QUANTIFYING URBAN GROWTH PATTERN OF RAJSHAHI CITY CORPORATION

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ABSTRACT

Rapid urbanization rate in the developing countries like Bangladesh is ongoing to be one of the critical topics of global change in the 21st century upsetting the physical magnitudes of cities. This non-urban to urban land transformation trend line is incising day to day and this could be the most powerful and visible anthropogenic force that has brought about fundamental changes in urban land cover and landscape pattern around the globe. Understanding and quantifying the spatiotemporal dynamics of urban growth and its drivers in Rajshahi city corporation, Bangladesh, is critical to put advancing appropriate policies and monitoring mechanisms on urban growth and make an informed decision for rapid populaton growth and planning practice performance status. In this study, the spatiotemporal patterns and processes of urban growth of Rajshahi City Corporation and its drivers were investigated from 1990 to 2015 by using satellite remote sensing images, spatial metrics, and logistic regression modeling.

Four separate land cover maps consequent from Landsat TM image of 1990, 2000, 2010 & LR 2015 were used to assess a set of nine certain spatial metrics to expose patterns and dynamics of urban growth in the study area. The multiplication of spatial metrics was directed at spatial scales. The instant descriptors of landscape heterogeneity at the city level are evaluated. Changing patterns of urban growths over time is linked to the major physical driving services in the study area via binary logistic regression modeling. Therefore, three models are built for 1990-2000, 2000-2010 and 2010-2015 study periods.

Results found from the synoptic scrutiny of built-up area dynamics for the past two and half decades revealed that the city has been undergoing extensive urban growth processes. The growth was prolonging both from urban center to contiguous non-built up areas in all direction approximately. The total built-up area in the city has grown up from 6 sq. km in 1990 to 31 sq. km in 2015 at an average growth rate of 8, 9.7 and 6.3% per annum during 1990-2000, 2000-2010 and 20102015 study periods respectively. The study period from 2000 to 2010 was registered as the time at which the city experienced the highest urban growth. The analysis of spatial metrics at the city level revealed that the urban landscape has experienced a process of sprawling and fragmented development pattern, particularly in the fringe areas while the city center underwent infill and edge expansion little development processes. The core area consolidated over time. This indicates the results of spatial metrics analyses at the city level are inclusive.

The results of binary logistic regression model revealed that distance to major roads, distance to sub-city centers, the proportion of built-up cell, distance to govt. higher education institutions, distance to public parks and distance to Padma River were the major driving forces of urban growth at different time phases with changing the level of consequence and correlation. The importance of distance to major roads, distance to sub-city center and distance to Padma River decreased over time while the distance to public parks and proximity to highly urbanized cells become more important confirming the results of spatial metrics that show typical fragmentation and outward expansion. Quantifying urban growth patterns and development processes of the past trends can help better understand the dynamics of the built-up area and guide sustainable urban development planning for the future urban growth. Thus, the methods used in this research can deliver the rich level of quantitative information on the development patterns and processes of the urban landscape.

Keywords: Urban growth; Spatial metrics, Remote sensing; Land cover change; Logistic regression.

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Md. Ashaduzzaman

November 2017

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List of acronyms

ASTER	**Advanced Space-borne Thermal Emission and Reflection Radiometer**
CBD	Central Business District
ETM+	Enhanced Thematic Mapper-plus
GCP	Ground Control Points
GIS	Geographic Information System
GPS	Global Positioning System
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red
RCC	Rajshahi City Corporation
RDA	Rajshahi Development Authority
RS	Remote Sensing
SPSS	Statistical Package for Social Sciences
TM	Thematic Mapper
UN	United Nations
UN-HABITAT	United Nations Human Settlements Program
USGS	United States Geological Survey
VHR	Very High Resolution
WB	World Bank
WGS	World Geodetic System

CHAPTER

01. Introduction

Urbanization has been a worldwide and fundamental social and financial marvel occurring far and wide. This increasing rate of urbanization increasing without sign of slowing down and could be the most effective and unique anthropogenic power. This has achieved crucial changes in arrive cover and scene design far and wide. Rapid urbanization and urban development, particularly in the developing countries, is proceeding to be one of the essential issues of worldwide change in the 21st century influencing the physical measurements urban areas.

1.1. Background

In a previous couple of decades, urbanization and urban development have definitely quickened in many developing nations. As indicated by United Nations; in 2011, 3.6 billion of the world's populace (52%) were urban occupants. Generally, the level of urbanization is required to climb to 67% out of 2050. In the low developed countries, the extent of urban will rise from 47% out of 2011 to 64% out of 2050. In Bangladesh, the urban population is increasing from 42 million out of 2010 to 126 million within 2050 (unicef.org). As an administrative divisional unite and growth center Rajshahi city corporation get a rapid urbanization in northern region of Bangladesh influencing by various physical driving factors in on an average of 08.58% annual urbanization rate.

In many nations; urbanization is perceived as a vital wonder of financial development and social change as it offers expanded open doors for work, specialization, generation and products and ventures. This has started countless to move from country to urban region. Subsequently, urban communities are becoming quicker than any time in recent memory (in physical measurement), is a colossal place for habitation, industry, exchange, and speculation, correspondences, foundation, social administrations and so forth. Be that as it may, this development likewise triggers various issues. Ecological contamination and debasement, expanded natural risks, for example, flooding, population blast, deficient sanitation and water supply, transport issues, poor housing conditions, increasing typical cost for basic items and unequal distribution in wealth, an expansion in wrongdoing, and loss of prolific farming and wetlands are the absolute most noticeable negative impacts of fast urbanization and urban development (UNHABITAT, 2012). If not oversaw legitimately, these may scare the supportable advancement of urban communities over the long haul (Dubovyk et al., 2011).

As of late, an expanding worry about practical advancement has cultivated another enthusiasm of the universal writing on the physical measurement of urban areas and, especially, on the issues of urban development design and urban shape (J. Huang et al., 2007; Van de Voorde et al., 2009). Various investigations have been directed concentrating on the marvel of urban sprawl and casual settlement and they are unfavorable ecological and financial results instead of the idea of minimal and formal advancement (Dubovyk et al., 2011). Be that as it may, following the developing interest for experimental information and methodical examination of urban development procedures and examples, there is an expanding interest in the improvement of quantitative techniques for urban investigation. It is huge to give significant data to enable neighborhood and local land to utilize organizers to better comprehend the urban development process and settle on an educated choice.

Urban Development Designs

Urban development designs are normal for spatial changes that occur in metropolitan regions (Aguilera et al., 2011). The spatial design and the elements of urban development are imperative themes of examination in the contemporary urban investigations (Bhatta, 2012). Wilson et al. (2003) recognized three noteworthy sorts of urban development as infill, extension, and peripheral. Infill improvement is another advancement inside staying open spaces in effectively existing developed zones while extension or here and there called urban expansion or edge development is a non-infill improvement expanding the urban impression an outward way infrequently called urban periphery improvement. Peripheral or jump frog development is a change from undeveloped to created arrive cover happening past existing created zones. Jump frog development has additionally suggested to urban sprawl as the development of the urban region is in a way that requests the expansion of open offices. Tian et al. (2011) looked at the spatial and transient dynamic example of the urban development for the five urban territories of Shanghai, Nanjing, Suzhou, Wuxi and Changzhou in the Yangtze River Delta area, China. The after effect of their examination uncovered amid the 15 years, urban development designs were drastically uneven over the three-time frames. The size dispersion of the five urban territories turned out to be all the more even with the fast urbanization process. The scene metric examination sloping over concentric cushion zones shows the blend procedure happened amid the fast-urban development from 1990 to 1995 and the direct development time frame from 2000 to

2005, however unique urban development period in the vicinity of 1995 and 2000. This approach demonstrates that the combination procedure was the significant development show for the locale and they reason that the distribution mix polarity speaks to endpoints as opposed to interchange conditions of urban development.

Remote Sensing of Urban Areas

A few strategies and systems have been created and connected to evaluate and portray the urban development procedures and examples. Generally, visual clarifications of high-resolution airborne photos were utilized to get exhaustive data for mapping of urban regions. This mapping procedure is costly and tedious for the estimation of urban development. Be that as it may, with the steady headway and accessibility of high worldly and spatial determination remote sensing representation; the potential outcomes of observing urban issues with a higher accuracy have turned out to be additionally inspiring. Consequently, accurate mapping of urban situations and observing urban development is ending up gradually vital at the worldwide level (Guindon and Zhang, 2009).

These days, there are a few remote detecting satellite frameworks, for example, Landsat (TM and OLI), ASTER, IKONOS, GeoEye, Quick feathered creature, RapidEye, WorldView giving from medium to high and high-resolution imagery. It is likewise trusted that remote sensing imagery is an effective instrument for procuring information to investigate and outline arrive utilize change and urban development process at various spatial scale (J. Huang et al., 2007). Especially, in developing nations, remote sensing may give essential perceptions of urban development and natural conditions that are not accessible from different sources (Miller and Small, 2003). However, it does not have the capacity to completely represent the basic urban procedures (Herold et al., 2005).

Urban Analysis Using Spatial Metrics

Given much less attention than remote sensing, spatial metrics are useful tools to objectively quantify and describe the underlying structures and patterns of the urban landscape from geospatial data. Spatial metrics are essential to better understand the characteristics of a landscape. Equivalent to the name of spatial metrics, landscape metrics are widely used in landscape ecology to describe the ecological important relationships such as connectivity and adjacency of habitat reservoirs (McGarigal et al., 2002). When used in the different field of studies, such as urban planning, landscape metrics referred to as "spatial metrics" (Herold et al., 2005). Though, these two phrases: 'spatial metrics' and 'landscape matrices' are used interchangeably on most published papers, in this research spatial metrics is used throughout.

Spatial metrics, in general, can be defined as 'numerical indices to describe the structures and patterns of a landscape' (O'Neill et al., 1988) as cited on (Bhatta, 2010, p. 87). Herold et al. (2003, p. 288) also defined spatial metrics as, 'quantitative and aggregate measurements derived from digital analysis of thematic categorical maps showing spatial heterogeneity at a specific scale & resolution.' Both definitions emphasized the quantitative nature of the metrics.

1.2. Justification

As deliberated earlier, there are many reasons why urbanization processes have been a hot research area for several decades. One of the most important reasons for such an interest is that, the size and spatial configuration of an urban area directly impacts energy and material flows such as carbon emissions and infrastructure demands and thus has direct or indirect consequences on the proper functioning of Earth as a system and on the quality of life of urban inhabitants. As the size of cities expands it begins to encroach on agricultural lands and natural areas (e.g. wetlands prone to environmental hazards such as flooding).

Although urban growth is a certain process, efforts can be made to protect natural resources, reduce natural hazards such as flooding and improve the livelihoods of urban dwellers through proper way of urban planning and management. To do so city planners, policy makers and resource managers need more advanced and quick techniques to acquire quantitative information on urban growth processes and patterns. It can facilitate the urgent establishment of management mechanisms and relevant policy interventions for proper allocation of resources and urban infrastructures based on empirical evidence. However, the available information on the city growth and evolution is insufficient and outdated. This makes decision making process complex and less transparent. Therefore, quantifying urban growth processes and patterns is crucial to monitor urbanization and its impact on the situation over time. However, they give insufficient information about spatial patterns of urbanization processes that characterize urban areas. Remote sensing data can provide time series land-cover maps explicitly exhibiting the dynamics of urban growth, yet some underlying patterns and characteristics could not be visualized clearly. Spatial metrics, in the form of a succession of indices, can reliably quantify and represent the spatial-temporal patterns and processes of urban growth. They provide an improved description and understanding of the structure and morphology of heterogeneous urban areas. Moreover, spatial metrics provides a linkage to structure, pattern, processes, and functionality in urban studies (Luck & Wu, 2002). Thus, remote sensing and spatial metrics are valuable tools to analyze urbanization processes and patterns empirically.

Therefore, assuming that urbanization will continue to be one of the major global environmental and social challenges in the foreseeable future, understanding and quantify the changing patterns of urban growth is critical to put forward appropriate policies and monitoring mechanisms on urban growth.

1.3. Research Problem

Urbanization in Bangladesh is relatively high compared to its neighboring countries like India, Myanmar, Nepal, Bhutan, and the Maldives yet is dramatically increasing (UNHABITANT, 2009). The rapid urban growth of Rajshahi is accompanied by high population growth, dramatic land use/cover change and social transformations. Such rapid demographic and environmental changes in the past decades have resulted in haphazard physical development, informal developments on wetlands and poor land use planning practices. Influenced by topography, most of these growths are taking place in close proximity to wetlands which are prone to flooding. This has aggravated the vulnerability of many inhabitants to natural and manmade disasters such as urban flood and diseases (Stephen, 2009). Basically, planning and management of urban spaces require a comprehensive knowledge of the development process and physical dimension of cities (Klosterman, 1999). As discussed earlier (see section 1.4), most literature ‘s on the analysis of the spatial characteristics of cites growths highlight the value of spatial metrics in the study of urban landscapes. However, Seto and Fragkias (2005) argue that most of these studies focus on cities in the USA. Recently few studies have been conducted in Europe (Aguilera et al., 2011) and some Asian countries (Jain et al., 2011; Tian et al., 2011). However, less is studied in relatively fast-growing cities of Bangladesh using spatial metrics for quantifying urban growth patterns. Combined with remote sensing, spatial metrics can give a better result than using either of them gives separately (Herold et al., 2003).

Therefore, this study will investigate the spatiotemporal patterns of Rajshahi city corporation urban growth and quantify the underlying spatial pattern of the urban landscape. Remote sensing and spatial metrics tools will be utilized to accomplish this task. The combined use of these tools is believed to lead to new levels of understanding of urban development process which can assist city planners and policymakers to make informed decision (Herold et al., 2005).

1.4. Research Objectives

General Objective:

The general objective of the study is to quantify the spatiotemporal trends and patterns of urban growth in fast developing Rajshahi city corporation using satellite remote sensing imageries and spatial metrics.

Specific Objectives:

The specific objectives of this research are:

I. To quantify the spatial pattern of urban growth and landscape fragmentation using spatial metrics.
II. To determine the major physical driving factors of urban growth.

1.5. Research Questions

Based on the above research objectives, the following research questions were also posed to assist in the analysis:

Questions for sub-objective I:

- How did the spatial pattern of urban growth change over time?
- What are the types of spatial urban growth patterns (infill, extension or leapfrog development)?
- Did the urban area get more fragmented over time?

Questions for sub-objective II:

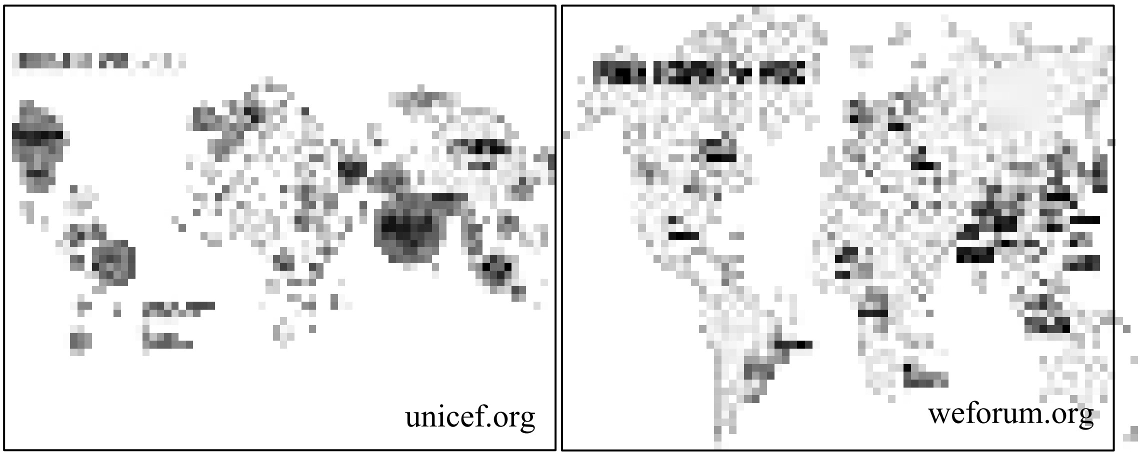
- What are the major physical driving factors of urban growths in the study area?
- How did these factors influence the urban growth process and pattern?
- How do the driving factors relate to each other?

1.6. Context of the Study Area

Rajshahi, the capital city of North Bengal, is one of the fastest growing cities of Bangladesh with an annual growth rate of 7.99% on an average. Figure1.1 shows that Bangladesh is amongst the fastest growing urban area in the world and in South Asia. Rajshahi City Corporation area 95.56 sq. km, located in between 24 20' and 24 24' north latitudes and in between 88 32' and 88 40' east longitudes. It is bounded by Paba upazila on all sides. RCC laid on the bank of Padma river, a major river of Bangladesh. It has a tropical monsoon climate and dries moderately. Average height from sea level is 18 m. The form and structure of RCC have been largely determined by the natural pattern of the landscape. It is surrounded almost plain land and consists a large number of wetlands and agricultural land, characterized by a huge amount of scattered informal settlements. Many of the open lands have been reclaimed and developed. They comprehend the central business district (CBD), slum dwellings, various service centers and industrial zones. Most of the major road surrounded open lands are developed and turn into non-built-up to the built-up area with flowing the service generating areas.

Located in the northern region of the country, RCC absorbs a certain part of the national urban population and 0.3% of the national population. Considering that the population was 388,811 in 2001, 449,756 in 2011 and 743,000 in 2016, this signals the population of the city was slowly increased but the built-up area increases rapidly. The RCC suburbs are also experiencing rapid urbanization leading to the development of satellite towns around the city. The City today has grown into a commercial, educational, cultural and administrative center of North Bengal. Currently, the urban population in Bangladesh is around 35% and is projected to reach 40% in 2025 of which the 5% will be in Rajshahi City Corporation. In the past two decades, RCC has expanded beyond the administrative city boundary through seizing to the adjacent townships and rural areas.

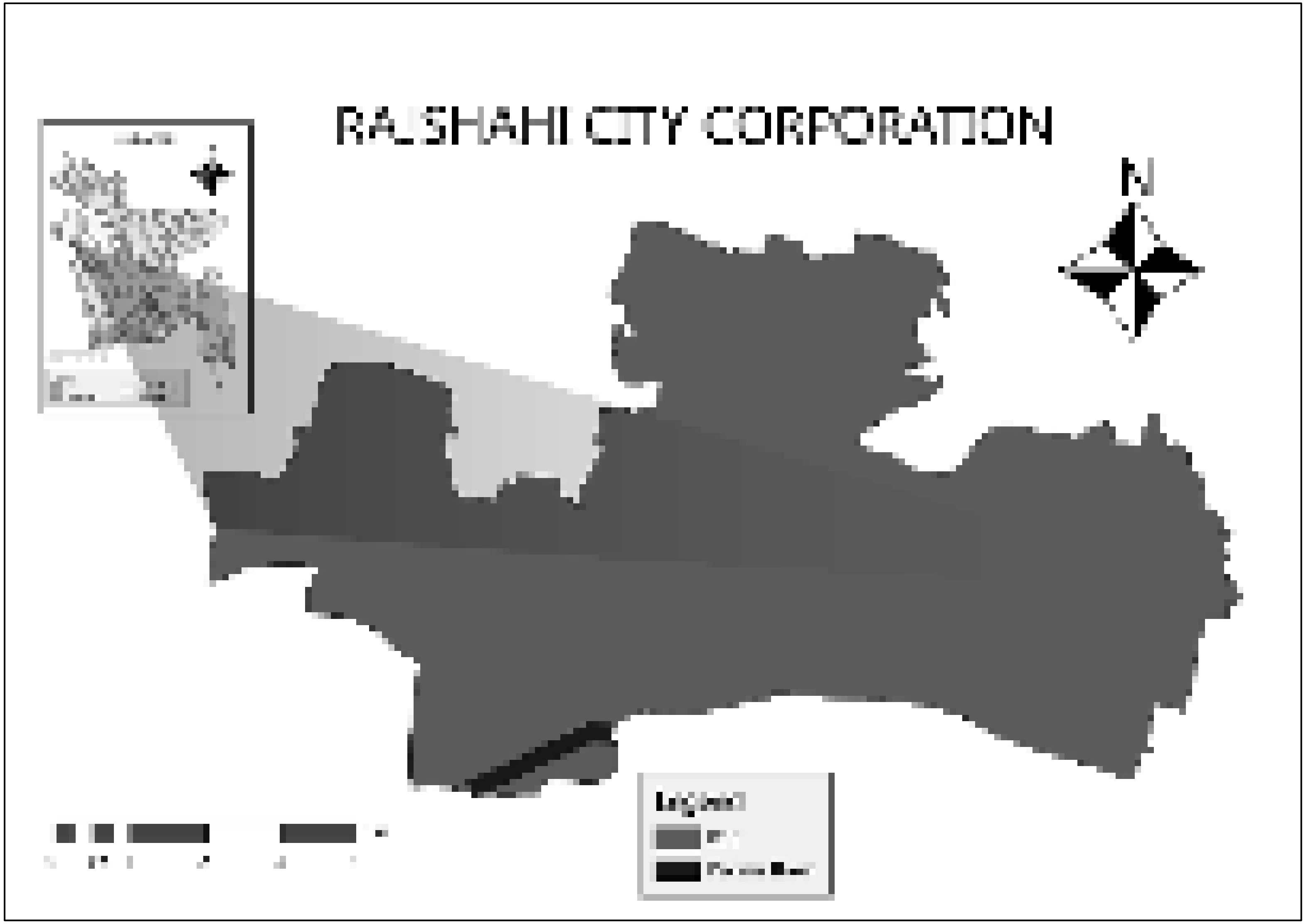
Figure 1.1: Fast growing urban area in the world



unicef.org

weforum.org

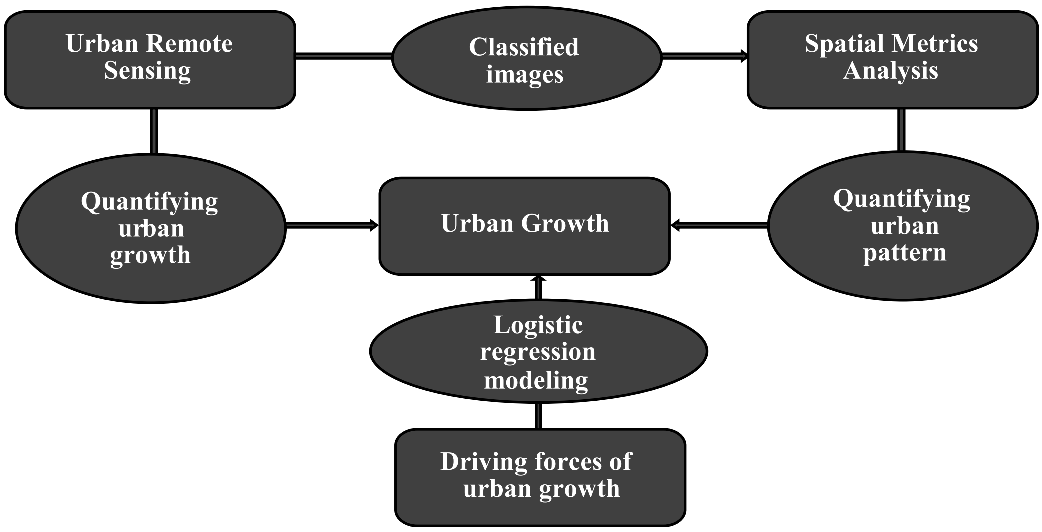
Figure 1.2: Geographical location of Rajshahi city corporation, Bangladesh



1.7. Conceptual Framework

This study makes use of both remote sensing and spatial metrics methods to get a deeper insight into spatiotemporal urban growth processes and the underlying patterns. A simple conceptual framework is adapted from (Herold et al., 2005). The conceptual framework is composed of three major elements interacting at different stages of the research. These are remote sensing, spatial metrics & urban growth. The arrow no.1 shows the potential use of classified temporal remote sensing images to quantify urban growth. Whereas the arrow no. 2 shows the interaction between urban remote sensing and spatial metrics, in which the output of classified remote sensing image is used as an input for spatial metrics computation (e.g. in FRAGSTATS) to quantify urban landscape fragmentation processes and patterns (arrow no. 3). Selected metrics (see section 3.4.1) are used to quantify urban growth pattern. These metrics are computed to quantify the spatial configuration of the urban landscape (e.g. size, shape, edge length, patch, density, fractal dimension) and the composition of the landscape, (e.g. richness, evenness, dispersion, contagion, diversity) (Gustafson, 1998). Finally, (arrow no. 4) binary logistic regression modeling is used to identify factors responsible for the changing patterns of the urban landscape. The results of the entire analysis are used to discuss on how these methods can improve the better understanding of urban growth processes and patterns and can help urban planners and policymakers to put forward informed decision.

