Scenarios of Urban Growth in Kenya Using Regionalised Cellular Automata based on Multi temporal Landsat Satellite Data

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TABLE OF CONTENTS

ACKNOWLEDGEMENTS VI

ABSTRACT VIII

ZUSAMMENFASSUNG X

ACRONYMS XII

LIST OF FIGURES XIII

LIST OF TABLES XV

LIST OF PAPERS XVI

1 INTRODUCTION 1

1.1 Purpose of the Research 1
1.2 Statement of the problem 4
1.3 Research Questions 5
1.4 Research objectives 5
1.5 Outline of the research 6

2 URBAN GROWTH MODELLING AND CELLULAR AUTOMATA 9

2.1 Introduction 9

2.2 Urban modelling 10
2.2.1 Models 10
2.2.2 Types of Models 11
2.2.3 Challenges 12
2.2.4 Model uncertainty 15

2.3 Modelling urban growth 18
2.3.1 Background 18
2.3.2 Modelling approaches 19
2.3.3 Current practices in urban land-use modelling 22
2.3.4 Complexity of Urban Growth 24
2.3.5 Role of GIS and remote sensing in urban growth modelling 26

2.4 Cellular automata modelling 28
2.4.1 Introduction 28
2.4.2 Elements of Cellular Automata 30
2.4.3 Cellular automata models 34
2.4.4 Advantages of CA urban models 38
2.4.5 Limitations of CA urban models 38
2.4.6 Developments in CA models 39
2.4.7 Cellular automata in urban growth modelling 41

3 URBAN GROWTH IN AFRICAN CITIES 43

3.1 Introduction 43

3.2 Sustainable growth and characteristics of African cities 45

3.3 Prosperity of cities 47

3.4 Factors influencing urban growth 49

3.5 Nairobi 51
3.5.1 Research area 51
3.5.2 Background 53
3.5.3 Physical characteristics 55
3.5.4 Urban growth in Nairobi 56

3.6 Nakuru 58
3.6.1 Research area 58
3.6.2 Background 59
3.6.3 Physical characteristics 62
3.6.4 Urban growth in Nakuru 63

4 MONITORING LAND-USE CHANGES 64

4.1 Introduction 64

4.2 Utility of multi-sensor satellite data 66

4.3 Land-use change analysis in Nakuru 70
4.3.1 Data 70
4.3.2 Land-use classification 71
4.3.3 Results and Discussion 75
4.3.4 Factors influencing land-use changes and urban growth 86
4.3.5 Consequences of Nakuru's urban growth 89

4.4 Land-use change analysis in Nairobi 90
4.4.1 Data 90
4.4.2 Land-use classification 91
4.4.3 Results and discussion 92
4.4.4 Factors influencing land-use changes and urban growth 95
4.4.5 Consequences of Nairobi's urban growth 98

5 MODELLING URBAN GROWTH 100

5.1 Introduction 100

5.2 The modelling framework (XULU) 103

5.3 Model Parameters and Growth Types 105

5.4 Model calibration 109

5.5 Model validation 109

5.6 Scenarios of urban growth 112

5.7 Scenarios of urban growth in Nakuru 114
5.7.1 Data 114
5.7.2 Modelling of urban growth in Nakuru 117

5.8 Scenarios of urban process in Nairobi 130
5.8.1 Data 130
5.8.2 Modelling of urban growth in Nairobi 132

5.9 UGM comparison 143

6 SPATIAL EFFECTS OF VARYING MODEL PARAMETERS 146

6.1 Introduction....................146

6.2 Model parameter variation....................146

6.3 Results 147

7 SUMMARY AND CONCLUSIONS 159

8 REFERENCES 162

9 APPENDICES 190

9.1 Appendix 1: Monitoring land-use 190
9.1.1 Landsat TM and ETM spectral and spatial properties 190
9.1.2 USGS Land-use classification system for use with Remote Sensor Data 191
9.1.3 Representative Image Interpretation Formats for various Land-use Classification Levels 192

9.2 Appendix 2: Urban growth modelling....................192
9.2.1 Urban growth types 192
9.2.2 UGM Calibration Resource Mapping script 194
9.2.3 UGM Resource Mapping script 195
9.2.4 UGM Resource Mapping Monte Carlo....................195

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ABSTRACT

The exponential increase of urban areas in Africa during the last decade has become a major concern in the context of local climatic change and the increasing amount of impervious surface. Major African cities such as Nairobi and Nakuru have undergone rapid urban growth in comparison to the rest of the world. In this research we investigated the land-use changes and used the results in urban growth modelling which integrates cellular automata (CA), remote sensing (RS) and geographic information systems (GIS) in order to simulate urban growth up to the year 2030.

We used multi-temporal Landsat imageries for the years 1986, 2000 and 2010 to map urban land-use changes in Nairobi and Nakuru. The use of multi-sensor imageries was also explored incorporating World view 2, and Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) data for urban land-use mapping in Nakuru. We conducted supervised classification using support vector machine (SVM) which performed better than maximum likelihood classification. Land-use change estimates were obtained indicating increased urban growth into the year 2010.

We used the land-use change analysis information to model urban growth in Nairobi and Nakuru. Our urban growth model (UGM) utilised various datasets in modelling urban growth namely urban land-use extracted from land-use maps, road network data, slope data and exclusion layer defining areas excluded from development. The Monte-Carlo technique was used in model calibration. The model was validated using Multiple Resolution Validation (MRV) technique. Prediction of urban land-use was done up to the year 2030 when Kenya plans to attain Vision 2030. Three scenarios were explored in the urban modelling process; unmanaged growth with no restriction on environmental areas, managed growth with moderate protection, and a managed growth with maximum protection on forest, agricultural areas, and urban green.

Furthermore, we explored the spatial effects of varying UGM parameters using the city of Nairobi. The objective here was to investigate the contribution of each model parameter in simulating urban growth. The results obtained indicate that

varying model coefficients leads to urban growth in different directions and magnitude. However, several model parameters were observed to be highly correlated namely; spread, breed and road. The lowest spatial effect was achieved by at least maintaining spread, breed and road while varying the other parameters. The highest spatial effect was observed by at least keeping slope constant while varying the other four parameters. Additionally, we used kappa statistics to compare the simulation maps. High values of Khisto indicated high similarity between the maps in terms of quantity and location thus indicating the lowest spatial effect obtained.

Kenya plans to achieve Vision 2030 in the year 2030 and information on spatial effects of our UGM can help in identifying different scenarios of future urban growth. It is thus possible to discover areas that are likely to experience; spontaneous growth, edge growth, road influenced growth or new spreading centres growth. Policy makers can see the influence of establishing new infrastructure such as housing and road in new areas compared to existing settlements.

Moreover, the outcome of this research indicates that Nairobi and Nakuru are experiencing fast urban sprawl with urban land-use consuming the available land. The results obtained illustrate the possibility of urban growth modelling in addressing regional planning issues. This can help in comprehensive land-use planning and an integrated management of resources to ensure sustainability of land and to achieve social equity, economic efficiency and environmental sustainability. Hence, cellular automata are a worthwhile approach for regional modelling of African cities such as Nairobi and Nakuru. This provides opportunities for other cities in Africa to be studied using UGM and its adaptability noted accordingly.

KEY WORDS: Urban growth model, multi-sensors, Radar, Cellular Automata, Geographic Information Systems, Remote sensing, Nairobi, Nakuru, Vision 2030, Sustainability.

ZUSAMMENFASSUNG

Das exponentielle Wachstum afrikanischer Städte im letzten Jahrzehnt ist mit Blick auf die lokalen klimatischen Veränderungen und der zunehmenden Menge an versiegelten Oberflächen von besonderer Tragweite. Im Vergleich zu anderen Metropolen erfuhren afrikanische Städte wie Nairobi und Nakuru ein extensives Wachstum der urbanen Flächen. Die vorliegende Arbeit setzt sich mit dem urbanen Landnutzungswandel auseinander und modelliert die Siedlungsflächenausdehnung für das Jahr 2030 mit Hilfe eines Zellulären Automaten (CA), Fernerkundungsdaten (RS) sowie Geographischen Informationssystemen (GIS).

Zur Kartierung der Siedlungsflächenausdehnung von Nairobi und Nakuru wurden multitemporale Landsat-Daten der Jahre 1986, 2000 und 2010 verwendet. Zusätzlich wurden multisensorale Daten von World View 2 und ALOS PALSAR für Nakuru eingesetzt. Die Landnutzungsklassifikation erfolgte mit *support vector machines* (SVM). Dieses Verfahren zeigte bessere Ergebnisse als eine Maximum-Likelihood-Klassifikation.

Auf Basis der klassifizierten Satellitendaten erfolgte die Landnutzungsmodellierung für Nairobi und Nakuru. Hierzu wurde die von Goetzke (2011) modifizierte Version von Clarke's Urban Growth Model (Clarke, Hoppen, & Gaydos, 1997) benutzt. Neben den Landnutzungskarten fungieren Informationen zum Verkehrsnetz, zur Hangneigung und zu Ausschlussflächen als Hauptinputdaten. Die Kalibration erfolgte mit Hilfe von Monte Carlo Iterationen. Zur Validation des Modells wurde eine Multiple Resolution Validation (MRV) durchgeführt. Die Siedlungsflächenausdehnung wurde für das Jahr 2030 simuliert. Zu diesem Zeitpunkt plant das Land Kenia die Umsetzung des Vision 2030 Programmes. Es wurden insgesamt drei Szenarien mit dem Wachstumsmodell gerechnet: (1) Wachstum ohne Planungszwänge, so dass auch Siedlungsflächen in Naturschutzgebieten entstehen dürfen. (2) Siedlungsflächenausdehnung unter moderaten Planungsbedingungen. (3) Wachstum mit sehr restriktiven Planungsbedingungen, unter Einschluss des Schutzes von Wald-, Grün- und- Agrarflächen.

Des Weiteren wurde eine Sensitivitätsanalyse der modelleigenen Wachstumsparameter am Beispiel von Nairobi durchgeführt. Es konnte gezeigt werden, welchen Einfluss die Parameter auf die Intensität und das Muster der modellierten Siedlungsflächenausdehnung ausüben. Dabei zeigten die Wachstumskoeffizienten „spread“, „breed“ und „road“ eine signifikante Korrelation. Zur weiteren Analyse der erzielten Modellierungsergebnisse und zum Vergleich der räumlichen Muster wurden *Kappa*-Statistiken herangezogen.

Die Arbeit sieht sich als Beitrag zum Vision 2030 Diskurs der kenianischen Regierung. Die simulierten Szenarien der Siedlungsflächenausdehnung von Nairobi und Nakuru identifizieren die für eine Urbanisierung wahrscheinlich in Frage kommenden Regionen. Die Studie zeigt zudem, dass sich die Siedlungsflächenausdehnung von Nairobi und Nakuru schnell und mit hohen Wachstumsraten vollzieht. Der Einsatz von CA Modellen ist ein wertvoller Ansatz zur regionalen Modellierung nicht nur von kenianischen sondern auch von afrikanischen Städten. Die Arbeit kann somit Entscheidungsträger aus Politik und Verwaltung unterstützen, indem sie die räumlichen Auswirkungen des zukünftigen Ausbaus der Infrastruktur und von Wohnflächen aufzeigt. Eine umfassende Planung von Landnutzungswandel und ein integriertes Management sind essentiell auf dem Weg zu einem bewussteren Umgang mit der Ressource Land sowie zu einer sozialen Gleichheit, wirtschaftlichen Effizienz und einer ökologischen Nachhaltigkeit.

ACRONYMS

AI	Artificial Intelligence
ALOS	Advanced Land Observing Satellite
CA	Cellular Automata
CBD	Central Business District
DEM	Digital Elevation Model
DSM	Digital Surface Model
GIS	Geographic Information Systems
GUI	Graphic User Interface
HRV	High Resolution Visible
ML	Maximum Likelihood
MRV	Multiple Resolution Validation
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PCC	Post classification comparison
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SLEUTH	Slope Land-use Exclusion Transport Hill shade
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
UGM	Urban Growth Model
UNECE	United Nations Economic Commission for Europe
UN-HABITAT	United Nations Human Settlements Programme
XULU	eXtendable Unified Land Use Modelling Platform

LIST OF FIGURES

Figure 1-1: Research flowchart 8
Figure 2-1: Data errors, model uncertainties, and error propagation in modelling 16
Figure 2-2: Typical neighbourhood configurations of one-dimension cellular automata. 31
Figure 2-3: Typical neighbourhood configurations of two-dimension cellular automata. 32
Figure 2-4: Cellular automata neighbourhoods 34
Figure 2-5: Underlying Urban Growth Model algorithms sorted by popularity 37
Figure 2-6: A cellular automata-generated urban development in a plain area. 42
Figure 3-1: Location of Nairobi 52
Figure 3-2: Location of Nairobi 53
Figure 3-3: Nairobi: Boundary changes, 1900-1963 55
Figure 3-4: Population trends in Nairobi 57
Figure 3-5: Location of Nakuru in the Central Rift Valley of Kenya 58
Figure 3-6: Location of Nakuru in the Central Rift Valley of Kenya 59
Figure 3-7: Municipality of Nakuru: Boundary changes, 1923-1992 61
Figure 4-1: (a) False colour composite Landsat TM (Path 169, Row 60) RGB of 1986 for Nakuru municipality (b) Panchromatic band of 1986 for Nakuru Municipality 68
Figure 4-2: Worldview-2 True colour image of year 2010 for Nakuru CBD 69
Figure 4-3: Image pre-processing workflow of the multi-sensor satellite data sets 72
Figure 4-4: Image workflow for classification and change detection of multi-sensor data sets 74
Figure 4-5: Land-use Map for Nakuru Municipality from Landsat for 1986, 2000 and 2010 76
Figure 4-6: Land-use estimates for Nakuru CBD (28.5 metres) 79
Figure 4-7: Land-use Map for Nakuru CBD using Landsat TM 1986 80
Figure 4-8: Land-use Map for Nakuru CBD using Landsat ETM 2000 80
Figure 4-9: Land-use Map for Nakuru CBD using Landsat ETM + 2010 81
Figure 4-10: Land-use Map for Nakuru CBD using World-view 2 2010 81
Figure 4-11: Land-use Map for Nakuru CBD using Landsat ETM + 2010 and ALOS . 82
Figure 4-12: Land-use change conversion in Nakuru CBD using Landsat TM (1986) and Landsat ETM (2000) 84
Figure 4-13: Land-use change conversion in Nakuru CBD using Landsat ETM (2000) and ALOS PALSAR (2010) 85
Figure 4-14: Economic structure of Nakuru Municipality (Source: Owour, 2006) 87
Figure 4-15: Settlement structure of Nakuru municipality (Source: Owour, 2006) 88
Figure 4-16: Land-use estimates for Nairobi 93
Figure 4-17: Land-use map for Nairobi using Landsat TM 1986 94
Figure 4-18: Land-use map for Nairobi using Landsat ETM 2000 94
Figure 4-19: Land-use map for Nairobi using Landsat ETM + 2010 95
Figure 5-1: Flowchart of urban growth modelling 102
Figure 5-2: Separation of the XULU modelling framework from a certain model implementation 104
Figure 5-3: The main window of the XULU modelling platform 105
Figure 5-4: Growth types simulated by the UGM model 107
Figure 5-5: Urban extent in Nakuru (1986) 116
Figure 5-6: Urban extent in Nakuru (2010) 116

Figure 5-7: Urban growth simulation in 2010 in Nakuru (scenario one) 119
Figure 5-8: Urban growth simulation in 2030 in Nakuru (scenario one) 120
Figure 5-9: Urban growth simulation in 2010 in Nakuru (scenario two) 120
Figure 5-10: Urban growth simulation in 2030 in Nakuru (scenario two) 121
Figure 5-11: Urban growth simulation in 2010 in Nakuru (scenario three) 121
Figure 5-12: Urban growth simulation in 2030 in Nakuru (scenario three) 122
Figure 5-13: Observed change 1986 – 2010 in Nakuru 125
Figure 5-14: Estimates of observed change 1986 – 2010 in Nakuru 126
Figure 5-15: Predicted change 1986 – 2010 in Nakuru 126
Figure 5-16: Estimates of predicted change 1986 – 2010 in Nakuru 127
Figure 5-17: Predicted error 1986 – 2010 in Nakuru 127
Figure 5-18: Estimates of predicted error 1986 – 2010 in Nakuru 128
Figure 5-19: Urbanisation probability map for Nakuru 129
Figure 5-20: Urbanisation probability map for Nakuru showing high urbanisation areas 129
Figure 5-21: Urban extent in Nairobi (1986) 131
Figure 5-22: Urban extent in Nairobi (2010) 132
Figure 5-23: Urban growth simulation in Nairobi in scenario one (2010) 134
Figure 5-24: Urban growth simulation in Nairobi in scenario one (2030) 135
Figure 5-25: Urban growth simulation in Nairobi in scenario two (2010) 135
Figure 5-26: Urban growth simulation in Nairobi in scenario two (2030) 136
Figure 5-27: Urban growth simulation in Nairobi in scenario three (2010) 136
Figure 5-28: Urban growth simulation in Nairobi in scenario three (2030) 137
Figure 5-29: Observed change 1986 – 2010 in Nairobi 138
Figure 5-30: Estimates of observed change 1986 – 2010 in Nairobi 139
Figure 5-31: Predicted change 1986 – 2010 in Nairobi 139
Figure 5-32: Estimates of predicted change 1986 – 2010 in Nairobi 140
Figure 5-33: Predicted error 1986 – 2010 in Nairobi 140
Figure 5-34: Estimates of predicted error 1986 – 2010 in Nairobi 141
Figure 5-35: Urbanisation probability map for Nairobi 142
Figure 5-36: Urbanisation probability map for Nairobi showing high urbanisation areas 143
Figure 5-37: UGM comparison for Nairobi and Nakuru 144
Figure 6-1: Urban Growth Simulation 152
Figure 6-2: *K* and *K*location values for urban growth simulation 153
Figure 6-3: *K*histo values for urban growth simulation 154
Figure 6-4: Lowest spatial effect based parameters values obtained from set 19 156
Figure 6-5: Highest spatial effect based parameters values obtained from set 5 157
Figure 9-1: Illustration of spontaneous growth 192
Figure 9-2: Illustration of new spreading centre growth 193
Figure 9-3: Illustration of edge growth 193
Figure 9-4: Illustration of road-influenced growth 193
Figure 9-5: Influence of slope on urban growth modelling 194

