SIMULATING URBAN GROWTH DYNAMICS OF DHAKA METROPOLITAN AREA: A CELLULAR AUTOMATA BASED APPROACH

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It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Md. Shakil Bin Kashem

Dedicated to:

My beloved parents,

Md. Abul Kashem

&

Mrs. Ferdous Ara

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Abstract

Foreseeing urban growth and accordingly predicting future urban extent is always accepted as a vital issue for any urban planning decision making process. Different techniques and models have already been developed for simulating the dynamics of urban growth that can be employed for this prediction process. This study applied the concept of Cellular Automata (CA) to simulate the historical growth pattern of Dhaka Metropolitan Area (DMA). It has calibrated the SLEUTH CA based model for this and predicted the future growth scenario for different policy decisions in this urban agglomeration.

The theory of Cellular Automaton (CA) has been widely used to simulate urban growth for past few years. It requires that the space should be represented as a grid of cells that can change state as the model iterates. These changes are regulated by rules that specify a set of neighborhood conditions to be met before a change in state can occur. Urban landscape can be tessellated according to its land use or spatial extent of development. This cell-based framework can be utilized to apply the theory of automata and thereby to model its complex structure using simple transition rules.

This study found that CA applies the same transition rules throughout the space. As a result same growth rate happens throughout the cell space irrespective of their location in relation to the existing urban areas. This study introduced a travel cost approach to the model which assumes that development probability will decrease through space with increased distance (and increased travel difficulty due to topography) from the existing urban centers. It introduced the travel cost as a part of the exclusion layer of the model. Through calibration of the two modeling frameworks (one with travel cost and one without travel cost) it was found that the model with travel cost has better capability to simulate the historical growth pattern of the study area. As a result, it employed the model with travel cost for future growth prediction of the study area for different policy scenarios.

Through observation of the best fit coefficients of the model it was found that the study area is experiencing high in-fill and edge growth throughout the urban centers. Diffused growth is also occurring significantly at the vicinity of the urban centers. These diffused settlements have some significant probability to evolve further as urban centers. Existing road networks are also significantly influencing the overall growth process of the study area.

The best fit coefficients were applied for future growth prediction of the study area for the period 2008-2030. Different policy scenarios were developed based on the development plans and policies for the study area (i.e. DMDP and STP) It was found that through introduction of new roads, the study area will experience an accelerated growth throughout the prediction time period. Through imposition of environmental restrictions, the study area will experience decelerated growth in future. Imposition of development restriction on agricultural land also will significantly retard the overall growth of the study area. Imposition of all restriction and introduction of the new roads also shows a reduced growth trend throughout the prediction time period.

Through analysis of the calibration results and the prediction capability of the model, this study has showed that CA is an effective approach to simulate urban growth dynamics of DMA. Sustainability of urban growth can be ensured through proper application of this kind of model in the planning decision making of this urban region.

Table of Content

Acronyms

BBS	Bangladesh Bureau of Statistics
BUET	Bangladesh University of Engineering & Technology
CA	Cellular Automata
CLUE	Conversion of Land Use and its Effects
DAP	Detail Area Plan
DCC	Dhaka City Corporation
DEM	Digital Elevation Model
DMA	Dhaka Metropolitan Area
DMAIUDP	Dhaka Metropolitan Area Integrated Urban Development Plan
DMDP	Dhaka Metropolitan Development Plan
DSS	Decision Support System
EPA	Environment Protection Agency
gcc	GNU C compiler
GIS	Geographical Information Systems
NASA	National Aeronautics and Space Administration
OSM	Optimal SLEUTH Metrics
RAM	Read Access Memory
SRTM	Shuttle Radar Topographic Mission
STP	Strategic Transport Plan
USGS	United States Geological Survey

List of Tables

List of Figures

List of Photos

Chapter 1: Introduction

1.1 Introduction

Foreseeing urban growth and accordingly predicting future urban extent is always accepted as a vital issue for any urban planning decision making process. Cities are the engines of the economy. As the driving force of economic development, the need to understand the dynamics of urban land use transitions and forecast urban growth patterns in an accurate and efficient manner is ever more pressing (Candau, 2002). Effectively monitoring and simulating urban sprawl and its effects on land-use patterns and hydrological processes in an urbanized watershed are essential for effective land-use and water resource planning and management (Lin et. al., 2008). Different techniques and models have already been developed for simulating the dynamics of urban growth. Urban researchers have used models to explain urban form since the early part of the 19th century when von Thunen published his classic model of agricultural location with respect to market places in 1826 (Candau, 2002). Since then different theories and models have been developed worldwide for capturing urban growth both at local and regional scale.

Urbanization is one of the most evident human induced global changes worldwide. In the last 200 years, world population has increased six times, and the urban population has multiplied 100 times (Radzicki, 1995). This rapid urban growth has not only exerted heavy pressures on land and resources in and around the cities, but also resulted in serious environmental and socio-economic problems. As a result, prediction of urban growth and forecasting its associated pros and cons on human beings has emerged as a challenge for the policy makers. Cities reflect economic, environmental, technological, and social processes in their change, yet all are in turn profoundly driven by the evolving urban spatial structure itself (Herold et. al., 2003). Modeling this urban spatial structure has now become a specialized field of study and shows the potential to be applied for effective planning of urban regions.

A model can be termed as an abstraction of an object, system or process that permits knowledge to be gained about reality by conducting experiments on the model. Towards this models generalize the complexities of the system and offer an abstraction of the reality they represent. This abstraction may not be as precise as reality, but can offer an accurate, and more easily understood picture of a process (Candau, 2002) which can assist towards better decision making. An urban system is a complex phenomenon that evolves through multiple dynamic forces. Research in the understanding, representation and modeling of the complex urban system has a long tradition in geographic research and planning (Alberti & Waddell, 2000; Batty, 1989, 1994). But still there are some major challenges to build an accurate and operational model of urban growth and land use dynamics. Predominant among these challenges are data availability and the need for improved methods and theory in modeling urban dynamics (Irwin & Geoghegan, 2001; Longley & Mesev, 2000; Wegener, 1994). But in general, the application, performance, and outputs of urban growth models depend strongly on the quality and type of the data available for parameterization, calibration and validation (Batty & Howes, 2001; Longley & Mesev, 2000)

At present there is a significant number of urban models developed worldwide based on different theoretical underpinnings. They vary a lot in terms of their complexities, data requirements, spatial resolutions and temporal resolutions. It can be said that there is currently a resurgence in urban modeling, primarily because new methods and data have made computer-based models functional and useful tools for urban planning (Herold et. al., 2003). This growth has been driven by two major factors: improved representation and modeling of urban dynamics; and increased richness of information in the form of multiple spatial data sets and tools for their processing (Clarke et. al., 2002). Enhancements in the field of Geographic Information Science and Remote Sensing have now enabled this process to be more robust and effective. But most of the urban growth models have been formulated in developed countries and have been applied for planning decision making in developed cities. Developing countries are lagging far behind in this case where unplanned urbanization and rapid growth of the cities are going on without any comprehensive decision making process (Kashem and Maniruzzaman, 2008). Applications of urban growth or land use change models are very limited in these cities primarily due to lack of resources and lack of detailed historical land use or socio-economic data. Poor documentation of historical data and lack of a unique mapping procedure is a common scenario in most of the developing countries. Considering these constraints, Kashem and Maniruzzaman (2008) found that SLEUTH urban growth model based on the concept of Cellular

Automata and developed under project Gigalopolis of United States Geological Survey (USGS) has good potentiality to be transferred to developing countries.

This study has simulated urban growth of Dhaka Metropolitan Area in a Cellular Automata (CA) based environment. It has calibrated the SLEUTH CA based model for this and predicted the future growth scenario for different policy decisions in this urban agglomeration. This study can be termed as the first urban growth modeling exercise in Bangladesh and one of the foremost of its kind in developing countries.

1.2 Urban Theory and Modeling

Any modeling initiative should have a sound theoretical basis. A significant number of urban theories have evolved worldwide to conceive the process of urban growth, though not all of them have found use in the modeling exercises. Through the development of a model a precise language is given to a theory about a system (Liu, 2001). The most widespread use of models in urban geography was during the period of the quantitative revolution in Geography, which began in the late 1950's and continued until the late 1960's (Batty, 1981). Formulation of transportation models in the late 1950's in the face of increased car ownership enhanced the application of urban models further (Candau, 2002). Later on in the late 1970's the attention shifted from using mathematical models to qualitative analysis in urban research. This emphasis on qualitative analysis continued until the late 1980's, when study on complex and open systems provided alternative ways to understand cities as evolutionary and complex systems (Allen, 1997). The development of geographic information systems and their integration with urban modeling has also facilitated urban modeling with rich data sources and new techniques. Despite these improvements in urban research, the urban theories need to be considered before any study on urban modeling. This section provides a brief discussion on some popular urban theories and their application in urban research.

1.2.1 The von Thünen Model

Early in the 19th century Johann Heinrich von Thünen developed a model of land use that showed how market processes could determine the spatial distribution of land uses over a theoretical geographic area (Figure 1.1). It is easiest to explain this model in the context of agricultural land use. The model is based on the following assumptions:

- The city is located centrally within an "Isolated State" which is self-sufficient and has no external influences.
- The Isolated State is surrounded by an unoccupied wilderness.
- The land of the State is completely flat and has no rivers or mountains to interrupt the terrain.
- The soil quality and climate are consistent throughout the State.
- Farmers in the Isolated State transport their own goods to market via oxcart, across land, directly to the central city. Therefore, there are no roads.
- Farmers behave rationally to maximize profits.

In an Isolated State with the above statements being true, von Thunen hypothesized that the agricultural land uses would segregate into a spatially hierarchic structure (Figure 1.1).

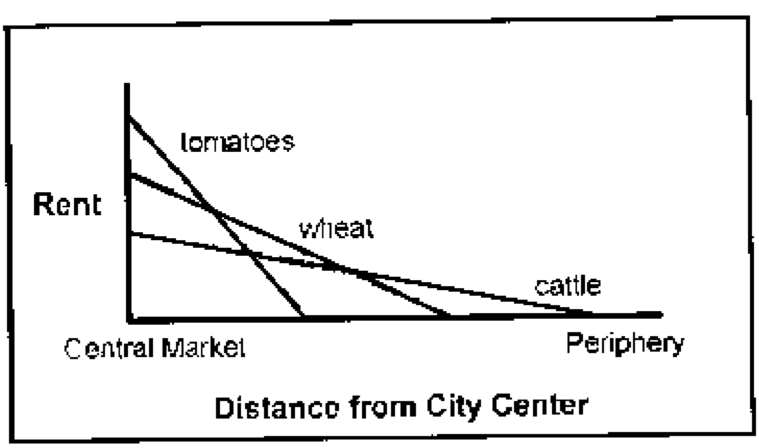


Figure 1.1: The von Thunen spatial organization of agricultural land uses.

Dairying and intensive farming occur closest to the city. Since vegetables, fruit, milk and other dairy products must get to market quickly, they would be produced close to the city. Since grains last longer than dairy products and fresh produce they can be located further from the city center. Ranching is located in the most peripheral areas surrounding the central city. Animals can be raised far from the city because they are self-transporting. Animals can walk to the central city for sale or for butchering. Beyond the ranch land lies the unoccupied wilderness, which is too great a distance from the central city for any type of agricultural product.

Even though the von Thünen model is simplistic and was created in a time before the era of factories, highways, and even railroads, it is still an important model in urban studies. The Von Thunen model is an excellent illustration of the balance between the cost of land and transportation. The price of land decreases with increasing distance from a city. The farmers of the Isolated State try to maximize profit by balancing the cost of transportation and land, and produce the most cost-effective product for market.

1.2.2 Concentric Zone Theory

Proposed by E.W. Burgess (1926), the Concentric Zone Theory evolved as an explanation of historical urban land use development in Chicago. Unlike the von Thunen approach, Burgess offers a descriptive rather than analytical account of these urban dynamics (Harvey, 1996). It is proposed that a city's land use may be classified as a series of concentric zones (Figure 1.2) and that the city grows by expanding these zones outward. Zone I is the central business district (CBD) and lies at the center of the city. Next is the multi-use transitioning Zone II with some migrant ghetto residences mixed with manufacturing. In Zone III are the working men's houses, the area of second generation immigrants, one step up from Zone II. Zones IV and V are residential; Zone IV for the better-off and Zone V for the commuters.

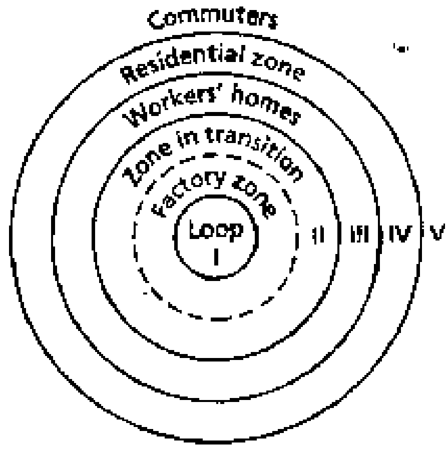


Figure 1.2: Concentric Zone Model

Like von Thunen, Burgess assumes a generalized geographic space and strict action space. Additionally, the important influence of topography and transportation are not considered, and the monocentric city is unreasonable for representing real land use patterns of an urban area.

1.2.3 Central Place Theory

Central Place Theory was devised by geographer Walter Christaller (1933) in the course of studying settlement patterns in Southern Germany. In the flat landscape where Christaller lived, he observed that towns of a certain size were roughly equidistant. Through this observation Christaller examined and defined the functions of each settlement structure and the size of the hinterland. He found it possible to model each pattern of settlement locations using geometric shapes such as triangles and hexagons (Figure 1.3) The theory defines a central place as a settlement having a number of smaller towns at an equal distance away from it. These smaller towns use the central places' shops and services. The central place offers many more goods and services than a smaller town can. This framework brought about simple rules:

- The larger the settlement, the fewer there are of them.
- The less there are of a settlement, the larger the hinterland (or sphere of influence) of its services.

The conurbation below is the largest settlement and has a vast hinterland. It also has the largest amount of services. Because of this, such conurbations will seldom occur on the landscape. The cities, which have fewer services, are more plentiful and have much smaller hinterlands. This pattern continues in a hierarchical fashion to include smaller settlements of towns and villages. Each type of settlement will place itself in relation to the next larger settlement equidistance from settlements of the same size. In this way a hexagonal pattern of urban settlements are dispersed across the landscape.

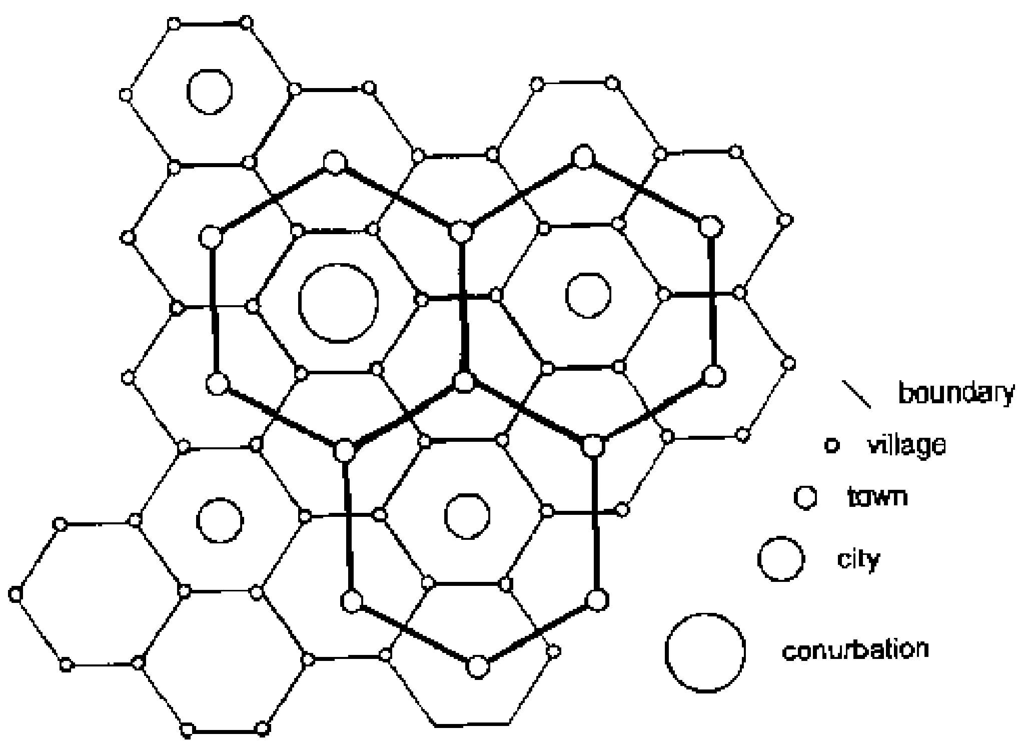
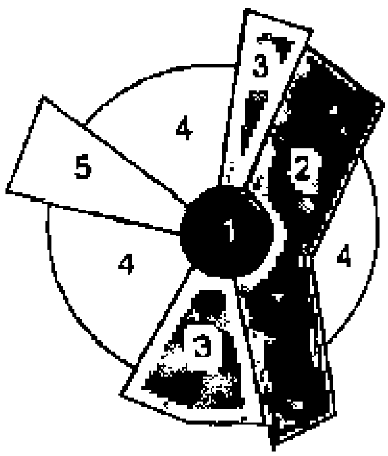


Figure 1.3: Christaller's central place model (Candau, 2002)

1.2.4 Sector Theory

The sector model also known as the 'Hoyt model' was proposed in 1939 by economist Homer Hoyt. He was able to improve upon Burgess' Concentric Zone model by advancing the Sector Theory of urban land use. Based on residential land patterns in the United States, the location of business is referred to indirectly. "The model seeks to explain the tendency for various socio-economic groups to segregate in terms of their residential location decisions...The model suggests that, over time, high quality housing tends to expand outward from an urban center along the fastest travel routes" (Torrens, 2000a). The sector model (Figure 1.4) considers direction in addition to distance as factors shaping residential allocation. Also, it recognizes that the CBD is not the only focal point of urban activity (Kivell, 1993).

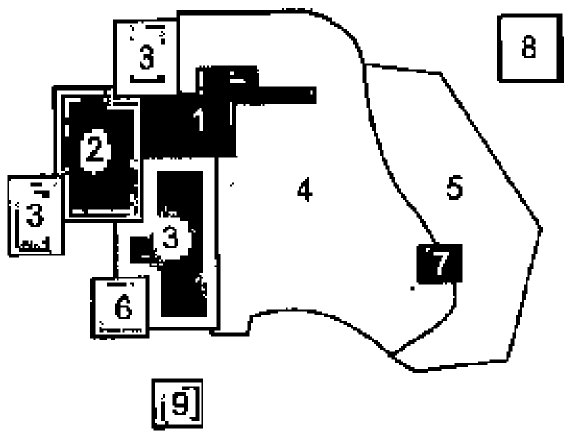


1: Central Business District
2: Wholesale Light Manufacturing
3: Lower-class Residential
4: Middle-class Residential
5: Upper-class Residential

Figure 1.4: Sector Model

1.2.5 Multiple Nuclei Theory

Multiple Nuclei Theory, advanced by C. D. Harris and E. L. Ullman (1945) is based on the fact that many towns and nearly all large cities have many nuclei that serve as centers of agglomerative growth rather than a simple CBD around which all urban activity revolves (Figure 1.5). "Some of these nuclei are pre-existing settlements, others arise from urbanization and external economies. Distinctive land-use zones develop because some activities repel each other; high-quality housing does not generally arise next to industrial areas, and other activities cannot afford the high costs of the most desirable locations. New industrial areas develop in suburban locations since they require easy access, and outlying business districts may develop for the same reason" (Mayhew, 1997). From this work, the idea of city spatial structure as predominantly cellular evolved. This theory surpassed previous attempts at explaining the spatial distribution of urban activity by acknowledging important influences such as topography, accessibility, and historical trends. Importantly, in recognizing the polycentric structure of cities multiple nuclei theory moves closer to explaining why urban spatial patterns emerge (Torrens, 2000b) instead of only how.



1: Central Business District
2: Wholesale Light Manufacturing
3: Lower-class Residential
4: Middle-class Residential
5: Upper-class Residential
6: Heavy Manufacturing
7: Outlying Business District
8: Residential Suburb
9. Industrial Suburb

Figure 1.5: Multiple-nuclei model

1.2.6 Zipf's Rank-Size Law

First explained by Zipf (1949) the rank-size law of cities has been one of the most conspicuous empirical facts in economics, or in the social sciences generally (Gabiax, 1999) This law links, through a linear relationship, cities' frequency of occurrence to their unit size. According to Zipf, if the population of a town is multiplied by its rank, the sum will equal the population of the highest ranked city.

As Gabiax (1999) explained:

To visualize Zipf's law, we take a country (for instance the United States), and order the cities by population: No. 1 is New York, No. 2 is Los Angeles, etc. When we draw a graph; on the y*-axis we place the log of the rank (N.Y. has log rank ln 1, L.A. log rank ln 2), and on the x-axis the log of the population of the corresponding city (which will be called the "size" of the city) We take, like (Krugman, 1996), the 135 American metropolitan areas listed in the Statistical Abstract of the United States for 1991.*

The result of such a plot is a strait line with a slope of -1 and an r^2 of nearly 1.0. What is so surprising about this result is that there is no top-down policy that would cause it to be so. The pattern is emergent. Further, similar results can be achieved for most countries in the modern period (Rosen and Resnick, 1980), for other periods in U.S. history (Zipf, 1949; Rosen and Resnick, 1980; Krugman, 1996), as well as in other countries for different periods. (It must be noted, however, that important examples of exceptions to the rule do exist: London, U.K., Paris, France, and Tokyo, Japan among others.)

1.2.7 Bid-Rent Theory

Taking the von Thünen model one step farther, the bid-rent theory popularized by Alonso (1964) offers an explanation of the spatial distribution that von Thünen described. Since transport costs rise with distance from the market, rents generally tend to fall correspondingly, but different forms of land use (retail, service, industrial, housing, or agricultural) generate different bid-rent curves (Figure 1.6). The urban land user seeks central locations, but is willing to accept a location further from the city center if rents are lower in compensation. The use that can extract the greatest return from a site will be the successful bidder. Illustrating bid-rent theory in an alteration of von Thunen's model, Alonso (1964) in a study of housing, compared the quantity of land needed, and variations in the amount of income used on land, transport costs, and on all goods and services. If the amount of goods and services is held constant, the price of land should decrease with increasing distance from the center and a pattern of housing stock will emerge. The quantity of land that may be bought should increase with distance from the center, but commuting costs will rise with distance from the center. From this basic principle Alonso illustrated how the well-off will choose the amenities of lower density housing at the edge of the city, and pay the price of commuting over distance, while the poor remain in high density residences near the city center. Each household represents a balance between land, goods, and accessibility to the workplace (Mayhew, 1997).

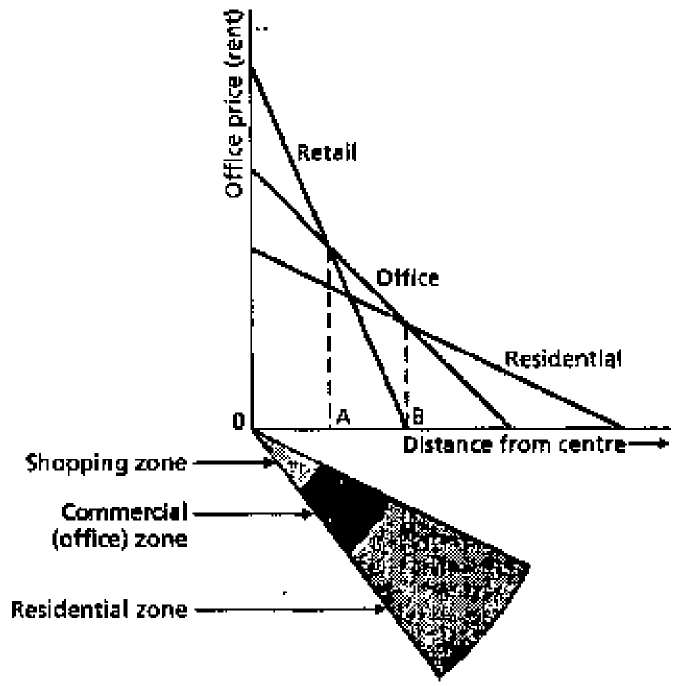


Figure 1.6: Bid Rent Curve

The assumptions of von Thünen and Alonso present a greatly simplified geographic and decision space that is far from reality. However, their models do reflect some aspects of dynamic urban morphology and the bid-rent curves describe how these patterns emerge.

1.2.8 Theory of automata

The theories discussed above are based primarily on empirical observation of a particular urban area. Many hypotheses on how these urban structures arise (such as equilibrium between forces of concentration and dispersion, agglomeration of economies, or maximization of social interaction) propose a constraint that controls system evolution (Candau, 2002). However, evidence to support such universal constraints has not been demonstrated explicitly. Rather, most convincing interpretations reveal macro-scale pattern arising from the micro-scale interactions of the components that make up the system (Candau, 2002). The theory of automata is primarily based on this idea which is now widely applied for explaining the evolution of different complex systems. Chapter 2 provides more discussion on this theory.

1.3. Brief History of Cellular Automata

In the 1930's Alan Turing proposed a hypothetical machine with limited specifications and ranges of action that was capable of computing anything that could be computed. Using simple rules and given an appropriate initial state, this machine, or automaton, could evolve into a replica of itself and have the ability to produce further copies. Hypothetically, this "Universal Turing Machine" was the one meta-machine needed to build any system. In the 1940's, inspired by Turing's work, John von Nuemann (originator of game theory and pioneer in set theory and quantum mechanics) in collaboration with renowned mathematician Standislav Ulam (who worked on Monte Carlo simulation and the Manhattan Project atomic bomb) developed Cellular Automata (CA) as a framework for investigating the logical underpinnings of life. Von Nuemann (1966) proposed his new "theory of automata" as a coherent body of concepts and principles concerning:

1 the structure and organization of both natural and artificial systems.

2. the role of language and information in such systems.

3. the programming and control of such systems.

This theory was expressed in Conway's CA *Game of Life* popularized by Gardner in 1970. Rules of this automata theory are as follows: If a black cell has 2 or 3 black neighbors, it stays black. If a black cell has less than 2 or more than 3 black neighbors it becomes white. If a white cell has 3 black neighbors, it becomes black. Despite its simplicity, the system achieves an impressive diversity of behavior, fluctuating between apparent randomness and order. One of the most apparent features of the Game of Life is the frequent occurrence of gliders, arrangements of cells that essentially move themselves across the grid. It is possible to arrange the automaton so that the gliders interact to perform computations, and after much effort it has been shown that the Game of Life can emulate a universal Turing machine. Later on the works of Wolfram (1983), Cook (1990), Wolfram (2002) etc. enriched this concept of CA further and still now a significant number of research is going on in various fields based on this theory.

A formal link between CA and geographic phenomena was made by Tobler's *Cellular Geography* (1979) where the implicitly spatial nature of the transition rules made CA "the geographical type of model par excellence" (Couclelis, 1985). In 1985 Helen Couclelis presented a simple cellular modeling framework for land use based on discrete structure theory. Also during the 1980's and early 1990's much work was done identifying urban systems as fractal forms and complex systems (Burroughs, 1981; Batty and Longley, 1986; Batty and Longley, 1987; Batty and Longley, 1988; Batty et al., 1989; Longley et al., 1990; Batty, 1991; White and Engelen, 1993; White et al., 1993).

1.4. Cellular Automata and Urban Modeling

CA offer an interesting and innovative approach to the study of urban systems. In recent years there has been prolific application of CA models to urban systems. CA models have been employed in the exploration of a diverse range of urban phenomena, from traffic simulation and regional-scale urbanization to land-use dynamics, polycentricity, historical urbanization, and urban development. CA models of sprawl, socio-spatial dynamics, segregation, and gentrification have been developed, as have simulations of urban form and location analysis (O'Sullivan and Torrens, 2000; Portugali, 2000; White, 1998). The popularity of urban CA models is in part due to weaknesses in the existing stock of urban models (Torrens, 2000b), but also owes much to several advantageous properties that CA offer. CA models have become popular largely because they are tractable, generate a dynamics which can replicate traditional processes of change through diffusion, but contain enough complexity to simulate surprising and novel change as reflected in emergent phenomena (Almeda et. al., 2003).

CA models are flexible in that they provide a framework which is not overburdened with theoretical assumptions, and which is applicable to space represented as a raster or grid. As planning tools, CA urban models have several benefits: they are interactive, potential outcomes can be visualized and quantified, they can be closely linked with GIS and raster based spatial data derived from remote sensing platforms are easily incorporated into the CA modeling environment (Couclelis, 1997).

Although pure CA models have been quite successful at recreating patterns of urban development, they have been criticized for their seeming inability to account for processes driving urban change (Jantz et. al., 2003). Recently, advances have been made in developing hybrid CA that can incorporate process-based factors. Webster and Wu (2001), for example, incorporate microeconomic urban theory into a spatially explicit CA to investigate the effects of alternative planning regimes on land-use patterns. CA models have also been used to simulate different types of urban forms (Yeh and Li, 2001) and development densities (Yeh and Li, 2002), and to investigate the evolution of urban spatial structure over time (White and Engelen, 2000). Chapter 2 provides more discussion on different CA applications for urban research.

1.5 Objectives of the Study

Simulation of historical urban growth paves the way for effective planning decision making for future Considering its importance, the aim of this study was determined to calibrate the SLEUTH urban growth model for Dhaka and thereby to simulate the growth dynamics of Dhaka Metropolitan Area. Specific objectives of this study can be specified as below:

1. Adapt the SLEUTH Urban Growth Model for Dhaka Metropolitan Area.
2. Simulate urban growth dynamics of Dhaka Metropolitan Area using CA-based urban growth model.
3. Predict urban growth of Dhaka Metropolitan Area for different policy scenarios.

1.6 Scope of the Study

Discussions of Chapter 1 revealed that, worldwide already significant research has been done in the field of urban growth modeling based on different theories and techniques. But this kind of exercise is yet to be conducted in Bangladesh and very few examples are there from other developing countries. From this perspective, the present study has got a huge scope to harness the theoretical and technical capabilities developed worldwide. The scopes of this study encircle around the simulation of the historical urban growth pattern of Dhaka Metropolitan Area. It is evaluated to what extent the urban growth pattern of the study area can be simulated in a Cellular Automata (CA) environment. Future growth scenarios for different planning contexts are also predicted here to identify their influences on the overall growth pattern of the study area.

1.7 Limitations of the Study

This study had to overcome lots of limitations towards its successful completion Some of the constraints have simply reduced the efficiency of the model and some has lengthened the duration of this study. Some of the limitations of the study can be briefly discussed as follows

1. Bangladesh has no formal documentation process of historical maps. Survey of Bangladesh (SoB) is the prime authority of Bangladesh assigned with the job of survey and map preparation. Different planning and development authorities also prepare maps of their respective area, but usually they also rely on the maps provided by SoB and do not have a good documentation process of historical maps. The problem with SoB is that, it is under the Ministry of Defense and most of the historical topographic maps here are gratuitously marked 'Restricted'. It was found that although SoB published different historical maps of Dhaka. that cover only the Dhaka City Corporation area. To get the data of whole Dhaka Metropolitan Area only the topographic maps can give some assistance. After continuous effort to collect these topographic maps, this researcher failed to come out with any map from SoB.
2. This study had to rely on maps from different sources to get the historical urban extent and transportation data of the study area. It is expected that maps from same source would increase the reliability on the data. But, after failing to collect maps from SoB, the study had to be done with data from different sources.
3. Non cooperation of government agencies is a common problem with any research in Bangladesh. Unnecessary restriction on data accessibility and undue time consumption for simple official paper work by these agencies dampen the spirit of any research initiative. Before going to the SoB, this

researcher also went to the Space Research and Remote Sensing Organization (SPARRSO) for getting access to the satellite images they have. But after three weeks of continuous efforts they informed that they do not have any recent satellite image of Dhaka and only the Landsat images before the year 2000 can be purchased from them (which is already available free of cost on the Internet).

4. Digital Elevation Model (DEM) data with good resolution could not be availed for this study. For preparing the Slope layer, this study had to rely on the 90 meter DEM data of Shuttle Radar Topographic Mission (SRTM) of NASA. After querying different local agencies it was found that none of them have the DEM data of whole DMA with any better resolution. DEM with higher resolution would surely increase the effectiveness of the findings of this study.

1.8 Organization of the dissertation

This dissertation has been organized in such a way that anyone can easily understand the work flow and findings of this study. Chapter two provides a review of different previous applications of CA models. Here it has particularly focused on the previous applications of the SLEUTH model. Chapter three discusses on the structure and working procedure of the SLEUTH model. This model has been explored in this chapter by its different components, data requirements, calibration and prediction procedure and different other characteristics. Chapter four discusses the methodology of this study. Chapter five provides a brief discussion on the study area, i.e. Dhaka Metropolitan Area (DMA). Chapter six elaborately discusses on the calibration results of SLEUTH for DMA. Chapter seven focuses on the prediction stage of the model. In this chapter discussion is provided on development of future policy scenario for DMA and prediction of its growth for those scenarios. Chapter eight concludes the dissertation with a brief review of the study

Chapter 2: Theoretical Framework and Literature Review

2.1 Introduction

Significant research on urban growth modeling and simulation has already been conducted worldwide. Chapter 1 has mentioned some of these works. But before going into further study on urban growth simulation, previous works on this issue need to be reviewed elaborately. City is a complex system that evolves through integrated effects of multifarious social, economic, environmental and geographical phenomena. So, modeling this kind of system should get adequate focus on how to simulate these complexities efficiently (Torrens, 2000a). CA is a good mechanism for exploring emergence in complex adaptive systems like urban areas. Modeling and simulations in the spatial domain is now extensively done using the techniques of CA, although there are other approaches to model process in space and time including the geo-statistical approaches, differential equations, etc (Sudhira, 2004). In this literature review, at first some classifications of urban growth models are discussed, which is followed by discussion on the theory of CA and review of some major applications of CA for urban growth modeling. Applications of SLEUTH urban growth model are broadly reviewed here based on which this study proceeded through its application for Dhaka Metropolitan Area.

2.2 Classification of Urban Growth Models

As stated in the previous section, a significant number of urban growth and land use change models have been developed worldwide, which have followed different theoretical basis. There have been several attempts to classify these models either based on their theoretical framework or on their level and extent of application. Wilson (1974) proposed a classification scheme based on the dominant technique used in model building. Batty (1976) distinguished between substantive and design criteria for model classification. Issaev et al. (1982) mentions four possible approaches to model classification: "(a) construction of a list of attributes characterizing aspects of the models, (b) specification of a set of criteria serving as a general evaluation framework, (c) construction of an 'ideal' model as a frame of reference for judging all other models, and (d) cross-comparison of models on the basis of general structure characteristics of these models. Stahl (1986) suggests a number of substantive criteria for classifying business location models including issues of theory and model purpose. Four main categories of models were distinguished by Briassoulis (2000):

a. statistical and econometric models
b. spatial interaction models
c. optimization models, and
d. integrated models.

Briassoulis (2000) categorized Cellular Automata based models as regional simulation model under the integrated models realizing its integrated approach of simulation considering almost all the vital players of urban growth.

2.3 Theory of Cellular Automata

The theory of Cellular Automaton (CA) has been widely used to simulate urban growth for past few years. It was developed by the physicist Stanislaw Ulam in the 1940s and was soon used by von Neumann to investigate the logical nature of self-reproducing systems (White and Engelen, 1993). Urban Cellular Automata have been developing rapidly for the simulation of complex urban systems since the late 80s (Yeh and Li, 2002). A number of interesting investigations have already been documented (Batty and Xie, 1994, White and Engelen, 1993, Clarke and Gaydos, 1998) CA models require that space should be represented as a grid of cells that can change state as the model iterates These changes are regulated by rules that specify a set of neighborhood conditions to be met before a change in state can occur (O'Sullivan, 2002). The main idea behind CA is "not to describe a *complex* system with *complex* equations, but let the complexity emerge by interaction of *simple* individuals following *simple* rules" (Schatten, n.d.). Essential properties of CA can be defined as (Schatten, n.d.):

- a regular n-dimensional lattice (*n* is in most cases of one or two dimensions), where each *cell* of this lattice has a discrete state,
- a *dynamical behavior*, described by so called *rules*. These rules describe the state of a cell for the next time step, depending on the states of the cells in the neighborhood of the cell.

Urban landscape can be tessellated according to its land use or spatial extent of development. This cell-based framework can be utilized to apply the theory of automata and thereby to model its complex structure using simple transition rules.