Figure 1.3: Conceptual framework for analysis of urban growth (Adapted from Herold et al., 2005 p.370)



1.8. Structure of the Thesis

The thesis is structured into five different sections in which the first section deals with the introduction to the research and mainly addresses the statement of the problem, research objectives, research questions, the context of the study area, conceptual framework, and organization of the thesis. The second section contains a review of related literature where the concept of urbanization and land cover change, urban remote sensing and spatial metrics, image classification techniques, spatiotemporal urban growth pattern, and urban landscape structures are reviewed. In section three, the data and methodology used in this study including methods of data collection and analysis, image classification method, accuracy assessment procedures, selection and description of metrics, definition of spatial domains, methods used for identification of major physical driving forces of urban growth, including variables used in logistic regression modeling, multicollinearity analysis method and methods of model evaluation are briefly discussed. Section four presents the results of data analysis and discussions including spatiotemporal urban growth analysis, presentation and interpretation of growth maps and spatial metrics, temporal patterns of land cover changes, intraurban comparison of metrics, logistic regression modeling and evaluation and interpretation of outcomes, identification of major driving forces of urban growth in the study area. In the last section, section five, conclusions are organized according to the research questions proposed in section one. Furthermore, the limitations of the research and some recommendation and future research directions are offered.

CHAPTER

02. Literature Review

The unprecedented growth of urban population and built-up area worldwide, have a massive influence on the natural landscape at different spatial scales (Herold et al., 2005). Land-use and land-cover changes are the processes in which the natural environments such as forest and grasslands are replaced by human-induced activities such as intensive agriculture and urbanization. This chapter reviews the important literature regarding land use/land cover change, urbanization, advances in remote sensing technology, classification methods, spatial metrics and their application in monitoring urban growth pattern and driving forces of urban growth and urban modeling techniques.

2.1. Land Cover Change

Human intervention and natural processes are responsible for the constant change in land cover all over the world. Land cover change is determined by the interaction in space and time between biophysical and human influences. Urbanization is a rapid land cover change process that produces different patterns depending on the proximity to large urban centers across the landscape (Wu, 2004). Many land cover change models have been used to identify the drivers assumed to affect conversions of land between built up and non-built up land cover categories. Information about urbanization, obtained from multiple multi-temporal images, can provide valuable knowledge about the patterns of urban growth and the probable factors driving the changes. This information is important for planners, policy makers and resource managers to make informed decisions. Nowadays decision makers are becoming more and more dependent on models of land use/cover change (Veldkamp & Verburg, 2004). Description and modeling of land systems are highly dependent on the availability and quality data (Tayyebi et al., 2010). The spatial dependency of land cover changes can be analyzed by the integration of remote sensing and GIS techniques. These techniques have an efficient spatial capability to monitor urban expansion in urban areas.

2.2. Urbanization and Urban Growth in South Asia

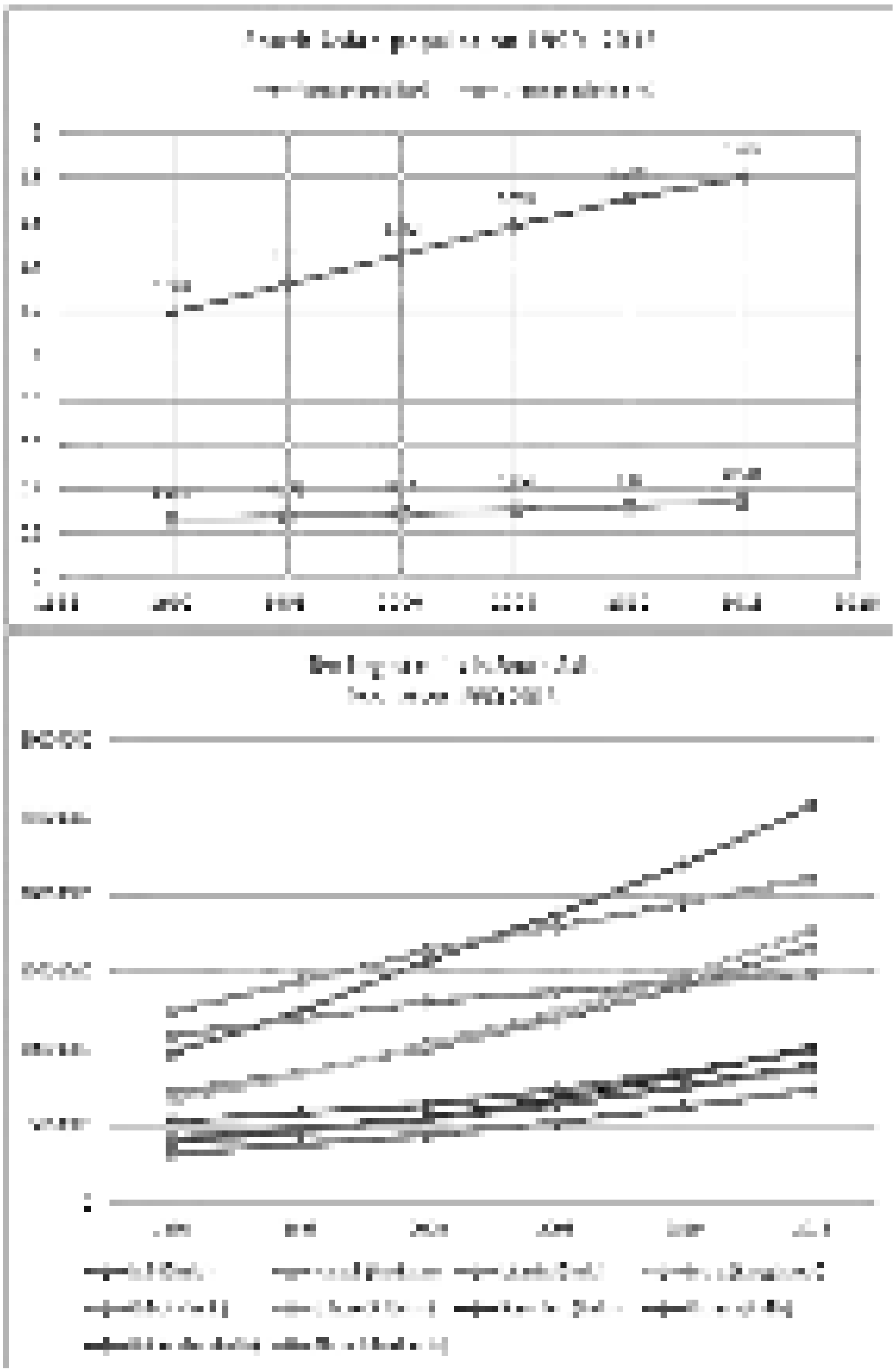
The definition of 'urban' and 'rural' varies from country to country and with periodic reclassification, can also vary within one country over time, making through assessments difficult. An urban area can be defined by one or more of the ensuing: administrative criteria or political boundaries (e.g., area within the jurisdiction of a municipality or town committee), a threshold population size (where the minimum for an urban settlement is typically in the region of 2,000 people, although this varies globally between 200 and 50,000), population density, economic function (e.g., where a significant majority of the population is not primarily engaged in agriculture, or where there is surplus employment) or the presence of urban characteristics (e.g., paved streets, electric lighting, sewerage). In 2010, 3.5 billion people lived in areas classified as urban (unicef.org, 2012).

Many South Asian cities are faced with difficult challenges arising from the rapid expansion of their built-up areas and the low-density sprawl that, all too often, has gone hand-in-hand with expansion (K. K. Jon & R. Marks, 2016). Addressing the ability of South Asian countries to manage their cities' spatial development is critical for two key reasons:

First, good connectivity and efficient spatial structure are essential to lightening crowding pressures that both challenge a city's livability and hamper the agglomeration economies that hold the key to prosperity. Second, dealing connectivity and spatial structure will be critical in avoiding South Asian cities from being further "locked in" to a pattern of urban sprawl that is excessively costly to the inverse (K. K. Jon & R. Marks, 2016).

Figure 2.1 below, shows that urban population in the South Asian region is increasing at the rate of 1.8% per decade approximately and the ten largest and populous cities in the South Asian region. It is easy to understand how fast these cities are growing just by comparing the population of these cities before and after 2000 from the graph.

Figure 2.1: Urbanization in South Asia (Source: data.worldbank.org, 2017)



2.3. Trends and Patterns of Urbanization in Bangladesh

Urbanization in Bangladesh has a very long urban history with the origin of cities like Pundranagara dating back to the third or fourth century BC. In 2001, only about 23% of the national population or more than 28 million people were found to be residents in cities and towns.

Urbanization received impetus after 1947 when the Indian subcontinent became two independent states. Between 1951-1961, there was a significant growth in urban population (45.11%) compared with the 1941-1951 period (18.38%) for large-scale migration of Muslims from India after 1947, who mostly settled in urban areas. In 1981 this rose to 15.5%. The intercensal change during this period (1974-81) was 111% with an annual growth rate of about 10%. Like the previous decade, both migration and natural growth contributed to this growth. But the most important contributory factor for 1974-81 was the redefinition of urban places. At about 20% level of urbanization the total urban population was 22.45 million in 1991 and at 23.1% level, the total urban population rose to 28.6 million in 2001. The table 2.1 below describe the urban growth of Bangladesh.

Table 2.1: Trends in urban population in Bangladesh, 1990-2015 (Source: data.worldbank.org, 2017)

Census Year	Total population (Million)	Urban Population (Million)	Urban population (%)	Urban growth
1990	106.2	21.3	20.00%	4.92
1995	118.7	26.0	21.90%	3.84
2000	131.8	31.2	23.70%	3.62
2005	143.4	38.7	26.80%	4.12
2010	152.1	46.1	30.30%	3.62
2015	161.2	54.9	34.10%	3.36

The table above shows that the urban population in Bangladesh was characterized by the relatively high growth rate of 4.92% and 4.12% between 1990 and 1995 and between 200 and 2005 respectively. However, there were regional variations in the distribution of the urban population. The level of urbanization is still low in most of the regions with the exception of the Central region, which had 11% of its population residing in urban areas in 2015. The high level of urbanization in the old four administrative division the prime urban area. The future projection of the national population figure estimated for 2051 ranges from a low point of 188.1 million to a median estimate of 199.3 million and to a high projection of 243.9 million (Islam, 2003). Components of urban growth and reasons for migration the rapid growth of urban population in Bangladesh has taken place during the last three decades because of a number of factors, such as:

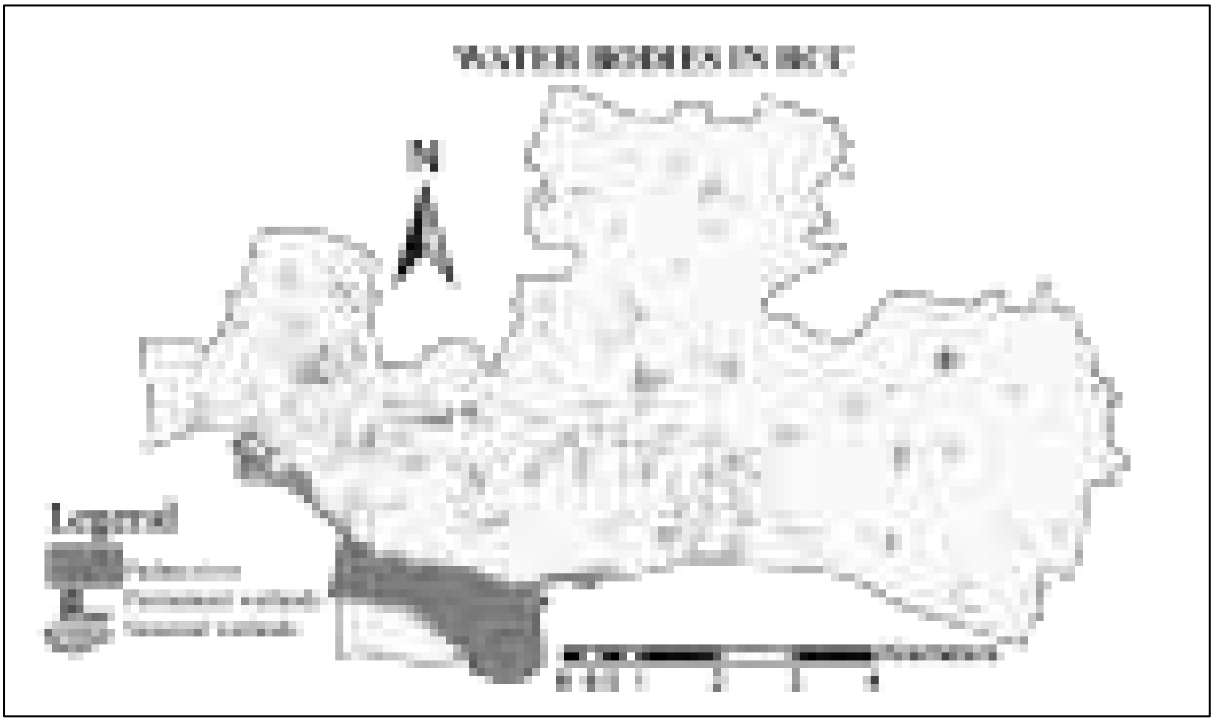
A. the high natural increase of native urban population
B. the territorial extension of existing urban areas and changes in the definition of urban areas
C. rural to urban migration.

In upcoming years total national population for 2021 and 2051, the total urban populations the period times may be assumed to be about 50 million (27%) in 2021 and 80 million (33%) in 2050. The urban population may rise to 120 million (50% of total) in around 2075. Changes in the definition of urban centers, policy intervention in population distribution and climate change effects may radically change the pattern of urban growth in the future. The 50% level may be reached much earlier, possibly well before 2050.

2.4. Driving Forces of RCC's Urbanization

The physical expansion of Rajshahi city corporation is mainly driven by urban population growth and demographic shifts in the form of rural-urban migration which has led to the formation of unplanned settlements within the city and at its periphery. Due to internal migration, high fertility rate (7.6%) and low mortality rate, the population of RCC has been steadily growing since the last few decades exceeding the pace at which urban services and housing are provided (econ.brown.edu, 2017). Economic transformation policies of Bangladesh which have mainly been pursued from and around the city through industrialization and the associated market forces of consumption derived from the population growth are also the other responsible factors for the urban expansion of RCC. Due to these factors, the expansion in RCC is steadily advancing at a fast pace leading to engulfing of adjacent rural landscape and urban centers. However, the urban the expansion a process of RCC is accompanied by the proliferation of unplanned settlements and informal sectors with inadequate services and infrastructure as well as environmental sanitation problems. The conversion of environmentally sensitive nonurban land uses, such as wetlands & agricultural land, to urban uses with serious social and health problems mainly at the fringes of the city are the major consequence of unplanned and informal urban expansion in RCC. The map presented in figure 2.2 shows the location of wetlands in the study area. This map is produced based on built-up area 2017 and wetlands 2010 data obtained from (time series Landsat data analysis).

Figure 2.2: Wetlands location in RCC (temporary and seasonal)



2.5. Remote Sensing and Urban Growth

Many scientists, resource managers, and planners agree that the future development and management of urban areas entail comprehensive knowledge about the on-going processes and patterns. As a result, understanding the urban growth patterns, dynamic processes, and their relationships and interactions is a key objective in the contemporary urban studies (e.g. Bhatta, 2009, 2010; Deng et al., 2009). Remote sensing is a helpful tool to better understand the spatiotemporal trends of urbanization and monitor the spatial pattern of urban landscape compared to traditional socioeconomic indicators such as population growth, employment shifts, etc. (Jun et al., 2009). However, the availability of multi-temporal data is important to analyze the dynamics of land cover change over time and space. In order to detect the changes and patterns of the different spatial phenomenon, it is important to make sure that the available images are acquired in the same season. This will help to avoid data inaccuracy generated due to seasonal variations. Nonetheless, it is difficult to find multi-date data taken at the same time of different years, particularly in tropical regions where cloud cover is prevalent (Mas, 1999). As a result, the selection of temporal dimension is mostly dependent on the availability of good quality data at that particular time of interest. Particularly, this is true for developing countries.

Although challenged by different factors such as spatial and spectral heterogeneity of urban environments, remote sensing is an appropriate source of data for urban studies (Roberts & Herold, 2004). According to a report published by NASA, the advances in satellite-based land surface mapping are contributing to an improved understanding of the underlying forces of urban growth and sprawl, as well as issues relating to territorial management. Nowadays, the physical expansions and patterns of urban growth on landscapes can be distinguished, mapped, and analyzed by using remote sensing data (Bhatta, 2010). Medium resolution Landsat images play the key role in the analysis of urban change at different spatial scale (e.g. Buyantuyev et al., 2010; Ding et al., 2007; Huang; et al., 2008)

Different studies have been conducted on urban change using medium resolution Landsat images. For instance, Yuan et al. (2005) used multi-temporal Landsat images to analyze urban growth pattern and to monitor land cover changes of two twin cities in Minnesota metropolitan area. The result shows that it has been possible to quantify the land cover change patterns in the metropolitan area and demonstrate the potential of multi-temporal Landsat data to provide an accurate and economical means to map and analyze changes in land cover over time. Yang and Lo (2002) used multi-temporal/multi-resolution satellite imageries to successfully extracted land use/cover data in the Atlanta, Georgia metropolitan area for the past 25 years. The result revealed that the loss of forest and urban sprawl have the major consequences of Atlanta 's accelerated urban development. Tang et al. (2008) used multi-temporal satellite images to analyze the dynamics of the urban landscape in two petroleum-based cities: Houston, Texas in the United States and Daqing, Heilongjiang province in China.

Accordingly, both cities expanded rapidly on the basis of the petroleum industries during the study period; however, under varying socio-political settings.

Shi et al. (2012) used three sets of Landsat Thematic Mapper (TM) images to characterize the growth types and analyze the growth density distribution in response to urban growth patterns in peri-urban areas of Lianyungang City. The result of this research depicted that, substantial arable lands were lost by urban growth in peri-urban & the pre-dominant growth types were edge-expansion and infilling growth respectively with important evidence of urbanization from a city 's central core. Deka et al. (2012) showed that the integration of remote sensing (RS) and Geographical Information System (GIS) technique to effectively detect urban growth, emphasizing on the potential applicability of Landsat TM data in the urban studies at both regional as well as local level. This study also indicates the value of medium resolution Landsat images for analysis of urban growth at the metropolitan scale, compared to the more resent VRH images.