LIST OF TABLES

Table 1: Datasets for land-use change analysis of Nakuru... 71
Table 2: Confusion Matrix for Land-cover classification for Nakuru municipality (Landsat data from 1986, 2000 and 2010) 76
Table 3: Land-use estimates for Nakuru municipality using Landsat (28.5 spatial resolution) 77
Table 4: Comparison of classification accuracies for the three multi-sensor data sets at 28.5 spatial resolution for Nakuru CBD 78
Table 5: Land-use estimates for Nakuru CBD (28.5 spatial resolution) 78
Table 6: Land-use estimates for Nakuru CBD (12.5m spatial resolution) 79
Table 7: Confusion Matrix for Land-use classification for Nakuru CBD (12.5 spatial resolution) 83
Table 8: Land-use change estimates based on post classification comparison 84
Table 9: Datasets for land-use change analysis of Nairobi... 90
Table 10: Land-use summary and error estimates for Nairobi 93
Table 11: Summary of growth types simulated by the UGM model........................... 107
Table 12: Data for urban growth modelling of Nakuru 115
Table 13: Best model parameters obtained for Nakuru 118
Table 14: Model evaluation for Nakuru 122
Table 15: Data for urban growth modelling of Nairobi 131
Table 16: Best model parameters obtained for Nairobi 133
Table 17: Model evaluation for Nairobi 134
Table 18: Model parameter variation in 1st combination 148
Table 19: Model parameter variation in 2nd combination 149
Table 20: Model parameter variation in 3rd combination... 150
Table 21: Model parameter variation in 4th combination... 150
Table 22: Model parameter variation in 5th combination... 151
Table 23: Model parameter sets with low spatial effect for UGM of Nairobi 155
Table 24: Model parameter sets with high spatial effect for UGM of Nairobi 155
Table 25: Statistics of spatial effect maps 157

LIST OF PAPERS

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1 INTRODUCTION

1.1 Purpose of the Research

Urban studies are becoming significant tools for planners knowing that in the year 2025 more than half the global population will be residing in cities (United Nations, 2013). Thus, suitable urban planning ought to be a top priority for future development but unfortunately sound planning has not taken place in many African cities as heavy rural-urban migration continues to cause cities to expand at uncontrollable rates (Mundia & Aniya, 2007). The population in urban areas in Africa has been increasing at a much faster rate than in the rest of the world and thus contributing to the augmentation of the existing problems such as unsuitable land-use planning (Lavalle, Demichili, Turchini, Casals Carrsco, & Niederhuber, 2001). The concentration of population in cities comprises almost 60% of the total population in most cases. In these immense urban settlements the environmental and social consequences are sometimes disastrous (Barredo & Demicheli, 2003).

Cities in Africa such as Nakuru have experienced a fast growth rate of 13.3 per cent and Nairobi at 4.9 per cent (UN-HABITAT, 2010). The magnification has been attributed to a number of factors for Nakuru, mainly the aperture of the new Naivasha-Nakuru road, which links the town with Nairobi. Post-election violence is verbally expressed to be one of the contributing factors, since many displaced people from neighbouring towns visually perceived Nakuru as a safe haven. In the case of Nairobi, there has been high rural urban migration as people search for jobs and social amenities.

The main consequences in these cities include; unsuitable land-use, inadequate transportation systems, pollution, depletion of natural resources, urban sprawl, collapse of public services, proliferation of epidemics, and other negative environmental and social effects (Mundia & Aniya, 2005). The changing of surrounding area due to city development and city residents ever-increasing demand for energy, food, goods and other options is behind the deterioration of local and localised environment which is harmful the basic environment solutions and bio-diversity.

Problems linked to unsustainable urban development in African cities are many and complex and requires an integrated approach. Such an integrated urban planning approach needs to recognise and anticipate urban dynamics and their consequences (Mundia, Aniya, & Murayama, 2010).

Remote sensing (RS) techniques have been valuable in mapping urban dynamics as well as data sources which aid in the analysis and modelling of urban growth and land-use change (Batty & Howes, 2001; Clarke, Parks, & Crane, 2002; Donnay, Barnsley, & Longley, 2001). Remote Sensing offers spatially coherent data sets that cover big areas with both high spatial detail and high temporal frequency. These kinds of data sets are necessary for land-use analysis and are an essential element of ecological studies. As urbanisation occurs, changes in land-use accelerate and land making up the natural resource base such as forests and agricultural land are replaced, leading to fragmentation and land degradation (Mundia & Aniya, 2005).

In this research we explored the use of multi-sensor datasets in monitoring land-use. SAR sensors are playing an increasingly important role in remote sensing due to their ability to operate day and night through cloud cover, and recent improvement in data availability (Rogan & Chen, 2004). Many studies have focused on the frequency and polarimetric dimensions of SAR data in land-use classification (Chen, Chen, & Lee, 2003; Cloude & Potter, 1997; Lee, Grunes, & Kwork, 1994), whereas SAR image texture is found helpful in improving map accuracy, particularly for urban and forest categories (Dekker, 2003).

The study of land-use changes is essential not only for land-use management but also in detecting environmental change and in formulating sustainable development strategies (Barnsley & Barr, 1997). Land-use changes should be accurately investigated and the information used in documenting urban growth, making policy decisions and improving land-use planning. Such information is also required for predictive modelling (Bullard & Johnson, 1999; Gross & Schott 1998; Jacobson, 2001; Epstein , Payne, & Kramer, 2002); Aitkenhead & Aalders, 2009; Mas, Pérez-Vega, & Clarke, 2012).

Models help in evaluation the land-use change phenomenon and predict plausible planning activities for sustainable cities. This is a vital topic in present research agenda and a noteworthy number of scientists are offering their efforts in the study of this phenomenon. Among all developed urban growth models, cellular automata (CA) urban growth models performance well in simulating urban development than conventional mathematical models. CA are able to predict urban growth based on the assumption that past urban development affects future patterns through local interactions among land-uses (Santé, García, Miranda, & Crecente, 2010). Thus, CA simplifies the simulation of complex systems. Moreover CA are appropriate in urban modelling due to the fact that the process of urban spread is entirely local in nature. Therefore, CA models are outstanding depicters of urban dynamics (Divigalpitiya, Ohgai, Tani, Watanabe, & Gohnai, 2007).

Models based on cellular automata are impressive in terms of their technological evolution in connection to urban applications. Development of a CA model involves rule definition and calibration to produce results consistent with historical data, and future prediction with set rules (Batty & Xie, 1994b; Clarke & Gaydos, 1998; Yang & Lo, 2003).

Many CA-based urban growth models are documented in the literatures (Triantakonstantis & Mountrakis, 2012). CA model involves reduction of space into square grids (White & Engelen, 1993). They implement the defined transition rules in recursive form to match the spatial pattern. CA models are usually designed based on individual preference and application requirements with transition rules being defined in an ad hoc manner (Li & Yeh, 2003). Most of the developed CA models need intensive computation to select the best parameter values for accurate modelling.

In this research, CA was used to study land-use change and prediction of future trends in Nairobi and Nakuru as Kenya attains Vision 2030 in the year 2030 (Government of Kenya, 2007). The model used was an urban growth model (UGM) which was a modification of SLEUTH model. We developed an UGM for our two cities with different parameters. Three scenarios were explored in the urban modelling process; unmanaged growth with no restriction on environmental areas, managed growth with moderate protection, and a managed growth with maximum protection on forest, agricultural areas, and urban green. Additionally, we explored the spatial effects of varying model parameters in the city of Nairobi. The objective here was to explore the contribution of each model parameter in simulating urban growth.

The UGM's for Nairobi and Nakuru were based on urban land-use change information obtained in the years 1986, 2000 and 2010. Furthermore, each model was calibrated using multi-stage Monte Carlo method and a 20 year prediction simulation ran until 2030. The models aimed at predicting the future land-use development under the existing and modified urban planning policies.

1.2 Statement of the problem

On a global basis, nearly 6.8 million km^2 of forest, woodlands and grasslands have been converted to other land-uses over the last three centuries (Agarwal, Green, Grove, Evans, & Schweik, 2002) and most of the changes were into urban land-use. These changes in land-use have significant implications on the earth's resources and climate.

On a local basis, there has been rapid urban growth in Nairobi and Nakuru. Nairobi being Kenya's capital city has witnessed high urban growth as Kenya gained independence in 1963. Much of the urban growth has been attributed to high rural urban as people search for jobs and social amenities. The land-use in Nakuru Municipality has been noted to have changed significantly; urbanisation began at a very high rate between 1973 and 1986, but still continued into year 2010 at a moderate rate (Mubea, Ngigi, & Mundia , 2011; Mundia, Mubea, & Gachari, 2011; Mubea & Menz, 2012; Mubea, Goetzke, & Menz, 2013). Nevertheless, in both cities there has been a decrease in agricultural land-use implying that such land has been converted into urban land-use. Furthermore, vegetation has decreased implying destruction of forests through deforestation and changing climatic conditions which inhibit natural growth of vegetation. Economic development and the rising population have been noted to be the major factors influencing land-use. Thus, consideration and careful assessment are required for supervising and designing land-use management, urban development and decision making.

This research on modelling urban land-use using GIS and RS is expected to provide a better understanding and give perspective into the impacts of human activities and associated land-use changes simulated over time till the year 2030 when Kenya attains Vision 2030. To achieve this we formulated three scenarios of urban growth. Specifically, the impacts of human activities and environmental conflicts that have risen as a result of competition over the limited resources in both cities were investigated. This in turn will allow for comprehensive land-use planning and an integrated management of resources. Thus, the resources should be managed in such a way as to ensure sustainability of land and to achieve social equity, economic efficiency and environmental sustainability.

1.3 Research Questions

i. How will the urban land-use classification using multi-sensor data perform?
ii. How dynamic is the urban land-use change?
iii. How precise can the urban land-use change be assessed and modelled?
iv. What will be the extent of the land-use changes in the future?
v. Which urban growth scenario will lead to sustainable development?

1.4 Research objectives

The main objective of this research was to develop a regionalised CA for Nairobi and Nakuru based on urban growth model (UGM) for better planning and management of resources. To achieve this, we formulated the following specific objectives:

i. To develop a calibration algorithm that takes into consideration spatial and temporal dynamics of urban growth in Nairobi and Nakuru.
ii. Monitor land-use information.
iii. Explore multi-sensor image classification
iv. Predict urban growth in Nairobi and Nakuru into the year 2030 under various scenarios.
v. Compare UGM of Nairobi and Nakuru.
vi. Explore spatial effects of varying our UGM parameters

1.5 Outline of the research

This dissertation is organised into seven chapters as shown on Figure 1-1. Chapter 1 is the introductory chapter. It gives a general overview of the research. Here the objectives are outlined as well as the purpose of the research.

Chapter 2 describes various modelling approaches. The history and elements of cellular automata as well as their theoretical background are explained. Additionally, modelling approaches are defined and explained. The role of GIS and RS is outlined. The role of CA in urban growth modelling is also described.

Chapter 3 addresses urban growth in African cities with Nairobi and Nakuru as the case studies. The research areas are explained alongside urban growth in the cities.

Chapter 4 illustrates the monitoring of land-use changes. The methods of RS data collection and processing are discussed. Land-use change dynamics are described using multi-temporal Landsat for the city of Nairobi and multi-sensor data for Nakuru. The results of land-use change analysis and urban growth in Nairobi and Nakuru are presented and discussed. We published the results of monitoring land-use using multi-sensor satellite data in our first journal paper and poster sessions as shown below:

- Mubea, K. and Menz, G. (2012) 'Monitoring Land-Use Change in Nakuru (Kenya) Using Multi-Sensor Satellite Data', *Advances in Remote Sensing*, vol. 1, no. 3, Dec, p. 74–84.
- Mubea, K. and Menz, G. (2012) ' Monitoring Urban Land-Use and Land-Cover Changes for Nakuru (Kenya) using Multi-Sensor Datasets ', AK Fernerkundung Bochum, 4 – 6 October 2011, Bochum.
- Mubea, K. and Menz, G. (2013) ' Monitoring Urban Land-Use Changes for Nakuru (Kenya) using Multi-Sensor Datasets ', ESA 4th Land Remote Sensing course - Harokopio University, 1 - 5 July 2013, Athens. (Best paper award in Land use land cover)

Chapter 5 presents the modelling of urban growth in Nairobi and Nakuru using cellular automata. The methodology adopted is outlined and discussed. XULU modelling framework is explained. Urban growth model (UGM) is discussed. The method of multiple resolution validation (MRV) for model comparison and validation is explained. The data sets used are introduced. The results of urban prediction Nairobi and Nakuru are presented and discussed based on the three urban growth scenarios. We published some of the results from this chapter in journals and poster sessions as follows:

- Mubea, K., Goetzke, R. and Menz, G. (2014) Applying cellular automata for Simulating and Assessing Urban Growth Scenario Based in Nairobi. International Journal of Advanced Computer Science and Applications, Vol.5 No.2. pp. 1 - 13. doi: 10.14569/IJACSA.2014.050201.
- Mubea, K., Goetzke, R. and Menz, G. (2013) Simulating Urban Growth in Nakuru (Kenya) using Java-Based Modelling Platform XULU, 2013 UKSim-AMSS 7th European Modelling Symposium, Manchester , pp. 97 - 102. doi: 10.1109/EMS.2013.18.
- Mubea, K., Goetzke, R. and Menz, G. (2013) ' Modelling Urban Land-Use in Nairobi Using Cellular Automata', AK Fernerkundung Tübingen, 26 – 27 September 2013, Tübingen.
- Mubea, K., Goetzke, R. and Menz, G. (2013) ' Simulating Urban Growth in Nakuru (Kenya) Based On a Constrained Cellular Automata Model And Decade Landsat-Data ', ESA Living Symposium, 9 – 13 September 2013, Edinburgh.

Chapter six explores the spatial effects of varying model parameters. The objective here was to explore the contribution of each model parameter in simulating urban growth. Each model parameter influences urban growth independently. The results of this chapter were submitted for publication as follows:

- Mubea, K., Goetzke, R. and Menz, G. (submitted to CEUS, Computers Environment and Urban systems journal) Spatial Effects of Varying Model Parameters in Urban Growth Modelling In Nairobi, Kenya (submitted on 29.11.13, status: Under review)

Chapter 7 summarises the findings of this research in comparison to the research objectives. The predicted results indicate rapid urban growth in both cities with urban land occupying a large percentage. Furthermore the chapter offers suggestions for further research.

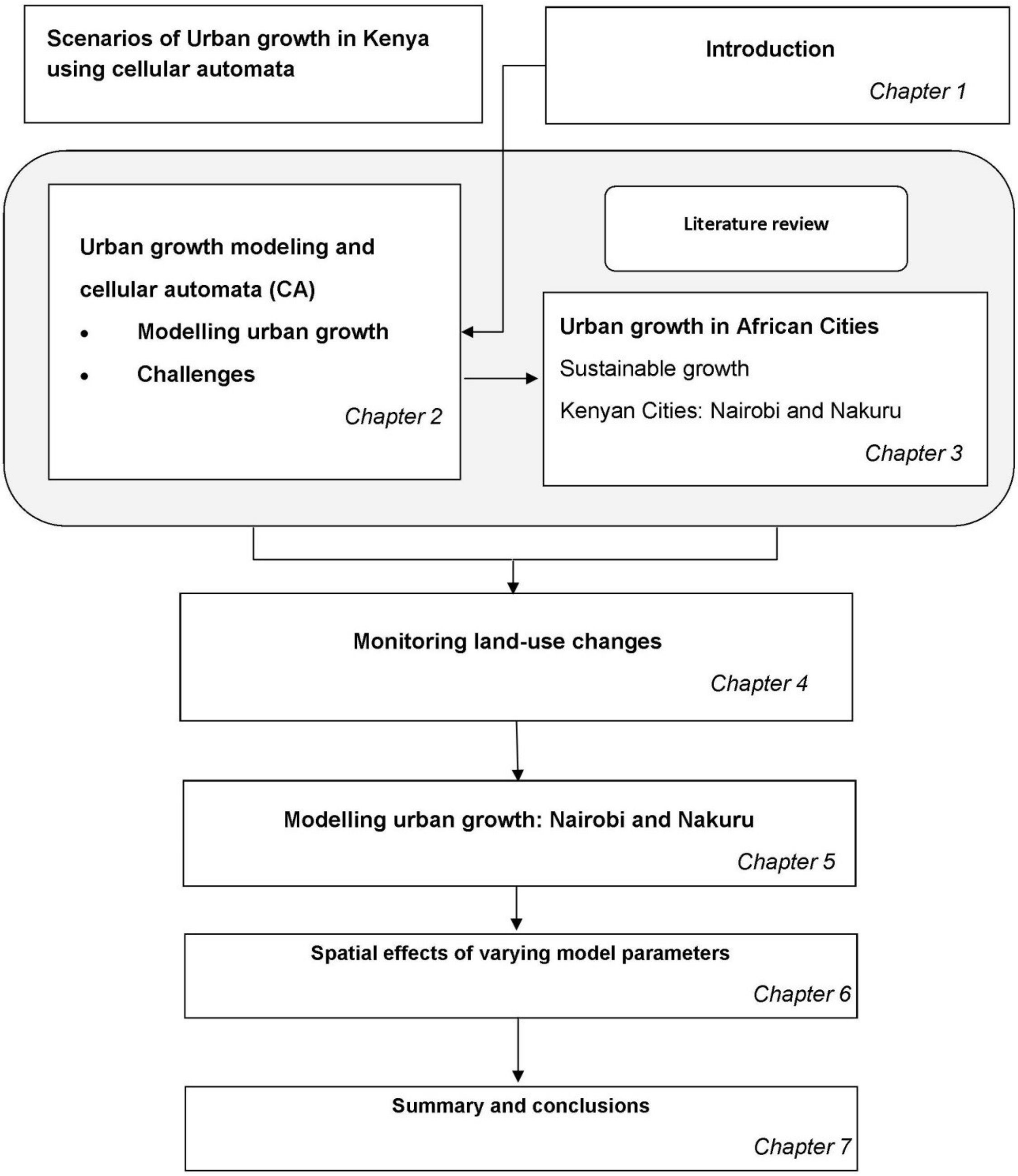

Figure 1-1: Research flowchart

2 URBAN GROWTH MODELLING AND CELLULAR AUTOMATA

2.1 Introduction

This research aims at developing regionalised cellular automata for Nairobi and Nakuru, Kenya. This chapter introduces urban growth modelling, cellular automata and modelling with cellular automata.

