land to urban land were distributed mostly on the outskirts of the old city. This was the result of a significant increase in population during this period and also by the industrial growth in the outer area of the city. Urban land areas converted from crop land have maximum transition probabilities for low-density urban and suburban land areas. This again shows growth on the outskirts of the city caused by urban expansion. The transition from high-density urban area to low-density urban area is also found during 1989–2005, as shown in Table 2.8. This reverse transition implies that there is a conversion of high-density urban areas into low-density urban areas, such as the 16 hectare area converted from high-density urban land to medium-density and low-density urban land; however, this area comprises less than 5% of the total area of high-density urban land. The same kind of trend is observed in the conversion from medium-density to low-density urban and suburban land during 1989–2005. This 3.8% hectare area was converted from medium to low-density urban land. Instead of this urban land is also converted to barren land during this period such as 53.46 hectare from medium-density urban and 81.7 hectare from low-density urban to barren land. In general, this kind of conversion is possible at great extent in a developing city due to illegal construction and encroachment of land. Although this conversion area is small compared to the total area of that category and it is also important to pay attention to such kind of reverse conversion of urban areas. This reverse transition also may be due to limitation of satellite resolution and also in classification of satellite data (Landsat) with 100% accuracy. It can be improved by using high resolution satellite data of 1-2 meter spatial resolution and also with field verifications.

Table 2.8 Transition Probability of Actual Land Use Data for 1989-2005

1989	2005										
	High-Density Urban	Medium-Density Urban	Low-Density Urban	Suburban	Villages	Industrial	Forest	Agriculture	Barren Land	Water	Airport
High-Density Urban	0.9559	0.0164	0.0113	0.0000	0.0000	0.0000	0.0000	0.0000	0.0164	0.0000	0.0000
Medium-Density Urban	0.0642	0.8716	0.0391	0.0000	0.0000	0.0048	0.0000	0.0000	0.0202	0.0000	0.0000
Low-Density Urban	0.0005	0.3297	0.5764	0.0099	0.0000	0.0283	0.0000	0.0000	0.0552	0.0000	0.0000
Suburban	0.0000	0.3278	0.0994	0.4669	0.0000	0.0360	0.0016	0.0086	0.0598	0.0000	0.0000
Villages	0.0000	0.0035	0.0390	0.1439	0.7019	0.0042	0.0026	0.0408	0.0640	0.0000	0.0000
Industrial	0.0000	0.0189	0.0339	0.0000	0.0000	0.9270	0.0000	0.0000	0.0201	0.0000	0.0000
Forest	0.0000	0.0005	0.0009	0.0059	0.0013	0.0010	0.6698	0.0230	0.2962	0.0013	0.0000
Agriculture	0.0000	0.0103	0.0247	0.0226	0.0133	0.0095	0.0109	0.4248	0.4835	0.0001	0.0002
Barren Land	0.0013	0.0402	0.0451	0.0237	0.0092	0.0122	0.0329	0.2314	0.6027	0.0008	0.0003
Water	0.0000	0.0078	0.0000	0.0351	0.0007	0.0007	0.0291	0.0699	0.3930	0.4636	0.0000
Airport	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0077	0.0036	0.0000	0.9887

Table 2.9 shows the expected transition probabilities during 1989–2005 prepared under the Markov hypothesis. These transition probabilities (Table 2.9) were calculated using the Chapman Kolmogorov equation by multiplying the transition probabilities of 1989–2000 and 2000–2005. From Table 2.9, it is found that low-density urban areas have maximum transition probabilities from barren land, followed by medium-density urban and suburban land. The transition probabilities of Table 2.9, from barren land to the different urban categories are very

similar to the value of the transition probabilities from barren land to the different urban categories of Table 2.9. If this transition follows the Markov process, then the transition probabilities from barren land to low-density and medium-density urban land will be 0.0451 and 0.0402 respectively.

Table 2.9 Expected Transition Probability of Land Use from 1989 to 2005 under Markov Hypothesis

1989	2005										
	High-Density Urban	Medium-Density Urban	Low-Density Urban	Suburban	Villages	Industrial	Forest	Agriculture	Barren Land	Water	Airport
High-Density Urban	0.9704	0.0101	0.0178	0.0000	0.0000	0.0000	0.0000	0.0010	0.0007	0.0000	0.0000
Medium-Density Urban	0.0160	0.8903	0.0230	0.0030	0.0010	0.0040	0.0030	0.0096	0.0501	0.0000	0.0000
Low-Density Urban	0.0100	0.0666	0.6934	0.0110	0.0010	0.0130	0.0050	0.0330	0.1650	0.0020	0.0000
Suburban	0.0156	0.0080	0.0880	0.6280	0.0010	0.0540	0.0050	0.0525	0.1470	0.0000	0.0010
Villages	0.0000	0.0001	0.0031	0.1050	0.4784	0.0100	0.0100	0.1640	0.2294	0.0000	0.0000
Industrial	0.0000	0.0002	0.0330	0.0090	0.0020	0.8128	0.0020	0.0170	0.1240	0.0000	0.0000
Forest	0.0000	0.0060	0.0110	0.0070	0.0030	0.0030	0.4910	0.0860	0.3920	0.0010	0.0000
Agriculture	0.0000	0.0170	0.0270	0.0220	0.0120	0.0100	0.0240	0.3260	0.5610	0.0010	0.0000
Barren Land	0.0020	0.0380	0.0446	0.0240	0.0110	0.0130	0.0400	0.2614	0.5640	0.0020	0.0000
Water	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0266	0.1220	0.5290	0.3224	0.0000
Airport	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0082	0.0600	0.0000	0.9318

The hypothesis of statistical independence was checked for transition of land use, indicating χ^2 is $4.6356*10^7$, which is more than the significant 124.3 for a critical region 0.05 with $(11-1)^2$ degrees of freedom. Therefore, the hypothesis is rejected for these data. Based on this, changes in land use are said to be dependent on a previous landscape development plan.

The goodness-of-fit test used to find the suitability of the Markov process for the land use change and test shows significant results. These results suggest that the data follow a Markovian process. The value of χ_c^2 is calculated by examining the observed transition probability and expected transition probability. This hypothesis is accepted for this data because the calculated value of χ_c^2 is 1.40, which is much less than the significant 18.3 for the critical region for 0.05 with 10 degrees of freedom.

This urban density change becomes stable or not is more important for planning purpose view of the Jaipur city. To find out, the stability of an urban change process, steady state probabilities have been computed and compared of three different periods (Table 2.10). The steady state can be defined as a stable condition that does not change over time or in which change in one direction is continually balanced by change in another. The Table 2.10 shows probabilities of different land use categories for 1989-2000, 2000-2005 and 1989-2005. These steady state probabilities do not show any similarity in probabilities for the land use categories and indicates the difference in the transition processes of different periods. These distinctly different values of probabilities imply that this urban density change process is not a stationary process. However, if someone assumes that three transition probability area to continue in a stationary manner, in that situation urban density change distribution can be projected by using steady state probabilities described in Table 2.10 for distant future.

Table 2.10 Steady State Probabilities

	High-Density Urban	Medium-Density Urban	Low-Density Urban	Suburban	Villages	Industrial	Forest	Agriculture	Barren Land	Water	Airport
1989-2005	0.403	0.275	0.058	0.009	0.006	0.071	0.013	0.045	0.108	0.002	0.006
1989-2000	0.157	0.375	0.073	0.009	0.009	0.033	0.016	0.089	0.232	0.001	0.005
2000-2005	0.215	0.323	0.032	0.038	0.006	0.048	0.028	0.094	0.201	0.002	0.016

2.4.4.4 Implications of Urban Change Modeling

Urban change estimation and projection have a variety of uses in planning, implementing, and managing policies. This growth information is helpful for planners in decision making and creating measures to control unplanned growth, especially in developing countries like India where illegal settlements are becoming the identity of every mega city. Once an unplanned settlement is established, it is very difficult for the developing country's local authorities to remove it. These unplanned developments also affect the residents who live in the settlements as well those who live nearby. These settlements are a huge threat to the environment and pose a big challenge for the government to provide all the basic amenities to the residents. To overcome and control the problem of unplanned growth, it is very important to assess past growth, project future growth, and generate future scenarios for different planning situations.

The urban change for Jaipur city was projected for 2011 using the Markov model and actual land use data of 1989 and 2005 to ascertain the growth prospects based on the master development plan of 2011. The master development plan for 2011 was downloaded from the website of the Jaipur Development Authority. The projected urban change of 2011 is very significant to assess the policy and master plan of the city.

The first case addressed in the study is the land proposed for different land uses in the 2011 master plan. As a report of the master plan pointed out, in the 1991 master plan 1,805 hectares of land were proposed for industrial use but actually only 1,300 hectares had been used for industrial development. Out of these 1,300 hectares of industrial development, 25% was in unplanned areas. In the master plan of 2011, 1,862 hectares of land are proposed for industrial development. This master plan information is evaluated with the projected urban data of 2011. The projected data of 2011 prepared using the Markov model shows 2,000 hectares of industrial land, which is 50% more than the area shown in the 2005 land use data based on satellite observations. With this growth rate, if the unplanned industrial development grew at the same rate as included with the same share as in the 1991 plan proposed by the local authority, then the unplanned industrial development will be 529 hectares in 2011. This analysis shows the need to control this unplanned growth as it may increase more than 25% in 2011. This information can be assessed on a higher scale of measurement such as an individual block of an industrial area and also used to ascertain the unplanned settlement growth in residential areas. This projected data is equally important for creating measures to control the unplanned development of industrial as well as residential areas and the encroachment on agricultural land and helpful to efficiently implement the land development policies.

Another case addressed in this research is the policy of the master plan of 2011. This policy explains the development measures that have been taken for land along highways up to 500 m on both sides, permitting only uses which are not harmful to the environment and do not affect the service level of these routes. Therefore, urban change has been demarcated along the highways in the periphery of the city by creating a buffer zone of 500 meters using GIS, actual, and projected land use data. The urban change in the sub categories was estimated in the 500 m buffer zone area along both sides of the highways using satellite based on actual data from 2000 and 2005 and the projected land use data of 2011 (shown in Table 2.11). Table 2.11 indicates the huge growth in urban land along the highways as well as an increase in density from 2000 to 2011. Medium-density urban areas did not exist in 2000, whereas 78 hectares were developed by 2005 and this is projected to reach 463.4 hectares in 2011. The rise in the medium-density area implies an increase in density of the urban area along the highways on the city periphery. Low-density urban land has also increased from 479.5 hectares in 2000 to 869.7 hectares in 2011, which shows an enormous increase in urban area (81%) along the highways. The suburban areas increased by 275% from 2000 to 2011, and industrial areas also increased by 305% during 2000–2011. This huge increase in urban area requires the attention of planners and decision makers for the reassessment of the policy adopted for highways. This is also important from an environmental perspective, considering the huge increase of industrial areas along the highways. It is very important to verify these policies with the actual situation in order to control unplanned growth and development.

Table 2.11 Urban Change in 500m Area along Both Sides of Highway on City Periphery

(Unit- Hectare)

Year	Medium-Density Urban(% Increase From 2000)	Low-Density Urban (% Increase From 2000)	Suburban (% Increase From 2000)	Industrial (% Increase From 2000)
2000	0	479.5	571.7	203.9
2005	78.0 (78%)	604.2 (26%)	889.4 (55%)	237.7 (17%)
2011	463.4(463%)	869.7 (81%)	2145.6 (275%)	827.6 (305%)

2.5 Influence of Natural Resources (Mining Area) on Urban Change of Emerging Town

2.5.1 Study Area and Data Used

Makrana is located at 27°03′N/74°43′E-27.05°N/74.72°E. Makrana is a town in the Nagaur district of Rajasthan state of India. Makrana is a small town, but it has plenty of marble outcrops. Makrana is famous for the white marble mined from the mines around it. It has an average elevation of 408 meters (1338 feet). It is said that the Taj Mahal was built from Makrana marble. Most of the residents in this town work as marble miners. The marble mines are located in the vicinity of the Makrana city. So these are directly affecting the human environment of the city. Therefore it is an interesting location for assess the influence of mines on urban sprawl.

This area has vast marble deposits which are providing opportunities to lots of people to grow. So it is an area which has plenty of prospects to study the impact of mining on land use change with special attention on urban sprawl.

Marble mines of Makrana city which is part of Nagaur district of Rajasthan. These mines have one of the world best deposits of marbles. Makrana marble is a metamorphic rock having 90 to 98 percent CaCo3. Makrana has various mining ranges, popularly known as Doongri, devi, Ulodi, Saabwali, Gulabi, etc. The Makrana marble has made a perceptible dent in marble industry because of its block ability, whiteness, high CaO 50-56 %, low MgO 0.90–177 %, as compared to other marbles (Natani et al. 2007).

The assessment of influence of mining on urban sprawl has been done using Landsat satellite data. It includes preprocessing of satellite data, visual and digital interpretation and change detection analysis. Landsat digital data of September1972, October 1989, October2000 and February 2003 were used to evaluate the changes in the study area. Reports of Census of India and Department of Mine and geology were also used as secondary data. Landsat data which provided by USGS Earth Resources Observation and Science Center was geometrically and radiometrically corrected.

2.5.2 Classification Method of Satellite Data

Landsat data were classified by using uniformity for all the data. The data were classified into 7 classes i.e. 1. Urban, 2. Rural 3. Agriculture, 4. Scattered Vegetation, 5. Water body, 6. Barren Land, 7. Mining. The different enhancement techniques were used (Linear, data scaling, histogram equalization, Gamma and Gaussian) for better interpretation.

The Erdas Imagine software was used for the classification of the satellite data. The satellite data were checked thoroughly before classification into land use groups and their respective range of reflectance values. Spectral signature charts were prepared to distinguish and find out the differences in pixel values of different land use classes in different bands. At first, the maximum likelihood algorithm of supervised classification was used for forest, agricultural, barren land, and water classes. For this, the algorithm was trained by training samples to perform the supervised classification. Each training sample consisted of at least 90 image pixels to satisfy the 10n criterion. The parameter n refers to the number of bands used for classification (Congalton 1991; Jat et al. 2008). For extraction of settlement area first area of interest was created with help of village points for small settlements then they were classified using Isodata method. Further classification of built up area in to urban and rural is based on density, compactness and connectivity of built up pixels.

2.5.3 Method for Assessment of Urbanization and Mining

To assess the urbanization and mining following equations were used to calculate the consumption rate and absorption coefficient. The formulas for Consumption rate and absorption coefficient are given below:

$$\text{Consumption Rate} = A/P \tag{2-9}$$

Where A is areal extent of land use class and P is population

$$\text{Absorption coefficient} = A2\text{-}A1/P2\text{-}P1 \tag{2-10}$$

A1, A2 are the areal extent early and later years and P1, P2 are population figure for the early and later years.

Population data are used for this research obtained from Census of India. These population data were not available exactly for the same year of land use map so nearby year data has been used for analysis. (Source for 2000 population data: http://www.crusadewatch.org)

2.5.4 Results and Discussion on Influences of Natural Resources (Mining Area) on Urbanization

Increase in urban and mining of marble has clearly seen in the last 30 years. There is significant increase in during this period. The temporal satellite data represents the degree of increase in mining as well as in urban. The urban of Makrana city was concentrated only in the city peripheral in 1972 but gradually the urban increase on the periphery. The built up patches near to mining site is gradually increased from 1972 to 2003.

The Figures 2.10, 2.11, 2.12 and 2.13 show land use of Makrana city for 1972, 1989, 2000 and 2003 respectively. By viewing these figures one can say that there is considerable increase in urban and mining area during this period. Rural area near to city in 1972 is gradually converted in to urban area in the year 2003. As shown in Table 2.12 Urban area has increased by 109.57 ha during 1972-89, 103.15 ha during 1989-2000 and 126.79 ha during 2000-03. Urban area increased by 339.52 ha during 31 years from 1972-2003.

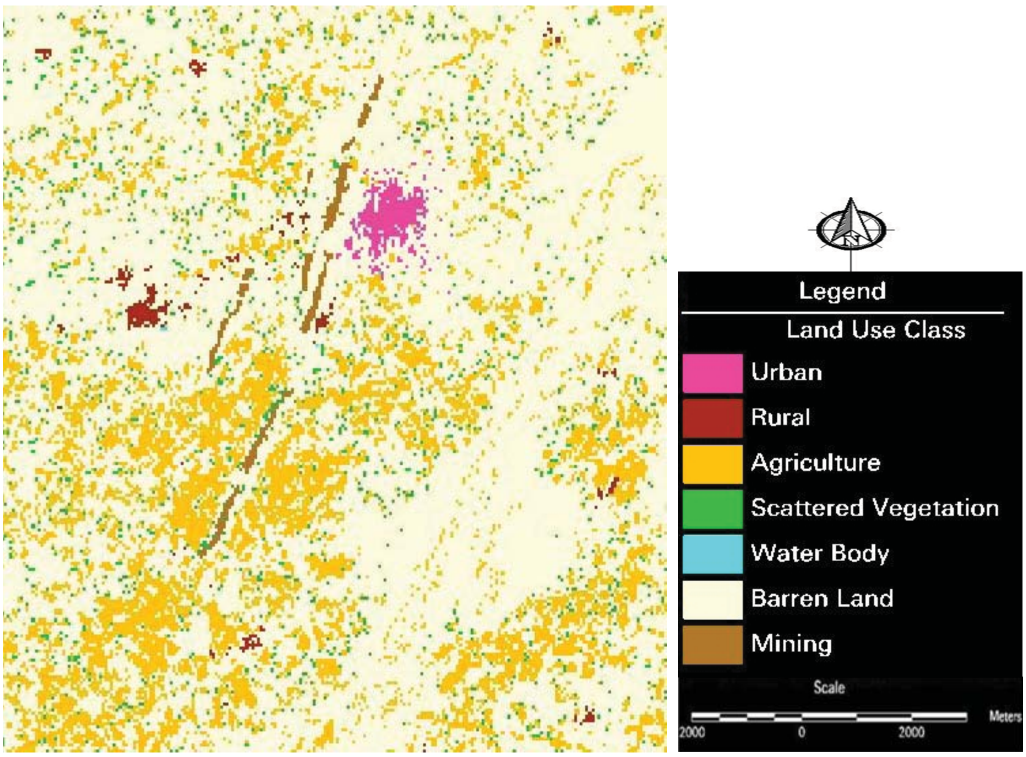

Figure 2.10 Land Use Map of Makrana City 1972

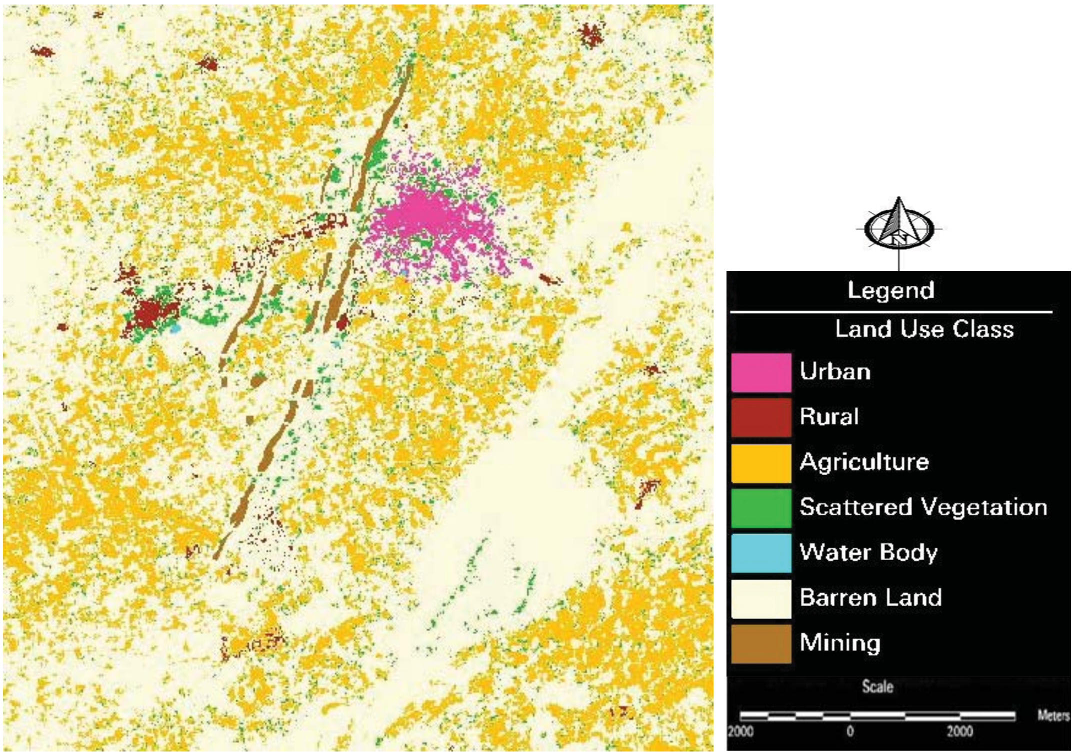

Figure 2.11 Land Use Map of Makrana City 1989

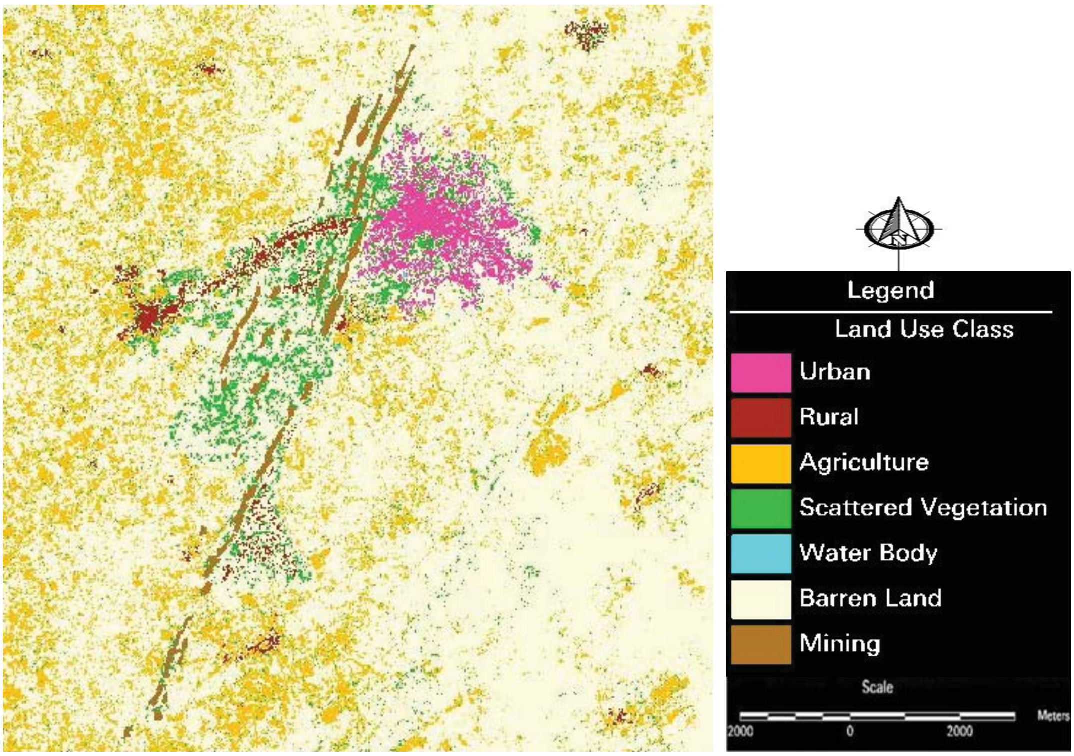

Figure 2.12 Land Use Map of Makrana City 2000

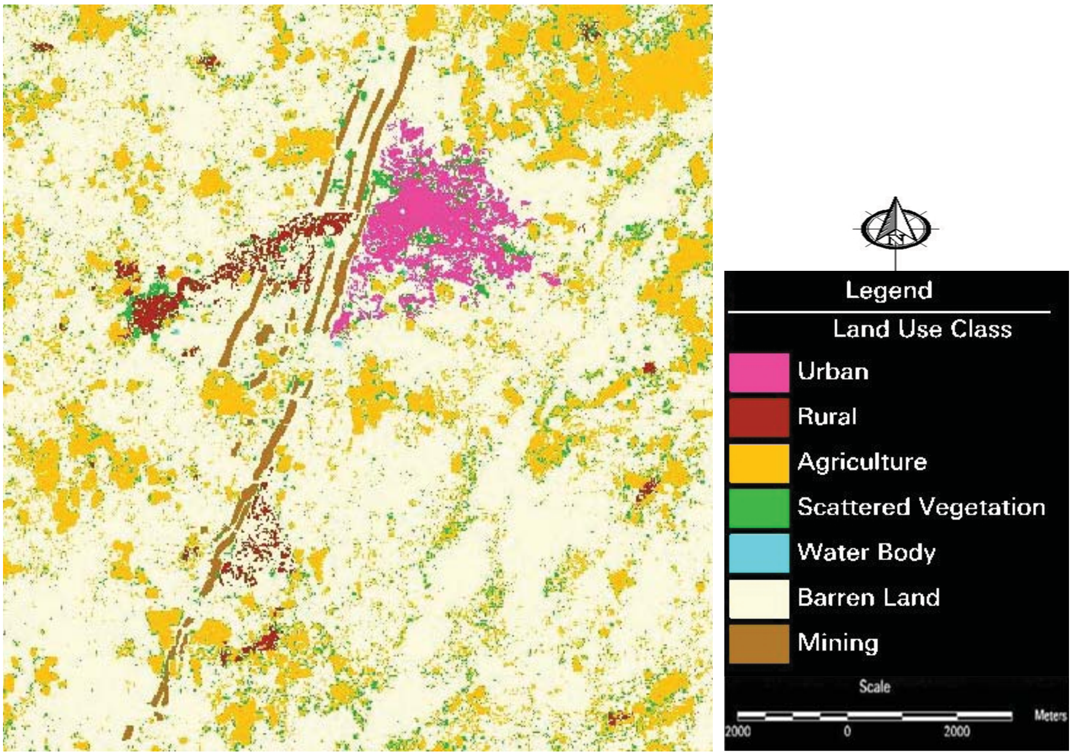

Figure 2.13 Land Use Map of Makrana Cit2003

Table 2.12 Change and Trend in Urban and Mining

	1972-1989		1989-2000		2000-2003		1972-2003	
	Urban	**Mining**	**Urban**	**Mining**	**Urban**	**Mining**	**Urban**	**Mining**
Area Change (Ha.)	109.57	25.01	103.15	58.80	126.79	65.10	339.52	148.93
% Change	0.57	0.13	0.54	0.31	0.66	0.34	1.78	0.78
Annual Change (Ha.)	6.44	1.47	9.37	5.35	42.26	21.71	10.95	4.84

Mining area has changed by 25.0173 ha during 1972-1989, 58.8069 ha during 1989-2000 and 65.1078 ha during 2000-2003. Total change in mining area during 1972-2003 is 148.932. So the annual increase in mining area is 4.84 ha from 1972-2003.

Table 2.13 Land Consumption Rate and Land Absorption Coefficient of Urban and Mining

Consumption rate			Absorption Coefficient		
Year	Urban	Mining	Year	Urban	Mining
1972	0.00578	0.00587	1972-1989	0.00300	0.00068
1989	0.00408	0.00270	1989-2000	0.00548	0.00312
2000	0.00442	0.00280	2000-2003	0.00787	0.00404
2003	0.00568	0.00342	1972-2003	0.00565	0.00247

Table 2.13 showing consumption rate and absorption coefficient of urban and mining. We can say that land consumption rate of urban 0.00578, 0.00408, 0.00442 and 0.00568 are for 1972, 1989, 2000 and 2003 respectively and land consumption rate for mining is 0.00587, 0.00270, 0.00280 and 0.00342 for the 1972, 1989, 2000 and 2003 respectively. The land absorption coefficient for urban is 0.00300 during 1972-89, 0.00548 during 1989-2000, 0.00787 in 2000-2003 and 0.00565 during 1972-2003. For mining land absorption coefficient in 1972-89 is 0.00068, in 1989-2000 is 0.00312, in 2000-03 is 0.00404 and in 1972-2003 is 0.00247. The marble production from Makrana mines was 466.66 Th. Tones in 1997-1998; revenue for this period was 101688.57 Th. Rupees. Where as in 1998-99 the production increased to 486.01 Th. Tones and revenue increased by 107817.45 Th. Rupees for this fiscal year. In 1999-2000 production reached to 581.62 Th. Tones for this 131744.23 Th. Rupees revenue collected. During 2000-02 production of marble was 773.37 Th. Tones and revenue from this production for this period was 190786.52 Th. Rupees (Source: Rajasthan Mineral Bulletin, Mine-vol.III, http://ppp.rajasthan.gov.in/).

Mining of Marble has very good prospect in Rajasthan State. Rajasthan has more than 90% of Marble deposit of India in which approx. 13% share by Makrana deposits. The production of Marble was 63.420 Th. Tones in 1970; it reached to 5686 Th. Tones in 2002 in Rajasthan State. In 1970 revenue collected by marble was 679.600 Th. Rupees in 1970 which reached to 780313 Th. Rupees in 2002 in Rajasthan (Goyal, et.al.2002). Makrana is the third largest producer of marble. It accounts for 13% of the total marble production in the Rajasthan state.

Mining in Makrana is significantly inducing industrialization in the city. There is a huge potential of mineral-based industries in the area. The present rate of marble production from Makrana is 0.12 million Tons per year with annual revenue of Rs 360 million. So there is a vast increase in Marble Cutting and Polishing units in the area. Mining based industries are providing lots of job opportunity to local as well as for people who are living near by the city.

The remote sensing satellite data provide useful information about the trend of urbanization as well as for mining in this study area. Remote sensing technique has been used to demonstrate the dynamic phenomenon like urban and mining. These spatial data have been analyzed for defining the relationship between urbanization and mining. There is considerable increase 306.71 Th. Tones in production of marble during 1997-2002 with the annual increase of 61.34 Th. Tones from 1997-2002. Revenue from 1997-2002 is increased by 89097.95 Th. Rupees with annual increase of 17819.59 Th. Rupees. If we compare the production of marble during 1997-2000 increased by 114.96 Th. Tones and in 2000-02 it increased by 191.75 Th. Tones in only 2 years. The revenue was increased by 30055.6 Th. Rupees during 1997-2000 where as in 2000-02 it increased by 59042.29 Th. Rupees. In 2000-03 the absorption coefficient for urban was highest in compare absorption coefficient of other periods. Makrana marble mines in that area is one of best resource for the people as it is providing resources for living for that area with the increase in population and urbanization. Further, association of other causative factors with mining like socio-economic condition, governmental investment for public, industrial development due to mining, development in infrastructure of transportation etc. can also be considered for urban sprawl in future research work.

These rich deposits in the vicinity of the city are providing jobs for more than 0.1 million people in which 60 thousands are deployed directly in mining. Indirectly employment in mining includes transporters, mechanics/workshop owner, masons, artisans etc. The production of Marble will reach to 7500 thousand tons in 2010 so this will provide more opportunity to people to grow in Rajasthan. This relationship between urban and mining plays an important role for the local development authorities and municipality. Also this relationship can be used to predict and quantify urban sprawl; this can be used for optimal planning of the land and natural resources. In the absence of planning policies it can cause to degradation of land. Therefore implementation of policies for planning of urban as well as techniques for management of the mining for better use of land for long span of time. Remote sensing technology is indispensable for dealing dynamic phenomenon of land use. Without remote sensing data, one may not be able to monitor and estimate the urban and mining sprawl effectively over a time period, for elapsed time period especially in developing countries (Jat et al. 2008).

2.6 Concluding Remarks

In this research, remote sensing, GIS, and the Markov model have been integrated to demonstrate the changes in urban development and its future growth trends Jaipur, the capital and administrative center of the state of Rajasthan was selected for this research due to the rapid growth in its population and urban area. This study describes how the Markov model with combination of remote sensing is used to explore the change in land use and land cover of Jaipur district during the period 1975-2002. The Markov model has enormous capabilities to show the trend and projection of land use and land cover. The interpretation from this can be used as an indicator of magnitude and direction of change in land use in the future.

The study of land use and land cover change is enhanced by integration of remote sensing and GIS with Markov model. The quality of input data for analysis has been improved by using GIS and remote sensing data.

During this study it was found that there was no stability in land use change process. All the categories of land use were changing very fast with time. Land use change for 1975-1989 and 1989-2002 had different transition mechanism. As built up and agricultural area is growing very fast whereas barren land and water body are decreasing rapidly. Agricultural area is converting into built up area and this is more common near to built up or city area.

This urban expansion is seen as one of the potential challenges to sustainable development because urban planning is a key to city planning. This study focused on exploring the expansion of the urban area of Jaipur. Density-based categorization, transition probabilities, and Markovian suitability were computed, which helped in understanding the form of urban expansion and its spatial pattern. The urban expansion was defined by quantifying the urban area into further categories based on density, use, and association using a knowledge-based classifier. A large percentage of barren land area was transformed into urban area during the study period. The urban change shows maximum expansion on the outskirts of the city. This expansion also indicates the influence of industrial growth, visible in the southern and north-western parts of the city. There was continuous urban growth at a faster rate in the outer areas as well as an increase in the density of the urban area in the central part of city.

The results indicate that the urban area showed an expansion of 181% over 16 years and this will increase in future. The population growth rate is influencing the urban expansion as it is about half of the rate of urban change during the study period. The results of and relationship between urban expansion and the factors influencing it are useful for local authorities to determine the spatial dimension of urban expansion. Only remote sensing data can provide complete spatial information for the efficient assessment of urban change in developing countries over a time period, especially for past periods. The quantification and assessment of urban change can be used for the urban planning of cities, and for determining their environmental impacts.

Planning and management in developing cities require new skills and approaches in the globalized and economically liberalized world. In this new era of globalization, Indian cities should have quality infrastructure, energy efficient service provisions, and environmental conditions to sustain growth and attract foreign investment. The planning authorities should adopt new technologies such as remote sensing and GIS to address these issues. Remote sensing and GIS are capable of providing the necessary information and intelligence for planning proposals and can be used as monitoring tools during the implementation of plans.

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CHAPTER 3

URBAN CHANGE SIMULATION USING REMOTE SENSING AND GIS

3.1 Introduction

The process of urban change is complicated and is influenced by both physical and human aspects. Urban change is usually associated with socio-economic developments. Urban change has recently heightened in Indian cities with population and economic development being the main factors behind it (Jat et al., 2008; Taubenböck et al., 2008; Bhatta et al., 2009). This incredibly rapid growth of cities has caused severe ecological, economic, and social problems. It is recognized that over 70% of this growth in developing countries currently takes place outside the formal planning process and that 30% it's of urban populations live in slums or informal settlements (Doytsher et al. 2010). Therefore, rapid urban change estimation and prediction are very important for a variety of planning and management issues as it can provide the baseline growth scenario to show future land development patterns and can be utilized to minimize the negative impacts of improper developments, especially in developing countries (Li and Yeh, 2002; Martinuzzi et al., 2007; Norman et al., 2009).

Urban change evaluation and estimation are the important processes for sustainable urban development. Modelling of urbanization requires spatially explicit factors. There are many factors, which influence the urbanization like population growth, good prospects for livelihood, proximity to daily life required facilities, etc. (Jat et al., 2008; Norman et al., 2009). Increase in urbanization necessitates more consideration for the planning and management of a city, particularly in developing countries. Cities in the developing countries confronted with increasingly overcrowded transportation systems, insufficient water supply, deteriorating sanitation and increase in environmental pollution (Bhatta et al., 2009; Martinuzzi et al., 2007). The concentration of urban population is becoming particularly characteristic of developing countries. During the last 50 years, the population of India has more than doubled, while the urban population has grown nearly five times (Taubenböck et al., 2008). According to UN-HABITAT in 2010, 30% of total populations live in cities and, which will increase up to 34% in 2020 in India. Rapid urban growth has been witnessed in most of the cities of India and Jaipur city is the one of them. Jaipur city urban area was less than 3,066 hectare in 1975 and reached to 14,000 hectare in 2006. Population of the city is also increasing rapidly with the annual growth rate of 5.5% and during 1991- 2001 more than 200,000 people migrated to the Jaipur city (Census India, 2001).

Conventional surveying and mapping techniques are expensive and time consuming for urban change evaluation and city growth information is not readily available, especially in developing countries. Therefore, different researchers used GIS and remote sensing to estimate urban change (Jat et al., 2008; Li and Yeh, 2002; Taubenböck et al., 2008).

India has been called a country of villages, but its high economic and population growth, especially in the last decade, has converted India to an urban society. Cities in the developing India are confronted with the concentration of urban populations, increasingly overcrowded transportation systems, insufficient water supply, deteriorating sanitation, and increased environmental pollution (Jain and Subbaiah, 2007; Taubenböck et al., 2008; Bhatta et al., 2009). These conditions, therefore, demand a method that is capable of simulating urban while assessing the change pattern and its related impact on the urban environment. Such a method can be used to encourage and maintain the sustainable development of this developing city. This study investigates the urban change pattern using remote sensing and GIS with an integrated approach involving the multi-layer perceptron (MLP)-Markov model. Hence, this research aims to ascertain the trends of urban growth by estimating growth using multi-temporal remote sensing images.

3.1.1 Global Urban Change Pattern

The 20th century is related to the phenomenon of rapid urban change. By 1900 13% of the world's population was urban. During the next years, improvements in medicine and science allowed higher city densities. According to UN reports, the urban population increased from 220 million in 1900 to 732 million in 1950 (29% of the world's population). By 2007 50% of the world population was living in cities; further improvements in technology, medicine and prevention of disease allowed even larger urban densities. According to latest predictions, 4.9 billion people, or 60% of the world's population, are expected to be urban dwellers by 2030. Investigations show significant differences in urban population change between the more developed regions and the less developed regions. The majority of the inhabitants of the less developed regions still live in rural areas, but in the more developed regions the population is already highly urbanized. As urban change tends to rise and as development increases urban change is expected to rise as well in the future. However, despite their lower levels of urban change, less developed regions have more than double the numbers of urban dwellers than the more developed (2.3 billion vs. 0.9 billion). By 1968, the urban population of the less developed regions surpassed for the first time that of the more developed regions and continues to do so thereafter. Furthermore, according to UN predictions, the rapid growth of the population of the less developed regions combined with the near stagnation of the population in the more developed regions implies that the gap in the number of urban dwellers between the two will continue to increase.