2.6. Image Classification Methods

Classification in remote sensing involves clustering the pixels of an image to a relatively small set of classes, such that pixels in the same class are having similar properties. The majority of image classification is based on the detection of the spectral response patterns of land cover classes (Brito & Quintanilha, 2012). In order to utilize remotely sensed images effectively, several image classification methods have been suggested and developed over the past decades. But there is no single ideal classification method for each and every remote sensing image (Tso & Mather, 2009). The choice of image classification method mostly depends on the objectives of the research, the nature of the image and the level of detail or accuracy required for specific application (Lillesand et al., 2008).

There are two broads of classification procedures: supervised classification unsupervised classification. Supervised classification is the process of assigning objects of unknown identity to one or more known features using training data. Maximum likelihood (ML) classification algorithm assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Each pixel is assigned to the class that has the highest probability (i.e., the maximum likelihood). Better results can be achieved in supervised classification technique by taking more features and training samples from the study area. Training data are objects selected as representative samples of known features. In supervised classification, prior knowledge of the ground cover is important to select training samples. The advantage of the ML classification algorithm is that it takes the variability of the classes into account by using the covariance matrix. However, the disadvantage of maximum likelihood classification arises from the time and effort required to prepare the training samples (Al- Ahmadi & Hames, 2009).

In unsupervised classification technique, an algorithm is chosen that will take a remotely sensed dataset and find a pre-specified number of statistical clusters in multispectral or hyperspectral space. Although these clusters are not always equivalent to actual classes of land cover, this method can be used without having prior knowledge of the ground cover in the study site (Mohd Hasmadi I et al., 2009). Contrary to the a priori use of analyst-provided information in supervised classification; unsupervised is a clustering of the data space without any information provided by any analyst. Analyst information is used only to attach information class (e.g. ground cover type) labels to the segments established by clustering. Clearly, this is an advantage of the approach. However, the result of clustering is simply the identification of spectrally distinct classes in image data. These classes do not necessarily relate to the informational categories that are of interest to the analyst. Hence, the proper interpretation of these classes is required along with reference data that requires an understanding of the concepts behind the classifier and familiarity with the area under analysis (Lillesand et al., 2008).

Maximum Likelihood classifier is one of the most popular and widely used types of image classification technique in remote sensing (Brito & Quintanilha, 2012). Several researchers have demonstrated the importance of supervised maximum likelihood classification technique for land cover change analysis. For example, Tang et al. (2008) analyzed the spatiotemporal landscape dynamics of two petroleum-based cities: Houston, Texas in the United States and Daqing, Heilongjiang province in China. They used the conventional Maximum Likelihood Classification method to classify six multi-temporal satellite images. Yuan et al. (2005) used supervised maximum classification method to map and monitor land cover change using multitemporal Landsat Thematic Mapper (TM) data in the seven-county Twin Cities

Metropolitan Area of Minnesota for 1986, 1991, 1998, and 2002. Zhou and Wang (2011) used maximum likelihood classifier to characterize the changing patterns and intensities of green space in Kunming, China from 1992 to 2009.

2.7. Remote Sensing and Change Detection Techniques

"Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times" (Singh, 1989, p. 989). Different change detection methods have been developed and documented over the past decades can be found in (D. Lu et al., 2004). All have their own advantage and disadvantage. Some of the most commonly used change detection methods have been discussed below.

Image Differencing

Image differencing is one of the most widely used to determine changes between images and has been used in a variety of geographical environments. The difference between two images is calculated by subtracting the imagery of one date from that of another and generating an image based on the result. The subtraction results in large positive or negative values in areas of radiance change, and values close to zero in areas of no change. A critical challenge of this method is deciding where to place the threshold boundaries between change and no change pixels. This method is also sensitive to miss-registration and mixed pixels. To obtain a good result, the two images must first be aligned so that corresponding points coincide. The complexity of image pre-processing needed before differencing varies with the type of image used.

Principal Component Analysis (PCA)

The principal component analysis is a technique used extensively in remote sensing images analysis in application well beyond that of change detection. PCA has been used for determining the intrinsic dimensionality of multispectral imagery, data enhancement for geological application, and land cover change detection. This method is often used to reduce the dimensionality of the data without reducing its overall information content. However, estimation of the PCA projection from data has its own limitations. Its computational complexity makes it difficult to deal directly with high dimensional data, like satellite images. Second, the number of examples available for the estimation of the PCA projection is typically much smaller than the ambient dimension of the data and this can lead to overfitting of the projection.

Post Classification Comparison

Post classification comparison is the most intuitive methods of change detection, is GIS overlay of two independently produced classified images. The post-classification comparison can be used to identify not only the amount and location of the change but also the nature of change. The method can produce from-to information (D. Lu et al., 2004). However, the accuracy of the change detection is highly dependent on the accuracy of the classification result. The method reduces the need to perform geometric and atmospheric corrections (Jensen, 2005; Y. Liu et al., 2004)

Post-classification comparison is made on classified images. Mas (1999) suggested that post classification is often considered a priory to be the superior change detection method and is, therefore, used as the standard for evaluating the results of other methods. However, every inaccuracy in the individual data classification map will also be propagated in the final change detection map. Therefore, it is imperative that the individual classification maps used in the post-classification change detection methods be as accurate as possible. In addition to these, the image classification stage of this method takes a long time because the accuracy of the classification needs to be high to get a good change detection result (D. Lu et al., 2004). The advantage of post-classification comparison is that it can provide from-to information which helps to differentiate which land cover or land use class is changed to another class.

Change Vector Analysis (CVA)

Change vector analysis technique is an empirical method of detecting radiometric changes between multitudes of satellite images in any number of spectral bands. This method yields information about the degree and type of spectral changes by calculating a vector magnitude and direction in multispectral change space for each pixel (Balcik & Goksel, 2012). Like image differencing, a threshold indicating change and no change area also needs to be determined by this method (Lambin & Strahler, 1994). A particular advantage of the change vector analysis method is the potential capability to process any number of spectral bands desired. This is important because not all changes are easily identified in any single band or spectral feature. Nevertheless, since no effective method has been developed to handle more than two spectral bands (Kontoes, 2008).

Image Rationing

Image rationing is another method for change detection in which two images from two dates are divided band by band and pixel by pixel. If the ratio of two images is equal to 1, then no change has occurred, but if the ratio is greater than or less than one that means change has occurred. A threshold needs to be decided. The common way for deciding this has been to set a threshold value and then evaluating the change detection. Image rationing produces images with a non-Gaussian distribution of pixel values and if a threshold is decided based on standard deviations from the mean, the change will not be equal on both sides. This feature of image rationing has been criticized (D. Lu et al., 2004; Singh, 1989). One of the most common ratios is called Normalized Difference Vegetation Index (NDVI) is: (NIR-RED) / (NIR+RED) or simplified as NIR /RED. The advantage of image rationing is that the effect of different Sun angles, shadows and topography is reduced, the disadvantage is the non-Gaussian distribution of the ratio image making threshold selection difficult (D. Lu et al., 2004).

Recently, numerous studies have indicated the use of post-classification comparison change detection technique for land cover change analysis in urban studies. Yin et al. (2011) used the post-classification comparison to detect changes of Shanghai metropolitan area, China based on Landsat MSS, TM and ETM+ images from 1979, 1990, 2000 and 2009. By overlaying the classified images over each other they were able to compare the changes in pixels of the layers pixel-by-pixel. Alphan et al. (2009) used post-classification comparison change detection method to assess the land cover changes in Kahramanmaraş (K.Maraş) and its environs from multi-temporal Landsat and ASTER imagery, respectively belong to 1989, 2000 and 2004. J. Liu et al. (2005) also used the post-classification comparison to analyze and map the magnitude and pattern of China‘s changing landscape during the 1990s from Landsat TM images covering the entire county. They classified the images into different land cover class identified. Then the classified images were compared using some statistical measurements.

2.8. Remote Sensing and Spatial Metrics

As discussed above, the main strength of remote sensing technique lays on its capability to deliver spatially consistent data set that covers a wide range of spatial extent with both high and detailed spatiotemporal resolution, including historical time series data (Herold et al., 2005). Yet, it cannot provide a full description of the underlying processes that are responsible for the changing patterns of the urban landscape. To bridge this gap spatial metrics are used. The thematic land cover maps obtained from the analysis of Landsat TM and ETM+ images will be used to further quantify and describe urban landscape pattern.

The interest to quantify landscape patterns are often driven by the premise that patterns are linked to ecological processes (Gustafson, 1998). Spatial metrics are expedient tools for quantifying spatial heterogeneity and to have better insight on how spatial structures impact the system interaction in a heterogeneous landscape. Heterogeneous landscape or spatial heterogeneity refers to the complexity and unevenness of a system property in time and space, spatial heterogeneity is considered synonymous with the spatial pattern. A system property is any measurable entity, for instance, the configuration of the landscape mosaic. Spatial structure is a major subset of the concept of spatial heterogeneity, usually referring to the spatial configuration of the system property (Turner et al., 1989).

Spatial metrics can provide a rich numerical description of the landscape structure at the patch, patch class or the whole landscape level (Herold et al., 2003). Spatial metrics can be categorized into three broad classes: patch, class, and spatial metrics (Bhatta, 2010). Patch is a relatively homogeneous area that differs from its surroundings (McGarigal & Marks., 1995). Patch metrics are computed for every patch in the landscape, class metrics are computed for every class in the landscape, and spatial metrics are computed for the entire landscape (Bhatta, 2010).

However, most spatial metrics are scale dependent and they are determined by the extent of the spatial domain, the spatial resolution and the thematic definition of the map categories (Šímová & Gdulová, 2012). It is up to the user to define the landscape, including its thematic content and resolution, spatial grain and extent, and the boundary of the study area, based on the phenomenon under consideration before conducting any kind of metrics computation (McGarigal et al., 2012). Attention should be paid while comparing the value of metrics computed from landscapes that have been defined and scaled differently.

2.9. Analyzing Urban Growth Pattern Using Remote Sensing & Spatial Metrics

Patterns are distinguished by spatial relationships among component parts in landscape metrics. A landscape pattern can be characterized by both its composition and configuration of its component parts (McGarigal & Marks., 1995). These two characteristics of a landscape can individually or in combination affect ecological processes.

A variety of metrics have been developed to quantify categorical map patterns in the past studies (see, for example, McGarigal et al., 2002). Despite the availability of plenty of metrics, offered by different literature, to describe landscape structure, they are still categorized under the two major components, namely, composition and configuration of a landscape (Gustafson, 1998). Composition metrics are easy to quantify and can be defined as features related to the presence, proportion and the variety and richness of patch types within the landscape mosaic. Nevertheless, composition metrics do not consider the spatial character, arrangement, or location of patches within the mosaic. A variety of quantitative descriptors of landscape composition are available, but the principal measure of the composition includes; the proportional abundance of each class in the entire landscape, patches richness, patches evenness, and patch diversity (McGarigal et al., 2002). Shannon‘s diversity index (SHDI), Shannon‘s evenness index (SHEI), dominance (DOM) and patch richness density (PRD) are some of the examples of commonly used composition metrics.

Conversely, configuration metrics is relatively more challenging to quantify. It refers to the spatial arrangement, character and position of patches within the class of patches or entire landscape (McGarigal & Marks., 1995). The principal aspects of configuration metrics include patch area and edge, patch shape complexity, core area, contrast, aggregation, subdivision, and isolation. Some of the most frequently used configuration metrics includes: number of patches (NP), percentage of landscape (PLAND), edge density (ED), landscape shape index (LSI), mean patch size (MPS) and number of patches (NP), largest patch index (LPI), total edge (TE), mean shape index (MSI), area-weighted mean fractal dimension (AWMFD), total core area

(TCA), mean Euclidean nearest neighbor index (MNN), contagion (CONTAG), effective mesh size (MESH), aggregation index (AI).

Urban growth and land cover change have been the major topic concerning remote sensing applications (Masser, 2001). The spatial and temporal dimensions are major concerns of remote sensing in urban studies. To better understand the complexity of urban systems and its spatial and temporal dimensions, urban growth analysis needs to be linked with land cover change model. Currently, there has been an increasing interest in applying remote sensing and spatial metrics techniques (see for example FRAGSTATS McGarigal et al., 2012) to analyze urban environment.

For instance, Kuffer and Barrosb (2011) used spatial metrics in a VHR remotely sensed images to analyze the morphology of unplanned urban settlements in Dar es Salaam and New Delhi. In this study, different sets of metrics were used for two case studies. After eliminating several highly correlating metrics, the authors selected a set of four metrics, i.e. is mean area, patch density, aggregation index and Shannon‘s diversity index for Dar es Salaam and a set of six metrics, i.e. effective mesh size, landscape division index, patch density, contagion, aggregation and Simpson‘s evenness index for Delhi. Both sets of metrics measure size, pattern, and density. Finally, the sets of spatial metrics were combined using spatial multi-criteria evaluation to produce a composite index indicating areas of the high likelihood of ‘unplanned’ in the study area.

Jain et al. (2011) applied spatial metrics and gradient analysis method for quantifying and capturing changes in urban landscape using LISS III imagery of Gurgaon, India. The combination of landscape metrics, i.e. the percentage of landscape, mean patch size, a number of patches, landscape shape index and largest patch index have been used to quantify the patterns of urban growth in different directions of the city in terms of size, shape, and complexity of development. Finally, they were able to demonstrate the potential of spatial metrics and gradient analysis to quantify the impact of regional factors on the growth pattern.

Pham and Yamaguchi (2011) showed the potential application of spatial metrics as secondary sources of information for supporting remotely sensed data and their use to characterize urban growth patterns of Hanoi, Vietnam. This study used the percentage of like adjacency (PLADJ) metric on the urban growth maps generated using maximum likelihood image classification technique to illustrate the changes in the urban structure in the study area. Six class-level landscape metrics, i.e. class area, number of the patch, edge density, largest patch index, mean nearest neighbor distance and area-weighted mean patch fractal dimension, were selected to characterize the urban the urban composition parameters of Hanoi.

Seto and Fragkias (2005) effectively compared the spatiotemporal pattern of urban land use changes in four Chinese cities, using three concentric zones and a set of landscape metrics. This study used a group of six spatial pattern metrics analysis indices namely: total urban area (UA), number of urban patches (NUMP), mean urban patch size (MPS), urban patch size coefficient of variation (PSCOV), urban edge density (ED) and area-weighted mean patch fractal dimension (AWMPFD). The results of this study indicate that urban form can be flexible over relatively short periods of time. Despite different economic development and policy background, the four cities exhibit common patterns in their shape, size, and growth rates, suggesting a convergence toward a standard urban form.

X. J. Yu and Ng (2007) used a combination of remote sensing images, spatial metrics and gradient analysis to analyze the spatial and temporal dynamics of urban sprawl in Guangzhou, China. The results of this study show that landscape change in Guangzhou exhibits distinctive spatial differences from the urban center to rural areas, with higher fragmentation at urban fringes or in new urbanizing areas. Population growth and rapid economic development were the two major driving forces of urban expansion in the study area. The authors were also able to demonstrate the importance of temporal data to reveal the complexity of landscape pattern and to capture the spatiotemporal dynamics of landscape changes.

Herold et al. (2005) explored the importance of spatial metrics in the study and modeling of urban land use change in Santa Barbara urban area, California, USA. Percentage of the landscape
(built up) (PLAND), patch size standard deviation (PSSD), contagion index (CONTAG), patch density (PD), edge density (ED), area-weighted mean patch fractal dimension (AWMPFD) are the spatial metric growth signatures used in the study. According to the research, the growth of Santa Barbara develops outward from the original downtown core. Generally, this study indicates that spatial metrics can be

utilized for the detailed mapping of urban land use change at different geographic scales and can help infer a number of socioeconomic characteristics from remote sensing data.

Schneider et al. (2005) used remotely sensed data to map changes in land cover in the greater Chengdu area and to investigate the spatial distribution of urban development by using spatial metrics along seven urban-to-rural transects corridors of growth. Pham et al. (2011) explored an approach for combining remote sensing and spatial metrics to monitor urbanization, and investigate the relationship between urbanization and urban land use plans. The study examined four cities of Asia namely: Hanoi, Hartford, Nagoya, and Shanghai, using Landsat and ASTER data. The results showed that the combined approach of remote sensing and spatial metrics provides local city planners with valuable information that can be used to better understand the impact of urban planning policies in urban areas.

Herold et al. (2005) stated that spatial metrics Combined with, time-series of high spatial resolution remote sensing data has the potential to characterize the dynamics of urban growth processes as well as it can reveal the spatial component in urban structure underlying the growth process (Herold et al., 2002). In this context, remote sensing and spatial metrics are used in a complementary way to better understand the urban growth processes and patterns.

Jianguo Wu et al. (2011) analyzed the spatiotemporal patterns of urbanization in two fast-growing metropolitan regions in the United States using: Phoenix and Las Vegas. Based on historical land use data and landscape pattern metrics at multiple spatial resolutions, they were able to characterize the temporal patterns of urbanization in the metropolitan regions. The results of this research showed that the two urban landscapes exhibited strikingly similar temporal patterns of urbanization with an increasingly faster increase in the patch density, edge density, and structural complexity of the landscape. That is, as urbanization continued to unfold, both landscapes became increasingly more diverse in land use, more fragmented in structure, and more complex in shape. Finally, the authors conclude that “a small set of spatial metrics is able to capture the main spatiotemporal signatures of urbanization, and that the general patterns of urbanization do not seem to be significantly affected by changing grain sizes of land use maps when the spatial extent is fixed”.

There are several methods to analyze and quantify the dynamics of urban growth patterns and processes. However, the selection of method depends on the objectives of the problem on hand and the clear understanding of the different tools and techniques used for analyzing urban environment. Several studies reviewed in this section indicate the value of medium resolution remotely sensed satellite images and spatial metrics for the analysis of urban change.

2.10. Urban Growth Modeling

Rapid urban growth accompanied by land cover change has become a global phenomenon observed all over the world. Several studies have endeavored to understand the spatiotemporal pattern of land cover change and its driving forces (Allen & Lu, 2003; Veldkamp & Lambin, 2001). There are two broad categories of land change models developed over the past several decades (Hu & Lo, 2007). These are dynamic simulation-based models and statistical estimation models. Simulation-based models such as:

Cellular Automata (CA) attempts to capture the spatiotemporal pattern of urban change by incorporating spatial interaction effect into the model However, the poor explanatory capacity of simulation models has limited the detailed understanding and interpretability of urban growth dynamics with its potential driving forces (Luo & Kanala, 2008). Moreover, most dynamic simulation models are not capable of incorporating adequate socioeconomic variables (Hu & Lo, 2007).

Empirical models use statistical analysis to reveal the interaction between land cover change and explanatory variables and have much better interpretability than simulation models. For example, regression analysis can help to identify the driving factors of urban growth and quantify the contributions of individual variables and their level of significance (B. Huang et al., 2009; Luo & Kanala, 2008; Nong & Du, 2011). Binomial (or binary) logistic regression is a form of regression, which is used to model the relationship between a binary variable and one or more explanatory variables yielding dichotomous outcome (Hosmer & Lemeshow, 2004). Logistic regression is based on the concepts of binomial probability theory, which does not assume linearity of the relationship between the independent and the dependent variables, does not require normally distributed variables, and in general has no strict requirements. In the context of urban growth modeling, a logistic regression model was used to study the relationship between urban growth and biophysical driving forces (B. Huang et al., 2009). The conversion of non-urban to urban land use is considered as state 1, while the no conversion is indicated as state 0 in the same period of time. A set of independent variables are selected to explain the probability of non- urban land use to conversion to urban. The main purpose of urban growth modeling is to understand the dynamic processes responsible for the changing pattern of urban landscape, and therefore interpretability of models is the most important aspect the modeling process. The advantage of statistical models is their simplicity for construction and interpretation or their capacity to correlate spatial patterns of urban growth with driving forces mathematically. However, statistical models lack theoretical foundation as they do not attempt to simulate the processes that actually drive the change (Koomen & Stillwell, 2007).