2.4 Application of CA for Urban Growth Modeling

Early proposals for the use of CA in urban modeling tended to stress their pedagogic use in demonstrating how global patterns emerge from local actions (Almeida et.al., 2003). But increasingly models have been proposed which depart from the basic elements (Couclelis, 1985; Tobler, 1979). Strict CA follows highly localized neighborhoods where change takes place purely as a function of what happens in the immediate vicinity of any particular cell. Action-at-distance is forbidden for it is argued that the intrinsic dynamics which generates emergent phenomena at the global level, is entirely a product of local decisions which have no regard to what is happening outside their immediate neighborhood (Batty, 2000). Early models such as Tobler's (1970) model of Detroit and Couclelis's (1989) model of developer behavior in Los Angeles were pedagogic in this spirit, yet the attractiveness of the approach which grew alongside the enormous interest in GIS, has eventually led to a flurry of more practical applications to urban problems. In this, the strict adherence of CA to the most local of neighborhood is inevitably relaxed, and the models that have emerged are best called cell-space—CS models rather than CA (Albin, 1975).

White and Engelen (1993) developed a CA to model the spatial structure of urban land use over time. They found that for realistic parameter values, the model produces fractal or bifractal land use structure for the urbanized area and for each individual land use type. They also found that the cellular approach makes it possible to achieve a high level of spatial detail and realism and to link the results directly to general theories of structural evolution.

Wu (1996) developed a linguistic CA based simulation approach. He integrated CA with heuristically defined transition rules to simulate land use conversions in the rural-urban fringe of a fast growing metropolis. He applied fuzzy set theory to capture the uncoordinated land development process. An innovative feature of this integrated approach lies in its definition of transition rules through a 'natural language interface', thus being more realistic and transparent.

O'Sullivan and Torrens (2000) focused on the difficulties with the representation of human systems, and suggest that many modifications to simple CA introduced in modeling cities are responses to these problems. They propose a two-pronged approach to research. First, for operational model-building many variations on the CA theme are required and should be welcomed; and second theoretically motivated variations of the CA formalism are required so that the possible effects on model dynamic behavior may be more systematically explored.

Almeida et. al. (2003) proposed a structure for simulating urban change based on estimating land use transitions using elementary probabilistic methods which draw inspiration from Bayes' theory and the related 'weights of evidence' approach. These land use change probabilities drive a CA model based on eight cell Moore neighborhoods implemented through empirical land use allocation algorithms. The model framework was applied to a medium-sized town, Bauru, in the west of Sao Paulo State, Brazil. They showed how various socio-economic and infrastructural factors can be combined using the weights of evidence approach which enabled them to predict the probability of changes between land use types in different cells of the system. These modeling experiments support the essential logic of adopting Bayesian empirical methods which synthesize various information about spatial infrastructure as the driver of urban land use change.

Liu and Andersson (2004) examined the impact of the degree of temporal dynamics on the behavior of an urban growth model which is based on a modified Markov random field and probabilistic cellular automata. Experimental results from this case study suggested that the degree of temporal dynamics does have an important impact on the urban morphology produced by the model. Too much or too little dynamics could both lead to unrealistic patterns. However, the impact seems to vary for processes with different levels of change intensity. In the case of a process with moderate changes, the impact of temporal dynamics is also moderate. For a process with high change rate, the degree of temporal dynamics affects the model output significantly.

2.5 Application of SLEUTH Model

The majority of SLEUTH applications have been for urban forecasting or for integrated modeling of urban growth with some other social or physical process model or planning effort. The application of SLEUTH to the San Francisco Bay area by Clarke et al. (1997) was the first major application of the model to a metropolitan region. In this research, the historical urban extent was determined from cartographic and remotely sensed sources from 1850 to 1990. Using this information, coupled with transportation and topographic data, animations of the spatial growth patterns were created, statistics describing the spatial growth were calculated, and the model was used to predict future urbanization.

In addition to modeling extant urban regions, SLEUTH has been used as a tool for theoretical investigations of urban processes. Bierwagen's (2003) dissertation focused on simulating generic urban forms and examining the connectedness in the landscape in order to asses the viability of different urban growth forms on butterfly habitat.

Goldstein et al. (2004) compared using SLEUTH for the "backcasting" of urban extent with spatiotemporal interpolation. As a backcasting tool, SLEUTH has been used extensively, most notably in Herold et al. (2003), where the use of landscape metrics in the historical development of an urban region is presented, and by Goldstein et al. (2000), where historical urban-wildfire conflicts are investigated.

While early applications of SLEUTH focused solely on the modeling of urban growth, the coupling of the Deltatron model, the portion that simulates land use change, increased the model's ability to represent multi-attribute landscape change over time. Candau and Clarke (2000) document this sub-model, and its use for modeling land use change in the MAIA (Mid-Atlantic Integrated Assessment) region of US Environment Protection Agency (EPA). Much like Clarke et al. (1997), the paper is a documentation on how the land use change CA model (Deltatron) functions.

In any application of SLEUTH, one of the most time consuming processes is the calibration. While briefly discussed in Clarke et al. (1997) and in Clarke and Gaydos (1998), Silva and Clarke (2002) present a more refined focus on the calibration of SLEUTH during the application of the model to Lisbon and Porto, Portugal The paper presents four key findings from the application: (1) SLEUTH is a universally portable model that can not only be applied to North American cities, but to European and international cities as well; (2) increasing the spatial resolution and detail of the input datasets makes the model more sensitive to local conditions; (3) using a multistage 'Brute force' calibration method can better refine the model parameters to find those that best replicate the historical growth patterns of an urban system; and (4) the parameters derived from model calibration can be compared between different systems, and the interpretation can provide the foundation for understanding the urban growth processes unique to each urban system.

The work of Silva and Clarke in documenting the calibration process of SLEUTH in their application of the model to Lisbon and Porto provided a basis for the work of others applying SLEUTH (Jantz et al. 2003; Yang and Lo 2003; Dietzel and Clarke 2004), and made those applications more robust through a better understanding of the calibration process.

Most recently an important advance has been made in the use of SLEUTH; coupling model outputs with other spatiotemporal models to provide greater insight into problems dealing with future urbanization. Some of these applications involved the coupling of SLEUTH outputs with social modeling efforts, while others rest more in the domain of physically-based modeling. Claggett et al. (2004) were successful in coupling SLEUTH with the Western Futures Model (Theobald 2001). By doing so, they demonstrated the ability of SLEUTH to move beyond just providing a spatiotemporal picture of urban growth, but actually categorizing the growth into different classes of 'development pressure' based on forecasted population growth. Working almost in parallel, Leão et al. (2004), coupled SLEUTH outputs with a multi-criteria evaluation of landfill suitability (Siddiqui et al. 1996) to determine zones around Porto Alegre City (Brazil) where future land would not be urbanized, yet was suitable for landfills. Arthur (2001) coupled SLEUTH to an urban runoff model in Chester County, Pennsylvania. Cogan et al. (2001) compared using

SLEUTH outputs with the California Urban Futures model (Landis, 1994) of urban development to assess stresses on biodiversity. Lin et. al. (2008) applied a framework to the SLEUTH with the Conversion of Land Use and its Effects (CLUE-s) model using historical SPOT images to predict urban sprawl in the Paochiao watershed in Taipei County, Taiwan. These researches demonstrate that SLEUTH can be successfully coupled with other models displaying the potential of the model to be incorporated into a wide array of applications ranging from urban development to environmental assessment and beyond.

SLEUTH has been used for exploratory visualization as well. Acevedo and Masuoka (1997) presented the general methodologies used to create 2-D and 3-D animations of the Baltimore-Washington DC region. Candau (2000) presented the possible ways of visualizing the uncertainty of the location of urban growth in a simulated landscape. Aerts et al. (2003) continued this thread by experimenting with subjects about their understanding of the uncertainty of the forecasted urban growth in a section of Santa Barbara using two different techniques. While the myriad of visualization techniques has expanded since SLEUTH's introduction, the understanding and interpretation of simulation forecasts is still a nascent research topic, especially given the accessibility of modern visualization techniques to stakeholders.

Candau (2002) applied the model to Santa Barbara in California as an example to study urban growth. It was found that SLEUTH calibration was not scalable across image resolutions and data from the last 40 years proved more effective for calibration than including the entire historical profile available. Jantz and colleagues applied the SLEUTH model in Baltimore-Washington metropolitan area (23, 700 km2) in the United States using a historic time series remote sensing imagery for assessing the impacts of alternative policy scenarios on declining water quality in the Chesapeake Bay estuary (Jantz et al. 2003). In this application, future growth was projected to 2030 under three different policy scenarios (current trends, managed growth, ecologically sustainable growth). Result showed that SLEUTH has an ability to address many regional planning issues, but spatial accuracy and scale sensitivity must be considered for practical applications.

Oguz et. al. (2007) used the SLEUTH urban growth model, closely coupled with a land transition model, to simulate future urban growth in the Houston metropolitan area, one of the fastest growing metropolises in the United States during the past three decades. The model was calibrated with historical data extracted from a time series of satellite images. Prior to the work of Oguz, Sangawongse (2006) integrated remotely-sensed images and Geographical Information Systems (GIS) data into the SLEUTH model to analyze land –use/land- cover dynamics in Chiang Mai city and its vicinity.

2.6 Conclusion

Urban growth and land use change models are already being applied for planning decision making in developed countries. As an integrated part of planning Decision Support System (DSS), urban models are now also proved to be an effective mean for public participation in urban and regional planning. But in developing countries, the application of urban models is very scarce and planning decision making process is lagging far behind here than those of the developed countries. Kashem and Maniruzzaman (2008) showed that SLEUTH urban growth model has prospects for being transferred to developing countries. They also found that, although the SLEUTH model does not consider the socio-economic factors of land use change explicitly within its framework, it is very effective to predict future urban growth based on the previous growth pattern. Different scenarios for different planning decisions can also be projected through this model by changing the input data. Other models can also be transferred to developing countries, but their data requirement or necessary expertise may make them difficult to be applied in developing countries. Although application of urban models depends on data availability and the context of the target area, further study and research is needed in this regard to find out which model has the highest potential for use in developing countries. This study is one of the first initiatives to adapt the CA based SLEUTH model in the developing country context.

Chapter 3: SLEUTH Urban Growth Model

3.1 Introduction

The urban growth model SLEUTH, uses a modified Cellular Automata (CA) to model the spread of urbanization across a landscape (Clarke et al., 1996, 1997). Its name comes from the GIS data layers that are incorporated into the model - Slope, Landuse, Exclusion layer (where growth cannot occur), Urban, Transportation, and Hillshade. It is a C program running under UNIX that uses the standard gnu C compiler (gcc) and may be executed in parallel.

The urban growth model is the main component of SLEUTH and this study will utilize it for simulating the growth dynamics of Dhaka. The Deltatron land use model is the second component, and it is implemented as an optional add-in that is tightly coupled with, and driven by, simulated urban growth. Complete documentation and downloadable code of this model can be found at the Project Gigalopolis website: www.ncgia.ucsb.edu/projects/gig.

In an effort to more realistically portray urban growth, some of the formalisms of simple CA have been relaxed in SLEUTH (Candau, 2002). Like a standard CA, SLEUTH begins with an initial set of conditions, after that some transition rules are applied. Here the initial conditions are defined by some input image data. The input data serve as layers of information that create a non-homogenous cellular space and influence cell transition suitability (Candau, 2002). Some growth parameters affect the transition rules sequentially. These growth parameters may be altered at the end of each time step by the self-modification behavior of SLEUTH. Calibration using the input image data produces these growth parameters which can be applied for predicting future growth scenario of the concerned urban area. This chapter discusses the data requirement, urban growth process, calibration and forecasting procedure of SLEUTH.

3.2 Data Requirement for SLEUTH

As stated in the previous section, some raster data defines the initial state of the CA simulation space for SLEUTH. It uses following geographic data to generate an initial system configuration and transition suitability surface (Candau, 2002):

Slope

Topography, in general terms, creates the most basic definition of area available for urban development. Because of ease of development, flat expanses are the easiest to build upon. Lands get less hospitable as slope increases, and eventually become impossible to develop due to structural infeasibility. The point where structures are no longer built due to slope constraints is defined as *CRITICAL_SLOPE*.

Land-use

Land-use classes additional to urban may be modeled in SLEUTH. This is an optional input, and was not utilized in this study.

Exclusion

Areas not available to urbanization are included in the exclusion layer. Water bodies, parklands, and national forest are all good examples of commonly excluded landuse types. The exclusion layer is not necessarily binary and may include levels, or probabilities, of growth resistance.

Urban

This is a binary classification: urban or non-urban. How "urban" is defined is application dependent. Methods used in the past include digitizing city maps and aerial photographs, thresholding remotely sensed images or block densities from census data. For calibration, the earliest urban year is used as the seed, and subsequent urban layers, or *control years*, are used to measure several statistical best fit values. For this reason, at least four urban layers are needed for calibration: one for initialization and three additional for a least-squares calculation.

Transportation

A transportation network can have an important role in a city's developing structure. Due to increased accessibility, urban corridors tend to reach out from the city core along modes of transportation. The transportation infrastructure expands with city growth. To include the dynamic effect of transportation in calibration, several road layers that change over time are desirable. SLEUTH is initialized with the earliest road layer. As growth cycles, or "time", pass and the date for a more recent road layer is reached, the new layer is read in and development proceeds. The roads are not necessarily binary, but may be weighted to simulate one section of road's greater attractiveness to urbanization relative to another section of road.

Hillshade

A grayscale background image gives context to the spatial data generated by the model. It is useful for describing location and scale as well as topography. This layer is not an active input for model simulation, but can greatly assist the visual examination and analysis of model output image.

3.3 SLEUTH Urban Growth Model

Calibration of SLEUTH produces a set of five parameters (coefficients) that describe an individual growth characteristic and when combined with other characteristics can describe several different growth processes (Teitz *et. al.*, 2005). For this model, the transition rules between time periods are uniform across space and are applied in a nested set of loops. The outermost loop executes each growth period, and an inner loop executes growth rules for a single year. Clarke and Gaydos (1998) describe the initial condition set as the "seed" layer, from which growth and change occur one cell at a time, each cell acting independently of the others, until patterns emerge during growth and the "organism" learns more about its environment. The transition rules involve taking a cell at random, investigating the spatial properties of its neighborhood, and then urbanizing the cell, depending on probabilities influenced by other local characteristics (Clarke, Hoppen, and Gaydos, 1997). Five coefficients (discussed in section 3.3.1) control the behavior of the system and are predetermined by the user at the outset of every model run (Candau, 2000; Clarke and Gaydos, 1998;

Clarke *et. al.* 1997). The parameters drive the four transition rules that simulate four types of urban growth: spontaneous (of suitable slope and distance from existing centers), diffusive (new growth centers), organic (infill and edge growth), and road-influenced (a function of road gravity and density). These growth rules are discussed in detail in section 3.3.2.

3.3.1 Growth Coefficients

Five coefficients, or parameters, affect how the growth rules are applied. Each coefficient may be an integer between 0 and 100. Comparing simulated land cover change to a study area's historical data and calculating linear regression, goodness-of-fit scores (r^2) calibrate these values. The descriptions below outline the five coefficient values, which transition rules they affect, and how the applied values are derived from the coefficients. This description is compiled from Candau (2002), Teitz *et. al.* (2005) and the Gigalopolis website.

Dispersion Coefficient:

The *dispersion coefficient* (or *diffusion coefficient*) controls the number of times a pixel will be randomly selected for possible urbanization during *spontaneous growth*.

An applied value is derived from the *dispersion coefficient* by:

$$dispersion\_value = (dispersion\_coefficient \times 0.005) \times \sqrt{(nrows^2 + ncols^2)}$$

so that *dispersion_value* at its maximum (where *dispersion_coefficient* is defined as 100) will be 50% of the image diagonal.

The dispersion_value is then applied to spontaneous growth by:

```
for ( k = 0; k < dispersion_value; k++ ) {
select pixel (i,j) at random;
try to urbanize (i,j);
}
```

The *dispersion coefficient* also controls how many "steps", or pixels, make up a random walk along the transportation network on a road trip as part of *road-influenced growth*.

The *dispersion coefficient* is applied to *road-influenced growth* by:

run_value= dispersion_coefficient

where *run_value* is the maximum number of steps traveled along the road network.

Breed Coefficient:

The *breed coefficient* determines the probability of a pixel urbanized by *spontaneous growth* becoming a *new spreading center*.

The *breed coefficient* is applied to *new spreading center growth* by:

Given: a newly urbanized *spontaneous growth pixel* (*i, j*).

```
if ( random_number < breed_coefficient ) {
attempt to urbanize two neighbors;
}
```

The *breed coefficient* also determines the number of times a road trip will be taken during *road-influenced growth*.

The breed coefficient is applied to *road-influenced growth* by:

```
for ( k = 0; k <= breed_coefficient; k++ ) {
head off on a road trip;
}
```

Spread Coefficient:

The *spread coefficient* determines the probability that any pixel that is part of a spreading center (a cluster of three or more pixels in a nine cell neighborhood) will generate an additional urban pixel in its neighborhood.

The *spread coefficient* is applied to *edge growth* by:

```
if ( random_number < spread_coefficient) {
attempt to urbanize neighboring pixel;
}
```

Slope Coefficient:

The *slope coefficient* affects all growth rules in the same way. When a location is being tested for suitability of urbanization, the slope at that location is considered. Instead of enforcing a simple linear relationship between the percent of slope and urban development, the slope coefficient acts as a multiplier. If the slope coefficient is high, increasingly steeper slopes are more likely to fail the slope test. As the slope coefficient gets closer to zero, an increase in local slope has less affect on the likelihood of urbanization (Figure 3.1).

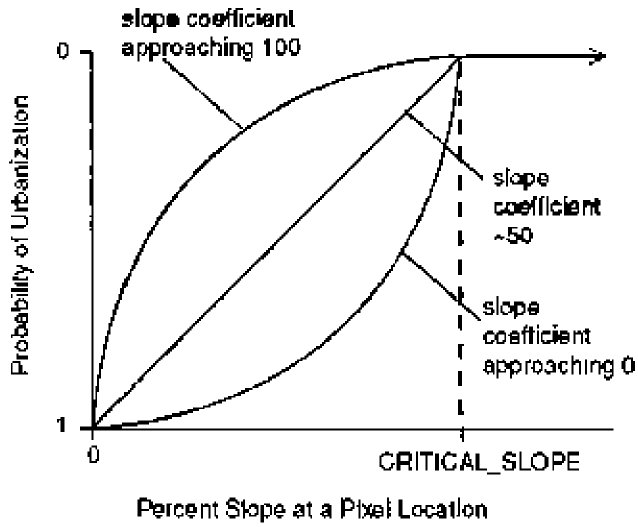


Figure 3.1: Affect of the slope resistance coefficient

Creating a lookup table that relates actual slope values to slope coefficient-influenced probabilities enforces this dynamic relationship.

The slope coefficient is used to calculate slope weights by first calculating:

ex= *slope*_coefficient/*MAX_SLOPE_RESISTANCE/2.0*

where *MAX_SLOPE_RESISTANCE* set to 100 and *ex* is an influencing exponent value.

Using the *ex* value, a lookup table is then built by:

```
for ( i = 0; i < lookup table size; i++ ) {
if ( i < critical_slope ) {
val= (CRITICAL_SLOPE-i)/CRITICAL_SLOPE
lookup_table[i] = 1.0 - val^ex;
} else {
lookup_table[i] = 1.0;
    }
}
```

Road Gravity Coefficient:

During *road-influenced growth* the maximum search distance from a pixel selected for a road trip for a road pixel is determined as some proportion of the image dimensions. The applied value is derived from the *road gravity coefficient* (*rg_coef*) by:

rg_value= (*rg_coef/MAX_ROAD_VALUE*)*((nrows+ncols)/16)

where *MAX_ROAD_VALUE* is defined as 100, and nrows and ncols are the row and column counts respectively. So *rg_value* at its maximum (when *rg_coef* equals 100) will be 1/16 of the image dimensions. If the *rg_coef* is less than 100, then the *rg_value* will be some proportion less than 1/16 of the image dimensions.

Rg_value is then applied to road-influenced growth by:

max_search_index = 4 * (*rg_value* * (1 + *rg_value*))

where *rg_value* defines the maximum number of neighborhoods from the selected urban pixel to search for a road.

The first neighborhood (*rg_value* == 1) is made up of the selected urban pixel's adjacent 8 cells. The second neighborhood (*rg_value* == 2) would be the 16 pixels outwardly adjacent to the first neighborhood, etc. In this way the outward search for a road will continue until (a) a road is found, or (b) the search distance is greater than *MAX_SEARCH_INDEX*.

3.3.2 Transition Rules

The five parameters control the four transition rules generated within SLEUTH: spontaneous, new spreading center, edge, and road influenced growth. The transition rules are applied in the order of rules described below.

Spontaneous Growth:

Spontaneous growth, much as its name describes, determines the occurrence of random urbanization in the landscape. In the cellular automaton framework this means that any non-urbanized cell on the lattice has a certain (small) probability of becoming urbanized in any time step. So the probability that a cell U, located in space at coordinates i,j, will become urbanized during the next time is defined as:

$$U(i,j,t+1) = f\,(\text{diffusion coefficient, slope coefficient, } U\,(i,j,t), \text{random})$$

Here the diffusion coefficient determines the probability of urbanization and the slope coefficient determines the weighted probability of the local slope. The random term indicates that there is stochasticity in the process. At any time in the urbanization process, cells that are already urbanized and those in the excluded layer are prohibited from changing classes (Figure 3.2). This process is described in pseudo code as follows:

```
F(diffusion coefficient, slope coefficient)
{ for (p < diffusion value)
{select pixel location (i,j) at random if ((i,j) is
available for urbanization) {
(i,j) = urban
new spreading center growth} }
} end spontaneous growth
```

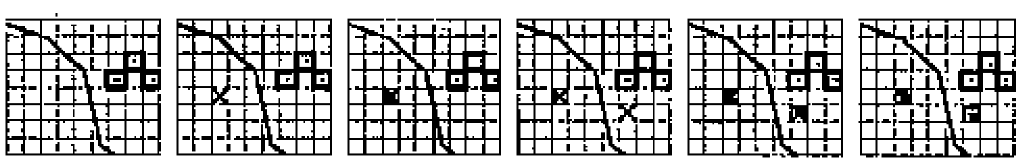


Figure 3.2 Process of Spontaneous Growth

New Spreading Centers:

After establishing spontaneous urban growth on the landscape, SLEUTH attempts to turn some of the newly urbanized cells into spreading centers. This is done largely through the breed parameter, which defines the probability that each newly urbanized cell, U(i, j, t + 1) will become a spreading center, U'(i, j, t + 1), if there are two or more neighbors that can be urbanized (Figure 3.3):

$$U'(i, j, t+1) = f\,(\text{breed coefficient}, U(i, j, t+1), \text{random})$$

This process is described in pseudo-code as follows:

```
F(breed coefficient, slope coefficient)
{ if (random_integer < breed_coefficient)
if (two neighborhood pixels are available for
urbanization)
(i,j) neighbors = urban
} end new spreading center growth
```

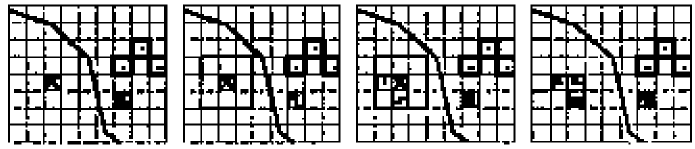


Figure 3.3: Process of New Spreading Centers

Edge Growth:

The most typical growth in urban systems is edge growth, whereby non-urbanized areas adjacent to existing urban areas are transformed from a non-urban into urban use. Edge growth attempts to capture these dynamics by propagating growth from urban areas, whether preexisting or those generated by spontaneous and new spreading centers growth. If a non-urban cell has three or more urbanized neighbors, then it has a probability of becoming urbanized that is defined by the spread coefficient but with the constraints placed upon that cell by the slope coefficient (Figure 3.4):

U(i, j, t+1) = f (spread coefficient, slope coefficient, U(i, j, t), U (k, l). random)

where (k, l) belongs to the nearest neighborhood of (i,j). This is described in pseudo-code below.

Edge Growth:

```
F(spread coefficient, slope coefficient)
{
for (all non-edge pixels (i,j))
if ((i,j) is urban) and (random_integer <
spread_coefficient)
if (at least two urban neighbors exist)
if (a randomly chosen, non-urban neighbor is
available for urbanization)
(i,j) neighbor = urban
} end edge growth
```

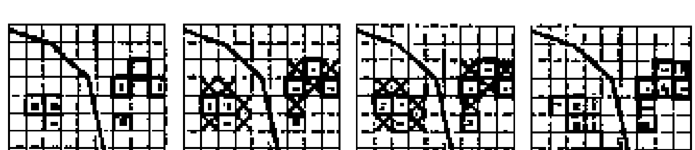


Figure 3.4: Process of Edge Growth

Road-Influenced Growth:

The last step in generating urban growth is to incorporate the influence of the transportation network in the urbanization process. This is done using the transportation input layers and the urbanization that was generated in the previous three steps. The breed coefficient determines the probability that newly urbanized cells (in the prior three steps) will be selected, and within their neighborhood the presence of a transportation route will be determined. If a portion of the transportation network is found within the radius of a particular cell (this radius is determined by the *road gravity coefficient*), then a temporary urban cell is placed at that point on the road closest to the already urbanized cell. This temporary cell then takes a random walk along the transportation network, where the number of steps is predetermined by the *dispersion coefficient*. The final location of the random walk is then considered as a new urban spreading nucleus. If a neighboring cell to the temporary urbanized cell (on the transportation network) can be urbanized, it will occur, as determined by a random draw among candidates. If two cells adjacent to this newly urbanized cell are also available for urbanization, that will happen (randomly picked among candidates). This process of road-influenced growth creating temporary urban cells along the transportation network is expressed through four steps:

$$U'(k, l, t+1) = f'(U(i,j,t+1), \text{road gravity coefficient}, R(m,n), \text{random})$$

Here i, j, k, l, m, and n are cell coordinates, with R (m,n) defining a road cell and (k,l) as the temporary urban cell. The random walk is described as

$$U''(i, j, t+1) = f''(U(k,l,t+1), \text{diffusion coefficient}, R(m,n), \text{random})$$

In this equation, (i,j) are the road cells neighboring (k,l). The final location of the temporary random cell is defined as (p,q). Using this, the new urban spreading center is defined as

$$U'''(i, j, t+1) = f'''(U(p,q,t+1), R(m,n), \text{slope coefficient}, \text{random})$$

To add two adjacent urban cells to the spreading center, the equation is

$$U''''(i, j, t+1) = f''''(U(p,q,t+1), \text{slope coefficient}, \text{random})$$

In this case, (i, j) and (k,l) belong to the neighborhood of (p,q), These are the four steps that constitute the random walk of a cell through the transportation network. The number of random walks that occur is determined by the breed coefficient.

The entire process of road influence growth can be described in pseudo-code as

```
F(breed coefficient, road gravity coefficient ,
diffusion coefficient, slope coefficient)
{
for (p <= breed_coefficient)
{
road_gravity = value which is a function of image
size and road_gravity_coefficient
max_search = maximum distance, determined by
road_gravity, for which a road pixel is searched
(i,j) = randomly selected pixel, urbanized within
the current growth cycle
road_found = search outward from (i,j), up to
max_search, for a road pixel
if (road_found)
{
walk along the road, in randomly selected
directions, for a number of steps determined by the
road_value and the dispersion_coefficient
if (a neighboring pixel is available for
urbanization)
(i,j) neighbor = urban
if (two neighbors of the newly urban pixel are
available for urbanization)
two urban pixel neighbors = urban
} } } end road-influenced growth
```

It is visualized in Figure 3.5.

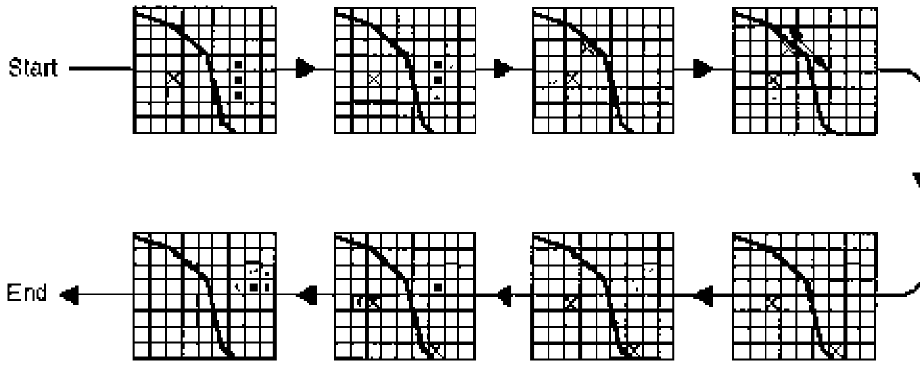


Figure 3.5: Steps in Road Influenced Growth

These four steps are the transition rules from non-urban to urban within the UGM portion of SLEUTH. At any time in the urbanization process, cells that are already occupied by existing urban areas or are excluded from development will by default cause a failure in the attempt to urbanize that particular cell. Implementation of these growth rules may in some cases lead to periods of excessively high or low growth rates. When this occurs, a second set of transition rules, known as self-modification, is implemented.

3.3.3 Self-Modification

A growth cycle is the basic unit of SLEUTH execution. It begins by setting each of the coefficients to a unique value. Each of the growth rules is then applied to the raster data. Finally, the resulting growth rate is evaluated. If the growth rate exceeds or falls short of limit values, model self-modification is applied. Self-modification will slightly alter the coefficient values to simulate accelerated or depressed growth that is related with system-wide boom and bust conditions in urban development (Figure 3.6).

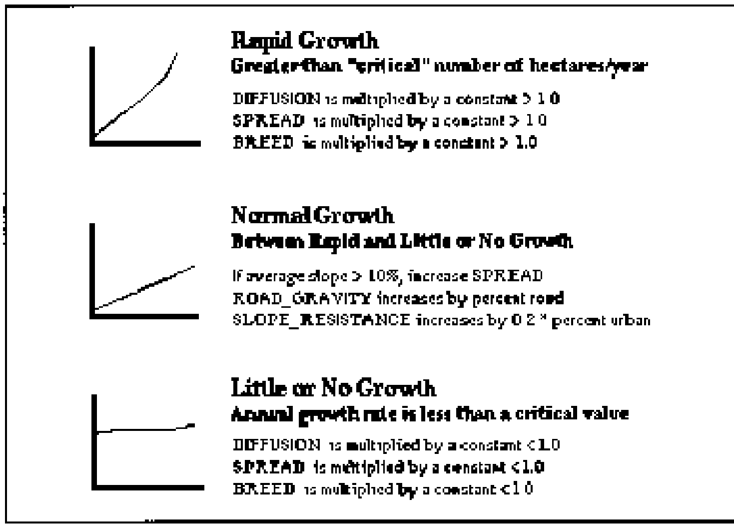


Figure 3.6: Growth pattern under Self-Modification Rules

To apply self-modification, the first step is to determine if the system is in a growth or stable period of development. A "boom" state occurs if the growth rate exceeds the *CRITICAL_HIGH* value and indicates a period of accelerating growth. Each of the coefficients is increased to encourage the continuation of this trend. A "bust" state occurs when the growth rate is less than the *CRITICAL_LOW*. In such an instance the coefficients will be lowered in order to decrease the rate of growth throughout the system. The *CRITICAL_HIGH* and *CRITICAL_LOW* values are mentioned in the Scenario file of the model.

The algorithm used to apply self-modification to the coefficients is given below;
Given:

$$growth\_rate = number\_growth\_pixels \,/\, total\_number\_urban\_pixels \times 100$$

$$percent\_urban = \left(\frac{100 \times (total\_number\_urban\_pixels + road\_pixels)}{total\_number\_pixels - road\_pixels - excluded\_pixels} \right)$$

where *number_growth_pixels* is the number of newly urbanized pixels from the current growth cycle, *total_number_urban_pixels* is the amount of urban pixels from the current and previous growth cycle, *road_pixels* is the number of road pixels used for the current growth cycle, and *excluded_pixels* is the number of pixels in the exclusion layer with an absolute exclusion value.

```
if (growth_rate > CRITICAL_HIGH) {
slope_res = slope_res-(percent_urban×SLOPE_SENSITIVITY)
road_grav = road_grav +
(percent_urban×ROAD_GRAV_SENSITIVITY)
if (dispersion < MAX) {
dispersion = dispersion × BOOM;
breed = breed × BOOM;
spread = spread × BOOM;
}
}
```

where *CRITICAL_HIGH* is the growth rate threshold above which a boom state exists for the system. *Slope_res, road_grav, dispersion, breed,* and *spread* represent the coefficient values *slope_resistence, road_gravity, dispersion, breed* and *spread* respectively.

SLOPE_SENSITIVITY, ROAD_GRAV_SENSITIVITY, and *BOOM* (as well as *BUST* used in the bust state) are used to modify the coefficient values and are defined in the application *scenario* file. *MAX* is the maximum value of a coefficient.

```
if (growth_rate < CRITICAL_LOW) {
slope_res = slope_res+(percent_urban×SLOPE_SENSITIVITY)
road_grav = road_grav -
(percent_urban×ROAD_GRAV_SENSITIVITY)
if (dispersion > 0) {
dispersion = dispersion × BUST;
breed = breed × BUST;
spread = spread × BUST;
} }
```

where *CRITICAL_LOW* is the lower limit for *growth_rate*, below which the system enters a bust state.

3.4 SLEUTH Calibration Approach

3.4.1 Fitting Historical Data

A major tenet of SLEUTH application is: by calibrating how a region has changed in the past, a reasonable forecast of future change can be made (Clarke et al., 1997). Following this assumption, the model is calibrated by fitting simulated data to historical spatial data. SLEUTH is initialized with the earliest data (signifying the date furthest in the past) and growth cycles are generated. It is assumed that one growth cycle represents one year. As growth cycles complete, "time" passes. Dates where historical data exist are referred to as control years. When a completed cycle has a corresponding control year, an image of simulated data is produced and several metrics of urban form (see Section 3.4.4) are measured and stored in memory.

3.4.2 Monte Carlo Averaging

Due to the high amount of randomness present in each growth cycle, growth simulations are generated in Monte Carlo fashion to bring a greater amount of stability to modeled results. Monte Carlo averaging reduces dependence upon initial conditions and stochasticity. When a coefficient set has completed a defined number of Monte Carlo simulations, the metric values stored to memory are summed and divided by the number of Monte Carlo iterations. These averaged values are then compared to the control data metrics and linear regression, best-fit statistics are calculated.

3.4.3 SLEUTH Brute Force Calibration

By running the model in calibration mode, a set of control parameters is refined in the sequential "brute-force" calibration (Silva and Clarke, 2002), although other methods of calibration, including the use of genetic algorithms, have been suggested and tested (Goldstein, 2004). SLEUTH utilizes five coefficients that may range independently between zero and 100. This poses a large set of possible solutions and a daunting number of computer processing unit (CPU) cycles required to explore the multidimensional coefficient space (Candau, 2002). Brute force calibration reduce the number of solution sets but still search the range of solutions. Instead of executing every permutation of possible coefficient sets, each parameter range is examined in increments. For example, the range {0-100} may be stepped through in increments of 25 resulting in the values {0, 25, 50, 75, 100} or 5^5 simulations being implemented in order to cover the range. In this way, the model may be calibrated to the data in steps, successively narrowing the range of coefficient values. Generally, this process is accomplished in three phases here referred to as *coarse*, *fine* and *final* (Candau, 2002).

Coarse Phase

In the initial, coarse phase of calibration, the entire range (0 – 100) of the five coefficients is explored using large increments (e.g.; for each coefficient, value = {0, 25, 50, 75, 100}) and a small number (4) of Monte Carlo iterations are used.

Fine Phase

Using the best-fit values found in the *control_stats.log* file produced in the coarse calibration phase, the range of possible coefficient values is narrowed. Ideally, the ranges will be narrowed so that increments of 5 - 10 may be used while still only using about 5-6 values per coefficient (e.g.; for a single coefficient, value = {25, 30, 35, 40, 45, 50}) and a larger number of Monte Carlo iterations are used (6).

Final Phase

Using the best-fit values found in the *control_stats.log* file produced in the fine calibration phase, the range of possible coefficient values is narrowed. Ideally, the ranges will be narrowed so that increments of 1 - 3 may be used while still only using about 5-6 values per coefficient (e.g.; for a single coefficient, value = {4, 6, 8, 10, 12}) and a larger number of Monte Carlo iterations are used (8).