Urban change is a major change taking place globally. It is estimated that a further 500 million people will be urbanized in the next five years. In sub-Saharan Africa, 90% of new urban settlements are taking the form of slums. These are especially vulnerable to climate change impacts as they are usually built on hazardous sites in high-risk locations. Even in developed countries unplanned or informal urban development is a major issue. Urban change is also contributing significantly to climate change. The 20 largest cities consume 80% of the world's energy and urban areas generate 80% of greenhouse gas emissions worldwide. Cities are where climate change measures will either succeed or fail.

3.1.2 Urban Change Pattern in India

During the last 50 years the population of India has more than doubled, but the urban population has grown nearly five times. The number of Indian mega cities will increase from the current three (Mumbai, Delhi and Kolkata) to six by the year 2021 (including Bangalore, Chennai and Hyderabad), then India will have the largest concentration of mega cities in the world.
In India, the definition of urban is more rigorous. Both civic status and demographic criteria are taken for declaring a settlement urban. The census of India defined the urban places on the basis of the following criteria (Census of India 2001).

i) All places with a municipality, corporation, cantonment board or notified town area committee etc.
ii) All other places which satisfy the following criteria:

a) Minimum population of 5000
b) At least 75 % of male working population engaged in non-agricultural pursuits and
c) A density of population of at least 400 persons per square km. (1000 per sq mile).

2005, 22 mega cities (urban agglomerations of 10 million inhabitants or more) around the world were identified; three of the cities, Mumbai, Delhi and Kolkata, were on the Indian subcontinent (United Nations, 2006). Two of the cities, Mumbai at 5.1% and Delhi at 4.1%, have among the highest population growth rates of all mega cities in the world. Less attention is paid to ‘‘smaller”, explosively fast growing cities, whose high growth rates may precipitate transition into mega city status. Besides the three current mega cities, nine more urban agglomerations in India (Ahmadabad, Bengaluru, Chennai, Hyderabad, Jaipur, Puna, Kanpur, Lucknow and Surat) currently have more than 2.5 million inhabitants.

3.1.3 Spatial Information to Manage Urban Change Pattern

The rapid growth of megacities causes severe social, economical and ecological problems. How can this growth be nurtured in a sustainable way? The challenge for land professionals is to provide the megacity 'managers', both political and professional, with appropriate 'actionable intelligence' that is up-to-date, citywide and in a timely manner to support more proactive decision making that encourages more effective sustainable development. Spatial information has become indispensable for numerous aspects of urban development, planning and management. The increasing importance of spatial information has been due to recent strides in spatial information capture (especially satellite remote sensing and positioning), management (utilizing geographic information systems and database tools) and access (witness the growth in web mapping services), as well as the development of analytical techniques such as high resolution mapping of urban environments. These more efficient techniques can lead to a wider diversity of information that is more up-to-date.

In some circumstances, a wealth of existing map, image and measurement data can already be found in areas such as land administration, natural resource management, marine administration, transportation, defense, communications, utility services and statistical collections. The challenge is for users both within and outside these areas of activity to break down the information silos and to discover, to access and to use the shared information to improve decision-making, business outcomes and customer services.

The study has found that spatial information technology is being recognized widely as one of the tools needed to understand and address the big urban problems, but there is still a general lack of knowledge amongst communities of practice about what spatial solutions exist and how they can used and prioritized.

Information to support the management of cities is traditionally channeled and aggregated up the vertical information highway from a local, operational level to a policy level. In developed countries, urban change and its characteristics can normally be measured through information derived from the land administration functions. However, in the megacities of the developing countries, informal settlements are the norm, growth is rampant and administrative structures are limited. The traditional source of change information is not readily available there.

3.2 Literature Review

Artificial Neural Networks (ANNs) are a powerful tool for urban simulation studies, as they use a machine-learning approach to quantify and model complex behavior and patterns, and allow for the integration of GIS tools and remote sensing data (Li and Yeh, 2002; Paola and Schowengerdt, 1997; Pijanowski et al., 2002). The multi-layer perceptron network described by Rumelhart et al. (1986) is one of the most widely used ANNs. However, there are many other types of neural networks available, including Probabilistic Neural Networks, General Regression Neural Networks, and Radial Basis Function Networks. The use of MLP has increased substantially over the last several years because of the advancement in computing performance and availability of powerful and flexible software such as IDRISI (Atkinson and Tatanall, 1997; Chan et al., 2001; García-Cuesta et al., 2008).

MLP consists of three-layers: input, hidden, and output layer, which can be used to identify relationships of a non-linear nature (Civco, 1993; Fiset et al., 1998; Pijanowski et al., 2002). MLP is a feed forward ANN model that maps different sets of input data onto a set of appropriate output. Pijanowski et al. (2002) used ANNs to learn the patterns of development in the region and test the predictive capacity of the model, whereas Dai et al. (2005) used ANNs to identify the factors driving changes in land use. Mas et al. (2004) used MLP to develop deforestation risk assessment maps.

Theobald and Hobbs (1998) described two approaches to modeling spatial patterns and future development of land: one is a regression model and the other is a spatial transition-based model. Pijanowski et al., (2002), Dai et al., (2005) and Aguayo et al. (2007) used ANNs with regression for land use change and urban change analysis, whereas Li and Yeh (2002) used the spatial transition-based model with ANN-Cellular Automata for land use simulation. The spatial-transition-based model is rooted in a stochastic Markov-chain technique, requires less data with no restriction for spatial resolution, and is useful for descriptive and predictive modeling (Theobald and Hobbs 1998). In this research, the spatial transition-based approach has been implemented for urban simulation by integrating MLP with the Markov model. Land use studies using the Markov model have a proclivity to focus on a large spatial level and engage both impervious and non-impervious land cover (Muller and Middelton, 1994; Weng, 2002; Wu et al., 2006; Fan et al. 2008). The Markov method is a stochastic process, which does not require historical socio-economic data and is able to explain a situation where statistical information is missing for the city (Fan et al. 2008). Wu et al. (2006) projected land use change using Markov chains for Beijing City, whereas Fan et al. (2008) used the Markov model to predict temporal changes for urban expansion and farmland.

Dai et al., (2005) formulate the dynamics of land use on the temporal and spatial dimensions from the perspectives of the Change-Pattern-Value (CPV) and driving mechanism, based on multi–temporal remote sensing data and socioeconomic data. The Artificial Neural Networks were used to identify the factors driving changes in land use. The Pearl River Delta Region of southeast China, which was experiencing rapid economic growth and widespread land conversion, has been selected as the study region.

Mas et al. (2004) research, aims to predict the spatial distribution of tropical deforestation. Landsat images dated 1974, 1986 and 1991 were classified in order to generate digital deforestation maps which locate deforestation and forest persistence areas. The deforestation maps were overlaid with various spatial variables such as the proximity to roads and to settlements, forest fragmentation, elevation, slope and soil type to determine the relationship between deforestation and these explanatory variables. A multi-layer perceptron was trained in order to estimate the propensity to deforestation as a function of the explanatory variables and was used to develop deforestation risk assessment maps.

Li, and Yeh, (2002) presents a new method to simulate the evolution of multiple land uses based on the integration of neural networks and cellular automata using GIS. A three-layer neural network with multiple output neurons is designed to calculate conversion probabilities for competing multiple land uses.

Pijanowski et al. (2002) used Geographic information systems (GIS) with artificial neural networks (ANNs) to forecast land use changes. ANNs are used to learn the patterns of development in the region and test the predictive capacity of the model, while GIS is used to develop the spatial, predictor drivers and perform spatial analysis on the results.

3.3 Remote Sensing and GIS Applications in Urban Study

In India, the complexity of urban development is so dramatic that it demands immediate attention and perspective physical planning of the cities and towns. The dynamic nature of urban environmental necessitates both macro and micro level analysis. Therefore, it is necessary and fundamental for policy makers to integrate like remote sensing into urban planning and management. Traditional approaches and technique designed for towns and cities may prove to be inadequate tools when dealing with metropolis. New approaches are required, and new methods must be incorporated into current practice. Until recently, maps and land survey records from the 1960's and 70's were used for urban studies, but now the trend has shifted to using digital, multispectral images acquired by EOS (Earth Observation Satellite) and other sensors. The trend towards using remotely sensed data in urban studies began with first-generation satellite sensors such as Landsat MSS and WAS given impetus by a number of second generation satellites: Landsat TM, ETM+ and SPOT HRV. The recent advent of a third generation of very high spatial resolution (< 5 meter/pixel) satellite sensors is stimulating. The high resolution PAN and LISS III merged data can be used together effectively for urban applications. Data from IRS P-6 satellites with sensors on board especially LISS IV Mono and Multispectral (MX) with 5.8 meter/pixel spatial resolution is very useful for urban studies Advancement in the technology of remote sensing has brought miracle in the availability of the higher and higher resolution satellite imageries. They are IRS-P6 Resourcesat imagery with 5.8 meter resolution in multispectral mode, IRS-1D Pan image with 5.8 meter resolution, Cartosat-I imagery of 2.5 meter resolution with stereo capabilities, Cartosat-II with 1 m, IKONOS imageries of Space Imaging with 4 meter in multispectral mode and 1 meter in panchromatic mode, Quickbird imagery of Digital Globe with 61 cm resolution in panchromatic mode and so on. These high resolutions of the sensors provide a new methodology in the application with newly raised technical restrictions.

Apart from Cartographic applications, P-6 data will be useful in cadastral mapping and updating terrain visualization, generation of a national topographic database, utilities planning and other GIS applications needed for urban areas. The satellite will provide cadastral level information up to a 1:5,000 scale, and will be useful for making 2-5 meter contour map. The output of a remote sensing system is usually an image representing the scene being observed. Many further steps of digital image processing and modeling are required in order to extract useful information from the image. Suitable techniques are to be adopted for a given theme, depending on the requirements of the specific problem. Since remote sensing 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 remote sensing data. This integration of spatial data and their combined analysis is performed through GIS technique. It is a computer assisted system for capture, storage, retrieval, analysis and display of spatial data and non-spatial attribute data. The data can be derived from alternative sources such as survey data, geographical/topographical/aerial maps or archived data. Data can be in the form of locational data (such as latitudes/longitudes) or tabular (attribute) data. GIS techniques are playing an increasing role in facilitating integration of multi-layer spatial information with statistical attribute data to arrive at alternate developmental scenarios. Application of Remote Sensing technology can lead to innovation in the planning process in various ways;

1. Digitization of planning base maps and various layout plans has facilitated updating of base maps wherever changes have taken place in terms of land development etc. Digital maps provide flexibility as digital maps are scale free. Superimposition of any two digital maps which are on two different scales is feasible. This capability of digital maps facilitates insertion of fresh survey or modified maps into existing base maps. Similarly superimposition of revenue maps on base maps with reasonable accuracy is great advantage compared to manually done jobs.

2. Since information and maps are available in digital format, correlating various layers of information about a feature from satellite imagery, planning maps and revenue maps is feasible with the help of image processing software like ERDAS Imagine, ENVI and PCI Geomatica, ILWIS. Such super imposed maps in GIS software like Map info, Geomedia, Arc View, Auto

CAD Map and Arc GIS provide valuable information for planning, implementing and management in urban areas.

3. Remote Sensing techniques are extremely useful for change detection analysis and selection of sites for specific facilities, such as hospital, restaurants, solid waste disposal and industry. An attempt has been made here to demonstrate the potentials of remote sensing techniques in base mapping, land-use and land-cover mapping, urban change detection and mapping, urban infrastructure and utilities mapping, urban population estimation, management.

(a) Aerial Photography and Satellite Data in Urban Studies

Aerial photographs have long been employed as a tool in urban analysis (Jensen 1983, and Garry, 1992). In India, city planning has been largely confined to aerial photography. It is being used for generation of base maps and other thematic maps for urban areas as it is proved to be cost and time effective and reliable. Wealth of information pertaining to land features, land use, built up areas, city structure, physical aspects of environment etc. are available from the aerial photography. Various types of cameras and sensors black and white, color, color infrared are used for aerial photography. Because of security concerns related to aerial photography, the use of photogrammetric techniques was confined to smaller cities. Aerial photographs provide information that can significantly improve the effectiveness of city and town planning and management in India. They are also relatively low in cost, accurate, reliable and can be obtained on desired scale, but they are not useful in large metropolitan areas. As discussed above, India very much dependent on Photogrammetry to provide information for urban planning purposes. But since the March 17, 1988 launch of its first satellite (IRS1A) equipped with the LISS-I sensor acquiring 72.5 meter/pixel data, the application of remotely sensed data (from various sensors) in urban and regional planning processes has gained momentum. LISS-I gathered data in four spectral bands (0.45 μm - 0.86 μm) and was mainly used for broad land-use, land-cover, and urban sprawl mapping. The IRS-1C and 1D satellites launched in 2003, carrying LISS-III and LISS-IV sensor with spatial resolutions of 23.5 meter/pixel and 5.8 meter/pixel using Landsat MSS optical bands (0.52 μm - 0.86 μm), have contributed to the effectiveness of urban planning and management. Early experiments with the first generation satellites found the data very useful for mapping large urban parcels and urban extensions. The development of Landsat TM data with 30 meter/pixel spatial resolution has helped in mapping Level-II urban land use classes. Cities and towns in India exhibit complex land use-patterns, with the size of urban parcels varying frequently within very short distance. The extraction of urban information from remotely sensed data therefore requires higher spatial resolution.

3.4 Materials and Method

3.4.1 Study Area and Data Used

Urban change is simulated for Jaipur city. Jaipur city is situated between the approximate Latitude 27.88 N, Longitude 74.88 E and Latitude 26.42 N, Longitude 76.29 E (Degree Decimal) and is the capital of Rajasthan state, India. An integrated approach using the multi-layer perceptron (MLP)-Markov model is used for modeling urban change pattern dynamics as shown in Figure 3.1.

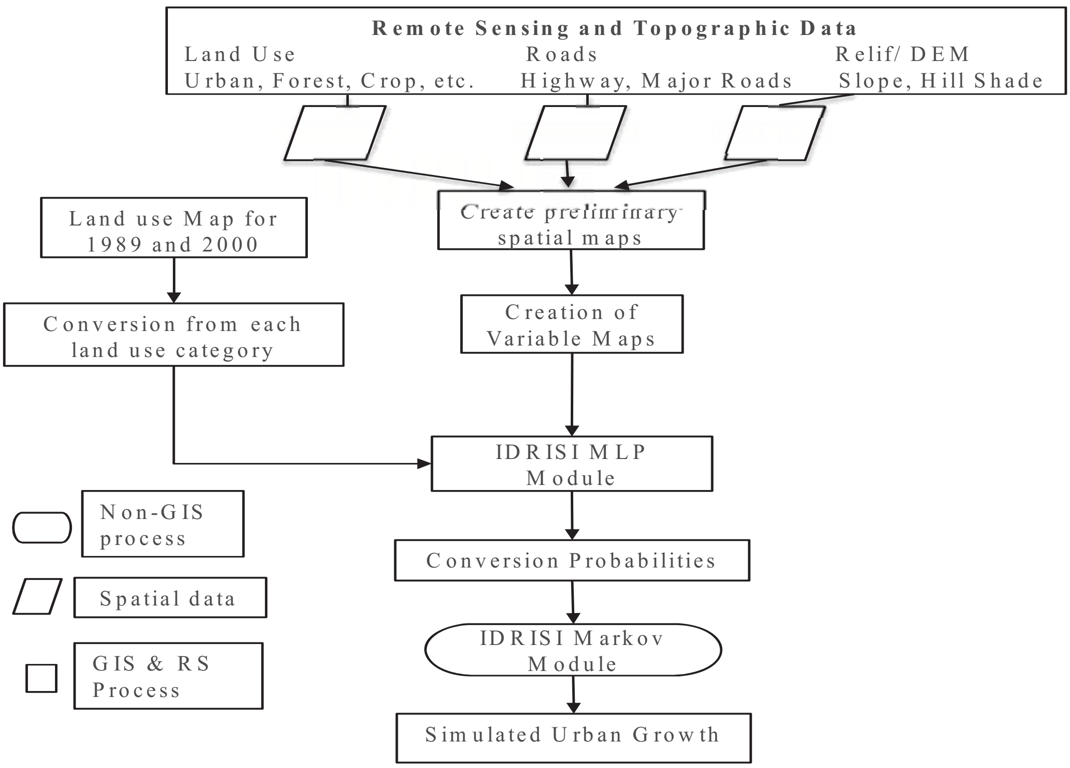

Figure 3.1 Method Flow Diagram of Urban Change Simulation

Landsat satellite data have been used to prepare land use maps of the city. Road and digital elevation models have been prepared by using toposheets of 1:50,000. The variables used in this study so far in the MLP have been created using general GIS capabilities.

The basic image processing methods—namely, image extraction, restoration, and classification—have been used for the analysis of Landsat satellite data of 1975, 1989, 2000, 2002, and 2006. Satellite data have been checked thoroughly to prepare land use classes and their respective range of reflectance values. Spectral signature charts were prepared to distinguish and determine the differences in pixel values of land use classes in all bands. Land use maps were prepared on the basis of Landsat data using the supervised maximum likelihood and unsupervised method. The classified data of 1975, 1989, 2000, 2002, and 2006 have been used for the analysis of urban growth processes.

3.4.2 Creation of Variables for Analysis

The urban change is simulated by classifying land use data in urban area, forest, crop land and barren land for 1989, 2000, 2002 and 2006. To maintain accuracy and similarity, same method has been implemented for classification of all satellite data. Classified urban area class includes residential, commercial, industrial and road area. All the variables used for analysis are created using GIS tools. Variables like slope and roads are prepared using toposheets. Distance variable such as proximity to city centre is created using GIS tools.

GIS-based predictor variables and the exclusion zones were compiled in Grid format (Table 3.1; Figure 3.2) using the IDRISI. The forest density variable represents the amount of forest, from the 1989 land use database, within a 1 km radius surrounding each cell. This variable describes the degree to which the landscape is dominated by forest land uses. Forest can be seen as an exclusion zone on the landscape that always avoid for urban development. For the variables of county roads distance, and highway distance, the minimum Euclidean distance to each feature was calculated. These features serve to either improve the access of the site to larger urban areas (i.e. roads and highways) or to increase the amenity value of a site. The built area distance variable was the minimum distance of each cell to an urban cell, from the 1989 Jaipur land use database. Since access to urban services affects development patterns, it is expected that sites nearer to existing built land uses would be more likely to develop. Slope is created using toposheets of Jaipur, high slope area is not suitable for urban development where flat terrain is always good for urban change. Slope area considered for Jaipur city because city is covered by hills in north and east directions.

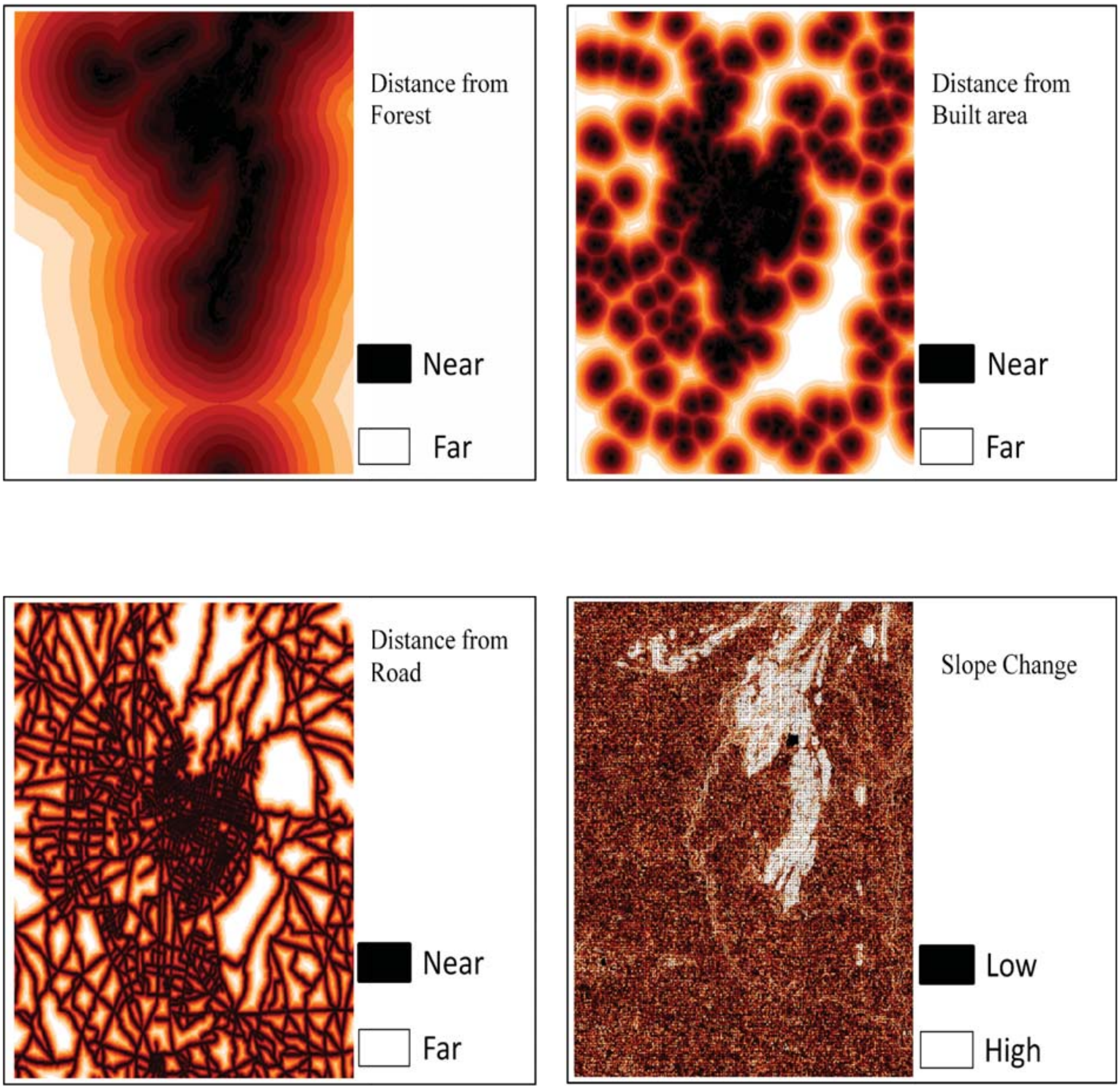

Figure 3.2 Maps of the predictor variables used for the Simulation

Table 3.1 Summary of the Predictor Variables Used for Simulation

Variable Name	Description
Distance from Forest	Distance from forest area
Road Distance	Distance to nearest road
Built Area distance	Distance to 1989 urban use
Slope	Change in Slope
Hill Shade	Avoid the hill shade area for urban development
Distance from City Centre	Distance to 1989 city centre

3.4.3 Validation of Variables

Different variables are validated using Cramer's V method and used as input layers in MLP classifier. Cramer's V is a statistic measuring the strength of association or dependency between two categorical variables (Van Den Eeckhaut et al., 2006; Vanacker et al., 2003). Cramer's V is calculated by using the following Equation:

$$V = Sqrt\ (c^2 / (n\ (k - 1))) \qquad (3\text{-}1)$$

Where c^2 is chi-square and k is the number of rows or columns in the table.

3.4.4 Multi Payer Perceptron Method for Urban Change Interpretation

The urban change is simulated using classified land use data, which include the urban area, forest, crop land, and barren land for 1989, 2000, 2002, and 2006. To maintain accuracy and similarity in classified land use data, a similar methodology has been implemented to classify all satellite images. Classified urban area classes include residential, commercial, industrial, and road features.

The MLP algorithm involves two major steps—forward and backward propagation (Martin, 1994; Pradhan et al., 2010)—and is used to calculate transition potential. At the initial stage, the pixels those are transitioned during 1989-2000 (for example from barren land to urban areas) are assigned randomly to one of the two groups—the first to a training set and the second to a testing set. The training set and identified input variables are introduced in forward pass, on the basis of the concept that the probability of conversion from land use to other uses is ascertained by geographical features and location factors. These variables are obtained by using the GIS tool defined in Equation 3-2.

$$X = x_1, x_2, \ldots\ldots x_n \qquad (3\text{-}2)$$

These variables are associated with a neuron in the input layer and are normalized using Equation 3. Normalizing each variable treats them as equally important inputs to neural networks and makes them compatible with the sigmoid activation function that produces a value between 0 and 1 (Li and Yeh, 2002).

$$x`_i = (x_i - \min)/(\max - \min) \qquad (3\text{-}3)$$

In the hidden layer, the signal received by neuron *j* from the input layer for pixel *k* is calculated by Equation 3-4.

$$net_j(k, t) = \sum W_{i,j} x`_i(k) \qquad (3\text{-}4)$$

where net $_j$ (k, t) is the signal that is received by neuron *j*, and w_{ij} represents the weight between the input layer *i* and hidden layer *j*. The output layer has 2 neurons that correspond to 2 possible significant states such as transition and persistence of the pixels. The neuron *l* generates a value that indicates the transition probability from the existing type of land use to targeted type of land use (the process is shown in Figure 3.3).

$$net_j(k, t, l) = \sum W_{j,l} \frac{1}{1 + e^{-net_j(k,t)}} \qquad (3\text{-}5)$$

The possible values of output transition range from 0.0 to 1.0. Informally, 0.0 indicates no likelihood of change and 1.0 indicates highest likelihood of change. These values are measured by comparing the test set of cells that were observed to undergo transition. In some circumstances, the calculated output may differ from the expected outcome; the difference is associated with error in the network and the weights are modified according to the delta rule defined by Rumelhart et al. (1988). The training set is defined to the network iteratively so that the network can generalize and simulate outputs from inputs until the error stabilizes at a low level (Atkinson and Tatanall, 1997; Pijanowski et al., 2002).

This study used a three-layer neural network for the simulation of multiple land uses (Figure 3.3). In this analysis, there were seven neurons in the input layers corresponding to the number of spatial variables (site attributes). 4 layers were specified to represent four classes of land uses in the output layer. Each output layer produces a conversion probability corresponding to one target type of land use. There is a need to determine the number of neurons in the hidden layer. According to Kolmogorov's theorem, the use of $2n+1$ hidden layers can guarantee the perfect fit of any continuous functions and reducing the number of neurons may lead to lesser accuracy. However, experiments indicate that $2n+1$ hidden layers may be too many in applications (Wang 1994). According to Li and Yeh (2002) $2n/3$ hidden neurons can generate results of almost similar accuracy but requires much less time to train. Here n is the number of input layers and six input layers are used in this study (input layers used in this study are described in Table 3.1). In this model, four hidden layers were used in the network to ensure a balance of both accuracy and simulation speed.

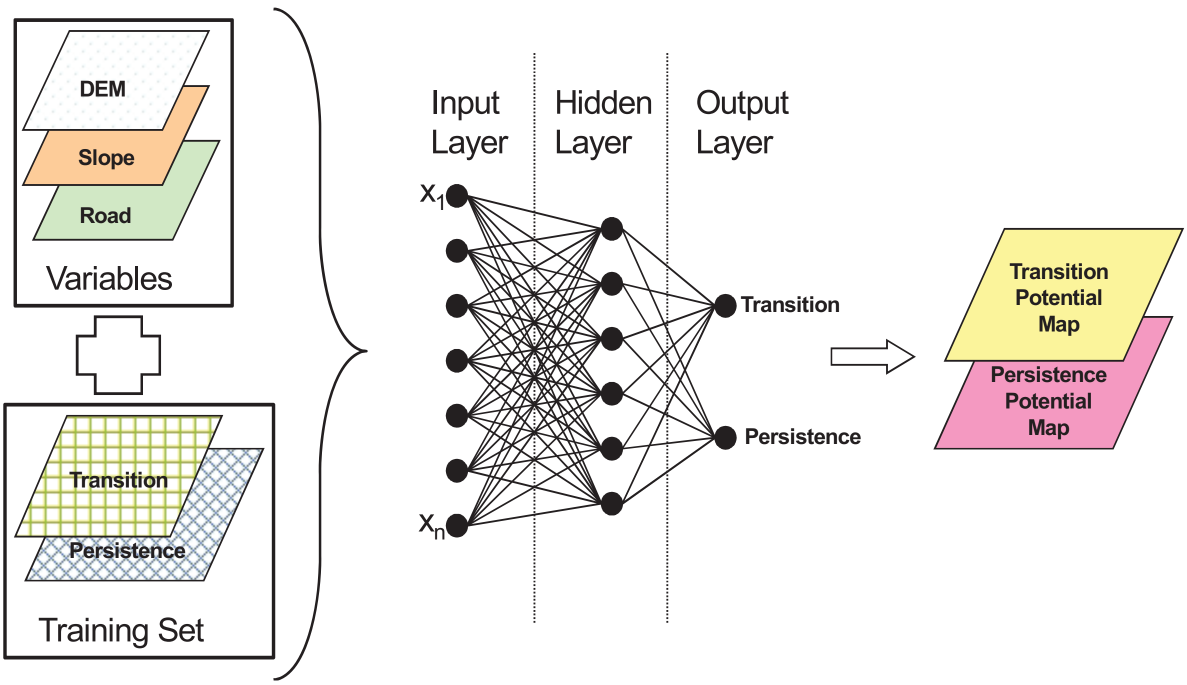

Figure 3.3 Multi-Layer Perceptron used for Urban Simulation

3.4.5 Markov's Model for Urban Change Simulation

The Markov model is increasingly incorporated into studies that analyze both the urban area and non-urban covers of land, due to the advancement of GIS computing technology and remote sensing (Muller and Middelton, 1994; Weng, 2002; Wu et al., 2006). A Markov chain is a random process in which the probability of future steps depends on the current state, not on the state of the system in previous steps (Bell, 1974). The Markov model has one important assumption in that it considers land use and land cover as a stochastic process and different categories of land use (such as urban area, agricultural, forest, and barren land) as the states of a chain. IDIRISI Markov module is used for land use simulation for the target period using transition probabilities.

A Markov chain is made of *S*, which is a vector of the distribution land use class at time t, and A (τ), a matrix of transition probabilities from land use *c* to land use *c*\` in a given time interval T.

$$S_{t+\tau} = A(\tau)\, s_t \qquad (3\text{-}6)$$

3.5 Results and Discussion

3.5.1 Monitoring Urban Change of Jaipur City (1975-2006)

Urban change mapped for 1975, 1989, 2000, 2002 and 2006 using Landsat data. The urban area was near to 4000 hectares in 1975 and reached to more than 6000 hectares in 1989. The average annual growth rate (AAGR) for this period was 4.0%. During 1989-2000 urban area was increased by 5800 hectares with an AAGR of 8.5% and this growth rate is more than double from the growth rate of 1975-1989. During 2000-2006, urban area is expanded by 5,677 hectare with an average annual growth rate of 8%. This expansion of urban area is visible in Figure 3.4, these maps are showing that urban area expanding on the periphery of the city and also increasing in density. Instead of this expansion of the city, the surrounding settlements were also expanded.

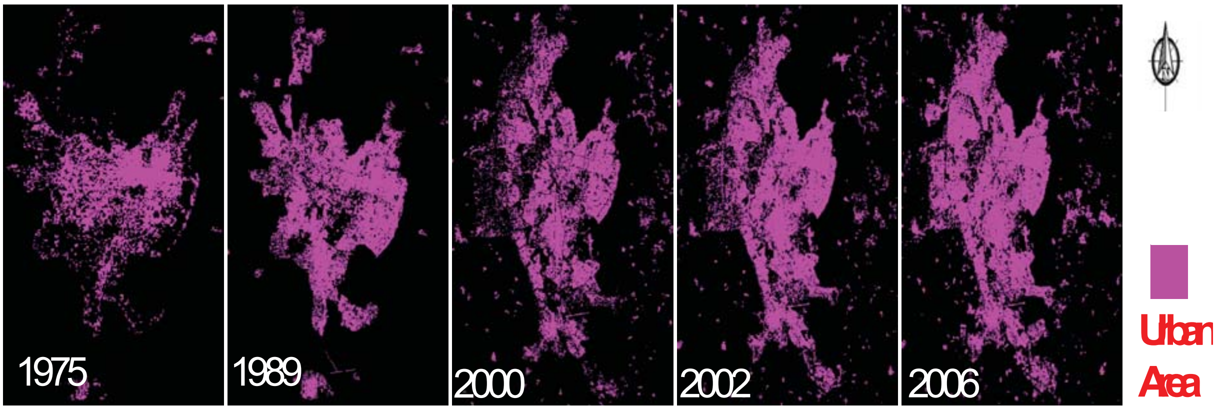

Figure 3.4 Urban Change Pattern of Jaipur city

3.5.2 Estimated and Simulated Urban Change of Jaipur City

Land use data of 1989 and 2000 have been used for simulation and validated with 2002 and 2006 data. Different spatial layers have been generated such as distance from road, distance from city center, and distance from urban periphery, distance from the forest, slope and hill shade to use in MLP. Cramer's V checked to find effectiveness of factors and overall value of Cramer's V is highest for distance from urban periphery (0.1481) followed by distance from roads (0.1207), distance from forest (0.0876). MLP classifier used for each transition from one class to another class, and create a transitions matrix, which used in markov model to simulate land use changes. Simulated land use maps and actual land use maps have shown in Figure 3.5.

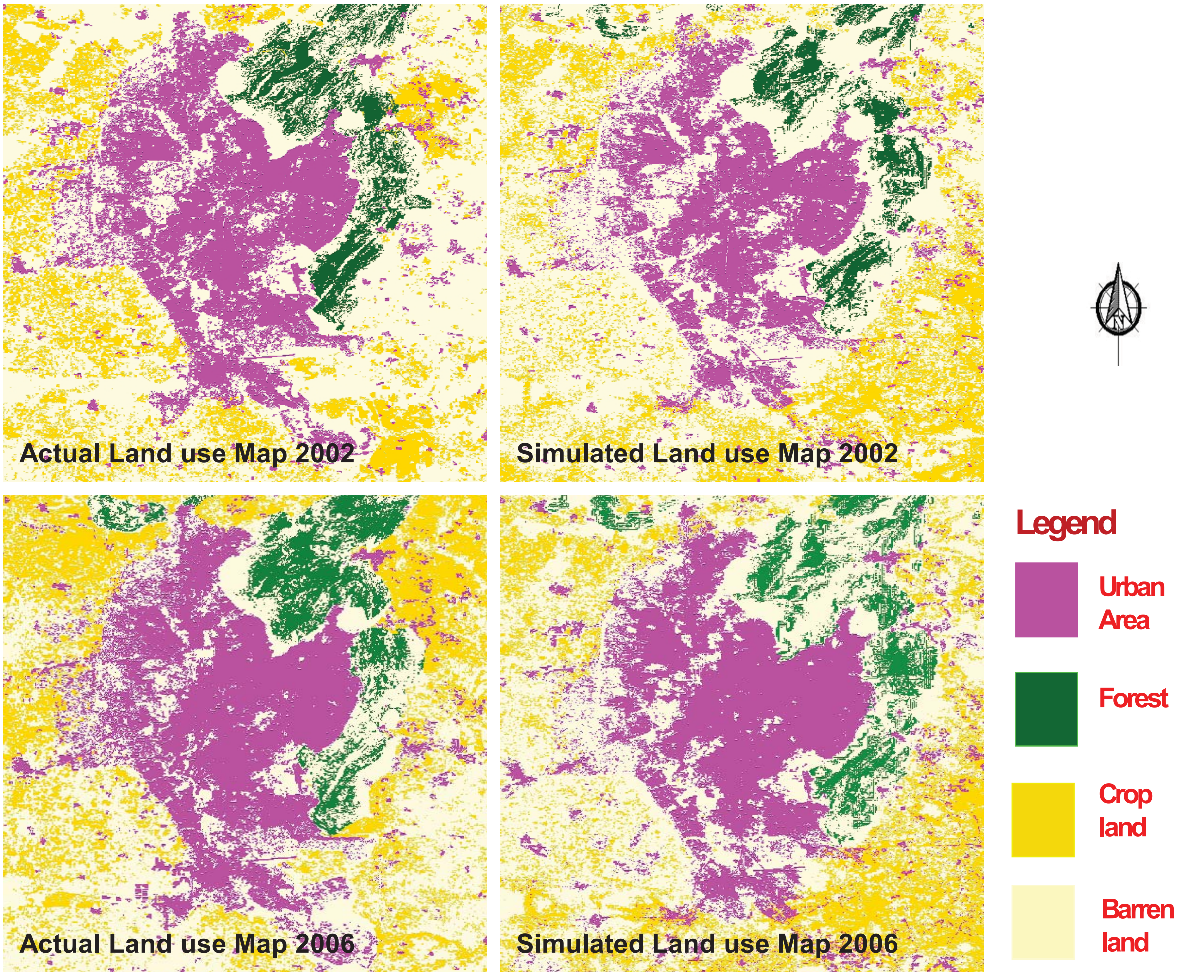

Figure 3.5 Actual and Simulated Land Use Maps of 2002 and 2006

Simulated and actual maps in Figure 3.5 have not much differences in dimension and magnitude of urban change for both periods. Urban change analysis indicates that, after 2000 maximum growth occurred on the periphery of main urban area and mainly along the major roads. Actual urban area showing high density compares to simulated urban area for both periods, especially in the southern part of the city. The urban change in southern part of the city shows an impact of industrial zone development and this has been verified by Google Earth. In the western part, actual suburban areas of 2006 have more density compared to simulated data. There are few new developments in suburban area showing impacts of road and infrastructure developments in the south western part of the city in actual data of 2006 and these are not observed in simulated data.