Approximately half of the world's population (47 per cent) lives in urban areas, a figure which is expected to grow tremendously by 2025 (United Nations, 2013). An urban area is a system of essentially related sectors of industry, housing and population (Forrester, 1969). Urban areas include cities, towns and conurbations. Additionally, urban areas represent a mix of related units, but the degree and nature of the relationships are sometimes hard to establish (Barredo, Kasanko, McCormick, & Lavalle, 2003). Likewise, urban areas are characterised by certain land-uses such as residential, commercial, and industrial. Anderson, Hardy, Roach, & Witmer, (1976) describe the major land-use groups and disparities in spatial decrees of the satellite remote sensing sensors in the field of remote sensing (see appendices 9.1.2 and 9.1.3).

Studies by Dalton (2006), Park (2007) and Hillier, Turner, Yang, & Park, (2007) suggest that three spatial factors could be involved in defining urban areas: internal structure, contextual structure, and the relation between the two. Urban areas typically have fuzzy boundaries which arise from the way space is structured internally and how this relates to the external structure of space. Fuzzy boundaries can be effective in supporting functional differentiation of areas or the growth of areal identities and characters, but do not depend on the area being either spatially self-contained or geometrically differentiated, or having clear spatial limits. It is the relation of urban parts and their further surroundings that determine fuzzy boundaries of these urban parts (Yang & Hillier, 2007).

Urban development and the migration of much of the population from rural to urban areas are important global phenomena in the 21st century. The driving forces of urbanisation include jobs and social amenities while in Africa, conflict, land degradation and depletion of natural resources are very significant (Mundia & Aniya, 2006). To a larger extent, more small isolated population centres are shifting into large metropolitan cities at the expense of agricultural land-use, deforestation, and the destruction of natural landscape and public open space (Liu, 2008). Consequently, this has been a topic of concern over the last few decades due to global climate change. Urban growth in African cities is explained in section 3.

2.2 Urban growth modelling

Urban growth modelling studies are currently considered an essential component for numerous complex environmental approaches (Triantakonstantis & Mountrakis, 2012). In this section we introduce models and their types.

2.2.1 Models

A model is a simplified representation of reality in either material form (tangible) or symbolic form (abstract) for purposes of description, explanation, forecasting of planning. GIS modelling involves symbolic representation of locational properties as well as thematic and temporal attributes describing characteristics and conditions of space and time (Berry J. K., 1995).

Spatial models are increasingly employed as decision support tools in urban planning in order to inform planners and decision makers (Hill & Lindner, 2011; Fuglsang, Münier & Hansen, 2013). Spatially explicit models support the evaluation of land-use change and predict plausible planning activities for sustainable cities. This is a vital topic in present research agenda and a noteworthy number of scientists are offering their efforts in the study of this phenomenon.

Urban models help scientists to analyse the form, speed, and impact of urban growth in the past, to assess current trends and to simulate scenarios of future development. A model maybe suitable for one area in terms of parameters and it has to be localised in another research area since the underlying factors of growth are different. An urban model has to be calibrated so as to “learn” the endogenous characteristics of the particular environment that they explain and simulate (Silva & Clarke, 2002). However, in order to model urbanisation processes across different areas, it is vital to test the efficiency of the model’s algorithms at capturing and simulating the land transformations that are specific to a place (Batty & Xie, 1994b; Clarke, Hoppen, & Gaydos, 1996; Li & Yeh, 2000).

Cellular automata (CA) models are ideal for modelling land-use in areas where data is unavailable and experiencing rapid urban growth (Hill & Lindner, 2011). CA and agent-based modeling, have shown potential in representing and simulating the complexity of the dynamic processes involved in urban growth and land-use change, and provide an additional level of knowledge and understanding of spatial and temporal change (Dietzel & Clarke, 2007).

Decisions made on land-use planning and allocations have a direct consequence in the future development. In this context urban models serve as tools which help policy makers achieve sustainable development through highlighting various simulations of land-use scenarios and understanding the consequences of different driving forces (Verburg, Schot, Dijst, & Veldkamp, 2004). Thus, policy makers are able to make more informed, comprehensive and objective decisions on land-use planning so as to achieve social equity, economic efficiency and environmental sustainability. Among all developed urban growth models, CA perform well in simulating urban development (Triantakonstantis & Mountrakis, 2012). This research aimed at developing regionalised cellular automata for Nairobi and Nakuru and Kenya.

2.2.2 Types of Models

Spatial models represent features under investigation in terms of space and attribute information. These models can be classified into the way they are formulated, representation of real-world phenomena, dimension and resolution, and whether they are static or dynamic.

Firstly, spatial models are classified into the way they are formulated and we obtain namely scale, conceptualisation and mathematical models (Steyaert, 1993). Scale models usually represent real-world physical features such as digital terrain models (DTM). Conceptual models use quasi-natural language or flowcharts to outline the components of the system under investigation and highlight the linkages. Mathematical models operationalize conceptual models by representing their components and interactions with mathematical rules. Additionally, mathematical models can use scale models to organise their data.

Secondly, spatial models are classified into how they deal real phenomena (Berry J. K., 1995). Deterministic models generate repeatable solutions based on the direct evaluation of defined relationships such that they do not allow for the presence of random variables. Probabilistic models are based on probability distribution of statistically independent events and generate a range of possible solutions. Stochastic models are probabilistic models with conditional probability distribution taking into account temporal or spatial persistence.

Thirdly, spatial models are classified according to their dimension and resolution in space which ranges from microscopic to macroscopic as well as according to time and attributes. The space dimension can be represented by objects with zero dimensions (points), one dimension (lines), two dimensions (areas) or three dimensions (volume). The size of the objects may range from a few metres to thousands or kilometres. Similarly, the time dimension is represented with zero dimensions (event) or one dimension (process), the resolution range of between a few seconds to hundreds of years. The attribute dimension can be single or multi-attribute while the resolution ranges from individual objects to large collectives.

Lastly, spatial models are classified as either static or dynamic. A static model treats time as constant and model variables that do not vary over time e.g. a map of timber value based on forest inventory and relative access to existing roads (Berry J. K., 1995). These models are associated with a steady state or equilibrium. Dynamic models use time as variable and model variables change as a function of time e.g. a map of the spread of pollution from a point source (Berry J. K., 1995).

2.2.3 Challenges

Models are used in a variety of fields, including land-use change science, to better understand the dynamics of systems, to develop hypotheses that can be tested empirically, and to make predictions and/or evaluate scenarios for use in assessment activities (Brown, Walker, Manson, & Seto, 2004). Usually the model results are verified against reality. Nonetheless, in the case of prediction of the future, it is hard to verify and validate the simulation results.

Moreover, verification and validation infers to the exactness and reliability of a model and its dependability in decision making (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Thus, once a model has been verified we can say that its truth has been achieved. Techniques of model verification involve debugging the simulation algorithms as well as ensuring that model structure is appropriate. Model validation involves comparing the outcomes of the model to reference data and observations. Once a model is verified and works correctly, then the modeller is concerned with validation comparing model outcomes to outside data and expectations. However, the descriptions above are tied to models notwithstanding their modelling operations (Oreskes, Sharader-Freschete, & Belitz, 1994).

Nevertheless, verification invokes the robustness of a model to be re-used in similar circumstances against a set of observations, reference data and assumptions. However, achievement of model verification involves striking a balance between theory and data (Batty 2001a; Batty 2001 b). Additionally, this involves varying model parameters and invovles modifying model objects and linkages among them in the software code. Currently, modellers are confirming to International Standard Organisation (ISO) standards so as to facilitate verification.

The key to verification is sensitivity analysis of relationships between model parameters and the state or time path of variables endogenous to the modelled system (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Thus, the changes in parameter are compared to model results so as to test the the limitations in applying the model in terms of spatial and temporal extent.

Validation concerns how well model outcomes represents real system behaviour (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Hence, this involves comparing model results with actual observations. Model results are compared to actual observation using a variety of techniques. Pontius Jr et al., (2008) compared results of 9 land-use change models using the method of multiple resolution map comparison.

Shortcomings in verification and validation in urban growth modelling are a result of scale related problems (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Nonetheless, Lam and Quattrochi (1992) disccuss the effects of changing scale and resolution in data analysis. Thus, analysing geographic phenomena at different scales and resolution can be advantageous for instance when a large area is represented at a small scale and analysis can be done with less computer times and memory. However, when a small area is represented using medium resolution data then this implies some geographic phenomena will not be captured fully depending on the focus of the research e.g. in urban planning studies.

The spatial extent (window size) from which pattern metrics are estimated has been shown to influence and produce biases in the results of these spatial analyses (Saura & Martinez-mlian, 2001). Saura and Martinez-mlian (2001) explored the sensitivity of eight commonly used landscape configuration metrics. Their approach makes it possible to control and isolate the different factors that influence the behavior of spatial pattern metrics.

The effects of scale have been noted to be mathematically casual, as the different variables vary as a function of the scale at which they are represented (Bian, 1997). Thus, the choice of data for urban growth modelling depends on the geographic phenoma being modelled. For the example of a city, a big sample size ought to be selected so as to represent the diverse urban land-uses including urban and peri-urban uses. Recently, high spatial scale data products have become available with recent developments in remote sensing and technology. However, urban growth modelling requires historical data of which most is still in low resolution such as old aerial photographs. The challenge for modellers is combining the various data sources at different scales for urban growth modelling.

There is need for assumptions necessary for verification and validation, such as normality and linearity (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Nonetheless, understanding complexity of modelling is difficult and involves use of techniques such as such as active nonlinear testing, which seeks out sets of strongly interacting parameters in a search for relationships across variables that are not found by traditional verification and validation.

Furthermore, another challenge lies in abstraction, since many outcomes of human interaction, such as trust or learning, are imputed or abstract (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). Hence, validating abstract outcomes is difficult, since they are ill defined or not easily measured.

In summary, after successful validation of a model, it can be used severaly to predict the real world. However, it should be possible to re-validate in case model parameters change considerably. As a common practise several sets of different validations are performed so as to ensure that the predicted results are in agreement with desired results or reference data. In this research we used a cellular automata UGM. Calibration and validation were performed in XULU. Calibration and validation are described in section 5.

2.2.4 Model uncertainty

Model uncertainty consists of four major components: uncertainty in model inputs, initial values, model structure, and uncertainty in the observations (Klepper, 1997). Nonetheless, accuracy of spatial models depends on the accuracy of model inputs and their sources. For example land-use models use remotely sensed data which contain uncertainty and error related to the sensor systems, processing, analysis and image processing software employed (Lunetta, et al., 1991). Besides, data used in simulation models also contain positional errors and attribute errors (Yeh & Li, 2006). This is illustrated in Figure 2-1.

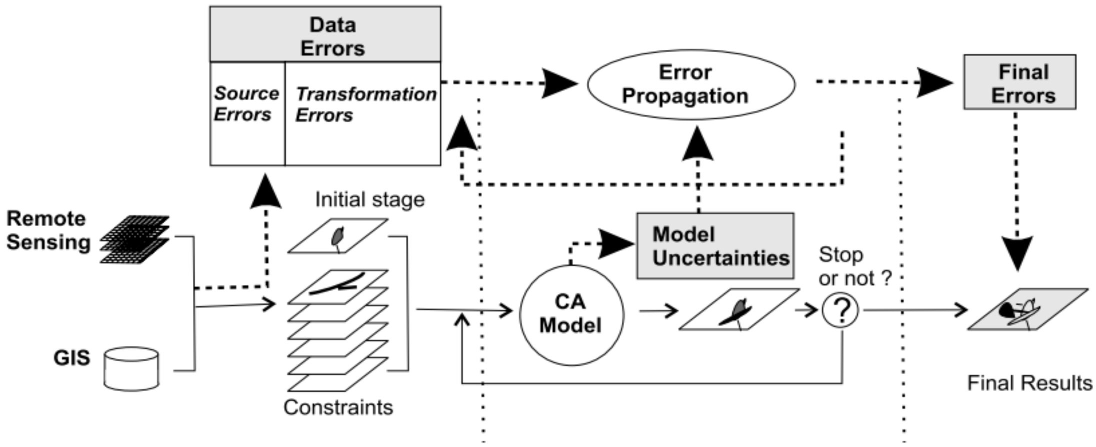

Figure 2-1: Data errors, model uncertainties, and error propagation in modelling

(Source: Yeh and Li, 2006)

The issue of uncertainty in model structure can be solved by reformulating the model parameters. For example if we have two alternative (sub)models M 1 and M2, we could use the hybrid model pM 1 + (1- p)M2, with p a switch parameter between 0 and 1 (Klepper, 1997). However, this solution might not work as different models are qualitatively different.

Nonetheless, a quantitative approach to uncertainty analysis is proposed as the most appropriate way to deal with uncertainty (Frey, 1992). Uncertainity occurs naturally in data randomly due to precise measurements conducted. As introduced earlier on, models are representation of real world and their structure can be source of uncertainity. Models apply mathematical formulars to represent reality. Additonally, models intially calibrated for one region must be re-calibrated so as to be applied in other areas. Likewise, we have uncertainity in the data and calibration errors being introduced as a result of system biases, errors in estimation of model parameters (Frey, 1992).

A majority of models are formulated using prior knowledge of the system rather than from observations and this often produces a large number of model parameters. Thus, uncertainity in model parameters involves conducting a parameter sensitivity or identifiability which is not a one-dimensional property, and differs for various outputs and output times (Klepper, 1997).

There is greater uncertainty (and potential for error) in predicting socioeconomic inputs in a model (Barton-Aschman Associates, Inc. and Cambridge Systematics, Inc., 1997). Thus, sources of significant uncertainty ought be identified early in an any operative validation process. Recent developments point to the use of intervals in analysis of uncertainty and thus to fuzzy set theory (Moore & Lodwick, 2003). Interval analysis has been used in mathematics in areas such as logic, probability, computation of the range of functions, and validation methods. These has both direct and indirect relationships to fuzzy set theory.

Interval mathematics is to estimate upper and lower limits on model predictions due to parameters that are known to be unknown while Fuzzy theory is used to represent uncertainty through the process of fuzzification (Pradhan & Kockelman, 2002). Moreover, uncertainity of model inputs are represented using probabilistic analysis which are delineated by probability distributions (Papoulis, 1991). Probabilistic approaches comprise analytical methods and sampling based methods.

Sampling based on uncertainity analysis methods involve running the original model for a set of input and parameter combinations, and using the model outputs at those points to estimate model sensitivity (Pradhan & Kockelman, 2002). Such methods include the Monte Carlo and Latin Hypercube methods (Fishman, 1996), Fourier Amplitude Sensitivity Test (FAST) methods (McRae, Tilden, & Seinfeld, 1982), reliability based methods (Bjerager, 1990), and response surface methods (Fedorov, 1983).

Monte Carlo (MC) methods have been used in most cases for analysing uncertainty in complex urban systems. They involve random sampling from the distribution of inputs, and successive model runs until a statistically significant distribution of outputs is obtained (Pradhan & Kockelman, 2002). MC methods are a convenient way to study error propagation when mathematical models are problematic to define (Yeh & Li, 2006). Thus, perturbations are inserted in spatial variables so that the sensitivities of the perturbations in urban simulation can be examined.

MC has been implemented in various urban growth models such as CLUE-S (Menz, et al., 2010), SLEUTH (Silva & Clarke, 2002) and UGM (Goetzke, 2011). In this research MC was perfomed for our UGM in XULU. Additionally, we carried out 100 MC simulation runs of urbanisation maps and achieved model calibration using several iterations as shown in section 5.6. Furthermore, we conducted spatial effects of varying model parameters as well as the sensitivity of the model in urban growth simulation in section 6.

2.3 Modelling urban growth

2.3.1 Background

Urban modelling thrived in the late 1950s and continued till the late 1960s. This was realised as the use of computer models of urban land-use and transportaion in urban planning began (Klosterman, 1994; Wegener, 1995). Computerised models of cities were introduced and developed further by emerging insights of regional science, linear programming, and operations research, to yield urban development models (Klosterman, 1994). In the 1970s urban modelling began to decline as a result of the massive transformation from an industrial to an information economy (Lee, 1973; Su, 1998). In the period 1960s till 1980s modelling approaches were static and linear and consisted of regression analysis, mathematic programming, input-output analysis. These tehcniques were inadequate to reflect the complex, dynamic and non-linear factors inherent in urban systems (Klosterman, 1994; Su, 1998). The models were too ambitious as they tried to replicate complex sytsems all at once with limited background of urban structures and process. Urban modelling shifted from macro to micro, aggregate to dissaggregate, static to dynamic, linear to non-linear due to the uncertanity that existed in the process of urban evolution (Su, 1998).

The development of the GIS as well as the integration of a GIS and transportation with urban modelling has facilitated urban modelling with rich data sources and new techniques (Liu, 2008). This has enabled users to go beyond data inventory and management stage to conduct sophisticated modelling and simulation including spatial analysis (Klosterman, 1994; Su, 1998).