CHAPTER

03. Data and Methodology

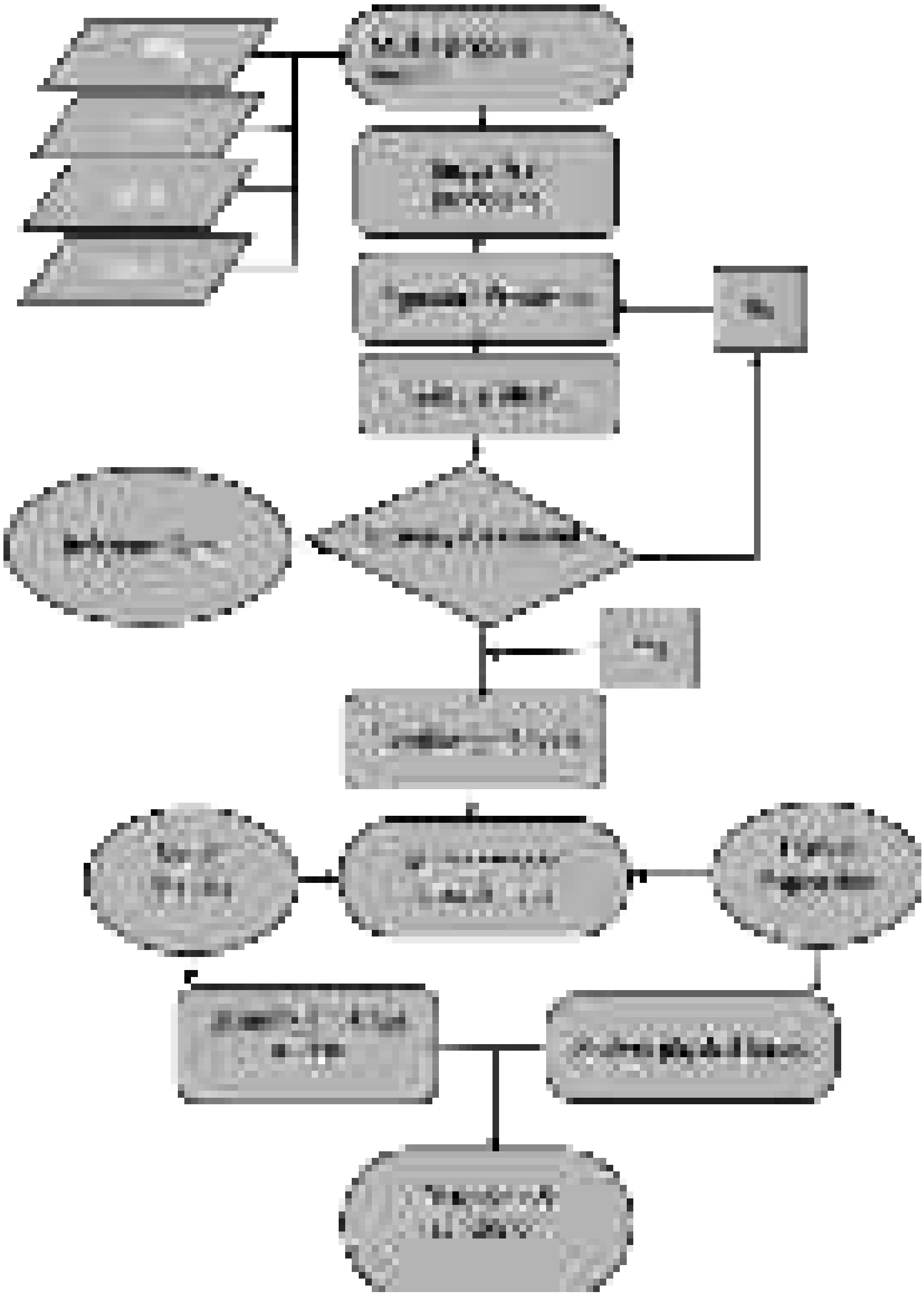
This chapter presents the available data, the overall methods, techniques, approaches, and materials used to achieve the research objectives. It mainly explains the data sources and types, methods of field data collection, reference data used the identification of driving forces of urban growth, image classification technique employed, and change detection methods used, accuracy assessment, selection of spatial metrics and list of software packages used in the research.

3.1. Research Design and Methodology

This research is conducted in three phases: pre-fieldwork, fieldwork, and post-fieldwork phases. The first phase is a preparation phase which consists of research proposal development, including problem definition, formulation of research objectives and associated research questions, defining methods, identifying required data types, clearly defining data collection methods and preparing (field) work plans. The second phase is information and data gathering phase (fieldwork phase). In this phase, important data required for carrying out the research including primary and secondary data are collected during fieldwork. These include interviewing local experts on the issues of urban growth driving forces, collecting ground truth data, visiting important places of the study area like the city center, new development sites, etc. to have the general impression of the study area. This task is carried out with the assistance of local dwellers. In the end, the collected data is processed, analyzed and the finding is presented (post-fieldwork phase) so as to meet the predefined objectives of the research, which is followed by conclusion and recommendation.

There are different kinds of methods, strategies, and techniques to process input data in order to generate the anticipated research output in an efficient and consistent way with desired quality. However, the choice of appropriate methodology and specific technical arrangements are largely dependent on the availability of quality data, the desired inputs, the strength of logistic support including the software employed, researcher's experience and skill to manipulate and the necessary fund allocated for the task. The methodology incorporated in this study involves remote sensing image classification techniques as well as spatiotemporal analysis of spatial metrics and logistic regression methods. First, four multi-temporal sets of Landsat images (TM 1990 & 2000 and TM 2010, 2015) covering the entire study area are used to produce the land cover map by using the maximum likelihood classification algorithm in

ERDAS Imagine 2014. Post-classification comparison is used to produce growth/change map, where the classified images are overlaid on top of each other in ArcGIS 10.4.1 using different spatial analyst tools. Consequently, the spatial extent and rate of urban growths are analyzed and quantified. Then, the classified images are used as an input data in FRAGSTATS 4.2.1 (McGarigal et al., 2012) to further describe and quantify the changing patterns and processes of the urban landscape. Finally, a binary logistic regression model is built to identify the major physical driving forces responsible for the changing patterns of the urban landscape in ArcGIS 10.4.1, Change Analyst software. A flow chart describing the general methodology used in this study is given below (see figure 3.1).



3.2. Data Source and Type

Different remote sensing and GIS data from different sources have been used in this research. Four medium resolutions Landsat TM images of 1990, 2000, 2010(ETM+) and 2015 were used to detect urban land cover change patterns of the study area (see figure 3.2). These images were obtained from the United States Geological Survey (USGS) website as standard products, i.e. geometrically and radiometrically corrected. In order to avoid the impact of seasonal variation, all images are selected from the same season in such a way that the cloud cover will not exceed 10%. The images are also of the same level of spatial resolution of 30m which makes it convenient for comparison of changes and patterns that occurred in the time under consideration. The DEM used to analyze driving forces of urban growth is downloaded from SRTM-USGS center. Most GIS data such as the location of satellite towns, Padma river, sub-city centers, CBD and existing built-up areas are derived VRH Google Earth image based on the information gathered from local experts during fieldwork period. Other data such as administrative boundaries, major roads, and wetlands are obtained from open web sources such as (geonode.wfp.org), (gadm.org) and (openstreetmap.org) and from RDA geodatabase. All dataset used in this study are geometrically referenced to the WGS 1984, UTM zone 45 N projection systems. The detail description of the characteristics all images used in this study are summarized in tables 3.1 & 3.2 below.

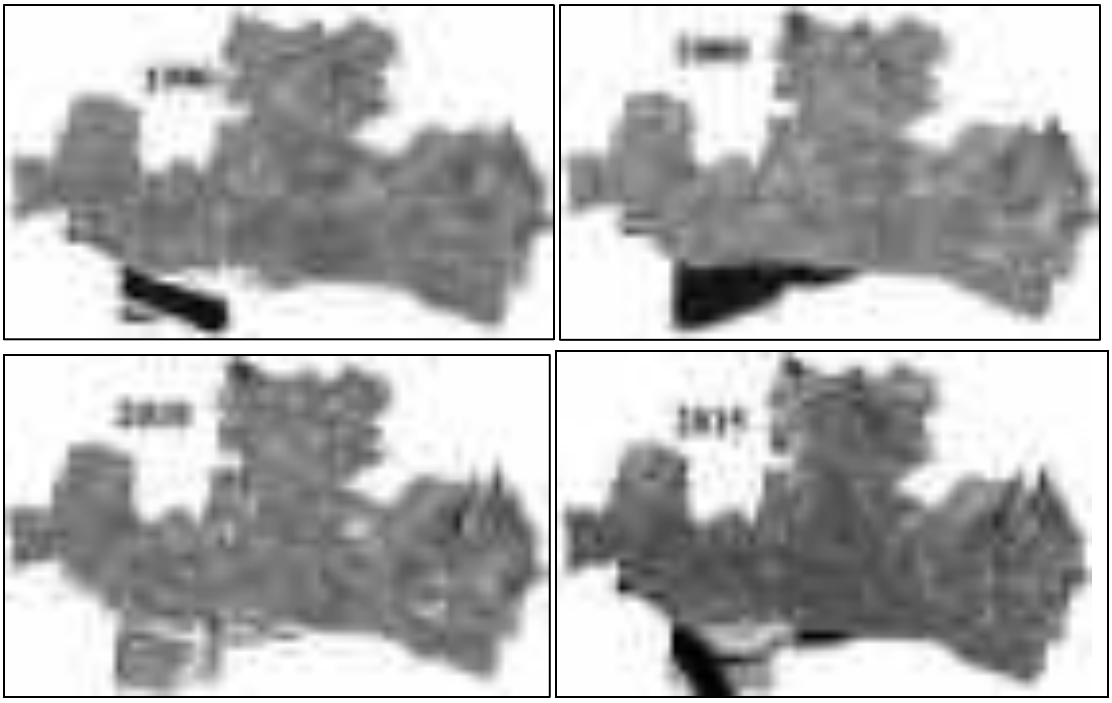
Table 3.1 List of satellite images (raster data) collected for the study area.

Satellite data	Acquisition Date	Spatial resolution	Path	Row	Data source
Landsat TM	30.01.1990	30 m	138	43	USGS
Landsat TM	26.01.2000	30 m	138	43	USGS
Landsat TM	06.02.2010	30 m	138	43	USGS
Landsat 8 OLI	04.02.2015	30 m	138	43	USGS
Slope	Raster	30 cm	-	-	USGS

Table 3.2 List of spatial data (vector data) used for the study area

Spatial data	Format/type	Source
Satellite towns	Shapefile	RDA
Major Roads	Shapefile	RDA
Padma River	Shapefile	Derived
Sub-city centers	Shape file	RDA
CBD area	Shape file	Derived
Existing built-up area	Shapefile	Derived
Administrative boundaries	Shapefile	data.humdata.org
Wetlands	Shapefile	Derived

Figure 3.2: Landsat images covering the study area in 1990, 2000, 2010 and 2015



3.2.1. Field Data Collection

This research made use of both primary and secondary data to make sure that the objectives of the study are met. Although some secondary data are collected from the literature review and open source websites, yet important information and data are gathered from fieldwork. The fieldwork for the study was carried out from 5th of June, 2017 to 12th of June, 2017 in RCC at major tasks relevant to the study as explained as below.

Identifying the Probable Physical Driving Forces of Urban Growth

The task of the field work was to collect relevant information about driving forces of urban growth in the study area. This task is carried out in the form of an interview with local and city planners on the issues of urban growth driving forces. The main objective of the interview was to identify the major physical driving forces of urban growth in the study area. Beforehand, list of probable driving forces of RCC urban growth was identified based on literature review. The interview was conducted with two experts on two different days.

During the interview, the list of probable driving forces of urban growths, which were identified from literature review, were presented by the researcher. Then the experts were interviewed with a guiding question to give their opinion based on their professional expertise & experience in the study area. The experts were given freedom to add or subtract from the given list of probable driving forces of urban growth identified from the literature review. Finally, it is possible to identify the final list of physical driving forces of urban growth in the study area to be included in the logistic regression modeling. Accordingly, thereby relevant information on identified driving factors such as the location of the main city center (CBD) and economically active and important sub city centers where fast development has been observed in the past few years was identified on the map.

3.2.2. Software's and Other Instruments Used

Erdas Imagine 2014, FragStats tool 4.2.1, ArcGIS 10.4.1, SPSS 23 statistical software are the tools used in this study.

3.3. Methods of Data Analysis

After collecting all the relevant primary and secondary data, the next task was to process and analyze the data. As discussed earlier this research applies remote sensing and spatial metrics techniques to quantify urban growth processes and patterns. Remote sensing image classification is a relevant method that can provide information on the extent and rate of urban growth whereas spatial metrics are computed based on the remote sensing image classification results to quantify the patterns of growth (Hai & Yamaguchi, 2008; Herold et al., 2003). Both together are believed to give a better understanding of urban growth processes and patterns. The methods are also quick ways of acquiring relevant information where availability of spatial data is scarce such as in South Asian countries. Apart from this binary logistic regression method has been used to identify the major physical driving forces of urban growth in the study area. Detail explanations of each method of data analysis are given in the subsequent sections.

3.3.1. Remote Sensing Image Classification

Four multi-temporal medium resolution Landsat images are used to analyze the urban growth trends and patterns of RCC for the past 26 years. As described in section 3.3, all images are acquired geometrically corrected and geo-referenced. Owing to its popularity and wide acceptance in remote sensing image classification (refer section 2.5), supervised maximum likelihood classification algorithm was applied in ERDAS IMAGINE 2014 software environment. Accordingly, the images were classified into different land cover classes which finally ended up generating four different year land-cover maps of the study area. In ML classification method, pixels with maximum likelihood are categorized into the corresponding class.

The land cover maps are composed of three major land-cover classes namely; built up, nonbuilt-up and water bodies. Each land cover classes comprise different land uses classes. The built-up area consists of commercial, residential, road and impervious features, continuous and discontinuous urban fabric, residential, industrial and commercial units, road and railway networks and other associated lands, airports, parking lots, dump sites, construction sites, sport and leisure facilities, etc. while the non-built up area includes cropland (agriculture) land, parks, grasslands, forests, woodland shrubs, green spaces, wetlands, bare soil and others. The water body consists of lakes, artificial ponds, swimming pools and others.

Training samples were collected with a visual interpretation of very high-resolution images of Google Earth are used whereas visual interpretation of the true color composite of the Landsat TM image is used for 1990 and 2000 images. Finally, to improve the accuracy of the classified images, post classification majority filter is carried out in Arc GIS 10.4.1 using a 3x3 window size (eight surrounding neighborhoods). Majority filter is a function that replaces cells in a raster based on the majority of their contiguous neighboring cells. This is helpful to remove isolated and dispersed pixels from the classified image.

3.3.2. Accuracy Assessment

In remote sensing-land cover mapping study, classification accuracy is a most important aspect to assess the reliability the final output maps. The main purpose of assessment is to assure classification quality and user confidence on the product (Foody, 2002). In this study, the accuracy of the classification results for the year 2010 and 2015 are assessed using 270 randomly sampled ground truth points, obtained from fieldwork and from previous work by Vermeiren et al. (2012). However, since it has been difficult to get reference data for accuracy assessment of image 1990 and 2000, visual interpretation of the true color composite of the Landsat TM image is used.

3.3.3. Change Detection

The change detection method used in this analysis is the post-classification comparison technique in which GIS overlay of two independently produced classified images in ARC GIS 10.4.1 (Alphan et al., 2009). The resulting land cover maps are then visually compared and change areas are simply those areas which are not classified the same at different times. This method is the most straightforward and intuitive change detection method. The advantages and disadvantages of this method are discussed in section 2.5 of this research. Following this method, maps are produced to show the newly built-up area between each subsequent year, i.e. 1990-2000, 2000-2010 & 2010-2015 for the study area (Yang & Lo, 2002). In combination with class area spatial metrics, these make it possible to quantify the spatial extent and rate of urban growth over time in the study area. In this context, urban growth is considered as an increase in the physical extent of the built-up area. Thus, it is possible to interpret the city's growth directions by visualizing the multi-temporal land cover maps. In this study, post classification comparison is used to detect a land cover change of the study area.

3.4. Quantifying Urban Growth Pattern Using Spatial Metrics

The processes of urbanization usually change the landscape pattern in urban regions. Such changes are mostly accompanied by decreasing the heterogeneity of landscape compositions and increasing landscape fragmentation by generating smaller patches (Yeh & Huang, 2009). Spatial metrics are useful tools to quantify the dynamic patterns of ecological processes. Changes in urban landscape pattern can be detected by using spatial metrics that quantify and categorize complex landscapes structure into simple and identifiable patterns.

3.4.1. Selection of Metrics and Definition of Spatial Domain

Metrics are often used to quantify several aspects of spatial pattern. As a result, it is seldom to find a one-to-one connection between metric values and pattern. Indeed, most of the metrics describe a similar aspect of landscape pattern and they are correlated among themselves (McGarigal et al., 2002). Some metrics are fundamentally redundant as they do not measure different qualities of spatial pattern. Some researchers have made an effort to recognize the most important aspects of landscape pattern for the purpose of categorizing a significant and independent set of metrics (e.g., Cushman et al., 2008; Riitters et al., 1995). These studies suggest that agreement does not exist in the selection of individual metrics. Looking at the increasing advancement of quantitative metrics, it seems implausible that a single set of metrics exists to fully describe a landscape. Thus, the choice of metrics ultimately depends on the purpose of the problem under investigation and the nature of the landscape.

For this specific study a group of nine metrics are selected based on the literature review and the potential of each metrics to best describe urban pattern (Buyantuyev et al., 2010; Deng et al., 2009; Dietzel; et al., 2005; Herold et al., 2005; Herold et al., 2003). These are: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED), area-weighted mean patch fractal dimension (AWMPFD), contagion (CONTAG), Shannon‘s diversity index (SHDI) and Shannon‘s evenness index (SHEI). These metrics measure different and important aspects of the urban landscape. For example, CA measure absolute area of each land cover classes, number of patches measure the total of patches in the landscape or it is the measure of landscape fragmentation and heterogeneity, PD measure the number of patches per unit area, LPI is the measure of dominance, ED, and AWMPFD measure the complexity of urban form, CONTAG measures the tendency of patches types to be spatially aggregated and SHDI & SHEI measures the diversity of landscape. These indices are computed for all (four years) land cover maps and compared temporally, to describe and quantify the spatial pattern of the urban land cover change both at landscape and class level. The detailed description of each metrics is given in the sections.

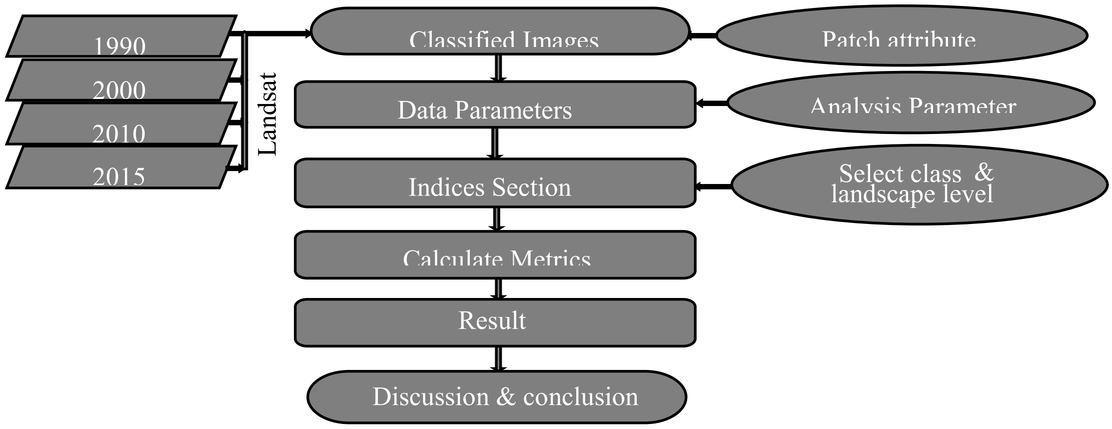
One of the most important issues in spatial metrics is defining the spatial domain of the study as it directly influences the spatial metrics.

Thus, the analysis of spatial metrics is conducted at two different spatial scales. First, selected metrics are computed at the whole landscape or city level to obtain the summary descriptor of landscape heterogeneity. Secondly, owing to the aggregating nature of spatial metrics over a large spatial scale, which might sometimes lead to misinterpretation of causal dynamics at disaggregated spatial scale like regions, administrative boundaries of the urban areas are used as a basis for disaggregating the study area into different regions as described above (Herold et al., 2003).

Accordingly, five among the selected nine metrics namely total areas (TA), number of patches (NP), patch density (PD), largest patch index (LPI) and area-weighted mean patch fractal dimension (AWMPFD) are identified to describe the pattern of urban growth at the whole landscape level. These metrics are initially selected based on their intuitiveness, ease interpretation and their ability to describe the composition and configuration of urban landscape pattern. Nevertheless, considering the fact that the growth of the city is going far beyond the metropolitan area, the analysis is conducted including areas outside RCC, but only focusing on built-up land cover class. Consequently, diversity and contagion metrics are excluded from the analysis at the whole landscape level as the thematic map contains only one class. For this kind of thematic map, it is impossible to calculate the diversity and contagion metrics such as ED, CONTAG, SHDI, and SHEI. The decision to exclude a non-built up area from the analysis is reached by considering no meaningful information can be extracted from the analysis of non-built up area at the whole landscape level. It would have been helpful if the analysis was limited to the RCC administrative boundary in the meantime meaningful comparison can be made between the built up and no-built up classes. The extent of the study area is defined based on its natural boundary, i.e. in such a way that to include the continuous built-up land in and around the metropolitan area visible from a satellite image.

However, unlike the analysis at the whole landscape level, all the selected (nine) metrics are used to evaluate landscape fragmentation in detail both at class and landscape level in the region-based analysis. In such way six metrics: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED) and area-weighted mean patch fractal dimension (AWMPFD are used quantify pattern at the class level. The remaining three metrics:
Contagions (CONTAG), Shannon‘s diversity index (SHDI) and Shannon‘s evenness index (SHEI) are used to quantify patterns at the landscape level. In this case, it makes sense to evaluate both built up and non-built up classes since the regions are defined purposefully. This will help to quantify the detailed pattern of urban land cover dynamics at the regional level which will, in turn, facilitate the implementation of appropriate and different policy measures in the different study regions. The following figure3.2 shows the flowchart used to calculate metrics in FRAGSTATS.

Figure 3.3: Detailed methodology used to derive spatial metrics



Generally, the selected metrics are supposed to describe the composition and configuration of the landscape pattern and they are computed for each land cover maps at the patch of classes and landscape mosaic level. Metrics at the class level are helpful for understanding how the landscape developed over time, whereas those at the landscape level provide aggregate information on the assessment of urban growth (McGarigal & Marks., 1995). All metrics are computed using public domain software FRAGSTAT 4.2.1 (McGarigal et al., 2012). The definitions and the significance the selected metrics are explained in the following section based on the documentation of the Fragstats software (McGarigal & Marks., 1995).

Class area (CA)

The class area is one of the most intuitive and straightforward metrics used to describe the pattern of urban growth in spatial metrics computation. It is sometimes known as total area implying the total area covered by a land cover class in hectares. In the context of this study, CA/TA refers to the total area covered by either built up or non-built up area.

$$\mathbf{CA} = \sum_{j=1}^{n} \mathbf{a_{ij}} \left(\frac{1}{100}\right) \text{..Equation 1}$$

(class level metrics)

Units: Hectares

Range: CA > 0, without limit.