Total urban area in actual land use data from 2002 is 13,278 hectare and, which is just 5% more than the simulated data of 2002 i.e. 12,630 hectare shown in Figure 3.6. Instead of urban area class, there is a significant difference, especially in the vegetation cover classes such as crop land and forest land. This may be due to seasonal variation of data used for simulation and actual land use map. The main concentration in this research is urban change so seasonal variation of satellite data does not affect to urban change analysis. Random points are generated for accuracy assessment and in 750 random points 658 points are true for 2002 simulated data for urban area. The pixel accuracy has been validated for the urban area using GIS tools. One by one pixel accuracy between actual and simulated data is 93.7% based on simulated urban pixels of 2002. AAGR for simulated urban area in 2002 was 11.3%, where as 12.4% for actual urban from 1989.

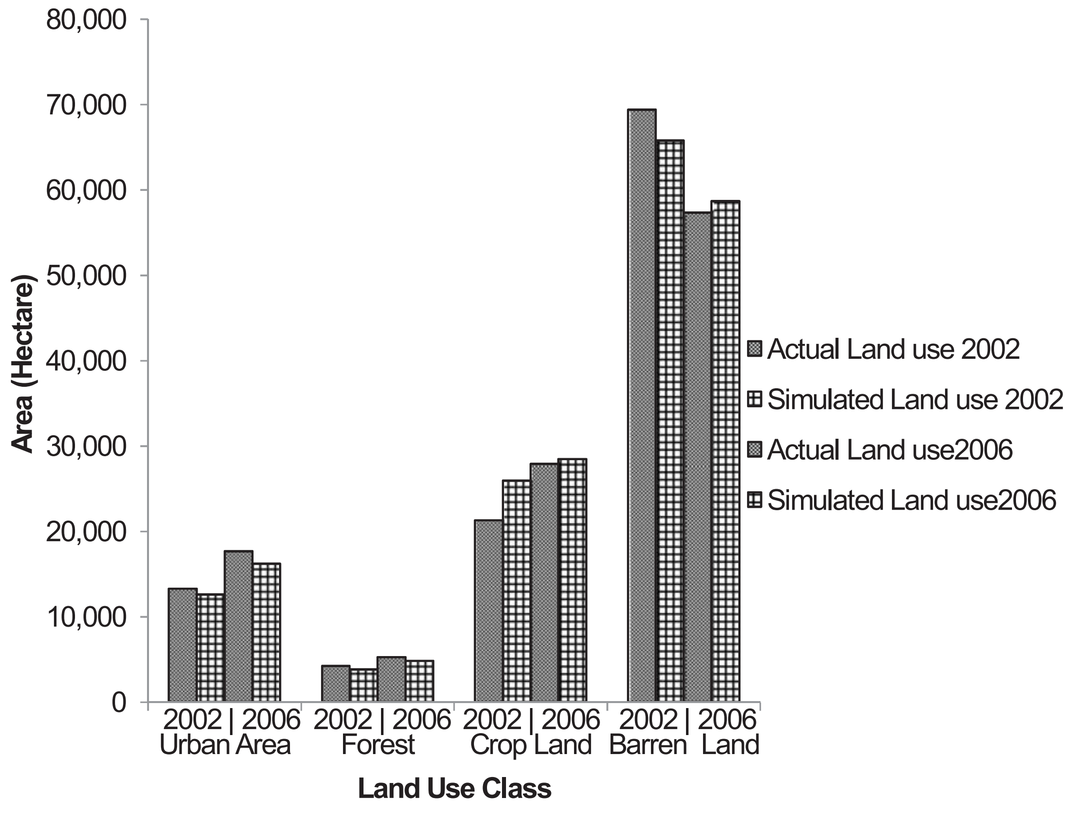

Figure 3.6 Graphical Representation of Actual and Simulated Land Use of 2002 and 2006

Simulated data of 2006 was having 16,207 hectare urban area, where as actual data was having 17,677 hectare. The density difference was significant between simulated and actual data of 2006. Density difference in urban area in actual data is found more on the periphery of the city. One by one pixel accuracy for based on simulated data of 2006 was 89.5%. AAGR for 2006 for actual data and simulated data are 8.2% and 7.1% respectively from 2002. This referred to steady urban growth for the city.

3.6 Concluding Remarks

Jaipur city is going through fast urban change. The city area grew by 145% from 1989 to 2002 in just 13years. The urban change is maximum on sub urban areas but as well as density is also increased in city centre areas. Urban change has been found in the almost all the direction of city. Mostly sub urban change showing impact of highways and industrial developments of city.

Urban change estimation and simulation in developing countries can be dependent on data availability, which can be easily gathered using widely available Satellite data and it can be integrated with GIS and automated databases with good quality levels.

Multi layer perceptron classifier approach used here has shown good results for urban change by integrating variables those that not only affect but also influence the transition of land and urban change. The analysis results of MLP–Markov model are showing high level of accuracy for the simulated data of urban change. Markov chain is widely used model, which help to describe pattern of urban change.

Urban simulation was successfully achieved using the MLP–Markov method for Jaipur city in India. This MLP–Markov method can overcome the limitation of using only the Markov model for simulating urban area and non-urban land cover by including the spatial predictable variables of urban change in a simulation model. The combination of these two is capable of describing the non-linear relationship. MLP is appropriate for describing complex relationships of land use as it is capable of describing $n*n$ conversion in land use. The Markov model has shown the potential to describe and predict urban change, which has been validated by comparing the estimated and simulated urban change.

The results are satisfactory enough to retain this method for the starting point to next step to simulate urban change for near future. However it is also important to simulate urban and checked with the actual urban for some other years and also need to include more policies that lead urban change of city. Urban change estimation and find out the dimension of change is necessary for urban planning and infrastructure development. This methodology shows good simulation results for the urban area of 2002 and 2006. It can be used for optimal planning of the land and urban change. It would be more interesting to use this method with high resolution satellite data such as 5m and 10m spatial resolution

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CHAPTER 4

URBAN CHANGE PATTERNS WITH LAND SUITABILITY

4.1 Introduction

Urban sprawl, a consequence of socioeconomic development under certain circumstances, has increasingly become a major issue facing by many metropolitan areas. Although a general consensus regarding the definition and impact of urban sprawl has not been achieved (Johnson, 2001), urban sprawl is often referred to as uncontrolled, scattered suburban development that increases traffic problems, depletes local resources, and destroys open space (Peiser, 2001). It is critically important to properly characterize urban sprawl in order to develop a comprehensive understanding of the causes and effects of urbanization processes. However, due to its association with poorly planned urban land use and economic activity (Pendall, 1999), urban sprawl is often evaluated and characterized exclusively based on major socioeconomic indicators such as population growth, commuting costs, employment shifts, city revenue change, and number of commercial establishments. This approach cannot effectively identify the impacts of urban sprawl in a spatial context. To fill this gap, remote sensing has been used to detect urban land cover changes in relation to urbanization. Remote sensing techniques have advantages in characterizing the spatiotemporal trends of urban sprawl using multi-stage images, providing a basis for projecting future urbanization processes. Such information can support policymaking in urban planning and natural resource conservation.

This study investigates the urban change pattern using remote sensing and GIS with an integrated approach involving multi-criteria evaluation (MCE) method for land suitability and landscape metrics analysis. In addition to this, scenario analysis is also performed to determine the impact of policy planning and implementation on the city and the effect of the time gap between the planning and implementation of policies for urban development. Hence, this research aims to ascertain the trends of urban change by estimating growth using multi-temporal remote sensing images. It explains how urban patterns are changing with land suitability during different periods and how the time gap between planning and implementation of a policy affects the management of urban development.

4.2 Literature Review

(i) Literature Review for Multi-Criteria and Land Suitability Analysis

Hopkins in 1977 describe the purpose and character of land suitability analysis, taxonomy of existing methods for identifying homogeneous areas and rating them as to suitability for specific uses, and a comparative evaluation of these methods. The integration of GIS and Multi–criteria Analysis method and present the reasons that have led to this integration and a conceptual framework to facilitate it (Laaribi et al. 1996). The three main objectives of the integration of GIS for land suitability analysis: (i) to provide an introduction to geographical information technology along with an historical perspective on the evolving role of Geographic Information Systems (GIS) in planning, (ii) to overview relevant methods and techniques for GIS based land-use suitability mapping and modeling, and (iii) to identify the trends, challenges and prospects of GIS-based land-use suitability analysis (Malczewski, 2004).

Tkach and Simonovic (1997) developed multi–criteria decision making technique by combining the conventional Compromise Programming technique with GIS technology. This new technique is referred to herein as Spatial Compromise Programming (SCP). The main contribution of the proposed technique is its ability to address uneven spatial distribution of criteria values in the evaluation and ranking of alternatives and spatial comparison of floodplain management alternatives in a raster GIS environment is conceptualized as a multi criteria decision making problem.

Steiner et al. (2000) did suitability analysis for the United States. Suitability analysis can be used for compliance with several elements of these plans. Here, a framework for land suitability analysis is presented for the upper Gila River watershed in Arizona and New Mexico. The framework is based on a thorough ecological inventory of the watershed. A goal of suitability analysis is to explicitly identify constraints and opportunities for future land conservation and development. This is accomplished by determining the fitness of a given tract of land for a defined use.

Baja et al. (2002) paper, presents the development of a conceptual model, within geographic information systems (GIS), for defining and assessing land management units from available biophysical information. The model consists of two main components (sub-models): land quality based suitability analysis and soil erosion estimation. Using a fuzzy set methodology, the first sub-model was constructed to derive a land suitability index (LSI) for a cropping land utilization type.

A multi-criteria evaluation (MCE) (Ceballos-Silva and López-Blanco, 2003) approach used to identify suitable areas for the production of maize and potato crops in Central Mexico is presented. Climate, relief and soil databases were used to integrate GIS raster coverage. Relevant criteria for crops and suitability levels were defined. This information was used to obtain the criteria maps, which in turn were used as input into the MCE algorithm. Several decision support procedures in the Idrisi GIS environment were applied to obtain the suitability maps for each crop.

Multi-criteria analysis used for selecting the location for housing sites by AL-Shalabi et al. (2006). The researcher found that it is a complex process involving not only technical requirement, but also physical, economical, social, environmental and political requirements that may result in conflicting objectives. Such complexities necessitate the simultaneous use of several decision support tools such as high spatial resolution remotely sensed data, Geographical Information System (GIS) and Multi Criteria Analysis (MCA) using analytical hierarchy process (AHP). In this research a model was developed to evaluate the possible location of building sites and to support decisions making in the location of additional housing areas in Sana'a city. This integration could benefit urban planners and decision makers.

(ii) Literature Review for Landscape Metrics Analysis

Herold et al. (2005) explores a framework combining remote sensing and spatial metrics aimed at improving the analysis and modeling of urban change and land use change. While remote sensing data have been used in urban modeling and analysis for some time, the proposed combination of remote sensing and spatial metrics for that purpose is quite novel. Starting with a review of recent developments in each of these fields, we show how the systematic, combined use of these tools can contribute an important new level of information to urban modeling and urban analysis in general.

Seto and Fragkias (2005) provide a dynamic inter- and intra-city analysis of spatial and temporal patterns of urban land use change. It is the first comparative analysis of a system of rapidly developing cities with landscape pattern metrics. Using ten classified Landsat Thematic Mapper images acquired from 1988 to 1999, quantify the annual rate of urban land-use change for four cities in southern China. The classified images were used to generate annual maps of urban extent, and landscape metrics were calculated and analyzed spatiotemporally across three buffer zones for each city for each year. The study shows that for comprehensive understanding of the shapes and trajectories of urban expansion, a spatiotemporal landscape metrics analysis across buffer zones is an improvement over using only urban growth rates. This type of analysis can also be used to infer underlying social, economic, and political processes that drive the observed urban forms.

Remotely sensed land cover data, landscape metrics were calculated for urban sprawl (Ji et al., 2006) the remotely sensed data and landscape metrics were used to characterize long-term trends and patterns of urban sprawl. Land cover change analyses at the metropolitan, county, and city levels reveal that over the past three decades the significant increase of built-up land in the study area was mainly at the expense of non-forest vegetation cover. The spatial and temporal heterogeneity of the land cover changes allowed the identification of fast and slow sprawling areas.

4.3 Urban Change Patterns with Land Suitability

Land suitability is the fitness of a given type of land for a defined use. The land may be considered in its present condition or after improvements. The process of land suitability classification is the appraisal and grouping of specific areas of land in terms of their suitability for defined uses. Land suitability analysis aims to identify the most appropriate spatial pattern for future land uses based on specific requirements (Hopkins, 1977; Collins et al., 2001; Malczewski, 2004). Land suitability analysis involves the application of criteria to the landscape to assess where land is most and least suitable for development of structures and infrastructure. MCE using GIS is a technique for standardization of criteria and multiplying each criterion with its weight factor to produce results (Store and Kangas, 2001). Land suitability analysis using GIS and the MCE approach has been applied to landscape evaluation (Miller et al., 1992), to land use planning and urban development (Dai et al., 2001; Jain and Subbaiah, 2007) and Ceballos-Silva and López-Blanco (2003) used MCE for delineation of suitable land for crops. MCE is able to handle the discrete decision situations where the choice-possibilities are measurable and data have a quantitative and/or a qualitative character (Pettit and Pullar, 1999). Laaribi et al. (1996) recommended the integration of GIS and multi-criteria analysis methods to enlighten decision makers in solving problems that contain a spatial dimension. A multi-criteria evaluation (MCE) method used for suitability analysis and process of modeling urban change pattern dynamics as shown in Figure 4.1.

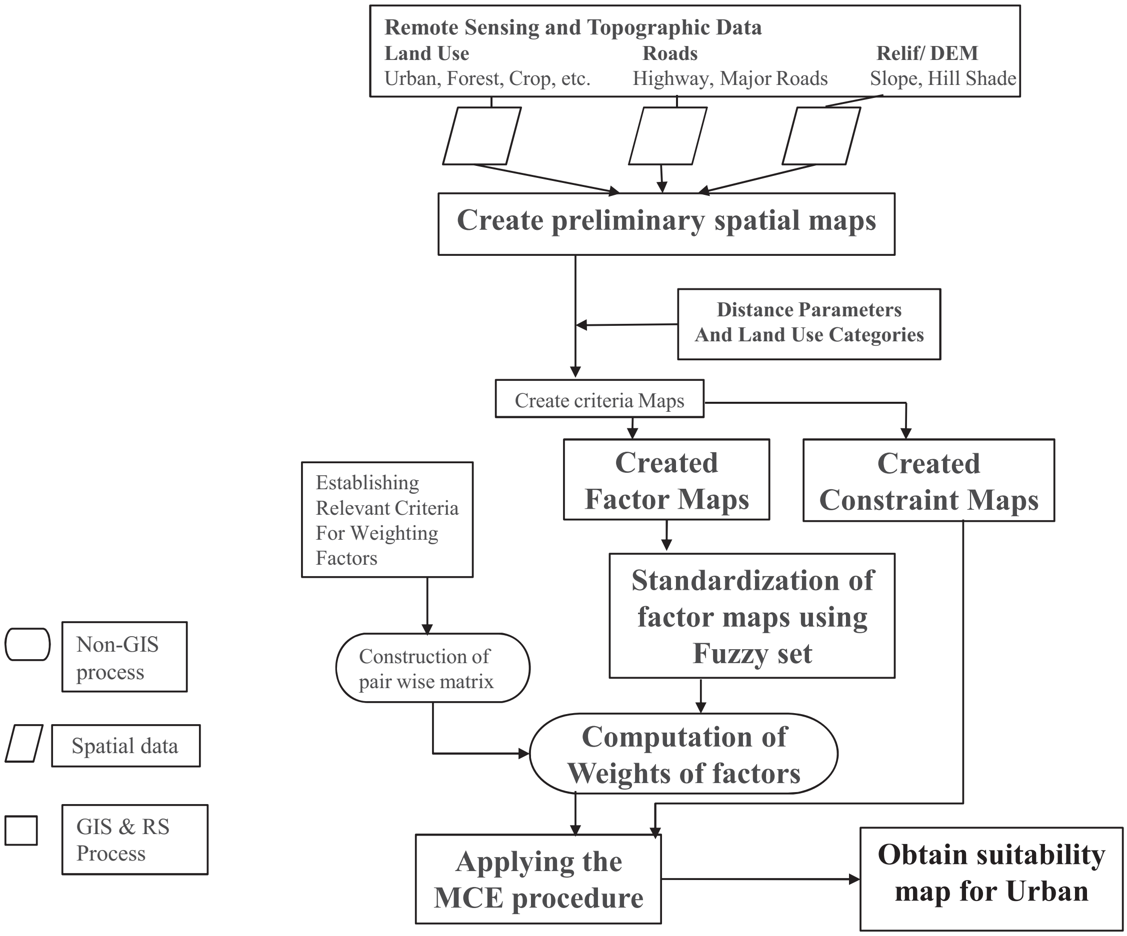

Figure 4.1 Method Flow Diagram of MCE Process

4.3.1 Materials and Methods for Land Suitability Analysis

Urban suitability helps to explain a city's growth patterns as well as environmental issues (Jain and Subbaiah, 2007). The MCE decision support tool has been implemented for urban land suitability analysis. A decision is a choice between alternatives such as actions or land allocations, etc. (Eastman et al., 1995). In MCE, an attempt is made to combine a set of criteria to achieve a single composite basis for decision making, according to a specific objective. This MCE method is based on a weighted linear combination where criteria may include both weighted factors and constraints. In weighted linear combinations, factors are combined by applying a weight to each factor and multiplying the suitability calculated from the factors by the product of the constraints as shown in Equation (4-1).

$$S = \sum (w_i x_i) * \prod c_j \qquad (4\text{-}1)$$

where S means suitability, w_i is the weight of factor i, x_i is the criterion score of the factor i, and c_j is the criterion score of constraint j.

Land suitability can be assessed by two main attributes, that is, geographical location and physical properties. Geographical location can be defined as distance, such as the relative distance of a piece of land from an urban centre, whereas physical properties include soil properties, water conditions, topography, and size. Urban suitability is more related to location factors, transportation conditions, and topographic features (Yeh and Li, 1998). Factor weights are very important in weighted linear combinations because they determine how individual factors will be traded off relative to each other. Factors established in this phase are not unique, but they are the most relevant. Suitability levels for each factor were classified and used as a base to construct the criteria maps (one for each factor). The levels are 5 (very high suitability), 4 (high suitability), 3 (medium suitability), 2 (low suitability), and 1 (very low suitability). Before calculating the weights for factors, it is also important to standardize all factors on a common scale of measurement to facilitate analysis, which is done using a fuzzy set approach. The process of standardization and of defining the factor weights is explained in the next sub-sections.

4.3.1.1 Data Used

Urban land suitability analyzed for Jaipur city, India. Jaipur city is situated between the approximate Latitude 27.88 N, Longitude 74.88 E and Latitude 26.42 N, Longitude 76.29 E (Degree Decimal) and is the capital of Rajasthan state, India. Landsat satellite data have been used to prepare land use maps of the city and simulated urban using multi-layer perceptron-Markov method. Road and digital elevation models have been prepared by using toposheets of 1:50,000. The different factors and constraints used in MCE process are created using GIS capabilities.

4.3.1.2 Standardization of Factors Using Fuzzy Set

A primary step is to ensure a standardized measurement system across all the factors being considered. Since most images still hold the cell values, the original map codes have different units and different scales of measurement. Therefore, these have to be standardized to a uniform suitability rating scale before being used in Equation 6 (Pereira and Duckstein, 1993).

A fuzzy set is most commonly used for classifications of objects or phenomena in continuous values, where the classes do not have sharply defined boundaries (Burrough et al., 1992; Collins et al., 2001). Fuzzy set theory suggests that the inclusion of an element within a set is a matter of determination of the degree of belongings. A fuzzy set is a class of objects with a continuum of grades of membership (Zadeh, 1965). Such a set is characterized by a membership function that assigns to each object a grade of membership ranging between 0 and 255 on a byte scale. A fuzzy set *A* may be defined (Banai, 1993) as follows.

Let $X = \{x\}$ denote a finite (or definable) set (or space) of n points (or objects/elements/properties). For example:

Road proximity properties X = {Urban area extremely far from road (x_1), Urban area moderately far from road (x_2), Urban area extremely near to road (x_3)}.

A fuzzy set A in X is a set of ordered pairs denoted by $A = \{x, mA(x)\}$, with *x E X* (which means that *x* is an element of, or is contained, in *X*). For example, urban area extremely near to road x_3 belongs to road proximity properties *X*.

$$A = \{x, mA(x)\} x \in X \tag{4-2}$$

where $X = \{x\}$ is a finite set (or space) of objects or phenomena, $mA(x)$ is a membership function of *X* in *A*. Therefore, a fuzzy set is defined by the membership function that defines the membership grades of fuzzy objects or phenomena in the ordered pairs, consisting of the objects and their membership grades. The membership function of a fuzzy set determines the degree of membership of *x* in *A* (Burrough, 1989).

The methods used in the standardization of factors have been defined in Table 4.1. Factors used for land suitability analysis were standardized to a common scale of suitability, i.e., 0–255 on a byte scale. For instance, as a method for standardization of the proximity to road factor, the area near to the road or at 400m distance is assigned a set of membership 255; those beyond 800m distance from the road are considered very far and assigned the value 0. Before this factor's standardization its values ranged from 0 to 2400m.

Table 4.1 Standardization of Factors

Factor	Membership Function	Details
Proximity to City Center	Linear monotonically decreasing	Area near to city assigned a set of Membership 255 (on a scale of 0-255), area far from city have value of 0.
Proximity to Major Roads	J-Shaped monotonically decreasing	This factor range from 50m to800m for suitability value of 255 and 0 respectively on scale 0-255.
Slope	Sigmoidal monotonically decreasing	Slope less than 0-4% assigned 255 and more than 15% assigned 0 on suitability scale 0-255.
Proximity to Water	Sigmoidal monotonically increasing	Distance less than 200 m assigned value 0 and more than it value of 255 (on a scale of 0-255).
Proximity to City Urban	Linear monotonically decreasing	Suitability range from 0-255 (nearest location to city urban 255 values) for the factor.

4.3.1.3 Weighting Criteria for the Factors

Defining the weight of factors began with assigning a potential ranking and potential weight to each factor. In the beginning, each factor was assigned a potential ranking based on its land suitability and was put into one of five categories. The suitability of the factors varied from very low suitability to very high suitability for urban change. For instance, proximity to the city center factor has been placed in five categories based on the distance from the city center, which is showing distance preferences to the city center (Table 4.2).

Table 4.2 Potential Ranking of Factors

Factors	Potential Ranking/Suitability of Each Category of Factors				
	1/Very Low Suitability	2/Low Suitability	3/Medium Suitability	4/High Suitability	5/Very High Suitability
Existing Land use	Forest Land/ Built Area	Wet Lands	Agriculture Land	Quasi Open	Barren Land/ Vacant land
Proximity to City Center	>10km	10-7km	7-4km	4- 1km	<1km
Proximity to Water	>1500m	1500-1200m	1200-900m	900m-600m	200-600m
Proximity to Major Roads	>8km	8-5km	5-2km	2-500m	<500m
Slope	>16%	12-16%	8-12%	4-8%	0-4%
Proximity to City Urban	>8km	8-5km	5-2km	2- 500m	<500m

At the same time, potential weights have been defined for these factors by analyzing the change in urban area from 1975 to 2006.

Here our objective was to find out the suitable land area for urban development. And urban land suitability is more related to location factors, transport conditions and topographic features. To achieve this objective location, transport related and topographic based factors were used for this analysis. Potential ranking and potential weights are used to calculate weight for these factors for land suitability analysis. Potential weights are defined based on past to current urban development of Jaipur city. Urban area estimated using satellite data of 1975, 1989, 2000, 2002 and 2006 to ascertain change in urban development from past to current. This estimated urban area is extracted from each factor of land suitability for 1975, 1989, 2000, 2002 and 2006. Based on extracted urban area from each factor, ordinal ranking is assigned to these factors. Factor, which has more urban area, is assigned high ordinal rank and less urban area assigned low ordinal rank.

The calculation of potential weights are completely based on past urban growth patterns, so this is the real representation of change in urban development and very important criteria for urban land suitability analysis. Limitation of this potential weight selection is that it is based only on past changes in urban growth not based on the future plan of urban growth.

Table 4.3 Potential Weights of Factor

Factors	Potential Weights
Existing Land use	2
Proximity to City Center	3
Proximity to Water	2
Proximity to Major Roads	7
Slope	7
Proximity to City Urban	6

These potential weights and potential rankings have been used in Equation (4-3) for computation of ratings for factors. The potential weights and rankings have been combined with the standard formula for the weighted average: the sum of the product of ranking multiplied by the respective potential weight for each factor, divided by the sum of potential weight.

$$Rating = \frac{w_1 r_1 + w_2 r_2 + \ldots\ldots + w_6 r_6}{w_1 + w_2 + \ldots\ldots + w_6} \tag{4-3}$$

where w is the potential weight of each factor and r is the potential ranking of each category of factors.

These calculated ratings of the factors have been used for computing the comparative importance between two factors. Ratings of factors are combined with their corresponding potential weight to create the pairwise comparison matrix using Equation (4-3) and by replacing rankings with ratings in the equation. For example, the calculated ratings of proximity to road and slope have been used in Equation (4-3) and these ratings of factors are multiplied by their corresponding potential weights and divided by the sum of potential weights. By this comparative calculation of these two factors, we obtained the value 3.88 as shown in Table 4.4. We compared every possible pairing of factors for developing the weights for the MCE procedure and prepared a pairwise comparison matrix. As the matrix is asymmetrical, only the lower triangular half, in fact, needs to be filled in, with the remaining cells then simply having the reciprocal values.

Table 4.4 Pairwise Comparison Matrix Assessing Comparative Importance of Factors

Factors	Existing Land use	Proximity To City Centre	Proximity To Water	Proximity To Major Roads	Slope Gradient	Proximity To City Urban
Existing Land use	1.00					
Proximity To City Center	1.44	1.00				
Proximity To Water	1.11	1.00	1.00			
Proximity To Major Roads	3.27	2.50	2.70	1.00		
Slope	2.94	2.70	2.90	3.88	1.00	
Proximity To City Urban	2.69	2.20	2.40	3.58	3.50	1.00

The principal eigenvector has been computed for the pairwise comparison matrix to produce a best fit set of weights (Table 4.5). The consistency ratio indicates the probability that the ratings were developed by chance. A consistency ratio indicates that the matrix whose value is greater than 0.10 should be re-evaluated (Saaty, 1987).

Table 4.5 Weights Derived from Pairwise Comparison Matrix using Principal Eigenvector

Factors	Weights
Existing Land use	0.0716
Proximity To City center	0.0896
Proximity To Water	0.0824
Proximity To Major Roads	0.1513
Slope	0.2474
Proximity To City urban	0.3576
Consistency Ratio = 0.09	

4.3.2 Results and Discussion

4.3.2.1 Analyzing Standardized Factors using Fuzzy Set

Factors used for land suitability analysis have been standardized to common scale of suitability i.e. 0-255 byte scale. Following figures in this section are results of standardized of factors.

Figure 4.2a and 4.2b are representing factor proximity to road before and after standardized. Before standardization distance values vary from 0 to around 2400m but after standardization maximum value is varying from 0 to 255. Thus area near to road or 50m assigned a set of Membership 255 those beyond 800m to road were considered very far and assigned value 0.

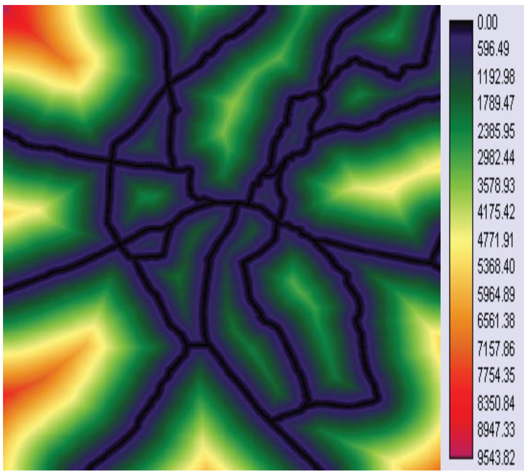

Figure 4.2a Proximity to Road-Before Standardization

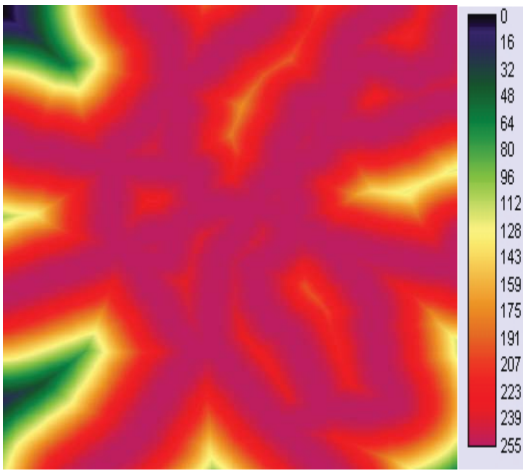

Figure 4.2b After Standardization

Figure 4.3a and 4.3b shows standardization of slope factor in that value vary from 0 to 177 percent before standardization but after standardization maximum value is vary between 0-255. Slope percentage 0-4 assigned value 255 and more than 15% assigned value 0.

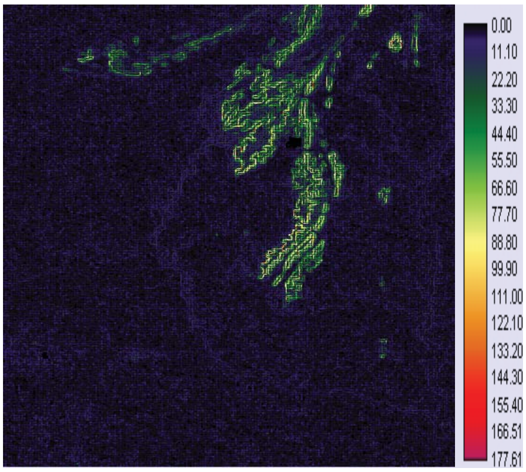

Figure 4.3a Slope-Before Standardization

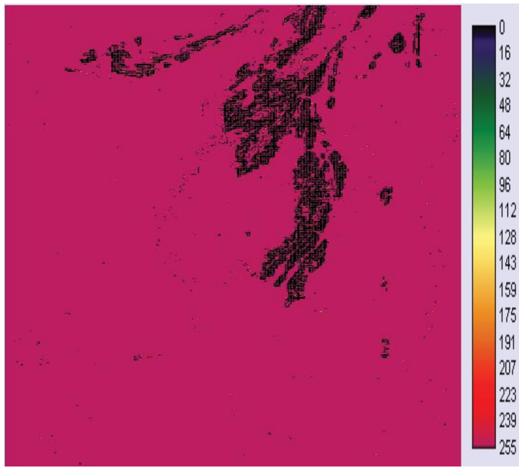

Figure 4.3b After Standardization

Factor proximity to water is shown in Figure 4.4a and 4.4b before and after standardization respectively in that maximum distance is 16000m before standardization. But after performing standardization value vary for this factor from 0 to 255. Less than 200 m near to water assigned value 0 on Membership 255 (on a scale of 0-255), and more than it have value of 255 using fuzzy set.

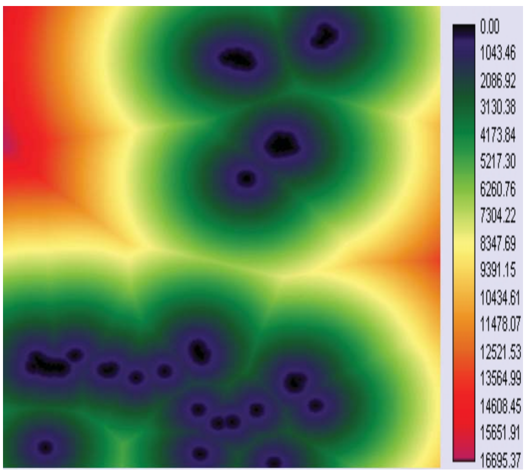

Figure 4.4a Proximity to Water-Before Standardization

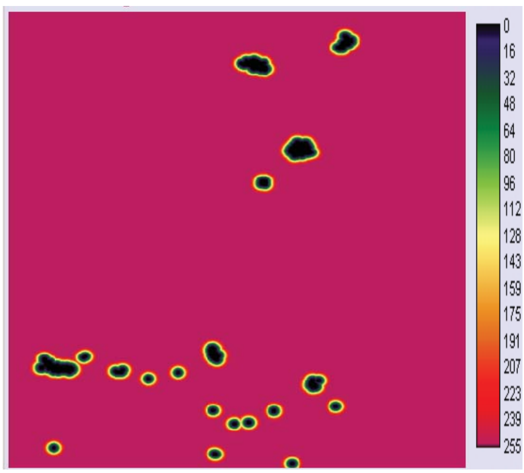

Figure 4.4b After Standardization

Figure 4.5 maps represent the factor proximity to city centre in that maximum distance from city centre 26300m before standardization. After performing standardization for the factor value vary from 0 to 255. Area near to city assigned a set of Membership 255 (on a scale of 0-255), area far from city have value of 0.

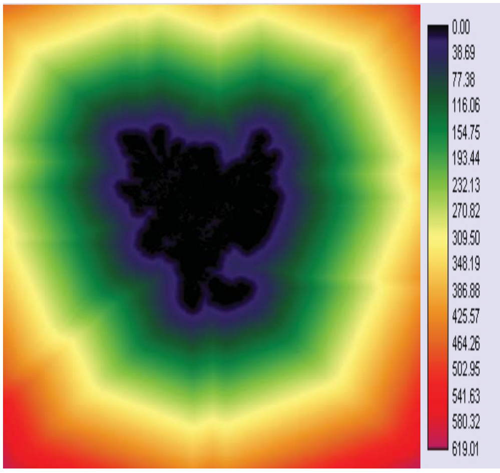

Figure 4.5a Proximity to City centre-Before Standardization

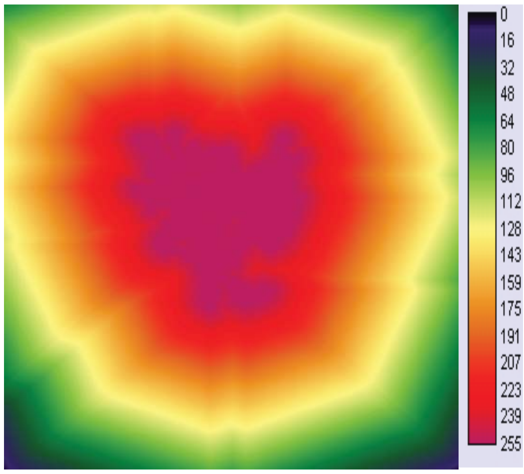

Figure 4.5b After Standardization

4.3.2.2 Urban Land Suitability Analysis for Jaipur City

Land suitability assessed for the urban area of Jaipur city and the factors mentioned in Table 1 have been used for this analysis. Forest, existing urban area, and water bodies have been used as a constraint. These factors and constraints have been integrated into the MCE process. The urban extent of 1989 has been used as a base urban area for the suitability map.

The suitability map is shown in Figure 4.6. The suitability map ranges between 0 and 255 where 0 is the unsuitable area and 255 is the most suitable area. Existing urban, forest, and water bodies are preserved as the unsuitable areas for urban growth. The suitability map shows the impact of factors like proximity to major roads and proximity to city urban and city center. Figure 4.6 indicates that the most suitable areas are near to the city urban and along the major roads.

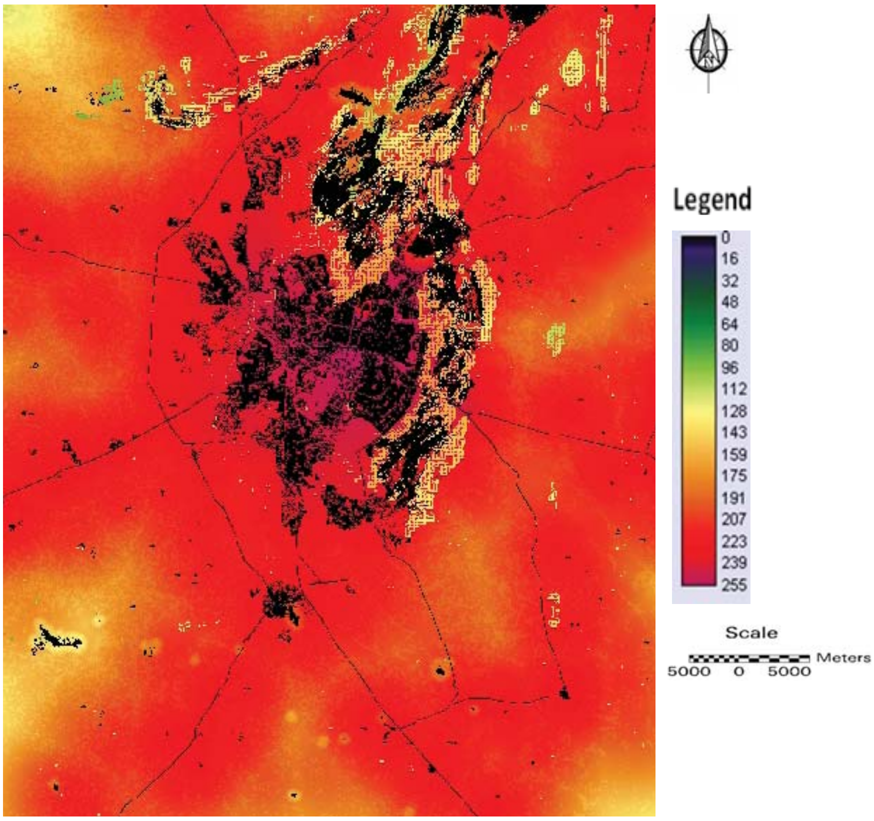

Figure 4.6 Urban Suitability Map of Jaipur City

4.3.2.3 Urban Change with Urban Land Suitability

Applying the GIS tool, urban land suitability is evaluated to investigate the urban change patterns. For the analysis, an urban suitability map has been reclassified into five categories: 1 very low suitability, 2 low suitability, 3 medium suitability, 4 high suitability, and 5 very high suitability. Here, very low suitability areas include the existing built area, forests, waterways, and roads.