The dimensions of time and space have been incorporated into urban modelling such as in CA models. CA focus on urban morphology and dynamics of urban growth and sprawl. These models have been recognised in simulating and predicting spatial patterns of urban development. CA represents a study area as fine-scale grid in which diffusion of development is embedded. These models are dynamic and much better at conducting spatial modelling compared to traditional models used in industrial revolution time such as Weber's (1909) industrial location model.

Tradition models were driven by policy. Recent models are dynamic and influenced by technological developments in GIS and remote sensing, and view cities as complex systems in a bottom up approach (Batty, 2001b). These models help policy makers in understanding complex cities and in exploring scenarios of urban growth.

2.3.2 Modelling approaches

The first use of models in urban modelling was von Thünen classical model of agricultural location (von Thünen, 1826). Von Thünen theory states that the best location will be selected by a farmer depend on distance to the market, prices fetched for sale of goods and rent paid on land. Thus most expensive agricultural products with high transportation cost will be located near to the city while the low value goods with low transport cost will be located further from the city.

Weber (1909) came up with an industrial location theory and was the first step into urban growth modelling. He noted that a location of an industry is guided by factors such as the availability of raw materials, power, politics, market, and transportation connection. Thus this can be regarded as location theory due to the availability of transportation networks.

Christaller (1933) invented the Central Place Theory. The theory accounts for the size and distribution of settlements within an urban centre. The assumption is that a rural farm population is dispersed over a homogeneous plain. Thus a consumer will purchase from the closest central point and the seller will supply goods to a centralised high purchasing power location.

Burgess (1925) invented the Concentric Zone Model. The model gave first instances on the concept of central business districts (CBD). This model was based on the notion that various elements of a heterogeneous and economically complex urban society actively compete for favourable locations within the city. The competion in this context implies successive outward expansion of urban land thus forming a series of concentric zones that surround the main centre. Thus a city expanded outward, led by successively lower income groups in a continuing process of invasion and succession (Adams, 1970). The model did not account for biophysical factors such as topography and transportation.

Hoyt's (1939) invented the Sector Model. He studied residential patterns and discovered that residential areas tend to grow outward from the centre as people's income increase. Unlike Burgess model which was static, Hoyt considered transportation and topography as well as land-use patterns. He concluded that as a city expanded in size and area the various economic activities and social-economic groups expanded their territories outward from the centre creating pie-shaped wedges of distinct land-use types (Adams, 1970). Thus high class residential areas were likely to spread to higher grounds and along waterfronts.

Harris and Ullmans (1945) invented the Multiple Nuclei Model. The model suggested that urban growth patterns followed general ecological principles observed by Burgess. Urban gorwth was spread over growing points or nuclei. Such multiple nuclei attracted new populations whereas others discouraged urban growth. Multiple nuclei grew into big cities with new districts attracting more urban growth compared to others.

Alonso (1964) invented urban land markets or bid-rent theory. He stated that land is developed in an area were rent is minimal and transportation costs are saved. He defined a bid-rent curve involving a set of combinations of rent and transport inputs to represent an equal satisfaction level for an individual. Thus the value of land decreases in a curvilinear function with increasing distance from the city centre.

Lowry (1964) developed the model of metropolis. The model assumed that residential areas were distributed in a logical way around centres of employment. Another assumption was that the location and employment levels of the service sector were strongly influenced by accessibility to local customers whose effect was progressively reduced the farther away they lived. Lowry categorised urban employment into basic and non-basic parts in an urban economic base.

Janelle (1968) described urban growth based on transportation and investigated the aspect of time and space interaction. He proposed a time-space convergence model in which transportation influenced growth between two neighbouring towns. Thus two towns will tend to converge more if the travel times between them decreases as a result of an increased travel speeds and developments in transportation modes.

Forrester (1969) developed the urban dynamics model. It was based on system dynamics technique and was used for simulating urban development. He applied the concepts of industrial dynamics and simulated the development of housing and industry over a city divided into 16 zones (Burdekin, 1979). Forrester (1969) distinguished between activities in urban systems as population, housing and industry as well their interactions. However, the model lacked spatial disaggregation and omitted suburb areas.

Crecine (1969) developed TOMM (Time-Oriented Metropolitan Model) and this among the first attempts into dynamic modelling. The model was designed for the Pittsburgh Community Renewal Program and was based upon a quasi-dynamic interpretation of Lowry's model of metropolis. However, the model was organised around the comparative-static framework used by Lowry, but was designed to simulate incremental changes in the structure of the urban system.

Adams (1970) explored residential land-use in Midewestern cites in USA. He came up with a hypothetical model illustrating residential pattern from construction data gathered from 1889 to 1960. The model was in agreement with distance-density decline interpretations of American urban population structre. He compared density gradients with the age of cities. His model assumed four transport eras: the walking/horsecar (before 1850), the electric streetcar (1880 – World War I), the recreational auto era (1920 – 1941) and the freeway era (post World War II). Residential development tended to occur at sites on the mrgins of built-up urban areas. Population densities dropped as as more people owned cars. Urban areas expanded further outwards from their centres due to increased mobility and economy.

During the 1970s and 1980s, the aggregate static approach to theory and modeling began to switch around to more bottom-up decentralised dynamics (Batty, 2009). Batty (1972) made attempts to address the integration of system behaviour within models and developed a dynamic simulation model. His model treated both the temporal and spatial dimensions together. The model incorporated land-uses, activities and their interactions.

2.3.3 Current practices in urban land-use modelling

Urban land-use models are crucial as they support planning and development of sustainable urban areas (Herold, Menz, & Clarke , 2001). These models have been classified into several categories (Herold, Menz, & Clarke , 2001; Agarwal, Green, Grove, Evans, & Schweik, 2002).

California Urban future 2 (CUF 2) is a deterministic and stochastic modelling framework for simulation of how growth and development policies might alter the location, pattern, and intensity of urban development (Landis & Zhang , 1998). It based on raster and for grid cell sizes of 100 m x 100 m. It has been used to model residential, commercial and industrial urban land-uses. It uses fixed time steps for prediction of land-use change in historical calibration time frame around 5 to 10 years. It requires input datasets on urban land-use, topography and transportation infrastructure.

Land-use change analysis system (LUCAS) is a stochastic model used to examine the impact of human activities on land-use and the subsequent impacts on environmental and natural resource sustainability (Berry , Flamm , Hazen , & MacIntyre , 1996) . Its raster based and its resoultion varies. 90 m x 90 m grid cells have been used in previous studies. It uses variable time steps for example a case study of 100 years and a 5 year time prediction step. It represents landscape as described by Anderson level I class (see appendices 9.1.2 and 9.1.3) and urban land-use comprises of residental land-use either as low or high density (Anderson, Hardy, Roach, & Witmer, A land use and land cover classification system for use with remote sensor data, 1976). The model requires input datasets on urban land-use, topography, population density and transportation infrastructure.

Land Transform Model (LTM) simulates land-use change processes using cellular automata (Pijankowski, Long , Gage, & Cooper, 1997). Forecasting of land-use change is based on ecological principles at the catchment scale. It is raster based and allows different spatial scales for process e.g. 30 x 30 m^2 parcel, 100 x 100 m^2 parcel and 300 x 300 m^2 parcel. It uses variable time steps of 5 – 10 years for prediction for a study period of 20 – 50 years. It represent landscape as described by Anderson level I class and this is urban which contains residental land-use divided by density (Anderson, Hardy, Roach, & Witmer, A land use and land cover classification system for use with remote sensor data, 1976). The model requires input datasets on urban land-use, topography, population, employment and transportation infrastructure.

Klosterman (1999) introduced What If, a scenario-based deterministic planning support system which supports traditional planning activities such as land-use planning, urban modelling and emerging modes of collaborative planning. It is based on vector data and entitles unifrom analysis of zones which are homogenous land units and are derived from overlay of relevant layers of natural and human parameters. It uses variable time steps for instance for 5 – 10 years time steps will be used for a 25 year prediction period. It has been used to model residential, commercial and industrial urban land-uses. The model requires input datasets on urban land-use, topography and transportation infrastructure.

UrbaSIM is a software based, semi-empirical, object-oriented modelling system for integrated planning and analysis of urban, development, incorporating the interactions between land-use, transportation, and public policy (Waddell, 1998). It is vector based and parcels are modelled as entities for land development with grid cell sizes of 150 m x 150 m. It uses variable time steps of 1 year. It has been used to model parcel attributes such as socio-economic and land-use characters. The model requires input datasets on urban land-use, biophysical and socio-economic datasets.

SLEUTH or Clark Urban Growth Model simulates urban growth in order to aid in understanding of interactions of urban areas with other land-uses (Clarke & Gaydos, 1998). It is raster based and case study areas are in grid sizes of 30 m x 30 m, 50 m x 50 m, 1 km x 1 km. Yearly predictions are possible with case studies ranging up to 90 years of future prediction. It models urban/non-urban but more focused on delineation of urban land-uses. The model requires input datasets on urban land-use, topography and transportation infrastructure.

Urban Growth Model (UPLAN) is a land use evalution and change analysis tool which aides communities create alternative development patterns based on local land development policies (Shabazian & Johnston, 2001). Its raster based with a resolution of 200 m x 200 m for low density residential areas and 50 m x 50 m in all other categories. It uses variable time steps for 20 to 40 years of prediction. It has been used to model residential (divided by density), commercial and industrial urban land-uses. The model requires input datasets on urban land-use, topography and transportation infrastructure.

Urban Growth Model (UGM) is a modification of SLEUTH and was first applied for the German federal state of North-Rhine Westphalia (Goetzke, 2011). It is raster based and case study areas are in grid sizes of 30 m x 30 m, 100 m x 100 m. Yearly predictions are possible with case studies ranging up to 30 years of future prediction. It models urban/non-urban but more focused on delineation of urban land-uses. The model requires input datasets on urban land-use, topography and transportation infrastructure. Thus, we applied UGM in this research to simulate urban growth in Kenya using the grid size of 30 m by 30 m for Nakuru (Mubea, Goetzke, & Menz, 2013), and 100 m by 100 m grid for Nairobi (Mubea, Goetzke, & Menz, 2014).

2.3.4 Complexity of Urban Growth

Urban growth modelling involves modelling complex processes within cities. Cities are among the most complex structures created by human societies and are characterised by complex patterns of land-uses (Barredo, Kasanko, McCormick, & Lavalle, 2003). Nonetheless, urban areas are dynamic and growth in different dimensions over time. Thus, understanding complexity helps in urban growth modelling successfully and eliminates uncertainty. Urban areas represent a mix of related units, but the degree and nature of the relationships are sometimes hard to establish (Barredo, Kasanko, McCormick, & Lavalle, 2003). Therefore, elucidation of complexity in cities depends on the complexity of interactions and conversions of land-use patterns. Additionally, understanding of urban land-use dynamics helps in addressing complexities in cities.

Tobler (1979) defined the first law of geography as follows, “Everything is related to everything else, but near things are more related than distant things”. Consequently, this has served as a basis in addressing urban land-use dynamics. Thus, for instance a new industrial area can attract urban land-use nearby as workers settle near factories and housing estates sprout in the periphery. Urban land-use dynamics are the direct consequence of the action of individuals, public and private corporations acting simultaneously in time over the urban space (Barredo, Kasanko, McCormick, & Lavalle, 2003). Subsequently, cities in Africa have grown from simple towns such as Lagos which began from a humble port to a modern megacity with a population of 11.2 million in 2011 (United Nations, 2013).

The urban transition can be seen as the passage from a predominantly rural to a predominantly urban society which takes place by the expansion of existing urban areas and the development of new cities (Mantelas, Prastacos, Hatzichristos, & Koutsopoulos, 2012). Thus, as a result of rural urban migration people move into urban areas in search for jobs, trade, and amenities. Furthermore, settlement in urban areas is influenced by environmental characteristics; local-scale neighbourhood characteristics; spatial characteristics of the cities (i.e. accessibility); urban and regional planning policies; factors related to individual preferences, level of economic development, socio-economic and political systems (Barredo, Kasanko, McCormick, & Lavalle, 2003).

Nonetheless, urban planning should be made upon the understanding and analysis of the various interrelated components of the urban development process (Rakodi, 2001). Hence, this will help in achieving appropriate plans and policies which address sustainable development. Additionally, understanding the complexity of cities enables us to envisage the intricate nature of the structure, and thus essential for the effective operation of the city (White, Engelen, & Uljee, 1997).

Complexity was previously associated with randomness, and the role of science was to lessen this uncertainty and reveal the order, either by inferential statistics or by the construction of analytic models (Silva & Clarke, 2005). However, new approaches have been formulated to represent and quantify the complexity. The complexity of urban growth can be envisioned using urban growth models which integrate GIS. Furthermore, the integration of Cellular Automata (CA) with GIS has facilitated the urban growth modelling in that urban dynamics can be simulated regardless of the complexities of the cities being investigated. Thus, CA need to be calibrated so that they can be applied in other cities such as in Silva and Clarke (2005) whom applied SLEUTH model for two cities in Portugal using complex systems theory.

Accordingly, CA models are preferably appropriate for modelling the complexity of urban systems since they have many more unknowns than measurable variables (Clarke & Gaydos, 1998). CA models have been used to simulate different types of urban forms and development densities and to investigate the evolution of urban spatial structure over time (Oguz, Klein , & Srinivasan, 2007). Thus, UGM model endeavours to curtail complexity via modelling the complex environment of cities merely using the physical parameters to development. UGM uses five parameters which are introduced in Chapter 5 (see section 5.3). Additionally, recent developments in remote sensing and GIS ensure the accessibility of data in several spatial and temporal scales.

2.3.5 Role of GIS and remote sensing in urban growth modelling

It is possible to conduct urban land-use modelling and prediciton with the aid of GIS using various data sets such as land-use, infrastructure, geomorphology and so on. GIS offers spatial analysis and representation of data in form of maps thus facililtating urban land-use modelling. GIS models are of varying degrees of comprehensiveness and sophistication and are applied to cities for purposes of research and policy analysis. GIS has been an indispensable tool in the model construction and calibration, and will play far more critical a role when the predictions are distributed and reproduced for other areas (Clarke & Gaydos, 1998).

Several approaches have been used to integrate GIS with urban growth modelling (Wegener, 1995; Takeyama & Couclelis, 1997; Su, 1998). Firstly, GIS like functionalities like spatial analysis and cartography are embeded in urban modelling packages (Openshaw, 1991; Clark et al., 1997). For example UrbanSim was designed specifically to address policy analysis requirements of metropolitan growth management and tested in Oregon in 1998 (Waddell, 2002). Secondly, urban modelling is embedded into GIS by software vendors e.g. network topology in version 5.0 ofARC/INFO (Miller, 1991). In Miller (1991) the analysis of requirements and feasibility for deriving space-time prism within a GIS and potential applications were explored. Vendors have made some progress to improve the analytical and modelling capabilities. Thirdly, loose coupling an urban model with GIS packages and urban modelling such that they are integrated through constant data exchanges. Examples include systems developed by Clarke and Gaydos (1998) whereby redundant programming was avoided. Lastly, urban models are embedded with commercial software package via GIS programming (Liu & Phinn, 2003). In Batty and Xie (1994a) they explored extending proprietary GIS (ARC-INFO) to embrace system modelling using residential location models. Cellular automata Markov chain urban land-use modelling has been explored in Idrisi software in a couple of studies (Mundia et al., 2011; Sang et al., 2011). Recently significant effort has been made to integrate urban models in open source modelling platforms such as XULU (eXtendable Unified Land Use Modelling Platform) developed by Schmitz et al., (2007).

The current GIS urban modelling techniques are technology driven and further refinement in understanding urban forms is necessary. Different cities have different driving factors of urban land-use change. The tools should help in designing effective urban planning policies for sustainable development to be achieved. With the shift of urban modelling from the conventional top-down approach to the current practices in addressing localities, models such as those using diffusion-limited aggregation and cellular automata techniques have demonstrated considerable potential in the mutual benefits of urban modelling and GIS (Liu, 2008).

The potential of remote sensing in providing information for land-use planning has been explored by various scholars (Donnay, Barnsley, & Longley, 2001). There have been several challenges in mapping the urban land-uses due to the various land-uses, heterogenity of the urban environment and impervious layer (Herold, Clarke , & Scepan, 2002). Urban areas consist of: built-up structures such as buildings and transportation networks; several vegetation cover types such as parks, gardens and agricultural areas; bare soil zones and water bodies (Barnsley M. J., et al., 1993).

With recent times remote sensing data has become available at high resolution and spatial scale making it possible to map larger heterogeneous areas. Developments such as synthetic apertutre radar (SAR) products such as ALOS Palsar are able to penetrate cloud cover rampant in tropical areas. The integration of multi-sensor data has been found to be useful in urban land-use mapping (Mubea and Menz, 2012; Zhu, Woodcock, Rogan, & Kellndorfer, 2011). High spectral capability of remote sensing allows the delineation of diverse urban land-uses such as built-up areas, vegetation and water. Remote sensing urban land-use datasets are used as inputs in most urban growth modelling tools.

2.4 Cellular automata modelling

2.4.1 Introduction

Von Neumann (1966) was one of the early pioneers of cellular automata (CA). He invented the idea of self-reproducing artificial structures. Von Neumann investigated whether mathematical-logical considerations could be used to discover the specific features of self-reproducing biological automata (Sipper , 1997). He worked together with his colleague Stanislaw Ulan at Los Alamos National Laboratories.

Alan Turing's computational machine (1936) illustrates an early innovation of automata. He created the Universal Turing Machine which served as a hypothetic automaton and was capable of many mathematical functions. Consequently, this was followed by the discovery of artificial intelligence (AI) by Wiener and Rosenblueth (1946). This formed a platform for viewing spatial systems as excitable media (Benenson & Torrens, 2004).

Early CA models viewed space as a lattice of identical cells in the 1960s and 1970s in modelling urban land-uses. Cities were considered as spatial distributed systems. CA models were improved once the concept of raster and regional modelling was incorporated in the 1970s and 1980s (Lee D. , 1973). Over the years CA models were applied to the study of general phenomenological aspects of the world, including communication, computation, construction, growth, reproduction, competition, and evolution (Sipper , 1997).