3.4.4 Determining Goodness of Fit

Results from each of the calibration phases are examined to determine the goodness of fit for each parameter set. Narrowing of the parameter set can be based on a variety of different goodness of fit measures (Jantz *et. al.* 2004; Yang and Lo, 2003); no sole metric has been shown to be the most effective. Traditionally the Lee and Sallee (1970) metric has been used to determine which parameter sets best describe the replication of the historical datasets. Lee-Sallee is the ratio of the intersection and the union of the simulated and actual urban areas, but others including the *compare* statistic, and *population* statistics have been used. Dietzel and Clarke (2007) found that the OSM (optimal SLEUTH metric, the product of the *compare*, *population*, *edges*, *clusters*, *slope*, *X-mean*, and *Y-mean* metrics) will provide the most robust results for SLEUTH calibration. Table 3.1 describes the 13 metrics that can be used to determine the goodness of fit of model calibration; they have a value range of 0 to 1, with 1 being a perfect fit.

After determining the parameter set that best fits the historical data, a range of values around that set of parameters is selected and the calibration is run again. The goodness of fit of the second calibration is evaluated, and an even narrower range of parameters is selected. The best fitting parameters from this third calibration are then the parameters used in forecasting urban growth and land-use change.

Table 3.1: Metrics that can be used to evaluate the Goodness of Fit of SLEUTH

Metric Name	Description
Product	All other scores multiplied together
Compare	Modeled population for final year/actual population for final year, or IF $P_{modeled} > P_{actual}$ { 1 – (modeled population for final year/actual population for final year)}
Pop	Least squares regression score for modeled urbanization compared to actual urbanization for the control years
Edges	Least squares regression score for modeled urban edge count compared to actual urban edge count for the control years
Clusters	Least squares regression score for modeled urban clustering compared to known urban clustering for the control years

Cluster size	Least squares regression score for modeled average urban cluster size compared to known average urban cluster size for the control years
Lee-Sallee	A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years
Slope	Least squares regression of average slope for modeled urbanized cells compared to average slope of known urban cells for the control years
% urban	Least squares regression of percentage of available pixels urbanized compared to the urbanized pixels for the control years
X-mean	Least squares regression of average x_values for modeled urbanized cells compared to average x_values of known urban cells for the control years
Y-mean	Least squares regression of average y_values for modeled urbanized cells compared to average y_values of known urban cells for the control years
Rad	Least squares regression of average radius of the circle which encloses the urban pixels
F-Match	A proportion of goodness of fit across land use classes {#_modeled_LU correct/(#_modeled_LU correct + #_modeled_LU wrong)}

3.5 Forecast Methodology of SLEUTH

SLEUTH forecasts rely on replicating growth trends from the past (Candau, 2002). Once a coefficient set is found that can best describe how urban change has occurred over time, these values are used to forecast future growth. The calibration process produces initializing coefficient values that best simulate historical growth for a region.

However, due to SLEUTH's self-modification qualities, coefficient values that initialize the model for a date in the past may be altered by the simulation end date. Therefore, for *forecast* run initialization, the coefficient values at the simulation end date are used to initialize a new simulation into a future date. Using the best coefficients derived from calibration to run a large number of Monte Carlo simulations will produce a single set of averaged coefficients for the simulation end date. Using the Best Solution Set (BSS) parameters derived from the simulation end date, a forecast run may be initialized (Candau, 2002).

For the image data, the most recent urban layer (the one that defined the calibration end date), the most recent transportation layer, and the exclusion and slope layers used in calibration, in addition to the background hillshade are used to initialize a forecast run. Growth rules are then applied to the data for a defined number of years. Forecasts are run in Monte Carlo fashion with 100 or more iterations. In addition to generating annual urban growth probability maps, a log of coefficient and metric values may be written to a file as output.

Chapter 4: Methodology of the Study

4.1 Introduction

This study followed a methodology that enabled it to accomplish its objectives successfully. Data preparation, calibration and prediction procedures followed here are mostly derived from the project Gigalopolis website (http://www.ncgia.ucsb.edu/projects/gig/) and different previous works on SLEUTH model. This chapter describes the procedure that was followed for this study.

4.2 Model Testing and Understanding

The source code of the model was collected from the Gigalopolis website which is maintained jointly by United States Geological Survey and Department of Geography, University of California at Santa Barbara. This study used the SLEUTH3.0beta_p01 version of the model. It was tested in Knoppix (a Linux based operating system) using gcc (GNU C compiler). A hypothetical dataset named as demo_city was provided with the model which was used to test it in the computer system of the present study. This study used a Pentium Duo processor with 2 GHz speed and 1 GB of RAM. A comprehensive understanding of the working procedure of the model was developed through the testing process of the model.

4.3 Data Preparation

Required data for this study was collected from different sources. As mentioned in Chapter 3, SLEUTH model needs data on Slope, Land use, Exclusion, Urban Extent, Transportation and Hill shade. Here land use data is an optional layer which is applied for land use change modeling and was not used for this study. Different data layers used in this study are discussed below.

4.3.1 Slope

Slope data used for this study was acquired from the 90 meter Digital Elevation Model (DEM) of Shuttle Radar Topographic Mission (SRTM). SRTM is maintained by NASA which provides digital elevation data (DEMs) for over 80% of the globe.

This data is currently distributed free of charge by USGS and is available for download from the National Map Seamless Data Distribution System, or the USGS ftp site. This study used the SRTM data as DEM with better resolution and for the whole of Dhaka Metropolitan Area (DMA) was not found from any local agencies. The collected DEM was clipped to the area of DMA and *Erdas Imagine 8.7* was used to convert it to slope data. As per the requirement of the model, the slope data was in percent (%). Figure 4.1 shows the slope data used for this study.

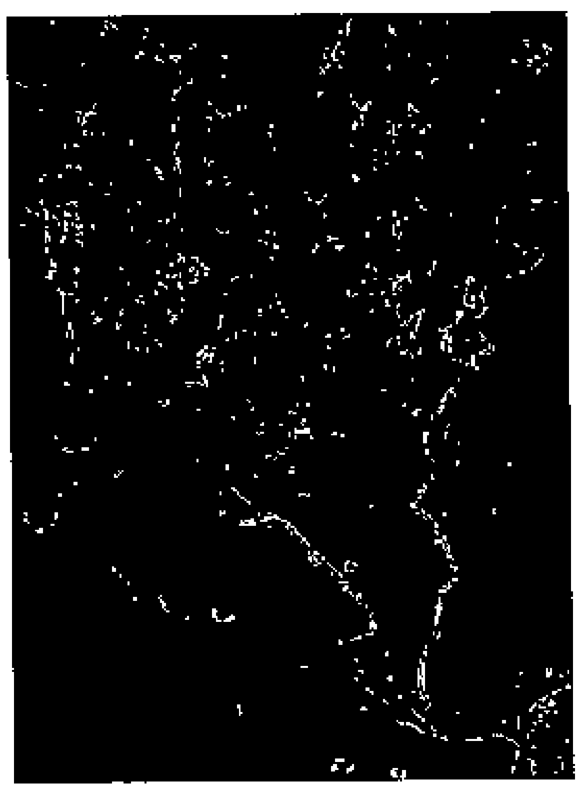


Figure 4.1: Slope Layer used in this study

4.3.2 Exclusion

Exclusion layer shows the area where urban growth would not occur without formal interventions. In this study, the excluded areas were identified as rivers, canals, military bases/cantonments, airports, zoo, botanical gardens, university campuses, national monuments and parks. These areas within the study area were digitized from Google Earth (figure 4.2). Exclusion value of 100 (i.e. full exclusion) was provided to these areas.

Figure 4.2: Exclusion Layer

4.3.3 Urban Extent

This study used five historical urban extent data. These were of 1980, 1989, 1996, 2000 and 2007. These urban extent maps were digitized from several different sources. Map of 2007 was digitized from Google Earth (GE). In GE, the study area was digitized in .kml format, which was converted to .shp format using kml2shp software. Maps of 2000 and 1989 were digitized from Landsat images. These images were further verified with the works of Basak (2006) which classified these images showing the urban extent of DMA. The map of 1996 was digitized from the IRS image of Dhaka. Paper maps provided in the Dhaka Metropolitan Area Integrated Urban Development Plan (DMAIUDP) was scanned and digitized to get the urban extent data of 1980. Table 4.1 provides a summary of the maps along with their sources. Figure 4.3 (a-e) shows the urban extent layers used in this study.

Table 4.1: Sources and acquisition procedures of urban extent maps

Year of Urban extent maps	Map sources	Acquisition procedure
2007	Google Earth	Digitized in GE and converted from kml to shp
2000	Landsat Image	Digitized from the image and verified with Basak (2006)
1996	IRS Image	Digitized from the image
1989	Landsat Image	Digitized from the image and verified with Basak (2006)
1980	DMAIUDM paper map	Digitized from the scanned map

Figure 4.3 (a): Urban Extent of 1980

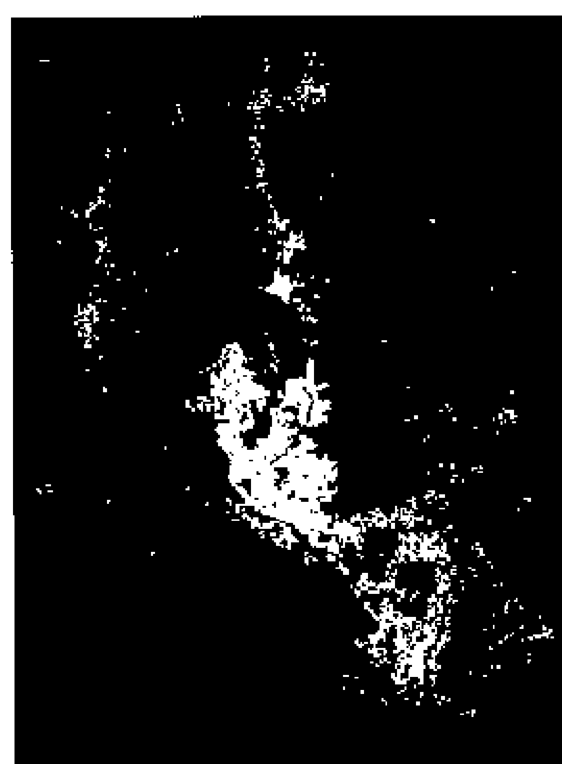


Figure 4.3 (b): Urban Extent of 1989

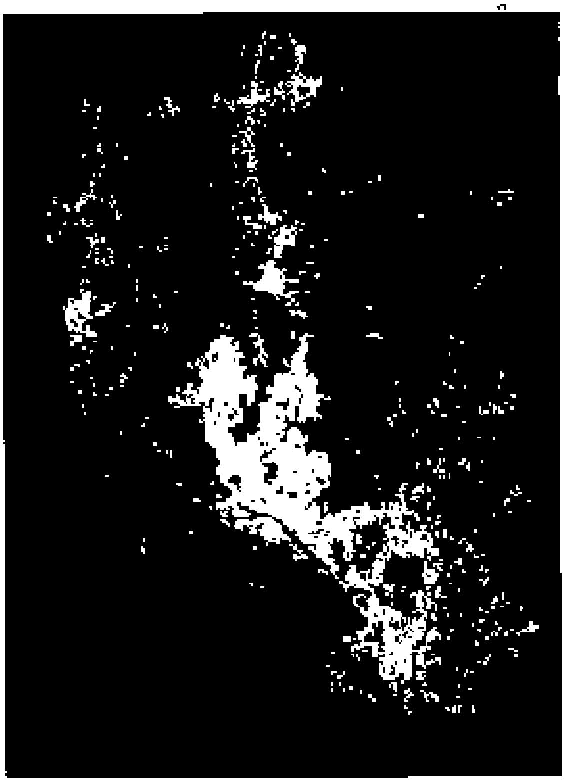


Figure 4.3 (c): Urban Extent of 1996

Figure 4.3 (d) Urban Extent of 2000

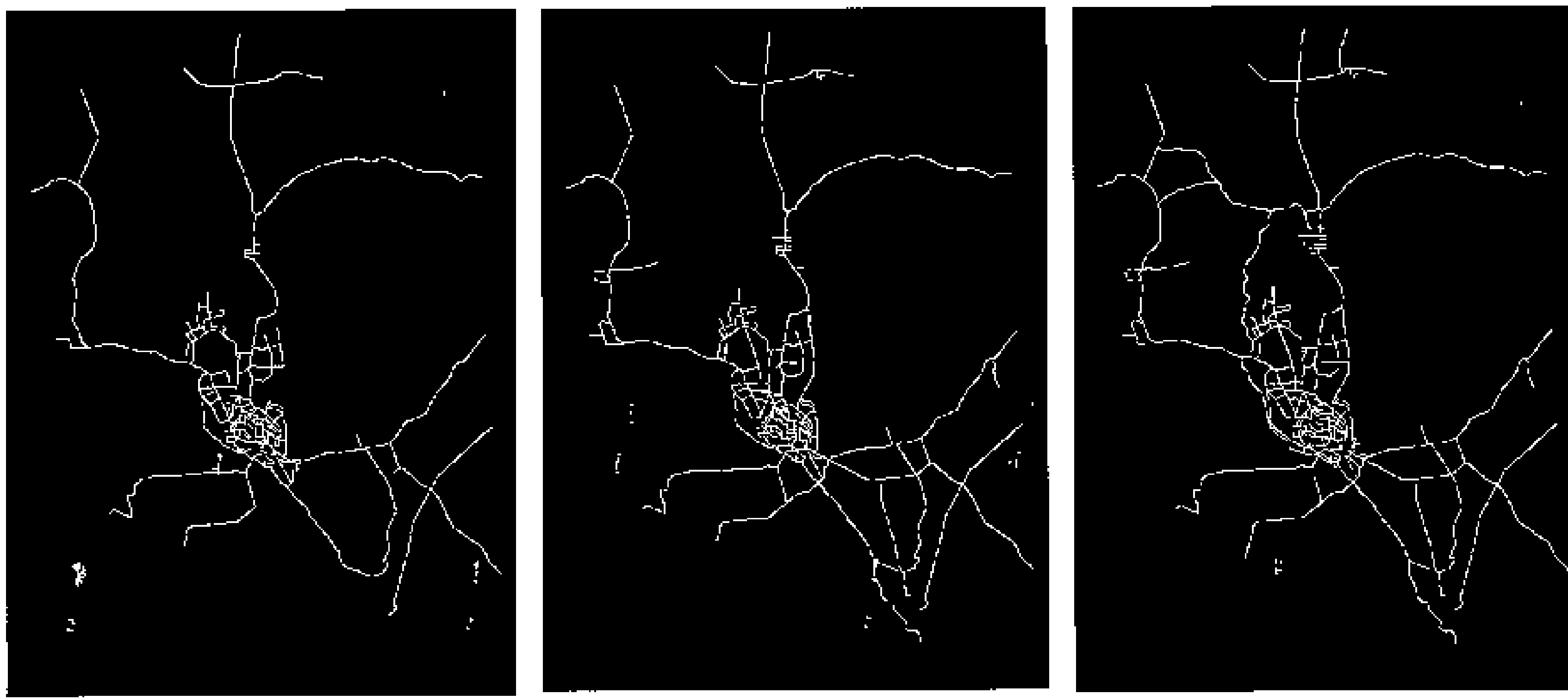
Figure 4.3 (e) Urban Extent of 2007

4.3.4 Transportation

Three historical transportation layers were used in this study. These were from the year 2007, 1996 and 1980. Road network of 2007 were digitized from GE following the same procedure of urban extent map. Data of 1996 was digitized from IRS image and that of 1980 was digitized from DMAIUDP map. Figure 4.4 (a-c) shows the transportation layers used in this study.

4.3.5 Hill Shade

Hill Shade is used only as a background layer and does not give any input to the model. Hill Shade layer used in this model was generated from the SRTM DEM data using the viewshed command of *Erdas Imagine 8.7.* To show the major rivers in and around DMA, these were also included with the hillshade (Figure 4.5).



a) 1980 b) 1996 c) 2007

Figure 4.4: Historical Transportation Layers of DMA

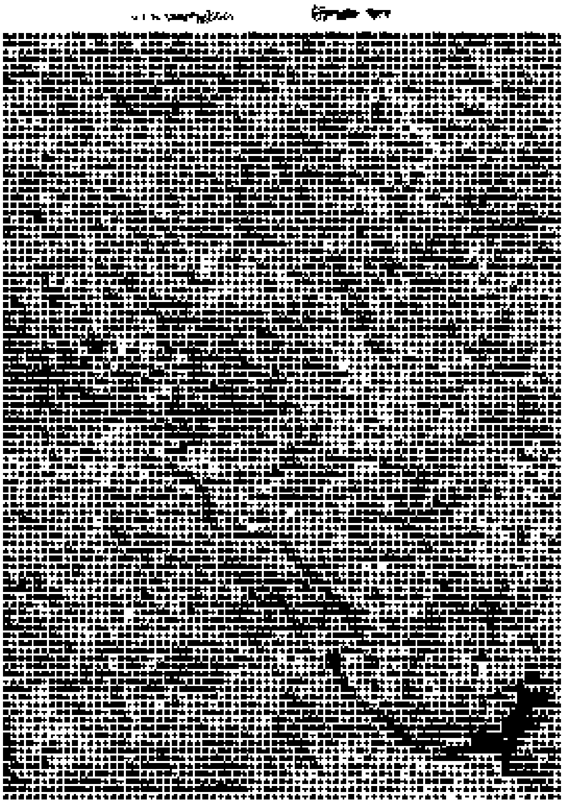


Figure 4.5 Hill Shade layer

4.3.6 Image processing

As mentioned in Chapter 3, SLEUTH requires grayscale GIF images with same map projection and same resolution (i.e. with the same number of rows and columns). So, all of the data layers were projected to the UTM (Universal Transverse Mercator) projection system. As the slope layer was with 90 meter resolution, all of the maps were resampled to 90 meter resolution ArcInfo grid files. These grid layers were then exported as TIFF format images. These images were converted to GIF images using XV image processing software. All of the data layers were with 464 columns and 632 rows. Following the requirement of the scenario.log file of the model, all the data layers were renamed as follows:

Slope layer:

- dhaka.slope.gif

Exclusion layer:

- dhaka.excluded.gif

Urban Extent layers:

- dhaka.urban.1980.gif
- dhaka.urban.1989.gif
- dhaka.urban.1996.gif
- dhaka.urban.2000.gif
- dhaka.urban.2007.gif

Transportation layers:

- dhaka.roads.1980.gif
- dhaka.roads.1996.gif
- dhaka.roads.2007.gif

Hill Shade layer:

- dhaka.hillshade.water.gif

4.4 Inclusion of Travel Cost to the Model

It was found through the model testing that SLEUTH applies same transition rules throughout the study region and shows same rate of growth to the cells irrespective of their location in relation to the existing urban centers. But in the real world development occurs with higher growth rate near the existing urban areas and with lower growth rate in further away from the urban centers. Distance or travel cost to the existing urban centers plays a significant role in the whole growth process. Areas near the urban centers or with less travel cost will experience higher growth than the areas far away from the urban centers or with higher travel cost. To overcome this problem with the model, this study has attempted to introduce a travel cost layer to it. It was decided that the model will be calibrated for DMA with both the situations regarding travel cost (i.e. considering travel cost and without considering travel cost) and the best fit model will be applied for growth prediction.

Travel cost layer for the study area was created using the Spatial Analyst extension of ArcGIS 9.0. Spatial Analyst can create raster image of travel cost from any object on the space. Here cost means relative travel distance from one point to the other based on topography, land use etc. So, to create the travel cost layer Spatial Analyst need to be provided with a target layer (from which travel cost will be measured) and a cost layer (which will contain information on relative travel difficulties). This study used slope data as the cost layer and the urban centers in the study area as the target layers from which travel cost was measured. Slope layer contains slopes of each of the cells in the region where higher value means steeper slope and higher travel difficulty.

Dhaka Metropolitan Area consists of one City Corporation and five municipalities (more discussion in Chapter 5). It was assumed that Dhaka City Corporation (DCC), being the largest urban agglomeration in the study area, will have the highest influence zone around it. Its maximum influence zone was assumed to be the whole Metropolitan Area (i.e. the full image) within which its influence will gradually decrease to zero (or travel cost will gradually increase from 0 to 100). Influence distances from other urban centers were assumed to be the distance in proportion to the population of those centers with that of the Dhaka City Corporation (which has the maximum influence distance).

Here,

Max. Influence Distance from DCC = 90*632 = 56880 meter (where 632 is the number of rows of the images and 90 meter is the image resolution)

Influence Distance of Urban Center i, C_i = (population of i/ population of DCC)* max influence distance of DCC

Table 4.2 shows the population of the urban centers in the study area and the influence distances from them as derived using the above equation.

Table 4.2 Population and Influence distance of different urban centers in DMA

Sl. no.	City Corporation/Municipalities	Population (BBS, 2001)	Influence Distance
1	Dhaka City Corporation	53,33,571	56880
2	Narayanganj Municipality	2,41,393	2574
3	Kadamrasul Municipality	1,28,561	1371
4	Savar Municipality	1,27,540	1360
5	Tongi Municipality	2,83,099	3019
6	Gazipur Municipality	1,22,801	1310

Travel cost layers from each of the urban centers were generated separately. These layers were classified further according to the distances ranging from 0 to 100. Here classification was done in such a way that travel cost will gradually increase from 0 to 100 within the influence distance of the centers. Using map algebra of Spatial Analyst, these travel cost layers were combined together generating a separate cost layer for the minimum cost of each of the cells. Figure 4.6 shows the travel cost layer for the study area.

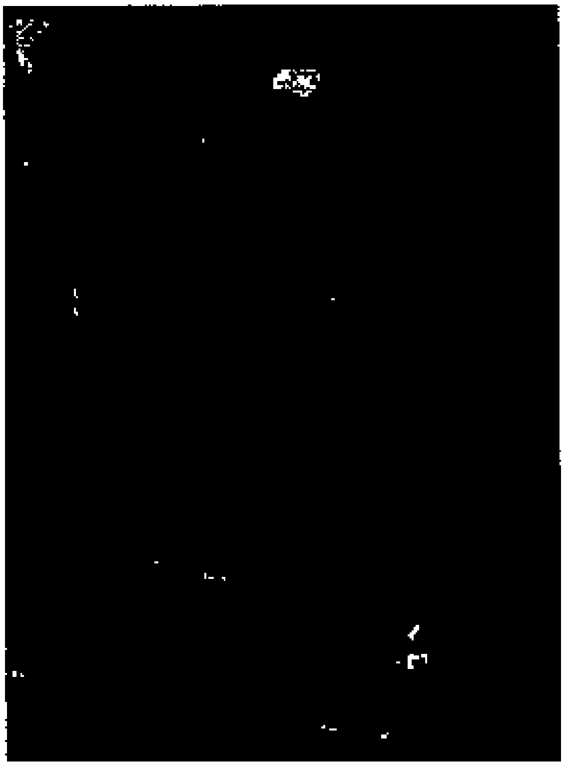


Figure 4.6: Travel cost layer of the study area.

The generated travel cost was incorporated with the exclusion layer of the model where gradually increasing value from 0 to 100 means zero exclusion to full exclusion from development possibility. Figure 4.7 shows the updated exclusion layer incorporating travel cost layer.

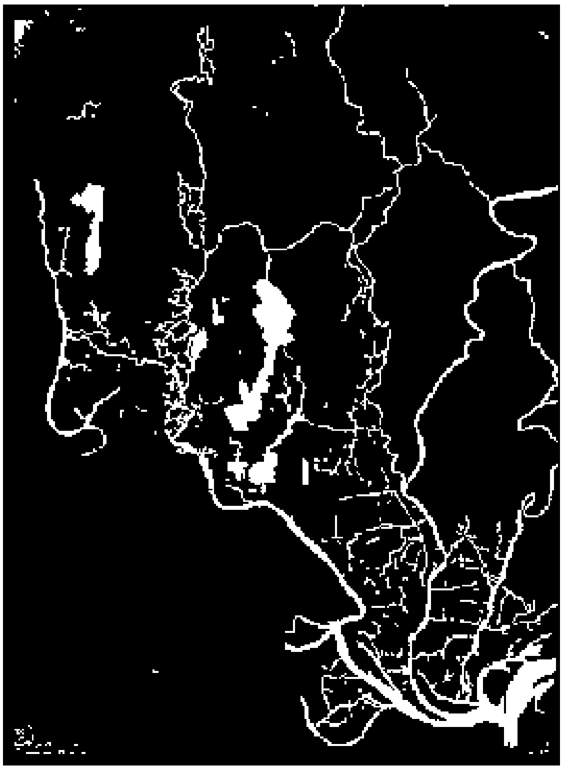


Figure 4.7: Travel cost incorporated exclusion layer of the model

4.5 Model Calibration

After preparing the required data, these were tested in the model to find out whether there was any error in the data and whether the model can read the images correctly. Several test runs were given changing the coefficient values. The LOG_0 files and the output images were examined to find out the impacts of these changes on the model. After testing the data, calibration was conducted in the brute force fashion (procedure discussed in chapter 3). This study maintained full resolution images throughout the calibration process although the Gigalopolis website suggested using half-resolution image at the fine calibration to reduce time requirement. This was done particularly because of the findings of Candau (2002), which showed that SLEUTH calibration is not scalable across image resolutions. As a result, calibration stage of this study required a significant period of time. Calibrations were conducted for both of the situations of the model regarding travel cost; one without considering travel cost (i.e. without including travel cost in the exclusion layer) and another after incorporating travel cost in the model (i.e. including travel cost layer into the exclusion layer)

Like model testing mode, calibration of the study also used Knoppix operating system (a Linux based operating system) and compiled the codes using the built-in gcc of this operating system. Screen shot of the calibration is provided in photo 4.1.

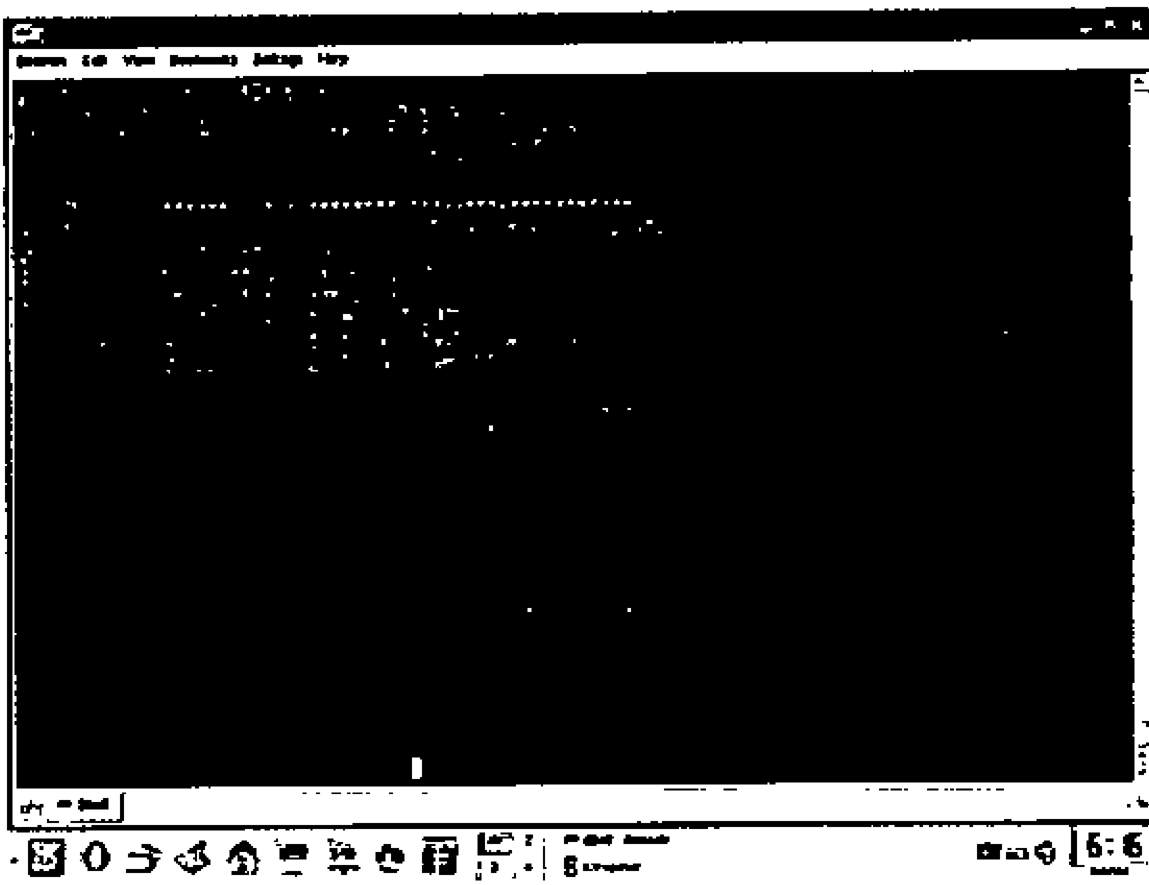


Photo 4.1: Screen shot of SLEUTH calibration in Knoppix

4.6 Model Prediction

At the end of the calibration phase, performances of both of the calibrations were evaluated to identify the best performing framework of the model (i.e. model without the travel cost and model with travel cost). Performances of the best fit coefficient sets of both of the calibrations were analyzed to find out which context of the model can better simulate the historical growth of the study area. The forecasting coefficients for both of the calibrations were determined which were used to predict future growth situation of the study area. Prediction run is given for this process with high number of Monte Carlo iterations. At this stage the prediction shows the general trend of development and what would be the future growth scenario if the present development process continues. This study predicted growth up to the year 2030.

4.7 Scenario Development and Urban Growth Prediction

Different policy scenarios based on the Dhaka Metropolitan Development Plan (DMDP) and Strategic Transport Plan (STP) were developed to predict future growth of the study area. The scenarios were based on particular proposals of these plans which were applied to the model to find out the growth pattern of the study area if these proposals are implemented. Prediction run of the model was conducted after updating the input images according to these scenarios. Outputs of the prediction runs were compared with each other to visualize the impacts of each of the policies. The output prediction statistics were used for this purpose.

Chapter 5: Dhaka Metropolitan Area

5.1 Introduction

Dhaka, a city of history and heritage of nearly 400 years, is the administrative capital of the People's Republic of Bangladesh. During the last four decades this city and its surrounding region has recorded phenomenal growth in terms of both population and area. At present it is one of the fastest growing metropolises in the world. This chapter provides a brief discussion on this area being it the target region of this study.

5.2 Location and administrative areas

This study has considered the Dhaka Metropolitan Development Plan (DMDP) area as the Dhaka Metropolitan Area (DMA). It is located in the central part of Bangladesh. It covers an area of 1,528 square kilometer or 590 square miles. It incorporates three districts (Dhaka, Narayanganj and Gazipur), one city corporation (Dhaka City Corporation) and five municipalities (Savar, Tongi, Gazipur, Narayanganj and Kadamrasul). It is the biggest urban agglomeration in Bangladesh which is well connected to other parts of the country and the world by road, railway, river and air.

DMA has a population of about 9.7 million as per the census of 2001 (BBS, 2001), within which only Dhaka City Corporation area has got a population of 5.3 million. Being the capital city of the Country, Dhaka attracts many migrants from all over the country. To accommodate this huge population the city has experienced unplanned expansion both through in-fill development and outward edge growth. Diffused growth of settlements mostly by different housing projects of private developers has added to the recent trend of growth of this urban region. Unplanned expansion of the city to the ecologically sensitive areas is already posing threats to the total living environment here.

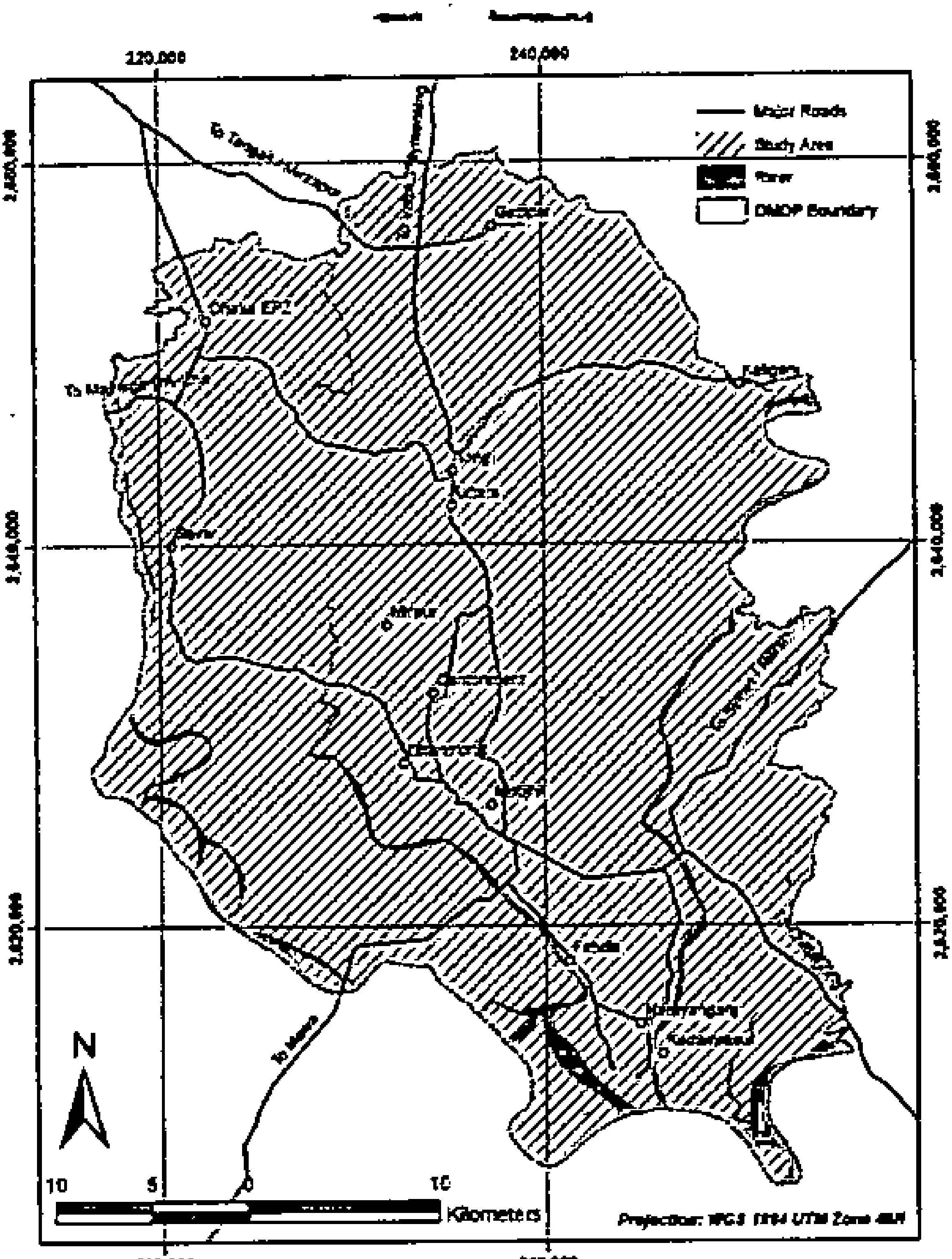


Figure 5.1: Map of the Study Area (Basak, 2006)

5.3 Physical Expansion of Dhaka City: A Chronological Study

Different physical and socio-economic issues have guided the development process of Dhaka. Political importance and trade played significant roles in the city's expansion in different time periods. This section briefly describes the growth and expansion of the city in five major periods: pre-Mughal, Mughal, British (1764-1947), Pakistan (1947-1971) and Bangladesh (after 1971). Although this discussion has focused on Dhaka City, it is also relevant to the growth of whole Dhaka Metropolitan region. Discussions here are mostly based on the website of Banglapedia (www.banglapedia.com) and Ahmed (1986).

5.3.1 Pre-Mughal Period

Growth and expansion of Dhaka city in the pre-Mughal period is obscure. The nearby capital city of Vikrampur was in the limelight from the 10^{th} to 13^{th} centuries. Some findings indicate human habitation of the area in the above period. After Muslim occupation of south-eastern Bengal (late 13th and early 14th century) the nearby city of Sonargaon rose into prominence which enjoyed the position of a metropolis in the region in the pre-Mughal period. It is evident from the various writings on Dhaka that the areas to the east, northeast and southeast of Babu Bazar up to the Dholai Khal on the left bank (northern bank) of the Buriganga formed the old town. The conglomeration of Hindu-named localities in this part of the city bears testimony to the predominance of Hindu craftsmen and professionals in the population of old Dhaka city at that time. Dholai Khal possibly formed the northeastern boundary of the old city, though it is difficult to determine the western limit of the pre-Mughal 'old city'. Considering testimony to the existence of a mosque at that time, however, it can be assumed the city limits went beyond Babu Bazar on the western side (Figure 5.2). It is quite likely that following the course of the Buriganga, settlements grew on the southern, western and north-western parts of the city.