A comparison of urban growth patterns with land suitability have been made in terms of actual and simulated data. Table 4.6 shows urban areas in all suitable categories using actual and simulated data of 2002 and 2006. Urban areas for both periods and for both kinds of data show the same trends, with the urban area showing the highest growth in the very highly suitable areas, then in highly suitable, followed by medium suitable land areas. At the same time, the urban area is increasing at a high rate in the highly suitable areas, compared to the other categories of suitability of 2006. This indicates that the impact of proximity to urban centers and major roads, as well as of the growth of urban areas is moving from the center of the city to the suburban areas.

Table 4.6 Actual and Simulated Urban Area with Suitability

(Hectare)

Suitability Level / Urban Area	Very Low Suitable	Low Suitable	Medium Suitable	High Suitable	Very High Suitable
Actual Urban Area 2002	0	0.3	346.9 (4%)	2785.4 (30%)	6378.7 (67%)
Simulated Urban Area 2002	0	0.1	245.0(3%)	2300.0 (29%)	5310.2 (67%)
Actual Urban Area 2006	0	1.2	556.4 (5%)	4345.5 (35%)	7379.1(60%)
Simulated Urban Area 2006	0	0.4	445.5 (4%)	3844.2 (34%)	7127.2 (62%)

Table 4.7 shows the categorical information of urban growth patterns along with land suitability during 1989–2000, 2000–2002, and 2002–2006. Urban growth during 1989–2000 was highest in terms of very highly suitable land area, i.e., 56%; followed by highly suitable area, i.e., 35%. It indicated that urban patterns followed proximity to city centers and proximity to roads. During 2000–2002, very highly suitable areas and highly suitable areas made up 58% and 33% of urban change, respectively, and showed the same patterns as in previous periods. Urban change from 2002 to 2006 showed a different pattern with highest urban change found in highly suitable land areas, i.e., 55%, followed by growth in very highly suitable land areas, i.e. 36%, compared urban change in previous periods (1989–2000 and 2000–2002). This indicates that urban change is more on the outskirts than near to the city centers, and the growth share is higher on the periphery of the city during 2002–2006. From this growth pattern, we can say that urbanization is increasing on the city periphery during the 2002–2006 periods, and it will increase in the future.

Table 4.7 Change in Urban Area with Suitability (Hectare)

(% From Total Change)

Suitability Level / **Urban Change**	Very Low Suitable	Low Suitable	Medium Suitable	High Suitable	Very High Suitable
Change 1989-2000	0	27(0.5%)	454(8%)	2042(35%)	3293(56%)
Change 2000-2002	0	17(0.5%)	330(8%)	1276(33%)	2275(58%)
Change 2002-2006	0	0.99 (0.04%)	228 (8%)	1589(55%)	1065 (36%)

4.4 Impact Assessment of Urban Change Patterns on Proposed Land Use Plans

Landscape metrics (indices) are numeric measurements that quantify spatial patterning of land cover patches, land cover classes, or entire landscape mosaics of a geographic area (McGarigal and Marks, 1995). Herold et al. (2002) and Herold et al. (2003) conducted a comprehensive study on measuring urban land cover dynamics using remote sensing and spatial (landscape) metrics that were analyzed and interpreted in conjunction with the spatial modeling of urban change. Based on a 72-year time series data set compiled from interpreted historical aerial photographs and from IKONOS satellite imagery, their study demonstrated that an approach that combines remote sensing, landscape metrics and urban modeling analysis may prove a promising new tool for understanding spatiotemporal patterns of urbanization. Other studies also explored various methods for applying landscape metrics in urban land cover research, such as urban gradient analysis (Luck and Wu, 2002) and the assessment of forest fragmentation (Civco et al. 2002).

4.4.1 Methodology and Data Used

Based on the remotely sensed land cover data, selected landscape metrics were calculated using the FRAGSTATS program (McGarigal and Marks, 1995) for Jaipur City.

Landscape metrics using FRAGSTATS version 3.3 (McGarigal et al., 2002) have provided platform for the description of spatial structure and pattern of urban density change. Landscape is comprised of spatial patches categorized in different patch classes used for spatial metric calculation (Herold et al. 2003). FRAGSTATS has been used for calculation of metric described in Table 4.8. Class area measures composition of landscape and describe how much of the area is comprised of a particular patch type. Patch density expresses number of patches on a per unit area basis that facilitates comparisons among landscapes of varying size. Largest patch index at the class level quantifies the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance. The Edge Density (ED) measures the total amount of the edge of the urban patches divided by the total landscape area. ED increase with the new urban development and decrease with merging and fusing of urban patches. While area weighted mean patch fractal dimension (FRAC_AM) value ranges between 1 and 2, and it explains the shape of urban class. As value increases for FRAC_AM, its mean that urban area is having a more irregular and complex shape, where as if a value is near to 1 then it indicates the relatively simple shape such as rectangular, circle or square.

Table 4.8 Description of Landscape Metrics

Metrics	Description/ Calculation Scheme	Units
CA—Class area	CA equals the sum of the areas (m2) of all urban patches, divided by 10,000 (to convert to hectares); that is, total urban area in the landscape.	Hectares
PD—Patch Density	PD equals the number of patches of the corresponding patch type divided by total landscape area (m^2)	Number per 100 hectares
LPI—Largest patch index	LPI equals the area (m^2) of the largest patch of the corresponding patch type divided by total landscape area (m^2), multiplied by 100 (to convert to a percentage)	Percent
ED—Edge density	ED equals the sum of the lengths (m) of all edge segments involving the corresponding patch type, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares).	Meters/ Hectare
LSI—Landscape Shape Index	LSI equals the total length of edge (or perimeter) involving the corresponding class, given in number of cell surfaces, divided by the minimum length of class edge (or perimeter)	None
AWMPFD—Area weighted mean patch fractal dimension	Area weighted mean value of the fractal dimension values of all urban patches, the fractal dimension of a patch equals two times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m2); the perimeter is adjusted to correct for the raster bias in perimeter.	None

Landscape metrics based on remotely sensed land use data have been calculated in this research. Landscape metrics can be used to quantify the spatial heterogeneity of classes and ascertain the changes in the urban pattern (Ji et al., 2006; Seto and Fragkias, 2005). Two landscape metrics named Edge Density (ED) and Area Weighted Mean Patch Fractal Dimension (AWMPFD) are measured using the FRAGSTATS tool for estimated and simulated data (McGarigal et al., 2002).

ED measures the total amount of the edge of the urban patches divided by the total landscape area. ED increases with new urban development and decreases with the merging and fusing of urban patches. At the same time, AWMPFD values range between 1 and 2, and explain the shape of urban classes. As the value for AWMPFD increases, the urban area takes on a more irregular and complex shape; whereas if its value is near to 1, the area takes on a relatively simple shape such as a rectangle, circle, or square.

4.4.2 Result and Discussion

4.4.2.1 Scenario Analysis based on Land use Plan and Policies 2011

Landscape metrics has been calculated for different urban classes to ascertain change in their spatial structure, complexity, size and shape using FRAGSTATS. The results of spatial metrics have been displayed in Figure 8. Figure 8 contain all six spatial metric class area (CA), patch density (PD), landscape patch index (LPI), landscape shape index, edge density (ED) and area weighted mean patch fractal dimension (FRAC_AM)analyzed in this study.

The class area (CA) has shown in Figure 4.7a, which indicates the increase in area of different urban classes. In general we can say that there is enormous increase in urban area in all categories during study period. Medium dense urban and low dense urban have maximum urban growth during 1989-2000 and 2000-2005. the other categories also have huge growth in their area, such as suburban was 462 hectare in 1989 and reached to 2312 hectare in 2005 and industries area was 408 hectare in 1989 and reached to 1329 hectare in 2005.

Patch Density (PD) is explained in Figure 4.7b. This indicates that urban classes those are on outskirt of city continuously increasing during study period such suburban and industries, where as classes near the urban centre are increasing from 1989-2000 and then decreasing from 2000-2005 such as high dense urban, medium dense urban and low dense urban. The increasing in PD in outskirt area of city is enormous such as PD for industries was 0.0455 in 1989 and it reached to 0.2588 in 2005 and same kind of trend found in suburban class.

Landscape patch index (LPI) is having continuous increase from 1989 to 2005 for all urban class instead of medium dense urban class (Figure 4.7c). This decrease in LPI for medium dense urban probably affected by the development of discontinuous urban feature in 2000. The LPI has increased by 267% for sub urban class and 198% for industries, where as LPI has increased for high dense urban by 40% and for low dense urban increased by 53% during 1989-2005.

Landscape shape index (LSI) describes the shape of class or patch. If LSI values are near to 1 then shape is square and if LSI increase without limit then patch types become more disaggregate. LSI has higher values for all urban classes. This LSI has higher values for urban classes more in low dense urban and sub urban, which indicated disaggregated patches on outskirt of city (Figure 4.7d). High dense urban has lowest LSI values, which imply that this urban class has less disaggregate patches.

Edge density (ED) increase always increase with patch and decrease with merging and fusing of patches. ED is increasing for medium dense urban, suburban and industries class and indicated that there is enormous increase fragmentation and development of continuous urban features during 1989-2005 (Figure 4.7e). ED for low dense urban is increased during 1989-2000, which indicates the new urban development and decreased during 2000-2005, which indicates merging and fusing of urban patches. ED for high dense urban decreased during 1989-2000 and then increased in 2000-2005.

Fractal property of patch has been measured area weighted mean patch fractal dimension (FRAC_AM) to find out shape complexity and this also improves the measure of class patch fragmentation. The value of FRAC_AM is range from 1 to 2. If the value is near to 1 than shape is less complex and near to 2 than shape is more complex. FRAC_AM is decreasing in all urban classes from 1989 to 2005 but have higher FRAC_AM values, which indicate complexity in shape (Figure 4.7f).

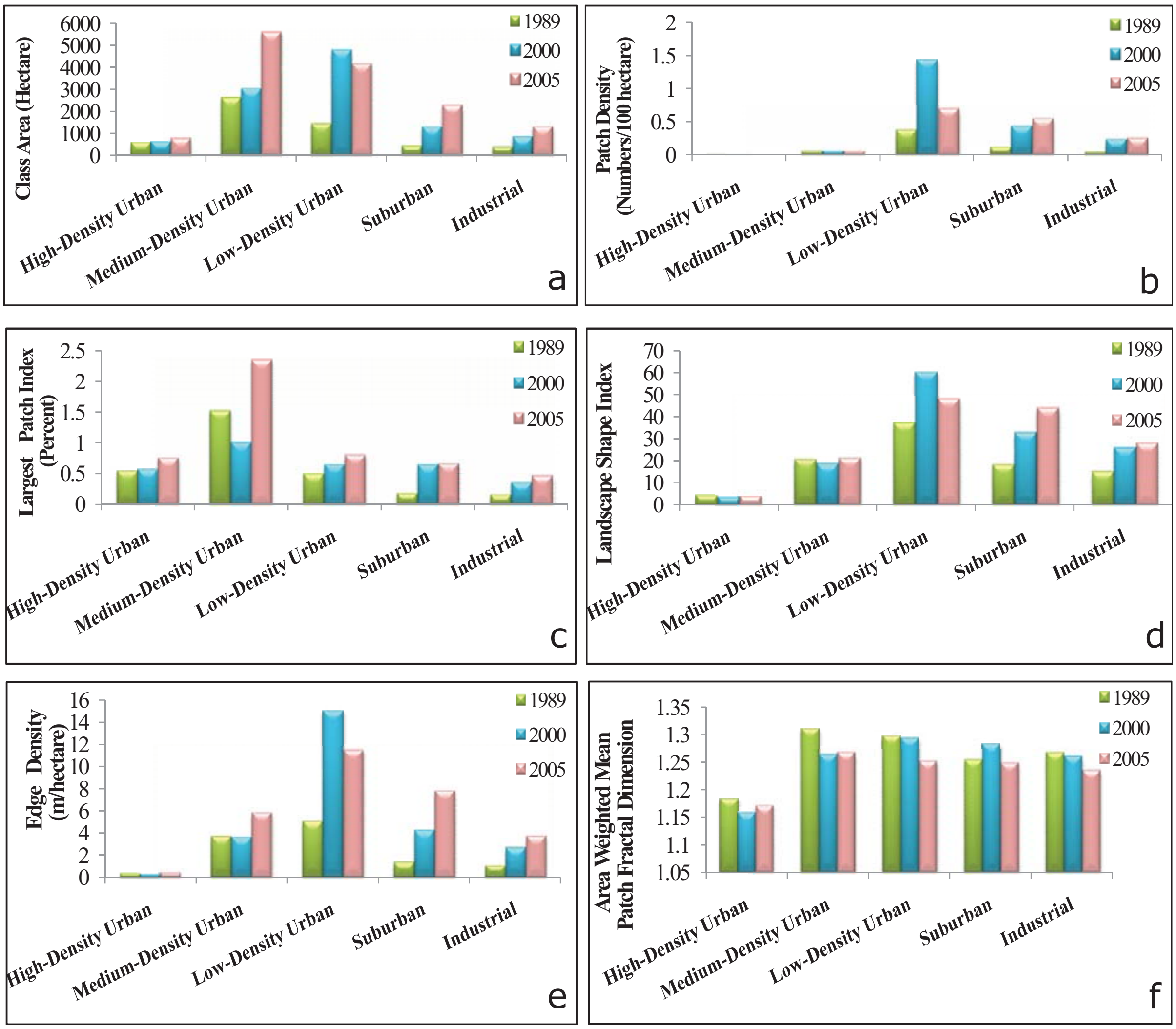

Figure 4.7 Landscape Metrics based Analysis for Plan and Policies of Jaipur City

4.4.2.2 Scenario Analysis based on Land use Plan and Policies 2025

Scenario I

The Jaipur city authority has proposed a land use plan for 2025 in its master plan. This proposed land use indicates the future demarcated and designated areas for different land use classes such as residential, commercial, institutional, and industrial. The aim of this scenario is to ascertain the growth pattern in the areas allocated for residential, commercial, and industrial use in the proposed land use of 2025 by using estimated data of 2006 and simulated data for 2015 and 2025.

The estimated data of 2006, simulated data of 2015, and simulated data of 2025 have been extracted from a proposed land use map of 2025 for all three of the above categories. The landscape metrics have been calculated including Edge Density (ED) and Area Weighted Mean Patch Fractal Dimension (AWMPFD) for all three periods.

The ED of the residential class shows enormous increases during both 2006–2015 and 2015–2025 from actual urban data of 2006 to simulated urban data of 2015 and 2025. This indicates an increase in new residential patches, which implies high growth in residential areas. The ED of commercial areas also indicates a continuous increase from actual data to simulated data during 2006–2025. ED was close to 1.7 in 2006 and will reach 5 in 2025 for commercial patches. The ED of the industrial class will double, which indicates enlargement of the industrial area during 2006–2015. ED in 2025 will decrease compared with 2015, which indicates the increased density of industrial areas (Figure 4.8a).

AWMPFD has also been measured for all these categories to ascertain the complexity of these classes. AWMPFD for the residential class is decreasing from actual urban data to simulated data during 2006–2015, which indicates that the residential area is moving toward the more regular shape of urban areas. However, AWMPFD during 2015–2025 is increasing, which implies that the complexity of the residential area is increasing and its shape is becoming more irregular. The commercial area shows a trend similar to that of the residential class, so that the commercial area is moving toward a regular shape during 2006–2015. However, the complexity and irregularity in shape of the commercial class increases during 2015–2025. AWMPFD for the industrial class indicates increased complexity and irregularity in shape during 2006–2015, whereas AWMPFD decreases during 2015–2025. This decrease means that the industrial area is becoming more regular and less complex in shape (Figure 4.8b).

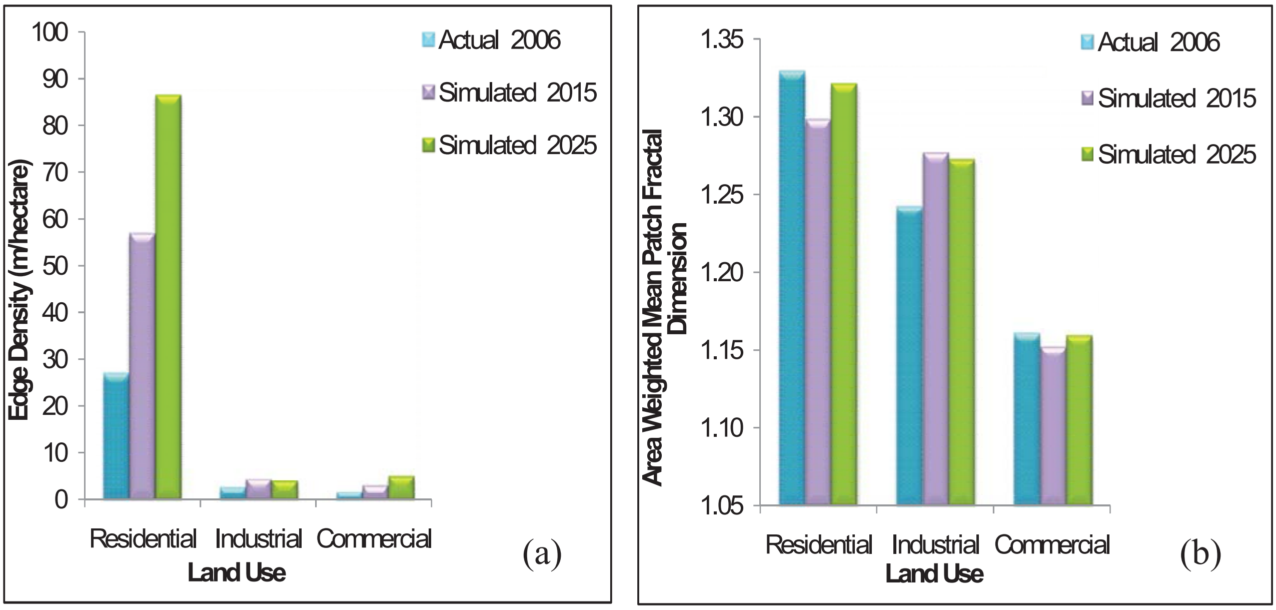

Figure 4.8 Edge Density (a) and Area Weighted Mean Patch Fractal Dimension (b) for different Periods and Land Use

Scenario II

In this scenario analysis, the urban area has been re-simulated for 2015 and 2025 by including commercial and industrial areas proposed in the 2025 land use plan. The aim of this analysis is to ascertain the impacts of commercial and industrial areas on urban change. The variable proximity to commercial and industrial areas has been created using the proposed land use plan for 2025 and is used as an input variable in the simulation model for predicting urban change for 2015 and 2025. This simulated data are analyzed with inclusion of proximity variable, termed as with inclusion (w/i) and also analyzed by excluding the above variable, termed as without inclusion (w/o). For further analysis of simulated urban data, different zones based on distance (such as urban change within 250m, 250–500m, and 500–750m distance from proposed commercial and industrial areas) have been created for the proposed commercial and industrial classes to explore the impact of proximity to commercial and industrial activities on urban change. These zones are categorized as zone1 (less than 250m), zone2 (between 250 and 500m), and zone3 (between 500 and 750m).

To analyze the urban change, landscape metrics are used for these simulated data. The aim of using metrics is to assess the absolute size, relative size, and complexity of urban area in these three zones. The absolute size has been described by the number of patches metrics. The number of patches metrics is expected to increase during periods of rapid urban nuclei development, but may decrease if urban areas expand and merge. Relative size is described by the mean patch area and patch area coefficient of variation. The mean urban patch area is a function of the number of urban patches and the size of each urban area—if the mean patch area decreases, then it implies that new urban centers are growing faster than existing urban areas. The patch size coefficient of variation is a normalized metric of the urban area. ED increases with new urban nuclei, but decreases with the merging and fusing of urban areas. AWMPFD describes the shape of the urban area, which describes the complexity of urban growth.

Results of these metrics analyses are presented in Figure 4.9. Each plot represents the individual metrics in all the three zones. The increment in the number of patches metrics indicates new urban nuclei development. The numbers of patches are more in the simulated data with inclusion (w/i) compared to without inclusion (w/o) for all the zones in 2015 and 2025. All the three zones have similar trends for numbers of patches. The difference between simulated w/i and w/o data for 2015 in zone1 is 722 patches, which is reduced to 200 patches in both types of simulated data of 2025. The difference between both types of data for 2015 and 2025 is 699 patches and 300 patches, respectively, in zone2, but increases to 820 in 2015, and decreases to 280 in 2025 in zone3. This increase in the number of patches implies an increment in the rate of new urban nuclei development in all three zones for both periods (Figure 4.9a).

When the number of urban patches and the mean urban patch area are evaluated together, they provide a platform to understand urban area change graphically. Figure 4.9b indicates that simulated w/i have more new urban centers compared to simulated w/o data for both periods, as simulated w/o data represent higher values in all zones. All the zones show the same trend for both periods of data and in both cases; importantly, however, the mean patch area values are decreasing as distance is increasing. This indicates high growth of new urban developments within the 750m distance from commercial and industrial areas, especially for simulated w/i data. The numbers of patches declined while the mean patch area increased for simulated w/o data compared to simulated w/i data for both periods. This verifies that urban growth will occur through expansion of extant urban areas rather than through spontaneous and separate development (Figure 4.9b).

The patch area coefficient of variance provides a measure of the variation within the urban area. Figure 4.9c indicates the decrease in variance between simulated w/i data and simulated w/o data for both periods in all the zones. Simulated data show that all zones reveal a slow increase in the variation within urban areas followed by a decline in variance especially in zone2. There is a variation in values of zone3 in both types of data for both periods unlike the other two zones (Figure 4.9c).

ED value is increasing with time and indicates an increase in the urban area. Simulated w/i data has higher ED values compared to simulated w/o data for both periods. ED values are higher for zone1 in both periods for all data compared to the other two zones. Both simulated data represent increases in ED, indicating the development of a new urban area within 750m distance from commercial and industrial areas. ED values are highest for simulated w/i for 2025 in zone1 and lower for simulated w/o data for 2015 in zone3 (Figure 4.9d).

AWMPFD varied significantly among all the zones (Figure 4.9e). The simulated w/i data have more irregularity compared to simulated w/o data in zone1. Zone2 has a pattern similar to zone1's but the shape of its urban area is less irregular when compared to zone1. AWMPFD values in zone3 have higher values compared to zone2 for both types of simulated data of 2015, which indicates greater irregularity in shape. Simulated data for 2025 in zone3 has lower value than those of zone2 and zone1, which fact indicates a more regular shape compared to zone2 and zone1. AWMPFD indicates that zone1 has the highest complexity in its shape for all simulated data compared to the other two zones. This trend of AWMPFD indicates that complexity increased with zone1 and then decreased with zone2 and zone3 (Figure 4.9e).

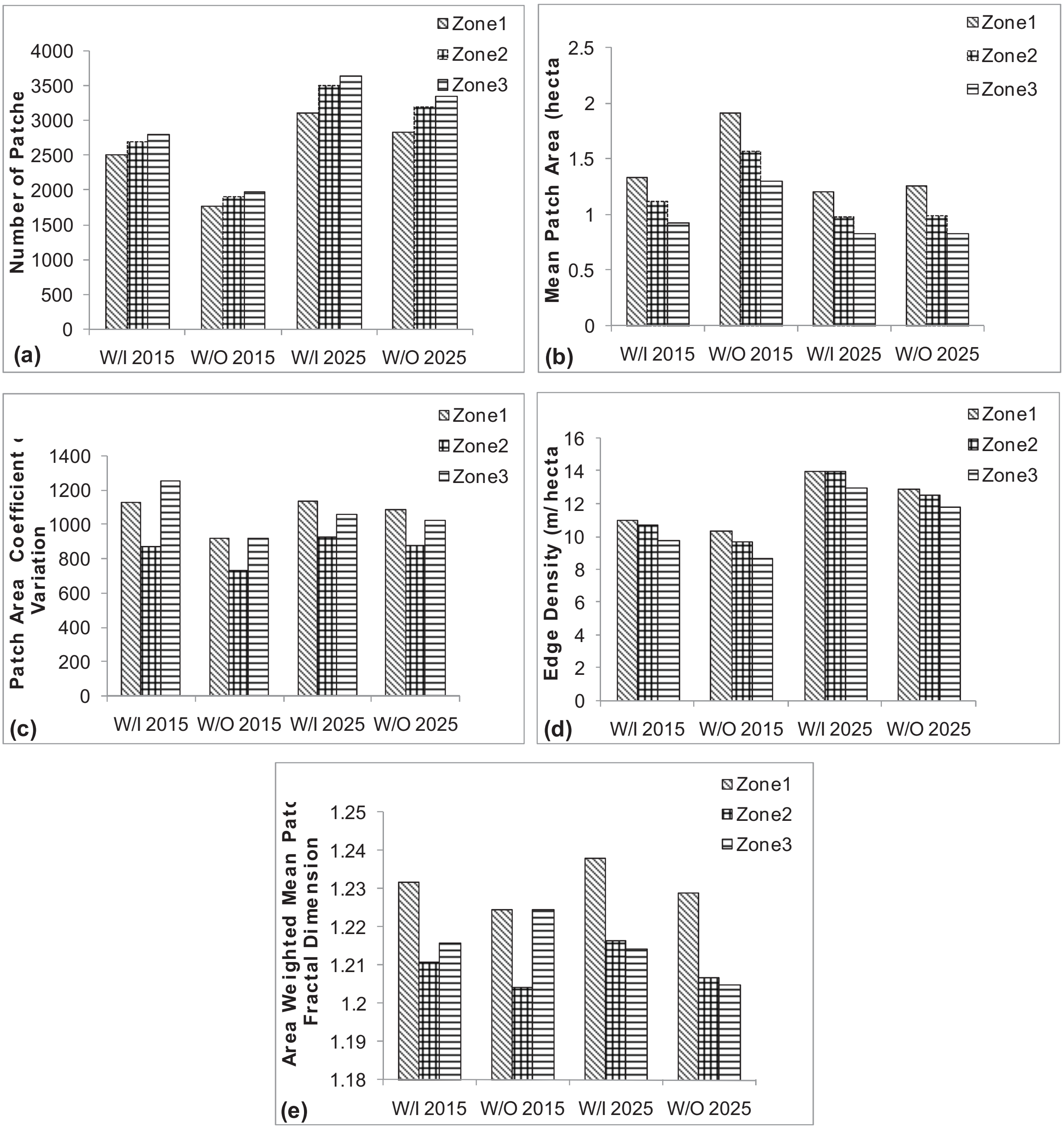

Figure 4.9 Landscape Metrics for simulated data for 2015 and 2025 with and without inclusion of proximity to commercial and industrial variable proposed for 2025- Number of Patches (a), Mean Patch Area (b), Patch Area Coefficient of Variation (c), Edge Density (d), and Area Weighted Mean Patch Fractal Dimension (e)

Scenario III

This scenario was generated to ascertain urban change in terms of the cause and consequences of a time gap in planning and implementing policy, particularly with respect to government policies. For this analysis, a proposed land use plan is used, which was prepared by local development authorities in 2010 under Jaipur city's master plan of 2025. The local authority demarcated a land use class, i.e., a special area in this proposed plan, which is located in the eastern part of the city at 7km distance from the core city (Figure 4.10). This land use class is defined as Naya (New) Jaipur, which covers 10,500 hectares of land area for the development of a new township.

According to the primary source of information, Master Plan 2025 (JDA, 2010), the existing structures in that area will be retained after the implementation of this planning policy, but further unplanned development will be restricted. However, an important requirement in this planning is the need for an entryway to the special area from the core city. The local authority is planning a 4 km long tunnel to that area and expects the tunnel will take five year to complete according to a primary source of information.

The simulated urban data for 2015 and 2025 are used to estimate the growth under the above planning conditions for this special area. Based on 2006 land use data, the urban area comprised 450 hectares in the special area. Simulation results of 2015 show that the urban area will increase to 1200 hectares and further increase to 1800 hectares in 2025 with no restrictions on unplanned development, as shown in Figure 4.10. Most of the urban change is taking place alongside roads, which can affect the prime location of planned development. Hence, in such a situation, if this policy's implementation is delayed, the area will experience more urban change, which will further complicate the situation with regard to the implementation of the plan for this special area.

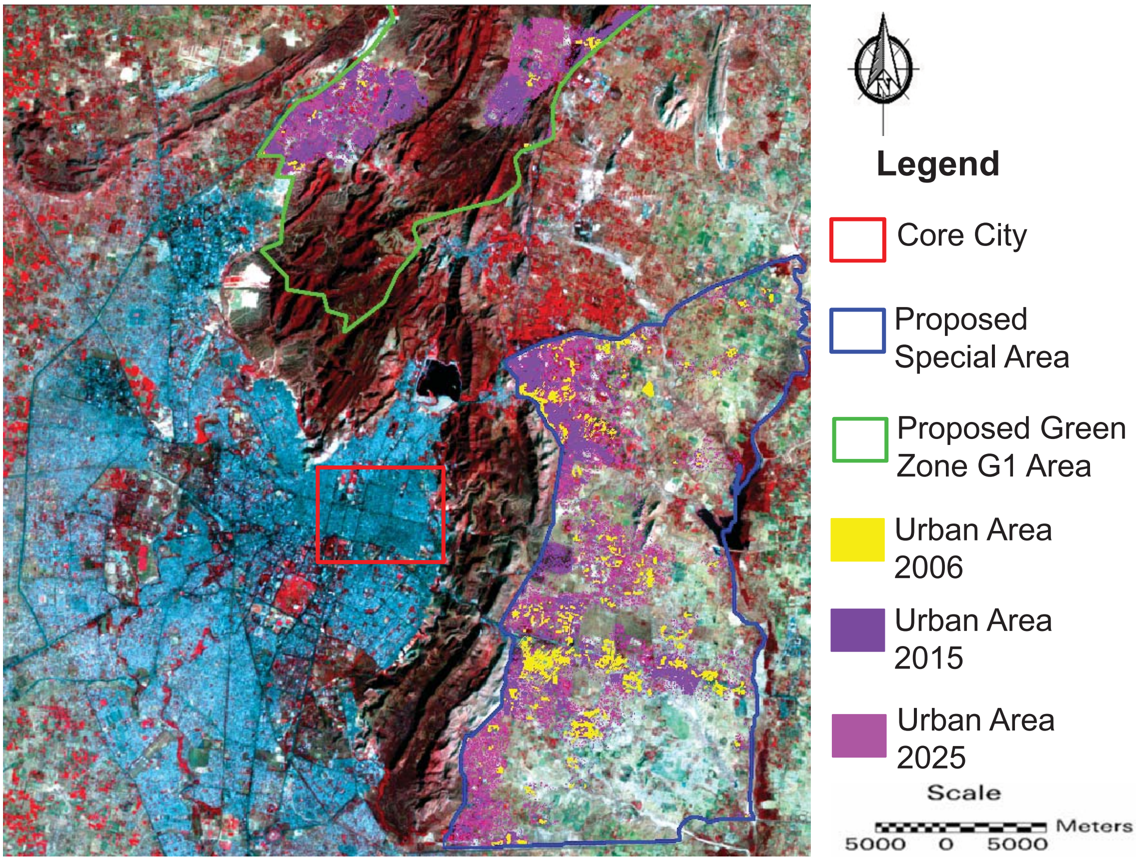

Figure 4.10 Proposed Special Area and Green Zone in Master Plan of 2025 with Change in Urban Area

Another area demarcated in the proposed master plan of 2025 is illustrated by a green polygon in Figure 4.10. This area is within the eco-sensitive area (green zone), located in the northern part of the city. The principal aim of this zone is to conserve the natural features such as hills, forest, flora, and fauna. The zone is strictly reserved and is to be protected from any development, according to the master plan and primary source of information. In this zone, the urban area was estimated at around 35 hectares using 2006 land use data; whereas simulated data have shown enormous growth and the area is expected to be 500 hectares and 845 hectares, respectively, in 2015 and 2025 (Figure 4.10). The major cause of high growth in respect to the simulated data is the two main highways passing through from both sides of this zone. Urban change is very important for this zone and it is essential to understand how to control this sprawl. The results of policy analysis indicate that simulation and prediction modeling are very significant to understanding the dynamics of urban change patterns in the future.

4.5 Concluding Remarks

The MCE method has proven its potential for urban land suitability analysis by integrating a weighting criteria based on the previous growth of urban areas into different factors of suitability. The topographical and locations-based components demonstrated their usefulness in the MCE process to delineate the suitable areas for future urban developments. This suitability is further categorized in different zones, to ascertain the urban change patterns for both simulated and estimated data. The simulation and estimated results combined with landscape metrics provided clear and better understanding of the urban development pattern and process.

The simulation and estimated results combined with landscape metrics provided a clear and better understanding of the urban development pattern and process. The results suggest that urban development in Jaipur city will continue through densification of existing urban areas and expansion of suburban areas toward the east, west, and south in the future. The integration of plan for urban simulation is provided the urban change pattern dynamics of Jaipur city. The assessment of proposed plan of Jaipur city is indicated the time gap between planning and implementing a plan may be crucial for developments of city and also from environment perspective.

The estimation of suitable land availability for urban area development will provide the base for future land development and assessment of proposed plan provides important information of future growth scenario of city. Therefore, these results can be used as an indicator of the magnitude and direction of change in urban for the future.

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CHAPTER 5

INVESTIGATION OF TEMPORAL URBAN FORM TO ASSESS IMPACT ON POPULATION WITH WALKING ACCESS TO BUS STOP

5.1 Introduction

Rapidly developing cities are characterized by immense urbanization, population dispersion, employment decentralization and land use fragmentation (Gutiërrez and García-Palomares 2008). Suburban development and population growth exerts considerable pressure on infrastructure in urban regions. Since urban change within metropolitan areas in developing countries is so rapid and dramatic, it can be said that integration of land use plan and urban transportation plan into consideration is much more important and necessary than it is in developed metropolises and at the same time in developing cities it is important to assess the current growth pattern and also need to understand the future scenario of city growth. However, very few developing countries have a planning body which covers these elements. They have neither the required institutional set-up nor the technological support.

Jaipur, rapidly growing city is also reflecting same situation, where urban area is growing rapidly with the enormous increase in population and prominent decentralization of employment. Jaipur city is one of the fastest growing mega cities of the India with an annual average growth rate of

5.3% twice that of the nation’s urban growth. With its current growth trend, it is likely to supersede many other cities. Over the last decade the city has experienced a growth in the range of 5-8% per annum (CMPJ, 2008). Urban area of city increased from 3,066.2 hectare in 1975 to 13,859.4 hectare in 2005. During 1975-2005, urban area increased by 352% of Jaipur city. High population density, high rate of population growth and urbanization is leading to unplanned development, strain on infrastructure facilities and deteriorating the living environment are the biggest threat for developing Jaipur city. According to City Development Plan for Jaipur (2006) that the city is lacking a good and reliable public transportation system and also the coverage area of public transportation is poor in Jaipur. A survey has been conducted for Jaipur city by a local authority under Comprehensive Mobility Plan for Jaipur (CMPJ, 2008). This survey report indicated that 45% trips are from two wheelers, 8% by bus and 5% by car, which indicates the maximum shares of the private vehicle in trips (CMPJ, 2008).

Urban change can be explained by urban form patterns, which also influence the access to transit services (Duncan et al, 2010). Urban form facilitates us to analyze the intensity of human activities and urban development. Centre for Sustainable Transportation (CST, 2002a) created indicators using aspects of urban form and named as Sustainable Transportation Performance Indicators (STPIs), which used to find the transportation related sustainable development. Indeed, the relationship between the transportation system, urban form, trip demand, and energy use is paramount in addressing the challenges presented by urban change and increased the requirement of transportation service to move and in the absence of an efficient public transportation system number of private vehicles will increase quickly. Public transportation is recognized as a key component in the management and planning of urban regions. Public transportation represents a means by which people can efficiently move throughout a region with the least amount of impact on the environment. The challenge for urban planners and decision makers is to identify effective strategies for dealing with resistance to travel by public transportation. So it is necessary to assess and locate the areas which have poor transportation infrastructure and have high rate of potential users to provide public transportation.

Public transportation services are accessed by its station, so it is very important to estimate coverage area to stop (Geurs et al, 2006). The significance of coverage is that the more people work and reside in the proximity of transit, the greater likelihood that the service will be used and if the distance or barriers to access transit are too great at either trip origin or destination, then it is unlikely to be utilized as a mode of travel (Murray et al, 1998; Gutiërrez and García-Palomares, 2008), but at the same time reliability and efficiency also enhance the opportunity to use services (Murray et al, 1998; Geurs et al, 2006). Adequate and efficient transit services are also relevantly important with environmental perspective as well for sustainable development of the city. In Jaipur city public transportation services are accessed maximum by walk (60%) and percentage of people who travel distance less than 500m to arrive at the stop is 45% (CMPJ, 2008).

To investigate the urban form pattern, the GIS can be used to analyze and provide valuable insights into the effectiveness of a transportation plan on the performance of the public transportation system. Geographical information system (GIS) technology offers extremely significant power in transportation modeling. The spread of GIS use facilitates the efficient and spatial data storage, updating and processing. In addition, a GIS system facilitates model accessibility, database maintenance and updating, and cartographic display of model results. This can greatly enhance the role of the transportation model in transportation planning and policy development. Transportation planners are responsible for improving system performance, and develop strategies based on often conflicting interests, and providing the public with increased transparency in the whole decision-making process. The greatest significance is the ability for planners and analysts to tackle decision making problems of ''what–if '' nature regarding plan changes and estimate the resulting impacts on travel patterns using GIS.