In the 1980s CA were used to study ecology and environmental phenomena but then urban CA were developed towards the end of 1980s (Benenson & Torrens, 2004). Early urban CA models represented the urban space based on raster and ignored neighbourhood relationship of pixels. Tobler (1979) explored urban CA simulation in his work and came up with a geographic model. The model was dynamic with several land-uses namely residential, commercial, industrial, public and agriculture, as cell states and enforced neighbourhood rules in the model. Wolfram (1984) did a systematic research on CA and their relationships with dynamic systems, and came up with classes of CA behaviour.

White and Engelen (1993) developed a constrained CA and this was a big step into urban modelling using CA. They integrated the CA models in 1960s and Tobler's geographic model (Tobler, 1979). Neighbourhood rules which are one of the fundamental elements of CA were refined from 3 by 3 grid space (Von Neumann, 1966) to 6 by 6 grid space.

Batty and Xie (1994c) developed life cellular automata models. The model was born on the idea of Conway's Game of Life. Cells are treated like life and cells are born which grown and later die within a certain time frame. The birth of cells is determined by neighbouring single cells which serve as parents and cells die as a function of the system.

Clarke, Hoppen and Gaydos (1997) developed self-modifying cellular automata. The model was called SLEUTH (**S**lope, **L**and-cover, **E**xclusion, **U**rban, **T**ransportation and **H**ill shade) and explored complexities of urban cells and incorporated biophysical factors namely: urban, road, transportation, slope and exclusion layer. The model used several factors in simulating urban growth namely diffusion, breed, spread, slope resistance and road gravity. SLEUTH was initially applied in Santa Barbara in California and then applied to other areas in North America. The model has also been used in other parts of the world (Silva & Clarke, 2002; Caglioni, Pelizzoni & Rabino, 2006; Mundia & Aniya, 2007).

Modern geographic applications combine geometry and simplicity of the von Neumann system with cybernetics views of Wiener and Rosenblueth (Benenson & Torrens, 2004). CA offer many advantages for modelling urban phenomena, including representing urban dynamics and space-time dynamics (Torrens & O'Sullivan , 2001).

2.4.2 Elements of Cellular Automata

CAs are dynamical systems in which space and time are discrete and consists of an array of cells, each of which can be in one of a finite number of possible states, updated synchronously in discrete time steps, according to a local, identical interaction rule (Sipper , 1997; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). The state of each cell is updated according to local rules, that is, the state of a cell at a given time depends on its own state and the states of its neighbours at the previous time step (Wolfram, 1994).

Cellular automata are seen not only as a framework for dynamic spatial modelling but as a paradigm for thinking about complex spatial-temporal phenomena and an experimental laboratory for testing ideas (Itami, 1994). A cellular automaton consists of five basic elements namely cell space, cell state, cell neighbourhood, transition rules and time. A cellular automaton (A) can be represented mathematically as shown in Equation 1 where (S) is the state of individual cells, (T) is a set of transition rules, (N) is a neighbourhood of all cells providing input input.

Equation 1

$$\mathbf{A} = (\mathbf{S}, \mathbf{T}, \mathbf{N})$$

Several approaches have been identified in defining the basic elements of a cellular automaton to simulate the process of urban development (Torrens and

O'Sullivan, 2001; Li and Yeh, 2000; Takeyama & Couclelis, 1997; White, Engelen, & Uljee, 1997).

The cell space

The space in which an automaton exists is called a cell space or lattice. A typical cellular automaton begins with a one- or two-dimensional lattice of sites or cells. In a one-dimensional cellular automaton the sites are a single row of identical cells while in a two-dimensional cellular automaton the sites are composed of a matrix of identical cells regularly arranged in rows and columns (Itami, 1994).

Figure 2-2 illustrates a one-dimension cellular automata where in (a) Neighbourhood consists of two cells on the left and on the right of a given cell and in (b) Neighbourhood consists of two cells on each side of the given cell. Figure 2-3 illustrates a two-dimension cellular automata where in (a) Von Neumann 3×3 neighbourhood; (b) Moore 3×3 neighbourhood; (c) Von Neumann 5×5 neighbourhood.

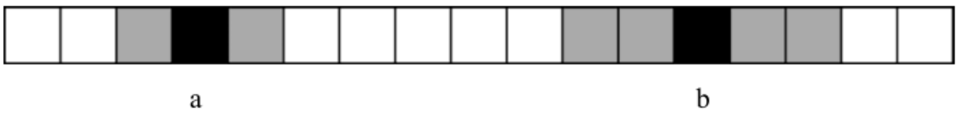

Figure 2-2: Typical neighbourhood configurations of one-dimension cellular automata.

(Source: Benenson and Torrens, 2004)

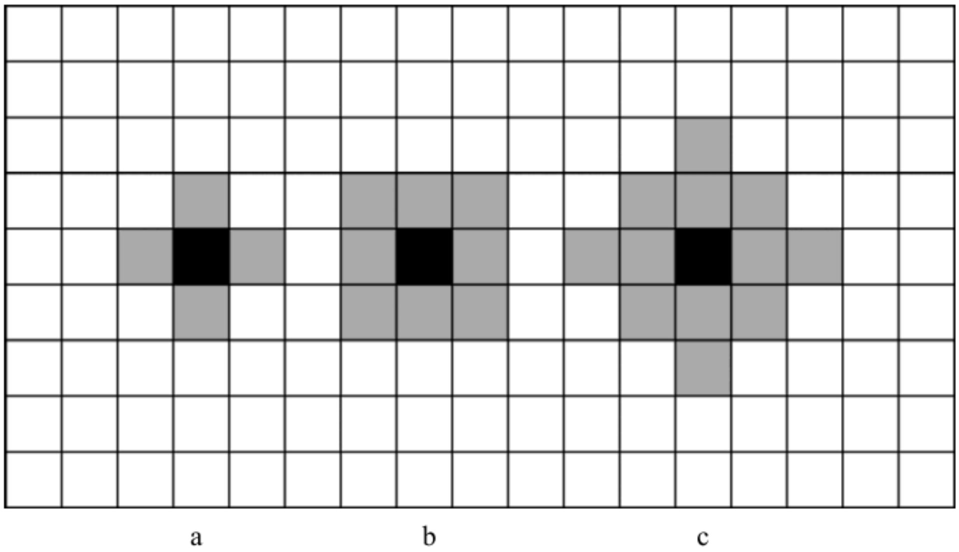

Figure 2-3: Typical neighbourhood configurations of two-dimension cellular automata.

(Source: Benenson and Torrens, 2004)

The two-dimensional grid of cells is the most common form of a cellular automaton used in modelling urban growth and land-use change (Liu, 2008). Rectilinear grid systems have obvious advantages both in terms of compatibility with raster-based data systems and in terms of computational efficiency (White & Engelen, 2000). Nevertheless, most grid space is typically assumed to be homogeneous, and usually different models adopted different grid size (Barredo, Kasanko, McCormick, & Lavalle, 2003; Clarke, Hoppen, & Gaydos, 1997; White & Engelen, 1993). Conversely, one-dimensional CA has been used to depict linear objects such as in urban traffic modelling (Nagel, Rasmussen, & Barrett, 1997; DiGregorio , et al., 1996). However, in one-dimension CA the linear CA are concatenated in order to represent the network structure of the road system (White & Engelen, 2000).

The state

Cell states most commonly represent land-use, but may be used to represent any spatially distributed variable for the purpose of modelling its spatial dynamics (White & Engelen, 2000). Each cell in CA can take only one state from a set of states at any one time and it can be a number that represents a property (Liu, 2008). Portugali and Benenson (1995) used cell states to depict social categories of populations (immigrant vs. native population). Urban development is therefore a continuous process in space and over time and thus there is no sharp boundary between non-urban and urban areas (Herbert, 1997). In some cases some cell states can be in a fixed state such as rivers and parks, so that while cells in these states can influence the state transitions of other cells, they are not themselves subject to changes of state (White, 1998).

The transition rules

Transition rules defines how the state of one cell changes in response to its current state and the states of its neighbours (Liu, 2008). These rules determine how CA states adapt over time and can be designed using any combination of conditional statements or mathematic operators (Benenson & Torrens, 2004). Transition rules may be deterministic or stochastic; very simple (e.g. a cell changes to the modal state of its neighbourhood), or quite elaborate, like the transition rules of the urban model (White, 1998).

In a strict CA, the transition rules are usually uniform and are applied synchronously to all cells within the system (Liu, 2008). The transition rules serve as the algorithms that drive the change of cells from one state to another over time. Fotheringham, Batty and Longley (1989) developed the diffusion-limited aggregation model for modelling the dynamic urban growth which was a cellular automaton in nature, and the rule applied in this model was simple: a vacant cell would convert to an occupied one if it is within the neighbourhood of an occupied cell.

The neighbourhood

The cellular neighbourhood of a cell consists of the surrounding (adjacent) cells (Sipper , 1997). The neighbourhood is outlined by the grid (cell space) in which the CA are located. In one dimension CA the neighbourhood comprises of two cells; one on the left and the other on right of a given cell as shown in Figure 2-2. In two dimensional rectilinear CA as shown in Figure 2-3 and Figure 2-4, the most commonly used neighbourhoods are the Von Neumann (4-cell) and the Moore (8-cell) (White, 1998).

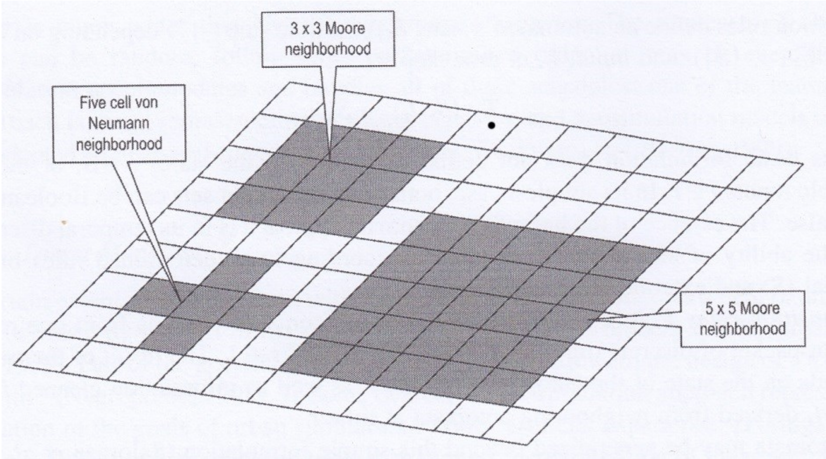

Figure 2-4: Cellular automata neighbourhoods

(Source: Benenson and Torrens, 2004)

There are also other types of neighbours e.g. de Kok et al., (2001) adopted RaMCo model whose neighbourhood is defined as circular region around a cell up to a radius of 8 cells. Normally, the size of the neighbourhood should is defined with reference to the distance over which the processes represented by the transition rules operate (White, 1998).

The time

Liu, (2008) defines time as the temporal dimension in which a cellular automaton exists and thus the states of all cells are updated simultaneously at all iterations over time. In the modelling of urban land-use, time steps are normally yearly but in other cases such as traffic flow modelling time steps of seconds or minutes are ideal.

There are situations where it is convenient to nest time scales, with some parts of the CA running a number of time steps for each step in the rest of the model (White, 1998). Uljee, Engelen & White (1996) used a model at different temporal speed for different cells which simulated the low-lying areas on a monthly basis and the upland areas on a yearly basis.

2.4.3 Cellular automata models

CA are worthwhile because of their ability to replicate complex spatial and temporal dynamics at a global scale using local rules (García, Santé, Boullón, & Crecente, 2012).

Tobler (1979) was the first to apply CA in modelling geographic phenomena. However, early applications of CA to urban growth modelling were theoretical as seen in Couclelis (1985), Itami (1988), White and Engelen (1993), Portugali and Benenson (1995), Takeyama and Couclelis (1997), Liu and Phinn (2003), and Kocabas and Dragicevic (2006).

Tobler's work in the development of urban CA modelling was further extended in the 1980s by Couclelis (1985). This formed the basis for linking theory and complex systems and unravelled the potential of CA in urban planning. She further developed CA through separating the neighbourhood set and transition rules from each cell. Hence, micro-macro dynamics could be captured by the cells which were able to possess their own set of neighbourhood and simple transition rules. Thus, complex spatial patterns of urban growth could be simulated.

Takeyama and Couclelis (1997) formulated Geo-Algebra, an extension and generalisation of map algebra, enabled integration of CA with GIS. This was a mathematical framework capable of expressing a variety of dynamic spatial models and spatial data manipulations. Additionally, map dynamics made it possible for modelling of supplementary dynamic behaviours and phenomena.

Urban simulation models which could simulate reality were designed based on the theoretical developments from the 1980s and subsequent developments in GIS. Nonetheless, calibration and validation were mandatory so that the models could simulate real world case scenarios as seen in Clarke, Hoppen, & Gaydos (1997).

White and Engelen (1993) introduced the notion of constrained CA. Their CA model which was able to simulate urban land-uses over time in Cincinnati, Ohio (USA). The modelling approach focused on the fractal dimensions of land-use patterns of an urban area. Thus, the potential for transition between cells for different land-uses was calculated as a function of the neighborhood and land-use suitability (White, Engelen, & Uljee, 1997). It was possible to capture a high level of spatial detail and reality.

Batty and Xie (1994c) developed an urban CA model through simulating the development of the historical 'cell' city of Savannah, Georgia (USA). Additionally, they illustrated how their model could be adopted to predict urban growth dynamics of a sub-urban city. Hence, such an approach was able to captured the microprocesses which lead to aggregate development patterns.

Xie (1996) invented the dynamic urban evolutionary modeling (DUEM). DUEM lay its foundation on the theoratical concept and technical fundamentals of Couclelis's CA model and contemporary techniques of GIS, and was applied in suburban area of Buffalo, New York. The model addressed the aspects of complexity and dynamics in urban growth modelling.

Clarke, Hoppen, and Gaydos (1997) came up with a self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area called SLEUTH. SLEUTH model was first used to predict urban growth in San Francisco and later applied to other regions in North America (Clarke & Gaydos, 1998). Our model UGM is a modification of SLEUTH (Goetzke, 2011).

Alongside the development of CA, other modelling techniques have been developed which apply the concept of CA in simulating urban growth. Such developments such as Fuzzy-logic have aimed at improving CA calibration and addressing complexity of urban growth.

Wu (1998a) developed a prototype of a simulation model based on cellular automata (CA), and multi-criteria evaluation (MCE) which was integrated in GIS. The CA was integrated into Arc/Info GIS software. Thus, with this method it was possible to visualise decision-making process enabling faster access to spatial information. The transition rules were addressed reality of urban growth.

Wu (1998b) further developed a computer-based approach for simulating land encroachment with fuzzy-logic-controlled CA. Additionally fuzzy logic was introduced in order to monitor land-use conversion processes and CA was applied to predict growth using local transition rules in GIS. Liu and Phinn (2003) developed and applied a CA model using fuzzy-set approaches in Sydney, Austrialia.

Benenson (1998) developed a muilti-agent (MA) simulation model of population dynamics in a city. The agents applied were autonomous units and were identified by the economic status and cultures which vary in nature. The MA model inegrated housing infrastructure information and socio-economic information of residents. Thus, the residents were considered as free agents whom migrate into the city and dwell in various residential areas based on social and cultural factors.

Li and Yeh (2001) formulated the first CA-based model that used artificial neural networks (ANN) for calibration and simulation of urban growth in Pearl River Delta, China. The model parameter values were automatically determined using artificial neural networks. The model performed well compared to traditional CA models in the simulation of nonlinear complex urban systems.

O'Sullivan (2001) developed a CA-based model that combined aspects of mathematical concepts - graphs and CA, and was applied in Hoxton in East London. This enabled research into relationships between spatial structure and urban dynamics processes. The irregular spatial units introduced were able to capture urban growth dynamics.

Triantakonstantis & Mountrakis (2012) conducted a review of urban growth models and concluded that CA remains the most popular modelling technique used today as seen in Figure 2-5. Thus, CA are currently a worthwhile approach to urban growth modelling.

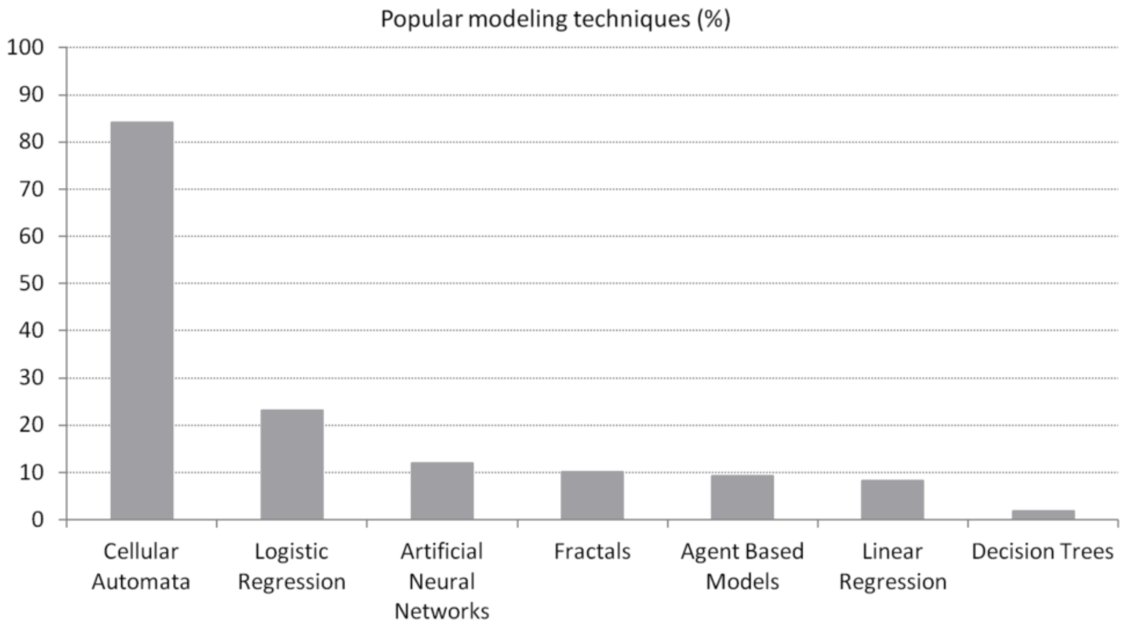

Figure 2-5: Underlying Urban Growth Model algorithms sorted by popularity

(Source: Triantakonstantis & Mountrakis, 2012)

2.4.4 Advantages of CA urban models

CA urban models have several benefits according to: Oguz, Klein , and Srinivasan, (2007); Santé, García, Miranda, and Crecente, (2010) and Blecic, Cecchini, and Trunfio, (2013):

- They are interactive and user friendly
- Their modularity and transparency
- Potential outcomes can be visualised and quantified,
- They can be closely linked and integrated with GIS and remote sensing,
- They can use raster based spatial data derived from remote sensing as input for modelling,
- CA are able to replicate emergent complex dynamics in cities using on simple transition rules,
- Visualisation of model results,
- They can be applied across large geographic areas ranging from cities to continents.