“CA approaches 0 as the patch type become increasingly rare in the landscape. CA = TA when the entire landscape consists of a single patch type; that is, when the entire image is consists of a single patch.

Description: CA equals the sum of the areas (m) of all patches of the corresponding patch type, divided by 10,000 (to convert to hectares); that is, total class area‖ (McGarigal & Marks., 1995, p. 86). The class area (CA) metrics simply describes the growth of urban areas in terms of area or size.

Number of patches (NP)

The number of urban patches is the measure of discontinuous urban areas or individual urban units in the landscape. During the period of rapid urban nuclei development number of the patch is expected to increase due to the emergence of new fragmented urban patches around the nuclei. A number of patches are an indication of the diversity or richness of the landscape. This index can be calculated and interpreted very easily. However, like other richness measures, this interpretation might give misleading results because the area covered by each class is not considered here. Even if a certain class covers only the smallest possible area, it is counted. The way to count the number of patches within a given landscape is:

NP=N…………………………..………………………………………Equation 2
(class level metrics)

Units: None

Range: NP ≥ 1, without limit.

NP = 1 when the landscape contains only 1 patch.

Description: NP equals the number of patches in the landscape. Note, NP does not include any background patches within the landscape or patches in the landscape border (McGarigal et al., 2002).

The number of patches (NP) measures the extent of subdivisions of urban areas. NP being high when the urban expansion is proportional to an increase in subdivided urban areas or when the landscape gets more fragmented and heterogeneous.

Patch density (PD)

Patch density is another measure of landscape fragmentation/spatial distribution of the patches of a land cover class which indicates the density of fragmented urban units within a specified area, (for example per hectares). This index is a good indicator of landscape fragmentation. Values of this indicator are affected by the size of the pixel and also the minimum mapping unit since this is the determining factor for delineating individual patches. Smaller mapping units imply more patches and therefore higher values. PD can increase or decrease based on different circumstances. For instance, when the number of small patches in the landscape increases without substantial increase of total landscape area, the PD will increase indicating more heterogeneous and fragmented urban development. Whereas, if the total landscape area increased without significant change in the number of urban patches, the patch density will degrease implying the formation of the continuous urban surface due to the merging of smaller urban patches. However, if the number of patches and total landscape area increased together proportionally, there wouldn't be significant variation in PD for that landscape. Thus, it is important to pay attention while interpreting this measurement. A patch represents an area, which is covered by single land cover class. The patch density (PD) expresses the number of patches within the entire reference unit on a per area basis. It is calculated as:

PD=N/A(10,000)*(100)……………………………. ………………….Equation 3

(class level metrics)

Units: Number per 100 hectares Range: PD > 0, without limit.

Description: "PD equals the number of patches in the landscape divided by total landscape area, multiplied by 10,000 and 100 (to convert to 100 hectares)" (McGarigal & Marks., 1995, p. 88). Patch Density depends on the grain size, which is the size of the smallest mapping unit of the input data and the number of different categories. The index is a reflection of the extent to which the landscape is fragmented. This index is important for the assessment of landscape structures, enabling comparisons of units with different sizes.

Edge density (ED)

Edge density is another indicator of urban expansion level which measures the total length of the edge of the urban patches. It is computed by dividing the length of the urban boundary to the total landscape area. The total length of the edge of a land cover class (urban patch) increases with an increase in the land cover fragmentation. ED has a direct relationship with NP. Similar to PD its value is affected by the pixel size and the minimum mapping unit since the smaller the mapping unit the delineation of the various patches will result in an increase of the edge length. Herein, the smallest mapping unit is a pixel. An increment in the number of patches can certainly lead to the increase of Edge Density. An edge is a border between two different classes. Edge density (in m/ha) or a ratio of Perimeter/Area equal to the length (in m) of all borders between different patch types (classes) in a reference area divided by the total area of the reference unit.

The index is calculated as:

ED=E/A(10,000)…………………………………… ………………….Equation 4

(class level metrics)

Units: Meters per hectare

Range: ED ≥ 0, without limit.

Description: "ED equals the sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares)" (McGarigal & Marks., 1995, p. 89). If a landscape border is present, ED includes landscape boundary segments representing true edge only (i.e., contrast weight > 0). If a landscape border is absent, ED includes a user-specified proportion of the landscape boundary.

Regardless of whether a landscape border is present or not, ED includes a user-specified proportion of background edge. In contrast, to patch density, edge density considers the shape and the complexity of the patches. Edge density is a measure of the complexity of the shapes of patches and similar to patch density an expression of the spatial heterogeneity of a landscape. In short edge density (ED) is a measure of the total length of urban patch edges.

Largest patch index (LPI)

The largest patch index (LPI) is the ratio of the area covered by the largest patch in the landscape divide by the total area of the landscape (Herold et al., 2002). This metrics describes the total area of land covered by the largest patch in the landscape expressed in percentage. LPI is a relative measure of all patches and this can be useful to compare different area (region) with varying spatial extent. It can be considered a measure of the fragmentation of the urban landscape into smaller discrete patches versus a dominant core. The LPI increases when the urban areas become more aggregated and integrated with the urban cores.

$$\mathbf{LPI}=\frac{\overset{n}{\underset{j=1}{\mathrm{Max}}}(a_{ij})}{A}*\mathbf{100}\ldots\ldots\ldots\ldots\ldots\text{Equation 5}$$

(class level metrics)

Units: Percept (%)

Range: 0 < LPI ≤ 100

"LPI approaches 0 when the largest patch in the landscape is increasingly small. LPI = 100 when the entire landscape consists of a single patch; that is when the largest patch comprises 100% of the landscape.

Description: LPI equals the area (m^2) of the largest patch in the landscape divided by total landscape area (m^2), multiplied by 100 (to convert to a percentage) ‖ (McGarigal & Marks., 1995, p. 87); in other words, LPI equals the percent of the landscape that the largest patch comprises.

Area-weighted mean patch fractal dimension (AWMPFD)

The fractal dimension is a measure of patch shape complexity which describes the convolution and fragmentation of a patch as a perimeter-to-area ratio. It is estimated as the weighted mean value of the fractal dimension values of all patches of the same class. AWMPFD gives an improved measure of class patch fragmentation as it averages the fractal dimensions of all patches by weighting larger land cover patches (Herold et al., 2003). The averaging of patches will reduce the overestimation of fractal dimension given the fact that the structure of smaller patches is often determined more by the spatial resolution of the image than by the spatial characteristics of natural or man-made features found in the landscape. Generally, when a patch has a compact regular form with a relatively small perimeter relative to the area the AWMPFD will be low. Conversely, if the patches are more irregular, complex and fragmented, the perimeter increases resulting in a higher fractal dimension (McGarigal et al., 2002). For instance, when a built-up area starts to become saturated taking the shape of the urban blocks, AWMPFD will get lesser. This metrics is most likely to have less value, i.e. simple shape, for cities having a compact and regular pattern of development such as gridiron pattern.

$$\mathbf{AWMPFD}=\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{2\ln(.25P_{ij})}{\ln a_{ij}}\right)\left(\frac{a_{ij}}{A}\right)\right]\ldots\ldots\ldots\ldots\text{Equation 6}$$

Units: None

Range: 1 ≤ AWMPFD ≤ 2

A fractal dimension greater than 1 for a 2-dimensional landscape mosaic indicates a departure from a Euclidean geometry (i.e., an increase in patch shape complexity). AWMPFD approaches 1 for shapes with very simple perimeters such as circles or squares and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

Description: AWMPFD equals the sum, across all patches, of 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2), multiplied by the patch area (m^2) divided by total landscape area; the raster formula is adjusted to correct for the bias in the perimeter. In other words, AWMPFD equals the average patch fractal dimension (FRACT) of patches in the landscape, weighted by patch area.

Shannon's diversity index (SHDI)

Shannon's diversity index is a quantitative measure of the variety and relative abundance of patch types represented on the landscape. The composition component of the pattern is typically quantified with diversity indices. The patch richness such as the number of land use or land cover classes in the landscape are the major aspects quantified using SHDI in urban planning.

$\mathbf{SHDI} = -\sum_{\mathbf{i-1}}^{\mathbf{m}} (\mathbf{P_i} * \mathbf{ln\,P_i})$……………………………………………...Equation 7

(Landscape level metrics)

Units: None

Range: SHDI ≥ 0, without limit

"SHDI = 0 when the landscape contains only 1 patch (i.e., no diversity). SHDI increases as the number of different patch types (i.e., patch richness, PR) increases and/or the proportional distribution of area among patch types becomes more equitable.

Description: SHDI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion‖ (McGarigal & Marks., 1995, p. 118).

Shannon's evenness index (SHEI)

Shannon's Evenness index is a quantitative measure of abundance or the area distribution of classes of different patch types. Generally, it is reported as the function of the maximum diversity possible for a given richness.

$$\mathbf{SHEI}=\frac{-\sum_{i-1}^{m}(P_i * \ln P_i)}{\ln m}$$ ……………………………………………………..Equation 8

(Landscape level metrics)

Units: None

Range: $0 \leq \text{SHEI} \leq 1$

"SHDI = 0 when the landscape contains only 1 patch (i.e., no diversity) and approaches 0 as the distribution of area among the different patch types become increasingly uneven (i.e., dominated by 1 type). SHDI = 1 when the distribution of area among patch types is perfectly even (i.e., proportional abundances are the same).

Description: SHEI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion, divided by the logarithm of the number of patch types. In other words, the observed Shannon's Diversity Index divided by the maximum

Shannon's Diversity Index for that number of patch types‖ (McGarigal & Marks., 1995, p. 120).

Contagion (CONTAG)

The contagion index measures the probability of neighborhood pixels being of the same class and describes to what extent landscapes are aggregated or clumped (O'Neill et al., 1988). In other words, contagion is the measure of adjacency. Landscape classes are described by a high contagion index; when the landscape consists of relatively large and contiguous patches. The presence of a relatively greater number of small or highly fragmented patches in the landscape will result in low contagion index. For example, when an urbanized area becomes more amalgamated the contagion index will be high. As an urbanized area becomes more fragmentation into a larger number of individual urban units, the contagion index will be low.

CONTAG= [1+$\frac{\sum_{i-1}^{m}\sum_{k=1}^{m}\left[(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m}g_{ik}}\right)\right]\left[\ln(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m}g_{ik}}\right)\right]}{2\ln(m)}$**]*(100)..................**Equation 9

(Landscape level metrics)

Units: Percept (%)

Range: 0 < CONTAG < 100

"CONTAG approaches 0 when the distribution of adjacencies (at the level of individual cells) among unique patch types becomes increasingly uneven. CONTAG = 100 when all patch types are equally adjacent to all other patch types.

Description: CONTAG equals minus the sum of the proportional abundance of each patch type multiplied by number of adjacencies between cells of that patch type and all other patch types, multiplied by the logarithm of the same quantity, summed over each patch type; divided by 2 times the logarithm of the number of patch types; multiplied by 100 (to convert to a percentage). In other words, it is the observed contagion over the maximum possible contagion for the given number of patch types" (McGarigal & Marks., 1995, p. 121).

3.5. Logistic Regression Modeling and Driving Forces of Urban Growth

3.5.1. Physical Driving Forces of Urban Growth

As an empirical estimation model, logistic regression modeling is a data-driven rather than a knowledge-based approach to the choice of predictor variables (Hu & Lo, 2007). In developing countries like Bangladesh, the choice of predictor variables is highly depending on the availability of well-organized and good quality data. Particularly, socio-economic data 's are the scarcest data in developing countries. Thus, to overcome the challenge, only physical driving forces of urban growths are considered in this study. Most of the spatial data used to analyze the interaction between urban growth and driving forces are obtained from different open source webs such as USGS, Google Earth, etc.

However, in this study, the selection of physical predictor variables is made systematically in two steps. First, the most probable driving forces urban growths are identified based on literature review (Cheng & Masser, 2003; B. Huang et al., 2009;

Nong & Du, 2011; Tayyebi et al., 2010). Accordingly, twelve predictors were identified and grouped into three categories: (1) environmental/site-specific factors; (2) proximity factors; (3) neighborhood characteristics factors. Most of the selected variables are in agreement with most dynamic simulation modeling practices, which usually reflect the determining factors of 'SLEUTH' (Slope, Land cover, Exclusion, Urban extent, Transportation, Hill-shade) as in Clarke's SLEUTH model (Clarke et al., 1997). These variables reveal the biophysical conditions, the spatial influences of major highways, economic activity centers, existing land cover status, etc. On the second step, based on the discussion made with local experts these driving forces are adapted to the local context. In the process, some variables are added and at the same time, some are removed from the list. The lists of these variables are given below.

Table 3.3: list of variables identified from literature review for logistic regression modeling

Type of factor	Variables	Nature
Environmental	Hazards	Dichotomous
	Slope	Continuous
	Soil type	Dichotomous
	Wetlands	Dichotomous
Proximity factors	Distance to CBD	Continuous
	Distance to satellite towns	Continuous
	Distance to sub-city centers	Continuous
	Distance to airport	Continuous
	Distance to major roads	Continuous
	Distance to minor roads	Continuous
	Distance to railways	Continuous
	Distance to river	Continuous
Neighborhood characteristics	Proportion of urban land	Continuous
	Proportion of undeveloped land	Continuous
	Distance to public parks	Continuous
	Distance to higher education institutions	Continuous

According to the discussion made with experts, distance to CBD, distance from satellite town, distance to major roads, distance to higher education center, distance to public parks, distance to Padma river, distance to rail station and proportion of urban land are major factors, whereas slope is minor factor and the rest are insignificant physical driving forces of urban growth in the study area. Thus, flood hazards, soil type, distance to minor road, distance to airport and availability of developable land are removed from the list. Generally, in this study, the probability of a land to convert from non-urban land to urban land is considered as a function of the identified predictor variables. Regression analysis, which will be discussed in the next section, is carried out to identify the degree of significance of each identified variable and to examine how they enhance or hinder urban growth/land cover change in the study area. The analysis is important to better understand the interaction between urban growth patterns and driving forces. It is also helpful for a variety of urban models which require selection of appropriate spatial variables for the modeling process.

3.5.2. Logistic Regression Modeling

In this study, the nature of the land cover change of a cell was considered as dichotomous: either the presence of non- urban–urban conversion (represented by value 1) or no change (represented by value 0). It was assumed that the probability of a non-built up cell changing to a built-up cell would follow the logistic curve. The general formula of logistic regression is given as follows:

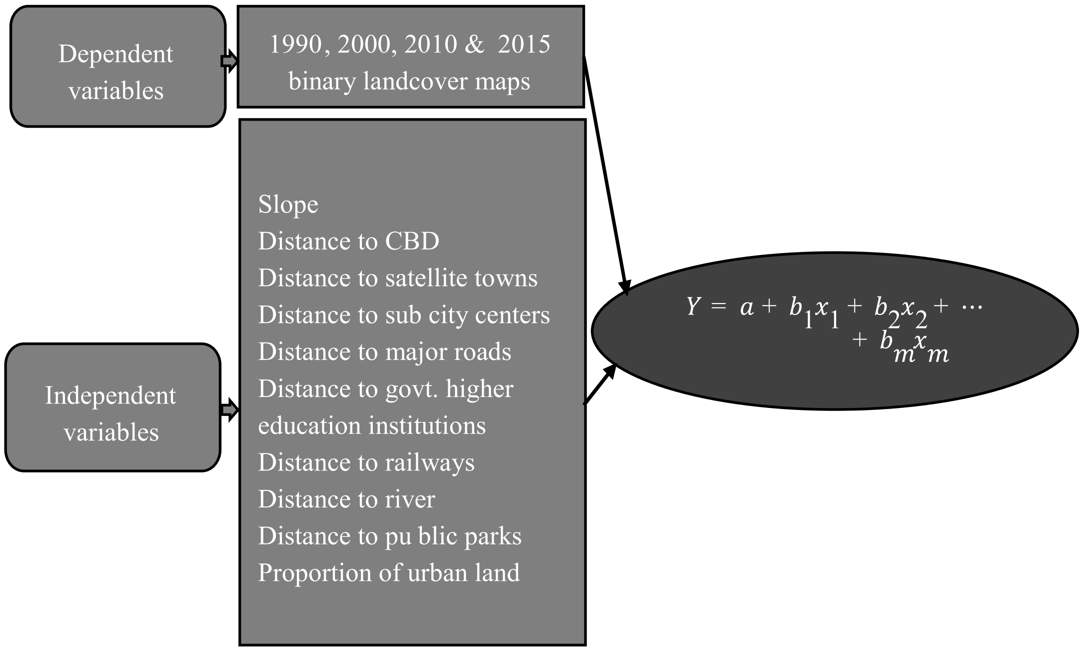
$$\mathbf{Y = a + b_1x_1 + b_2x_2 + \ldots + b_mx_m}$$

$$\mathbf{Y = \log_e\left(\frac{P}{1} - P\right) = logit\ P}$$

$$\mathbf{P(z=1) = \frac{e^y}{1+e^y}}$$

where x_1, x_2 ,… ,x_m are explanatory variables. The utility function y is a linear combination of the explanatory variables representing a linear relationship. The parameters b_1, b_2 ,…, b_m are the regression coefficients to be estimated. If z is denoted as a binary response variable (0 or 1), value 1 (z=1) means the occurrence of a new unit (i.e. the transition from a rural unit to an urban unit), and value 0 (z=0) indicates no change. Prefers to the probability of occurrence of a new unit, i.e. z=1. Function y is represented as log it (P), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1. As the y value increases, probability P inevitably increases. ArcGIS 10.4.1 software Change Analyst tool is used to conduct the logistic regression modeling. The flow chart showing general procedure followed in logistic regression modeling is given below (See figure 3.4).

Figure 3.4: Flow chart showing procedures followed in logistic regression modeling



3.5.3. Preparation of Input Data for Logistic Regression Model

The independent variables or the factor maps for the regression analysis are prepared for the three different periods under study. These maps are prepared in ARC GIS 10.4.1 software environment. All the input data are in raster format in a cell size of 30X30 so as to match the resolution of Landsat images.

Dependent variables

In this model four binary land cover maps of 1990, 2000, 2010 & 2015 are used as dependent variables to carry out the logistic regression analysis. These maps are classified into two land cover classes 0 & 1. 0 represents non-built up land cover class whereas 1 represents the built-up land cover class. The conversion rule is based on the assumption that land cover only changes from non-built up to built-up land. This because of the fact that the possibility of land cover to change from built-up to non-built up is very unusual or rare in developing countries like Bangladesh.

Independent variables

Nine independent variables are finally screened out based on literature review and discussion with the expertise to include in the model. However, as described in previous segment most land use/cover change models are data-driven. Major roads (as a major) and wetlands (as a minor) were identified as an important physical driving force of urban growth both in literature and on discussion made with local expertise. These variables are the proportion of urban land, slope, and distance from CBD, distance from higher education center, distance from major roads, distance from sub city centers and distance from public parks, distance from Padma river, distance from rail station. All of them are of the same resolution of 30X30m. Slope, distance from CBD, distance from the rail station and distance from satellite towns, distance from public parks, distance from Padma river are the same for all study periods of 1990-2000, 2000-2010 & 2010-2015. The variables distance from major roads and distance from higher education centers are different for the study period (1990-2000, 2000-2010, 2010-2015); however, distance from higher education centers is the same for the first two study periods (2000-2010 & 2010-2015). The proportion of built-up land is different for all the study periods and they are calculated based on the land cover map.

The proportion of built-up land (P_URBAN) is computed using a function focal statistic in Arc GIS. This function calculates the proportion of built-up area within a neighborhood of 7X7 window size for each pixel and assigns the central cell the mean value of all cells. The selection of the size of the neighborhood window is based on the most widely used window size in dynamic simulation models where sizes are often 3 X 3, 5 X 5, or 7 X 7 (Hu & Lo, 2007). Slope map is derived from the ASTER digital elevation model (DEM) of 2017 obtained from USGS website. The image was resampled to a resolution of 30cm to match the resolution of land cover images. Distance to CBD (DIST_CBD), distance to rail station (Dist_Rail Station), distance to major roads (Dist_Mjrd), distance to sub-city centers (Dist_Scc) and distance to Padma river (Dist_Padma), distance to public parks(Dist_Pub_Park), distance to higher education centers (Dist_H_Edu) are computed in Arc GIS using Euclidean distance function.

The function calculates the shortest distance from the center of the source cell to the center of each of the surrounding cells. These locations of the source cell or cells are represented by a point or line in Arc GIS. The values of all variables are standardized to 0-1 range.

3.5.4. Multicollinearity

Multicollinearity is a situation where two or more independent variables, are strongly correlated with each other than they are with the dependent variable. The existence of multicollinearity in a model may cause a very high standard error and low t-statistics, unexpected changes in coefficient magnitudes or signs, or insignificant coefficients despite a high R-square value. Such problems are misleading in the interpretation of outputs and will result in incorrect conclusions about associations between independent and dependent variables. Thus, to some extent performing multicollinearity analysis is the basis or a prerequisite for conducting multiple regression (Cheng & Masser, 2003).