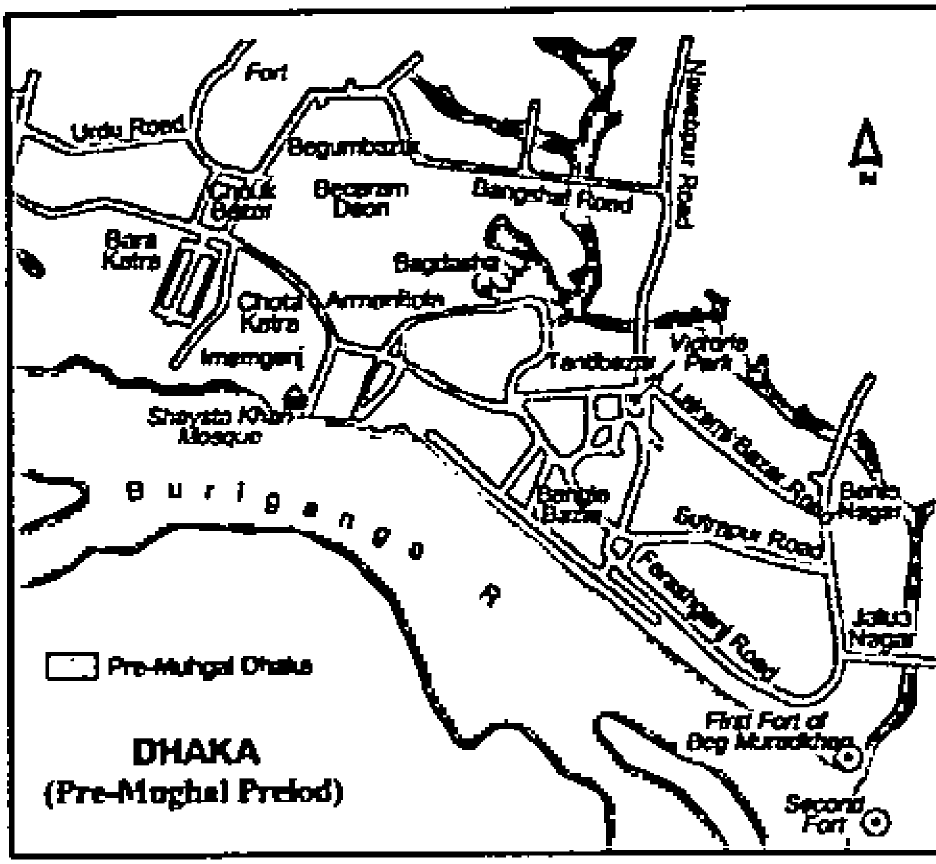


Figure 5.2: Dhaka during pre-Mughal Period (from www.banglapedia.com)

5.3.2 Mughal Period

The pre-Mughal Dhaka was turned into a *Thana* (military outpost) during the military operations of Akbar. But it rose to prominence only after the transfer of the capital of the *Subah* by Islam Khan Chisti in 1610 AD, when it was named Jahangirnagar. The fort (in the site of present central jail) and Chandighat, on the river bank straight to the south of the fort have grown in his time. The bazar occupying the area between the fort and Chadnighat (present Chawk Bazar), originally known as Badshahi Bazar, as also Urdu Bazar (market place of the camp) to the west of the fort are likely to have grown at the same time. Islam Khan is credited to have excavated a canal joining the Buriganga near Babu Bazar with the Dulai Khal near Malitola-Tantibazar. This canal practically demarcated the seam between 'old Dhaka' and the 'new Dhaka' of Islam Khan. Mughal Dhaka encompassed 'old Dhaka' within itself and extended to the east up to Narinda, to the west up to Maneswar and Hazaribagh and to the north up to Fulbaria area on the fringe of the Ramna area (Figure 5.3).

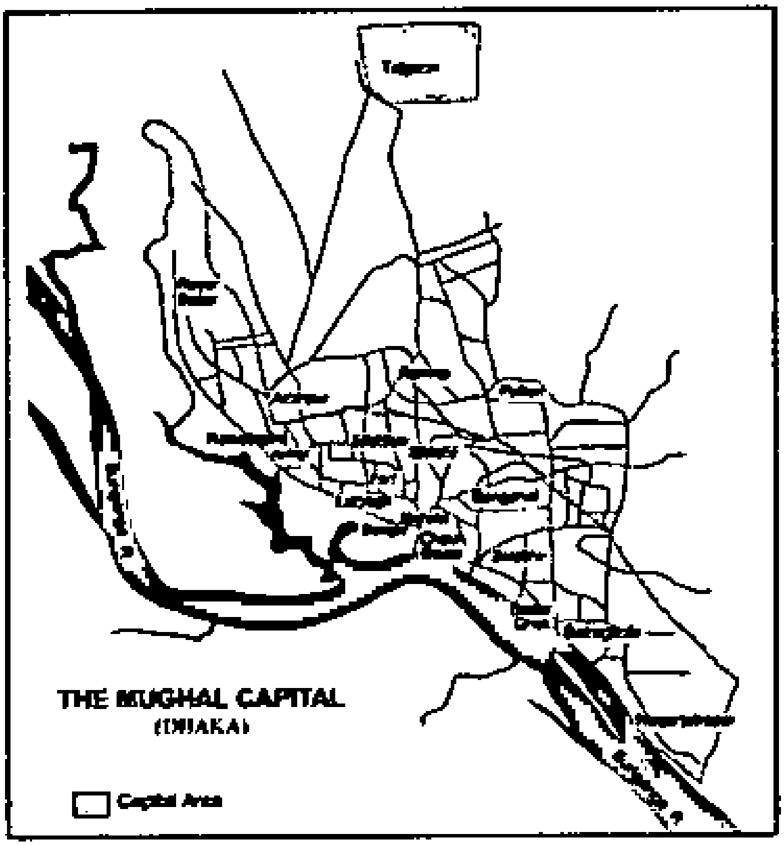


Figure 5.3: Dhaka during Mughal Period (from www.banglapedia.com)

5.3.3 British Period (1764-1947)

After the acquisition of the *Diwani* in 1765 by the East India Company and the shift of the Bengal's capital to Calcutta, Dhaka lost its political importance. Gradually the administrative and commercial importance of the city dwindled and by 1828 the city was reduced to a mere district headquarters, though it retained its position as a provincial Circuit Court of Appeal. By 1840, this decline had reached its nadir and most of the former Mughal city had been deserted or had fallen victim to the encroaching jungle. The decline affected Dhaka seriously and during this period Dhaka also suffered physical shrinkage (Figure 5.4). In 1905, Dhaka was made the capital of the new province of East Bengal and Assam. Building the new town started beyond the railroad in Ramna. The only locality developed as a fully planned residential area was Wari.

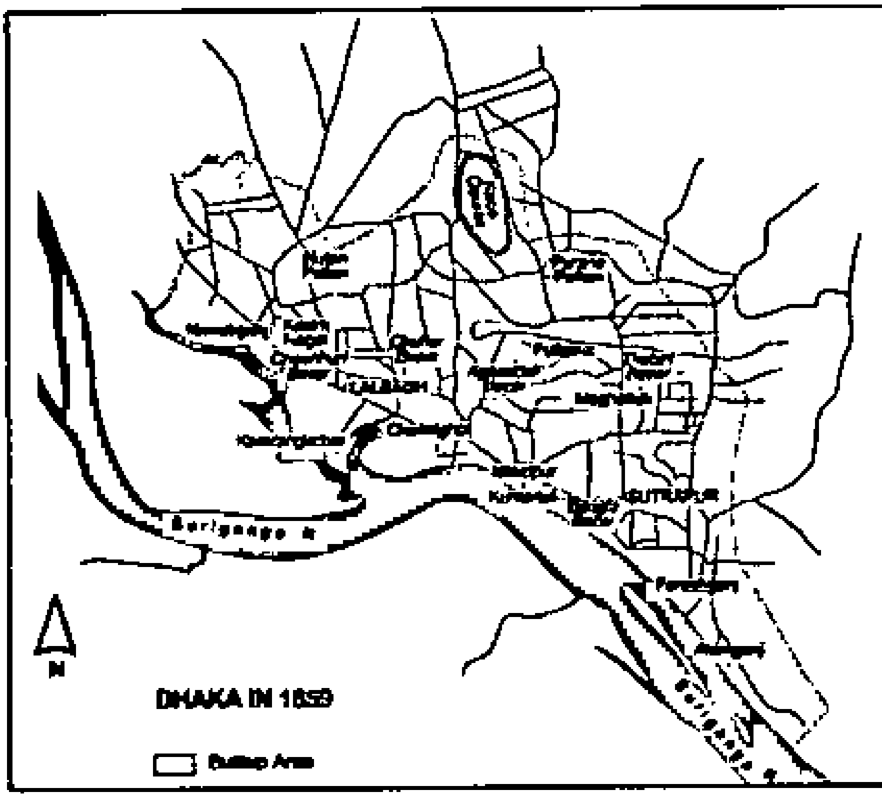


Figure 5.4: Dhaka in 1859 (from www.banglapedia.com)

The impetus for growth created by the 1905 partition of Bengal was seriously jolted by the annulment of the partition in 1911 when Dhaka reverted back to the status of a district town (Figure 5.5). The establishment of the University of Dhaka which came to occupy many of the buildings of the Ramna area was an important event in Dhaka's history when Dhaka again attained the status of the provincial capital of the eastern part of Pakistan, initially called East Bengal and later named East Pakistan.

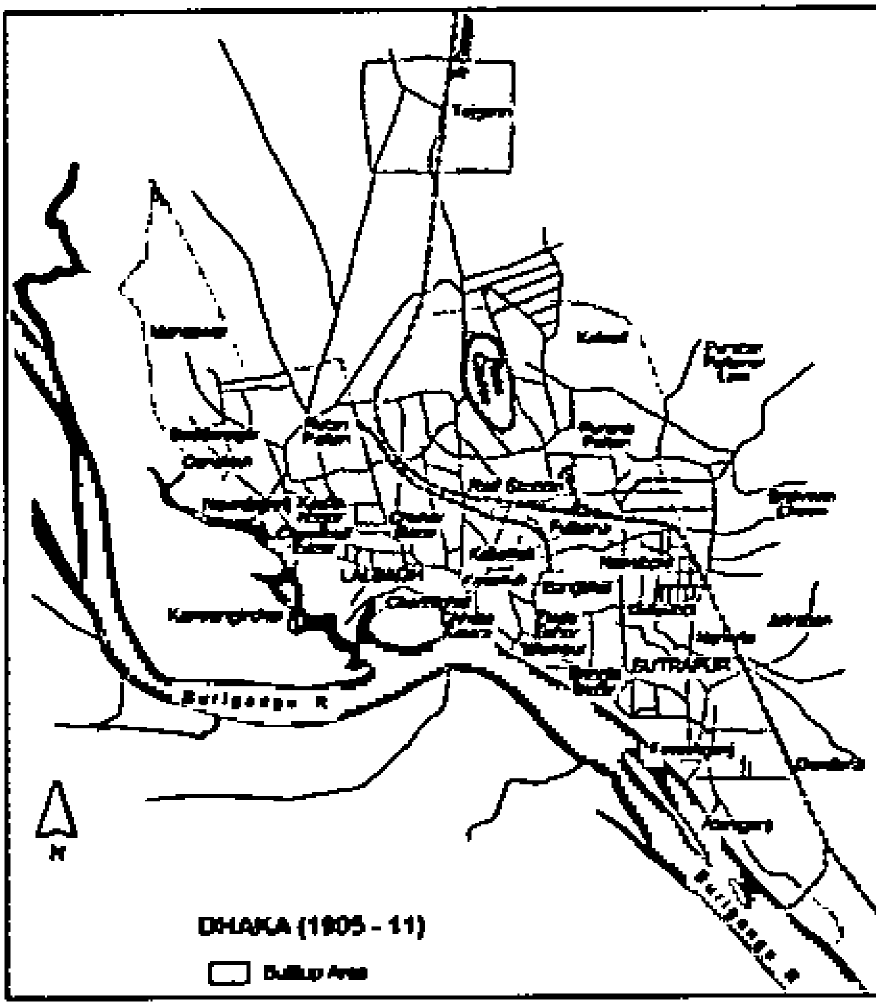


Figure 5.5: Dhaka during the period of 1905-1911 (www.banglapedia.com)

5.3.4 Pakistan Period (1947-1971)

In 1947, India become independent of British rule and Pakistan was created. Dhaka restarted its life as the capital of East Pakistan. The needs of the officials engaged in administration, the business community and the residents grew out of the sudden onrush of people to Dhaka. To cater to the ever increasing residential needs of the new capital, the Dhanmondi area, covered with paddy fields in the early 1950s, was developed as a residential area after 1955. The Mirpur Road formed an axis and the highlands on both sides of the road came to be occupied right up to Mohammadpur and Mirpur. The Tejgaon Airport and the Tejgaon Industrial area came under governmental schemes in the early 1950s.

In the mid-1960s the main railway line was shifted and directed eastward after Tejgaon and before Kawranbazar before rejoining the old track near Swamibagh–

Jatrabari cutting through Rajarbagh, Basabo and Kamalapur. The Dhaka Railway Station was moved from Phulbaria to Kamalapur. The rapid growth and development of the area between the old railway track and Kawranbazar necessitated this change. Since then the old track has been developed into a broad road connecting Kawranbazar with Phulbaria through Palassy and Nilkhet to the northwest and Swamibagh-Jatrabari through Wari to the north and Narinda to the southeast.

5.3.5 Bangladesh (1971 onward)

The creation of the independent state of Bangladesh in 1971 bestowed glory and prestige on Dhaka, now capital of a sovereign country. This additional factor led to Dhaka's phenomenal growth since 1971. The low-lying areas on the eastern side, such as Jurain, Goran, Badda, Khilgaon, Rampura and Kamrangir Char, Shyamali, Kalayanapur on the western side came under occupation. Dhaka's growth picked up at a tremendous pace and private initiatives played the dominant role. With increased population pressure the highlands spreading northward were occupied and built up. The intervening ditches, swamps and marshes were filled in, not in any planned manner, but as necessities arose both by public and private initiatives.

Since Dhaka became the capital of an independent country the pressure on it has been enormous. Huge influx of people from all around the country has resulted in the growth of slums on any available vacant land. The recent phenomenon of high rise buildings, both in the commercial and residential sectors occupy the city's highlands and demonstrate ever-increasing pressure on Dhaka as it builds upwards. Since the 1990s, Dhaka has been on the verge of change in its urban character with vertical growth replacing horizontal expansion (Chowdhury and Faruqui, 1989). Over the years most of the low-lying areas of western Dhaka have been filled in to meet the city's residential and commercial demands. The eastern side of the city is also being filled in by private interventions.

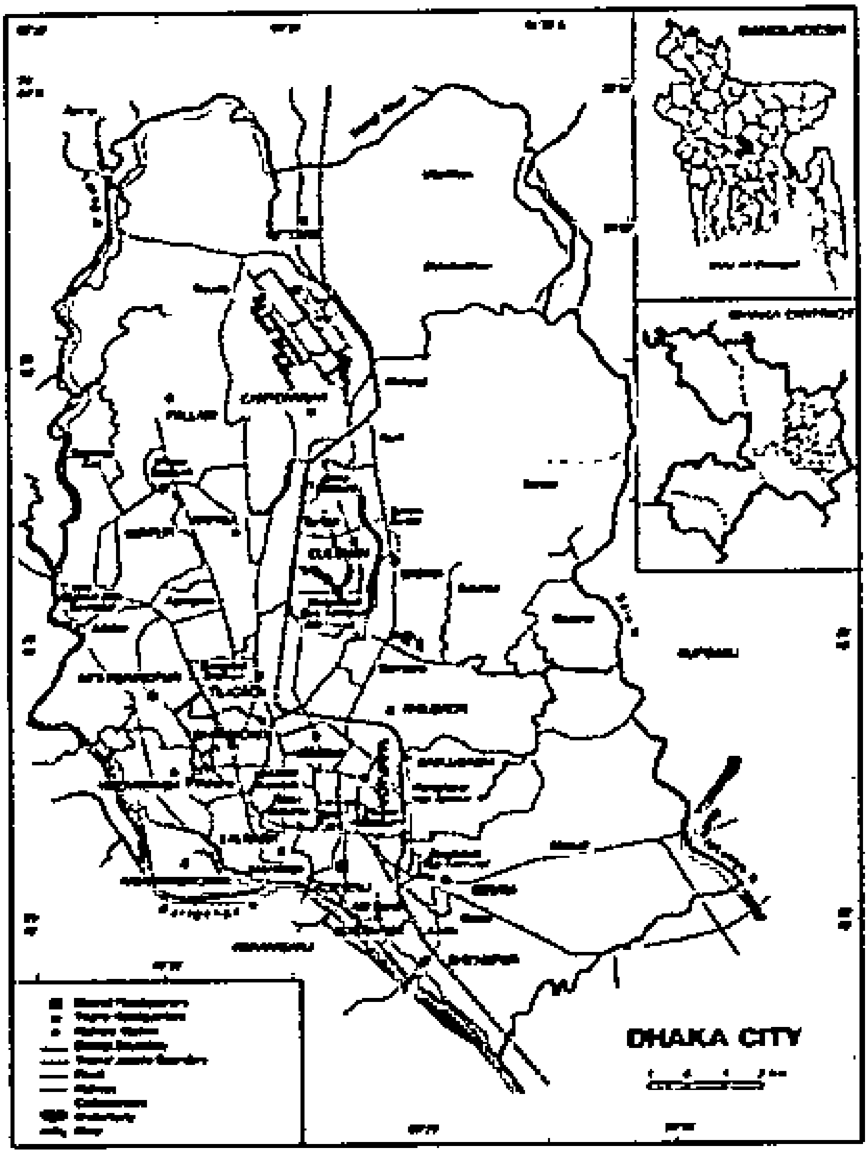


Figure 5.6 Dhaka City at present

5.4 Recent Planning Initiatives for Dhaka

As mentioned in previous sections, Dhaka has faced an unplanned haphazard growth in the face of rapid population growth. But this city had got several planning documents for guiding its growth in different times, none of which experienced adequate implementation. Latest planning document for Dhaka is the Dhaka Metropolitan Development Plan (DMDP), a long term structure plan (1995-2015). It is a three-tier plan, namely: Structure Plan, Urban Area Plan and Detail Area Plan. The structure plan gives some long term policy decisions for the city, mid-term development guideline is provided by the Urban Area Plan and detail planning guideline is due to be given by the Detail Area Plan (which is yet to be completed). Chapter 7 gives some more discussions on this plan, where some future scenarios are prepared based on this plan to predict the future growth of DMA.

Strategic Transport Plan (STP) is another long term plan for Dhaka city which is now under process of implementation. This plan has focused on improving road transport system of the city over a period of 20 year (2005- 2025). Some major road projects along with mass transport services are proposed in this plan which would be gradually implemented within next 20 years. Chapter 7 provides more discussion on this plan to predict future growth scenario of Dhaka based on the road projects proposed in this plan.

5.5 Conclusion

From a Mughal military outpost to a metropolis of about hundred million people, Dhaka has been going through some major transformations for last 400 years. But within last three to four decades this urban agglomeration has to feel the pressure of political and global economy, and expanded itself both horizontally and vertically. With increased population, this city has to expand its spatial extent with increased rate of rural to urban land use conversion. No planning document was able to guide this growth process and as a result both the city and its surrounding regions are suffering multitudes of problems at present. This study has simulated this historical growth process of the city and tried to assist the planning process of it by predicting future growth of it for different planning scenarios.

Chapter 6: SLEUTH Calibration for Dhaka

6.1 Introduction

Calibration is done to find out the best fit parameters of a model. As described in Chapter 3 and 4, SLEUTH calibration is done in a Monte Carlo Brute Force fashion. Here the wide parameter space is gradually narrowed down step by step and the best fit coefficients are determined at the end. It is particularly done to reduce the total time period for calibration. This chapter discusses the calibration results of SLEUTH for Dhaka Metropolitan Area.

6.2 Calibration of SLEUTH

SLEUTH through its brute force calibration method gradually narrows down the parameter space in three consecutive calibration stages. These are Coarse Calibration, Fine Calibration and Final Calibration. At the end of each calibration stage, the best fit parameter intervals are identified and those are further applied in the next calibration stage with reduced intervals. Identification process of the best fit coefficients during SLEUTH calibration is still an issue of research and there is yet to develop any unique way to find out the goodness of fit of the coefficients (Jantz *et. al* 2004; Yang and Lo, 2003). At the end of each calibration, SLEUTH produces some spatial fit metrics in the `control_stats.log` file. This file stores the metrics for each of the coefficients sets which are applied to the model (more discussions on the metrics in section 3.4.4). Different researchers have used different metrics to determine the best fit coefficients. Some have used the product metric (which is simple multiplication of all other metrics), some have used Lee-Salle metric (ratio of the intersection and the union of the simulated and actual urban areas). This study has utilized the recent findings of Dietzel and Clarke (2007). They proposed Optimal SLEUTH Metrics (OSM) to identify the best fit coefficients. OSM is the product of the *compare*, *population*, *edges*, *clusters*, *slope*, *X-mean*, and *Y-mean* metrics. More discussions on these metrics are provided in section 3.4.4. At the end of each calibration, OSM for each of the coefficient sets are calculated and based on the OSM the best fit coefficients are selected. For each coefficient the minimum value is taken as '`_start`' value and the maximum value is taken as the '`_stop`' value. '`_step`' value is determined considering adequate interval between the '_start' and '_stop' value. Calibrations were conducted for both of the model framework regarding travel cost (i.e. one without considering travel cost and other considering travel cost)

6.2.1 Coarse Calibration

It is the first stage of the SLEUTH calibration. Here parameter space is sparsely defined upon the whole parameter space (0-100). 5 `monte_carlo_iterations` were mentioned in the `scenario.log` file including the coefficients as shown in Table 6.1. Locations of input files and the output directory were also mentioned in the `scenario.log` file.

Table 6.1 Input coefficients for coarse calibration (for both model frameworks)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
_start	0	0	0	0	0
_step	25	25	25	25	25
_stop	100	100	100	100	100

6.2.2 Fine Calibration

Outputs of the coarse calibration were used to execute the fine calibration. At the end of coarse calibration the `control_stats.log` file of the output directory was opened using Microsoft Excel. Here the OSM for each of the coefficient sets are calculated and then the whole table is sorted in descending order of OSM. A portion of this table for both of the model framework is shown in Table 6.2 and 6.3. In these tables the first 10 parameter sets are taken as the best fit parameter combinations. Observing the results of the coefficients of these tables the coefficient values necessary to execute the fine calibration were determined. Table 6.4 and 6.5 shows the input coefficients for the fine calibration for both of the model framework which were determined from the output of the coarse calibration. For fine calibration 8 `monte_carlo_iterations` were mentioned in the `scenario.log` file.

Table 6.2 Coefficient selection from coarse calibration output (model without travel cost)

Run	Product	Compare	Pop	Edges	Clusters	Cluster Size	Leesalee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG	OSM
1031	0.07689	0.98768	0.88015	0.90413	0.96469	0.44179	0.42233	0.84961	0.88057	0.84139	0.96615	0.89366	0	25	75	25	25	25	0.523664
2575	0.149	0.96878	0.94492	0.94556	0.98554	0.7316	0.45073	0.83408	0.93846	0.77169	0.94283	0.94952	0	100	1	75	1	1	0.507074
2583	0.19722	0.95627	0.94182	0.93524	0.96294	0.95455	0.46121	0.82649	0.9353	0.77999	0.96786	0.94644	0	100	1	75	25	75	0.508069
2582	0.19537	0.95634	0.94491	0.93894	0.96106	0.95455	0.46075	0.80986	0.93816	0.79293	0.95243	0.94942	0	100	1	75	25	50	0.498734
902	0.07165	0.95446	0.90481	0.91945	0.96439	0.40553	0.43062	0.86414	0.90279	0.77784	0.96475	0.91521	0	25	50	25	1	50	0.496575
1030	0.07933	0.96863	0.88098	0.90457	0.96171	0.48137	0.42673	0.8541	0.88134	0.83616	0.9266	0.89378	0	25	75	25	25	1	0.490234
1958	0.18264	0.96168	0.93546	0.92838	0.95741	0.90737	0.47157	0.83713	0.92967	0.7414	0.98314	0.94082	0	75	1	75	25	75	0.488012
903	0.08596	0.9701	0.90569	0.92219	0.95881	0.50286	0.42878	0.86363	0.90362	0.77308	0.92797	0.9166	0	25	50	25	1	75	0.481321
1957	0.18044	0.95437	0.93637	0.92545	0.95249	0.90737	0.47197	0.82595	0.93036	0.75684	0.97689	0.94147	0	75	1	75	25	50	0.48104
1956	0.18263	0.95398	0.93851	0.928	0.95536	0.92302	0.47159	0.82564	0.93229	0.74736	0.9738	0.94355	0	75	1	75	25	25	0.476962
2552	0.18322	0.88725	0.9532	0.9497	0.96483	0.93976	0.45324	0.83135	0.94481	0.76238	0.98944	0.9582	0	100	1	50	1	50	0.476137
2580	0.18504	0.95064	0.94265	0.9386	0.96157	0.95455	0.46173	0.82965	0.93605	0.72027	0.97892	0.94703	0	100	1	75	25	1	0.473597
2606	0.17974	0.93248	0.93537	0.93667	0.96465	0.95455	0.45587	0.83652	0.9301	0.74655	0.95852	0.94135	0	100	1	100	25	25	0.471754
1925	0.18401	0.09428	0.94698	0.94299	0.96136	0.95455	0.48324	0.83368	0.93942	0.76412	0.95307	0.95063	0	75	1	50	1	1	0.46597
575	0.16374	0.93218	0.93899	0.93178	0.97541	0.81794	0.48912	0.84887	0.93253	0.71876	0.95876	0.94308	0	1	100	75	1	1	0.465376
2579	0.13661	0.9848	0.94517	0.94512	0.96583	0.7316	0.4502	0.83023	0.93877	0.70665	0.95256	0.94977	0	100	1	75	1	100	0.46519
904	0.06415	0.97271	0.90475	0.92544	0.96303	0.38908	0.42898	0.85918	0.9028	0.75048	0.91924	0.91575	0	25	50	25	1	100	0.464892
1954	0.17853	0.94844	0.937	0.93963	0.96129	0.95455	0.45834	0.83167	0.93151	0.71361	0.97541	0.94275	0	75	1	75	1	100	0.464686
1408	0.12232	0.89295	0.89468	0.9128	0.95954	0.75749	0.43044	0.84744	0.89363	0.80552	0.97171	0.90438	0	50	25	25	25	75	0.464198
1352	0.18598	0.9954	0.95329	0.95243	0.95956	0.94113	0.47094	0.82704	0.9458	0.72554	0.89176	0.95629	0	50	1	100	1	50	0.464049

Table 6.3 Coefficient selection from coarse calibration output (model with travel cost)

Run	Product	Compare	Pop	Edges	Clusters	Cluster Size	Leesalee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG	OSM
986	0.09573	0.96131	0.93041	0.94346	0.97565	0.42237	0.47423	0.85028	0.92592	0.80176	0.98114	0.93734	0	25	50	100	50	25	0.550672
1240	0.0002	0.97643	0.93091	0.95244	0.98664	0.00098	0.45356	0.83991	0.92677	0.77114	0.97621	0.93881	0	25	100	100	75	1	0.529128
855	0.20429	0.96458	0.94016	0.93783	0.97174	0.92223	0.48442	0.85133	0.93438	0.74829	0.9833	0.94536	0	25	25	100	25	1	0.517688
1427	0.12776	0.98474	0.93748	0.94731	0.97134	0.62103	0.45911	0.8489	0.93253	0.71613	0.98495	0.94472	0	50	25	50	1	50	0.508639
929	0.05425	0.9627	0.93478	0.94422	0.97411	0.26207	0.46644	0.85514	0.92998	0.73556	0.97313	0.9419	0	25	50	50	1	100	0.50665
856	0.17282	0.97459	0.94149	0.94219	0.96129	0.80328	0.48129	0.85053	0.9357	0.7258	0.98349	0.94683	0	25	25	100	25	25	0.504553
1089	0.0002	0.98601	0.91499	0.93632	0.97111	0.00101	0.46351	0.8486	0.9124	0.75199	0.96349	0.92525	0	25	75	75	50	100	0.504374
827	0.1971	0.99071	0.94107	0.94221	0.96426	0.92486	0.47933	0.84898	0.93549	0.71464	0.97673	0.94683	0	25	25	75	1	50	0.501961
1213	0.05099	0.9078	0.91198	0.94106	0.97353	0.26819	0.46172	0.83612	0.90986	0.81595	0.96701	0.92455	0	25	100	75	50	75	0.500386
1455	0.06416	0.91813	0.91927	0.93308	0.96895	0.32582	0.46292	0.85385	0.91843	0.78317	0.98026	0.92983	0	50	25	75	25	1	0.499171
925	0.04341	0.93864	0.93577	0.9413	0.96569	0.21212	0.46990	0.85208	0.93066	0.74337	0.98176	0.94232	0	25	50	50	1	1	0.496506
1487	0.13781	0.96018	0.93078	0.93947	0.9691	0.67982	0.47143	0.85562	0.92621	0.7226	0.98445	0.93745	0	50	25	100	50	50	0.495249
850	0.15886	0.955	0.94837	0.95029	0.96908	0.76564	0.47047	0.84415	0.94224	0.70705	0.98609	0.9535	0	25	25	100	1	1	0.490889
1086	0.00442	0.99421	0.9111	0.92881	0.96092	0.02358	0.46228	0.85262	0.90876	0.72337	0.9719	0.92131	0	25	75	75	50	25	0.484614
829	0.06649	0.99695	0.9418	0.94678	0.97772	0.32534	0.47651	0.84642	0.93621	0.67575	0.97224	0.9478	0	25	25	75	1	100	0.483327
2050	0.02935	0.91178	0.92733	0.94322	0.97039	0.15915	0.44256	0.85611	0.92379	0.74184	0.979	0.93742	0	75	25	50	1	1	0.481178
2055	0.13094	0.98317	0.91805	0.9315	0.96734	0.70413	0.4556	0.84748	0.915	0.72349	0.98455	0.92741	0	75	25	50	25	1	0.480998
1050	0.01176	0.93358	0.92653	0.9454	0.97178	0.06251	0.45306	0.85726	0.9231	0.72051	0.97813	0.93661	0	25	75	50	1	1	0.480113
2056	0.09166	0.99913	0.91663	0.9319	0.97308	0.49992	0.45381	0.84095	0.91376	0.7022	0.97295	0.92665	0	75	25	50	25	25	0.477151
1428	0.13338	0.97291	0.93642	0.94299	0.97292	0.69084	0.46117	0.84881	0.93141	0.68399	0.9819	0.94331	0	50	25	50	1	75	0.476491

Table 6.4 Input coefficients for fine calibration (model without travel cost)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
_start	25	0	25	0	0
_step	15	15	10	5	15
_stop	100	75	75	25	75

Table 6.5 Input coefficients for fine calibration (model with travel cost)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
_start	25	25	50	0	0
_step	5	15	10	15	20
_stop	50	100	100	75	100

6.2.3 Final Calibration

Final calibration was executed using the outputs of the fine calibration. In this stage the parameter space is narrowed down further. Selection of best fit coefficients here followed the procedure discussed in the previous section. Table 6.6 and 6.7 shows a portion of the metrics generated in the `control_stats.log` file in the output directory at the end of fine calibration for both of the model frameworks. Here also the metrics are sorted in the descending order of the OSM. Input coefficients for the final calibration (Table 6.8 and 6.9) are determined from this table. First 10 parameter sets are identified as the best fit parameter combinations and coefficients are determined according to that. For the model framework with travel cost, first 3 parameter sets were considered due to high variation of the coefficients in the first 10 sets. The minimum coefficient value is used as the `_start` value and the maximum coefficient value is used as the `_stop` value. The `_step` values are determined in such a way that the `_start` value can reach the `_stop` value after 5-7 intervals. For final calibration 10 `monte_carlo_iterations` were mentioned in the `scenario.log` file.

Table 6.6 Coefficient selection from fine calibration output (model without travel cost)

Run	Product	Compare	Pop	Edges	Clusters	Cluster Size	Leesalee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG	OSM
1450	0.21079	0.98866	0.94512	0.94542	0.96596	0.96026	0.45659	0.83263	0.93876	0.78325	0.96844	0.95025	0	85	1	65	5	60	0.538943
1444	0.2115	0.98832	0.94684	0.94616	0.96598	0.96598	0.45554	0.82904	0.94037	0.78873	0.96035	0.95166	0	85	1	65	1	60	0.537082
189	0.18038	0.98101	0.94814	0.94761	0.96541	0.83066	0.45221	0.83055	0.94138	0.78663	0.96341	0.95238	0	100	1	75	5	45	0.535593
1547	0.15683	0.93102	0.90933	0.92779	0.96494	0.85471	0.41777	0.84288	0.9069	0.8671	0.96371	0.91879	0	85	15	25	25	75	0.533841
1412	0.18074	0.94331	0.94921	0.94478	0.96459	0.8288	0.45864	0.83164	0.94189	0.79668	0.97935	0.95335	0	85	1	55	5	30	0.529477
1457	0.20681	0.99206	0.94787	0.94555	0.96437	0.95455	0.4587	0.83756	0.94122	0.76546	0.95816	0.95273	0	85	1	65	10	75	0.526734
1683	0.15661	0.95174	0.90738	0.91887	0.96658	0.7987	0.45051	0.86621	0.90507	0.8118	0.97197	0.91734	0	25	30	35	10	45	0.524233
213	0.20426	0.96091	0.94232	0.93706	0.96061	0.95455	0.46076	0.82082	0.93586	0.81415	0.96205	0.947	0	100	1	75	25	45	0.524017
2087	0.07585	0.98661	0.89573	0.91482	0.9703	0.41846	0.42624	0.85395	0.89477	0.79591	0.98156	0.90821	0	25	60	25	15	75	0.523332
170	0.17542	0.9232	0.94855	0.94377	0.9628	0.81906	0.46026	0.8325	0.94121	0.80062	0.97875	0.95243	0	100	1	65	20	30	0.519088
204	0.20046	0.9684	0.94026	0.93332	0.95845	0.93175	0.47114	0.83098	0.9341	0.78087	0.97846	0.94529	0	70	1	75	20	1	0.517148
205	0.20046	0.9684	0.94026	0.93332	0.95845	0.93175	0.47114	0.83098	0.9341	0.78087	0.97846	0.94529	0	70	1	75	20	15	0.517148
1492	0.1856	0.95345	0.94406	0.94371	0.96747	0.8833	0.45624	0.83302	0.93807	0.79106	0.95475	0.94956	0	85	1	75	10	60	0.517045
2936	0.12427	0.94604	0.90642	0.92421	0.96597	0.6771	0.42861	0.88441	0.90473	0.80596	0.9688	0.91648	0	40	30	25	5	30	0.516703
1454	0.20104	0.99973	0.94561	0.9428	0.96523	0.95455	0.45717	0.83714	0.93914	0.73562	0.97398	0.95089	0	85	1	65	10	30	0.515987
1482	0.20333	0.97298	0.94676	0.94295	0.96827	0.95455	0.46157	0.84048	0.94017	0.75929	0.963	0.95163	0	85	1	65	15	60	0.515813
191	0.15217	0.97525	0.94578	0.94428	0.96547	0.7316	0.45183	0.83106	0.93924	0.80179	0.92043	0.95029	0	100	1	75	5	75	0.515738
202	0.20473	0.99145	0.94684	0.94599	0.96701	0.98012	0.4542	0.83471	0.94035	0.75769	0.94626	0.95163	0	100	1	75	15	60	0.513928
200	0.19773	0.99467	0.94633	0.94506	0.96485	0.94705	0.45515	0.83389	0.93986	0.76298	0.93971	0.95111	0	100	1	75	15	30	0.513164
2750	0.16732	0.92566	0.91448	0.92184	0.96129	0.86159	0.45087	0.86225	0.91126	0.81558	0.97142	0.92242	0	40	15	35	1	30	0.512439

Table 6.7 Coefficient selection from fine calibration output (model with travel cost)

Run	Product	Compare	Pop	Edges	Clusters	Cluster Size	Leesalee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG	OSM
2515	0.00164	0.98598	0.91941	0.94724	0.97136	0.00777	0.44901	0.83834	0.91639	0.81215	0.9747	0.92904	0	30	100	60	75	20	0.553535
870	0.00374	0.94174	0.92461	0.94195	0.97846	0.01781	0.45222	0.85652	0.92143	0.80884	0.97168	0.93542	0	25	85	50	15	1	0.539132
1710	-0.10043	0.98394	0.92987	0.93825	0.96519	0.46125	0.47191	0.84815	0.92549	0.774	0.98051	0.93696	0	30	40	100	45	1	0.532062
4104	0.04209	0.97382	0.932	0.94453	0.9716	0.20026	0.45555	0.85183	0.92788	0.75439	0.98753	0.94074	0	40	40	50	1	1	0.528563
697	0.00172	0.98142	0.91144	0.92764	0.975	0.00843	0.46328	0.84679	0.90915	0.78818	0.97522	0.92216	0	25	70	60	30	20	0.526588
2784	0.17333	0.99494	0.93296	0.93372	0.96428	0.79323	0.47606	0.84334	0.92825	0.75674	0.98657	0.93871	0	35	25	100	30	1	0.526207
1374	0.17054	0.96124	0.93994	0.94205	0.97411	0.76588	0.48006	0.85436	0.93447	0.7568	0.97867	0.9461	0	30	25	70	15	1	0.524653
3446	0.0049	0.91456	0.9191	0.94116	0.96892	0.02449	0.45015	0.83528	0.91631	0.83089	0.98071	0.93023	0	35	70	100	60	40	0.521726
6525	0.09793	0.96934	0.93064	0.94362	0.97369	0.46495	0.46382	0.85381	0.92671	0.75433	0.97706	0.93951	0	50	25	60	15	60	0.521578
1559	0.07598	0.98941	0.93189	0.94216	0.97217	0.35689	0.46786	0.85837	0.92776	0.73404	0.98017	0.94038	0	30	40	60	15	100	0.521559
1556	0.08047	0.99803	0.92762	0.93776	0.9735[illegible]	0.38169	0.46915	0.86316	0.92379	0.73122	0.97403	0.93616	0	30	40	60	15	40	0.519602
181	0.16681	0.95541	0.94619	0.85059	0.98667	0.7613	0.47217	0.85732	0.94034	0.73633	0.98911	0.95148	0	25	25	100	1	20	0.51868
1290	0.00504	0.96292	0.93148	0.85218	0.98896	0.02449	0.45583	0.83873	0.92716	0.76582	0.97694	0.93898	0	25	100	100	75	1	0.518213
1490	0.20284	0.98066	0.93453	0.934[illegible]6	0.96076	0.93078	0.48111	0.84479	0.92944	0.7592	0.98152	0.9407	0	30	25	100	30	40	0.518065
3814	0.02726	0.93252	0.91871	0.85158	0.97419	0.14111	0.4376	0.82695	0.91609	0.81124	0.97203	0.93041	0	35	100	80	75	80	0.517886
2852	0.0756	0.95635	0.92763	0.94038	0.97191	0.36407	0.46372	0.85729	0.92403	0.75865	0.98046	0.9373	0	35	40	60	15	40	0.517035
108	0.14171	0.99116	0.94048	0.94342	0.97313	0.64766	0.47656	0.84563	0.93499	0.72291	0.98737	0.94644	0	25	25	80	1	1	0.516684
6517	0.04298	0.939	0.93214	0.94472	0.9702	0.20903	0.45599	0.85565	0.92804	0.76632	0.98185	0.94079	0	50	25	60	1	20	0.516491
5221	0.11409	0.98281	0.93514	0.94391	0.97302	0.54277	0.46407	0.85248	0.93052	0.72816	0.98539	0.94274	0	45	25	60	1	20	0.516319
516	0.05523	0.98498	0.91508	0.92335	0.9627	0.27022	0.47093	0.84828	0.91233	0.77878	0.97189	0.92483	0	25	55	70	30	1	0.514417

Table 6.8 Input coefficients for final calibration (model without travel cost)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
_start	25	0	25	0	30
_step	15	10	10	5	9
_stop	100	60	75	25	75

Table 6.9 Input coefficients for final calibration (model with travel cost)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
_start	25	40	50	15	0
_step	1	12	10	10	5
_stop	30	100	100	75	20

6.3 Determination of forecasting coefficients

The calibration process produces initializing coefficient values that best simulate historical growth for a region. However, due to SLEUTH's self-modification qualities, coefficient values at the `start_date` of a run may be altered by the `stop_date`. For forecast initialization, the `stop_date` values from the best calibrated coefficients are desired. Using the best coefficients derived from the final calibration stage and running SLEUTH for the historical time period produces a single set of `stop_date` coefficients to initialize forecasting. However, due to the random variability of the model, averaged coefficient results of many Monte Carlo iterations produces a more robust forecasting coefficient set.