The aim of this chapter is to discuss the characteristics of urban form pattern and its correlation with travel demand of public transportation. The main objective is to explore the spatio-temporal impact of urban form pattern on travel demand of transit service and coverage area of public transportation plan. To achieve the objective, it is divided in two parts: mapping and monitoring of urban form pattern to assess population in coverage area of public transportation plans in both current and future scenario. Second part is to study how urban form pattern of a coverage area and non-coverage area of a ward and neighboring ward affect the trips/users of public transportation of that ward. Using a spatial statistical method in this analyzed the spatial patterns in the trips of public transportation change process in Jaipur city based on current situation and also in future scenario. Coverage area is delineated using a road/street network based distance method for current and proposed plan of public transportation for this study. GIS used for spatial statistical analysis to ascertain the influence of urban form on travel demand and also to monitor the effectiveness of plan by producing different what if scenario. To attain this, GIS and remote sensing tools are used to prepare urban form indicators at zone and ward scale of the city. The analysis performed using current or base year data of 2009 and projected data of 2031 based on the future planned projects for transit service. In current, Jaipur city have only buses on the name of public transportation mode but the local government is planning to build Bus Rapid Transit System and Metro for the city. In this study currently operating bus routes and as well proposed bus routes are used for this analysis.

5.2 Literature Review

Rapid urban change in developing countries is important to understand from different planning perspectives. This rapid urban change leads to unplanned development, illegal construction and haphazard growth in developing cities (CPD, 2006). This urban change creates pressure on infrastructure of a city such as affect the transportation system of a city. The structural organization of urban area: the more dispersed and less structured the development, strongly influenced, both in terms of efficiency and competitiveness of public transportation (Camagni et al, 2002). Rapid urban change and rise in population influence the urban form and design. Urban form and design affect the access to transit service, such as core city, which usually has a grid street pattern and enhances access to transit service, where as the suburban area, limits access to transit service due to street network and neighborhood design (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008). There are several factors of urban form that influence the access to transit services such as urban density, population density, employment density, land use mix and compactness (Handy, 1996; Cervero and Kockelman, 1997). Urban form ruminate the degree of mixed land use, which can be used to assess the travel demand (Cervero and Kockelman, 1997; Hu and Huapu, 2007). Urban form facilitates us to analyze the intensity of human activities and urban development. Estimation and prediction urban change pattern is necessary to find out impact on transportation system of a city. This estimated and predicted urban change can be explained by urban form indicators to assess its impact on transportation of a city, especially in case of lack of related data for analysis.

Remote sensing and GIS is a versatile tool for urban change studies and it is very significant for creation of indictors, which represent the urban form of a city (Cervero and Kockelman, 1997; Hu and Huapu, 2007; Litman, 2011). Zhang and Guindon (2006) addresses indicator quantification, using the remote-sensing derived urban land use data resulting from urban sprawl. Guindon and Zhang (2007) created urban form indicator using remote sensing and GIS such urban density, urban compactness and land use mix for the quantification of transportation related energy sustainability.

Litman (2011) examines how various urban form factors such as density, regional accessibility, mix and roadway connectivity affect travel behavior, including per capita vehicle travel, mode split and non–motorized travel. This information is useful for evaluating the ability of land use policies such as Smart Growth, New Urbanism and Access Management to help achieve transportation planning objectives. Tsai (2005) developed four quantitative variables to measure four dimensions of urban form at the metropolitan level: metropolitan size, activity intensity, the degree that activities are evenly distributed, and the extent that high-density sub-areas are clustered. Zhang and Guindon (2006) described on quantification of sustainability indicators involves extraction of information about the characteristics of urban form (density, compactness and land use mix) and analysis of its impacts on land use efficiency, transportation and the environment.

GIS has capabilities to manage and analyze spatial data. Recently, applicability of GIS is increased in transportation planning and management (Chen et al, 2011; Lei and Church, 2010). Dueker and Ton (2000) describe capabilities and effectiveness of GIS in transportation planning. GIS gives a supple platform to estimate the transit coverage area and population for study (Kwan et al, 2003; Gutiërrez and García-Palomares, 2008; Biba et al, 2010). Such estimation begins with demarcation of a geographical area using GIS and further determination of population in each coverage area (Hsiao et al, 1997; Gutiërrez and García-Palomares, 2008). Coverage area of public transportation stops is describes that the proximity of demand (population and employment) to stops or stations on the network to a great extent explains its greater or lesser usage by potential users (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008; Biba et al. 2010). There are different method for estimation of coverage area such as straight line and road network method (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008).

Zhao et al. (2003) Compared the results of the traditional buffer method as well as network ratio methods that consider actual walk distance along streets show that both the buffer method and network ratio methods tend to overestimate transit walk accessibility. Regression analysis also showed that the new transit walk accessibility measure was a stronger predictor of transit use than that produced using the buffer method. Gutiërrez and García-Palomares, (2008) assessed the overestimation of the straight-line-distance method, which is the most widely used in coverage analysis, by comparing it with that of network distances method. It investigates systematically the factors influencing this overestimation, such as the density of stops or stations, the coverage distance thresholds and the characteristics of the area analyzed (street-network design, barriers, and population distribution in the neighborhood of the bus stop or station).

The GIS and its concept are widely used by researchers for a variety of purposes ranging from transportation planning to management (Zhao et al, 2003; Gutiërrez and García-Palomares, 2008; Biba et al. 2010). Zhao et al. (2003) describes a methodology using GIS for estimating transit walk accessibility that overcomes the problems associated with barriers and uneven distribution of population, and a methodology for forecasting transit walk accessibility for a future year given forecast population and employment data, transit route information, and street configuration type. Gutiërrez and García-Palomares (2008) used GIS to describe the difference in over estimation of population in coverage area by using buffer method and road network method. Biba et al. (2010) used GIS and proposed a new method for determining the population with walking access to transit. GIS is an important tool for creation of if what scenarios and it used by many researchers for assessment of plan and policies adopted for development of transportation system. Karlaftis, et al. (2004) used GIS for special events public transportation planning, specifically examining the case of the Athens 2004 Summer Olympics and the purpose of the study was to monitoring and managing information regarding the network, supporting decisions about planning and operations and deriving information that are useful for planning. Arampatzis, et al. (2004) used geographical information system (GIS) for the analysis and evaluation of different transportation policies and objective of the study is to assist transportation administrators enhance the efficiency of the transportation supply while improving environmental and energy indicators.

Spatial analysis using GIS helps us to capture important facets of the realities of spatial processes based on correlation or non-independence of spatial data and implies a focus on location, area, distance and interaction (Miller, 1999; Anderson and Gråsjö, 2005; Anselin, 1989). Anselin and Getis (1992) described that how the results of data analyses may become invalid if spatial dependence and spatial heterogeneity are ignored. GIS is a powerful tool to explore and analyze spatial relationships in data analysis and flexible enough to transform data (Holl, 2004). The quality of GIS is display capabilities that provide visualization of the results of spatial statistical analysis. The role of GIS in to pre processes of the data such as extracting values, estimation distance or proximity and in post process the results by plotting estimated and analyzed information (Anselin and Getis, 1992).

5.3 GIS for Spatial Analysis

GIS is a computerized database management system for the capture, storage, retrieval, analysis and display of spatial data. In the 1970s, research in image processing with GIS elements was conducted at the Jet Propulsion Laboratory and the Purdue University Laboratory for Applications in Remote Sensing. In the 1980s, GIS systems were significantly improved. At present there are several companies which develop market and offer consulting services in the area of GIS. Commercially available GIS software varies in terms of capabilities such as database management interfaces, computing environment and data structure. A G1S consists of five elements: data acquisition, pre-processing, data management, manipulation and analysis, and product generation.

GIS Mapping software helps perform various spatial and data base operations, and the optimization software helps model, solve, and analyze decision problems. Two key features of GIS for analysis are: 1) data manipulation and analysis and 2) product generation. Each type of spatial data is referred to as a data layer in a GIS. Each data layer consists of geometric entities such as points, lines and polygons. Attribute data is associated with each spatial object. For example, location of a manufacturing facility represented as a point may have attributes such as capacity, number of machines, production volumes, and number of employees. Nodes on the map are represented by coordinates and arcs by coordinate pairs. GIS consists of programs for measurement of distances and areas. Also, spatial operations such as connectivity and neighborhood operations can be performed. Connectivity operations deal with the identification of items in proximity to each other. The measurement and spatial operations are useful in formulating an optimization model for the distribution problems. GIS uses four types of files for making maps. These include: Boundary files - to represent bounded regions such as countries, states, counties, and census tracts; map files - to represent line objects such as streets, highways, and power lines; point files - to represent point objects such as cities, street addresses, automated teller machines, and fire hydrants; and image files - to represent labels such as names of cities, streets, and landmarks. These types of files are common in any GIS or mapping software product. Data acquisition involves the identification and data collection for an application. Data is converted into a form suitable for computer storage in the pre-processing stage. Data management is the important element of a GIS. Data base contents can be manipulated, analyzed, and presented in the form of maps and other graphical forms (bar and pie charts, histograms and scatter plots) on the computer screen or printed on paper.

The central element of a GIS is the use of a location referencing system so that data about a specific location can be analyzed in its relationship to other locations. Both plane and global coordinate systems are commonly used. A system may be capable of easily transforming one referencing system (e.g. Universal Transverse Mercator (UTM)) to some other referencing system (e.g. State Plane Coordinates). This makes it possible to take data that has been stored in one form and combine it with data that has been entered and stored in some other form. The use of GIS has come of age as a result of several interrelated factors. First, there are many GIS software products that are available from commercial vendors and universities. Second, computer workstations are now capable of handling many of the computational, retrieval, and storage problems within a reasonable amount of time and at reasonable cost. Third, graphical displays and plotters are now sophisticated and fast, producing high-quality and high-resolution output. Fourth, geographic data vendors as well as governmental agencies such as the Bureau of the Census of the US Government have made large amounts of geographic data available at reasonable cost. Fifth, the use of remote sensing has expanded, especially in land use and environmental monitoring, and this has led to the need for systems that are capable of handling large amounts of data as well as serve as a major source of land coverage information. Sixth, the emergence of the satellite based Global Positioning System (GPS) has made it easy to collect attribute data along with its location at relatively low cost and with relatively high accuracy. Each of these factors has contributed to the growth of the GIS industry.

5.4 Material and Method

The monitoring of the coverage of public transportation intends to be verifying throughout the city with correspondence through urban form and proposed the plan. It aims to be a system able to produce synthetic information, selected through standardized criteria, to represent the course of the main phenomena connected with trip to check the progress and performances of the plan. The method flow used for analysis is showed in below Figure 5.1.

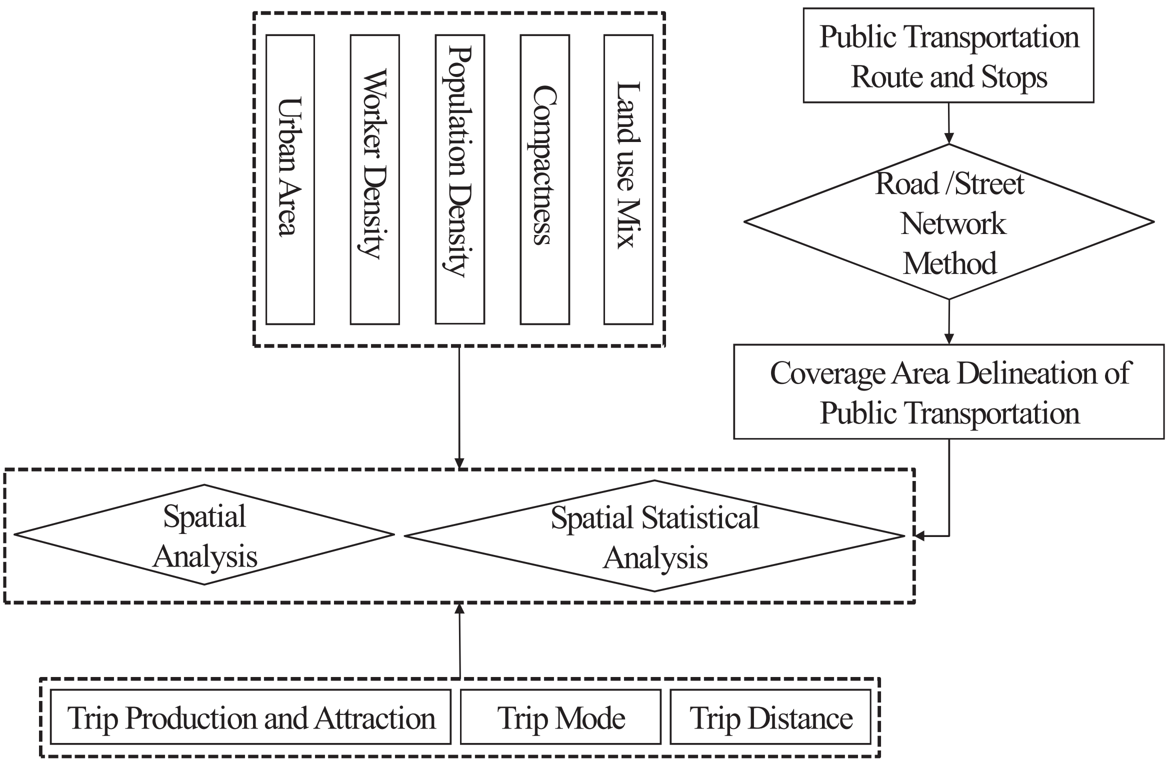

Figure 5.1 Flow Chart of Method

The data used in the analysis to create different indicators are described in following sub sections.

5.4.1 Urban Form Indicator Selection

An indicator is a statistical measure derived directly or indirectly from data, as opposed to having been inferred from scenario-based model analysis. As such, it acts a surrogate or indirect measure of some state of a complex system. For example, urban form, through its impact on travel patterns and travel mode feasibility, can influence transportation-related activities. An indicator based on the morphology of a specific urban centre may then be a feasible surrogate measure of that city's 'public transportation system efficiency'. The explicit value of an indicator typically is not important. On the other hand, the relative indicator values of different systems can be used to inter-compare these systems and to monitor system temporal trends. In summary, in this paper we consider urban areas as systems and address the utility of geospatial based indicators for transportation applications. Our indicators are formulated at the macro-scale (block–ward–city) not the micro-scale (building–street–block) level of detail. To be relevant, indicators must be selected based on well-defined criteria. Here, we utilize the following criteria, namely, those indicators:

a. meet the needs of targeted objects, in our case the need to assess impact of urban growth on public transportation system;

b. are easily understood;

c. are efficient and, ideally, unambiguous measures of the targeted issue;

Public transportation development requires a balance among diverse social goals, e.g. good coverage/ level of service. No single indicator can reflect all aspects of a complex system and a suite of comprehensive indicators must be sought to support development plan-making. Furthermore, for urban transportation system, urban form is recognized as one of its most influential components. Many urban form characteristics such as population and employment distribution, population and land use density, land-use diversity and areal compactness have the potential to impact urban transportation activity. A comprehensive study to address transportation-related sustainable development (CST, 2002a) was commissioned by the Centre for Sustainable Transportation (CST). One of the outputs of the study was a list of proposed 'Sustainable Transportation Performance Indicators' (STPIs), suitable for the urban form based impact assessment of public transportation. A number of these indicators encapsulate aspects of land cover, land use and urban form. Satellite remote sensing can be used to generate these geospatial information layers at a synoptic level. We believe that geospatial information, derived in part from Landsat satellite image data can play an important role in realizing the operational quantification of each of these indicators. It should be noted that the original STPI study considered general transportation issues and was not completely focused on urban areas. Because of the importance of urbanization as a locale for transportation development, our indicator list is augmented with additional urban-specific measures such as spatial compactness.

5.4.2 Indicator Formulation

Urban change is prominent in India with the population growth. Jaipur city has well inter-connectivity (both rail and road) with other metro cities. Urban change not only reflects the intensity of suburban sprawl but also urban density. Urban change is a useful way to identify, quantitatively evaluate and explain urban development and changes based on densities. The urban changes have direct and indirect effect on the urban transportation system. It may lead to increase in two wheeler users and decrease in public transportation users. Different indicators are created of urban form using GIS, remote sensing and aspatial data. Urban form based indicators have defined in following subsections.

5.4.2.1 Compactness

Urban land use per capita is a primary indicator of urban form, which distinguishes low density and high density settlement (CST, 2002a). Consumption of land describes that how is a city spatially spreading. It is well understood that riders from low density settlements or suburban areas need to travel great distance to achieve their travel goals. These also make public transportation less feasible and stimulate private vehicle use (CST, 2002a; Zhang and Guindon, 2006). Compactness measure incorporates urban form and defined the intensity of density of urban concentration of the city. Compactness indicates the complexity of urban structure and design. If compactness is high it indicates regular shape (such as rectangle, square) of urban patch, which create better street and neighborhood design and this shape enhance the access to transit services. Low compactness indicates the zigzag pattern of urban patch and increase the access distance to transit services (Figure 5.2). Compactness estimated using following Equation 5-1, which is a comparison between the perimeters of each developed urban and area of same patch (Fan et al, 2009).

$$S = 2\,\sqrt{\pi A}/P \tag{5-1}$$

where S is the compactness index, A is the area of urban land patch and P is perimeter of the same patch.

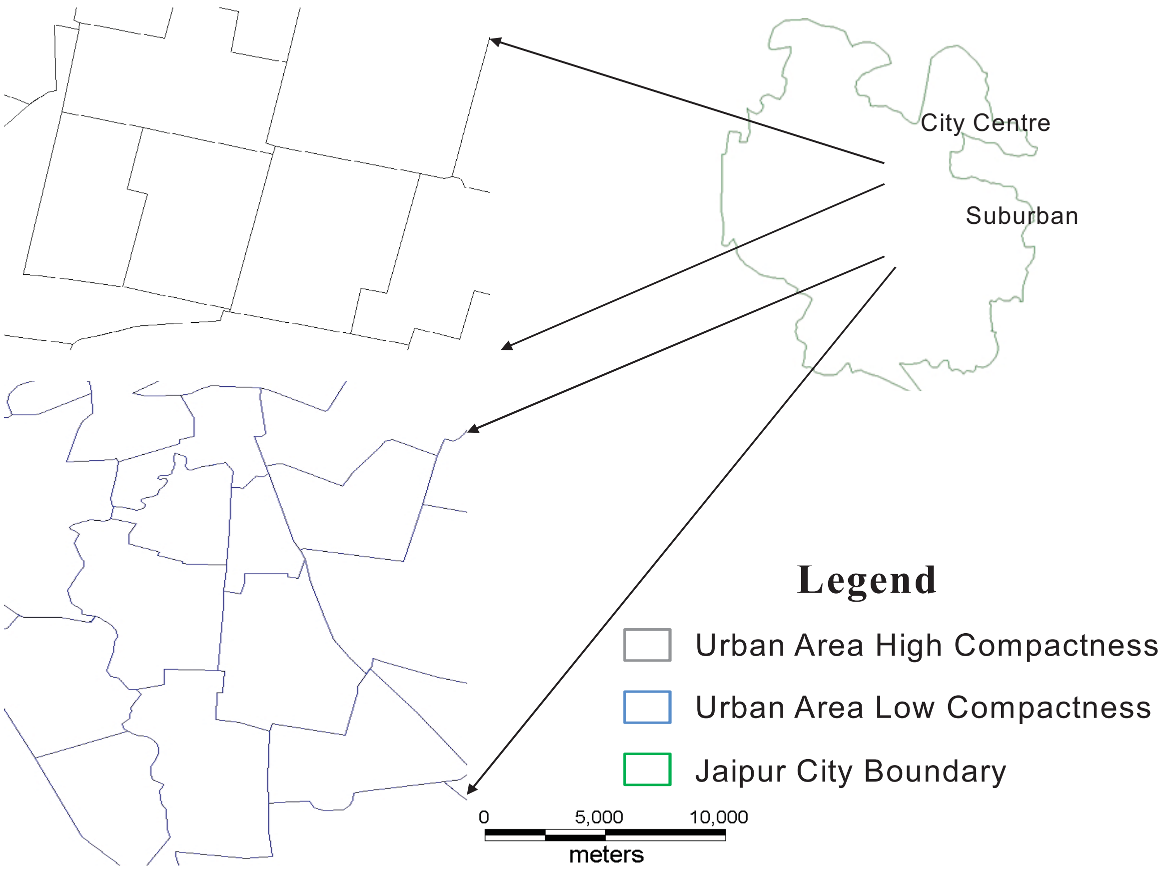

Figure 5.2 Compactness varying from City Centre to Suburban

5.4.2.2 Land Use Mix

Land use mix index is used to ascertain the level of commercial activity in each ward of Jaipur city. This indicator is very important to know the level of commercial and industrial activities as these affect the travel demand. For example if a ward/zone has more non-residential activities then more people will travel to that zone for job, service and commercial activities and in absence of adequate public transportation system it will give rise to more private vehicle use. At present, there is no available data source that provides the degree of non-residential activities for a ward of Jaipur city. In this study land use mix index has been created by using worker and non-worker population and number of person travelling for job/employment data at ward level. The survey analysis report of CMPJ (2008) is used to get a percentage of the job travel (services and employment trips) for Jaipur city. Worker and non-worker population is projected using census data of 2001. Land use mix index has been calculated using the formula in below Equation 5-2.

$$Land\ use\ Mix = \frac{(Wpop+Jtpi-Jtpo)}{(Wpop+Rpop+Jtpi-jtpo)} \tag{5-2}$$

where *Jtpi* is the submission of total person travelling to that ward for job/employment from rest of wards, *Wpop* is the total worker population of that ward, *Jtpo* is the submission of total person travelling from that ward to rest of ward for job/employment and *Rpop* is total residential population of that ward.

Typically, land use mix show that people living in suburban and rural–residential areas (e.g. villages near to suburban/outskirt of the city) have more job travel. A ratio of 1:1 of land use mix indicates the equality of non-residential/commercial and residential activity.

Low land use mix levels, i.e. residential areas that are segregated from potential work while the high level land use mix indicates higher level of non-residential/commercial activities. In our calculation land use mix index ranges from 0 to 1. The land use mix value divided in low, medium and high using natural interval/breaks of land use mix value. The wards which, exhibit value less than 0.45 are categorized in low, in 0.45-0.65 range defined as medium and more than

0.65 categorized in high in this land use mix. The wards that exhibit less than 0.45 values are categorized as the low for the year 2009 and most of the ward exhibit low level of land use mix. Only few ward exhibit medium land use mix value in 2009 (Figure 5.3).

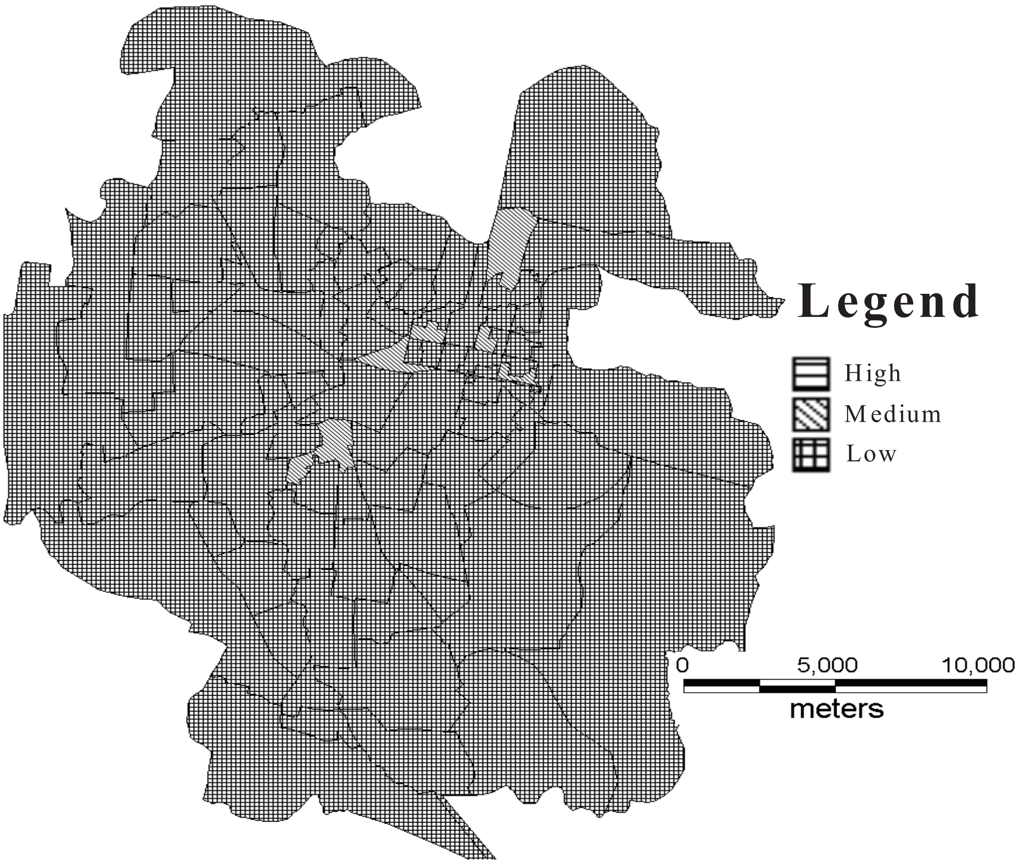

Figure 5.3 Land Use Mix Index of 2009 Epoch

There is high increase in land use mix in 2031 from 2009 of Jaipur city. In 2031, most of the wards exhibit medium level land use mix and only few wards have high land use mix value. One ward has low level land use mix value in 2031 (Figure 5.4).

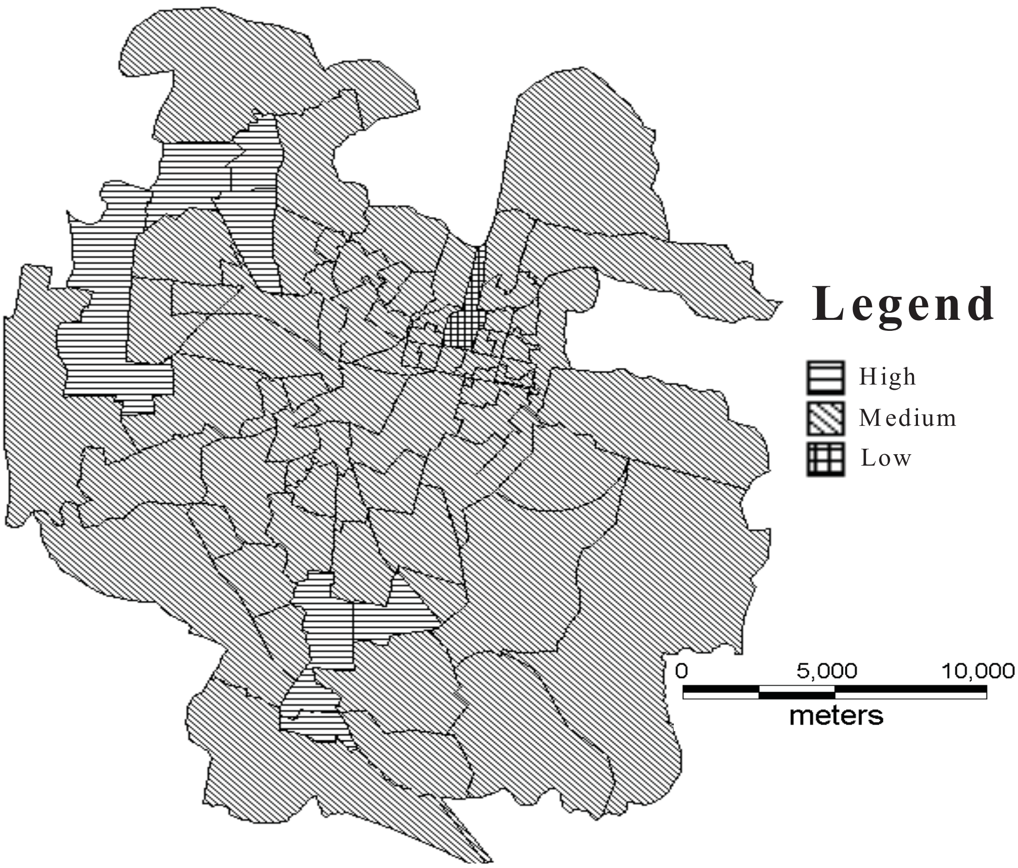

Figure 5.4 Land Use Mix Index of 2031 Epoch

5.4.2.3 Worker and Travel Population Estimation for Coverage Area

Population, workers and trips are used in this study for analysis so far. So all these data have been collected on ward level but at the same time these data also used to ascertain information at public transportation coverage area. The area ratio method used to estimate population, workers and trips of public transportation for the coverage area (O'Neill et al, 1992; Chakraborty and Armstrong, 1997; Gutiërrez and García-Palomares 2008). The formula has shown in following Equation 5-3.

$$P = P_w \frac{a_{bi}}{a_{zi}} \tag{5-3}$$

where P is the population/worker/trip in coverage area, Pw is the population/worker/trip of the ward, a_{bi} is the urban area of the polygon formed from the intersection of coverage area and a_{zi} is the urban area of the ward.

5.4.2.4 Estimation of Total Trips of Ward based on Trip Distance

This indicator has been created to study impacts of different urban forms on trip distance from public transportation. Total trips for each ward are calculated on a basis of travel distance, and two criteria are defined based on travel distance method such as less than 5km and more than 5km. For estimation of travel distance from each stop, bus route-network based distance has been used and then trip distribution data is used for calculation of number of trips with in specific distance from each ward. GIS tools are integrated with spatial data to calculate data for this indicator.

5.4.3 Delineation of Coverage Area of Bus Stops

The straight line distance method around stops or stations can be used to estimate coverage area of transit service. This procedure is very simple to use and did not consider a street network which is most important as it provides a way to population to use services (Gutiërrez and García-Palomares, 2008). Therefore, road network based distance approach is used to estimate coverage area. Network based distance measurement avoid the overestimation of coverage area, and it can be created using GIS capabilities (O'Neill et al, 1992; Hsiao et al, 1997; Gutiërrez and García-Palomares, 2008). Gutiërrez and García-Palomares (2008) estimated the coverage area using Euclidian distance and network based distance method and detailed the factors which affect the estimation of coverage area. The distance from stop used to create coverage area is 400m, and it can be defined as a comfortable walk under normal situations for all people (Murray et al, 1998; Gutiërrez and García-Palomares, 2008).

Therefore, bus stop coverage area is delineated by estimation of the 400m walk able area on a street network from every stop of a public transportation and then irregular polygon created to demarcate the coverage area. These polygons are created for all current route stops and also for future planned route stop of transit service (Figure 5.5).

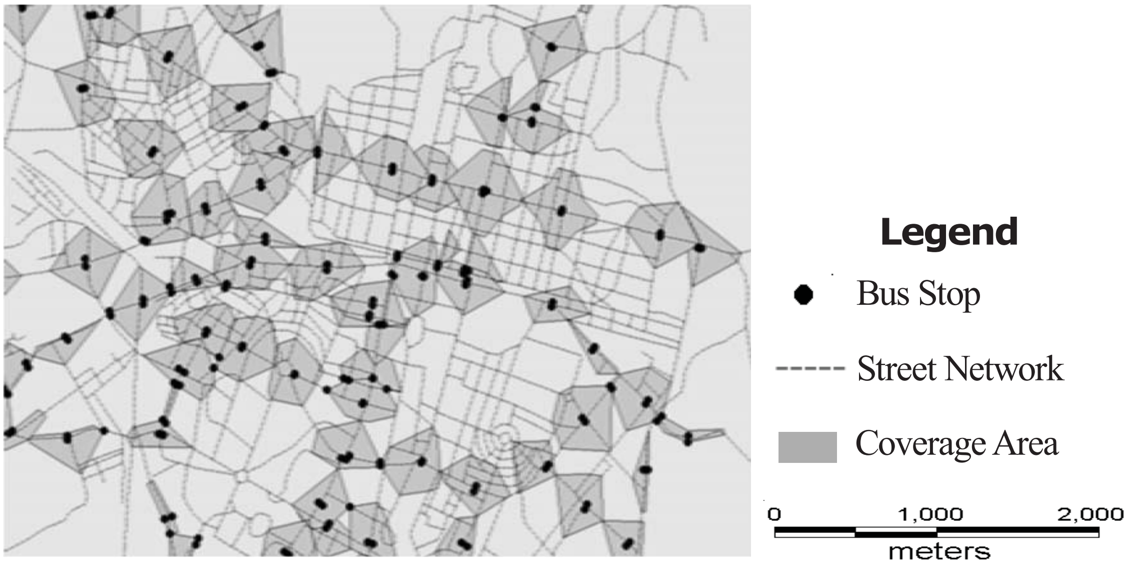

Figure 5.5 Coverage Area Representations for Public Transportation-Bus Stop

The methodology used with the GIS for delineation of coverage area.

Delineation Steps are following:

- 400m distance is used for coverage area delineation by referring Murray et al, 2001; Zhao et al, 2003; Gutiërrez and García-Palomares, 2008 , it represents the maximum distance that most people are willing to walk to use bus services.
- Calculation of distance over the street network, in accordance with 400m distances specified from each stop.
- Obtainment of polygons using this distance over the road network to calculate the coverage area of each PT stop.
- Overlapping of layer of polygon with the built area layer in order to calculate the built area within each polygon.

Obtained built area in each polygon used as coverage area for further analysis. Overlapping coverage area of bus stops are separated using GIS tools. It is well known that the way in which demand data are georeferenced (points or polygons) conditions the final results. Unfortunately, exact location information for individuals (points) is not available in the Jaipur (in compliance with laws of confidentiality and secret statistics). It is only possible to use spatially aggregated information (polygons), which obviously causes errors of variable magnitude in estimates (Horner and Murray, 2004). In order to minimize this type of error, data at the highest possible level of spatial disaggregation must be used. In the case of the Jaipur these units are municipal boundary, ward boundary, and urban sectors. The main advantage of urban sectors over census tracts is that the latter are not adapted to the characteristics of the territory, whereas urban sectors are homogeneous units from the morphological and functional points of view. Therefore, urban sectors are more appropriate than census tracts for coverage analysis of public transportation networks, by offering units with relatively homogeneous land-use and population density.

5.4.4 Mapping and Monitoring Impact of Urban Form on Population in Coverage Area

As mentioned above that Jaipur is a rapidly developing city with high population and economic growth. It is also reported that in current situation city does not have good public transportation system and private vehicle users are increasing with high growth rate (CMPJ, 2008). Now local authority of city has some proposed plan for development of public transportation. The present important problem of public transportation is that it does not have good network coverage in the city. Another issue of public transportation is the low frequency. So in this case, city needs analysis of current coverage of public transportation and also for future scenario. To understand above problem of Jaipur city, it required to monitor the coverage and change in trips of public transportation with change in urban form of the city with current plan and also with proposed plan. The process is described in following subsections and started with evaluation framework.

5.4.4.1 Evaluation Framework

The analysis is meant to make unbalanced areas emerge by comparing results from different years, and plans. Finally it is useful to classify geographical areas or fields at different levels of intervention priority: such a range could provide a preliminary element to appraise different conditions.

Key elements of such an analysis are:

• A database that contains the necessary information to map and monitor the plan;

• A set of indicators to monitor and assess the plan;

The proposed evaluation framework is shown in Table 5.1. It will provide guidance to the GIS based analysis. In this framework goal has been defined based on objectives using performance measures. The efficiency and effectiveness terminology are used to indicate the

Table 5.1 Evaluation Framework

System Goal	Objective	Performance Measures
Mapping - monitoring of urban form and population in coverage area of public transportation plan to reveal possible imbalance.	Mapping–monitoring population distribution in coverage area (Model 1)	Zone classification
		Population classification
		Worker classification
	Mapping–monitoring with urban form pattern in coverage area (Model 2)	Compactness
		Land use Mix
		Number of Trips <5km
		Number of Trips >5km

5.4.4.2 Performance Measures

The analysis for the monitoring and assessment of the plan of public transportation is based on a group of indicators conceived to monitor the coverage of the plan as a whole and with change in urban form.

In this study, used a number of selected indicators for each strategic objective of the plan (effectiveness, efficiency), divided in two groups. For each indicator the following features have to be defined:

• Its meaning, related to the specific objective of the plan, which it is referred to;

• How to calculate it: different approaches may be identified according to data availability;

• The data needed to calculate the indicator;

• The different levels of aggregation: the level of maximum relevant detail and further meaningful levels of aggregation;

Performance measures to be implemented in the GIS analysis are divided into two categories

(i) Mapping–Monitoring Demographic Distribution in Coverage Area (Model 1)

Monitoring of development plan is a fundamental requirement to improve public transportation system. Monitoring of plans enhance the effectiveness of proposed plan of the public transportation. It is also important in case of rapidly developing city with high population growth, which increases the need of adequate public transportation system. In such situation population growth and density is important aspect to monitor for assessment of transit service, especially when related research information is not available for a developing cities. This kind of situation is very common in developing cities of India. Measures consider are following:

- Zone Classification
- Population Classification
- Worker Classification

(ii) Mapping–Monitoring with Urban Form Pattern in Coverage Area

The developing cities lack the efficient public transportation service at the same time high urbanization rate increase the necessity of public transportation system. It is important to assess feasibility of the plans with urbanization of developing city.