2.4.5 Limitations of CA urban models

The background conventions of CA limit their ability to realistically simulate complex geographical phenomena. Such challenges include:

- There is difficulty in addressing urban dynamics,
- Integration of CA with real databases is a tough exercise due to different database design and dimensions of spatial data,
- The use of regular grids in CA is not sufficient to implement high resolution data in urban growth modelling,
- Spatial heterogeneity. Growth in cities is not homogeneous as assumed by conventional CA,
- CA assumes regular neighbourhoods which in turn limits modelling,
- CA assumes spatial and temporal invariance for transition rules. Thus, they are unable to address stochasticity,

- CA need significantly larger computational power in terms of running models and their calibration.

The above challenges have been addressed by developments in CA models as seen in section 2.4.6.

2.4.6 Developments in CA models

Several approaches have been formulated to overcome the limitations of CA and thus improve CA models. Such modification involves modifying the original structure of CA in order to introduce more complexity (Couclelis , 1997) . The most common modifications as noted by Santé, García, Miranda, and Crecente, (2010) include:

Modification of cell space

In a typical CA, the cell space exists in a regular grid which is classically made of square cells. However, Iovine, D'Ambrosio, and Di Gregorio (2005) proposed the use of hexagonal cells so as to represent a more homogeneous neighbourhood. Likewise, Semboloni (2000) proposed a three-dimensional (3-D) model which was applied to an urban area and the results were found to be more realistic. Thus, with a 3-D model there is the possibility of representing the critical aspects of urban development such as clusters and variation of density.

There have been attempts to modify the regular grid space. Shi and Pang (2000) used Voronoi-based CA in which the CA was modified using a Voronoi spatial model as the spatial framework. The Voronoi spatial model delivered an immediate solution to handling neighbourhood relations among spatial objects dynamically. Additionally, the Voronoi-based CA was able to model local interactions amid spatial objects to produce multifaceted global patterns. Hence, irregular spatial units may provide a more authentic representation of the objects being modelled (Santé, García, Miranda, & Crecente, 2010).

Classically the cell space in CA is homogeneous. Thus, the cells are usually equal in dimension and are identified by their states which can be either urban or non-urban. Nonetheless, land-use is dynamic and is influenced by a myriad of factors such as altitude, gradient and accessibility to transportation and. Nevertheless, the cell space needs to be modified so as to represent a mix of land-uses and thus, this forms a step into making the cell space to be non-uniform.

Modification of neighbourhood

Ideally the CA neighbourhood is the same for all cells and comprises of a grid of cells as shown in Figure 2-4. Thus, neighbourhood is outlined by the grid (cell space) in which the CA are located. However, extending the local neighbourhood ensures that the model is dynamic and able to simulate urban growth which is complex. The influence of extending neighbourhood depends on the extended distance between neighbouring cells so as to effectively represent complexity of urban systems.

The neighbourhood space for each cell can be delineated differently, an approach which has been recognised, but hardly applied. Several attempts have been made in implementing models in which cell neighbourhoods have different sizes and shapes. White and Engelen (1993) made such an attempt in that they developed a CA model which produced fractal land-use structures for the urbanised area and for each individual land-use type. Hence, such an approach makes it possible to model reality fully in that we are able to capture high level of spatial detail.

Modification of transition rules

Typically the CA transition rules are static and determine how states adapt over time. However, they depend on the neighbouring cells. Nevertheless, land-use is dynamic and depends on factors such as altitude, urban land-use policies. Thus, the transition rules of CA can be modified so as to consider external factors influencing urban growth. Hence, it is crucial that the transition rules are able to adapt to the specific characteristics of the area the CA model is applied as well as the time period. This makes it possible for a model to be applied in another research area through model calibration.

Clarke, Hoppen, and Gaydos (1997) developed a self-modifying cellular automaton model of historical urbanisation in the San Francisco Bay area. Their model was called SLEUTH and had transition rules that vary over time. Thus, the model used in this research, UGM, is a modification of SLEUTH and can be applied in other areas through calibration using Monte Carlo techniques (see section 5.4).

Constraints

Classically, the CA transition rules determine the cell states. Nevertheless, urban growth is influenced by a myriad of factors among them being physical constraints such as steep slopes which inhibit growth. Additionally, urban growth is influenced by social constraints such as the segregation of residential areas into low, middle and high income residential areas. Moreover, urban land-use policies determine which areas can be developed.

Accordingly, it has been possible to introduce constraints in modern day CA urban models such as an exclusion layer depicting areas restricted from development as integrated in our UGM model (Goetzke & Judex, 2011). Other constrains introduced include slope and transportation as witnessed in SLEUTH and UGM. Thus, the constraints enable reality to be achieved while modelling urban growth.

2.4.7 Cellular automata in urban growth modelling

CA models have been used to simulate different types of urban forms and development densities and to investigate the evolution of urban spatial structure over time (Oguz, Klein , & Srinivasan, 2007). Liu (2008) illustrates CA modelling of a city in a two-dimensional regular grid of n x n cells or land parcels as shown in Figure 2-6. The black cells represent urban while grey cells are non-urban and the time step is t. A land parcel can either be urban or non-urban and is determined by transition rules (stochastic or dynamic) within a neighbourhood.

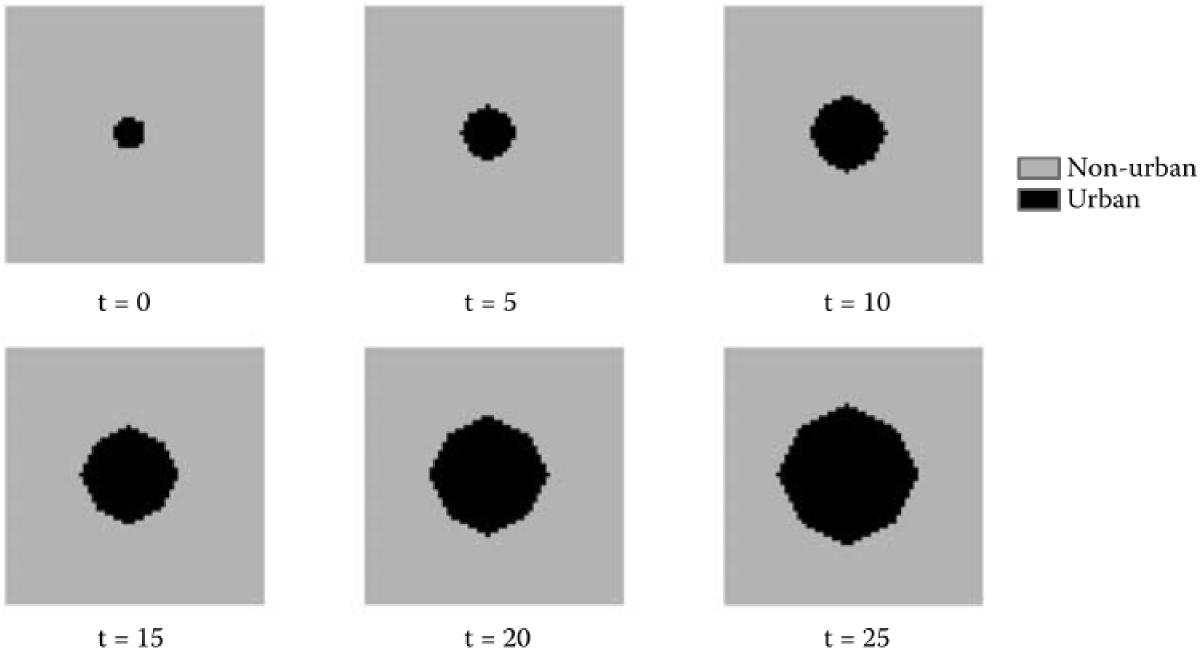

Figure 2-6: A cellular automata-generated urban development in a plain area.

Thus, our UGM operates as shown above in Figure 2-6. The input data include land-use, exclusion layer, slope data and road data. Urban growth simulation is done using simple transition rules adopted from SLEUTH. Model calibration is achieved through varying five model parameters in XULU using Monte Carlo calibration technique. UGM modelling is described in section 5.

3 URBAN GROWTH IN AFRICAN CITIES

3.1 Introduction

Since the beginning of the industrial revolution in 1850s, cities have gone from being a minor feature on our planet to a major one and global population has increased almost six times while the earth's urban population has increased over 100 times (Hauser, Gardner, Laquian, & El-Shakha, 1982). Rapid urbanisation has been noted globally. Urbanisation can be defined from a global environmental context as the conversion of natural to artificial land-use characterised by human settlements and workplaces (Clarke, Hoppen, & Gaydos, 1997). This occurs as agricultural land is converted to urban use.

Urbanisation has continued unabated into the 21st century and by 2008 the largest cities by continent with high urban population were Tokyo (Asia) with 35 million, New York (North America) with 19.18 million and Cairo (Africa) with 15.55 million (UN-Habitat, 2012). Additionally, it is expected that half of the population of Asia will live in urban areas by 2020, while Africa is likely to reach a 50 per cent urbanization rate only in 2035 (United Nations, 2013). Urbanisation and urban growth go hand-in-hand, and generate many other land transitions, with several varied land use types eventually converting to urban use (Clarke & Gaydos, 1998). Urbanisation has become a positive force for transformation that makes countries more advanced, developed and richer, in most cases (UN-Habitat, 2012) . However, persistent dynamic urban change processes, especially the remarkable worldwide expansion of urban populations and urbanised areas, affect natural and human systems at all geographic scales, and are expected to accelerate in the next several decades (Thapa & Murayama, 2012).

Africa was the least urbanised continent in the world in 1950s, with only 14.7% of its population living in urban settlements. However, the proportion of urban population has risen with 42.7% of the African population living in urban areas in the year 2010 and 52.9 % in 2030 (United Nations, 2013). Nevertheless, these figures are still lower compared to other continents as the annual growth rates of the urban population are high in Africa (Owour, 2006). The total population increased about three-fold between 1950 and 1990 within a sample of 39 countries in sub-Saharan (United Nations, 1995) but the urban population increased about ten-fold during the same period. In Kenya, the share of its urban population increased from 596,757 in 1960 to 9,549,269 in the year 2010 (United Nations, 2013).

Moreover, Kenya's population is growing rapidly and has more than tripled from 10.9 million people in 1969 to 38.6 million people in 2009 (Population Reference Bureau, 2011). Thus the population will continue to increase steadily due to the fact that there are high numbers of births per woman and it is projected to 65.9 million in 2030. The average annual growth for our research cities were noted as 4.9 % for Nairobi and 13.3% for Nakuru between 1990 and 2006 (UN-HABITAT, 2010).

In the last decade sustainability has been considered a relevant issue in most forums on environment (European Environment Agency, 2002). The ramifications of poorly planned urban growth in the megacities of developing countries can be less catastrophic if sustainable urban planning activities are adopted (Barredo & Demicheli, 2003). Likewise, urban population is increasing in developing countries at a much faster rate than the overall average (Lavalle, Demichili, Turchini, Casals Carrsco, & Niederhuber, 2001). This has been due to rural urban migration, thus posing a strain on existing amenities.

There has been a trend where agricultural land is converted into urban land-uses in the urbanisation processes and this has become a serious issue for sustainable urban development in the developing countries (Li & Yeh, 2000). Unsuitably, in recent years, a large amount of such land has been unnecessarily lost and the forms of existing urban development cannot help to sustain its further development (Yeh & Li, 1997; Yeh & Li, 1998). For example this has been seen in Kenya over last decade where coffee and tea zones have been converted into commercial and residential plots. However, the use of land unsuitable for development may cause harm to both the natural environment and human life (Yeh & Li, 1997). The fundamental issue of sustainable urban development is the search for better urban forms that can help to sustain development, especially the minimization of unnecessary agricultural land loss (Li & Yeh, 2000).

Dynamism and growth are two of the elements which are used to characterise most urban areas (Barredo, Kasanko, McCormick, & Lavalle, 2003). However, modelling these two elements can be difficult without tools which embrace their complexity. White & Engelen, (1993) define cities as complex objects from the point of view of their intricate mix of urban activities. Furthermore, cities' complexity can be seen from two points of view: the complexity represents the information-rich nature of the system, and the complexity is necessary for the successful functioning of the city as system (White, Engelen, & Uljee, 1997).

Assessing the impact of urban growth on the environment and understanding the dynamics of complex urban systems involves modelling and simulation (Oguz, Klein , & Srinivasan, 2007). This is achieved using urban growth models. Model building using Cellular Automata (CA) has recently gained attention for its utility in predicting spatial patterns of urban development and in the investigations on planning regimes and land use patterns (Silva & Clarke, 2002). In this research we used an urban growth model based on cellular automata to model and predict urban growth in Nairobi and Nakuru. Thus this chapter introduces sustainable development, factors that influence urban growth and gives a background of urban growth in African cities. Later on the cities Nairobi and Nakuru are described in detail.

3.2 Sustainable growth and characteristics of African cities

Sustainable development refers to the development that meets the needs of the present generation without compromising the ability of future generations to meet their own needs (World Commission on Environment and Development, 1987). Additionally, sustainable development is one of the most fundamental objectives in policy making and planning activities (Shi & Pang, 2000). Thus, sustainable urban planning is ideal so as to improve the quality of life in urban cities.

However, sound planning has not taken place in most African cities due to high rural urban migrations as people search for employment and basic amenities. Such cities continue to attract population from surrounding areas while they still lack basic amenities and infrastructure. Subsequently, urban population has increased at a much faster rate than the rest of the world and these has resulted to negative consequences (Lavalle, Demichili, Turchini, Casals Carrsco, & Niederhuber, 2001). Such problems include unsuitable land-use, inadequate transportation systems, pollution, urban sprawl and propagation of epidemics.

Cities in developing world are characterised by rapid growth in population which is not matched by growth in delivery of land for housing, services, utilities and infrastructure important to sustain a reasonable quality of life (Bishop, Escobar, Karuppannan, Williamson, & Yates, 2000). This is witnessed by establishment of informal settlements in African cities such as Kibera in Kenya. Additionally, there is lack of spatial information making it difficult to plan and cater for the increasing population. For example some cities still use development plans which were developed in the 1970s. Thus informal settlements continue to growth within and around most cities as the demand for housing, energy and other resources increase. This leads to degradation of local and regional environment and possess a threat to ecosystem and biodiversity.

Nonetheless, addressing urban dynamics is one of the most complex tasks in sustainable planning of cities while also conserving natural resources. Cities are made up of complex and numerous components which need to be documented and incorporated in the legislation of land-use policies. Nevertheless, sustainable urban planning ought to be implemented at national, regional and local levels. However, most cities in developing countries typically lack the capacity to obtain the necessary data and to carry out the comprehensive analyses needed in order to set and achieve sustainability targets (Lavalle, Demichili, Turchini, Casals Carrsco, & Niederhuber, 2001). The use of new technologies such as remote sensing and GIS can help these cities monitor their resources and be prepared for any eventualities in the near future. Therefore, there is need for capacity development as developing countries adopt new technologies in terms of personnel, data and procedures. Hence, if sustainable urban planning actions are taken into account, the consequences of poorly planned urban growth in the megacities of developing countries can be less dramatic (Barredo & Demicheli, 2003).

Accordingly, problems associated with sustainable urban development in African cities are myriad and complex. Thus, an integrated approach should be adopted which anticipates urban growth dynamics and ramifications. The integration of remote sensing and GIS in sustainable land development is useful in updating the land information in the GIS database, improvement of land-use change detection and environmental modelling and analysis (Yeh & Li, 1997). This research explored scenario based urban growth of two Kenyan cities so as to come up with plausible development agenda. The pillars of sustainable development are social, economic, political and equity. Thus these ought to be addressed so that Kenya can achieve Vision 2030 (Government of Kenya, 2007) with the goal of transforming Kenya into a newly industrialised middle-income country by 2030.

3.3 Prosperity of cities

The State of the World's Cities Report 2012/2013 report introduces prosperity of cities as places where successful, flourishing or thriving conditions prevail for the 21st Century (UN-Habitat, 2012). Prosperity is viewed as development which integrates economic success with tangible and more intangible aspects. Thus this includes environmental sustainability, equity and social inclusion, quality of life, infrastructure, and productivity. Prosperity is seen as a step further over sustainable development with the inclusion of intangible aspects such as the quality of life of citizens.

There have been demands by developing countries in Africa such as witnessed in the uprisings in Egypt and Tunisia in 2011 for more equality and inclusion in the national economy. This was a result of social, political and cultural inequalities. Additionally, unequal access to opportunities and resources has pushed many people into informal settlements within cities. Cities can offer remedies to the worldwide crises if only we put them in better positions to respond to the challenges of our age, optimizing resources and harnessing the potentialities of the future (UN-Habitat, 2012).