The presence or the absence of multicollinearity is not a problem in multiple regressions, but rather the degree of presence matters. The higher the degree of multicollinearity, the greater will be the likelihood of the disturbing consequences of multicollinearity. There are several ways of detecting the manifestation of multicollinearity in a regression model. Variance inflation factor (VIF) perhaps the most commonly used test is the other way of detecting multicollinearity in statistical analysis. The variance inflation factors measure how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related. It has been shown that the variance inflation factor for the kth predictor is given by:

$$\mathbf{VIF_k} = (\mathbf{I} - \mathbf{R^2_k})^{-\mathbf{1}}$$

where R^2 is the R^2 value obtained by regressing the kth predictor on the remaining predictors. Note that a variance inflation factor exists for each of the k predictors in multiple regression models. In most scholarly articles and advanced statistical textbooks, VIF>10 is regarded as a sign of severe or serious multi-collinearity (O‘brien, 2007). There are a number of ways of dealing with multicollinearity problem

(Field, 2009). The first, and most obvious, the solution is to eliminate some of the highly correlated variables from the model. For instance, if two variables are highly collinear, then it means that they proving the same information. Thus, we can pick one variable to keep in the model and discard the other one. When unable to decide an appropriate variable to omit from the model, we can combine the variables into a reduced set of variables.

3.5.5. Model Evaluation

The predicting capacity of the proposed models is evaluated based on Percentage Correct Prediction (PCP), which is a simple tool indicating how good the model is at predicting the outcome variable. The PCP statistic assumes that if the estimated p is greater than or equal to 0.5 then urban growth or change from 0 to 1 is expected to occur and automatically will be assigned 1. However, if the estimated p is less than 0.5 then urban growths is not expected to occur and automatically will be assigned 0. By assigning these probabilities 0s and 1s and comparing these to the actual 0s and 1s, the correct prediction, wrong prediction, and overall percent correct prediction scores are calculated (Pampel, 2000). The result is obtained as a cross-classified 2x2 table of the two categories of an observed dependent variable with the two categories of predicted dependent variable. A highly accurate model would show that most cases fall in a cell defined by 0 on both observed and predicted group membership and by 1 on both observed and predicted group membership. Relatively few cases fall into the cells defined by a mismatch of observed and predicted group membership. The overall summary of correct prediction, wrong prediction, and percentage of correct prediction (PCP) is given in the preceding rows respectively. A perfect model would correctly predict a group membership for 100% of the cases. The PCP from 50 to 100% is considered as a crude measure of predictive accuracy (Pampel, 2000).

CHAPTER

04. Results and Discussions

In this chapter, the outcomes of this research are presented and discussed in detail sequentially. Starting from spatiotemporal quantification of urban growth, it goes through the most important findings of growth pattern analysis using spatial metrics. The pattern analysis is conducted at citywide level. Most of the discussions are supported by maps, tables, and illustrative graphs. The key factors responsible for the changing patterns of urban growths are presented and discussed through results of logistic regression modeling and driving forces.

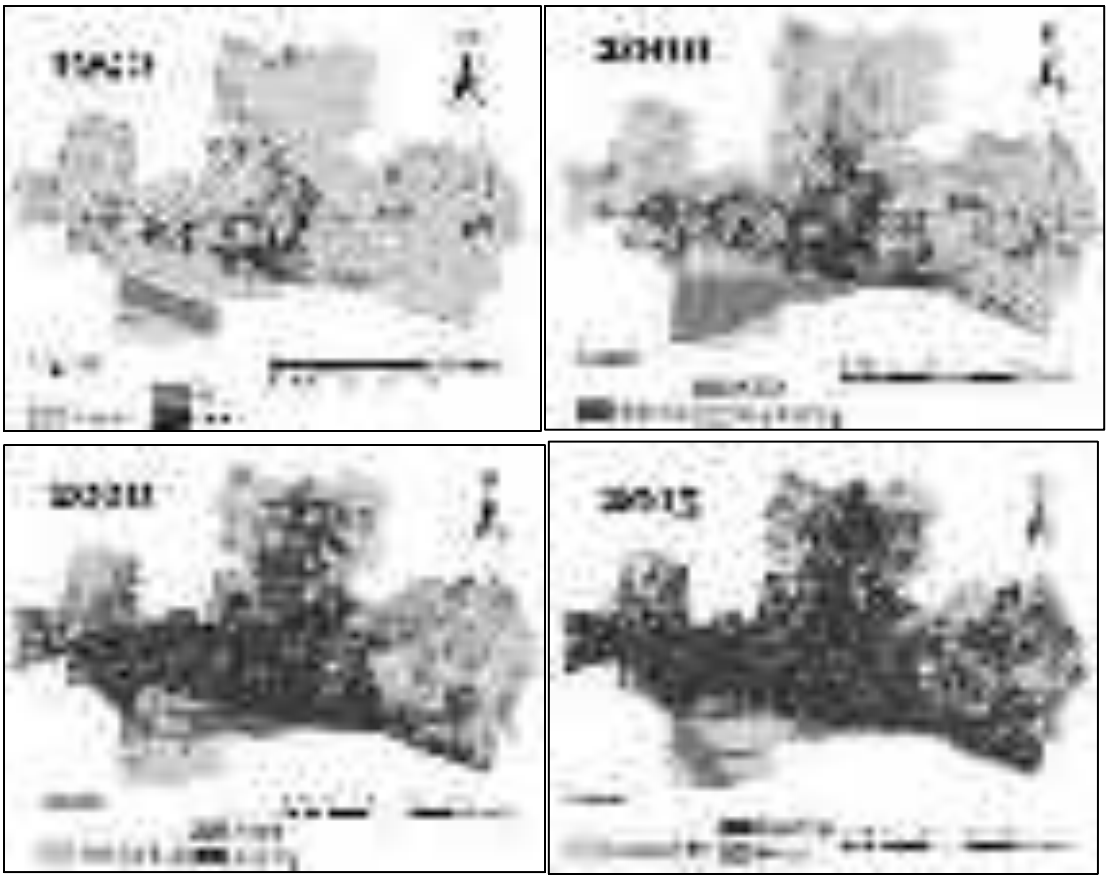
4.1. Results of Image Classification and Accuracy Assessment

According to the results of accuracy assessment, the extraction of water body has relatively higher accuracy in all images. Conversely, the built-up class has the lower accuracy due to the mixed pixels in the classes. The improved spectral information content of Landsat 8 OLI sensor could record small bright surfaces missed by Landsat-5 TM that has been manifested on Landsat ETM+ 2010 image in this study. Thus, the results presented based on TM 2010 image in this research are subject to the images variations described above. However, the overall accuracy of all images was found to be greater than 87.87%, which is considered as a good result for remote sensing image-based analysis (Herold et al., 2005). The following table presents the accuracy of classified images for the different time periods. The results of image classification are given in figure 4.1.

Table 4.1 Results of accuracy assessment

Year	Sensor	Acquisition Date	Classified Image	Overall Classification Accuracy	Overall Kappa Statistics
1990	Landsat 4-5 Thematic Mapper (TM)	30.01.90	Built Up 1990	94.52%	0.7714
2000	Landsat 4-5 Thematic Mapper (TM)	26.01.00	Built Up 2000	87.87%	0.7864
2010	Landsat 4-5 Thematic Mapper (TM)	06.02.10	Built Up 2010	92.86%	0.8732
2015	Landsat 8 Operational Land Imager OLI	04.02.15	Built Up 2015	89.64%	0.7295

Figure 4.1: Results of image classifications



4.2. Spatio-Temporal Analysis of Urban Growth Pattern Using Spatial Metrics

The classification of the multi-temporal satellite images into built-up, non-built up and water body for the four different time periods of 1990, 2000, 2010 & 2015 has resulted in a highly simplified and abstracted representation of the study area (See figure 4.1). These maps show a clear pattern of increased urban expansion extending both from urban center to connecting non-built-up areas along major transportation corridors. The maps show the spatiotemporal urban growth pattern in the study area. Post classification comparison of the classified images revealed the growth pattern of the city in different directions, the infilling of the open spaces between already built-up areas and the dynamics of urban expansion in the study area. However, it is important to assist the findings with statistical evidence as it is useful to describe the spatial extent and the different patterns of urban growths that have been occurring in the study area. This will help understand how the city is changing over time and to compare the various growth patterns taking place in different time periods quantitatively.

Spatial metrics are powerful tools to quantitatively describe and compare multi-date thematic maps. Five frequently used spatial metrics are selected based on literature review for the synoptic analysis of built-up area dynamics over space and time at the landscape level. The metrics are used to describe the trends and changing patterns of the actual built-up land extracted Landsat images. Detail discussion on metrics can be found in section 3.5.1 of this thesis. All metrics are computed only for the built-up area. The outputs presented in Table 4.3 were generated for the selected metrics in the form of numeric values for the whole study area in FRAGSTATS 4.2.1.

The results presented in table 4.3 shows that the total built-up area (TA) has grown from 578.52 ha in 1990 to 1087.92 ha in 2000, to 2249.91 ha in 2010 and to 3095.64 ha in 2015. The highest rate of urban growth is observed during the second period of urbanization (2000 to 2010) in which the built-up area increased more than 106.8% within 10 years (Table4.3). This is followed by 88.05% and 37.6% during the first (1990 to 2000) and the third (2010 to 2015) period of urbanization respectively. This indicates a more rapid urbanization has been taking place in the study area during the period of 2000 to 2010 compared to the two other periods. It could be also related to the construction of Jamuna multipurpose bridge on Jamuna River to connect north Bengal with capital Dhaka. Which gives a high opportunity of traveling faster than before and reduce 50% traveling time and ensure safety and security than before bridge construction.

Table 4.2: Analysis of Built-up Area expansion based on Total area (TA) metrics

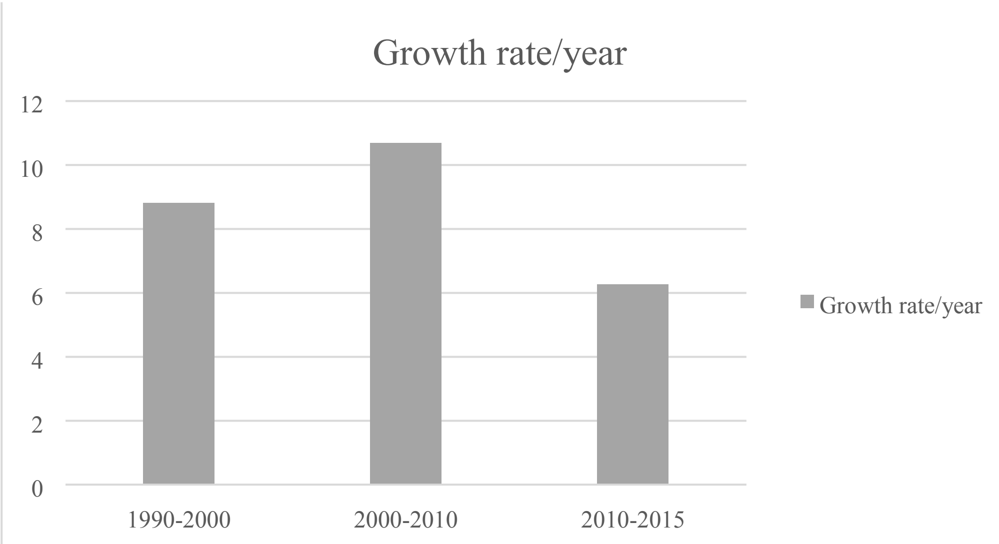
Study period	built up change	% change	year	growth rate/year	average
1990-2000	509.4	88.05	10	8.80	8.58
2000-2010	1161.99	106.80	10	10.68	
2010-2015	845.73	37.58	6	6.26	

Totally 2517 ha of non-built-up land has been converted to built-up land over the period 1990 to 2015. As the statistics found from the area metrics computation confirms, the built-up area has been increasing at an average annual growth rate of 8.80, 10.68 & 6.25% during the periods 1990-2000, 2000-2010 & 2010-2015 respectively in the study area (refer figure 4.2).

Table 4.3 Results of spatial metrics calculation at the entire landscape level.

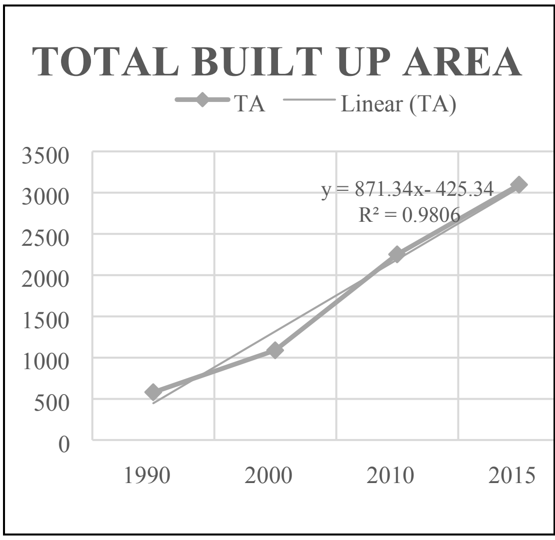
Study period	LUC	TA	NP	PD	LPI	FRAC AM
1990	Built Up	578.52	1183	12.0813	1.1029	1.1902
2000	Built Up	1087.92	1383	14.1238	4.8364	1.1985
2010	Built Up	2249.91	1104	11.2745	18.2482	1.1888
2015	Built Up	3095.64	712	7.2712	26.5441	1.1857

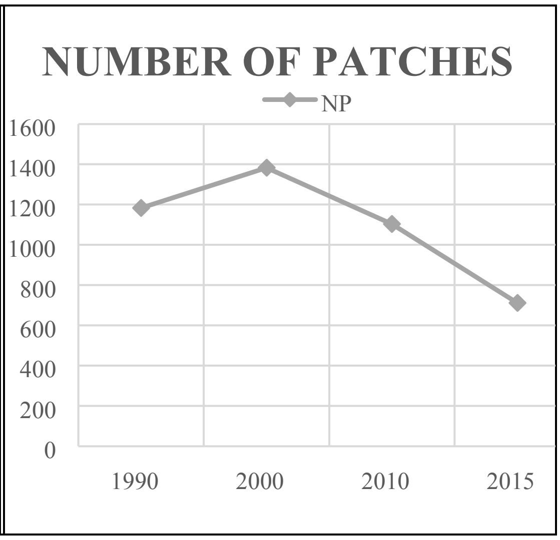
Figure 4.2 Built up area growth rate (%) per annum per study period.



The rapid urban growth process in the study area has been discovered but the continuous decrease of a number of patches (NP) in the landscape throughout the study periods. This could be an indication of the similar and non-fragmented urban growth process taking place in the study area. A significant change in NP the pick occurred in 2000 indicating the highly influential factor ruling development of scattered and fragmented urban patches in the study area. The situation can be attributed to the emergence of big and dense built-up patches in the core area of the city. This could happen as the city expands inward in the form of connected development, the gap between the peri-urban regions and the urban core will decrease by increasing the attractiveness the peri-urban area for development.

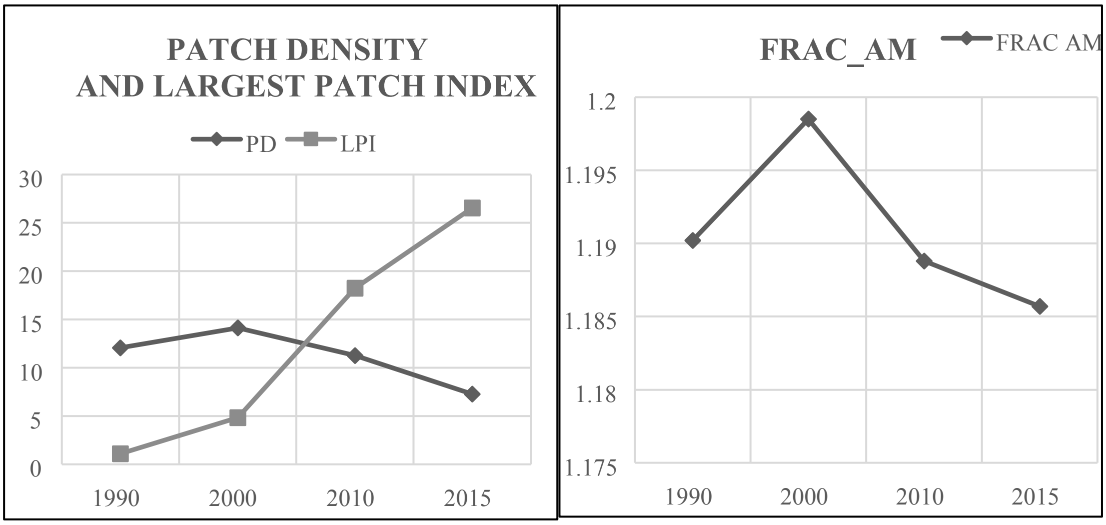
Figure 4.3: Graph showing total area (TA) & number of patches (NP) for the entire landscape area





The patch density (PD) continuously decreased from 14 in 2000 to 7 in 2015 throughout the study period. The highest reduction is observed during the third period of urbanization (2010-2015). These show that the built-up area (TA) is increasing at a much faster rate than NP. The phenomena can be observed from the slope of the two graphs (figure 4.3). Between 2000 & 2010 the slope of TA is steeper than the slope of NP in the same period on the graph. In other words, a decrease of patch density means that some patches located in close proximity to the city center are merging with the urban core to form a homogeneous urban fabric. The effect has been manifested on the increasing largest patch index (LPI), signifying the agreement between the metrics. Inherently, the dominant or largest patch in the landscape, which is supposed to be the urban core, is growing over time (Jun et al., 2009). Visual comparison of the classified images confirms the development of urban core in the form of infill and edge expansion (see figure 4.1 & 4.5). The gradual expansion of the urban core might have changed the city into urban agglomeration. This could be one reason for the combine and complete development of the city as urban agglomeration may push development towards the already established urban areas.

Figure 4.4: Graph showing patch density (PD), largest patch index (LPI) and FRAC_AM for the entire landscape area

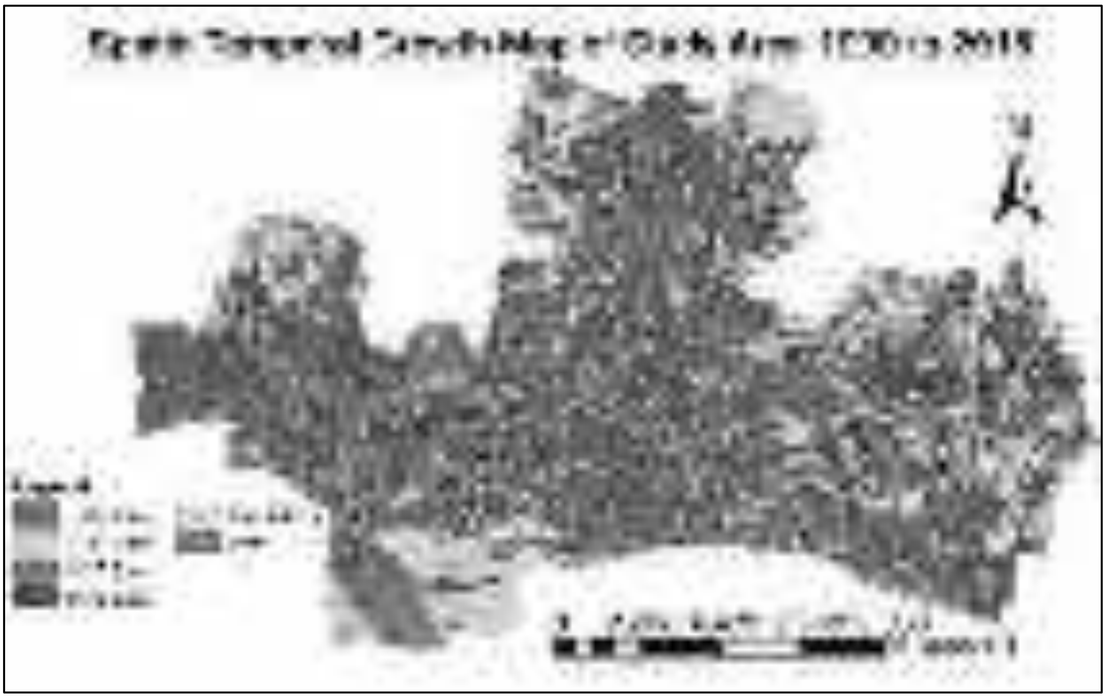


The area weighted mean patch fractal dimension (FRAC_AM/AWMPFD) is the measure of urban patch shape complexity which describes how patch perimeter increases per unit increase in patch area. In 1990, FRAC_AM was 1.19 which indicates that for a unit increase of patch area, the perimeter is increasing by 19% and by 18.5% in 2015. Nevertheless, during 200-2010 & 2010-2015 FRAC_AM decreased from 1.19 to 1.18 which might be due to the merger of existing smaller urban patches into relatively larger urban patches having simple geometric shapes (see figure 4.1). It could be also related to the stabilization and join up of the built-up area around the urban core into a simple and relatively regular urban form. Yet, looking at the highest value witnessed in 2000, it seems that the geometry of urban patches is getting more complex over time. This could be an indication of the prevalence fragmented low-density development in the marginal areas (see figure 4.1). It is also important to note that topography might have played a certain role in the fragmented development of the city. The wetlands are not suitable areas for urban development, those they break the continuity and isolate or fragment the built-up patches.

From the results of spatial metrics analysis of the built-up area, it has been possible to quantify the trends and patterns of urban dynamics at the city level using the selected five metrics. Accordingly, three metrics namely: the total built-up area (TA), number of urban patches (NP) and the largest patch index (LPI) showed consistent increasing trend while patch density (PD) exhibited a decreasing trend. Nevertheless, the fractal dimension (FRAC_AM) showed both increasing and decreasing trend with a remarkable upturn in 2000. Despite the increasing trend of the largest patch index (urban core), the built-up area remains to get more combine over time.