- Compactness Classification
- Land Use Mix Classification
- Trip Classification
- Trip Length Classification

5.4.4.3 Scales for Individual Measures

It is also necessary to set up scales for individual performance measures employed in the GIS analysis. The following tables (Tables 5.2 and Table 5.3) detail the proposed scale and description for each individual measures. For each measure, considerations are given to the following issues:

- Minimum and maximum values
- System average
- Desired levels

(i) Mapping–Monitoring Demographic Distribution in Coverage Area (Model 1)

Table 5.2 Scales for Mapping–Monitoring using Demographic Distribution

Measures	Measuring Scale	Description
Zone classification	Coverage area of Public Transportation	Coverage area in 400m
	Coverage area of Public Transportation	Coverage area in 500m
	Coverage area of Public Transportation	Coverage area in 600m
Population classification	High	Population distribution at ward level
	Medium	
	Low	
Worker classification	High	Population distribution at ward level
	Medium	
	Low	

(ii) Mapping–Monitoring with Urban Form Pattern in Coverage Area

Table 5.3 Scales for Mapping–Monitoring using Urban Form Patterns

Measures	**Measuring Scale**	**Description**
Compactness	High	Compactness for both coverage area and non-coverage area
	Medium	
	Low	
Land use Mix	High	Mix ratio for both coverage area and non-coverage area
	Medium	
	Low	
Number of Trips <5km(By PT)	Ward	Trips distance less than 5km from each stop for each ward
Number of Trips >5km (By PT)	Ward	Trips distance more than 5km from each stop for each ward
Total Trips (By PT)	Ward	Total Trips by PT(public transportation)
Total Trips (By PV)	Ward	Total Trips by PV(private vehicle/mode)

5.4.4.4 Data Framework and Availability

Due to the great variety of data to be treated (e.g. demographic statistics, information about infrastructures or the organization of public transportation services) and consequent dispersion of primary sources (often external to regional archives), the optimal choice to build up a database for transportation planning and monitoring is to create and enhance synergies with other existing systems, also external to the regional administration, instead of centralizing information.

In this study, took a bottom-up approach in the GIS analysis. Figure 5.6 shows the pyramid shaped GIS based data analysis which consists of three levels of data abstractions in the course of forming of performance measures, objectives, and ultimately the system goal. By first developing building blocks at the bottom level, upper level components can be subsequently implemented on top of them. One of the objectives of this undertaking is to take advantage of existing information accumulated in the GIS platform through previous efforts and integrating them for analysis. During the analysis, focuses were on the development of data components at performance measure level. The data sets compiled for this purpose are listed in Table 5.4. Information regarding their sources, GIS platform compatibility presented in this table.

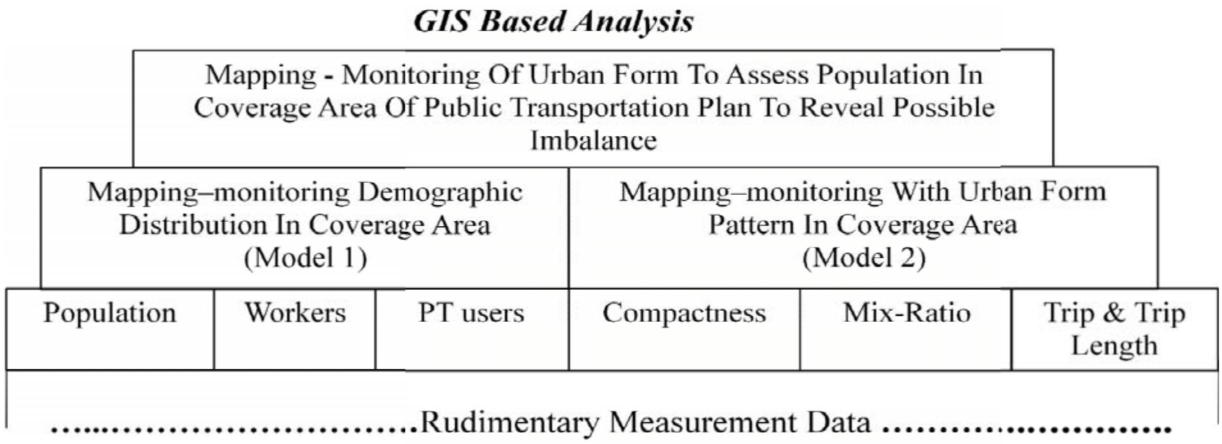

Figure 5.6 Data Framework

Table 5.4 Summary of Information for Analysis

Measures	**Data Source**	**Data Year**
Zone Classification	GIS / JDA	2009 / 2031
Population Classification	GIS / Census	2009 / 2031
Worker Classification	GIS / Census	2009 / 2031
PT users	GIS / JDA	2009 / 2031
PV users	GIS / JDA	2009 / 2031
Compactness	GIS / Remote Sensing / JDA	2009 / 2031
Land Use Mix	GIS / JDA	2009 / 2031
Number of Trips < 5km	GIS	2009 / 2031
Number of Trips < 5km	GIS	2009 / 2031

The information represented in the table consists of huge space of spatial and attribute data from a variety of sources. Many data sets in their original format often cannot be directly linked the GIS platforms. Since multiple GIS platforms are involved in the development, compatibility with these platforms is also an important characteristic of the data sets which will ensure the proper data linking and data integrity. Data sets containing attribute data need to be rearranged or restructured prior to the integration with spatial data.

The below Figure 5.7 describe the flow of data process in GIS used for analysis. The input data GIS layer (such as worker density map, Compactness map, Land use mix etc.) used for analysis of public transportation plan. This analysis is performed to assess the efficiency and effectiveness of public transportation.

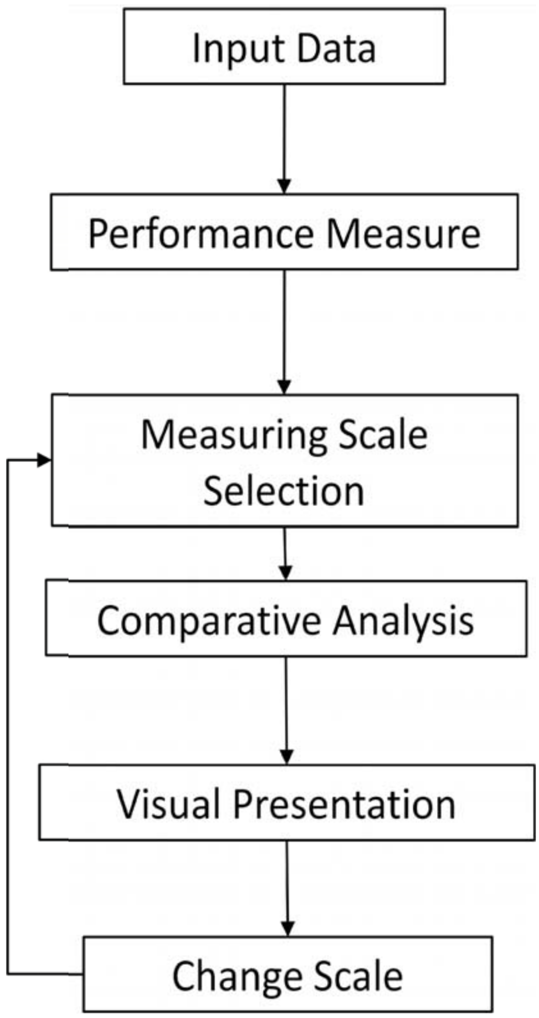

Figure 5.7 Data Processing Flow in GIS

Data Creation

Most analyses conducted using GIS will involve multiple data sets. This presents a unique set of problems regarding data integration. Within the scope of the GIS, Compactness data has been created by using urban area for each ward. This urban area is estimated using remote sensing satellite data. This estimated data for different periods used in multi-layer perceptron–Markov method for simulation of urban area. Then this simulated urban area for different years used to estimate compactness for each ward. Therefore, substantial amount of effort was made to create database and link it to GIS platform. The network based distance method used for coverage area delineation for each public transportation stops. During the project, when data sets are integrated together, the data structure of the combined databases was expanded to accommodate fields from multiple data sources, and an extra number of records were added to account for conditions where location information from individual data sets does not match. Meanwhile, the original data sets were kept intact to ensure data integrity, which benefits quality control of the analyses and future linking efforts.

In order to obtain the average density and to recognize the actual distribution of various densities, spatial interpolating technique has been used to calculate the density distribution of demographic data. Inverse Distance Weighted (IDW) method has been adopted to create the spatial continuous GRID for all densities. IDW method is the most common spatial interpolating method. The nearest points to the sampling points have the largest contribution to the calculated value, and the contribution is inverse to the distance between points and sample point. The expression can be described using the following equation:

$$Z = \frac{\sum_{i=1}^{n} \frac{1}{(D_i)^p} Z_i}{\sum_{i=1}^{n} \frac{1}{(D_i)^p}} \tag{5-4}$$

where Z denotes the estimated value, Z_i is the i-th (i = 1, n) sample point, D_i is the distance, and p is the distance power. It significantly affects the outcome of the interpolation, and the selection standard is the smallest average absolute error. The higher the power, the smoother are the results obtained from interpolation results are. The method has been put forward to reduce the size of the area so as to overcome the homogeneity in the average density to a certain extent.

5.4.5 Spatial Statistical Analysis of Urban Form Impact on Trips of Public Transportation

Spatial statistical analysis is used to analyze change in urban form with trips of public transportation mode for two year 2009 and 2003 at ward level of the Jaipur city.

5.4.5.1 Data for Spatial Statistical Analysis

The spatial data used for this analysis are, ward boundary of city, urban area, and coverage area of public transportation. Instead of it non-spatial data used such as trips data, population data, and worker data collected from local department of Jaipur city. The data used for analysis area based on year 2009 and 2031.

5.4.5.2 Model for Spatial Statistical Analysis

The spatial statistical analysis performed using 2009 and 2031 year data at ward level. The Jaipur city area has 77 wards and ward can be defined as division of city area in to small areas. The spatial dependence analysis process is described in Figure 5.8.

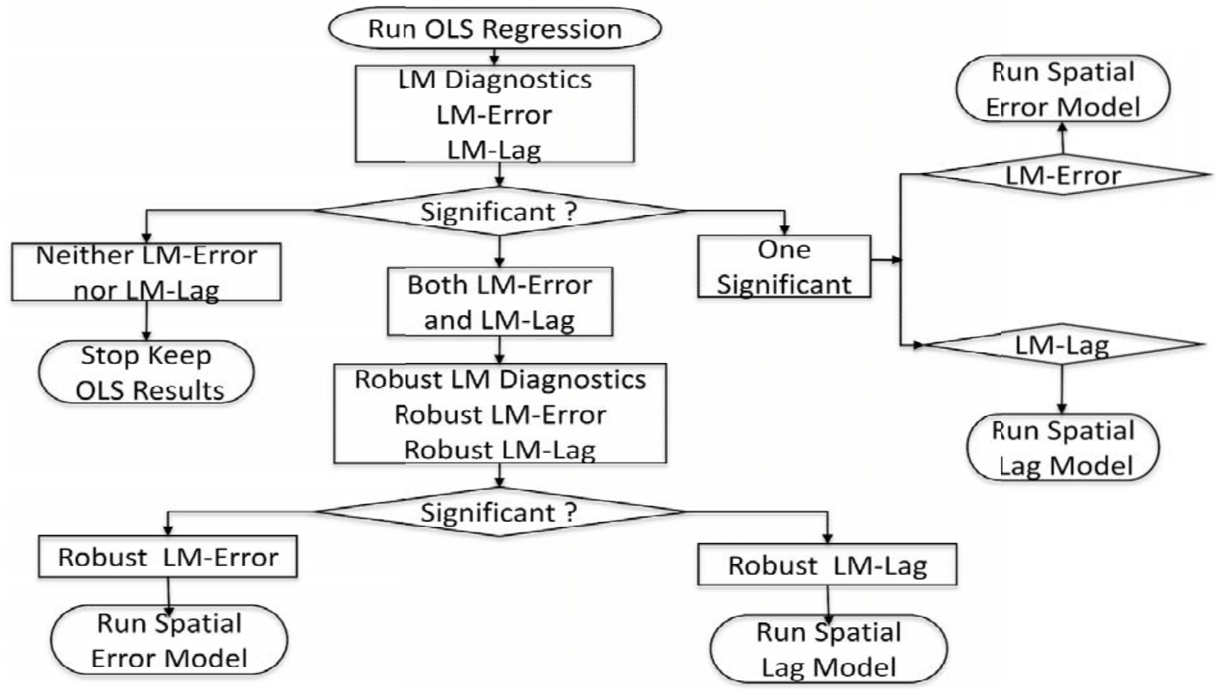

Figure 5.8 Spatial Dependence Analysis Process (Source: Anselin, 2005)

There are two method used first one is OLS model described in Equation 5-5 and another is spatial lag method with spatially-weighted lag described by Equation 5-8.

$$TRIPSPTCA = \alpha_0 + \alpha_1 (TOTAREAPTCA) + \alpha_2 (WRKRDENSPTCA) + \alpha_3 (COMPACPTCA) + \alpha_4 (LUMIXPTCA) + \alpha_5 (TOTAREARTWD) + \alpha_6 (WRKRDENSRTWD) + \alpha_7 (COMPACRTWD) + \alpha_8 (LUMIXRTWD) + \alpha_9 (TRIPLT5KMWD) + \alpha_{10} (TRIPMT5KMWD) + \in_i \quad (5\text{-}5)$$

In next step spatial diagnostic tests are used for spatial dependence analysis. According to Anselin and Rey (1991), to ascertain the asymptotic properties of the tests (Moran and LM) are reflected in a wide range of situations, for different sample sizes, alternative spatial structures, and in the presence of nonstandard error distributions. Their main interest was to find out the power of these tests to be discriminate between spatial error autocorrelation and a spatial lag, under a variety of circumstances with respect to sample size, form of spatial dependence, and boundary effects. In this research, two tests for diagnostics of spatial dependence are used for quantifying spatial patterns of urban form on trips in coverage area. Those are Moran's I and Lagrange Multiplier test.

Anselin and Rey (1991) tried to figure out how the Moran I and Lagrange multiplier are used by different situations, different sample sizes, alternative spatial structure, and under the non-standard error distributions. Their results are highly sensitive to the properties of the tests by using what kind of spatial weight matrix. They suggest that the Lagrange multiplier tests are most powerful in deciphering between a spatial error model and a spatial lag model. For this study Anselin's method is used to analyze and quantify spatial effects. GeoDa has two tests of spatial dependence: Moran's I and Lagrange Multiplier test.

The Moran I, which measure the spatial autocorrelation in regression and the value of this test, vary between -1 to +1, where negative values indicate the dispersed data, and positive values indicate that area is clustered. Getis (2007) described advantages of spatial autocorrelation for the spatial analysis.

$$I = \frac{N \sum_i \sum_j W_{i,j} \, (X_i - \bar{X})(X_j - \bar{X})}{(\sum_i \sum_j W_{i,j}) \sum_i (X_i - \bar{X})^2} \tag{5-6}$$

where, N is the number of cases, X_i is the variable value at a particular location, X_j is the variable value at another location, $\bar{X}$ is the mean of the variable and $W_{i,j}$ is a weight applied to the comparison between location i and location j. If Moran's I show the positive spatial autocorrelation in model–A, then it describes that level of trip in coverage area of ward has a similar trend to their neighboring wards. If Moran's I value found negative then it indicates that level of trip is unlike to its neighboring wards. Lagrange Multiplier is used to distinction and to chose between a spatial error and a spatial lag alternative (Anselin and Rey, 1991) for spatial dependence analysis.

Spatial lag/error model has been constructed using Equation 5-8 and define spatial lag/error models as autoregressive model shown in below Equation 5-7 (Anselin and Rey, 1991; Yong-Lyoul, 2007).

$$y = \rho W y + X \beta + u \tag{5-7}$$

where W is spatial weight matrix, ρ is spatial autoregressive coefficient, y is expressed in deviation from the mean, X is a matrix of J*K exogenous variables, β is a k*1 vector of corresponding coefficients and u is a an independent identical distributed error term.

For the spatial lag model, there is distinction between the residual and prediction error. The latter is the difference between observed value and predicted value that uses only exogenous variables, rather than treating the spatial lag Wy as observed.

In this model local spatial multiplier WX measures the spatial spillovers, when only direct neighbors interact. Here ρ is the spatial autoregressive coefficient that is reflecting the reaction of Y to trips production in public transportation coverage area in neighboring regions (Yong-Lyoul, 2007). Below Equation 5-8 has been used in the spatial lag/error analysis.

$$TRIPSPTCA = \alpha_0 + p(W\_TRIPSPTCA) + \alpha_1 (TOTAREAPTCA) + \alpha_2 (WRKRDENSPTCA) + \alpha_3 (COMPACPTCA) + \alpha_4 (LUMIXPTCA) + \alpha_5 (TOTAREARTWD) + \alpha_6 (WRKRDENSRTWD) + \alpha_7 (COMPACRTWD) + \alpha_8 (LUMIXRTWD) + \alpha_9 (TRIPLT5KMWD) + \alpha_{10} (TRIPMT5KMWD) + \epsilon_i \quad (5\text{-}8)$$

The dependent variable is the total trip of public transportation (TRIPSPTCA) in coverage area of each ward in 2009 and 2031. The trips data are collected at ward level from Jaipur development authority and then area ration method used to calculated trips in coverage area of each ward. Trips of public transportation are used to reflect the public transportation infrastructure development because public transportation usage growth is a common objective for development.

Table 5.5 Details of Independent Variables used for Spatial Statistical Analysis

Variable	Definition	Scale	Expected Effect	Data Source
TOTAREAPTCA	Total urban area in coverage area of public transportation service	Public transportation coverage area	+	Remote sensing/ GIS
WRKRDENSPTCA	Worker density in public transportation coverage area	Public transportation coverage area	+	Demographic and GIS
COMPACPTCA	Compactness in public transportation coverage area	Public transportation coverage area	+	GIS
LUMIXPTCA	Land use mix in public transportation coverage area	Public transportation coverage area	+	GIS and JDA
TOTAREARTWD	Total urban area in remaining ward area	Ward area	-	Remote sensing/ GIS
WRKRDENSRTWD	Worker density in remaining ward area	Ward area	+	Demographic and GIS
COMPACRTWD	Compactness in remaining ward area	Ward area	+	GIS
LUMIXRTWD	Land use mix in remaining ward area	Ward area	+	GIS and JDA
TRIPLT5KMWD	Total no. of trips with in 5km trip distance from each ward	Ward area	+	GIS and JDA
TRIPMT5KMWD	Total no. of trips with more than 5km trip distance from each ward	Ward area	+	GIS and JDA

JDA=Jaipur Development Authority

The demographic data, such as population, worker population are obtained from census, India. Urban area is created using satellite data using remote sensing and GIS and coverage area delineated using public transportation route and stop maps in GIS environment. Compactness is created using urban area of 2009 and 2031.Table 5.5 contains explanations of the variables used for this analysis.

Total urban area in coverage (TOTAREAPTCA) and ward (TOTAREARTWD) are used to explain urban area increase impacts on trips of public transportation. The urban area calculated for each coverage area and ward area based on predicted urban area data for 2009 and 2031 using integration of remote sensing and GIS.

Worker density in coverage area (WRKRDENSPTCA) and ward area (WRKRDENSRTWD) are calculated for both coverage and ward area using census data for each ward. This census data are available for 2001 and by using worker growth rate projected for 2009 and 2031. These variables are used to explain measure of labor market size in coverage and ward area.

Compactness is created for both coverage (COMPACPTCA) and ward area (COMPACRTWD) using urban area in that coverage and ward area. Compactness represents the sprawl of urban area. High compactness represents the less dispersed area and less compact area defined the high dispersion in urban area. Compactness explains the street design and network, which is very important to use public transportation services. Jaipur has grid pattern-street in the city centre, which implies less distance to public transportation stop, while it has irregular street network in inner and outer suburban areas indicate more distance to public transportation stop.

Land use mix in coverage (LUMIXPTCA) and ward area (LUMIXRTWD) are used to explain the impact of existing non-residential activities in coverage and ward area on trips of public transportation. It indicates that high non-residential activities have more impact on travel demand compare to less non-residential activities.

Trip distance variables (TRIPLT5KMWD and TRIPMT5KMWD) are created to explain the impact on trips in coverage area of travel distance using public transportation in each ward. It represents the use of public transportation for long or short travel distance. The distance 5km is used, as it separate the core urban to suburban areas of Jaipur city.

The expected effect of the variable belongs to coverage area are positive and all variables belong to ward area also have positive expected effect, instead these, urban area of ward level variable expected effects are negative.

5.5 Results and Discussion

5.5.1 Mapping and Monitoring Impact of Urban Form on Population in Coverage Area

The mapping and monitoring of urban form impact on public transportation plan is performed in two steps using existing and proposed public transportation routes. The proposed routes are prepared by local government body for Jaipur city transportation service limited, which include radial and circular routes (Figure 5.9). First step is based on demographic data and second is by using urban change pattern data.

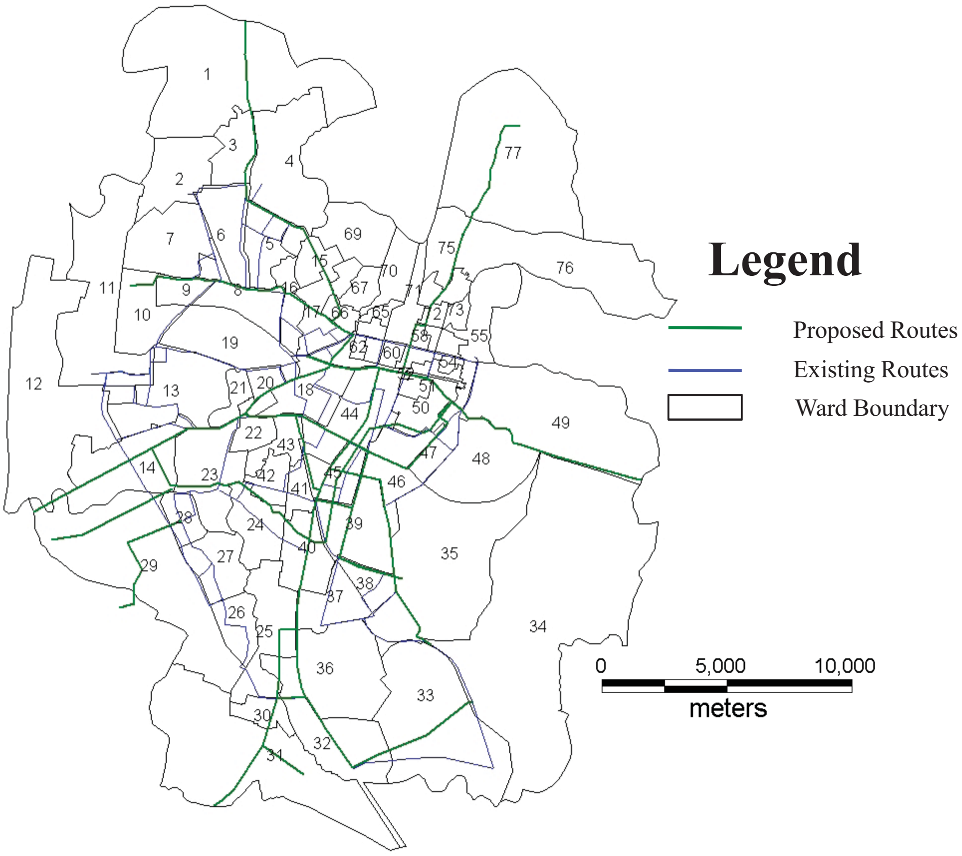

Figure 5.9 Existing and Proposed Bus Route Map of Jaipur City

5.5.1.1 Analysis using Demographic Data (Model 1)

This analysis performed using measures mentioned for Model 1 in Table 5.2. To analyze this, a three level scale has been created for all measures Such as for population- low population, medium population and high population. This change has been assessed with change in coverage area 400m, 500m and 600m. This analysis of public transportation plan is assessed for 2009 and 2031 by including proposed plan.

In the beginning population, worker population and trips of public transportation are mapped with change in coverage area for each ward. The population, worker population and trips of coverage area are calculated Equation 5.3. The below Figures 5.10 and 5.11 implies the changes in population with change in coverage area for each ward for 2009 and 2031. The analysis results of 2009 indicate the increase in coverage area is always increase opportunity to use public transportation (Figure 5.10). The 2031 data showing high increase in population compare to 2009, in such case one can say that coverage of public transportation is going to play very significant role to increase usefulness of public transportation (Figure 5.11). The coverage area indicates presence of high potential users and with increase in coverage area from 400m to 600m distance, with this there is a huge increase in users of that ward. This brings out the significance of coverage area of public transportation stop.

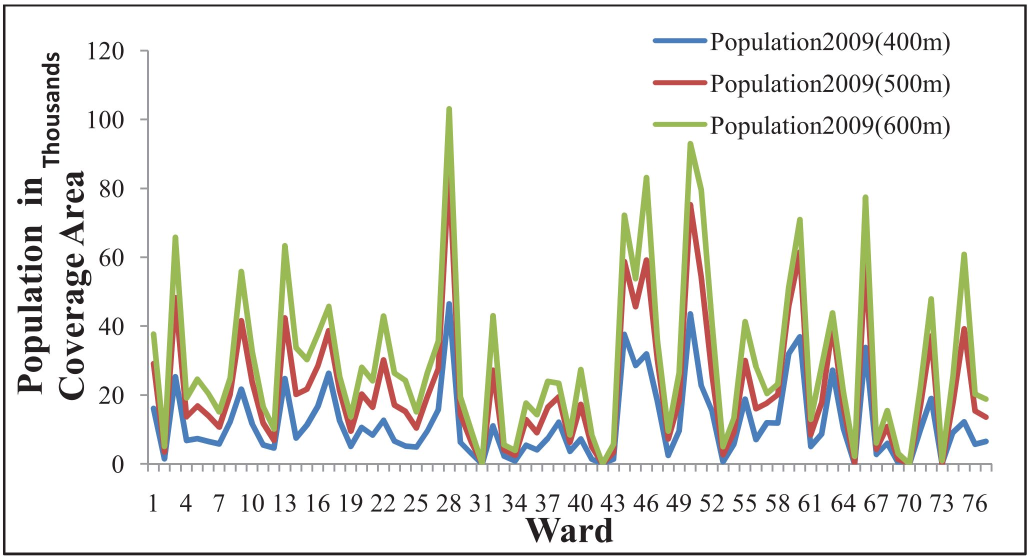

Figure 5.10 Change in Population with Change in Coverage Area for Each Ward (2009)

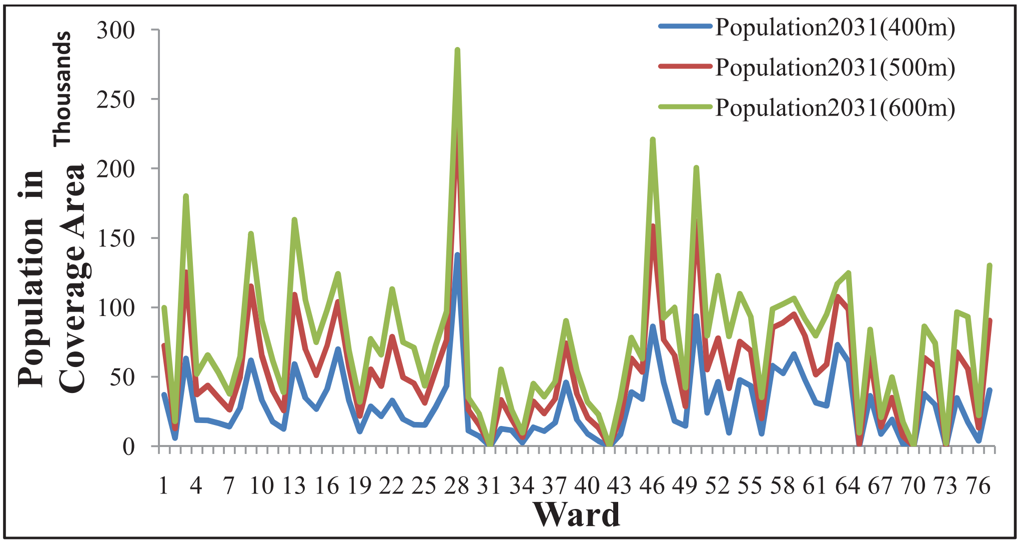

Figure 5.11 Change in Population with Change in Coverage Area for Each Ward (2031)

Worker population is measured for all three coverage area for 2009 and 2031 for each ward of Jaipur city. The Figure of 2009 indicates that ward those have good coverage of public transportation have high number of potential users. Most of the wards have almost similar workers in 400m coverage area that is less than ten thousand workers. Ward1 and ward2 have only 15% and 10% worker respectively in 400m coverage area of total worker population of those wards. This implies poor coverage of public transportation system. The worker population is increasing with the increase in coverage area is a significant point for improvement of public transportation system for Jaipur city (Figure 5.12).

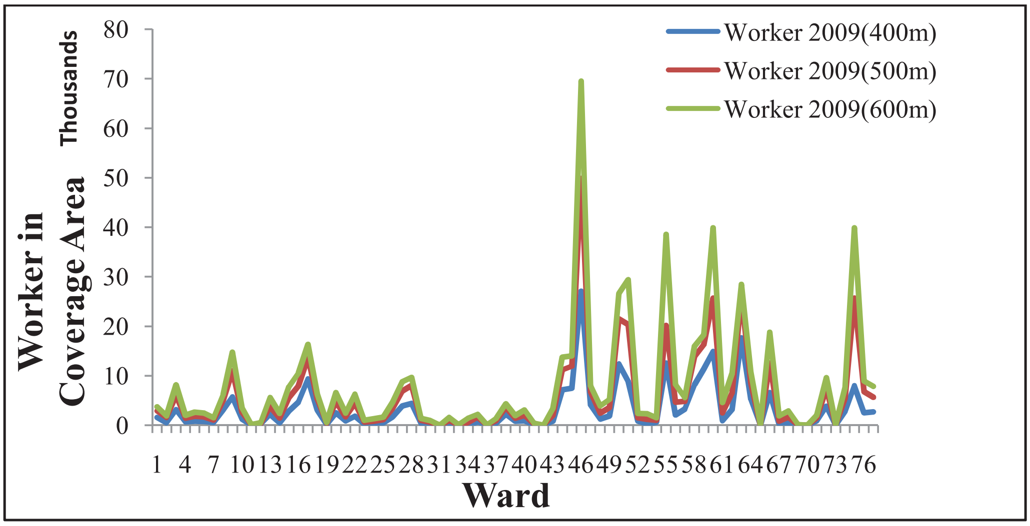

Figure 5.12 Change in Worker with Change in Coverage Area for Each Ward (2009)

The high growth in worker population of 2031 for coverage area of ward compare to 2009. This growth indicates increasing pressure in future on infrastructure of public transportation. The most of the wards have less than ten thousand workers in 400m coverage area (Figure 5.13). However, worker population is increasing with the increase in coverage area but still most of the wards have less than forty thousand workers in 600m coverage area. Some high peaks in graph indicate those ward which have full/higher coverage area.

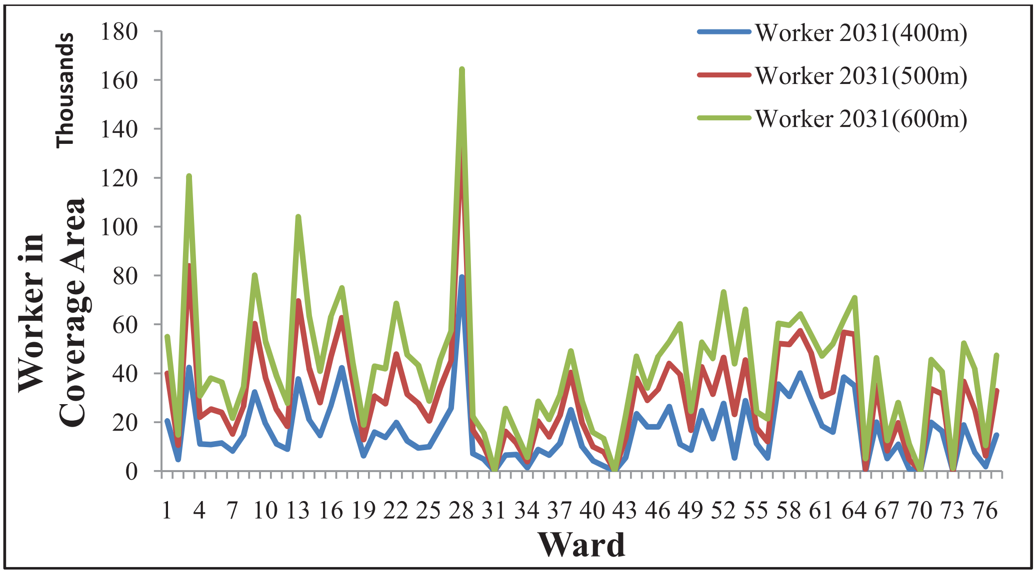

Figure 5.13 Change in Worker with Change in Coverage Area for Each Ward (2031)

The total trips from public transportation (PTTrips) are shown in Figure 5.14 for 2009 with change in coverage area from 400m to 600m. The PTTrips are mapped using coverage area of each ward and estimated the PTTrips in each coverage area. In 400m coverage area most of the wards have less than 500 PTTrips (Figure 5.14). PTTrips are increasing with increase in coverage area but even in 600m coverage area most of the wards have less than 15 hundred PTTrips. This indicates the coverage area of public transportation is not enough to serve people of that ward.

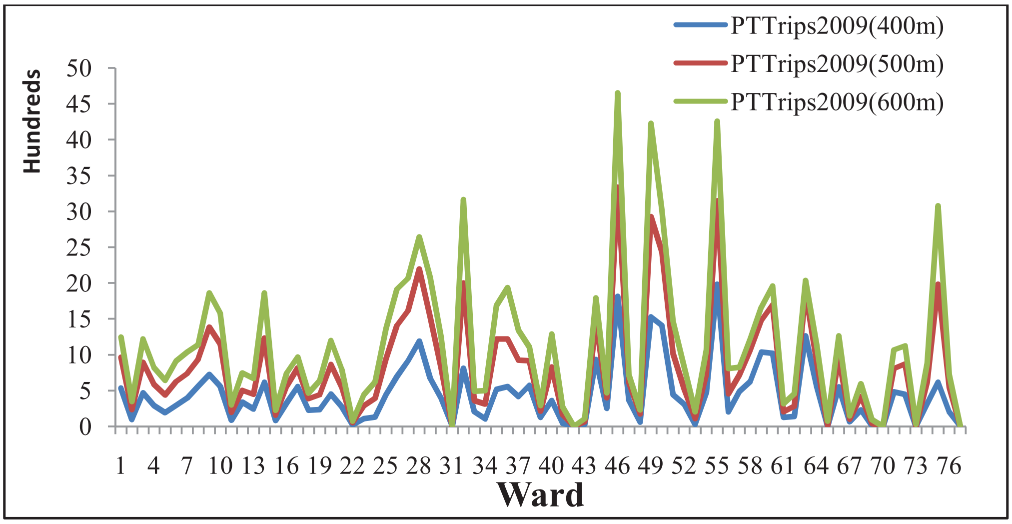

Figure 5.14 Change in PTTrips with Change in Coverage Area for Each Ward (2009)

The geographical mapping of PTTrips using coverage area is providing distribution of trips in different wards. PTTrips are increased in 2031 compare to 2009 in all coverage area excluding some exceptional wards like ward 31, which has poorest coverage of public transportation in both periods. Most of the wards still in 2031 have less than 10 hundred trips of 400m coverage area (Figure 5.15). But increase in coverage area from 400m to 600m indicates the high increase in PTTrips. As many wards is showing 40 hundred trips from 600m coverage area. This means coverage of public transportation is significant to viable to increase users for transit services.

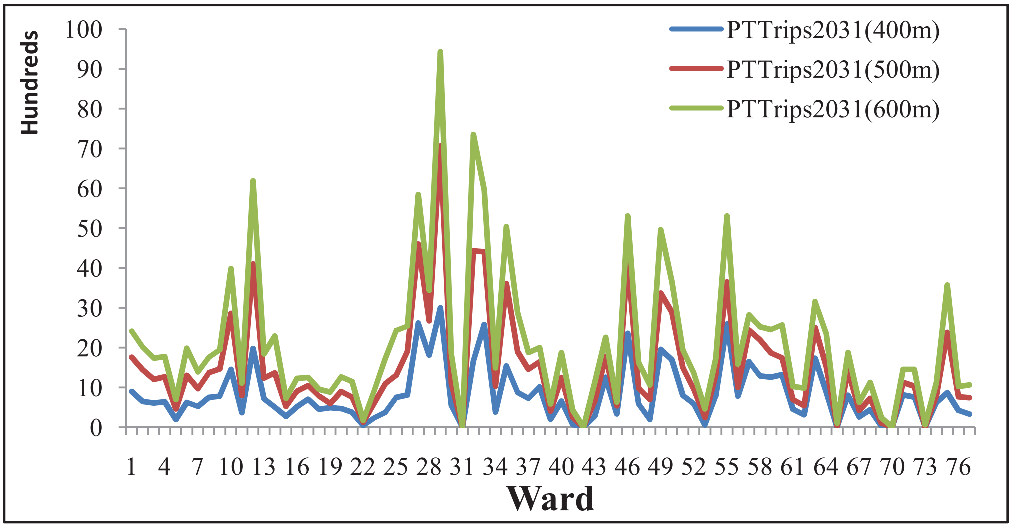

Figure 5.15 Change in PTTrips with Change in Coverage Area for Each Ward (2031)

The population and worker density is estimated under different distance of coverage area for 2009 and 2031. The both densities are estimated in GIS environment and Figure 5.16 and 5.17 is analysis of area of Jaipur city based on change in total population and workers from low to high in different distance from coverage area. The geographical area is estimated for each population and worker density with change in coverage of public transportation such as 638.85 hectare area is estimated in 400m coverage area for low population density. The mapping of population density and worker density is significant to assess the effectiveness of coverage area as it provides geographical distribution of population and worker density with change in coverage area. This GIS spatial analysis implies that population and worker density is increasing from 400m to 600m coverage area in both periods and this is very obvious results. Main important point is that low and medium density has poor coverage compare to high density in both periods.