Best calibrated coefficients were selected from the output of the final calibration (Table 6.10 and 6.11) following the procedure discussed in previous two sections. In this case only the first coefficient set is selected based on the performance of the

Table 6.10 Coefficient selection from final calibration output (model without travel cost)

Run	Product	Compare	Pop	Edges	Clusters	Cluster Size	Leesalee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG	OSM
1720	0.18867	0.99074	0.94007	0.93667	0.9651	0.84897	0.46211	0.83757	0.9343	0.8038	0.96025	0.94568	0	85	1	75	20	66	0.544292
1676	0.21135	0.9721	0.94989	0.94416	0.96497	0.95455	0.46182	0.83024	0.94307	0.78064	0.97678	0.95455	0	85	1	65	15	48	0.532592
701	0.11247	0.96814	0.90616	0.91793	0.9624	0.57045	0.44909	0.88326	0.90407	0.84324	0.93907	0.91663	0	25	30	35	10	75	0.529784
1966	0.13788	0.91661	0.90698	0.92273	0.96423	0.7316	0.43114	0.85571	0.90475	0.86055	0.96783	0.91651	0	55	20	25	15	68	0.527145
3184	0.17892	0.9823	0.95053	0.9472	0.96478	0.83277	0.4557	0.83174	0.9432	0.77563	0.97107	0.95455	0	100	1	65	10	68	0.523647
1626	0.17632	0.94368	0.94919	0.94514	0.9648	0.81906	0.45843	0.82978	0.942	0.78811	0.97875	0.95334	0	85	1	55	5	30	0.522908
1661	0.20369	0.99353	0.94642	0.94452	0.96356	0.9637	0.45637	0.83222	0.93986	0.75485	0.96375	0.95113	0	85	1	65	1	75	0.518105
1743	0.13873	0.91533	0.92899	0.93987	0.96648	0.7316	0.42305	0.85378	0.92437	0.82627	0.95031	0.93641	0	85	10	25	10	57	0.517825
3275	0.15764	0.80483	0.92787	0.93769	0.96126	0.83615	0.42353	0.83421	0.92228	0.94451	0.97572	0.9325	0	100	10	25	25	75	0.517598
1671	0.20188	0.98011	0.94612	0.9434	0.96564	0.95455	0.45749	0.83473	0.93965	0.77495	0.92842	0.95122	0	85	1	65	10	57	0.517172
3232	0.20335	0.98033	0.94466	0.94045	0.96493	0.9637	0.45817	0.82887	0.93813	0.77537	0.95752	0.9493	0	100	1	75	20	68	0.517157
1711	0.1785	0.96817	0.94394	0.94375	0.96655	0.84568	0.45866	0.83889	0.93798	0.77487	0.95356	0.9495	0	85	1	75	15	39	0.516725
3224	0.20387	0.99061	0.94593	0.94538	0.96673	0.97165	0.45425	0.83311	0.93953	0.74975	0.96565	0.9508	0	100	1	75	15	48	0.516548
194	0.1869	0.99536	0.94342	0.93902	0.96345	0.87547	0.46586	0.834	0.93706	0.75955	0.95811	0.94846	0	70	1	75	10	48	0.515617
3192	0.17535	0.92329	0.94819	0.94324	0.96279	0.82513	0.46031	0.83258	0.94086	0.79511	0.97825	0.9521	0	100	1	65	20	30	0.515388
353	0.14671	0.98097	0.90456	0.91238	0.95624	0.75942	0.46022	0.8539	0.90258	0.80261	0.97131	0.91474	0	40	10	55	20	75	0.515353
3168	0.17341	0.97391	0.94961	0.94925	0.96617	0.82718	0.45308	0.83102	0.94237	0.76399	0.95625	0.95348	0	100	1	65	1	30	0.514954
198	0.19014	0.98838	0.94301	0.93822	0.96136	0.88776	0.46843	0.8358	0.93668	0.7462	0.98208	0.94801	0	70	1	75	15	30	0.514915
1726	0.19317	0.98434	0.94172	0.9355	0.96187	0.91113	0.46472	0.82354	0.93565	0.77688	0.96233	0.94702	0	85	1	75	25	68	0.51488
485	0.14312	0.99571	0.9041	0.92047	0.96647	0.76215	0.44164	0.86192	0.90222	0.8074	0.9237	0.91547	0	40	20	35	10	75	0.514795

Table 6.11 Coefficient selection from final calibration output (model with travel cost)

Run	Product	Compare	Pop	Edges	Clusters	Cluster Size	Leesalee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG	OSM
154	0.13079	0.99735	0.93214	0.93664	0.96261	0.59408	0.4762	0.84239	0.92761	0.76616	0.98033	0.93973	0	25	40	90	35	20	0.550343
189	0.17098	0.99143	0.93007	0.93433	0.96658	0.79089	0.4747	0.84868	0.92573	0.75448	0.98421	0.93742	0	25	40	100	35	20	0.524802
1009	0.00142	0.99699	0.92607	0.94654	0.9732	0.00687	0.45822	0.84013	0.92244	0.74323	0.98588	0.93517	0	25	88	90	65	20	0.523564
4145	0.02213	0.96485	0.92544	0.93679	0.96305	0.10589	0.46681	0.84658	0.92185	0.77965	0.97747	0.93462	0	28	52	90	45	1	0.519721
4146	0.02213	0.96485	0.92544	0.93679	0.96305	0.10589	0.46681	0.84658	0.92185	0.77965	0.97747	0.93462	0	28	52	90	45	5	0.519721
4147	0.02213	0.96485	0.92544	0.93679	0.96305	0.10589	0.46681	0.84658	0.92185	0.77965	0.97747	0.93462	0	28	52	90	45	10	0.519721
4148	0.02213	0.96485	0.92544	0.93679	0.96305	0.10589	0.46681	0.84658	0.92185	0.77965	0.97747	0.93462	0	28	52	90	45	15	0.519721
249	0.04595	0.97538	0.92774	0.93628	0.97964	0.2202	0.46589	0.85735	0.92403	0.73834	0.98482	0.93686	0	25	52	60	15	20	0.517421
2594	0.04782	0.95451	0.92752	0.93732	0.97492	0.22823	0.46832	0.85909	0.92378	0.75774	0.98188	0.93661	0	27	40	70	15	20	0.517104
834	0.06545	0.96617	0.92593	0.94072	0.97026	0.3174	0.46341	0.84706	0.92197	0.76275	0.97981	0.93366	0	25	76	100	65	20	0.516914
245	0.02559	0.98157	0.92849	0.93939	0.97402	0.12236	0.46685	0.85283	0.92472	0.74073	0.98082	0.93752	0	25	52	60	15	1	0.516683
246	0.02559	0.98157	0.92849	0.93939	0.97402	0.12236	0.46685	0.85283	0.92472	0.74073	0.98082	0.93752	0	25	52	60	15	5	0.516683
247	0.02559	0.98157	0.92849	0.93939	0.97402	0.12236	0.46685	0.85283	0.92472	0.74073	0.98082	0.93752	0	25	52	60	15	10	0.516683
248	0.02559	0.98157	0.92849	0.93939	0.97402	0.12236	0.46685	0.85283	0.92472	0.74073	0.98082	0.93752	0	25	52	60	15	15	0.516683
2635	0.12066	0.9778	0.92379	0.92831	0.9686	0.56979	0.47926	0.85175	0.92001	0.76361	0.97576	0.93171	0	27	40	80	35	1	0.515451
2636	0.12066	0.9778	0.92379	0.92831	0.9686	0.56979	0.47926	0.85175	0.92001	0.76361	0.97576	0.93171	0	27	40	80	35	5	0.515451
2637	0.12066	0.9778	0.92379	0.92831	0.9686	0.56979	0.47926	0.85175	0.92001	0.76361	0.97576	0.93171	0	27	40	80	35	10	0.515451
2638	0.12066	0.9778	0.92379	0.92831	0.9686	0.56979	0.47926	0.85175	0.92001	0.76361	0.97576	0.93171	0	27	40	80	35	15	0.515451
400	0.08156	0.99486	0.92782	0.93689	0.9639	0.38801	0.47224	0.85067	0.92375	0.74161	0.97948	0.93547	0	25	52	100	45	1	0.515085
401	0.08156	0.99486	0.92782	0.93689	0.9639	0.38801	0.47224	0.85067	0.92375	0.74161	0.97948	0.93547	0	25	52	100	45	5	0.515085

OSM. Table 6.12 shows that for model without travel cost diffusion value of 85, breed value 1, spread value 75, slope resistance value 20 and road gravity of 66 produces the optimum OSM of 0.544. For the model with travel cost diffusion value of 25, breed 40, spread 90, slope resistance 35 and road gravity of 20 produces the optimum OSM of 0.55. These are the starting coefficient values that produced the optimum goodness of fit to the control layers. But SLEUTH through its self modification characteristics change these values. For deriving the forecasting coefficients, another calibration run was conducted with the data using these best fit coefficients (showed in Table 6.12 and 6.13) with 110 Monte Carlo iterations.

Table 6.12 Input coefficients for identifying the forecasting coefficients (model without travel cost)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
`_start`	85	1	75	20	66
`_step`	1	1	1	1	1
`_stop`	85	1	75	20	66

Table 6.13 Input coefficients for identifying the forecasting coefficients (model with travel cost)

Coefficient ranges	Coefficients				
	Diffusion	Breed	Spread	Slope	Road
`_start`	25	40	90	35	20
`_step`	1	1	1	1	1
`_stop`	25	40	90	35	20

Calibration run for deriving the forecasting coefficients produced the output presented in Table 6.14 and 6.15. These are the edited versions of the `avg.log` file produced through the calibration run with the best coefficients of final calibration. It shows that all of the coefficients have changed from 1989 to 2007. The `stop_date` coefficients of 2007 are the final coefficients that are used for further growth prediction of the study area.

Table 6.14: Output showing the self-modification nature of SLEUTH (model without travel cost)

Year	Area	xmean	ymean	diffus	spread	breed	slp_res	rd_grav	grw_rate
1989	19328.48	243.12	359.48	92.04	81.21	1.08	13.7	66.63	4.51
1996	25490.35	245.33	354.61	98.68	87.07	1.16	6.41	67.36	3.55
2000	29271.05	245.68	352.65	100	86.82	1.18	1.36	67.86	3.34
2007	38118.25	244.89	351.26	100	88.82	1.18	1	69.06	3.27

Table 6.15: Output showing the self-modification nature of SLEUTH (model with travel cost)

Year	Area	xmean	ymean	diffus	Spread	breed	slp_res	rd_grav	grw_rate
1989	17932.72	244.19	363.43	27.07	97.46	43.31	28.47	20.65	4.17
1996	23719.35	247.07	358.55	29.02	100	46.44	21.11	21.39	3.85
2000	27773.91	247.62	356	30.2	100	48.32	15.96	21.9	3.89
2007	37263.24	247.14	352.01	32.38	100	51.81	5.11	22.99	4.28

Figure 6.1 and 6.2 show gradual changes of the coefficients over time due to the self modification nature of SLEUTH. Figure 6.1 and 6.2 shows that for both model frameworks diffusion, spread, breed and road gravity has increased over time, but slope resistance has decreased significantly. It is particularly due to the fact that urbanization occurs gradually in less suitable area (i.e. low lying areas or land with high slope) with decreasing amount of developable land (i.e. flat land). As a result, slope resistance for urbanization gradually decreases over time.

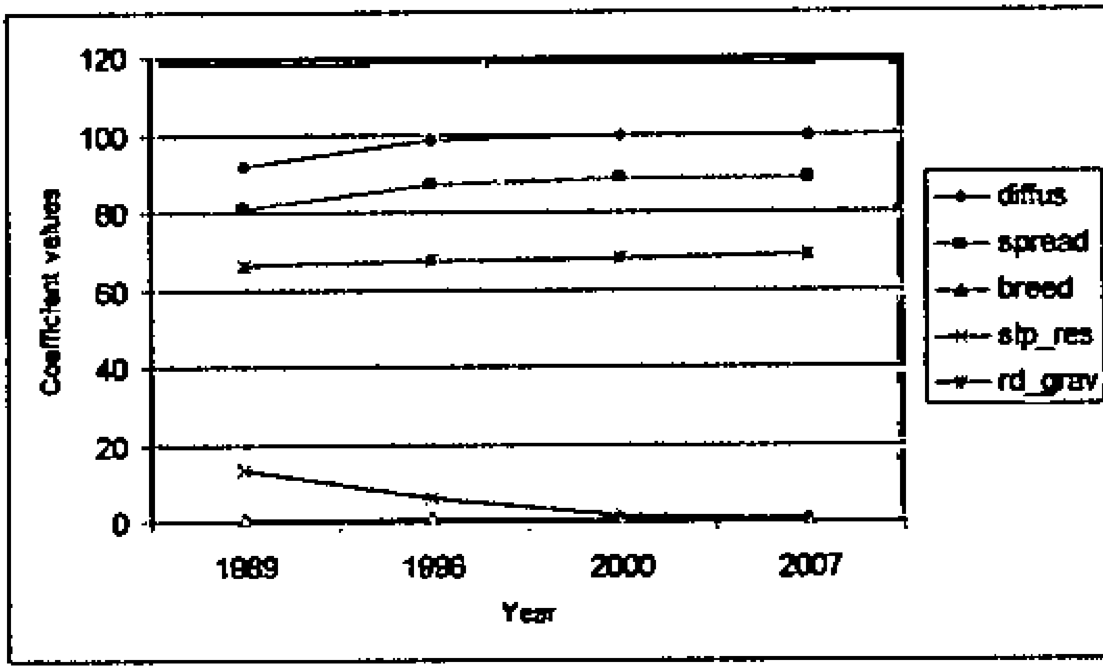


Figure 6.1 Gradual changes of coefficients over time through self modification (model without travel cost)

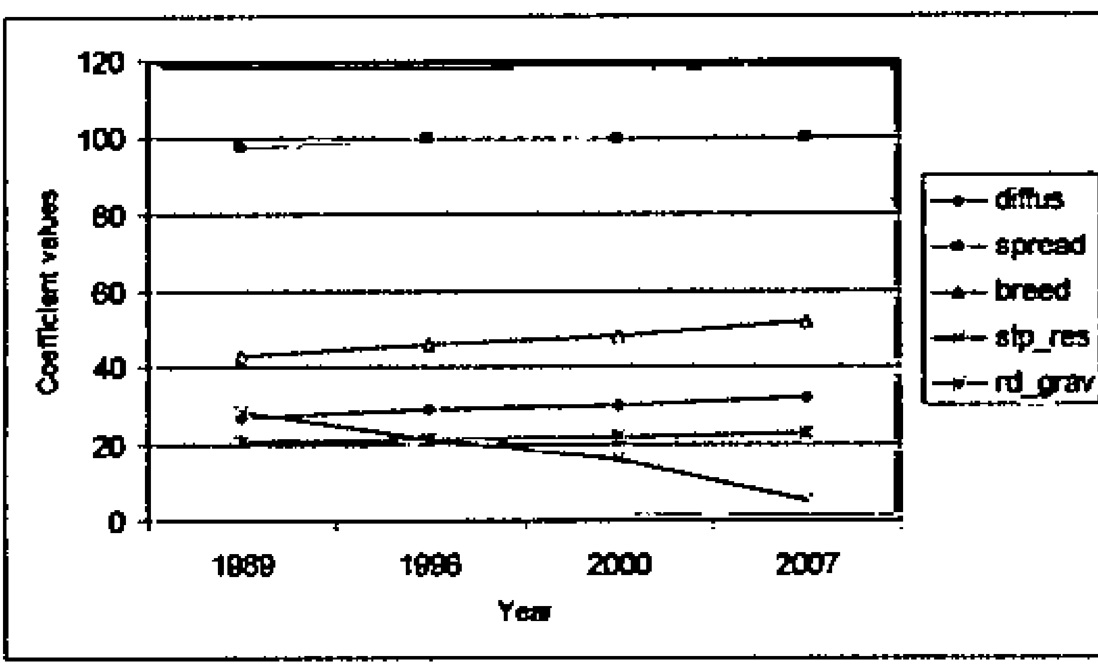


Figure 6.2 Gradual changes of coefficients over time through self modification (model with travel cost)

From Table 6.14 and 6.15, the forecasting coefficient set can be derived. Table 7.16 shows the forecasting coefficients that were used for prediction runs of the model.

These are the rounded values of the coefficients at the `stop_date` of the calibration. These coefficient values represent the present trend of urbanization in the Dhaka Metropolitan Area as revealed by the two model frameworks. It shows that only in terms of spreading growth and slope resistance these two model frameworks show same trend, but for other factors (i.e. for diffusion, breed and road gravity) they significantly differ from each other. It is particularly due to the inclusion of travel cost in the model. Before going to prediction stage of the model, these two modeling frameworks need to be evaluated further to identify which framework has better capability to simulate the historical growth pattern of DMA. Section 6.4 describes the evaluations between these two model frameworks.

Table 6.16: Forecasting coefficient values derived through calibration

Coefficients	**Forecasting values (model without travel cost)**	**Forecasting values (model with travel cost)**
Diffusion	100	32
Breed	1	52
Spread	89	100
Slope Resistance	1	5
Road Gravity	69	23

6.4 Evaluation of model frameworks

In order to measure the success of modeled growth, a simulation must be compared to historical urban data. In this study different simulated metric (pop or number of urban pixels, edges and clusters) are compared to the control year data. Outputs of the derive calibration metrics were plotted against the control year data. Values of the highest OSM (Optimum SLEUTH Metrics) for the three calibration stages were also evaluated to identify which model framework provides better goodness of fit.

Figure 6.3 shows the number of urban pixels modeled by the two modeling frameworks and that of the control years. It shows that both of the frameworks were successful to simulate the historical growth of the study area. In this case r^2 value for the model without travel cost was found to be 0.94 and that of the model with travel cost was found 0.93. So, model without travel cost give better result in this case although the difference is negligible.

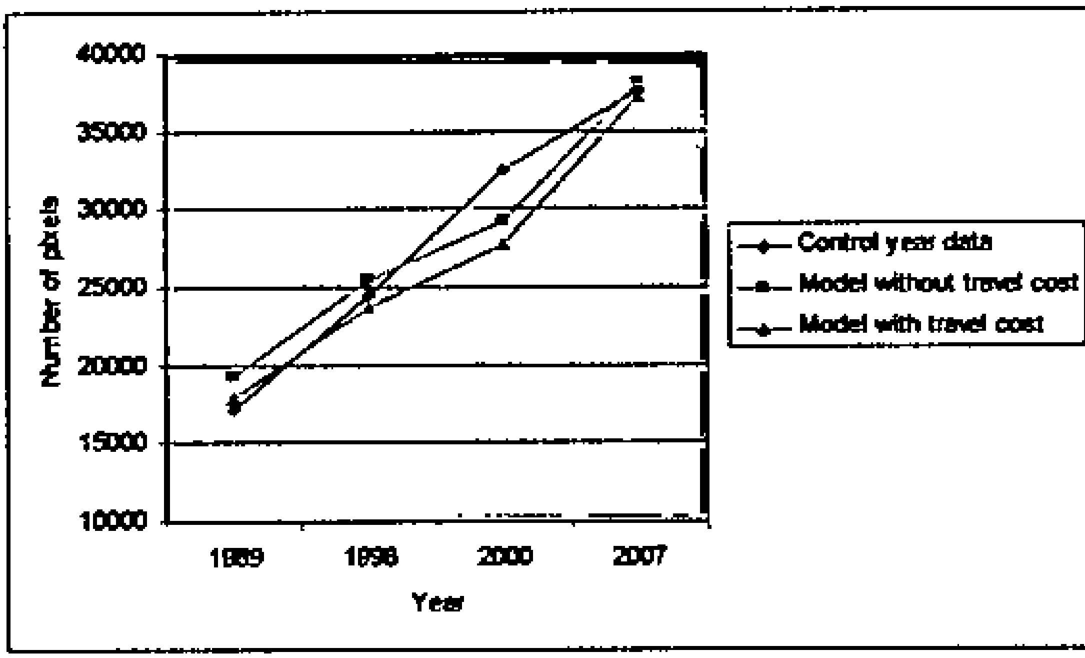


Figure 6.3: Comparison of number of urban pixels

In case of comparison of the urban edges of the modeled growth with the control year data, model with travel cost give better result then model without travel cost. But in this case also the difference is not that significant. It was found that for urban edges r^2 value for the model without travel cost was 0.94 and for model with travel cost it was 0.95. Figure 6.4 shows the modeled number of urban edges and number of urban edges in the control years.

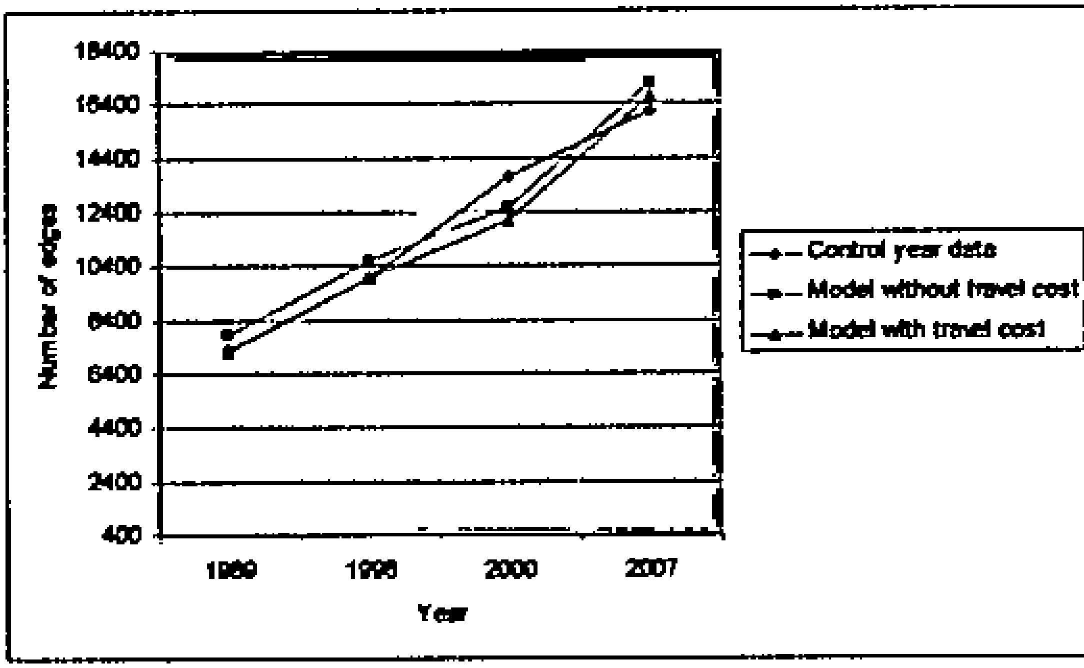


Figure 6.4: Comparison of number of urban edges

In case of modeling the urban clusters, the model with travel cost gives better result than the model without travel cost. Figure 6.5 proves it where the modeled numbers of urban clusters are plotted with the number of urban clusters for the control years. It shows that the model without travel cost simulated significantly high number of urban clusters than the control year data, whereas the model with travel cost was better capable to simulate the urban clusters with small deviations from the control years. In this case, the r^2 value for the model without travel cost was found to be 0.96 and that of the model with travel cost was found 0.97. Although in terms of r^2 difference between the two model frameworks is not that significant, from Figure 6.5 we can see that the model with travel cost has much better capability to simulate the urban clusters than the model without travel cost.

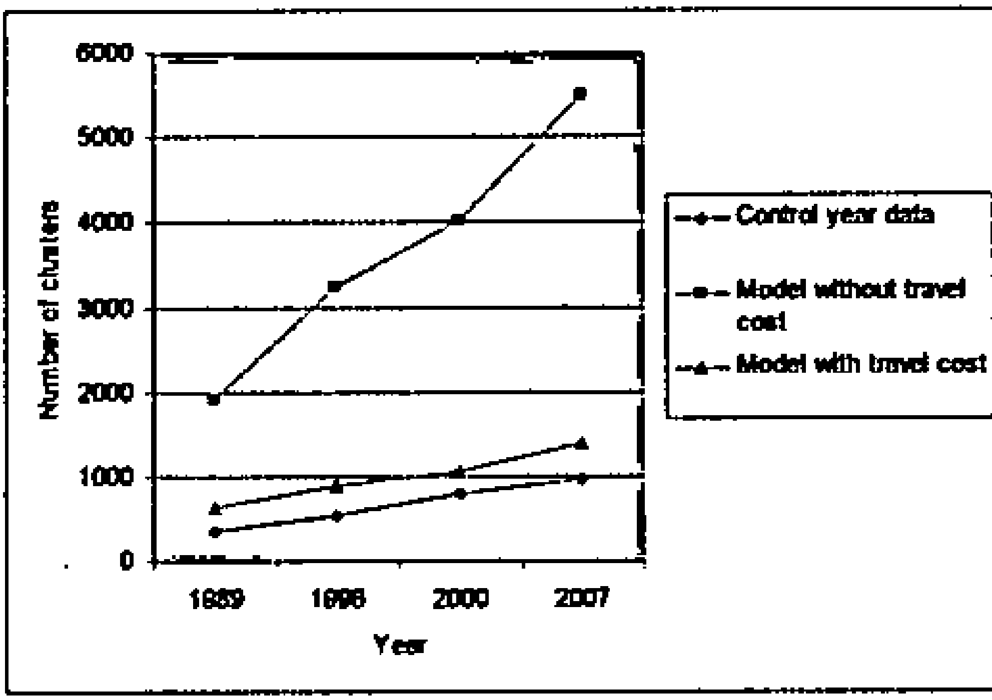


Figure 6.5: Comparison of number of urban clusters

OSM values are utilized in this study to measure the goodness of fit of the coefficient values. Here it is also used to evaluate the performance of the two model frameworks. Figure 6.6 plotted the highest OSM values for the three calibrations stages (i.e. coarse, fine and final) of the two modeling frameworks. It shows that the model with travel cost provide better result throughout the calibration process than that of the model without travel cost.

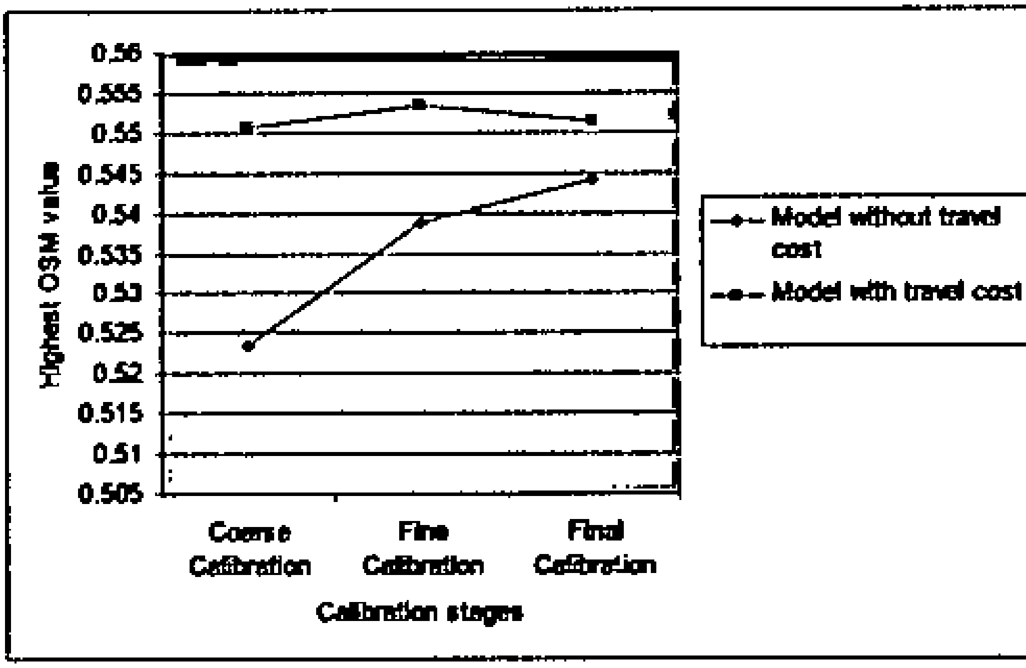


Figure 6.6: Highest OSM values for three calibration stages

6.5 Conclusion

This chapter describes the calibration results of SLEUTH urban growth model for Dhaka Metropolitan Area for two model frameworks (with travel cost and without travel cost). It shows how the brute force Monte Carlo fashion of calibration gradually reduces the parameter space and can effectively select the best-fit coefficient values. Through the calibration process the best-fit coefficients required for growth forecasting are derived. Through the evaluation of the calibration results of the two modeling frameworks, it was found that the model with travel cost performed better to simulate the historical growth of DMA than the model without travel cost. So, the forecasting coefficients derived through the calibration of the model with travel cost were used for predicting the future urbanization process of the study area. Chapter 7 discusses the prediction of the model.

Chapter 7: Scenario Development and Urban Growth Prediction

7.1 Introduction

Best fit coefficients derived through the calibration process were applied for predicting future growth scenario of the study area. It is done through the prediction mode of the SLEUTH model. The `scenario.log` file was updated for this purpose where the calibrated forecasting coefficients were mentioned in the `PREDICTION_*_BEST_FIT` flag (where * indicate the name of the coefficient). 110 `MONTE_CARLO_ITERATIONS` were used for the prediction runs for getting the optimum result which was also indicated in the `scenario.log` file. This study used a prediction time duration from the year 2008 to 2030. At first the original input images were used for the prediction run to find out the growth if the present trend of development continues in the prediction time period. This prediction was conducted for both the model with travel cost and model without travel cost. After adding the travel cost layer, some future scenarios were developed based on the Dhaka Metropolitan Development Plan (DMDP) and the Strategic Transport Plan (STP) of Dhaka. These scenarios are:

1. Improved road network scenario
2. Moderate environment protection scenario
3. Strict environment protection scenario
4. Agricultural land protection scenario
5. Growth considering roads and all protections

For all of the scenarios, the updated model was given a prediction run and the growth pattern for all of these scenarios were predicted. Development probability map for all of the scenarios were also produced through the prediction run. This chapter provides brief discussions on the model prediction process and different development scenarios along with the development probability maps.

7.2 Urban Growth Prediction

After updating the `scenario.log` file a prediction run was given to the original input images of the model to find out the growth pattern of the study area if present trend of development continues within the prediction period (2008-2030). Figure 7.1

shows the cumulative development probability map of 2030 of Dhaka Metropolitan Area as found through the prediction run of the model without travel cost. It shows that in this period Dhaka will experience high diffusion growth as well as spreading growth of the existing urban areas.

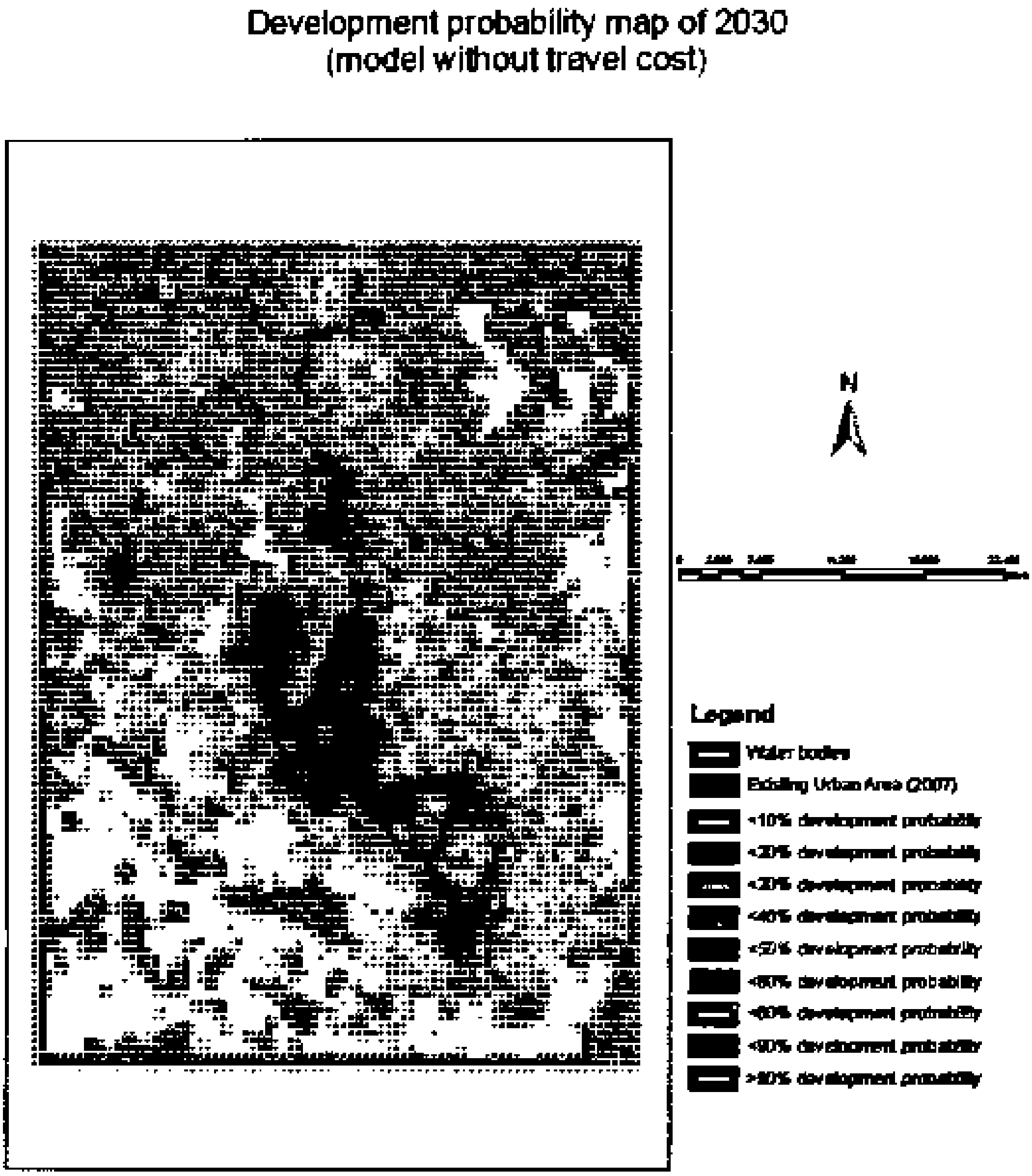


Figure 7.1 Cumulative development probability map of DMA in 2030 (model without travel cost)

Figure 7.2 shows the growth pattern of the study area as found through the prediction run of the model with travel cost. It shows that the study area will experience high infill and edge growth as well as high diffusion growth in the vicinity of existing urban areas.