Nevertheless, prosperity means different things to different people around the world and ultimately refers to a sense of general and individual socioeconomic security for the immediate and foreseeable future, which comes with the fulfilment of other, non- material needs and aspirations (United Nations, 2013). Thus, the development agenda and policies of each country should incorporate all the citizens so as to ensure sustainable urban development is attained. This approach to prosperity will put cities and countries in a better position not just to respond to the effects of the crisis and provide safeguards against new risks, but also to steer the world towards economically, socially, politically and environmentally urban futures (United Nations, 2013).

Prosperity echoes the ideal city of the 21st Century. Thus these cities are able to respond to disasters and vulnerabilities such as food security. Furthermore, jobs should be created so as to achieve socio-economic equity and ensure citizens have equal access to social amenities and infrastructure. Additionally, citizens should have equal rights promoting good governance and policies ensuring sustainable development. Lastly, the five dimensions of prosperity should be harmonised so as to boost the prospects for a better future.

Prosperity implies success, wealth, thriving conditions, and well-being as well as confidence and opportunity (UN-Habitat, 2012). Hence, a prosperous city offers stable economic growth, equitable distribution of infrastructure, equity and social inclusion of its inhabitants, and environmental sustainability. Thus informal settlements should be minimised through construction of low cost houses and sustainable urban planning policies. Likewise, natural resources should be preserved so as to ensure that there is adequate land for future generations and thus achievement of sustainable development.

The UN-Habitat has identified eight factors which promote prosperity of cities. These are: effective urban planning and management; decentralisation polices and appropriate institutions; a system that creates equal opportunities for all; participation of civil society; elected local officials; a favourable business environment; access to basic amenities; and public transport and mobility (United Nations, 2013).

Kenya has made some progress such as the introduction of a new constitution in 2010 which advocated for the devolution of government. The general elections in 2013 introduced a devolved government with the establishment of 47 counties (Government of Kenya, 2010). Such counties will enable equitable distribution of social, economic, and political pillars of sustainable development. Besides, Kenya plans to achieve Vision 2030 and incorporating the concept of prosperity of the 21st Century cities will be resourceful. Hence, this will ensure that sustainable development is achieved countrywide alongside prosperous cities.

3.4 Factors influencing urban growth

In the 1960s most countries in sub-Saharan Africa gained independence from their colonialists, a transitional period ensued in which the achievement of autonomous economic and political status was attempted by means of state-centred, interventionist strategies paralleled by a regulatory approach to urban development (Rakodi, 1997). The colonialists sold land to African governments and the major challenge was equal distribution to its citizens. The new governments experienced economic or urban development challenged as they endeavoured in integrating into the world economy in terms of trade and industrialisation.

Rapid urbanisation has been rampant and has resulted to poverty which has outpaced the financial and administrative capacity of governments to ensure that cities provide efficient locations for economic activity and satisfy the basic needs of all their citizens (Rakodi, 1997).

The urban population has increased over the last couple of decades in Africa and this has strained the economic growth rates due to global recession. The incomes per capita fell considerably in the 1980s and 1990s as real wages continued to decline while open unemployment and cuts in government expenditure on infrastructure and services increased (Rakodi, 1997).

As some sub Saharan countries have been crippled by governance issues over the years there have been sanctions from International Monetary Fund policies such as limiting subsidies, increasing food prices and restricting wage levels. These have been disproportionately borne by the urban poor (Tacoli, 2002). As a consequence urban poverty has increased posing a challenge to urbanisation. This has led to informal settlements within towns and growth in crime. The existing amenities have not been expanded to cope with the high growing population trends. Thus this has led to negative effects on the social and economic development.

Reports from World Bank, International Monetary Fund (IMF), Organization for Economic Co-operation and Development (OECD) and United Nations Development Programme (UNDP), including national studies, indicate that approximately over 40% of the population of sub-Saharan Africa is living in absolute poverty or on a Purchasing Power Parity of less than one US dollar per day (Obura, 1996; Odhiambo and Manda, 2003). Thus this implies that nearly half of the urban population in most sub Saharan countries live below the poverty line.

In the 1980s and 1990s urban economies in sub- Saharan Africa declined significantly (Maxwell, 1999). Urban poverty has been increasing with undesirable consequences such as unemployment, as the population continues to increase. Life has become very expensive in most urban areas in terms of high food prices, fuel, and other essential commodities.

In most sub-Saharan countries, wage employment in the modern sector has fallen in absolute terms over time (Odhiambo & Manda, 2003). In the 1980s and 1990s there were massive retrenchments in the public sectors in Kenya as most parastatals and corporations downsized or collapsed. With the fall in formal-sector employment, many former wage earners have moved into the informal sector (Owour, 2006). The informal sector was coined a Swahili name *jua kali.*

The gross domestic product (GDP) in Kenya was 5.9 % in 2005, 6.3 % in 2006, 7.0 % in 2007, 1.6 % in 2008 and 2.6 % in 2009 (Republic of Kenya, 2010). The decline in GDP in 2008 was due to the post-election violence witnessed after the general elections in December 2007 until early January 2008. Nonetheless, the GDP grew to 5.8 % in 2010 and dropped to 4.4 % in 2011 (Republic of Kenya, 2012). This was due to high oil prices globally and uncertainties as the country approached general elections in 2013. Agriculture has been the major contributor of the Kenyan economy followed by industries. There has been a gradual decline in the share of the GDP attributed to agriculture, from over 30 % during the period 1964 - 1979 to 25 % in 2000 – 2002 (Kenya National Bureau of Statistics and ICF Macro, 2009). However, in 2007 and 2008 the agricultural sector contributed directly 22 and 23 % of the GDP.

As discussed above, Kenya has also experienced rapid urban growth over the last few decades. This served as the impetus to explore model urban growth using remote sensing techniques in Nairobi and Nakuru. Background on Nairobi and Nakuru are explained in the following sections below.

3.5 Nairobi

3.5.1 Research area

Nairobi extends between latitudes 1° 09' and 1° 28' South, and longitude 36° 04' and 37° 10' East in Kenya, with an average altitude of 1,700 meters above sea level, covering an area of 696 km^2 (Figure 3-1 and Figure 3-2). Nairobi is the capital city of Kenya. The administratively defined town has land-uses divided roughly into urban use, agriculture, rangeland, open/transitional areas, and remnants of evergreen tropical forests.

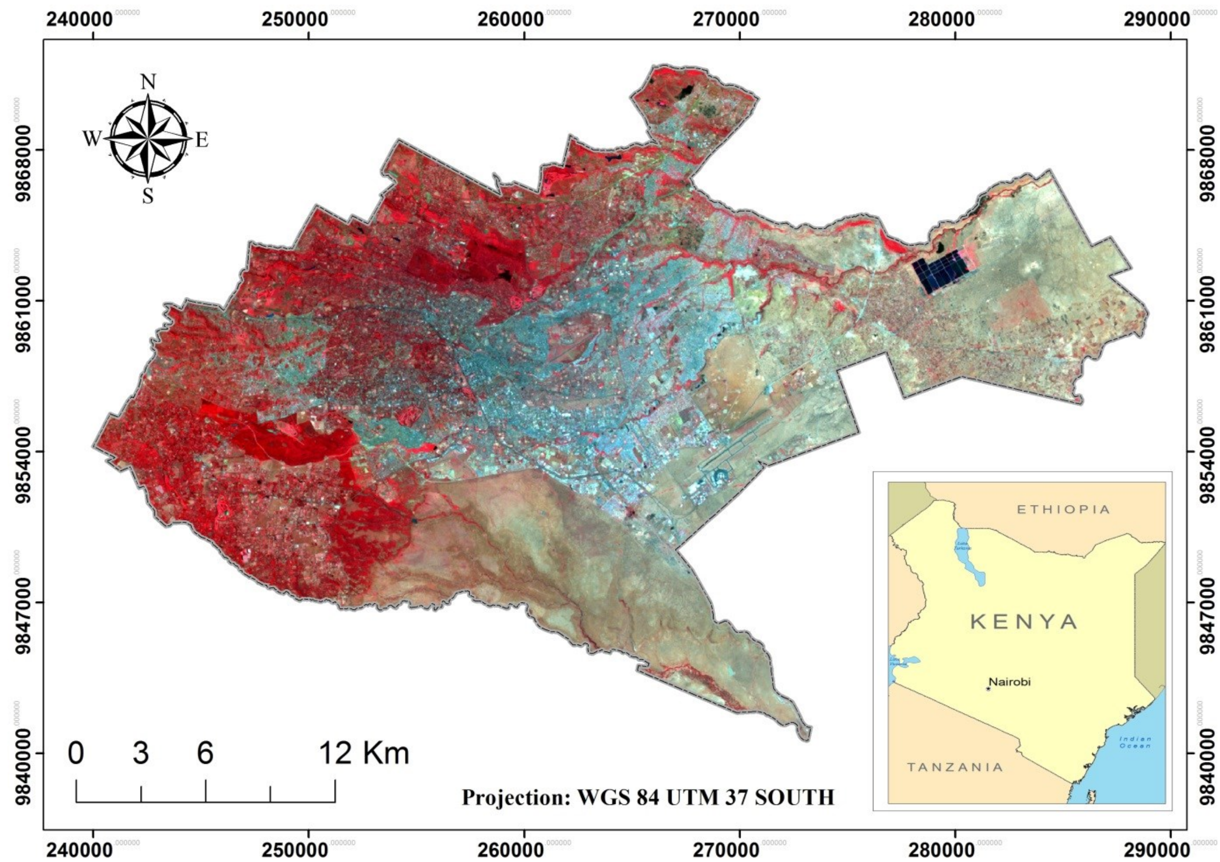

Figure 3-1: Location of Nairobi

(Source: False colour composite using bands 4, 3, 2, Landsat 2010)

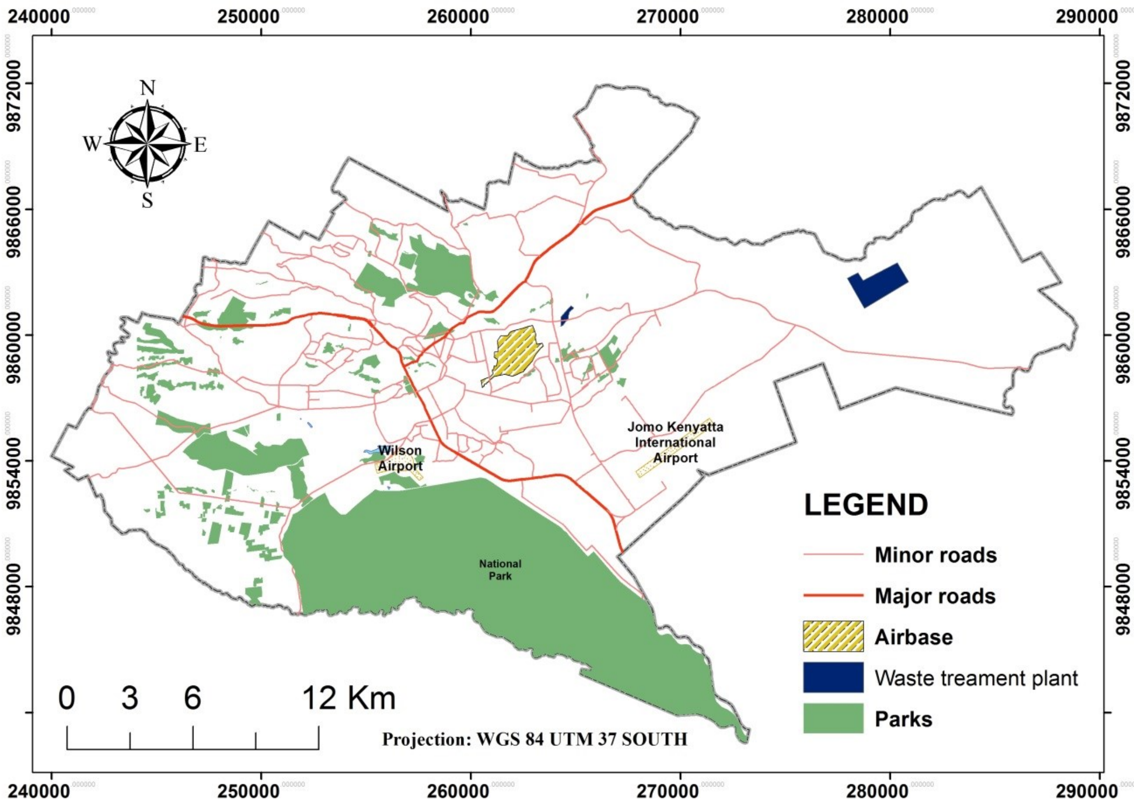

Figure 3-2: Location of Nairobi

3.5.2 Background

The name Nairobi originated from the Maasai phrase *enkare Nairobi*, which means a place of cold waters. In the early times Nairobi served as grazing land and a livestock watering point for most pastoralists among them the Maasai community (City Council of Nairobi, 2007).

Nairobi was selected a terminal railway station connecting Mombasa and Kisumu by the colonial Government because it offered a suitable stopping place; adequate water supply from the nearby Nairobi and Mbagathi rivers; ample level land for railway tracks and sidings; elevated cooler ground to the west suitable for residential purposes; and apparently deserted land offering freedom for land appropriation (Rakodi, 1997). The railway to Uganda reached Nairobi in 1899 and thus making it the administrative centre for the British East Africa protectorate and headquarters of the Kenya Uganda Railway. Consequently this led to Nairobi's growth as a commercial and business hub of the British East Africa protectorate (Mitullah, 2003).

In 1900 Nairobi was officially defined as an urban centre under the Nairobi Municipal Community regulations and it became the capital of Kenya in 1907 (Mitullah, 2003). Later on in 1919, the Nairobi Municipal Community was replaced by Nairobi City Council (NCC). The administrative boundaries were extended in 1926 with the introduction of the first urban plan of Nairobi. In 1948 a master plan of Nairobi was developed and covered approximately 90 Km^2. Kenya gained independence in 1963 and thus the boundaries were extended to cover 696 Km^2. The expansion included neighbouring peri-urban settlements, game parks, Embakasi ranch and other ranches as shown in Figure 3-3.

However, the factors which facilitated the establishment and growth of Nairobi led to undesirable consequences which the city experiences as a burgeoning African metropolis (Lamba, 1994). The choice of the railway yard was challenging especially in terms of sanitation due to poorly drained black cotton clay soils. This has been noted to be a constraint in the development of the city.

Most commercial and official activities are located within the central block and it is commonly referred as the central business district (CBD). Subsequently after independence residential areas have sprawled outwards from the CBD into the eastern areas typically referred to as eastlands, to the western areas commonly referred as westlands and the southern areas referred as southlands. The industrial area has grown adjacent to the CBD to the east with the growth of industries such as manufacturing, processing and vehicle assembly industries.

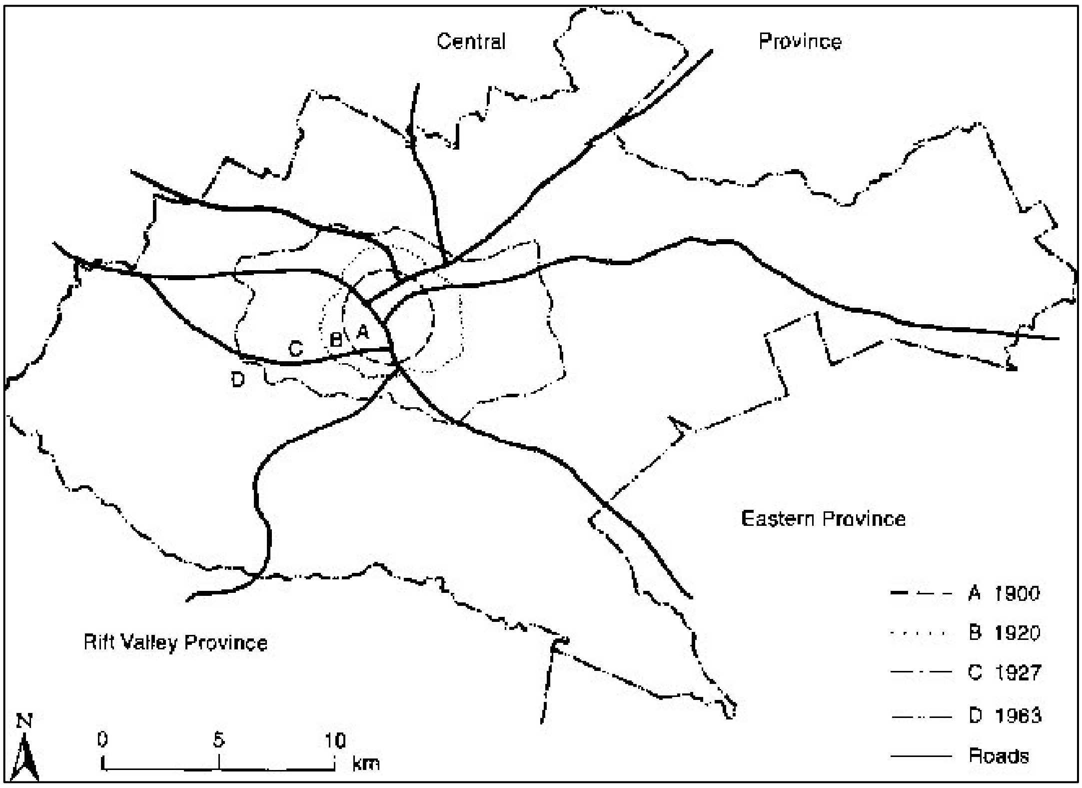

Figure 3-3: Nairobi: Boundary changes, 1900-1963

(Source: Mitullah, 2003)

Nairobi has blossomed into a vibrant city with a current population of 3.2 million. The city has emerged as one of the leading hubs of business, education and informational technology (IT) in Africa. It serves as the headquarters for United Nations Environment Programme (UNEP) and the United Nations Centre for Human Settlements (UN-Habitat) plus also hosting other United Nations agencies. Nairobi serves as the administrative, commercial, industrial and social-cultural centre for the republic of Kenya.