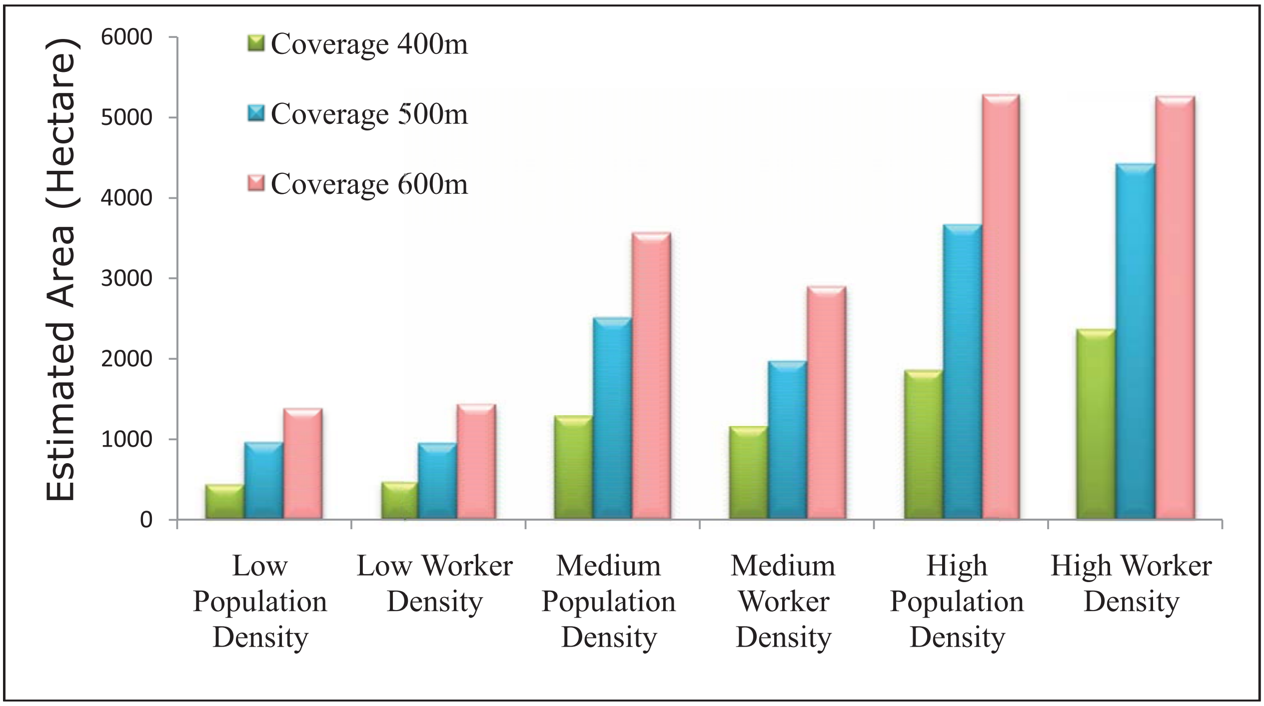

Figure 5.16 Changes in Population and Worker Density with Change in Coverage Area (2009)

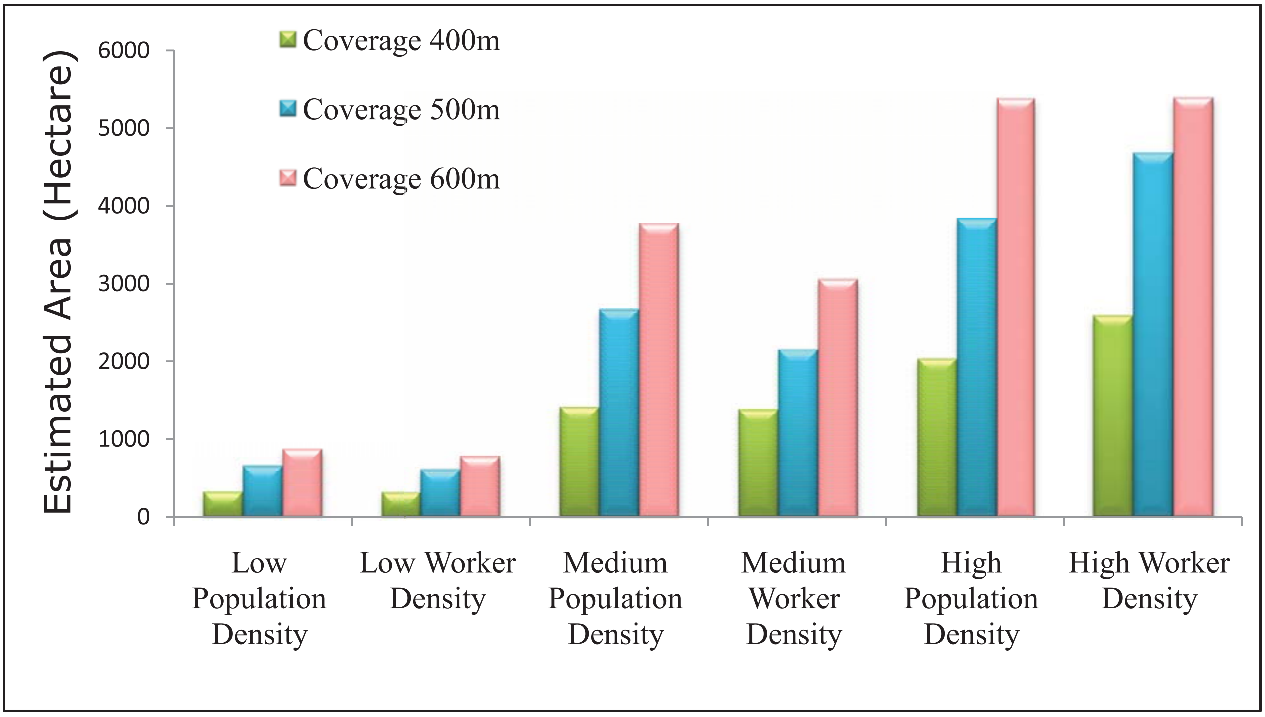

Figure 5.17 Changes in Population and Worker Density with Change in Coverage Area (2031)

5.5.1.2 Analysis using Urban Form Data (Model 2)

(I) Urban Form Pattern and Trips of Public Transportation at Ward Level

Urban change pattern identified using change in compactness and land use mix. Compactness represents the dispersion or sprawl of urban area and land use mix indicate the increase in non-residential activities, which is very important from change in travel pattern point of view.

To analyze efficiency and effectiveness under this model different scenarios are created for compactness and land use mix.

A. Scenario for Compactness

Scenario (i) - Compactness restricted to Low

Scenario (ii) - Compactness restricted to Medium

Scenario (iii) - Compactness restricted to High

B. Scenario for Land Use Mix

Scenario (i) - Land use Mix restricted to Low

Scenario (ii) - Land use Mix restricted to Medium

Scenario (iii) - Land use Mix restricted to High

These scenarios examine the impacts of restricting compactness and mix-ratio on PTTrips, PVTrips, and Trip-length (by PT). This all three scenarios analysis is performed for both 2009 and 2031 year data.

Figure 5.18 below showed the analysis for 2009 and implies that if compactness restricted to low then private mode trips is highest in scenario1. Public transportation trips is 26 % from scenario 1 and trip length more than 5 km is pretty high than the less than 5km trip length. Scenario2, which represents the medium compactness, has more PT trips compare to scenario1 and also increase in trips in both case of trip length. Trips from private mode also increased from 34% to

37% in this scenario2. Compactness restricted to high in scenario3 and found that trips from public transportation are increased from previous two scenarios. Trip of PT is 26% in scenario1 and reached to 42% in scenario3. PT trips with trip length less than 5km is also increased in the scenario3 by 18% from scenario1. Trip length of more than 5km is also increased by 15% from scenario1 to scenario3. Trip of private mode is much higher than the trip of public transportation in all scenarios. However trip of private mode is decreased in scenario3 compare to two other scenarios but still total trip in scenario3 is almost double to trip of public transportation. It indicated from above analysis that increase in compactness is influencing trips of public transportation but at the same time trips of private mode is also significant.

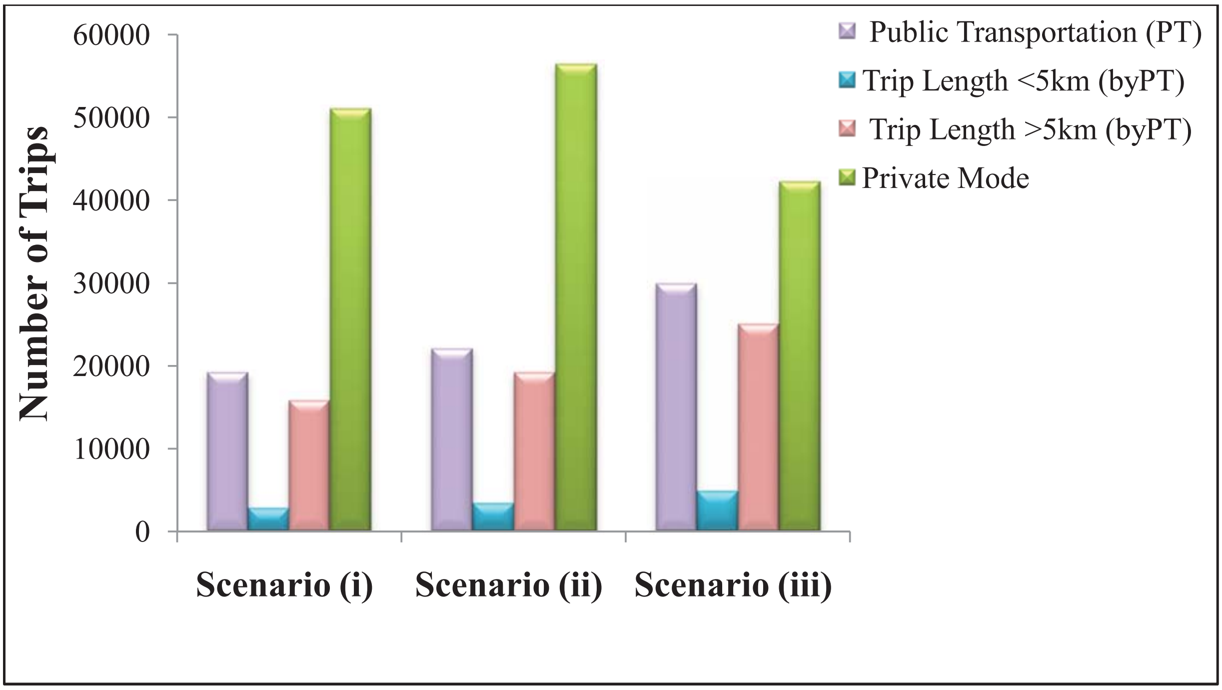

Figure 5.18 Change in Trips by Trip Mode and Trip Distance under different Scenarios of Compactness (2009)

Figure 5.19 above showed the analysis for 2009 and analyzed the land use mix based scenarios. It implies that if land use mix increase trips will also increase. In first scenario land use mix restricted to low and found private mode trips is highest in scenario1. Public transportation trips is 9 % in scenario 1 and trip length more than 5 km is higher than the less than 5km trip length. Scenario2, which represents the medium land use mix, has more PT trips compare to scenario1 and also increase in trips in both case of trip length. Trips from private mode also increased from 34% to 37% in this scenario2. In scenario3 land use mix restricted to high and found that trips from public transportation are increased from other two scenarios and share 50% of total trips. Trip of PT is 9% in scenario1 and reached to 53% in scenario3. PT trips with trip length less than 5km is also increased in the scenario3 by 39% from scenario1. Trip length of length more than 5km is also increased by 46% from scenario1 to scenario3. Private mode trips are much higher than the public transportation trip in all scenarios. Trip of private mode is increased in scenario3 compare to two other scenarios and total trip in scenario3 is almost double to trip of public transportation. We can conclude that increase in land use mix is influence the increase in overall trips of public transportation but at the same time trips of private mode is also significantly increasing, which indicate the poor public transportation in Jaipur city.

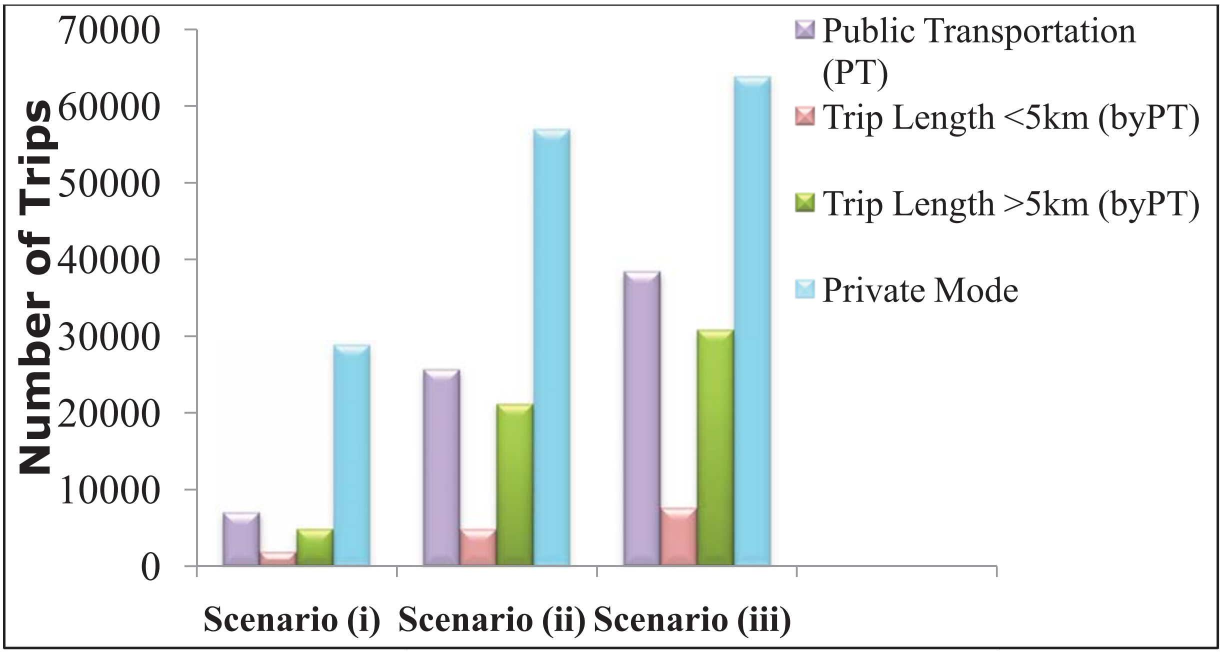

Figure 5.19 Change in Trips by Trip Mode and Trip Distance under different Scenarios of Land Use Mix (2009)

Figure 5.20 below showed the analysis for 2031 using compactness and implies that if compactness restricted to low then private mode trips is highest in scenario1 i.e. 47%, this is 13% higher than the 2009 analysis. Public transportation trips are 30 % from scenario 1, this is 4% higher than the 2009 and trip length of more than 5 km is higher than the less than 5km trip length but the trips in more than 5km are much higher in 2031 compare to 2009. Scenario2, which represents the medium compactness, has more PT trips compare to scenario1 and also increase in trips in both case of trip length. Trips from private mode are decreased from 47% to 28% in this scenario2, which is completely different from 2009. Compactness restricted to high in scenario3 and found that trips from public transportation are increased from previous two scenarios. Trip of PT is 30% in scenario1 and reached to 36% in scenario3. PT trips with trip length less than 5km is also increased in the scenario3 by 23% from scenario1. Trip in trip length more than 5km is also increased by 6% from scenario1 to scenario3. Trip of private mode is much higher than the trip of public transportation in first two scenarios but decreased in scenarios3. We can conclude that increase in compactness is influencing trips of public transportation but at the same time trips of private mode is also noteworthy.

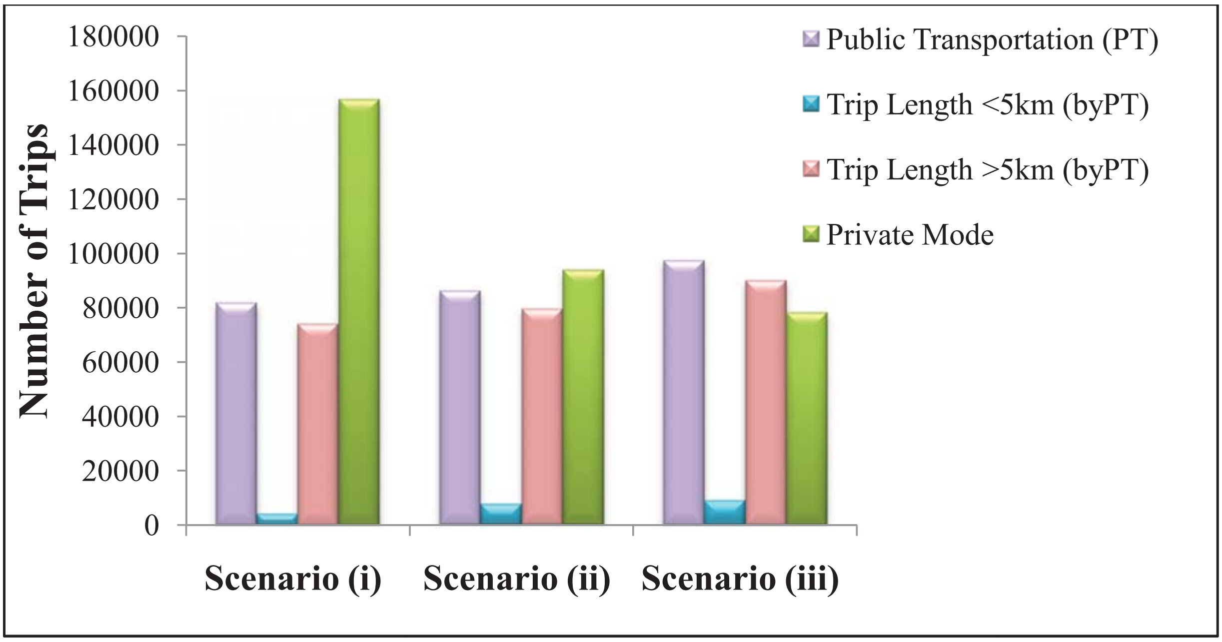

Figure 5.20 Change in Trips by Trip Mode and Trip Distance under different Scenarios of Compactness (2031)

Figure 5.21 above describe the analysis for 2031 and analyzed the land use mix based scenarios. It implies that if land use mix increase trips will also increase same as 2009. Land use mix restricted to low in first scenario and private mode trips is highest in scenario1. Public transportation trips are 14 % in scenario 1 and increased by 5% from 2009. Trip length more than

5 km is double than the less than 5km trip length in scenario1. Scenario2, which represents the medium land use mix, has more than double PT trips compare to scenario1 and also huge increase in trips in both case of trip length. Trips from private mode also increased from 19% to 37% in this scenario2. In scenario3 land use mix restricted to high and found that trips from public transportation are increased from other two scenarios and share 50% of total trips. Trip of PT is 14% in scenario1 and reached to 50% in scenario3. PT trips with trip length less than 5km is also increased in the scenario3 by 47% from scenario1. Trips in trip length more than 5km are also increased by 38% from scenario1 to scenario3. Private mode trips are much higher than the public transportation trip in all scenarios. Trip of private mode is increased in scenario3 compare to two other scenarios. We can conclude that increase in land use mix is influence the increase in trips of public transportation but at the same time trips of private mode is also significantly increasing.

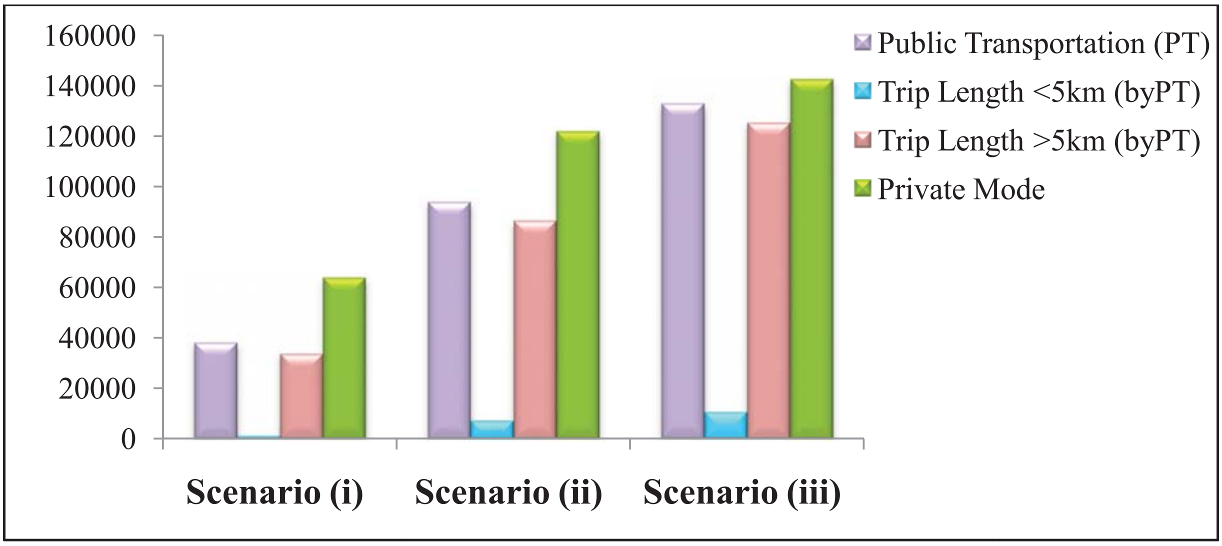

Figure 5.21 Change in Trips by Trip Mode and Trip Distance under different Scenarios of Land Use Mix (2031)

(II) Urban Form Pattern and Trips of Public Transportation at Zone Level

As mentioned above that the data is analyzed at two level–zone level and ward level. The both zone level and ward level analysis performed for 2009 and 2031. The zone boundary is created using ward boundary and based on urban area and population. These zones represent the sprawl intensity of urban area and divided into the core urban (zone 1), core urban ring (zone 2), inner suburban (zone 3), and outer suburban (zone 4) (Figure 5.22).

Trip production and its relationship with compactness, mix-ratio and worker density have been spatially analyzed by creating zones for the Jaipur city. These zones represent the sprawl intensity of urban area and divided into the core urban (zone 1), core urban ring (zone 2), inner suburban (zone 3), and outer suburban (zone 4) using ward boundary. The zones are described in Figure 5.22.

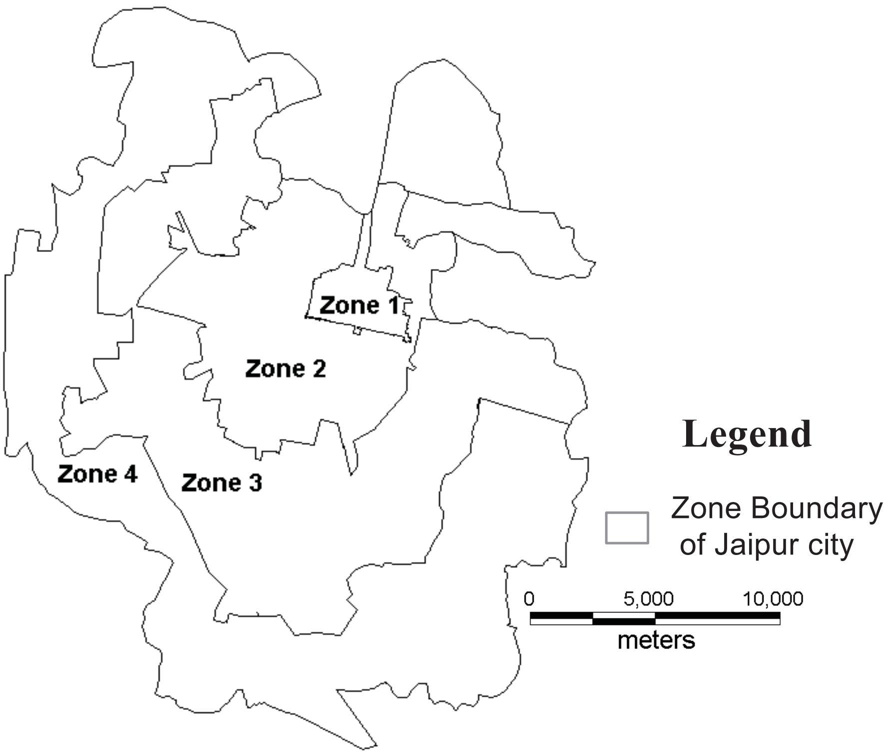

Figure 5.22 Zone Divisions of Jaipur city

Figure 5.23, 5.24 and 5.25 are used to represent the relationship among trips, compactness, land use mix index and worker density and PTCA trips term used in all figure is defined as trips of public transportation in coverage area. The relationship between trip and compactness is shown in figure 5.23. It can conclude by viewing the graph that compactness is decreasing as we are moving from zone 1 to zone 4 in both periods. And at the same time trips are increasing from zone 1 to zone 2 but from zone 2 to onwards it is decreasing. Therefore, we can conclude that as moving away from the city centre (from zone 1 to zone 4) urban area is dispersing, and at the same time use of public transportation in coverage area is also decreasing. In the outer suburban area (zone 4) has the maximum dispersed urban area, and lowest public transportation users compare to other three zones. But there is a big gap between compactness and trips of zone 4 compare to other zone. This indicates the poor coverage of public transportation system.

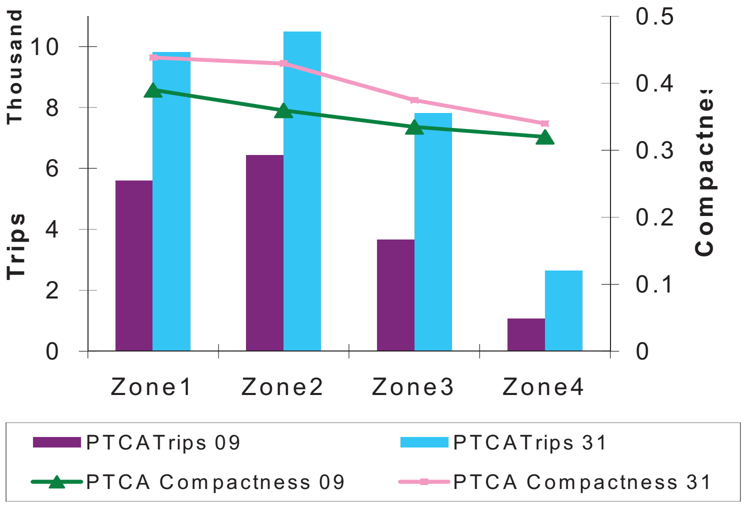

Figure 5.23 Relationships between Trips and Compactness at Zone Level

Figure 5.24 imply the relationship between land use mix and trip of 2009 and 2031. Land use mix for both periods has shown a same trend. It is decreasing from zone 1 to zone 4. This indicated that core urban has maximum land use mix values and outer suburban has lowest land use mix due to sprawl of city urban. The trips are decreasing with a decrease in the land use mix, instead of zone 2, where trips increased with a decrease in the land use mix in 2009 data. Zone 4 has low trips compared to its land use mix and also significant difference in trips from other zones in both 2009 and 2031.

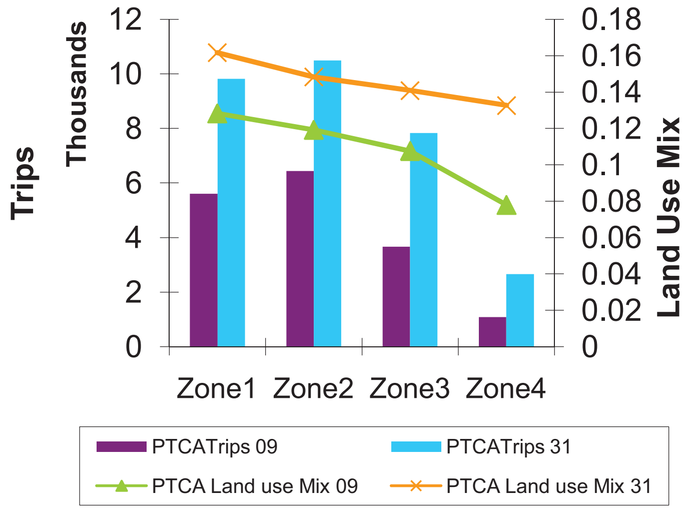

Figure 5.24 Relationships between Trips and Land Use Mix at Zone Level

Worker density is decreasing from zone 1 to zone 3 but there is an increase in worker density in zone 4 for both periods (Figure 5.25). This may represent the effects of industrial zone plans in outer suburban (Draft Master Development Plan 2025). In 2031 there is an enormous increase in worker density in zone 4 compared to 2009. Trips for all zones have the same trend as worker density instead of zone 2 where worker density is decreasing but trips are increasing for both periods. Worker density is decreasing from zone 2 to zone 3 and public transportation trip in coverage area is also decreasing with this. Worker density in 2031 in zone 4 has a significant difference from 2009 data but at the same time there are not significant increases in trips of public transportation in 2031 for this zone (Figure 5.25).

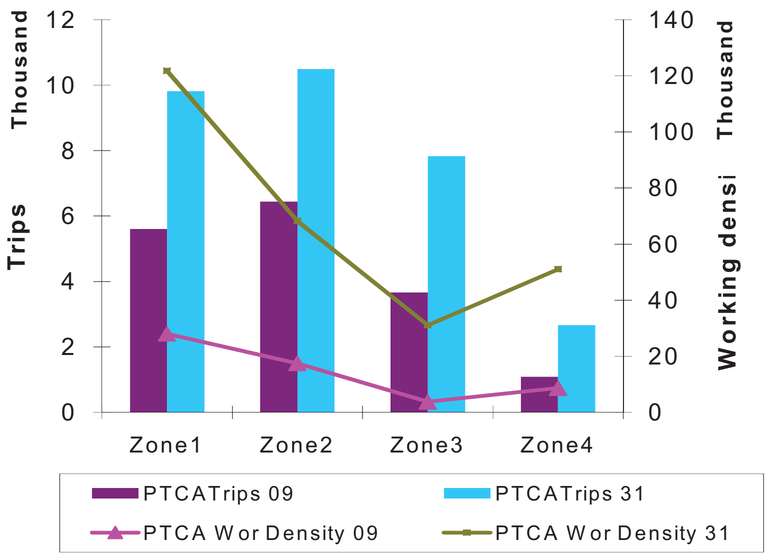

Figure 5.25 Relationships between Trips and Working Density at Zone Level

In general, trip production always increases with the increase in worker density, compactness and land use mix. However, our findings from above spatial analysis for two periods suggested that the trip production is not increasing monotonously and showing distributed pattern with the urban form indicators. The compactness, land use mix and worker density is increasing from 2009 to 2031 in all zones indicates the increase in demand of public transportation in the future.

5.5.2 Spatial Statistical Analysis of change Urban Form Impact on Trips of Public Transportation

Spatial statistical analysis is used for analyzing the impact of change in urban form on trips at ward level of Jaipur city (Figure 5.26). GIS has been used to create all variable including dependent and independent variables for this analysis (all variables described in Table 5.5). GeoDa 0.9.5 software is used for spatial relationship analysis (Anselin, 2005). Two models are prepared for this analysis using data of 2009 and 2031 data. The Figure 5.26 shows the ward boundary and ward numbers.

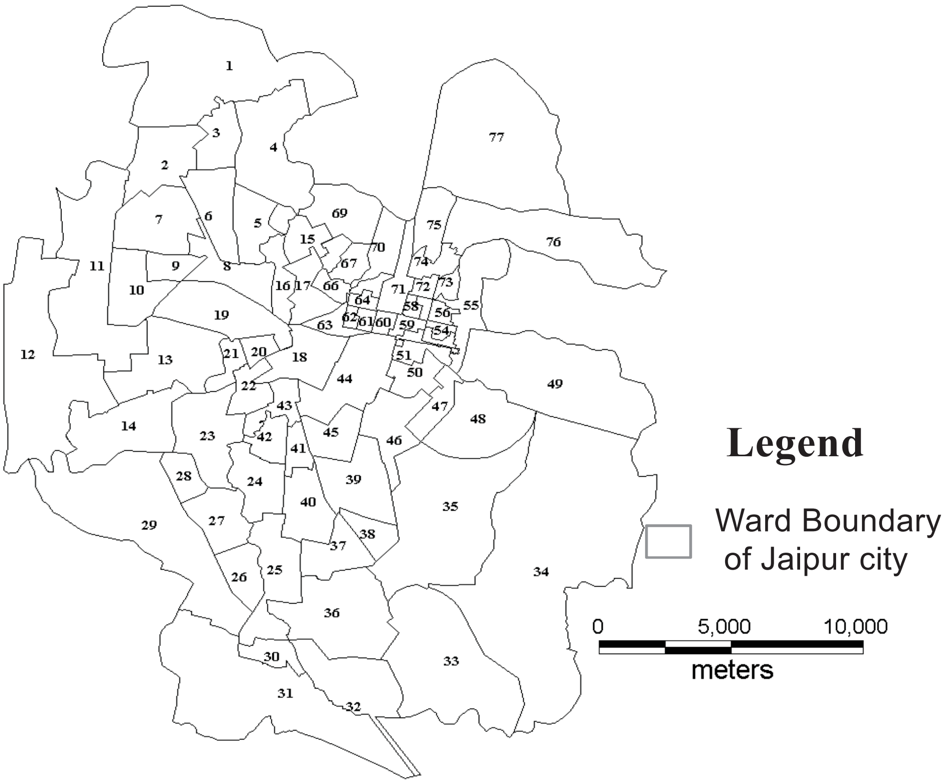

Figure 5.26 Ward Divisions of Jaipur city

5.5.2.1 Spatial Statistical Analysis using Model–A (2009)

The model–A is created using urban form and public transportation trip data of 2009. The variable described in Table 5.5 used for analysis and variable TRIPSPTCA used as a dependent variable. The rest of variables from Table 5.5 are used as the independent variables for analysis. In the first step OLS regression is used and then spatial lag/error model selected based on spatial diagnostic analysis.

The OLS regression analysis results have shown in Table 5.6. Urban form indicators like total area of the coverage area (TOTAREAPTCA), land use mix (LUMIXPTCA), worker density (WRKRDENSPTCA) in coverage area are statistically significant at the 0.05 level with positive coefficient values and implying that an increase would lead to increase in trips of public transportation in coverage area, these variables are showing the expected positive effects. Other variables at rest of ward level like worker density (WRKRDENSRTWD), compactness

(COMPACTRTWD) are also positively significant and indicate that change in urban form in the rest of ward area will affect the positively to trips in coverage area and they are also showing the positive expected effects. Instead of above variables, COMPACPTCA, TRIPLT5KMWD are negatively insignificant while LUMIXRTWD and TRIPMT5KMWD are negatively significant and do not correspond to expected out come. The negative impact of variable compactness of coverage area (COMPACPTCA) indicated that compactness is not effectively represented due to small coverage areas in each ward, while at the ward level compactness is satisfactorily representing the urban area compactness.

Table 5.6 OLS Regression Results for Model–A

Variables	**Coefficient**	**Std.Error**	**t-Statistic**	**P-value**
CONSTANT	115.7227	56.0269	2.0654	0.0429
TOTAREAPTCA	80.2619	20.1612	3.9810	0.0001
WRKRDENSPTCA	0.0186	0.0078	2.3798	0.0203
COMPACPTCA	-90.8889	77.3581	-1.1749	0.2443
LUMIXPTCA	896.4309	325.1130	2.7572	0.0075
TOTAREARTWD	-5.4603	2.5391	-2.1505	0.0352
WRKRDENSRTWD	0.0054	0.0031	1.7912	0.0779
COMPACRTWD	31.1821	11.6944	2.6664	0.0096
LUMIXRTWD	-599.6913	323.5107	-1.8536	0.0683
TRIPLT5KMWD	-0.0101	0.0467	-0.2159	0.8297
TRIPMT5KMWD	-0.0210	0.0110	-1.8978	0.0622

The residuals of trips in coverage area have been mapped to establish if spatial patterns exist or not. Residual can be calculated by subtracting predicted values from observed values. A residual map showed over and under predicted ward of the city. This indicates the spatial autocorrelation, created by a standard deviation of OLS residuals.

Figure 5.27 is showing OLS residual results, and it suggested that similarly-colored wards clustered throughout the city. The negative residual (over-prediction) is concentrated in the inner suburban, mostly in south east and north direction of the city. Outer suburban wards in the west of the city have over predicted residual and besides few are near to the core urban area of the city in the north. The wards in outer suburban on the eastern side of the city implied positive residuals (under prediction) and as well dominating in core urban and core urban ring with few exceptions in northern outer suburban wards. These over prediction in the outlying and under prediction in the core area are suggesting the possible presence of spatial heterogeneity (Anselin, 2005). The portion of under and over prediction is somehow equal and indicated the clustering. The boundary of core urban, core urban ring and inner suburban have been defined approximately in the Figure 5.27.