Development probability map of 2030
(model with travel cost)

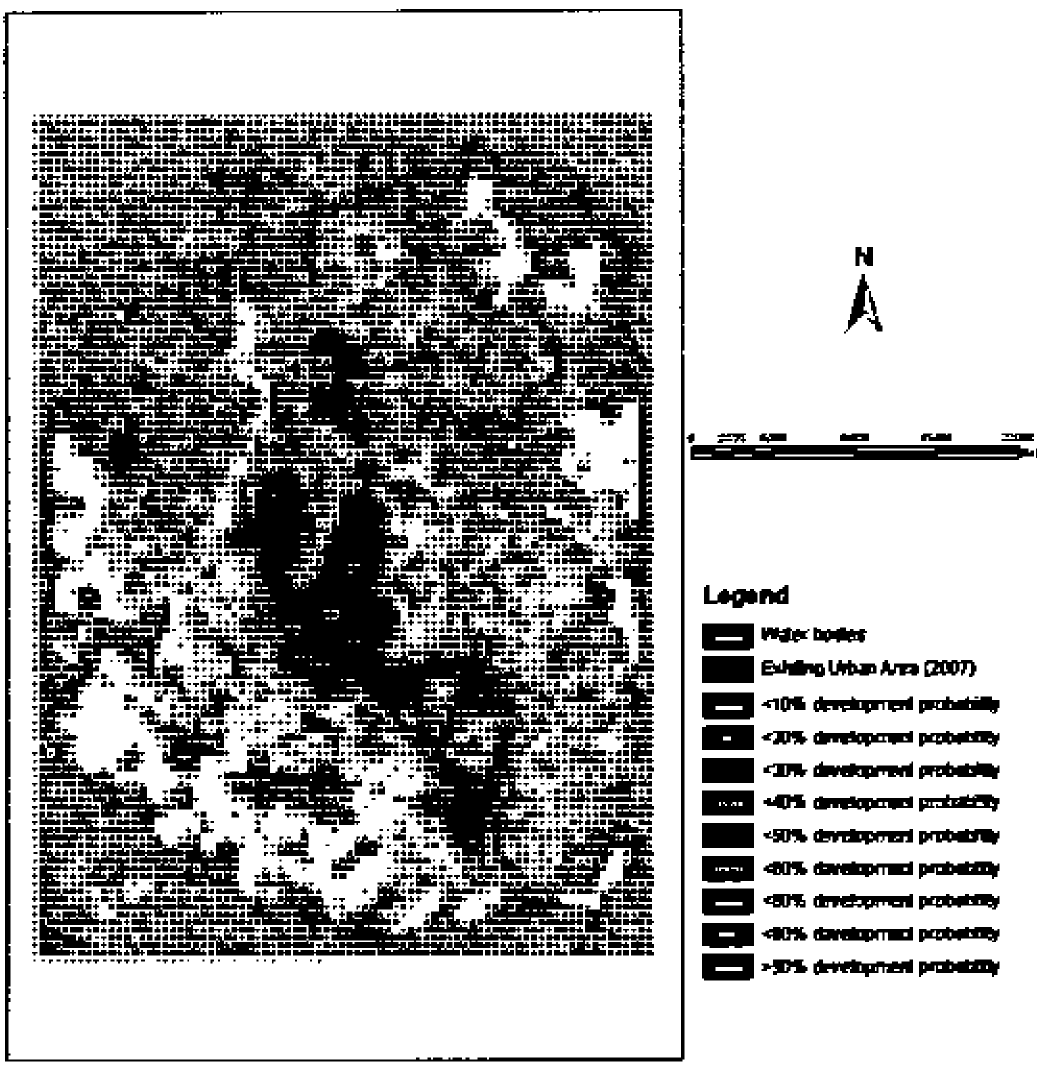


Figure 7.2 Cumulative development probability map of DMA in 2030 (model with travel cost)

Growth pattern predicted by the two modeling frameworks differs from each other significantly. But as it was found in Chapter 6 that the model with travel cost has better capability to simulate the historical growth pattern of DMA, this study utilized this model for further growth predictions for different development scenarios. Figure

7.3 shows the difference of predicted growth of the study area as found through the two modeling frameworks. It can be seen here that the study area experienced a reduced rate of growth through inclusion of the travel cost although it gradually showed about same growth in 2030 for the model without travel cost.

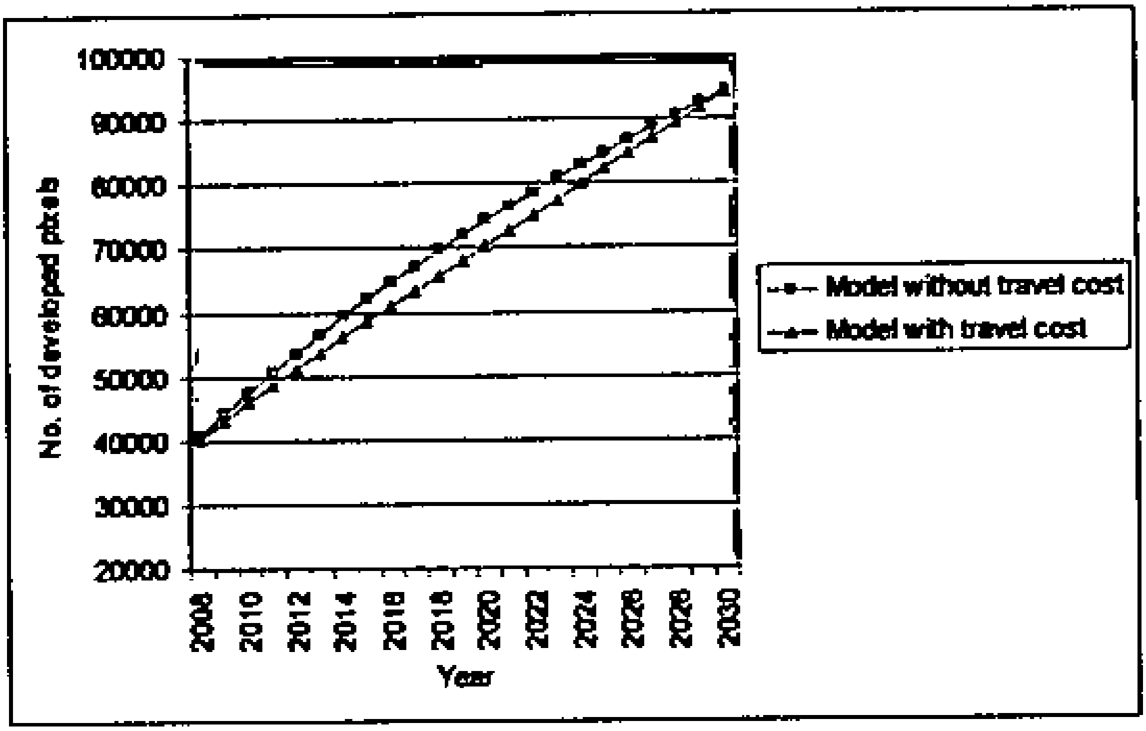


Figure 7.3: Predicted development for the two model frameworks

Growth rate for the model without travel cost has decreased more rapidly than the model with travel cost. Figure 7.4 shows this difference of the growth rates as predicted by the two modeling frameworks.

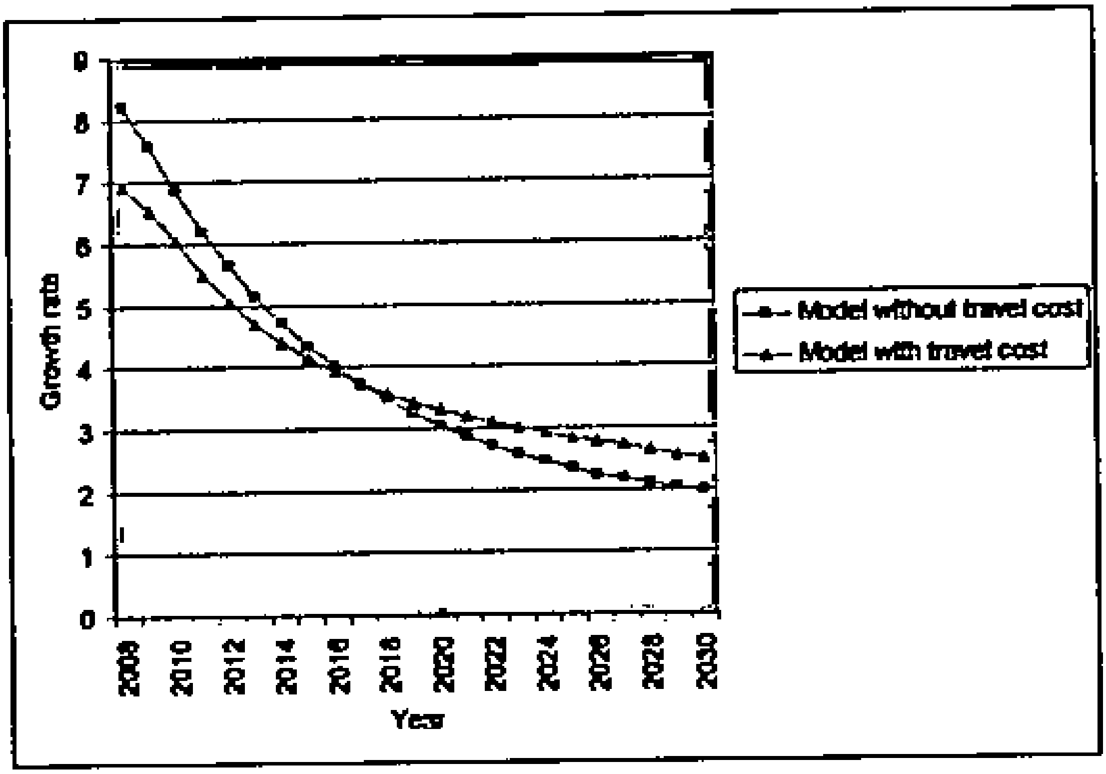


Figure 7.4: Growth rate predicted by the two model frameworks

7.3 Scenario Development and Growth Prediction

After updating the model with the calibrated coefficients, different future development scenarios were developed for the study area based on different planning documents. Following sections provide brief descriptions on the scenarios and the prediction outputs that were generated for those scenarios. It utilized the model with travel cost as this modeling framework was found to be more effective to model the growth pattern of DMA (as discussed in Chapter 6).

7.3.1 Improved Road Network Scenario

Some new road networks are proposed in the Strategic Transport Plan (STP) of Dhaka. This study has considered four major roads from this plan. These are Eastern Bypass, Eastern embankment-cum-road, Road parallel to the Pragati Sarani and eastern embankment-cum-road and Road connecting Purbachal New Town. Figure 7.5 shows the new road network after inclusion of the new roads to the existing network. Although detail alignments of these roads are yet to be determined, this study has taken these from the STP document. Exact completion date of the roads are also not yet determined, so this study assumed these roads to be introduced in 2010.

Figure 7.5 Road network in 2010

Figure 7.6 shows the predicted urban growth probability map after introduction of new roads in 2010. It shows that the study area experienced an increased urban growth through introduction of the roads.

Development probability map of 2030
(Improved road network scenario)

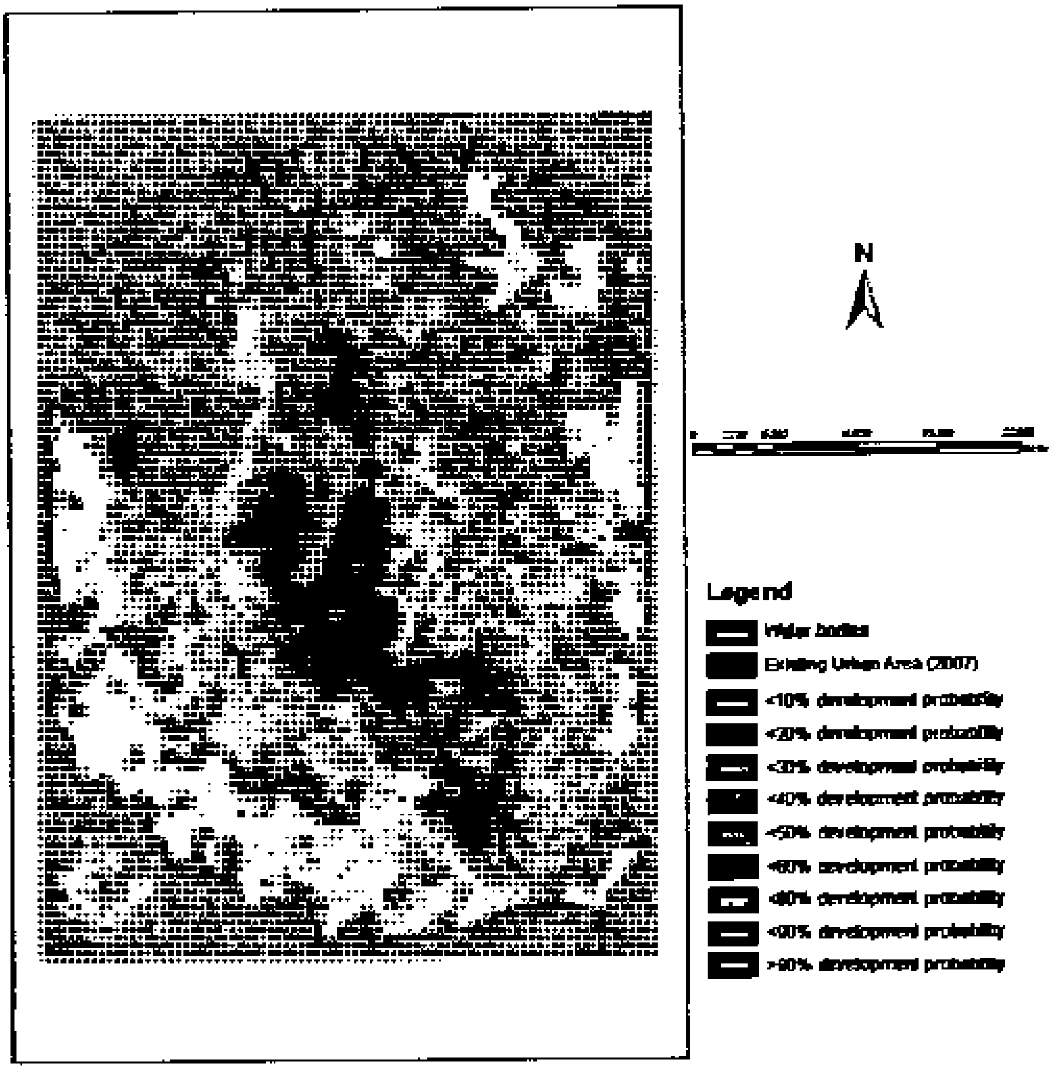


Figure 7.6: Development probability map of 2030 after introduction of new roads

Figure 7.7 shows the growth trend of the study area after introduction of new roads. It can be found here that the area experienced an accelerated growth after introduction of the new roads.

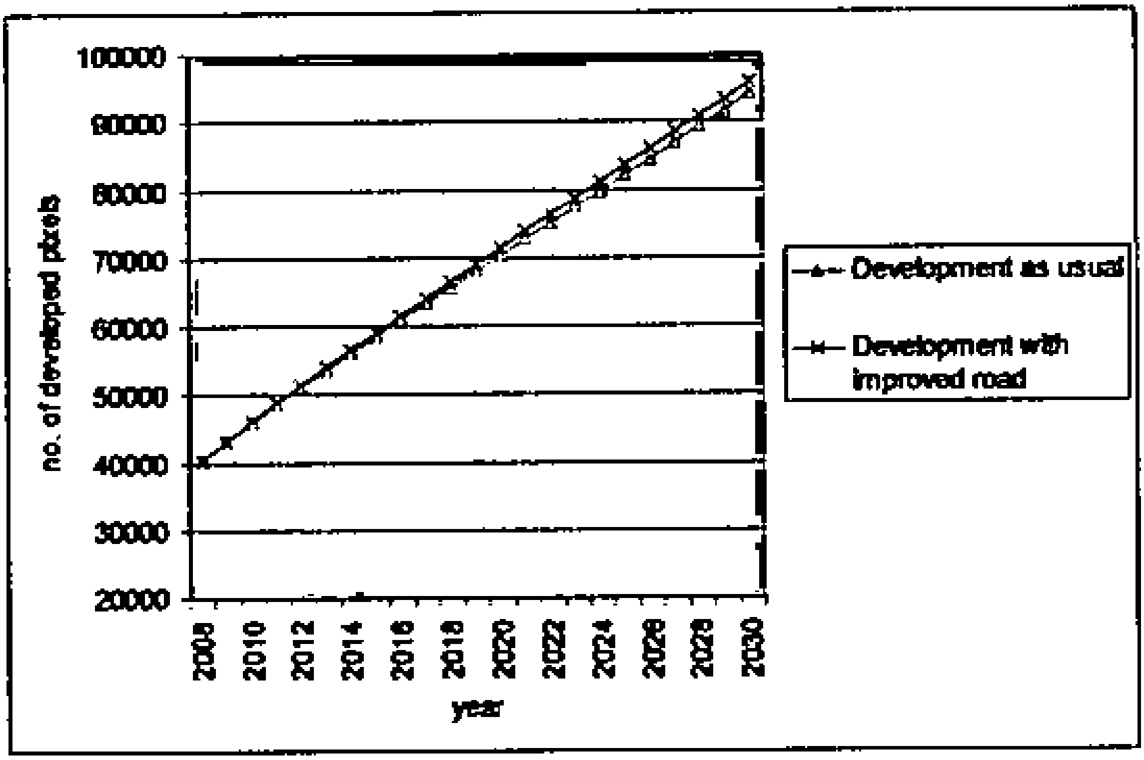


Figure 7.7: Growth trend of the study area after introduction of new roads

Spatial difference map was produced to identify the locations which experienced accelerated growth of urbanization through introduction of the new roads. Figure 7.8 shows this spatial difference map which indicates that the new roads have influenced the growth of the areas along their alignments.

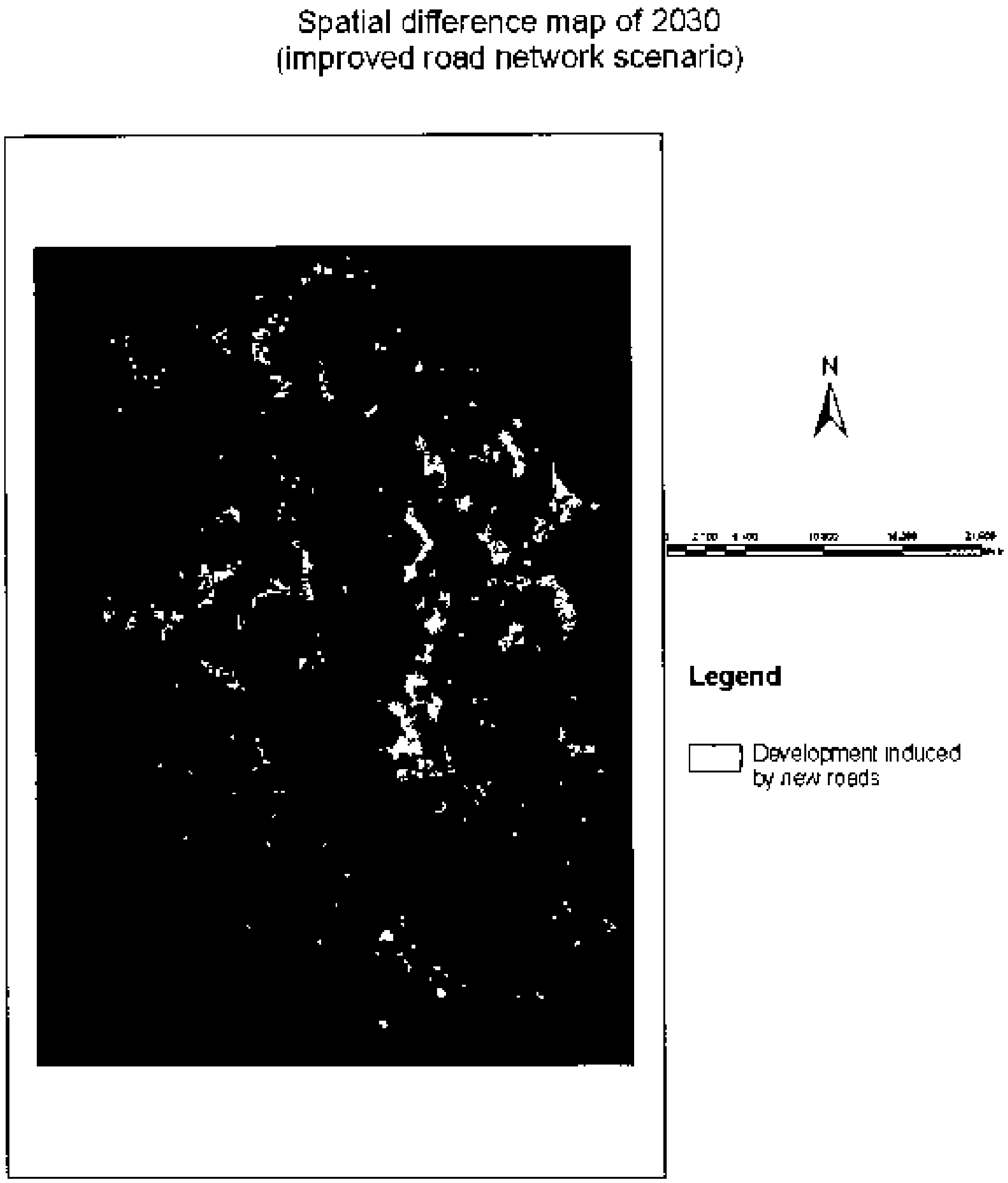


Figure 7.8 Spatial difference map of development for introduction of new roads

7.3.2 Moderate Environmental Protection Scenario

Dhaka Metropolitan Development Plan (DMDP) proposed some flood retention ponds and flood flow zones in different locations of the study area. In this scenario it was assumed that these environmental protection measures will be moderately imposed in the prediction time period. Although these zones are yet to be precisely demarcated through Detail Area Plan (DAP), this study identified these zones from the DMDP documents. In this moderate protection scenario, these protection zones were given 50% exclusion in the exclusion layer (i.e. 50% less development probability). Figure 7.9 shows the exclusion layer after imposing 50% exclusion to the environmental protection zones.

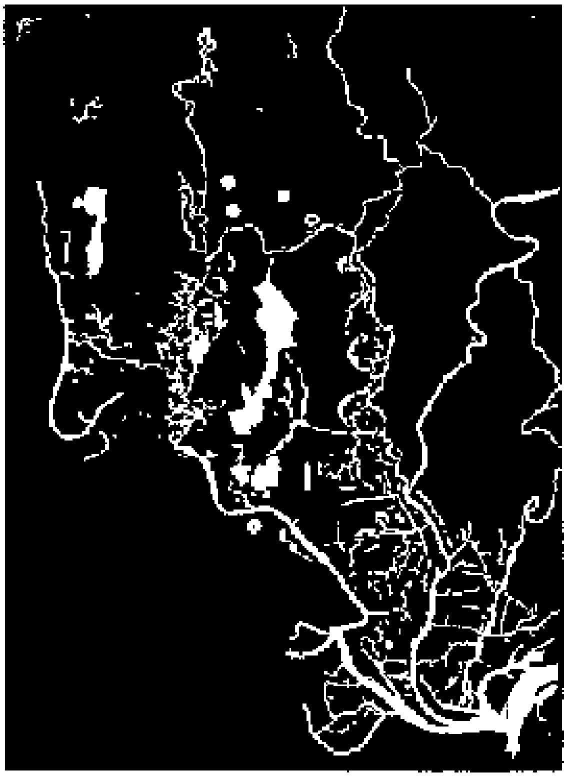


Figure 7.9: Updated exclusion layer after imposing moderate environmental protections

Figure 7.10 shows the development probability map after imposing moderate environmental protections to the study area. It shows less development in the locations of the flood retention ponds and the flood flow zones.

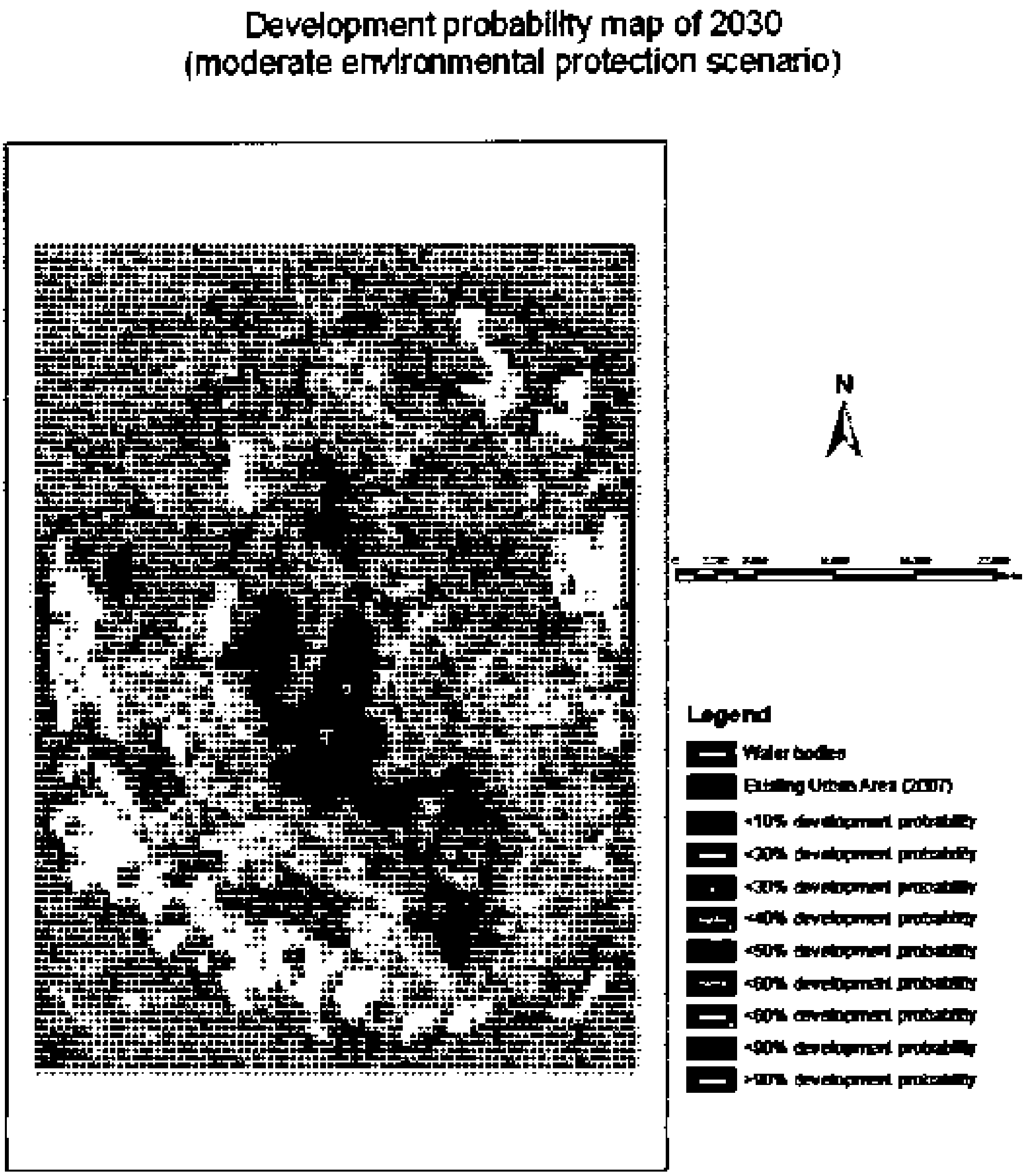


Figure 7.10: Development probability map after imposing moderate environmental protection.

7.3.3 Strict Environmental Protection Scenario

In this scenario strict protection to the flood retention ponds and flood flow zones was assumed. In this case, these areas were given 100% exclusion from development probability (i.e. full exclusion from further development). Figure 7.11 shows the exclusion layer with full exclusion to the locations of the environmental protection zones.

Figure 7.11 Exclusion layer for strict environmental protection scenario

Through strict environmental protection, the study area experienced significantly reduced growth for the prediction period. Figure 7.12 shows the development probability of the area in 2030 after imposing strict environmental protection.

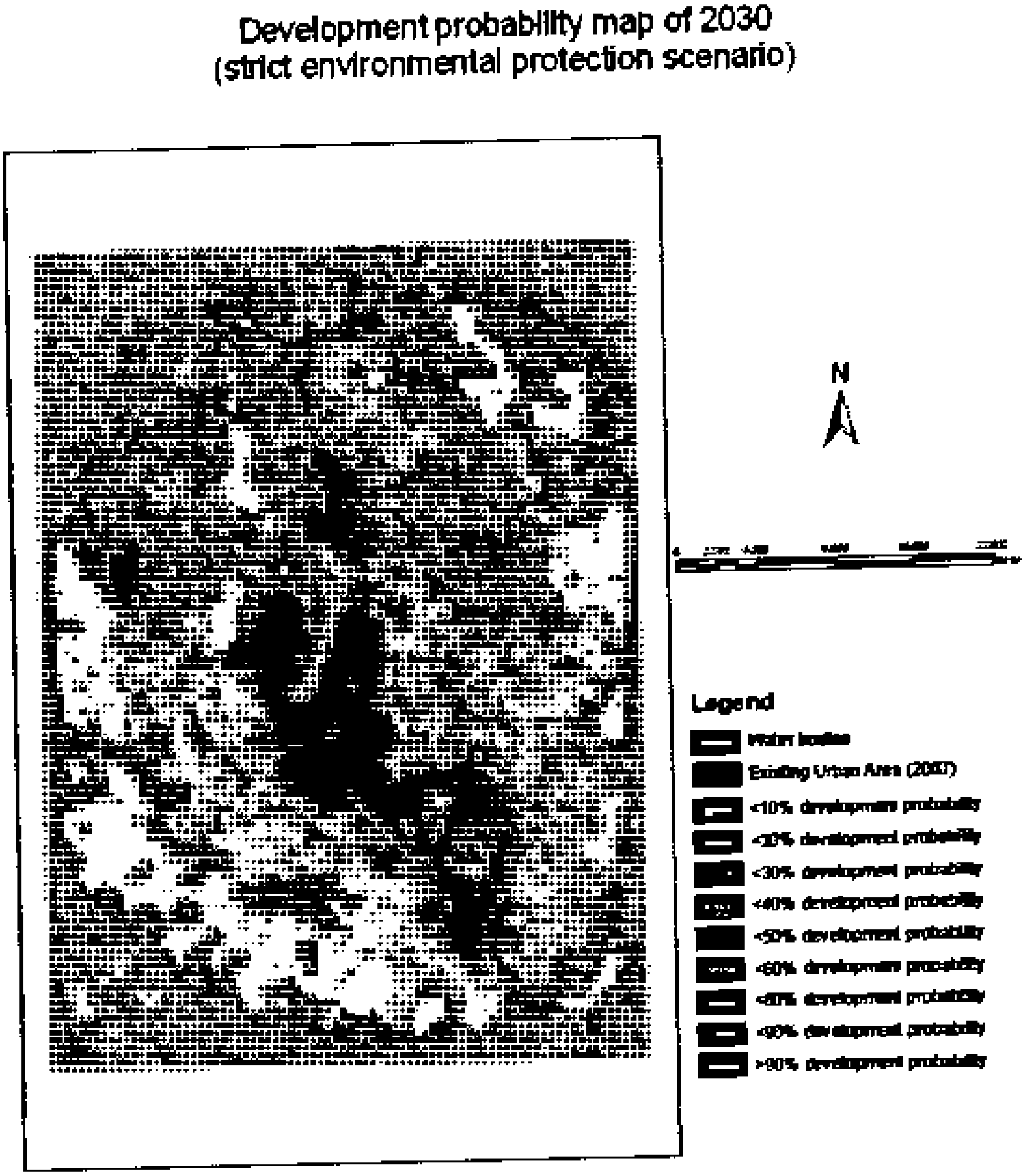


Figure 7.12: Development probability map after imposing strict environmental protection.

Through imposition of environmental protections, the study area experienced a decelerated growth rate throughout the prediction period. Figure 7.13 shows the reduced trend of development after imposing environmental protections in the area.

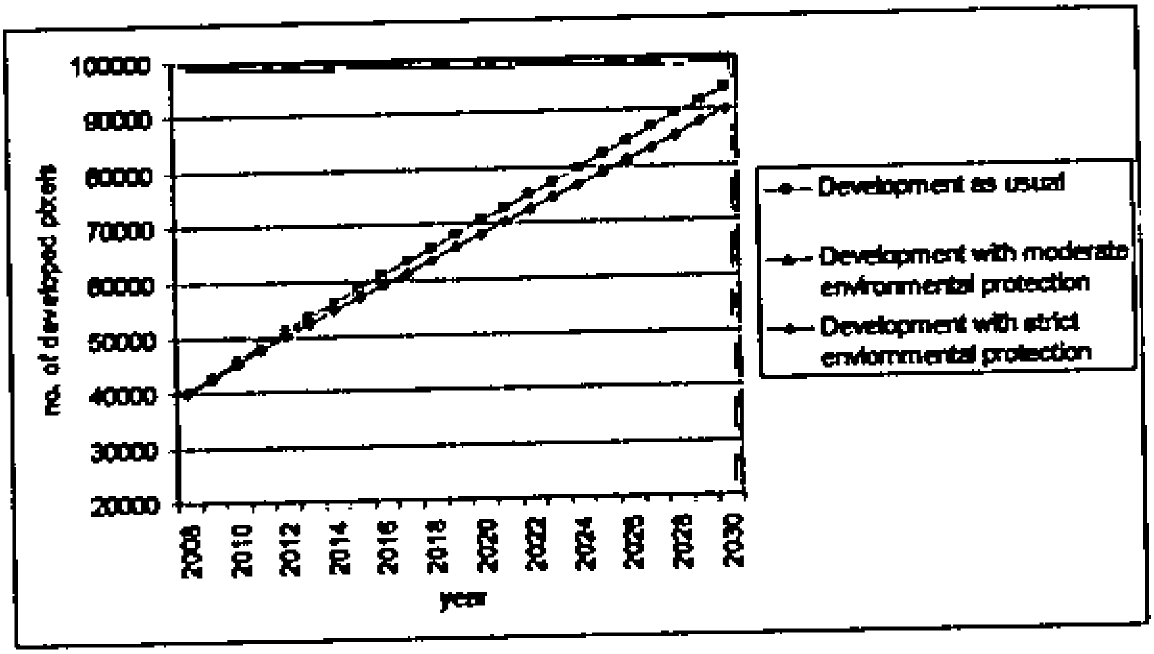


Figure 7.13: Growth rate after imposing environmental protections

Spatial difference map for the strict environmental protections is shown in Figure 7.14. It shows the locations of the study area that will experience retarded development due to the imposition of the environmental restrictions.