Generally, the spatiotemporal analysis of spatial metrics over the entire study area described here, indicates that the urbanization has substantially changed the land cover of the study area, with a significant land conversion. Built up area has been undergoing combine development process in all study periods, with a substantial increase of built-up area during the second period of urbanization, 2000-2010. In addition to the urban extension, which can be witnessed from the significant increase in a number of patches over time, patch density and the largest patch index also revealed that the city is experiencing infill rather than edge expansion around the urban core mainly during 2000-2010 (refer figure 4.5). The result of fractal dimension analysis also unveiled the increasing patch shape complexity of the study area except a slight decrease observed in 2010 which could be as a result of infill development or the merger of new patches with the existing patches during 2000-2010.

Figure 4.5: Spatio-temporal growth map of the study area (1990-2015)



4.3. Results of Logistic Regression Modeling

4.3.1. Variables Used in The Model

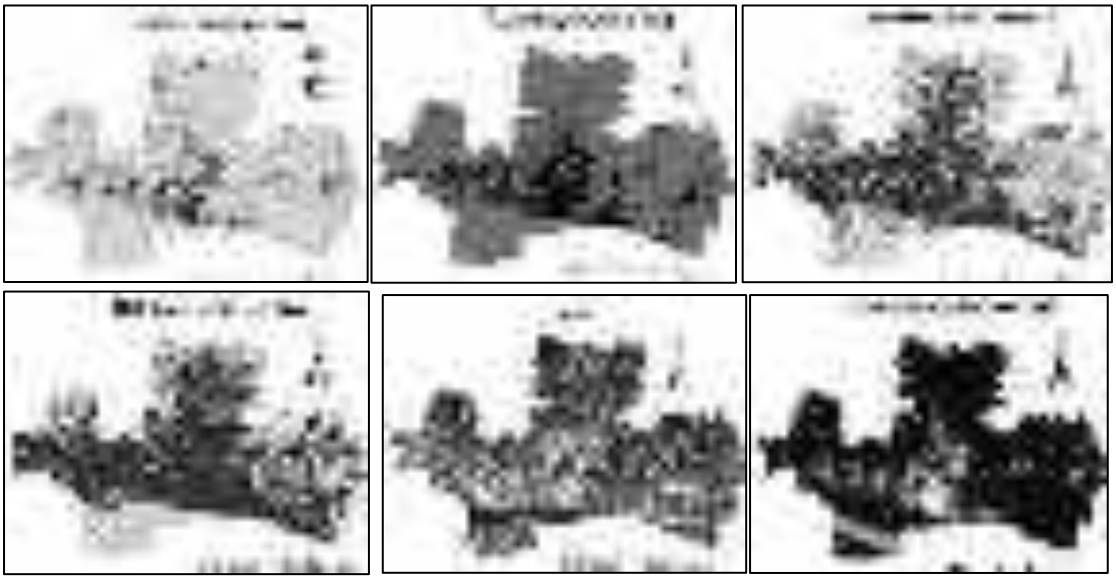
As discussed in the previous chapter (section 3.6.2) the main purpose of logistic regression, in this study, is to understand and statistically quantify the interaction between urban growth and its drivers. In this model urban growth is considered as a dichotomous dependent variable to be explained as a function of seven predictor variables listed in table 4.4 below. Each cell in the dependent variable has only two categories, either to change to the built-up cell (represented by 1) or remain as it is non-built up (represented by 0). Thus, the only change allowed in the model is from 0--->1. However, the seven predictor variables included in this model are continuous in nature.

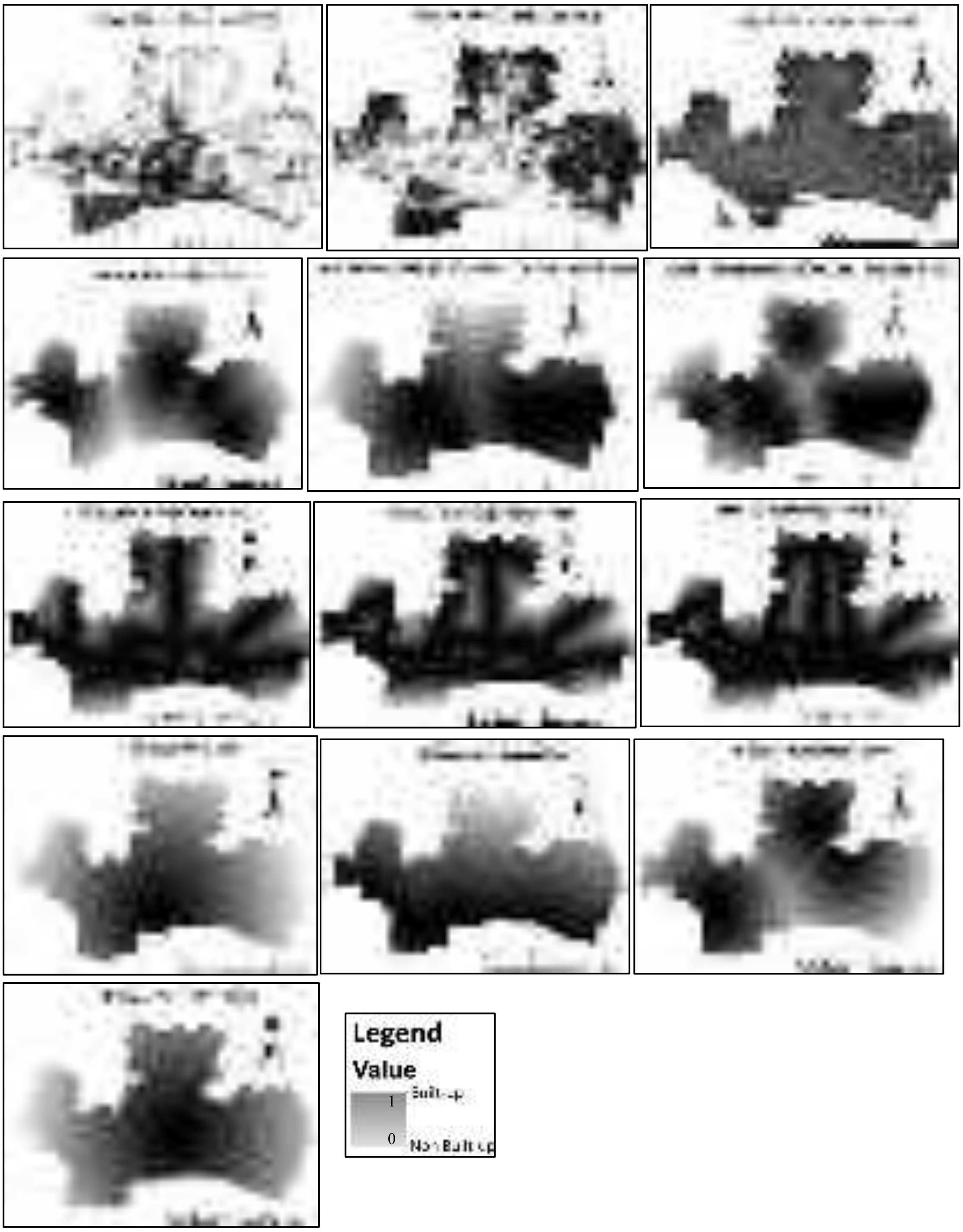
The logistic regression analysis is conducted for three different time periods of 1990-2000, 2000-2010 & 2010-2015. The number of predictor variables used for all study periods is the same however, the information content is slightly different for few variables. For example, the proportion of built-up land or area is different for all study periods, whereas since the location of rail station is never changed from the very beginning distance from Rajshahi railway station is the same for all periods. For further information refer to 3.6.3 section of this research. List of all variables included in the regression model are summarized in table 4.4 and the raster layers of all independent variables used in the model are given in figure 4.5 below.

Table 4.4: List of variables used in the logistic regression model.

Variable	Meaning	Nature of data	Shape
Dependent			
Y	Land cover maps	Discrete	Polygon
Independent			
Slope	Slope	Continuous	Line
P_Urban	Proportion of urban land within 7*7	Continuous	Polygon
Dist_CBD	Distance to CBD	Continuous	Polygon
Dist Rail Station	Distance to rail station	Continuous	Polygon
Dist_Mjrd	Distance to major roads	Continuous	Line
Dist_SCC	Distance to sub-city center	Continuous	Point
Dist_Padma	Distance to Padma river	Continuous	Line
Dist_Pub_Park	Distance to public parks	Continuous	Polygon
Dist_Gov._H_Ed	Distance to govt. higher education institutions	Continuous	Polygon

Figure 4.6: Raster layers of independent and dependent variables of the logistic regression.




Legend
Value
Built up
1
0
Non Built up

4.4.2. Multicollinearity Analysis

To exclude redundant variables from the model and maintain the stability of coefficients, multicollinearity diagnostic has been conducted for each set of variables used in different time periods. The analysis is carried out in SPSS 23 statistical software package by regressing one of the independent variables against the remaining six variables in an iterative way. In this manner, each variable is diagnosed for multicollinearity. Fortunately, none of the variables have scored variance inflation factor, VIF, >10. The analysis revealed that almost the entire variable scored VIF <5, which is a good result. This shows that the proposed independent variables will measure different aspects of the dependent variable being modeled. The results of multicollinearity analysis for all study periods are summarized below.

Table 4.5: Results of multicollinearity analysis

Variables	Description	VIF (1990-2000)	VIF (2000-2010)	VIF (2010-2015)
Slope	Slope	4.581	4.623	4.881
P_Urban	Proportion of urban land within 7*7 cell size	3.805	3.861	3.954
Dist_CBD	Distance to CBD	4.051	4.296	4.305
Dist Rail Station	Distance to rail station	2.785	2.850	2.996
Dist_Mjrd	Distance to major roads	3.524	3.702	4.001
Dist_SCC	Distance to sub-city center	4.925	4.543	4.801
Dist_Padma	Distance to Padma river	2.802	3.560	3.960
Dist_Pub_Park	Distance to public parks	4.392	3.393	2.996
Dist_Gov._H_Ed	Distance to govt. higher education institutions	3.819	2.861	4.057

4.4.3. Model Results

4.4.3.1. Urban growth model 1990-2000 results

Model summary: Log Likelihood = -35602.5934, PCP =98.42%, Total sample size = 30564, Overall Model Fit: Chi Square = 68521.9640 with df =21, P-Value=0.0000, 95% Confidence Intervals

Table 4.6: Estimated coefficients and odds ratios for the logistic regression model of 1990-2000

Variables	Coefficient	Std. Error	z_Value	T_Test(p)	Odds_Rate
Slope	0.700	0.500	2.009	0.077**	1.586
P_Urban	5.3290	0.345	23.906	0.000*	183.654
Dist_CBD	-1.713	0.500	-4.990	0.000*	0.265
Dist Rail Station	2.010	0.482	4.001	0.003*	3.000
Dist_Mjrd	-7.056	0.951	-8.766	0.000*	0.000
Dist_SCC	-6.002	0.590	-4.653	0.000*	0.015
Dist_Padma	-0.080	0.289	-1.163	0.870*	0.892
Dist_Pub_Park	-2.846	0.612	-2.168	0.140*	0.846
Dist_Gov._H_Ed	3.884	0.991	13.264	0.049	2.491

Constant= -2.90515 Variables with * sign is significant at α=0.05

Variables with ** sign are significant at α=0.1

Table 4.6 presented above summarizes the regression results of 1990-2000 urban growth model. The results are generated by a binary logistic regression model using the maximum possibility algorithm. Accordingly, seven variables: proportion of urban land (P_Urban), distance to CBD (Dist_CBD), distance to railway station (Dist_Rail_Station), distance to major roads (Dist_Mjrd) and distance to sub-city centers (Dist_SCC), distance to Padma river (Dist_Padma), distance to public parks (Dist_Pub_Park) are significant at α=0.05 and the variable Slope is found to be significant at α=0.10. However, one variable distance to government higher education center (Dist_Govt._H._Ed) has become insignificant in this model yielding higher P value, which is 0.04923. Among the significant variables three of them: P_Urban, Dist_Rail_Station, and Dist_Gov._H_Ed are positively correlated with urban growth. The remaining five variables: Dist_CBD, Dist_Mjrd, Dist_SCC, Dist_Pub_Park,

Dist_Padma are negatively correlated with urban growth means that the higher the distance from these variables the lower is the probability of urban growth to occur or in other words, urban growth tends to occur in close proximity to these variables. The relative significance of the predictor variables can be concluded from odds ratio. Odds ratios (OR) are an important parameter for the interpretation of logistic regression modeling. It is an indicator of the change in odds resulting from a unit change in the predictor. Variables with a higher odds ratio (>1) are regarded as highly influential variables in the model. Three variables: proportion of urban land (P_Urban), Slope, Distance to railway station (Dist_Rail_Station) and Distance to government higher education center (Dist_Govt._H._Ed) are possessing OR>1 with z_Value significantly different from zero which indicates that the presence of these three variables has highly contributed to the growth of the city in that specific period.

4.4.3.2. Urban growth model 2000-2010 results

Model summary: Log Likelihood = -41125.1154, PCP=94.78%, Total sample size=59331 with an overall Model Fit: Chi Square = 70158.7449 with df = 21, P-Value = 0.0000, 95% Confidence Intervals

Table 4.7: Estimated coefficients and odds ratios for the logistic regression model of 2000-2010

Variables	Coefficient	Std. Error	z_Value	T_Test(p)	Odds_Rate
Slope	4.685	0.296	20.014	0.000*	28.156
P_Urban	6.469	0.436	34.356	0.000*	789.846
Dist_CBD	2.565	0.305	5.209	0.000*	4.615
Dist Rail Station	3.215	0.439	16.649	0.360	13.546
Dist_Mjrd	-5.164	0.584	-5.621	0.000*	0.497
Dist_SCC	-6.002	0.590	-4.653	0.000*	0.946
Dist_Padma	-0.591	0.289	-5.566	0.681*	0.736
Dist_Pub_Park	1.948	0.861	5.562	0.061*	5.649
Dist_Gov._H_Ed	6.164	0.649	15.459	0.023*	3.451

Constant= -3.53101 Variables with * sign is significant at α=0.05

The parameters of 2000-2010 growth models are summarized in table 4.7. The result of the regression modeling witnessed that all variables except distance to Rail Station (Dist. Rail Station) are found to be statistically significant at α=0.05. Remarkably, in similar fashion to the 1990-2000 model; proportion of urban land (P_Urban), Slope, distance to Rail Station (Dist Rail Station), distance to CBD (Dist._CBD), distance to public parks (Dist_Pub_Park) and distance to government higher education center (Dist_Govt._H._Ed) are observed positively correlated with urban growth. The other three variables: distance to major roads (Dist_Mjrd), distance to sub-city centers

(Dist_SCC) and distance from Padma River (Dist_Padma) are negatively related to urban growth. However, distance from Rail Station (Dist. Rail Station) which yielded P value greater than 9%, had a significant contribution to urban growth in the study area during the period of 2000-2010. The level of significance of each variable can be determined based on their odds ratio. The variables proportion of urban land (P_Urban), slope, distance to CBD (Dist_CBD), distance to Rail Station (Dist Rail Station), distance to government higher education center (Dist_Govt._H._Ed) and distance to public parks (Dist_Pub_Park) had an odds ratio > 1 which indicating the presence of these variables the probability of urban growth is high.

4.4.3.3. Urban growth model 2010-2015 results

Model summary: Log Likelihood = -5661.1568, PCP=95.99%, Total sampling size= 29548, Overall Model Fit: Chi Square = 51848.518 with df = 21, P-Value = 0.0000, 95% Confidence Intervals

The results of the 2010-2015 regression modeling revealed that all predictors except distance to Major roads are able to explain the dependent variable with different level of significance. Unlike the two other models presented earlier many of the predictor variables in this model are negatively related to urban growth. The proportion of urban land (P_Urban) and slope remain positively associated with urban growth. The odds ratio of these two variables is >1 indicating the presence of these variables yields a high probability of urban growth.

Table 4.8: Estimated coefficients and odds ratios for the logistic regression model of 2010-2015

Variables	Coefficient	Std. Error	z_Value	T_Test(p)	Odds_Rate
Slope	0.359	0.239	-0.967	0.432	0.761
P_Urban	6.262	0.415	35.646	0.000*	305.659
Dist_CBD	-2.059	0.421	-6.959	0.292*	0.515
Dist Rail Station	4.656	0.861	12.475	0.000*	80.513
Dist_Mjrd	-0.217	0.271	0.801	0.5169	2.024
Dist_SCC	3.616	1.050	13.464	0.000*	12.054
Dist_Padma	-8.664	1.052	-6.861	0.120*	1.235
Dist_Pub_Park	9.216	0.420	25.215	0.140*	0.058
Dist_Gov._H_Ed	-3.546	0.500	-5.981	0.395*	4.385

Constant= -3.00515

Variables with * sign are significant at α=0.05 Variables with ** sign are significant at α=0.1

4.3.4. Model Interpretation and Discussion

As witnessed from the models, urban growth is more likely to occur in the proximity to existing built-up areas where the proportion of urbanized cell is high. This is true for all study periods under investigation. The slope has been consistently significant and positively related to urban growth in all study periods. The estimated coefficients and odds ratios are 0.700163, 4.68541 & 0.359431 and 1.586418, 28.15648 & 0.761339 for the study periods 1990-2000, 2000-2010 and 2010-2015 respectively. For all study periods slope is positively related to urban growth, indicating the higher the slope of an area the higher probability to be occupied by a new built up cell rather than the nearest area of low land. The likelihood of a non-built up a cell to change to the built-up cell is 1.586418 times, 28.15648 times & 0.761339 times as large as the probability of change in an area one percent less in slope. This could be attributed to the moderately high topographic nature of Rajshahi, where settlement on a lower slope or close to wetlands is hostile due to the presence water logging, flood hazards and others. Thus, steeper slopes were more preferred for settlement than low laying or wetland areas. During 2000-2010 most of the growths were taking place in areas relatively having a high slope. However, the level of significance of slope during the period 1990-2000 has been at α=0.1 having P-value 0.0776 which makes it the only significant variable in all study period with α=0.1. The rest of significant variables are important at the significance level of α=0.05.

The proportion of urban land (P_Urban) is positively correlated with urban growth with an estimated coefficient of 5.329051, 6.46908 and 6.262958 and odds ratio of 183.654314, 789.8469 and 305.65900 for the study periods 1990-2000, 2000-2010 and 2010-2015 respectively. The odds ratios can be interpreted as; the probability of urban growth will increase with 183.654314, 789.8469 and 305.65900 with an increase of one urban cell are in the neighborhood for the periods 1990-2000, 2000-2010 and 2010-2015 respectively. The odds ratios of the independent variable P_Urban are far larger (>1) in all study period indicating that proportion of urbanized cell within a 7X7 window size is the major factors driving urban growth in the study area for all study periods.

Distance to Rail Station (Dist. Rail Station) has been consistently significant and positively related to urban growth in all study periods. The estimated coefficients and odds ratios are 2.01005, 3.21512 & 4.656827 and 3.000095, 13.54619 & 80.51334 for the study periods 19902000, 2000-2010 and 2010-2015 respectively. For all study periods (Dist. Rail Station) is positively related to urban growth, indicating the closer distance to the railway station of an area the higher probability to be occupied by a new built up cell. The likelihood of a non-built up cell to change to the built-up cell is 3.000095 times, 13.54619 times & 80.51334 times as large as the probability of change in an area one percent less in distance to Rail Station. For all study periods distance to Rail Station (Dist. Rail Station) is positively correlated with urban growth indicating the higher the distance from Rail Station, the lower is the probability of urban growth to occur. Thus, areas within close proximity of the Rail Station were more favorable for urban development during study periods. However, through time, Rail Station might gain its significance in attracting urban growth when the availability of developable land is scarce. It may be the peoples trust refection on the public transport modes to communicate with the capital and in others long distance

Distance to government higher education center (Dist_Govt._H._Ed) is one of the variables that have been significantly correlated with urban growth in the study area over study periods. In contrast to distance to the Padma, distance to government higher education center. (Dist_Govt._H._Ed) is positively correlated with urban growth at a significance level of $\alpha=0.05$ for all study periods. The estimated odds ratios are 2.491365, 3.451365 and 4.385645 for the periods respectively which means that the odds of urban growth in the area one unit farther away from government higher education center are estimated as 2.491365 times, 3.451365 times and 4.385645 times as large as that in an area close to the government higher education center. The closer a cell is to government higher education center; the high likelihood it is to be urbanized. Since most of the growths were taking place closer to the rail station, sub-city centers and where a high proportion of built up cell is found, more developments were happening around the urban core (RCC) where maximum government educational centers are located.

The models also show that urban growth has been significantly influenced by proximity to a major road in all study periods. This variable (Dist_Mjrd) is negatively associated with urban growth. The estimated odds ratios for distance to major road (Dist_Mjrd) are 0.000821 (1/1218.026797), 0.497561 (1/2.0098) & 2.024851 (1/0.49386) for the study periods 19902000, 2000-2010 and 2010-2015 respectively. The likelihood of urban growth in an area close to major roads is estimated as 1218.026797 times, 2.0098 times and 0.49386 times as large as the odds of urban development in an area a unit further away from major roads. The road is one of the major urban elements that facilitate movement of goods and people in urban areas and thus, influencing the spatial pattern of urban growth.

The variable distance to Padma River has been affecting urban growth throughout the study periods with a significance level of 0.05. This variable (Dist_Padma) is also negatively related to urban growth in all study periods demonstrating the closer to the Padma the higher is the probability of urban growth to occur. The odds ratio for distance to the Padma is 0.892613 (1/1.12031), 0.736491 (1/1.3577) and 1.1256447 (1/0.809294) for the study periods 1990-2000, 2000-2010 and 2010-2015 respectively. These indicate that the odds of a non-built up cell to convert to a built-up cell within an area close proximity to the Padma is estimated as 1.3577 times, 1.12031 times and 0.89294 times as large as that in an area one unit further away from sub city centers for 1990-2000, 2000-2010 and 2010-2015 study periods respectively. In a bird's eye view, the Padma river get moderately high influence in urbanization of Rajshahi city corporation.