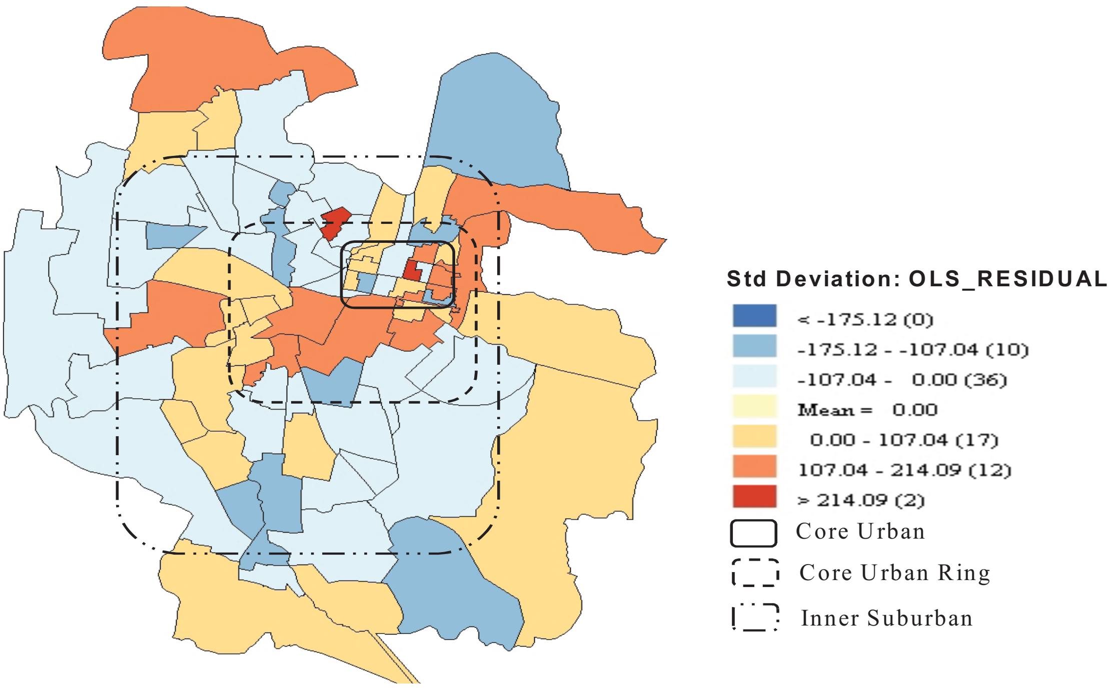

Figure 5.27 OLS Residual of Trips in Coverage Area Model–A (2009)

Table 5.7 Diagnostics for Spatial Dependence

Model–A (Year 2009)			
Test	**MI/DF**	**z-value**	**P-value**
Moran's I (error)	0.1207	3.1712	0.0015
Lagrange Multiplier (lag)	1	14.5930	0.0002
Robust LM (lag)	1	8.80564	0.0030
Lagrange Multiplier (error)	1	6.4015	0.0114
Robust LM (error)	1	0.6141	0.4332

Moran's I test for the model–A has shown in Table 5.7, and it indicates a positive and significant spatial relationship ($z = 3.17$ and $p < 0.00151$), which indicate the similar trend of trips with its neighboring wards. Moran's I indicated clustering of wards. Those have a similar impact of change in urban form on a trip of public transportation. Test for Lagrange Multiplier displayed in Table 5.7. All tests for lag and error have shown positive and significant values instead of Robust LM (error) test. The higher and significant values of lag models suggest that lag tests are more significant than the error tests. In the lag test LM (lag) test has higher positive values ($z = 14.593$ and $p < 0.000133$) and significant compare to Robust LM (lag) values ($z = 8.8056$ and $p < 0.003003$). The interpretation of these test suggested that the spatial lag model for correlation is the best (Anselin, 2005).

Anselin (2005) described that spatial lag model directly specifies the concept of "neighborhood" for each region with the introduction of the spatial weight matrix, W. This weight matrix reveals the effects of spatial dependence between regions. Spatial lag model used the all explanatory variables and also include exogenous variables. The autoregressive coefficient ρ of the spatially weighted lag trip production in coverage area (W_TRIPSPTCA) is shown in Table 5.8 has positive value (0.649) and significant probability ($p < 0.0000$). The values of a spatial autoregressive coefficient indicated that high trips in coverage area considerably increase the trips in nearby wards and it denotes the existence of a positive spatial relation in neighboring wards. Compactness of the coverage area (COMPACPTCA), land use mix index in the rest of ward (LUMIXRTWD), Trip less than 5km and more than 5km in ward (TRIPLT5KMWD and

TRIPMT5KMWD) are negatively insignificant in the model and do not correspond to expected effects of variables. Total coverage area (TOTAREAPTCA), worker density in the coverage area (WRKRDENSPTCA), land use mix in coverage area (LUMIXPTCA), worker density (WRKRDENSRTWD) and compactness (COMPACRTWD) in the rest of ward are positively statistical significant at the 0.05 level and correspond to positive expected effects (Table 5.8). There are some minor differences in the significance of the regression coefficient of spatial lag and OLS model: TOTAREAPTCA, WRKRDENSPTCA and LUMIXPTCA variables are more significant in lag model compare to OLS model. The significance of COMPACRTWD variable is changed from OLS model ($p < 0.0090$) to lag model ($p < 0.0133$).

Table 5.8 Spatial Lag Results for Model–A (2009)

Variables	Coefficient	Std.Error	t-Statistic	P-value
CONSTANT	-84.1361	58.4417	-1.4396	0.1499
W_TRIPSPTCA	0.6490	0.1448	4.4805	0.0000
TOTAREAPTCA	93.9887	16.5205	5.6892	0.0000
WRKRDENSPTCA	0.0153	0.0064	2.3861	0.0170
COMPACPTCA	-49.8667	63.3876	-0.7866	0.4314
LUMIXPTCA	736.6037	266.4129	2.7648	0.0056
TOTAREARTWD	-3.8838	2.0807	-1.8666	0.0619
WRKRDENSRTWD	0.0051	0.0025	2.0360	0.0417
COMPACRTWD	24.0458	9.7234	2.4729	0.0133
LUMIXRTWD	-355.2622	267.3623	-1.3287	0.1839
TRIPLT5KMWD	-0.0291	0.0387	-0.7530	0.4514
TRIPMT5KMWD	-0.0112	0.0092	-1.2258	0.2202

The spatial lag residual results have shown in Figure 5.28, and it indicated that the spatial patterns of trips in coverage area are distinguishable from OLS residual. The residuals in over prediction and under prediction areas for the trip are almost equal and under prediction area is dominating in western part of the city. Over predicted area is mostly in the inner and outer suburban areas of north and south eastern part of the city. Residuals in OLS model indicated a significant difference in over prediction and under prediction areas but in a lag model over prediction and under prediction are almost equal.

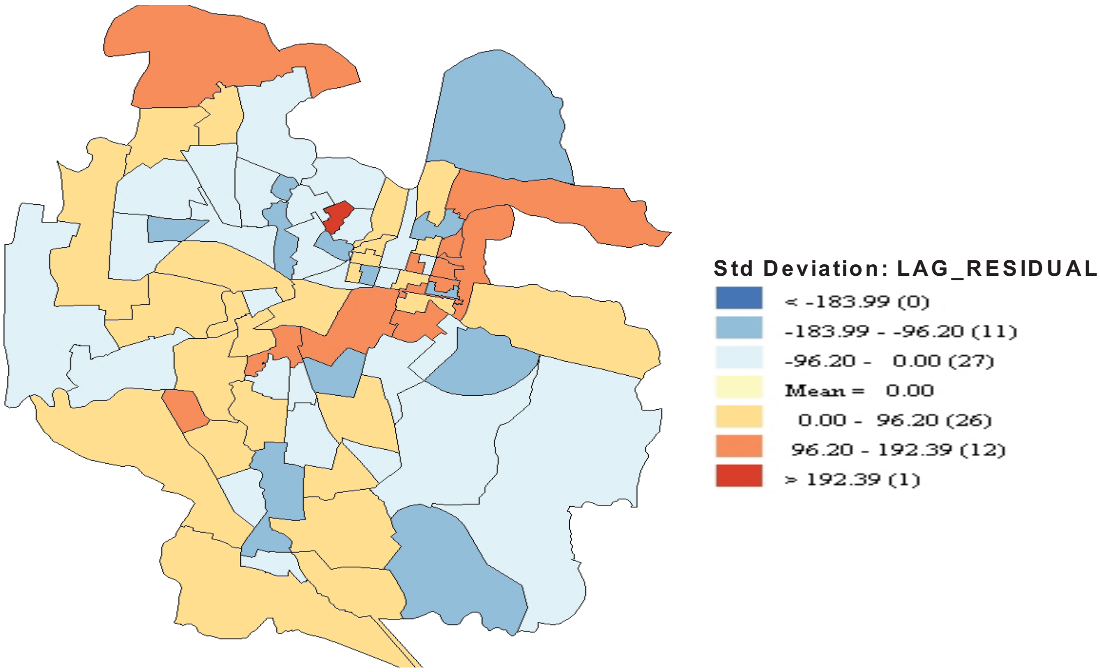

Figure 5.28 Lag Residual of Trips in Coverage Area Model–A (2009)

5.5.2.2 Spatial Statistical Analysis using Model–B (2031)

Model–B created to analyze predicted and projected 2031 data and produced a scenario based analysis for future impact of change in urban form on travel demand by public transport of Jaipur city. The variable described in Table 5.5 used for this scenario and variable TRIPSPTCA used as a dependent variable. The remaining variables in Table 5.5 are used as the independent variables for analysis. In the beginning OLS regression and then spatial lag model are used for spatial statistical analysis.

The results of OLS regression presented in Table 5.9. Independent variables in coverage area such as total area (TOTAREAPTCA), worker density (WRKRDENSPTCA), and land use mix (LUMIXPTCA) are statistically significant at the 0.05 level, which follow the expected positive effects, while compactness in coverage area (COMPACPTCA) do not correspond to expected effect. The variables in the rest of ward area like total urban area (TOTAREARTWD), compactness (COMPACRTWD) are positively significant in the model –B. The urban area of ward (TOTAREARTWD) does not show the expected effect in this model. One more important point, which is different from OLS of 2009, is that trip distance of more than 5km (TRIPMT5KMWD) and worker density in the rest of ward area (WRKRDENSRTWD) have positively significant values, which represent the positive expected effects. It indicates that travel distance of trip will also affect the trips of public transportation in the future.

Table 5.9 OLS Regression Results for Model–B

Variables	Coefficient	Std.Error	t-Statistic	P-value
CONSTANT	268.4261	107.6318	2.4939	0.0152
TOTAREAPTCA	121.9511	46.4540	2.6251	0.0108
WRKRDENSPTCA	0.0022	0.0008	2.4479	0.0171
COMPACPTCA	-194.0421	81.5665	-2.3789	0.0203
LUMIXPTCA	315.1268	246.2121	1.2799	0.0205
TOTAREARTWD	10.2483	4.7696	2.1486	0.0354
WRKRDENSRTWD	0.0000	0.0009	0.0094	0.0917
COMPACRTWD	487.1323	199.0547	2.4472	0.0171
LUMIXRTWD	-173.2174	253.0253	-0.6845	0.4960
TRIPLT5KMWD	-0.0361	0.0378	-0.9564	0.3424
TRIPMT5KMWD	0.00401	0.0054	0.7365	0.0464

OLS residuals have been estimated for model–B by subtracting predicted value from observed values. The results of residuals have shown in Figure 5.29. OLS residuals results are pretty different from model–A OLS residual results. In a model–B residuals have more positive values (under prediction) compare to model–A. Under predicted area is mostly in the core urban, core urban ring and also in the eastern and western part of the outer suburban area of the city. The over predicted area is mostly in the inner suburban and outer suburban area in the northern and southern part of the city. Under predicted area is dominating in the OLS residual analysis. This residual analysis implies that under and over predicted area showing clustered pattern.

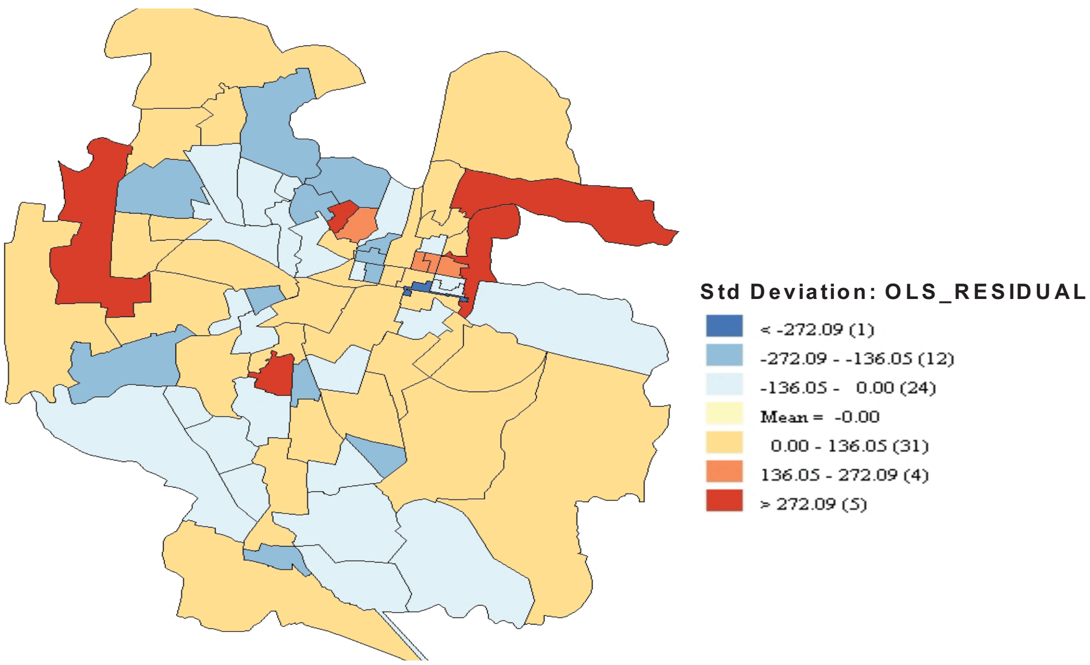

Figure 5.29 OLS Residual of Trips in Coverage Area Model–B (2031)

Moran's I test conducted for model–B and represented in Table 5.10. Moran's I value is positive (z = 0.938) and not significant (0.03483) for model–B. The Moran's I indicate a positively significant and it is different from analysis of model–A. For this model–B only lag models value are significant and Lagrange Multiplier (lag) tests for spatial dependence indicated positive and higher values compare to Robust (lag) test (Table 5.10). Based on Table 5.10 results spatial lag model has been selected for spatial correlation.

Table 5.10 Diagnostics for Spatial Dependence

Model–B (Year 2031)			
Test	**MI/DF**	**z-value**	**P-value**
Moran's I (error)	0.3109	0.9379	0.0348
Lagrange Multiplier (lag)	1	3.3670	0.0665
Robust LM (lag)	1	5.4715	0.0193
Lagrange Multiplier (error)	1	0.1953	0.6585
Robust LM (error)	1	2.2998	0.1293

Spatial lag model has been selected based on diagnostic of spatial dependence. The spatially weighted lag trips in coverage area (W_TRIPSPTCA) represent the autoregressive correlation coefficient, ρ which has positive value (0.3963) and significant probability (0.0301). The positive spatial autoregressive coefficient indicates that a higher level of trips in ward significantly increases the trips in the neighboring wards. Independent variables such as TOTAREAPTCA, WRKRDENSPTCA and LUMIXPTCA are positively significant and correspond to expected effects. TOTAREARTWD and COMPACRTWD are positively significant, while the total urban area of ward (TOTAREARTWD) do not correspond to expected effect (Table 5.11). The land use mix of ward area (LUMIXRTWD) insignificant, which is unexpected effect. There are some minor differences found in the significance of the regression coefficient of spatial lag and OLS model: TOTAREAPTCA have more positive and significant value and WRKRDENSPTCA and LUMIXPTCA variables are more significant in lag model compare to OLS model.

Table 5.11 Spatial Lag Analysis for Model–B (2031)

Variables	Coefficient	Std.Error	t-Statistic	P-value
CONSTANT	-456.2640	124.6643	-3.6599	0.0002
W_TRIPSPTCA	0.3962	0.1826	2.1698	0.0301
TOTAREAPTCA	132.6463	41.3344	3.2091	0.0013
WRKRDENSPTCA	0.0023	0.0007	3.0495	0.0022
COMPACPTCA	-155.3052	74.0297	-2.0978	0.0359
LUMIXPTCA	301.1364	217.6829	1.3833	0.0166
TOTAREARTWD	10.8004	4.2172	2.5610	0.0104
WRKRDENSRTWD	-0.0002	0.0008	-0.2559	0.7980
COMPACRTWD	523.0505	176.4542	2.9642	0.0033
LUMIXRTWD	-82.6306	224.5744	-0.3679	0.7129
TRIPLT5KMWD	-0.0257	0.0335	-0.7687	0.4423
TRIPMT5KMWD	0.0031	0.0048	0.6308	0.5281

Spatial lag model has the similar results as OLS results and important change in the land use mix of coverage area, which is negative compare to OLS results. The lag residuals have been shown in Figure 5.30 for model–B. The results indicate significant similarity with the OLS residuals of model–B. The important difference is over predicted area is more than under predicted area in lag residual, this is a reverse of OLS residuals results of model–B. Lag residual results from model–A have higher positive values than the negative and lag residual in model–B have higher negative values than the positive. Positive values are dominating in core urban ring and inner suburban area, where as negative values are dominating in the inner suburban area of model–B (Figure 5.30).

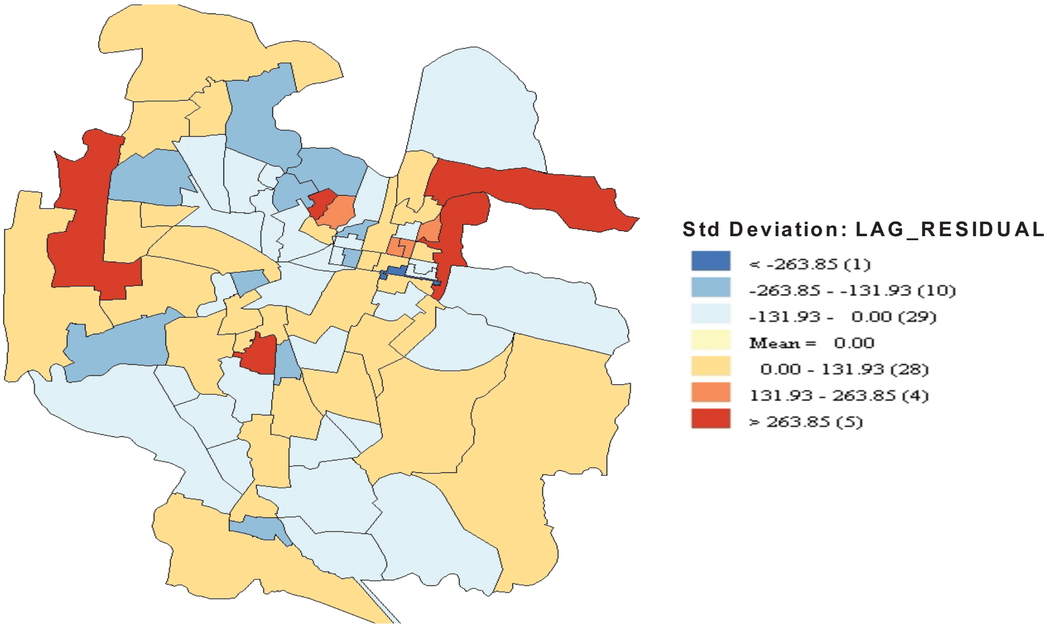

Figure 5.30 Lag Residual of Trips in Coverage Area Model–B (2031)

5.6 Concluding Remarks

Urban form is an important aspect that influence and control the trips of public transportation. Urban form based indicators play an important role in improving the sustainability of public transportation. Various indicators based on urban form are created in this study, and results indicated that their values and desired impacts are changing with spatial scale. It directly as well as indirectly controls the coverage of public transportation service. Urban from change pattern indicated that urban form based indicators (such as- land use mix, compactness and worker density) are increasing at both ward level as well as zone level of city. The increasing in these indicators especially in suburban area/ wards in suburban area is significant but at the same time there is not much increase in public transportation trips in suburban areas.

Public transportation coverage is an important part that allows people to use services. Detailed information about coverage area is required to understand the travel behavior. In this research, network based distance method used for coverage area delineation and found more suitable and has more accuracy compare to Euclidian distance method. This delineated coverage area used to ascertain population, worker density and other important indicator. Those indicators are found useful to assess the travel demand in coverage area. The coverage area delineated using road network method is useful for estimation of potential riders and also provide the effectiveness of public transportation system in respect of its coverage for city. The coverage area estimation indicate suburban area or wards in sub urban area has less riders of public transportation but at the same time these suburban areas are growing rapidly especially in commercial and industrial activities.

Spatial statistics method integrated in GIS and used to analyze how the urban form influence the trips of public transportation in coverage area. Zone wise spatial analysis revealed Jaipur as a sprawling city. Urban form and relationship between trips of public transportation in coverage area are monotonically changing from 2009 and 2031. It is found from spatial analysis that trips production of public transportation will increase along with the increase in worker density and mix ration but at the same time coverage area of service is also very important for mobility. Spatial statistical analysis is provided important relation between change in urban form and trips especially when the change in urban form at coverage area and also at rest of ward level prepared to assess impact on trips of public transportation in coverage area. The analysis indicated that coverage area has higher relationship to increase trips of public transportation. Lag coefficient values indicates that trips in coverage area are highly dependent on trips in coverage area of neighboring wards. This implies that all wards are showing similar relationship between trip and change in urban form.

This research investigated the extent to which trip production in coverage area of ward influenced by different indicators of urban form by using spatial statistical analysis. For this purpose two models have been created, one is representing the current condition of the city and another showing future scenario of the city. Table 5.12 prepared to find out the change in coefficient value and significance of explanatory variables from 2009 based data analysis to 2031 based data analysis. The most of the variables which are significant in 2009 are also showing significant value in 2031 and have higher coefficient values compare to 2009 in both OLS and lag analysis. For example, variable TOTAREAPTCA have significant value in both OLS model and lag model for 2009 and 2031 but coefficient value is increased from 80.26 to 121.95 during 2009-2031 in OLS model, where as 93.98 coefficient value in 2009 increased to

132.64 in 2031in lag model. Some variables have shown different value in the analysis such WRKRDENSRTWD variable is not significant in OLS model for both year but significant in lag model of 2009. TRIPMT5KMWD variable is positively significant for OLS model in 2031 compare to 2009.

Table 5.12 Change in Coefficient and Significance from 2009 to 2031 in OLS and Lag Model

Variables	Coefficient2009-OLS	Coefficient2031-OLS	Coefficient2009-LAG	Coefficient2031-LAG
CONSTANT	115.723	268.426	-84.136	-456.264
TOTAREAPTCA	80.262*	121.951*	93.988*	132.646*
WRKRDENSPTCA	0.018*	0.002*	0.015*	0.002*
COMPACPTCA	-90.888	-194.042	-49.867	-155.305
LUMIXPTCA	896.431*	315.127*	736.604*	301.136*
TOTAREARTWD	-5.461	10.248*	-3.883	10.800*
WRKRDENSRTWD	0.005	0.0000	0.005*	-0.001
COMPACRTWD	31.182*	487.133*	24.046*	523.050*
LUMIXRTWD	-599.692	-173.217	-355.262	-82.630
TRIPLT5KMWD	-0.011	-0.036	-0.029	-0.026
TRIPMT5KMWD	-0.021	0.0041*	-0.012	0.003

* The statistical significance $p < 0.05$

The statistical analysis brought out one important thing from these analyses that compactness in coverage area may induce a decrease in trip production among coverage area of ward. Therefore, it can be generalized that too dense urban in coverage area not lead to increase to trip production. The increase in coverage area indicated the increase in the trip of public transportation in this study. This analysis guided to recognize and measure the spatial association between change in urban form and its impact on trip production in coverage area. This study entails that developing the coverage area will lead to sustainable urban transportation development of the city. This research is also important for sustainability perception specially the future scenario based statistical analysis.

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CHAPTER 6

CONCLUSIONS

In this chapter, summarized the key conclusions from the dissertation according to the objectives mentioned in Chapter 1, and suggest avenue for further research.

6.1 Research Summary

The objectives of this study have been explained in chapter 2, 3, 4, and 5. In this section, the objectives are restated and the findings are summarized.

6.1.1 Urban Modeling to Assess Urban Change Pattern

The availability of spatial data and advanced evaluation techniques offers a significant improvement for analysis, ascertaining, depiction, and modeling of urban dynamics. The combination of spatial data and analytical methods should provide support to city planners, economists, ecologists, and resource managers in their planning and decision making. Dynamic spatial urban models provide an enhanced capability for evaluating future development and generating planning scenarios; these models also allow the exploration of the impacts of different urban planning and management policy implementations.

The conventional surveying and mapping techniques are time consuming and costly. Mapping from remote sensing techniques have very much advantage because it is synoptic, repetitive and multi temporal. Remote sensing technique is cost effective and a versatile tool for mapping and monitoring of natural features and as well as manmade features. The technology of remote sensing includes both aerial and satellite-based observations with high resolution and high temporal frequency. This method, along with geographic information systems (GIS), facilitates spatial data analysis and offers a platform to produce various options for modeling and planning process.

(i) Evaluate Spatio-Temporal Land Use and Urban Density Change Analysis

In this section, assessed the long term land use and urban density change analysis over a 30-year period and explored the future prospects of growth by using Markov method. The land use change analysis indicated rapid change in built-up area and also in agriculture area. In this analysis agriculture area is sub-categorized in crop land and fallow land, to capture complete agriculture area. Barren land and agriculture area maximum contributed to built-up area development. The future prospects of land use change indicated huge built-up growth.

In urban density change analysis using remote sensing, GIS and Markov method, it is found that urban density is increase very rapidly for Jaipur city and it will increase in future also. In this analysis urban area is further sub-categorized in high-density, medium-density, low-density and sub urban based on density, association and use. The rule based approach is used in remote sensing for this sub-categorization of urban area. Urban density change analysis indicated that city is rapidly growing as well increasing density of urban area and this urban growth will also increase in future and there is no stability in urban density change.

In last part of this objective, influence of natural resources (mining area) find out on urban growth. For this study Makrana city is selected, because it has enormous deposits of Marble in the vicinity of urban area of town. This Marble deposit has both direct and in-direct impact on the people of Makrana city and influence the sprawl of city. To find out this urban growth and mining area is mapped for over 30-years. These rich deposits in the vicinity of the city are providing jobs for more than 0.1 million people in which 60 thousands are deployed directly in mining. Indirectly employment in mining includes transporters, mechanics/workshop owner, masons, artisans etc. This indicates that urban growth is influenced by natural resources. The consumption rate of built-up and mining indicates parallel growth in built-up area and mining area.

(ii) Simulate Urban Change by Multi-Layer Perceptron–Markov Method

Urban growth is simulated using multi-layer perceptron–Markov method of Jaipur city. This MLP-Markov method can overcome the limitation of using only the Markov model for simulating urban area and non-urban land cover by including the spatial predictable variables of urban growth in a simulation model. The combination of these two is capable of describing the non-linear relationship. MLP is appropriate for describing complex relationships of land use as it is capable of describing $n*n$ conversion in land use. Remote sensing data integrated with GIS has been used to for urban growth simulation. Predictor variable like distance from road, distance from city center, slope and Hillshade are integrated in this simulation. Urban growth simulated and verified for 2002 and 2006 by using actual estimated data. The high accuracy found in verification of simulated data with actual data. Simulation of urban growth is very important from planning and management of urban ecosystem for a city.

(iii) Evaluate Urban Change Pattern with Change in Urban Land Suitability

Land suitability analysis aims to identify the most appropriate spatial pattern for future land uses based on specific requirements. Multi-criteria evaluation (MCE) using GIS is a technique for standardization of criteria and multiplying each criterion with its weight factor to produce results. MCE is able to handle the discrete decision situations where the choice-possibilities are measurable and data have a quantitative and/or a qualitative character. The factors and constraints used in MCE process are created using GIS capabilities. A primary step is to ensure a standardized measurement system across all the factors being considered. Since most images still hold the cell values, the original map codes have different units and different scales of measurement. Therefore, these have to be standardized to a uniform suitability rating scale before being used in MCE. For standardization of criteria fuzzy set approach is used and after that weight is assigned to criteria using GIS based analysis. Applying the GIS tool, urban land suitability is evaluated to investigate the urban change patterns. For the analysis, an urban suitability map has been reclassified into five categories: 1 very low suitability, 2 low suitability, 3 medium suitability, 4 high suitability, and 5 very high suitability. Here, very low suitability areas include the existing built area, forests, waterways, and roads. . This urban suitability analysis indicates that the impact of proximity to urban centers and major roads, as well as of the growth of urban areas is moving from the center of the city to the suburban areas. This also indicates that urban growth is more on the outskirts than near to the city centers, and the growth share is higher on the periphery of the city during 2002–2006. From this growth pattern, we can say that urbanization is increasing on the city periphery during the 2002–2006 periods, and it will increase in the future.

6.1.2 Assessment of Impact of Urban Change Pattern on Proposed Land Use Development Plan Using GIS and Landscape Metric Analysis

Landscape metrics (indices) are numeric measurements that quantify spatial patterning of land cover patches, land cover classes, or entire landscape mosaics of a geographic area. Landscape metrics are used to analyze plan in the proposed master plan of 2011 and 2025. To analyze the plans different scenario is created using simulated and estimated urban data and interpreted using landscape metric analysis. The simulation and estimated results combined with landscape metrics provided clear and better understanding of the urban development pattern and process. The results suggest that urban development in Jaipur city will continue through densification of existing urban areas and expansion of suburban areas toward the east, west, and south in the future.

6.1.3 To Evaluate Impact of Urban Change Pattern on Public Transportation Development Plan

Rapidly developing cities are characterized by immense urbanization, population dispersion, employment decentralization and land use fragmentation. Suburban development increased the requirement of transportation service to move and in the absence of an efficient public transportation system number of private vehicles will increase quickly. Same situation is reflecting in Jaipur city, where urban area is growing rapidly with the enormous increase in population and prominent decentralization of employment.

(i) Coverage Area for Bus Stops (Current and Proposed Plan Both) using Road-Network Distance Method

Public transportation services are accessed by its station, so it is very important to estimate coverage area to stop. The significance of coverage is that the more people work and reside in the proximity of transit, the greater likelihood that the service will be used and if the distance or barriers to access transit are too great at either trip origin or destination, then it is unlikely to be utilized as a mode of travel. Coverage area is delineated using a road/street network based distance method for current and proposed plan of public transportation.

The distance from stop used to create coverage area is 400m, and it can be defined as a comfortable walk under normal situations for all people.

(ii) Spatial Statistical Analysis of Change in Urban Form and Its Impact on Trip of Public Transportation

Spatial analysis is used to analyze change in urban form with trips of public transportation mode at two levels. One is at a zone level and second is at ward level of the Jaipur city. Urban form indicators are created for analysis. Urban form indicators like compactness index, land use mix index, worker density etc. These urban form indicators are used to analyze the impact on travel demand. Spatial statistical analysis is used to analyze the relationship between urban form and its impact on travel demand using GIS. Urban form and relationship between trips of public transportation in coverage area are monotonically changing from 2009 and 2031. It is found from spatial analysis that trips production of public transportation will increase along with the increase in worker density and mix ration but at the same time coverage area of service is also very important for mobility. This research investigated the extent to which trip in coverage area of ward influenced by different indicators of urban form by using spatial statistical analysis. For this purpose two models have been created, one is representing the current condition of the city and another showing future scenario of the city. The statistical analysis brought out one important thing from these analyses that compactness in coverage area may induce a decrease in trip production among coverage area of ward. Therefore, it can be generalized that too dense urban in coverage area not lead to increase to trip. The increase in coverage area indicated the increase in the trip of public transportation in this study. This analysis guided to recognize and measure the spatial association between change in urban form and its impact on trip production in coverage area.

(iii) To Evaluate and Monitor Plan by Comparing Information among Different Year

This analysis is performed to assess the efficiency and effectiveness of public transportation. The effectiveness of public transportation plan is assessed in two steps. First step is based on demographic data and second is by using urban data.

(i) To analyze using demographic data, a three level scale has been created for all measures Such as for population-low population density, medium population density and high population density. This density change has been assessed with change in coverage area 400m, 500m and 600m. This analysis of public transportation plan is assessed for 2009 and 2031 by including proposed plan. The analysis results of 2009 indicate the increase in coverage area is always increase opportunity to use public transportation. The 2031 data showing high increase in population density compare to 2009, in such case one can say that coverage area is going to play very significant role in increasing efficiency and effectiveness of public transportation.

Three different scenarios are created using urban form indicators. These scenarios examine the impacts of restricting compactness and mix-ratio on PTTrips, PVTrips, and Trip-length (by PT).

This all three scenarios analysis is performed for both 2009 and 2031 year data (here PT means public transportation and PV private vehicle).

The analysis for 2009 and implies that if compactness restricted to low then private mode trips is highest in scenario1. Scenario2, which represents the medium compactness, has more PT trips compare to scenario1 and also increase in trips in both case of trip length. Compactness restricted to high in scenario3 and found that trips from public transportation are increased from previous two scenarios. We can conclude that increase in compactness is influencing trips of public transportation but at the same time trips of private mode is also significant.

In the analysis of land use mix based scenarios for 2009. It implies that if land use mix increase trips will also increase. In first scenario land use mix restricted to low and found private mode trips is highest in scenario1. Private mode trips are much higher than the public transportation trip in all scenarios. Trip of private mode is increased in scenario3 compare to two other scenarios and total trip in scenario3 is almost double to trip of public transportation. We can conclude that increase in land use mix is influence the increase in trips of public transportation but at the same time trips of private mode is also significantly increasing

The analysis for 2031 using compactness and implies that if compactness restricted to low then private mode trips is highest in scenario1. Scenario2, which represents the medium compactness, has more PT trips compare to scenario1 and also increase in trips in both case of trip length. Trips from private mode are decreased from 47% to 28% in this scenario2, which is completely different from 2009. Compactness restricted to high in scenario3 and found that trips from public transportation are increased from previous two scenarios. Trip of private mode is much higher than the trip of public transportation in first two scenarios but decreased in scenarios3. We can conclude that increase in compactness is influencing trips of public transportation but at the same time trips of private mode is also noteworthy.

The analysis of the land use mix based scenarios for 2031. It implies that if land use mix increase trips will also increase same as 2009. Land use mix restricted to low in first scenario and private mode trips is highest in scenario1. Public transportation trips are 14 % in scenario 1 and increased by 5% from 2009. PT trips compare to scenario1 and also huge increase in trips in both case of trip length. Trips from private mode also increased from 19% to 37% in this scenario2. In scenario3 land use mix restricted to high and found that trips from public transportation are increased from other two scenarios and share 50% of total trips. Trip of PT is 14% in scenario1 and reached to 50% in scenario3.

6.2 Synthesis and Prospects for Future Research

(i) Synthesis

This research has focused on urban change pattern assessment using developments plans of city. It has been shown that increase in urban area resulting high population growth and economic growth would not only increase pressure on land use plans but also on infrastructure development plans of public transportation. Jaipur city is not only facing sprawling but also huge increase in density of urban area. Urban change assessed with land suitability indicated that urban area change is following land suitability trend so such analysis brings a platform to understand the growth pattern for planning perspective. Proposed land use plan used to assess urban change pattern provided significant findings that suggest the gap between conceive and implement a plan for city development. This analysis also suggested that monitoring is a very important criterion to manage the urban development using simulated urban data. Urban change has also impact on public transportation system due to rapid sprawl of city. Urban change pattern have been examined to assess its impact on public transportation system. It found from analysis that urban form indicators significant enough to explain the current and future prospects of public transportation system of Jaipur city. The coverage area of public transportation stop is also significant for Jaipur city as city has poor and inadequate coverage of public transportation.

(ii) Prospects for Future Research

This study demonstrates significant results from the analysis and modeling approaches in accordance with the research objectives. However, a number of directions for future research are found:

a. Remote Sensing For Urban Studies

Urban studies using remote sensing technology is very significant for monitoring, planning and management of growth. Remote sensing based study of urban development is very important for management of informal settlement such as slum area. Slum area is a big issue in all developing cities. In this study Landsat satellite data are used for urban change mapping, which has 30m spatial resolution. Use of Landsat data for identification of slum area is difficult due to its low resolution and when slum area patches are small, scattered and mixed with the other urban categories. Slum area of Jaipur is also have same kind of trend- small, scattered and mixed with planned urban areas. The satellite data can also be used for income level based classification of urban area but for this we require high resolution satellite data to differentiate the micro structure of land use for analysis along with ancillary data or field survey for verification. Landsat satellite data used in this research have certain limitation for such kind of classification. It is difficult to distinguish micro-structures, such as individual house and roads less than 30m width using Landsat satellite data. The urban mapping derived from higher-spatial resolution imagery (e.g. IKONOS, QuickBird) have more prospects for efficient planning and management of city developments.

b. Urban Change Modeling

Urban change is modeled in this research by using MLP–Markov approach. Different factors and constraints are used in this modeling, which influence as well control the urban change such as proximity to road, proximity to city urban and distance from forest etc. In this modeling, we also included some proposed policy for urban development and this kind of approach is very significant from planning and management perspective. Human behavior is very important to assess the urban dynamics. So it is found in this research that if we include more factors and constraint, which represent the human behavior will make this urban growth modeling more significant. At the same time, it is good to use high resolution satellite data for high accuracy of urban modeling with respect to the field data/ground data.

c. Urban Form and Coverage Area

As this research is established the importance of urban form for assessment of travel demand. The problem in developing India is availability of data for analysis. This is a big constraint for any research and also collecting information at owns is also difficult for developing cities. In our research we mapped coverage area mapped at ward level of Jaipur city based on road network distance approach. But if we have parcels level spatial and aspatial data and integrate with the network distances from parcel to bus stop locations method, this analysis will provide high accuracy in estimation of population in coverage area.

In current situation of Jaipur city, only bus is available on the name of public transportation therefore, in this research only bus based public transportation is used for the analysis. The local authority is also planning to build mass rapid transit (MRT) for the city. So for the future work I like to use MRT network data, when data will available, then create the coverage area of MRT based on local people preference survey to use MRT services. Then established the relationship between change in urban form and public transportation system including bus routes and as well as MRT routes.

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