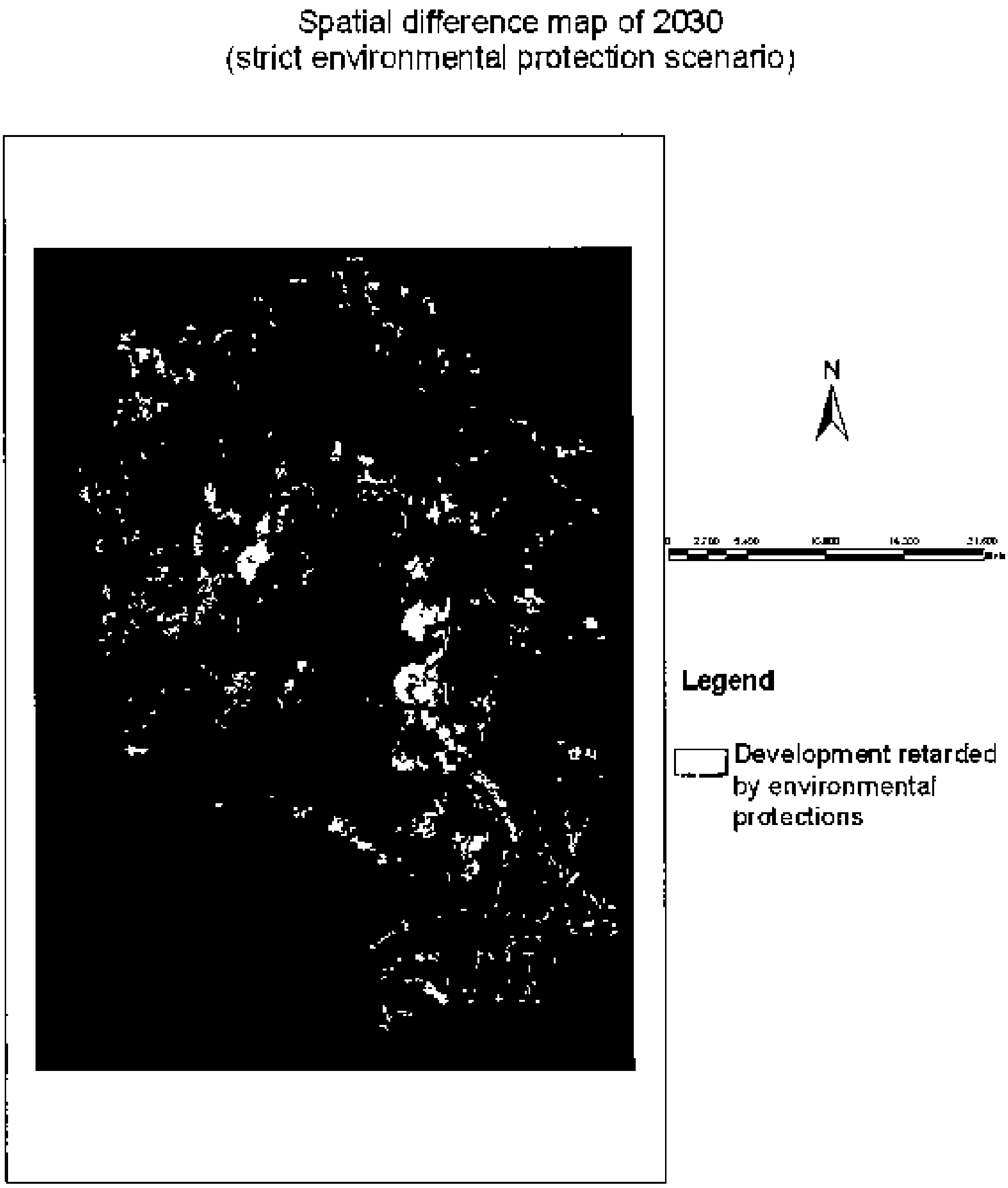


Figure 7.14: Spatial difference map for environmental protection scenario

7.3.4 Agricultural Land Protection Scenario

Dhaka Metropolitan Development Plan (DMDP) proposed some agricultural lands in different locations of the study area. This scenario considers these agricultural lands as reduced development probability there. Although these areas are yet to be detailed out through Detail Area Plan (DAP), this study outlined the agricultural lands from the DMDP documents. In this case, the agricultural lands were given 70%

development probability (or 30% exclusion from development). The exclusion layer was updated with the agricultural lands (Figure 7.15) for this purpose.

Figure 7.15: Exclusion layer for the agricultural land protection scenario.

Through imposing restrictions on the agricultural lands the study area experienced significantly reduced growth in the prediction period. Figure 7.16 shows the development probability of the study area after imposing restriction on the agricultural lands.

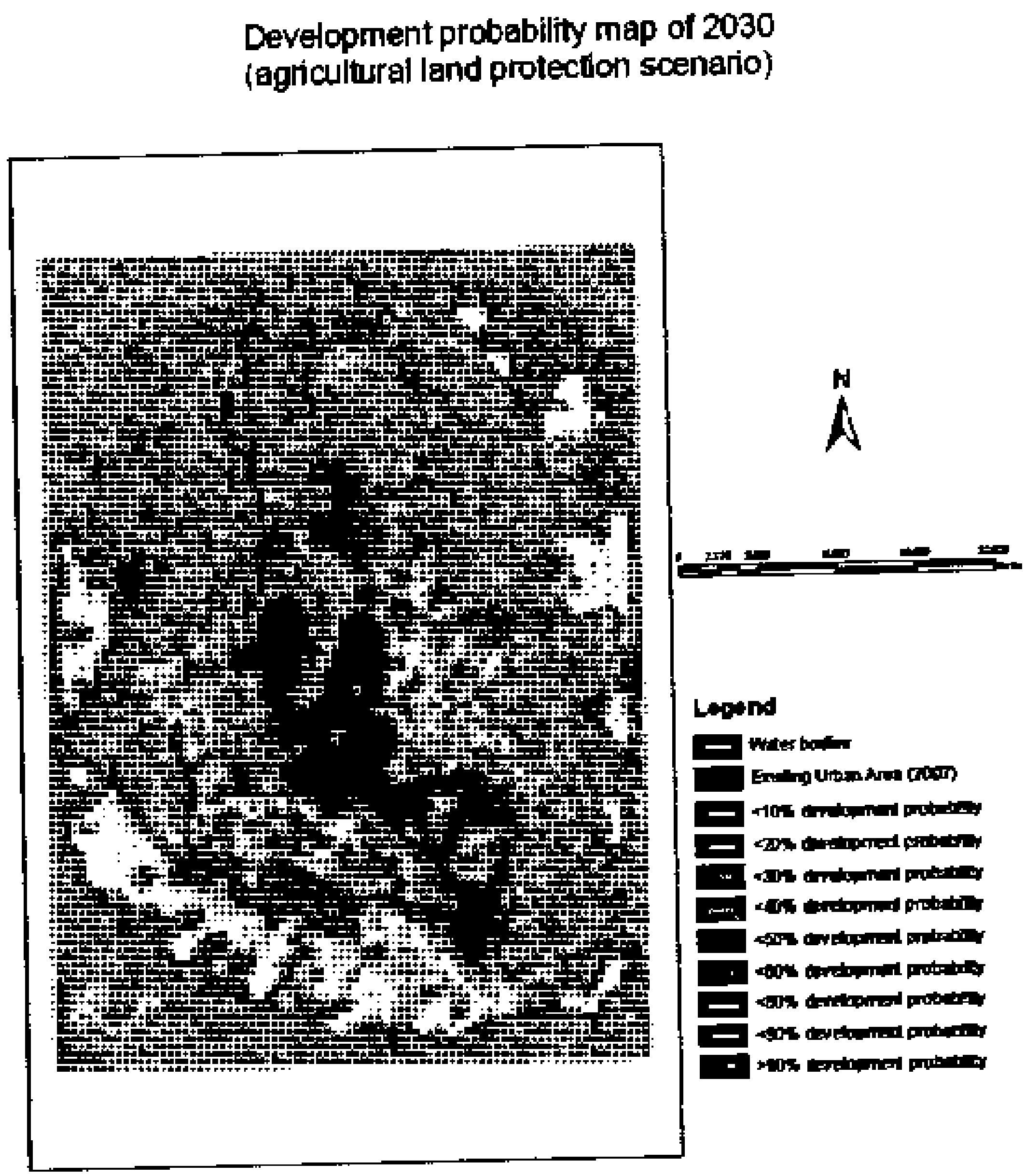


Figure 7.16: Development probability map of 2030 after imposing restriction on agricultural lands

The study area experienced reduced growth rate through imposition of restriction on agricultural land also. Figure 7.17 shows this reduced trend throughout the prediction period.

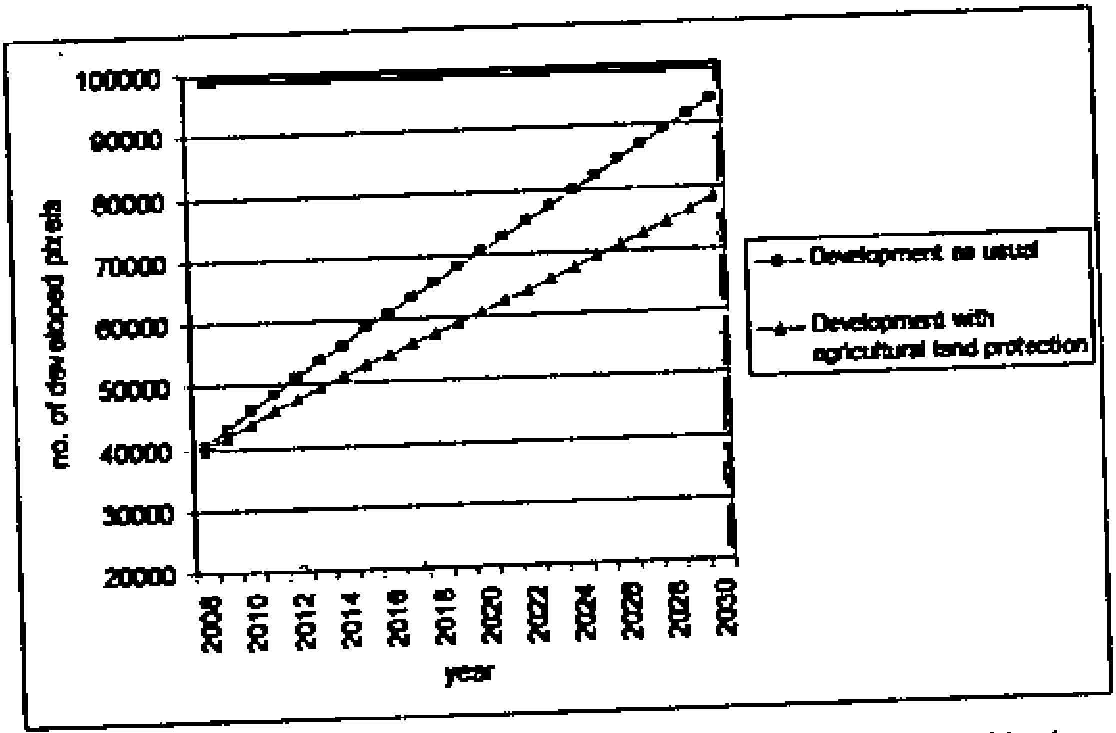


Figure 7.17 Development trend after imposing restriction on agricultural lands

Spatial difference map for the agricultural land protection scenario is shown in figure 7.18. It shows the locations throughout the study area that will experience retarded development due to the imposition of protections on the agricultural lands. This spatial difference is with respect to the development as usual.

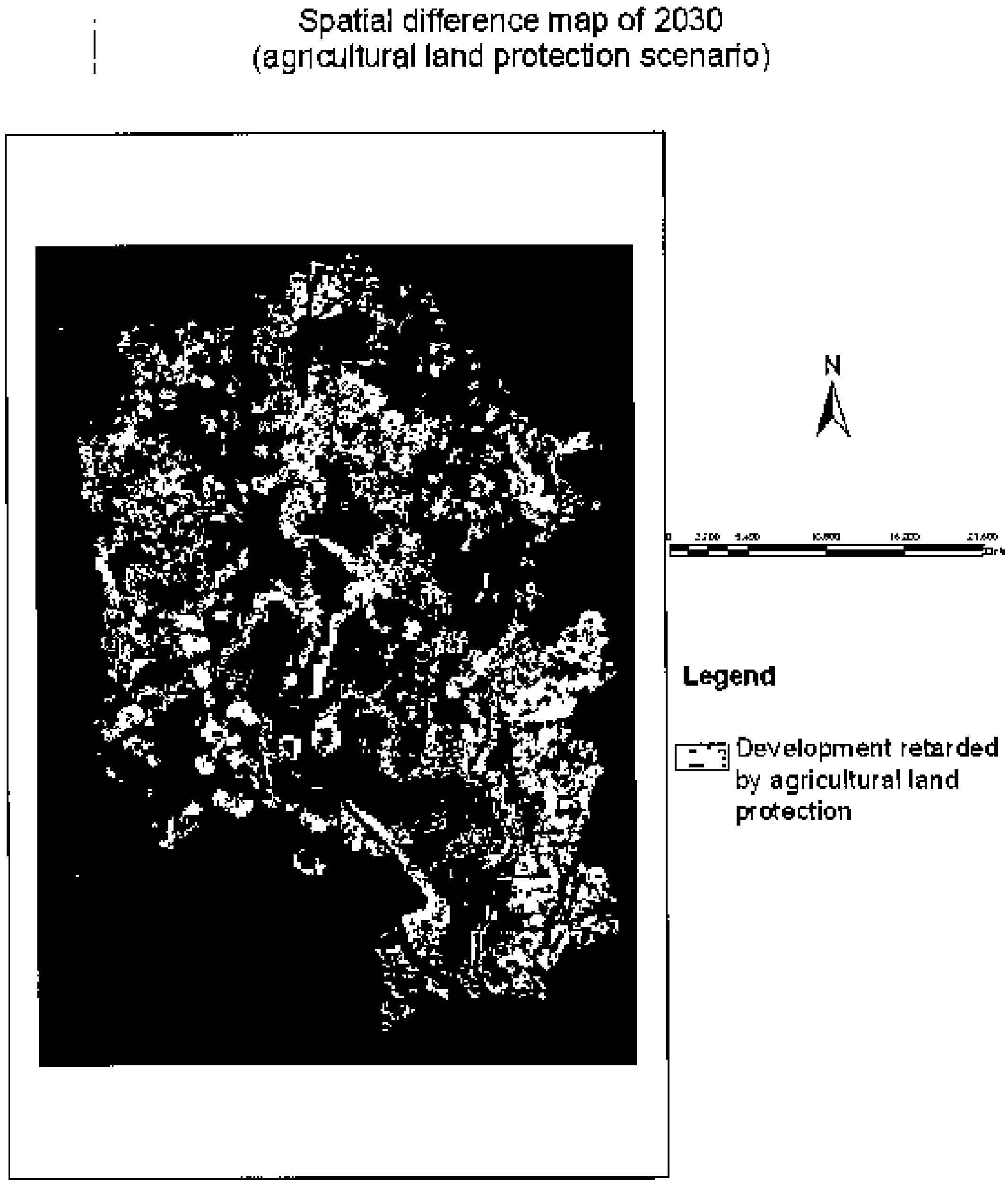


Figure 7.18: Spatial difference map for agricultural land protection scenario

7.3.5 Growth Considering Roads and all Protections

In this scenario all the development protections were considered with introduction of the new roads. In this case, the flood retention ponds and main flood flow zones were given full exclusion from development and the agricultural lands were given 30% exclusion from development. Figure 7.19 shows the development probability of the study area in 2030 after imposing all the protections and introduction of the new roads.

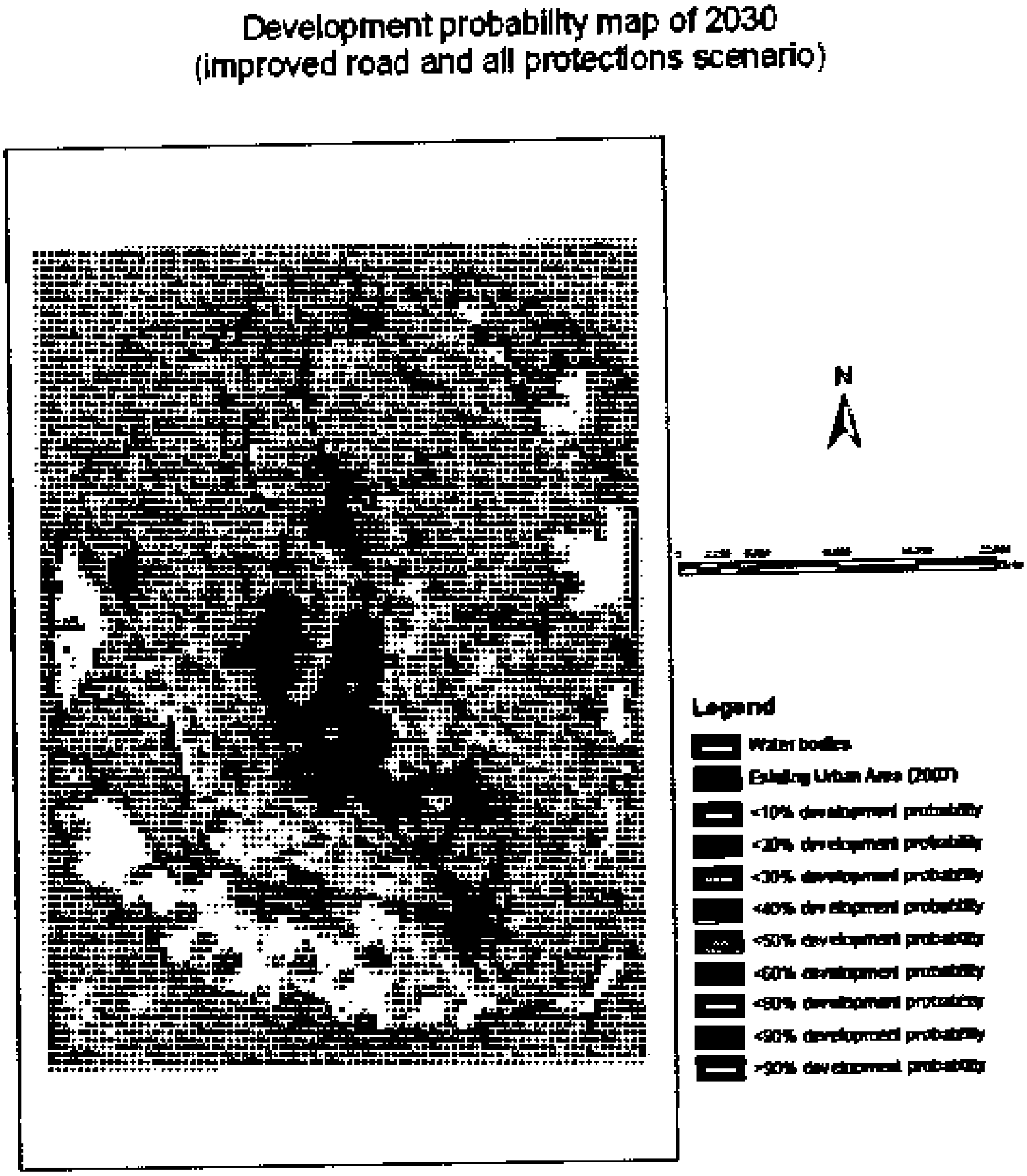


Figure 7.19: Development probability map of 2030 after introducing new roads and imposing all restrictions

Through imposition of all restrictions, the study area experienced significantly reduced rate of growth. Figure 7.20 shows this decreased rate of growth in comparison to the growth as usual.

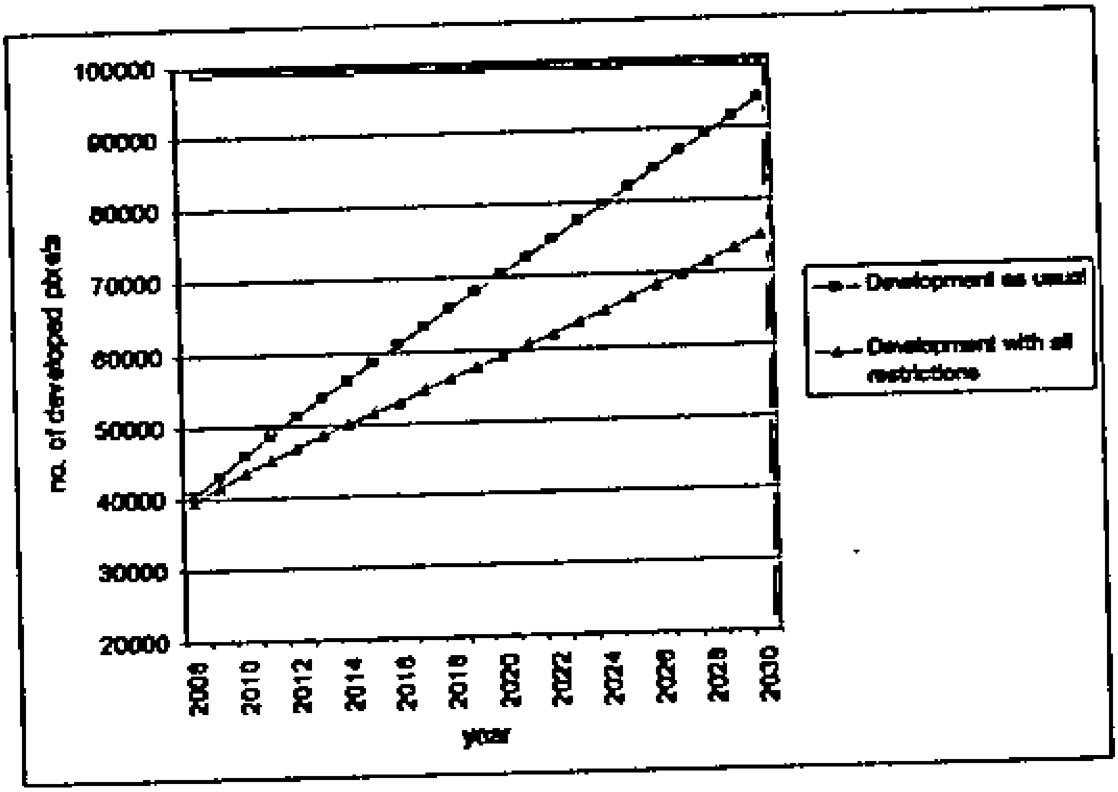


Figure 7.20: Growth trend after imposing all restrictions and new roads

Figure 7.21 shows the spatial difference map for this scenario. It indicates the changes of development due to introduction of new roads and imposition of different development protections. This spatial difference is with respect to the development as usual scenario of the study area.

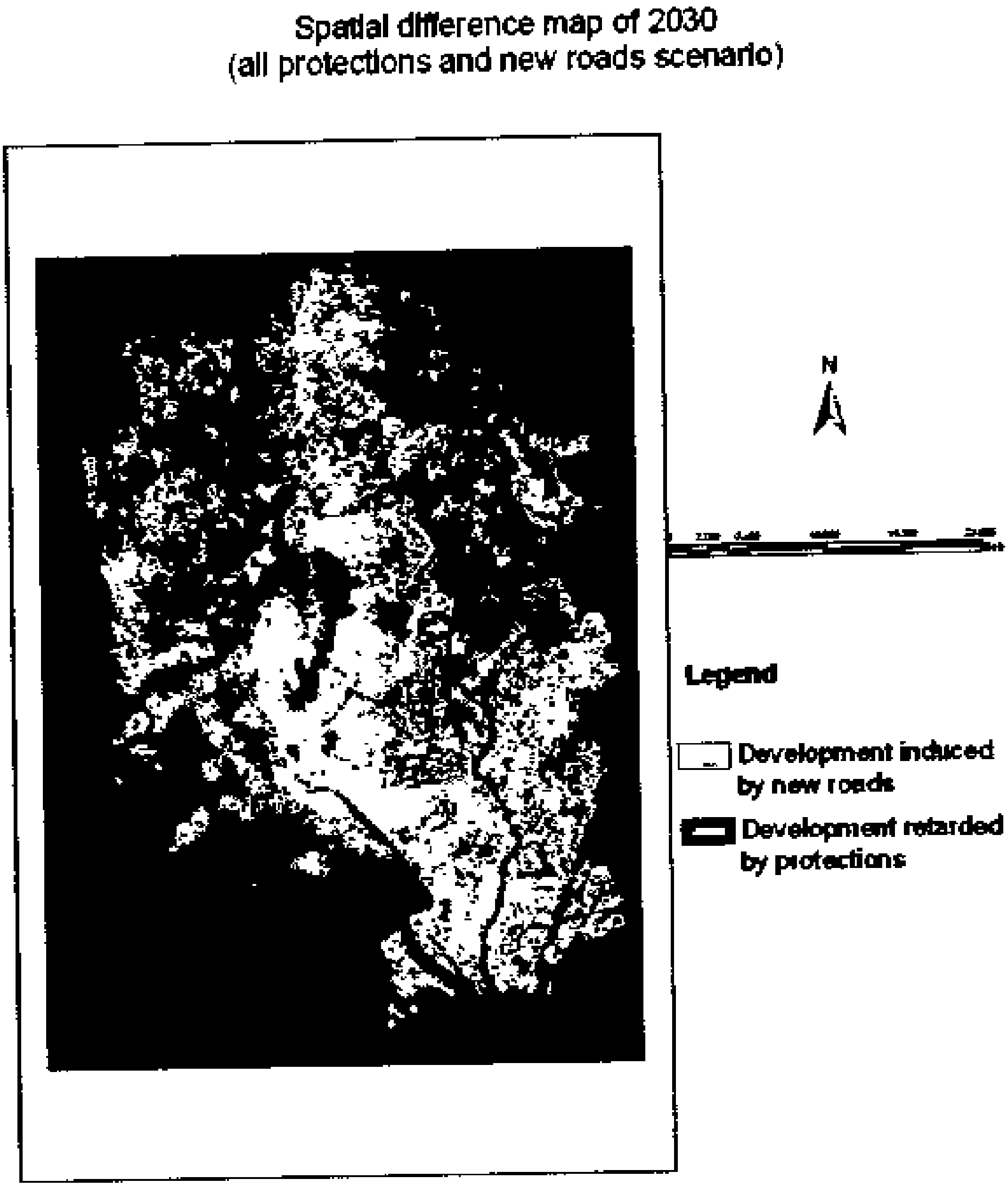


Figure 7.21: Spatial difference map for improved road and all protections

7.5 Conclusion

Development predictions for different policy scenarios in Dhaka Metropolitan Area are presented in this chapter. Here the prediction time period is considered from 2008 to 2030. Implication of travel cost on the development probability is also introduced here for existing urban centers. Through the model prediction run it was found that the study area will experience an accelerated growth through the introduction of the new roads. It was also revealed here that through imposing restriction on environmental protection zones and agricultural lands, the study area will experience significantly reduced rate of growth. Through spatial difference maps specific locations influenced by these development policies can be identified and can be utilized for effective implementation of these policies.

Chapter 8: Conclusions

8.1 CA for Urban Growth Modeling

Cellular automata (CA) models have been applied to urban systems with a recent fervor and have used to explore research questions in applications from location to urban morphology (Torrens, 2000b). But most of these researches are conducted in developed countries focusing the specific growth pattern of the developed cities. There are very few researches for simulating the urban growth of the cities in developing countries. This research is the first initiative in Bangladesh and one of the foremost in developing countries to simulate the historical growth pattern of an urban agglomeration. It simulated the growth pattern of Dhaka Metropolitan Area (DMA) in a CA based environment. Because of an ability to simulate the complex behavior of urban systems, CA models represent a possible approach for urban and regional scale modeling (Oguz, 2007). This research explored this possibility of simulating the growth pattern of DMA utilizing a CA modeling approach.

8.2 Simulating Growth Dynamics of DMA

Urbanization is a complex phenomena evolved through the interplay of multifarious social, economic and physical factors. Modeling an urban system considering all of these factors need a highly complex modeling approach. But, CA considers that this complex system is an outcome of simple interaction of different factors at the local level. It tries to simulate the complex urban system using simple transition rules applied at the local context. This study simulated the urban system of DMA utilizing SLEUTH CA urban growth model. It was found that CA applies the same transition rules throughout the space. As a result same growth rate happens throughout the cell space irrespective of their location in relation to the existing urban areas. This study introduced a travel cost approach to the model which assumes that development probability will decrease through space with increased distance (and increased travel difficulty due to topography) from the existing urban centers. It introduced the travel cost as a part of the exclusion layer of the model. Through calibration of the two modeling frameworks (one with travel cost and one without travel cost) it was found that the model with travel cost has better capability to simulate the historical growth pattern of the study area. As a result, it employed the model with travel cost for future growth prediction of the study area for different policy scenarios.

Through observation of the best fit coefficients of the model it was found that the study area is experiencing a high in-fill and edge growth throughout the urban centers. Diffusion growth is also occurring significantly at the vicinity of the urban centers. These diffused settlements have some significant probability to evolve further as urban centers. Existing road networks are also significantly influencing the overall growth process of the study area.

The best fit coefficients were applied for future growth prediction of the study area for the period 2008-2030. Different policy scenarios were developed based on the development plans and policies for the study area (i.e. DMDP and STP). It was found that through introduction of new roads, the study area will experience an accelerated growth throughout the prediction time period. Through imposition of environmental restrictions, the study area will experience decelerated growth in future. Imposition of development restriction on agricultural land also will significantly retard the overall growth of the study area. Imposition of all restriction and introduction of the new roads also shows a reduced growth throughout the prediction time period.

8.3 Recommendations

At present Dhaka Metropolitan Area is experiencing rapid unplanned growth which is threatening the overall sustainability of this region. In absence of the Detail Area Plan (DAP), the policies prescribed in the structure plan of DMDP are yet to be employed effectively. This study has showed the impacts of some of these policies on the overall growth pattern of this urban region. From the spatial difference maps it was found that the new road induced growths would propagate into the environmental protection areas (i.e flood retention ponds and flood flow zones). It indicates that if the new roads are introduced without proper development restrictions in those areas, then there will be a high rate of environmental degradation there (through filling of wetlands and blocking natural water channels). So it is recommended here that, before introduction of the new roads there should be proper demarcation of these environmental protection zones and strict restrictions should be imposed there as per the directives of the DMDP.

8.4 Conclusion

Any modeling exercise depends highly on the data availability and accuracy. In developing countries it is very hard to achieve both of these at a satisfactory level. Despite this constraint this study tried to simulate the urban growth pattern of DMA in a CA modeling environment. It was found that this approach was very effective to simulate the growth pattern of the study area. But more research should be done on this issue further to make it more robust and to employ it as an effective tool for the planning decision making of the study area. Incorporation of slope data acquired from DEM with better resolution and inclusion of more historical urban extent data would increase its efficiency. This study dealt only with the urban growth dynamics of the study area; land use change modeling was not explored here due to lack of adequate data. Effectiveness of this model would increase significantly if the land use change modeling component of SLEUTH can also be calibrated for the study area. This study also showed that through the simulation exercise the sustainability of any urban development plan or policy can be analyzed. If the planning authorities can be equipped with this kind of model, then it can highly contribute towards sustainable spatial development both at local and regional level.

References:

Acevedo, W., and Masuoka, P. (1997) Time-series animation techniques for visualizing urban growth. *Computers and Geosciences*, 23:423-435.

Aerts, J.C.J.H., Clarke, K.C., and Keuper, A.D. (2003) Testing popular visualization techniques for representing model uncertainty. *Cartography and Geographic Information Science*, 30:249-261.

Ahmed S.U. (1986) *Dhaka – A Study in Urban History and Development*, London, 1986, P - 14.

Alberti, M., & Waddell, P. (2000) An integrated urban development and ecological simulation model. *Integrated Assessment*, 1(3), 215–227.

Albin, P. S. (1975) *The analysis of complex socio-economic systems*. Lexington, MA: D. C. Heath.

Almeida, C. M., Batty, M., Monteiro, A. M. V., Camara, G., Soares-Filho, B. S., Cerqueira G. C. and Pennachin C. L., (2003) Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. *Computers, Environment and Urban Systems*, 27 (2003), 481–509

Alonso, W., (1964) *Location and Land Use*, Harvard University Press.

Arthur, S. T., (2001) A satellite based scheme for predicting the effects of land cover change on local microclimate and surface hydrology. PhD Dissertation, Department of Meteorology, Pennsylvania State University.

Bashak, P., (2006) Spatio-temporal trends and dimensions of urban growth in Dhaka Metropolitan region. MURP thesis, Department of Urban and Regional Planning, BUET, Dhaka

Batty, M. (1981) Urban Models. In N. Wrigley and R. J. Bennett (Ed.) *Quantitative Geography: a British view.*. London, Routledge.

Batty, M. (1989) Urban modeling and planning: Reflections, retrodictions and prescriptions. In B. Macmillan (Ed.), *Remodeling geography* (pp. 147– 169). Oxford, UK: Basil Blackwell.

Batty, M. (1976) *Urban Modeling: Algorithms, Calibrations, Predictions*. Cambridge: Cambridge University Press

Batty, M. (1994) A chronicle of scientific planning: The Anglo-American modeling experience. *Journal of the American Planning Association*, 60(1), 7 –12.

Batty, M. (2000) Geocomputation using cellular automata. In S. Openshaw, & R. J. Abrahart (Eds.), *Geocomputation* (pp. 95–126). London: Taylor & Francis.

Batty, M., & Howes, D. (2001) Predicting temporal patterns in urban development from remote imagery. In J. P. Donnay, M. J. Barnsley, & P. A. Longley (Eds.), *Remote sensing and urban analysis* (pp. 185–204). London: Taylor and Francis.

Batty, M. and Xie, Y. (1994) From cells to cities. *Environment and Planning B: Planning and Design*, 21: 531-548

BBS, (2001) Bangladesh Population Census Report 2001, Bangladesh Bureau of Statistics (BBS), Dhaka

Bierwagen, B. (2003) The effects of land use change on butterfly dispersal and community ecology. PhD Dissertation, Bren School of Environmental Management and Science, University of California – Santa Barbara.

Briassoulis, H., (2000) *Analysis of Land Use Change: Theoretical and Modeling Approaches*, The Web Book of Regional Science Regional Research Institute, WVU. http://www.rri.wvu.edu/WebBook/Briassoulis/content.htm

Burroughs, P. A. (1981) Fractal dimensions of landscapes and other environmental data. *Nature,* 294: 240-242.

Candau, J. T. (2002) Temporal Calibration Sensitivity of the SLEUTH Urban Growth Model. MA thesis submitted to the University of California, Santa Barbara, USA.

Candau, J (2000a) Calibrating a Cellular Automaton Model of Urban Growth in a Timely Manner, presented at the *4th International Conference on Integrating GIS and Environmental Modeling* (GIS/EM4), Banff, Alberta, Canada.

Candau, J. (2000b) Visualizing modeled land cover change and related uncertainty. *First International Conference on Geographic Information Science*. Savannah, GA.

Candau, J., and Clarke, K.C. (2000) Probabilistic land cover modeling using deltatrons. *Proceedings of the 38th Annual Conference of the Urban Regional Information Systems Association*. Orlando, FL.

Charles Dietzel and Clarke, K. C. (2007) Toward Optimal Calibration of the SLEUTH Land Use Change Model. *Transactions in GIS* , 2007, 11(1): 29–45

Chowdhury A.M. and Faruqui S., (1991). Physical Growth of Dhaka City. In Ahmed S.U. (ed), *Dhaka Past Present Future*. Asiatic Society of Bangladesh, Dhaka.

Claggett, P., Jantz, C.A., Goetz, S.J. and Bisland, C. (2004) Assessing development pressure in the Chesapeake Bay watershed: An evaluation of two land-use change models. *Environmental Monitoring and Assessment* 94:129-146.

Clarke, K. C., Parks, B. O., & Crane, M. P. (2002) *Geographic information systems and environmental modeling*. New Jersey: Prentice Hall.

Clarke, K., Hoppen, S., & Gaydos, L., (1996) Methods and techniques for rigorous calibration of cellular automaton model of urban growth. *Third international conference/workshop on integrating GIS and environmental modeling*. Santa Fe, New Mexico.

Clarke, K., Hoppen, S., & Gaydos, L. (1997) A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design*, 24, 247–261.

Clarke, K.C., and Gaydos, L. (1998) Loose-coupling a cellular automaton model and GIS: Long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographic Information Science* 12:699–714.