The results of the regression models revealed that distance from public parks (Dist_Pub_parks) has influenced urban growth during the latter two study periods (2000-2010 and 2010-2015) at α=0.05. However, it had no significance during the period of 1990-2000. The coefficient and odds ratio of distance to public parks (Dist_Pub_parks) is 1.94822 & 9.21641 and 5.649947 (1/0.17699) & 0.058021 (1/17.2351) for the periods 2000-2010 and 2010-2015 respectively. This shows that the probability of urban development to occur in an area close proximity to public parks is as 0.17699 times and 17.2351 times as large as that in the area one unit farther away from public parks for the study periods 2000-2010 and 2010-2015 respectively. This is reasonable as public parks are located farther away from the city during earlier periods of urbanization and thus, they do attract urban growth significantly.

4.3.5. Model Evaluation

Model evaluation is an important step in logistic regression modeling. Change analysis software generates an output that could be used to evaluate the predictive power of the constructed model. Percentage correct prediction (PCP), the most commonly used type of evaluation method, is used in this study. It tells the percentage of correctly predicted pixels out of the sampled pixels in the model. The higher the PCP the higher is the predicting power of the model. Accordingly, the PCP of the three models, i.e. 1990-2000, 2000-2010 & 2010-2015 is 95.00%, 94.80% & 96.50% respectively, which is pretty good prediction power. The outputs of model evaluation analysis are presented below.

Table 4.9: Results of regression model evaluation

1990 to 2000

	Predicted			
Observed		0	1	Total
	0	361264	6261	367525
	1	36505	45131	81636
	Total	397769	51392	449161

Correct Prediction: 3655154

Wrong Prediction: 220151

PCP: 95.00%

2000 to 2010

	Predicted			
Observed		0	1	Total
	0	3489215	11952	3501167
	1	92461	26521	118982
	Total	358167	38473	362014

Correct Prediction: 3844913

Wrong Prediction: 180534

PCP: 94.80%

2010 to 2015

	Predicted			
Observed		0	1	Total
	0	306900	15029	321929
	1	156481	356129	512610
	Total	463381	371158	834539

Correct Prediction: 359205

Wrong Prediction: 20650

PCP: 96.50%

4.3.6. Physical Driving Forces of Rajshahi City Corporation's Urban Growth

Understanding the complex interaction between urban growth and its drivers over space and time is helpful to predict future urban development's and construct alternative scenarios. Despite the fact that availability of data is one of the major problems to conduct research in developing countries like Bangladesh, it is evident that logistic regression model can be built based on few, but widely available spatially explicit data such as satellite images to provide relevant information for urban planners and policymakers (Fragkias & Seto, 2007). Thus, logistic regression urban growth modeling is an ideal approach to look at significant drivers of urban growth over time, particularly for developing countries. Different kinds of literature have reported that driving forces of urban growth might differ based on the local context in which the development is taking place and the spatiotemporal dimension at which the analysis is considered (e.g. Cheng & Masser, 2003; B. Huang et al., 2009). In this study, three spatially explicit binary logistic regression models have been developed for 1990-2000, 2000-2010 and 2010-2015 study periods. The main purpose of the models is to figure out the major driving forces of urban growth and their level of significance in the study area. Accordingly, the models were able to reveal significant driving forces of urban growth during the three study periods for the past 26 years.

Among the variables included in the 1990-2000 model, distance to major roads (Dist_mjrd) (-ve), the proportion of built-up cell (P_Urban) (+ve), distance to govt. higher education centers (Dist_Gov_H_Edu) (+ve), distance to Rail station (Dist_Rail Station) (+ve), distance to public parks (Dist._Pub_Park) (+ve) and Slope (+ve) is found to be significant drivers of urban growth in a descending level of importance with their indicated sign of correlation with urban growth. However, distance to sub-city centers (Dist_Scc) (-ve) is found to be an insignificant factor for this study period. This might be due to the wide gap between satellite towns and the city in the earlier stage of urbanization. According to Tobler‘s first law of geography "Everything is related to everything else, but near things are more related than distant things." The order of significance of the variables is also in a logical sequence as roads are major urban elements attracting urban growth in the early stage of development.

During 2000-2010, Slope (+ve), proportion of built up cell (P_Urban) (+ve), distance to CBD (Dist_CBD) (+ev), distane to rail station (Dist_Rail Station) (+ev), distance to major roads (Dist_mjrd) (-ve), distance to Padma(Dist_Padma) (-ve), distance to public parks (Dist_Pub_Parks) (+ev) and distance to government higher education centers (Dist_Gov_HEdu) (+ve) are found to be significant driving forces of urban growth in a decreasing level of influence and with their indicated sign of correlation. Distance from major roads has been the third influential variable in the 2000-2010 model. However, in this model, it is not any more significant. Following the rapid urban growth witnessed during 2000-2010 (refer section 4.3); the city has expanded outward to the periphery areas in all direction. This indicates developments were occurring in close proximity to sub-city centers, existing built-up areas and probably closer to CBD than major roads. Consequently, the significance of distance to CBD (Dist_CBD) will be negligible or insignificant at all. Distance to sub-city centers (Dist_SCC) and proportion of built up cell (P_Urban) were the second and third influential variables in the 1990-2000 model, however, they become the second and first important factors in the 2000-2010 model.

Slope (+ve), proportion of built up cell (P_Urban) (+ve), distane to rail station (Dist_Rail Station) (+ev), distance to major roads (Dist_mjrd) (+ve), distance to Padma(Dist_Padma) (ve), distance to public parks (Dist_Pub_Parks) (+ev), Distance to sub-city centers (Dist_SCC) (+ve) and distance to government higher education centers (Dist_Gov_H_Edu) (-ve) were significant drivers of urban growth in 2010-2015 study period in a decreasing sequence of importance with their designated sign of correlation with urban growth. Distance to CBD appeared insignificant in this model. However, distance to public parks becomes an important variable in this model. This means most of the new growth tends to occur at the periphery of the city next to the already urbanized areas, i.e. edge expansion. However, there are also some infill developments that have been taking place close to public parks during the 2010-2015 period. However, following the gradual expansion of the city, satellite towns become increasingly important due to their proximity to the main city.

Assuming that distance to major roads might have been the most important variable above all before 1990, the pattern (order of significance) observed on the driving forces is reasonable. In the early stage of urbanization roads are major urban elements structuring urban growth pattern followed by proximity to the built-up area such as sub-city centers. Then, sub-city centers are created at the junction or nodes of roads. These sub- city centers eventually start to attract urban development around them. Gradually, when the availability of developable land in close proximity to CBD, major roads and sub-city centers become rare, the available land immediately next to existing built-up area will be attractive. Some negative impacts such as congestion, overcrowding, etc. due to the agglomeration of the city center might have pushed development away from the established urban core (CDB).

The results of spatial metrics analysis can be also related to the findings of these models. The combined development pattern witnessed during the early period of urbanization could be driven by the major roads and economically active sub-city centers. This means, urban development has been taking place in all direction and dispersed around sub-city centers. The proportion of built up cell and distance to government higher education centers were also fair attracting urban growth during 1990-2000 study period.

During 2000-2010, the number of patches decreased substantially, and therefore the city experienced a combine rapid urban growth (refer section 4.3). The result of logistic regression analysis confirms that those growths were mostly driven by the proportion of urban land and distance to government higher education centers. This is reasonable as the probability of finding developable land close to Padma River and public parks is less, the locally distributed sub-city centers (Dist_Scc) and proportion built-up area (P_Urban) will attract urban growths. However, it is important to note that there is still some development going on within close proximity to major roads although it is not as important as the growth taking place around sub-city centers and a high proportion of built-up areas. The variable slope confirms that following the rapid urban growth observed during 2000-2010, developments were taking place in relatively higher slope areas. The insignificance of distance to CBD during this period does not necessarily indicate the absence of development around CBD because urban development is also taking place in close proximity to where a high proportion of built up cell is found. This could be in the form of edge expansion at the edge of the urban core, which can be confirmed by the increasing largest patch index (LPI) metric (refer section 4.3).

Interestingly, during 2010-2015 due to the lack, developable land in close proximity to major roads and sub-city centers, the variable distance to public parks become the dominant factor attracting urban growth in the study area followed by distance to Padma River (Dist_Padma). Yet, the proportion of urban land the third important factor attracting urban growth. The position claimed by the distance to sub-city centers (Dist_SCC) is rational as the gap between the main city and satellite towns will decrease and thus, satellite towns become more attractive for development. The variable distance to CBD, which was insignificant in the previous period, become a significant factor during 2010-2015 indicating that infill development or redevelopments have been taking place in the City Center. This is reflected by the decreasing patch density (PD) and increasing largest patch index (LPI) during this period given, the patterns observed during these three study periods, satellite towns will be the next significant drivers of urban growth in the foreseeable future. The top four driving forces of urban growth during the three different study periods are presented in table 4.10.

Table 4.10: Major driving forces of urban growth in 1990-2000, 2000-2010 & 2010-2015 study periods

Study periods	Order of Significance	Major driving forces	Correlation with urban growth
1990-2000	1st	Distance to major roads	Negative
	2nd	Distance to sub-city centers	Negative
	3rd	Proportion of built-up land	Positive
	4th	Distance to govt. higher education institutions	Positive
2000-2010	1st	Proportion of built up land	Positive
	2nd	Distance to govt. higher education institutions	Positive
	3rd	Distance to sub-city centers	Negative
	4th	Distance to major roads	Negative
2010-2015	1st	Distance to public parks	Negative
	2nd	Distance to Padma River	Positive
	3rd	Proportion of built up cell	Positive
	4th	Distance to sub-city centers	Positive

Generally, three variables: distance to major roads (Dist_Mjrd), distance to sub-city centers (Dist_Scc) and proportion of built up cell (P_Urban), remain among the top four driving forces of urban growth in first two study periods with varying order of significance. Distance to public parks (Dist_Pub_Parks), distance to govt. higher education institutions (Dist_Gov_H_Edu) and distance to Padma river (Dist_Padma) were among the top four drivers of urban growth at different time periods with varying (see table 4.10).

4.4. Impact of Urban Growth on Wetlands

As described in section 1.2 and 1.6, wetlands are slightly common characteristics of the study area. Although they are considered minor driving forces of urban growth by local experts, an effort has been made to include wetlands in the logistic regression modeling at an early stage of this research. Results of spatial metrics analysis revealed that wetlands have played a considerable role in the fragmented development of the city areas. This could show the pressure of urban development that might have impacted the wetland. Thus, quantifying and mapping the extent of urban growth that has been taking place in wetlands during 1990-2015 periods is worthy of consideration.

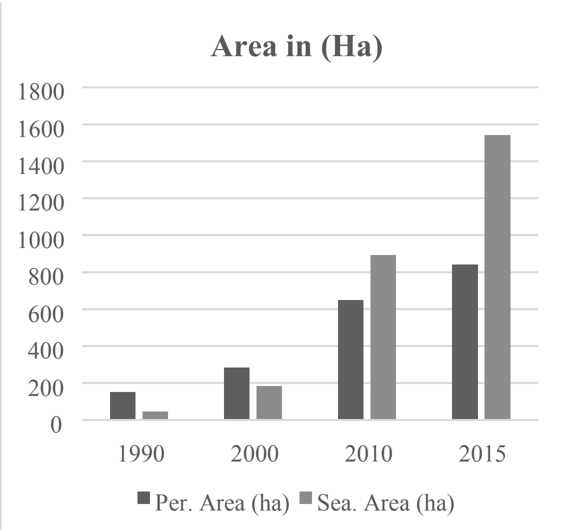
The quantification and mapping of wetlands intrusion are based on the data analysis of land for over 25 years monsoon and pre-monsoon wetland. According to this data, wetlands are categorized into permanent and seasonal wetlands. Permanent wetlands are those located near open water bodies and some of them are preserved ponds and some of these are privet wounded and they are permanently waterlogged whereas seasonal wetlands are flooded during the rainy season and they are not flooded during the dry season. It was believed that wetlands environmentally sensitive since they are home to a high number of plant and animal species. Both permanent and seasonal wetlands are analyzed in this study. The analysis is conducted in ArcGIS using "clip" spatial analyst tool. The built-up area falling inside respective wetlands is clipped by the wetlands-1996 shapefile for each year, i.e. 1990, 2000, 2010 & 2015 and the area is summed up separately (see table 4.10).

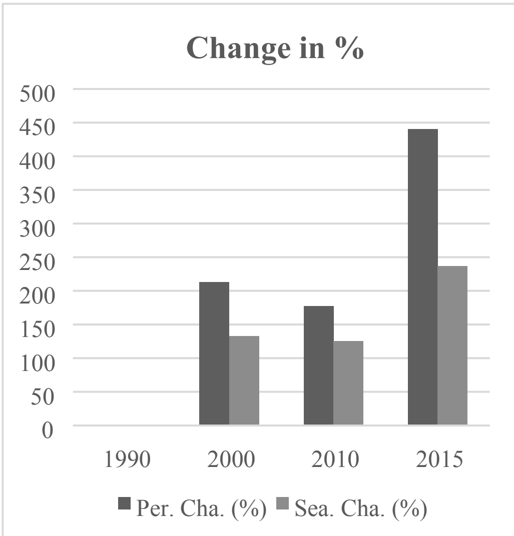
The results indicate 150 ha, 283 ha, 650 ha and 841 ha of permanent wetlands have been converted to urban (built up) area in 1990, 2000, 2010 and 2015 respectively. Most of the encroached wetlands are found inside and at fringe areas of RCC (figure 4.17). This confirms to the suggestion given in region-based analysis of central Rajshahi (CR) based on PD and LPI metrics. The bar chart presented in figure 4.17 illustrates seasonal wetlands were more vulnerable compared to permanent wetlands. This could be due to the suitability of seasonal wetlands for settlement compared to permanent wetlands as they are dry for the most part of the year. The result shows that 45ha, 181ha, 890ha and 1540ha of wetlands have been developed for urban use in 1990, 2000, 2010 and 2015 respectively.

Table 4.11: Wetland encroachment in RCC

Wetland Encroachment						
Study period	Permanent wetlands			Seasonal wetlands		
	Area(ha)	Change(ha)	Change (%)	Area(ha)	Change(ha)	Change (%)
1990	150			45		
2000	283	133	212.782	181	136	133.0882
2010	650	367	177.1117	890	709	125.5289
2015	841	191	440.3141	1540	650	236.9231

Figure 4.7: Urban growth dynamics in wetland areas (permanent vs. seasonal wetlands)





CHAPTER

05. Conclusion and Recommendations

Conclusions are structured based on the research objectives formulated. Specific conclusions are given per sub-objective so as to answer the formulated research questions. The general conclusion is offered as per the general objective of the research. This will be followed by recommendation and indication of future research direction.

5.1. Conclusion

5.1.1. Specific Conclusions and Key Findings

Sub-objective-i: To quantify the spatiotemporal pattern of urban growth and landscape fragmentation using spatial metrics.

For the past 26 years, 1990-2015, Rajshahi City Corporation (RCC) has been undergoing extensive land cover change. The classification of multi-temporal satellite images of four different time periods, i.e. 1990, 2000, 2010 & 2015 into built-up and non-built up land cover classes has resulted in a highly simplified and abstract representation of the study area. These maps show a clear pattern of increased urban expansion prolonging both from urban center to adjoining non-built up areas in all directions mainly in the south-west, east and north direction alongside major transportation corridors. The synoptic analysis of spatiotemporal land cover change revealed that urbanization has significantly transformed the urban landscape of Rajshahi. The built-up area in the city has grown from 6.00 km² in 1990 to 31.00 km² in 2015 at an average growth rate of 8.00%, 9.70% and 6.26% per annum during 1990-2000, 20002010 and 2010-2015 study periods respectively. In total, 25.00 km² of non-built upland has been converted to an urban area. Analyzing the spatial extent and rate of urban growth and identifying the growth direction alone does not give sufficient insight into the patterns of urban development processes, which are important to better understand the urban pattern. To bridge this gap, spatial metrics are used in this study. Nine spatial metrics namely: class area (CA), number of patches (NP), patch density (PD), largest patch index (LPI), edge density (ED), area-weighted mean patch fractal dimension (AWMPFD) were used to evaluate the urban growth patterns and processes of Rajshahi City Corporation at class and landscape level. These metrics were selected based on literature so as to measure different aspects of the landscapes such as configuration, area, shape, etc. Five metrics evaluated at the city level, i.e. CA, NP, PD, LIP, and FREC_AM, revealed the processes and patterns of urban growth over the entire study area indicating urbanization has substantially changed the landscape pattern of the study area, with a significant land conversion or formation of new patches and thereby decreased fragmentation. Based on the number of patches (NP), built up area has undergone fragmented development process in all study periods with a substantial increase of built-up area (TA) occurred during the second period of urbanization, 2000 to 2010.

The decreasing trend witnessed by PD shows the merger of new patches with the existing ones, particularly, in the vicinity of the urban core that eventually gives rise to the largest patch. The increasing trends observed on LPI throughout the study periods could reveal that the city center or the core area has been relatively undergoing infill and edge expansion type of development process. Nevertheless, the fractal dimension (FRAC_AM) showed both increasing and decreasing trend with a remarkable upturn in 2000. This illustrates, despite the increasing trend observed on the largest patch in the landscape (urban core), the built-up area remains to get more complex and thus, fragmented over time mainly at the fringe areas. Unorganized development that could be due to poor planning scheme and topography such as hills and wetlands could have played an inevitable role in the fragmented development process of the city. Thus, as per sub-objective-i this research has successfully analyzed and quantified the extent, rates and directions of spatiotemporal urban growth in the study area.

Sub-objective-ii: To determine the main physical driving factors of urban growth pattern.

Finally, to better understand the interaction between the changing patterns of urban growth and its physical driving forces, binary logistic regression model has been built for three different time periods of 1990-2000, 2000-2010 & 2010-2015. The probable driving forces of urban growth are first identified and categorized into site-specific, proximity and neighborhood factors-based literature review, and then subjected to local experts to contextualize them to the specific study area. All models are subjected to multicollinearity analysis and found to yield VIF <10. The results of the model evaluation indicate 98.42%, 94.78% and 95.99% for the 19902000, 2000-2010 & 2010-2015 models respectively indicating the high predicting capacities of the models.

The result of model 1989-1995 shows that distance to major roads (-ve), distance to sub-city centers (-ve), the proportion of built-up land (+ve) and distance to government higher education centers (+ve) were the top four driving forces of urban growth with their indicated sign of correlation with urban growth. During 2000-2010 proportion of built up land (+ve), distance to government higher education centers (+ve), distance to sub city centers (-ve), distance to major roads (-ve) were the top four driving forces of urban growth in the study area with their indicated sign of correlation urban growth, whereas distance public parks (-ve), distance to Padma river(+ve), proportion of buildup land (+ve) and distance to sub city centers (+ve) were found to be the top four drivers of urban growth during 2010-2015 study period with their indicated sign of correlation with urban growth.

If policy measures are not taken factors will continue to play a vital role in expanding the city in a messy way. Thus, the results of this model can help planners and policymakers better understand the drivers of urban growth in the study area and develop different alternative urban growth scenarios for the future development.

5.1.2. General Conclusions

In this study, it has been possible to successfully capture the changing subtleties of urban growth pattern both at metropolitan and at disaggregate urban regions level. At metropolitan scale, the city has experienced fragmented urban growth process, particularly, at the fringe areas with substantial built-up increase while, the city center underwent relatively compact growth by infilling open spaces and through edge expansion over time.

This study has demonstrated the value of logistic regression analysis for understanding and identifying the potential causal factors responsible for the changing patterns of urban development processes learned from spatial metrics analysis. Thus, proximity factors such as distance to major roads, distance to sub-city centers, proximity to the built-up area, and distance to satellite towns were the major factors driving urban growth in the study area at different period of time with the different level of significance. The importance of distance to CBD and distance to major roads decreased over time while the distance to sub-city centers and proximity to highly urbanized cells become more important confirming the results of spatial metrics that show typical fragmentation and outward expansion.

Using images acquired from the different sensor (e.g. Landsat-8 OLI and Landsat-4-5 TM) for spatial metrics analysis could perhaps create consistency problem like ETM+ 2000 image in this study. Thus, although studies conducted in developing countries frequently suffer from the lack of data, as much as possible it is advisable to use consistent images acquired from the same sensor.

Given the results presented in this study, remote sensing satellite images and spatial metrics coupled with logistic regression modeling are valuable tools for the analysis and extraction of information on urban growth patterns at different spatial scale and they can offer a comprehensive opportunity for the description of the process, and facilitate intra urban comparison.

5.2. Future Research Directions

To this end, this study has successfully explored the potential use of satellite remote sensing and spatial metrics in the light of quantifying the spatiotemporal urban growth patterns and processes in Rajshahi City Corporation. However, results of this study are exclusive to the specific study area. Further researches are required on different cities to conclude on the efficiency and effectiveness of the tools for developing a planned Bangladesh.

Owing to the spatial extent of the city corporation area, it seems imperative to look at driving forces of urban growth at disaggregate spatial scale including more variables such as socioeconomic and demographic variables and most importantly land tenure policy (system) and wetlands. This could reveal detail causal factors of urban growth pattern at the local level and could give a good explanation why CBD has been a constraint or insignificant factor for urban growth in the study area. However, the results of this model can be used as a base for future studies and can help planners and policymakers develop alternative urban growth scenarios.

CHAPTER

06. References List

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