Cogan, C.B., Davis, F.W. and Clarke, K.C. (2001) *Application of urban growth models and wildlife habitat models to assess biodiversity losses*. University of California-Santa Barbara Institute for Computational Earth System Science. U.S. department of the Interior, US geological Survey, Biological Resources Division, Gap Analysis Program, Santa Barbara, CA.

Constanza, R. (1989) Model goodness of fit: a multiple resolution procedure. *Ecological Modelling*, 47, 199–215.

Couclelis, H. (1985) Cellular worlds: a framework for modeling micro-macro dynamics. *Environment and Planning A*, 17, 585–596

Dietzel, C.K., and Clarke, K.C. (2004) Spatial differences in multi-resolution urban automata modeling. *Transactions in GIS* 8:479-492.

Gabiax, X. (1999) Zipf's Law ant the Growth of Cities. *The American Economic Review*, 89(2): 129-132.

Goldstein, N. C. (2004) Brains VS Braun—Comparative Strategies for the Calibration of a Cellular Automata-Based Urban Growth Model, in P. Atkinson, G. Foody, S. Darby, and F. Wu (eds), *Geodynamics*, CRC Press, Boca Raton, Florida.

Goldstein, N.C., Candau, J.T., and Clarke, K.C. (2004) Approaches to simulating the "March of Bricks And Mortar". *Computers, Environment and Urban Systems* 28:125-147.

Goldstein, N.C., Candau, J.T., and Moritz, M. (2000) Burning Santa Barbara at both ends: a study of fire history and urban growth predictions. *Proceedings of the 4th International Conference on Integrating GIS and Environmental Modeling (GIS/EM4)*. Banff, Alberta, Canada. Available online at: http://www.colorado.edu/research/cires/banff/pubpapers/60/

Herold, M., Goldstein, N.C., and Clarke, K.C. (2003) The spatio-temporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment* 86:286- 302.

Irwin, E. G., & Geoghegan, J. (2001) Theory, data, methods: Developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment*, 85, 7–23.

Issaev, B., Nijkamp, P., Rietveld, P., and Snickars, F., eds. (1982) *Multiregional Economic Modeling*. Amsterdam: North-Holland.

Jantz, C.A., Goetz, S.J. and Shelley, M.K. (2003) Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore/Washington metropolitan area. *Environment and Planning B* 31:251–271.

Kashem, M.S.B. and Maniruzzaman, K. M. (2008) A Critical Review of Some Selected Urban Land Use Change Models and Evaluating their Transferability to Developing Countries. Paper presented at *10th Pacific Regional Science Conference Organization (PRSCO) Summer Institute*, Dhaka; 15-17 May 2008

Kivell, P. (1993) *Land and the City: Patterns and processes of urban change*. London, Routledge.

Krugman, P. (1996) Confronting the Urban Mystery. *Journal of the Japanese and International Economies*, X: 399-418.

Landis, J.D. (1994) The California Urban Futures Model - a new generation of metropolitan simulation models. *Environment and Planning B* 21:399-420.

Leão, S., Bishop, I. and Evans, D. (2004) Spatial-temporal model for demand allocation of waste landfills in growing urban regions. *Computers Environment and Urban Systems* 28: 353-385.

Lee, D. R., and Sallee, G. T. (1970) A Method of Measuring Shape. *The Geographical Review*, Vol. 60, pp. 555–563.

Lin, Yu-Pin., Lin, Yun-Bin., Wang, Yen-Tan. and Hong, Nien-Ming. (2008) Monitoring and Predicting Land-use Changes and the Hydrology of the Urbanized Paochiao Watershed in Taiwan Using Remote Sensing Data, Urban Growth Models and a Hydrological Model. *Sensors*, Vol. 8, pp. 658-680

Liu, X. H. and Andersson, C. (2004) Assessing the impact of temporal dynamics on land-use change modeling. *Computers, Environment and Urban Systems*, 28, 107–124

Longley, P. A., & Mesev, V. (2000) On the measurement and generalization of urban form. *Environment and Planning* A, 32, 473– 488.

Mayhew, S. (1997) Multiple nuclei model. A Dictionary of Geography, xrefer.com Oxford University Press. 2001.

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

O'Sullivan, D. (2002) Exploring spatial process dynamics using irregular cellular automaton models. *Geographical Analysis*, 33: 1-17.

O'Sullivan, D. Torrens, P. M. (2000) Cellular Models of Urban Systems. Paper appears in Bandini, S. & Worsch, T. (eds) 2001, *Theoretical and Practical Issues on Cellular Automata*, Proceedings of the Fourth International Conference on Cellular Automata for Research and Industry (ACRI 2000), pages 108–116, October 4-6, Karlsruhe, Germany,

Radzicki, M.J. (1995) A system dynamics approach to sustainable cities. *Proceedings of the International System Dynamics Conference*, Tokyo, Japan, 30 July–4 August, 1995. p. 191–210.

Rosen, K and Resnick, M. (1980) The Size Distribution of Cities: An Examination of the Pareto Law and Primacy. *Journal of Urban Economics*, VIII: 165-186.

Sangawongse, S. (2006) Land -Use/Land- Cover Dynamics In Chiang Mai: Appraisal from Remote Sensing, GIS and Modelling Approaches. CMU Journal, Vol. 5(2) 243

Schatten, A., (n.d.) "Cellular Automata Tutorial", available online at: http://cocoon.ifs. tuwien.ac.at/info/ca/ca.html (accessed on 29 April 2008)

Siddiqui, M.Z., Everett, J.W., and Vieux, B.E. (1996) Landfill siting using geographic information systems: A demonstration. *Journal of Urban Planning and Development* 122:515–523.

Silva, E.A., and Clarke, K.C. (2002) Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems* 26:525–552.

Stahl, K. (1986) Theories of Urban Business Location. In *Handbook of Regional and Urban Economics*, Vol. 2, ed. E.S. Mills, 759 -820. Amsterdam: North-Holland

Sudhira, H. S. (2004) Integration of Agent Based and Cellular Automata Models for Simulating Urban Sprawl. MSc. Thesis, International Institute for Geo-information Science and Earth Observation, Enschede, the Netherlands.

Teitz, M. B., Dietzel, C. and Fulton, W. (2005) *Urban Development Futures in the San Joaquin Valley*, published by the Public Policy Institute of California, San Francisco, CA, USA.

Theobald, D. (2001) Land-use dynamics beyond the urban fringe. *Geographical Review* 91:544-564.

Tobler, W. R. (1970) A computer movie simulating population growth in the Detroit region. *Economic Geography*, 42, 234–240.

Tobler, W. R. (1979) Cellular geography. In S. Gale, & G. Olsson (Eds.) *Philosophy in Geography* (pp. 279–386). Dordrecht, The Netherlands: D. Reidel.

Torrens, P. M. (2000a) *How Land-Use-Transportation Models Work*. Centre for Advanced Spatial Analysis. University College London.

Torrens, P. M. (2000b) *How Cellular Models of Urban Systems Work*. Paper-28, Working Paper of Centre for Advanced Spatial Analysis, University College London. Available on-line at: http://www.casa.ucl.ac.uk/working_papers.htm

Webster, C. and Wu, F. (2001) Coarse, spatial pricing and self-organising cities. *Urban Studies* 38: 2037 - 2054

Wegener, M. (1994) Operational urban models: State of the art. *Journal of the American Planning Association*, 60(1), 17– 30.

White, R. and Engelen, G. (1993) Cellular Automata and fractal urban form: a cellular modeling approach to the evolution of urban land-use patterns. *Environment and Planning A*, Volume 25, page 1175-1199.

Wilson, A.G. (1974) *Urban and Regional Models in Geography and Planning*. New York:

Wolfram, S. (2002) *A New Kind of Science*, Published by Wolfram Media, Inc., USA

Wu, F. (1996) A Linguistic Cellular Automata Simulation Approach for Sustainable Land Development in a Fast Growing Region. *Computer, Environment and Urban System*, Vol. 20, No 6, pp. 367-387.

Yang, X., and Lo, C.P. (2003) Modelling urban growth and landscape change in the Atlanta metropolitan area. *International Journal of Geographical Information Science*, 17:463–488.

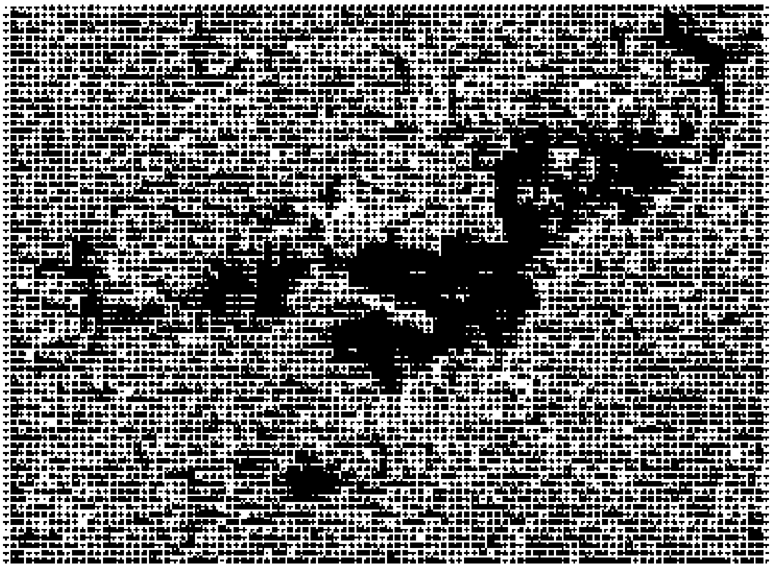
Yeh, A. G., and Li, X. (2001) A constrained CA model for the simulation and planning of sustainable urban forms by using GIS. *Environment and Planning B: Planning and Design* 28 733 - 753

Yeh, A. G. and Li, X. (2002) *Urban simulation using neural networks and cellular automata for land use planning*, Symposium on Geospatial Theory, Processing and Applications, Ottawa.

Zipf, G. (1949) *Human Behavior and the Principle of Least Effort*. Cambridge, MA, Addison-Wesley.

Appendix

Development Probability Maps (Model with travel cost)



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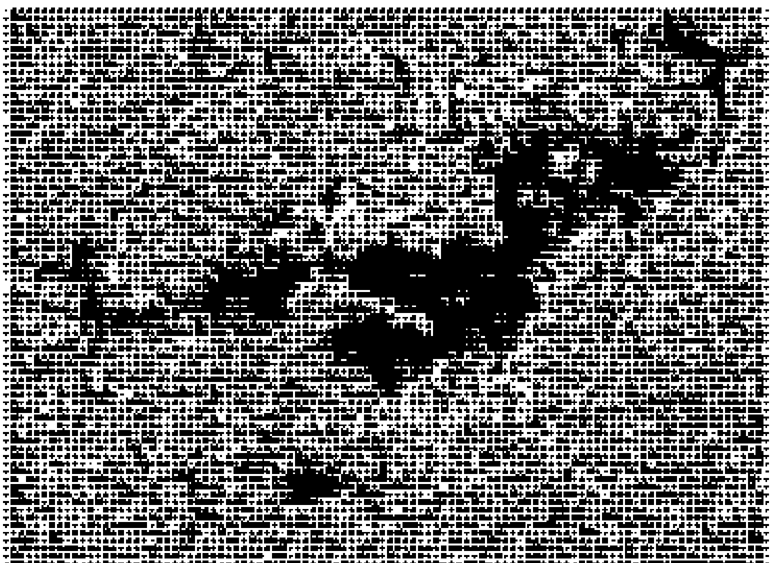

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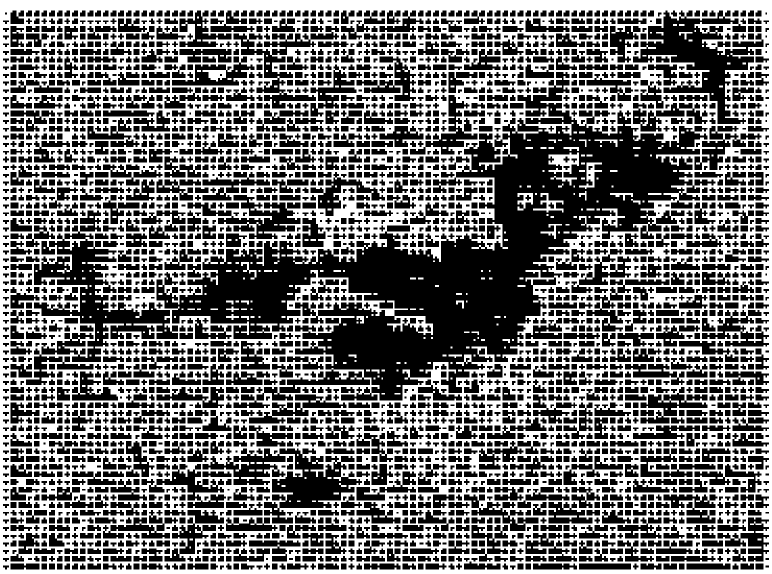

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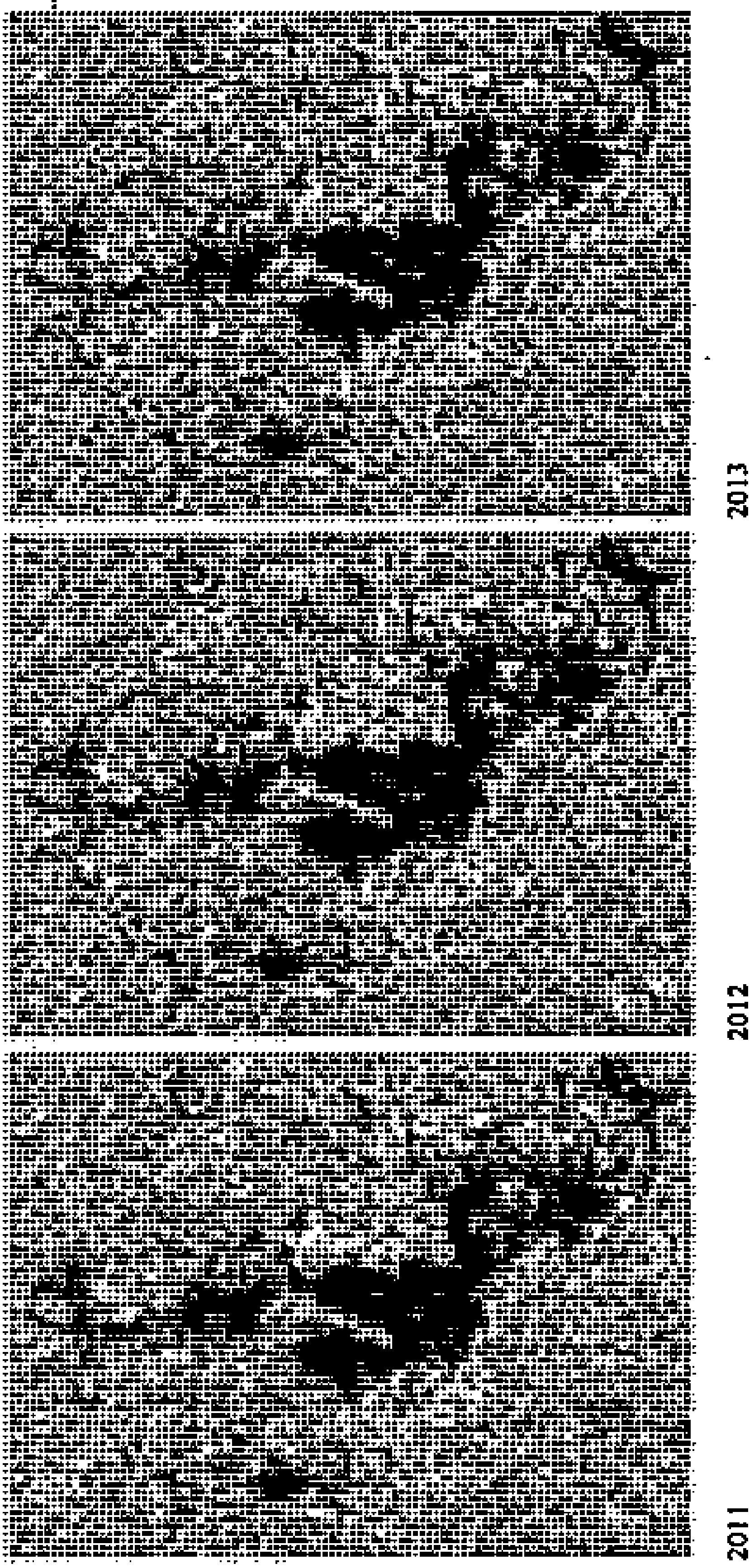
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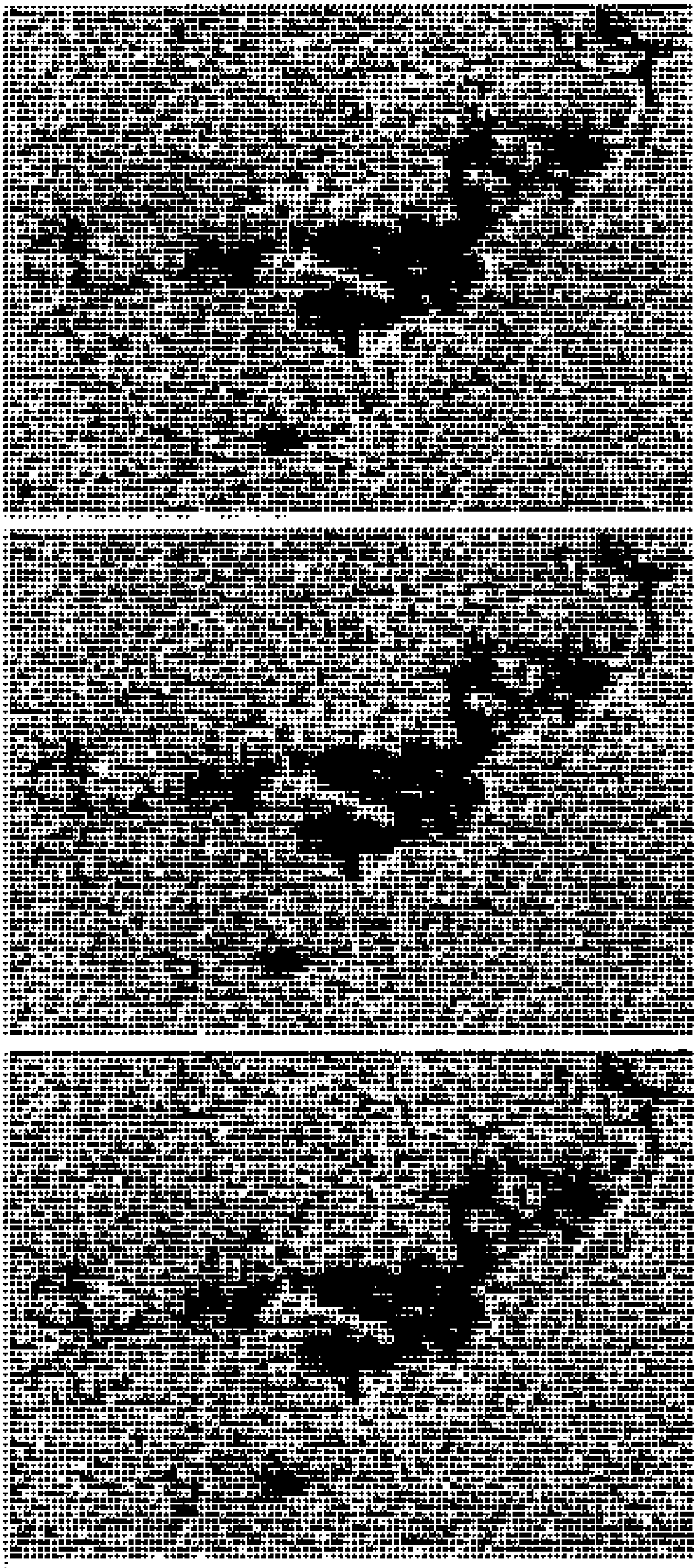
2012
2013



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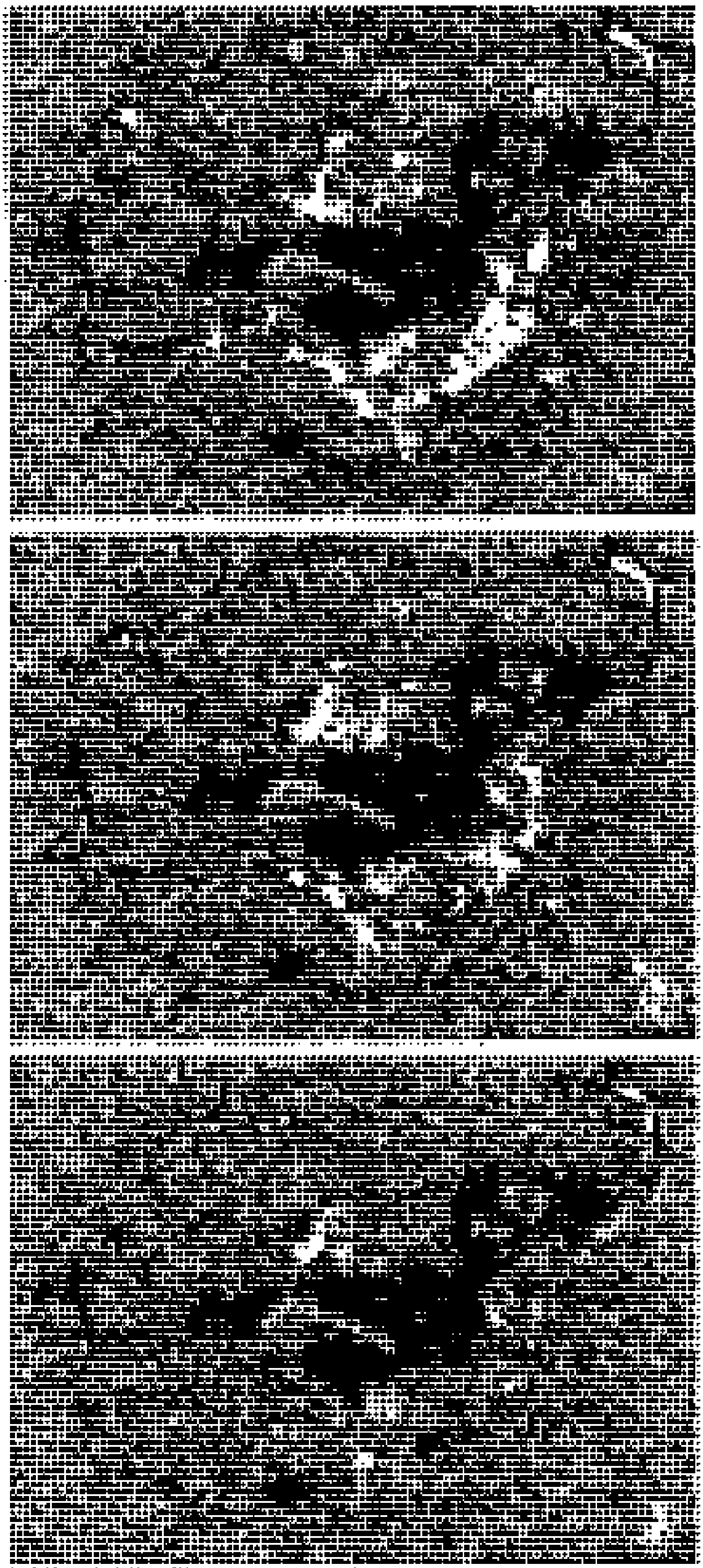

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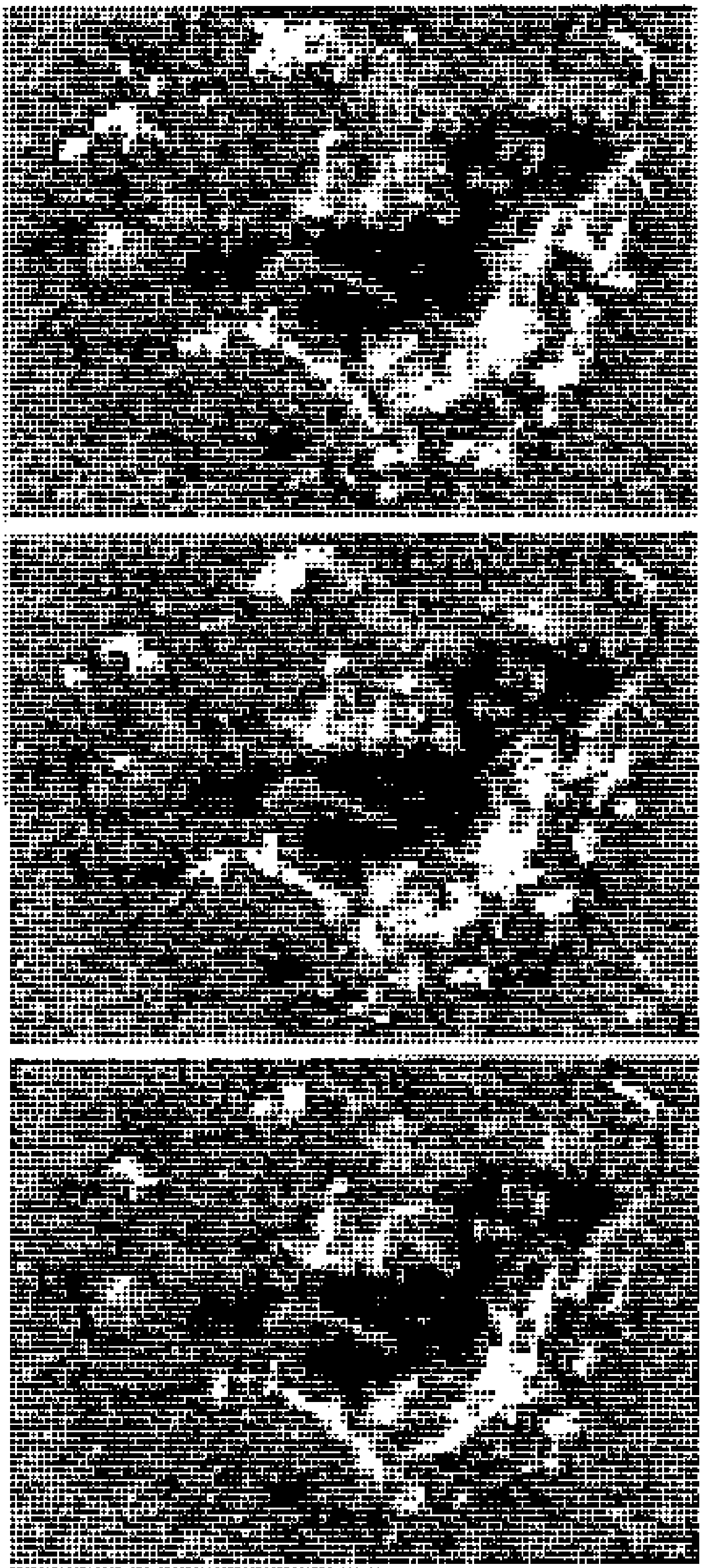

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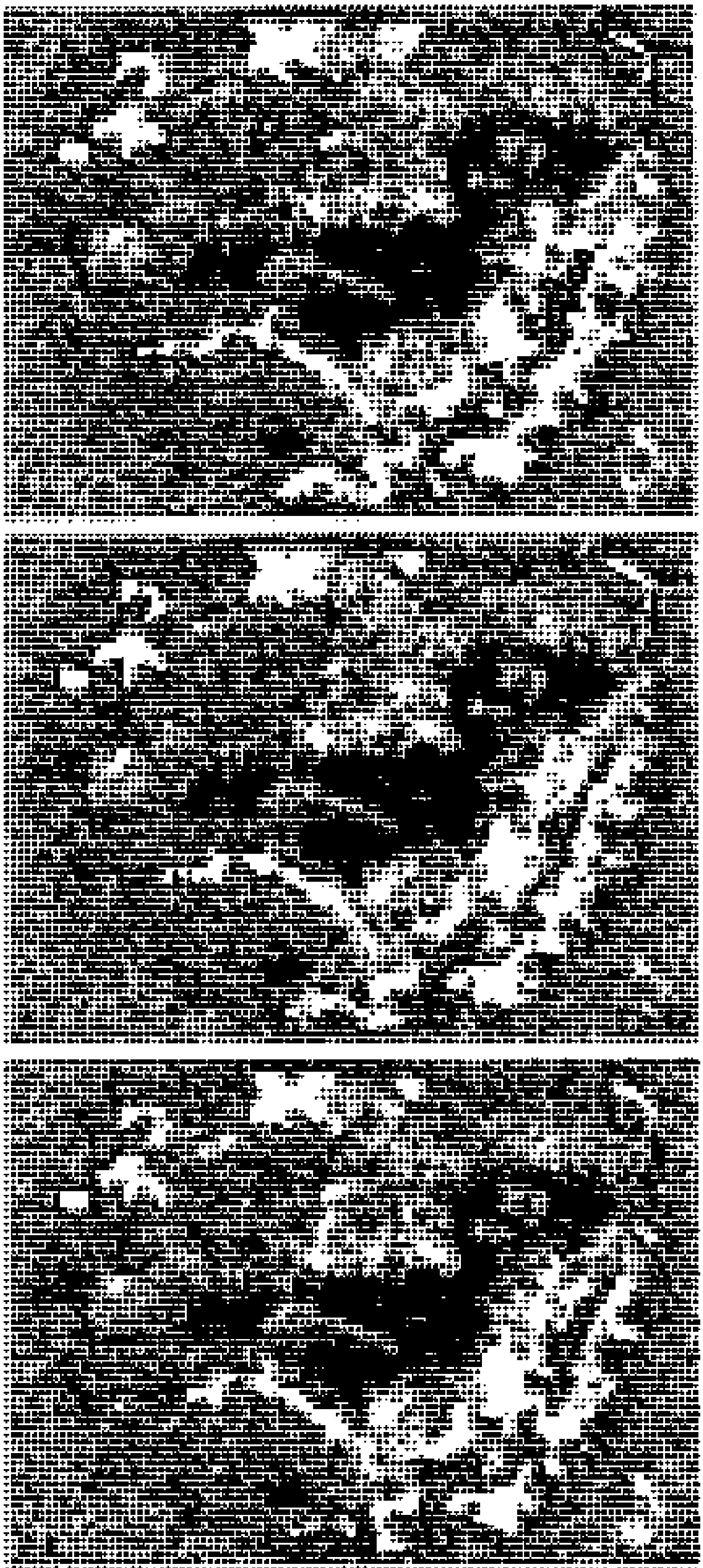
2020



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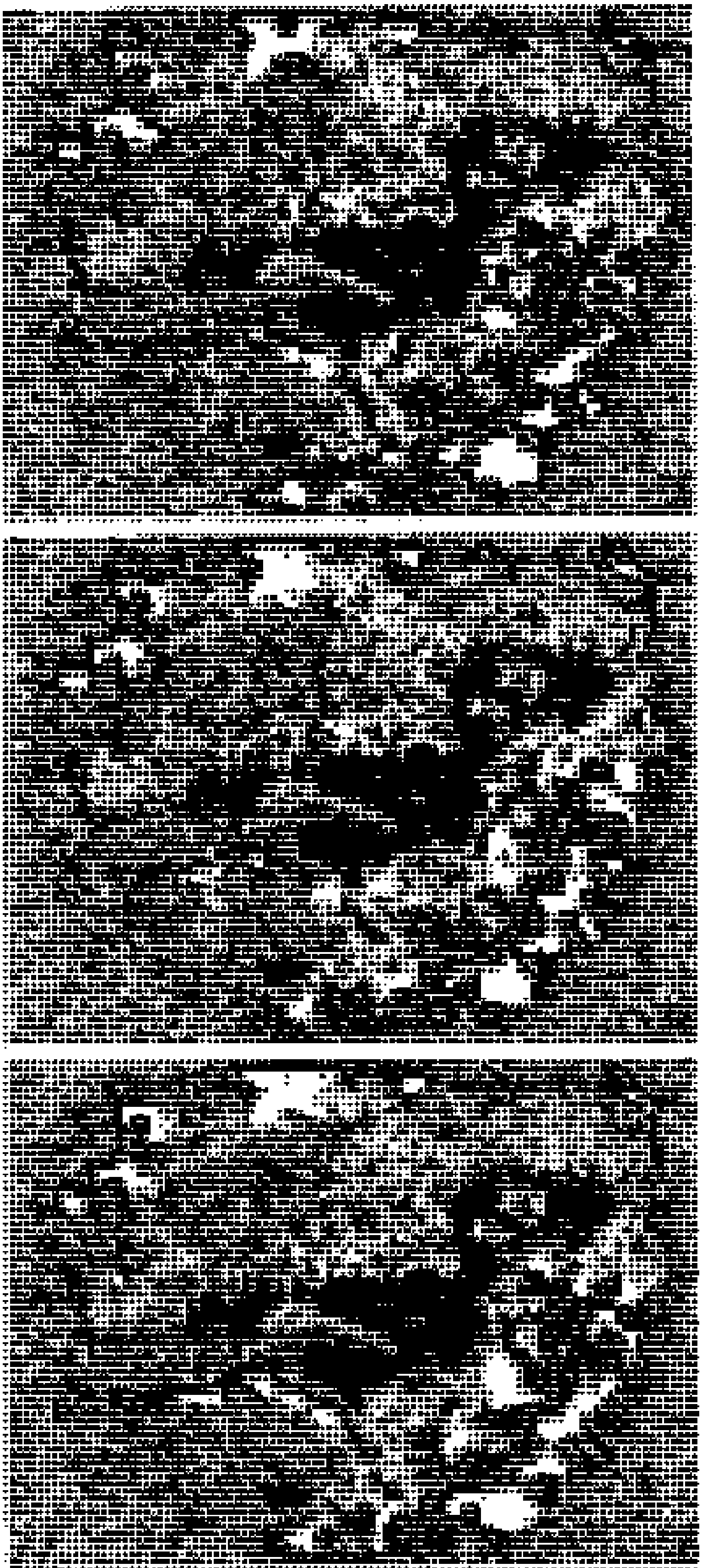

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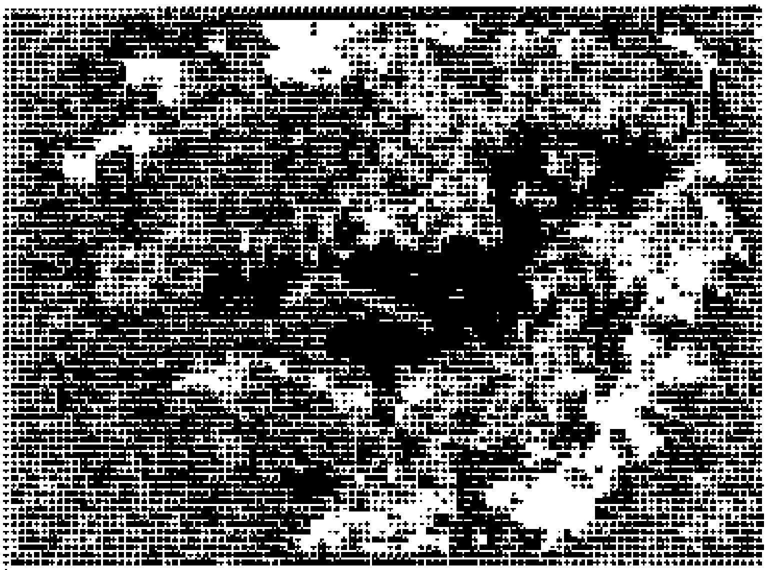

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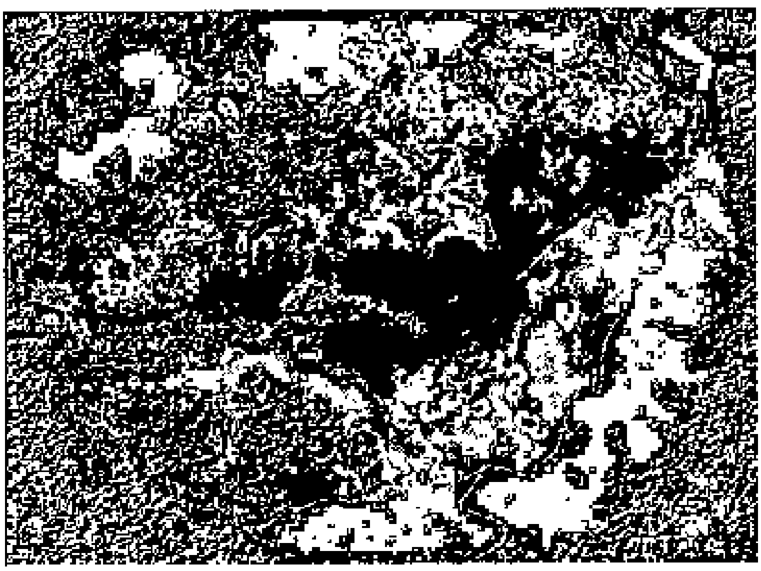

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