3.5.3 Physical characteristics

The geological history of Nairobi has been dominated of volcanic activities and resulted in different types of rocks in two physiographic regions; the plateau and the plains (Lamba, 1994). The altitude of Nairobi ranges from 1,455 to 1,945 metres above sea level as obtained from digital elevation model (DEM). The northern and western parts of the city are part of the plateau, which is characterised by ridge and valley landscape with steep slopes with an elevation of 1,905 to 1,975m. The southern and eastern portions of Nairobi are part of the flat and rather feature low-lying plains.

Soils in Nairobi fall into several categories (Lamba, 1994). Deep, well drained red volcanic soils cover the high western and northern zones; on the plains the impermeable phonolite strata has led to the formation of black and dark grey clays known as black cotton soils. These soils cover about 35 % of the city's area, while shallow yellow to yellow-red friable soils overlying a laterite horizon or rock cover about 16 %. Swamp grey soils, alluvium and clay soils occur along the river valleys.

The climate is generally temperate tropical climate as Nairobi lies near the Equator. There are two rainy seasons; long rains which occur between March to May and short rains which occur between October to December. The southwest and northeast trade winds influence the rainfall patterns with a mean annual rainfall of 900mm. The average temperatures are 29 degrees Celsius in the dry season and 24 degrees Celsius in the rest of the year.

The lower eastern areas were grassland with scattered acacia trees. The higher areas to the west and the north were forested with hardwood trees. The valley bottoms were poorly drained and supported grassland or swamp vegetation. Most of the natural vegetation has been cleared to pave way for urban developments.

3.5.4 Urban growth in Nairobi

Nairobi has a high growth rate per annum compared to other growth rates in Africa with 75 % of urban population living in informal settlements (UN-HABITAT, 2005). From a population of 8,000 in 1901 the population reached 118,579 in 1948, 310,000 in 1960, 510,000 in 1970 (Republic of Kenya, 1970), 828,000 in 1979 (Republic of Kenya, 1981), 1,321,000 in 1989 (Republic of Kenya, 1994), 2,137,000 in 1999 (Republic of Kenya, 2000) and 3,138,369 in 2009 (Republic of Kenya, 2010) as shown in Figure 3-4. The projected population in the year 2020 will be almost six million (UN-HABITAT, 2005).

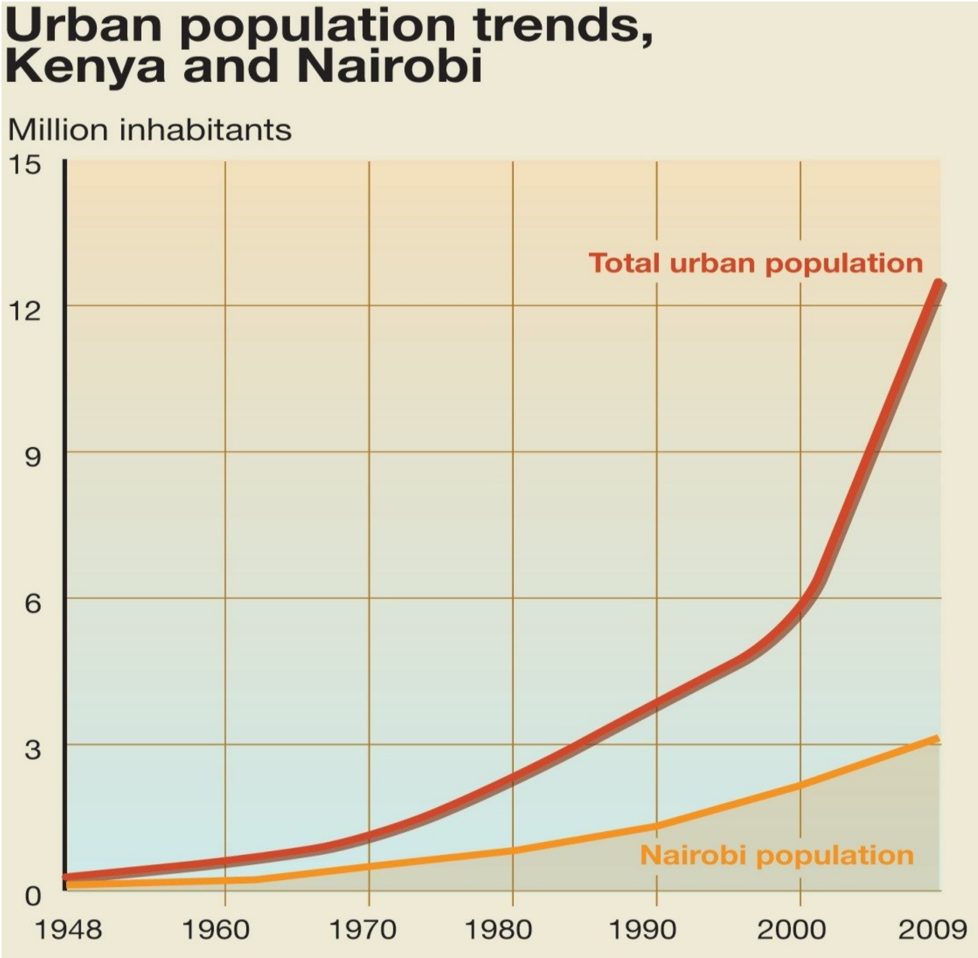

Figure 3-4: Population trends in Nairobi

(Source: Pravettoni, R; GRID-Arendal, UNEP, 2011)

Urban sprawl has a negative impact on infrastructure and the sustainability of cities (UN-HABITAT, 2010). This is exhibited for instance in the increase of transport costs, public infrastructure of residential and commercial development. Most African cities show characteristic patterns of urban sprawl where urban development evolves around the nexus of the main transportation routes, with urban growth tending to grow in sectors emanating from city centres (Mundia & Aniya, 2007). Many urban areas are faced with environmental problems like water pollution, uncontrolled waste disposal, bad air quality and noise.

3.6 Nakuru

3.6.1 Research area

Nakuru municipality lies in Central Rift Valley in Kenya between latitudes 0° 15' and 0° 31' South, and longitude 36° 00' and 36° 12' East, with an average altitude of 1,859 meters above sea level, covering an area of 290km² (Figure 3-5, Figure 3-6, and Figure 3-7). Within Nakuru municipality is Nakuru town, and Lake Nakuru National Park. The Lake Nakuru National Park is a tourist attraction of great economic value for the country with Lake Nakuru being one of the largest bird sanctuaries in the world with the flamingo and pelican bird species.

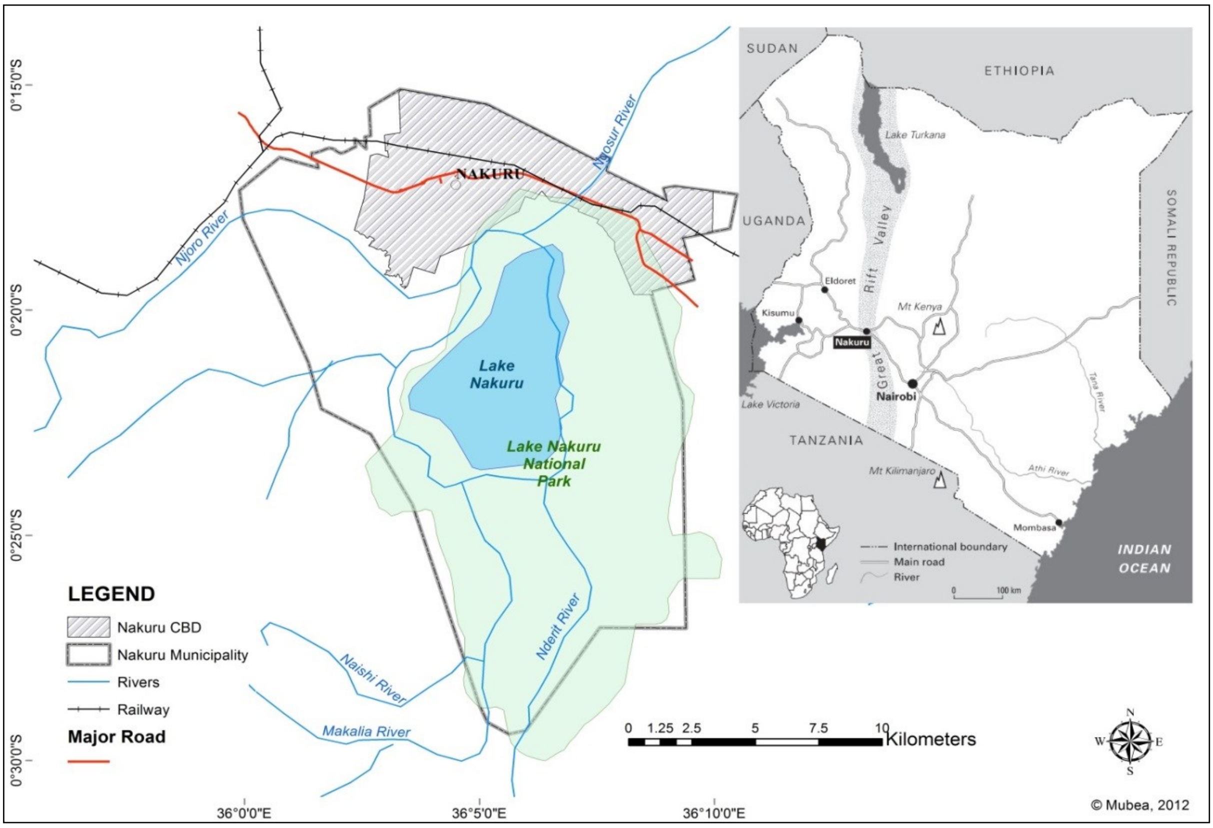

Figure 3-5: Location of Nakuru in the Central Rift Valley of Kenya

(Source: World Resource Institute)

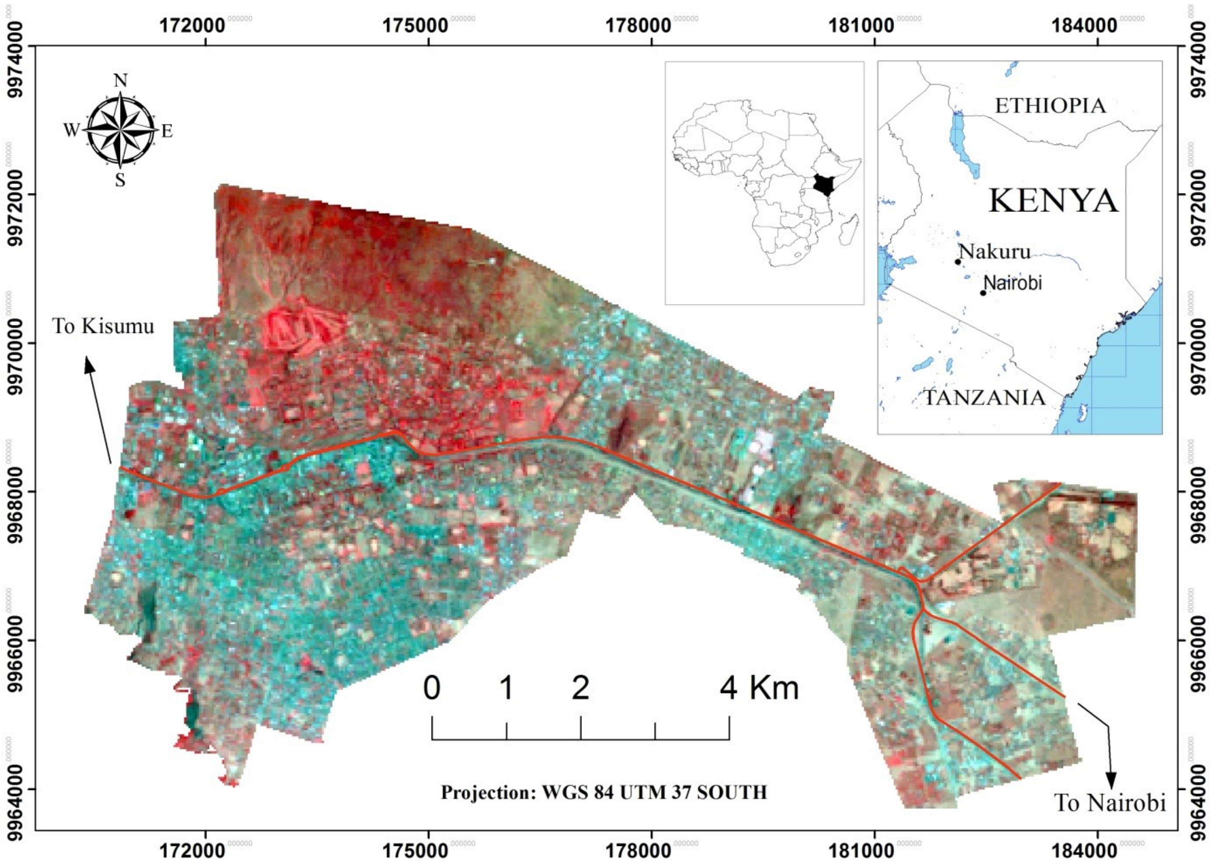

Figure 3-6: Location of Nakuru in the Central Rift Valley of Kenya

(Source: False colour composite using bands 4, 3, 2, Landsat 2010)

The town of Nakuru is located 160 km North West of Nairobi along the twin east-west railroad transport route from Mombasa to Kampala and is the fourth largest city in Kenya following Nairobi, Mombasa and Kisumu. The administratively defined city has land-uses divided into urban use, agriculture, rangeland and remnants of evergreen tropical forests. Such land-uses are similar to other cities in Kenya and sub-Saharan Africa (Mundia & Aniya, 2007).

3.6.2 Background

Nakuru was formerly occupied by nomadic pastoral communities, mainly the Maasai, as grazing land until the arrival of the railway at the beginning of the 20th century (Municipal Council of Nakuru, 1999). The name Nakuru means a place of winds in the Maasai language. Similar to Nairobi and Kisumu, the town owes its existence to the

Kenya-Uganda railway. Nakuru came into existence in 1904 as a railway station on the great East-African railway (or Kenya-Uganda railway) and soon developed into an important regional trading and market centre because of its strategic location in the so called “White High-lands” (Mwangi, 2003; Foeken & Owuor , 2000; Municipal Council of Nakuru, 1999).

In the 1920s, the town began to grow outside its original boundary. In the zoning plan of 1929, Nakuru’s further expansion was laid down in accordance with the then generally accepted principles of functional zoning, i.e. with an industrial quarter, residential districts for the various social classes, a suitable location for a hospital and cemetery, recreational facilities, a site for the airfield, etc (Foeken & Owuor , 2000). Since independence, Nakuru Municipality has had three major extensions of its boundaries, namely in 1963, 1972 and 1992 (Figure 3-7).

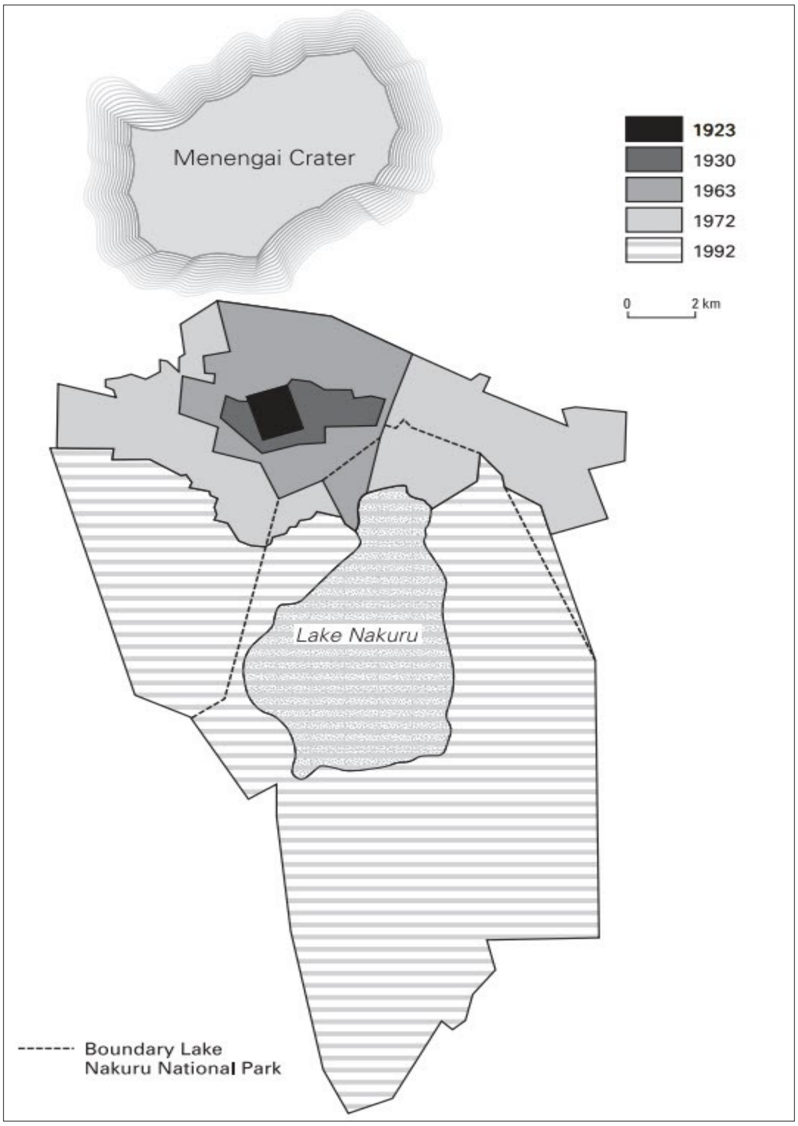

Figure 3-7: Municipality of Nakuru: Boundary changes, 1923-1992

(Source: Owour, 2006)

The 1992 extension included Lake Nakuru National Park and the agricultural land to the northwest and northeast boundaries of the park within the municipality's boundaries (Mwangi, 2003). However, as a result of the subdivision of former farms into small plots for residential use, this stretch is now largely a sub-urban area and is part of the Nakuru planning area (Foeken & Owuor , 2000). The total area of the municipality is approximately 290 Km^2, of which Lake Nakuru covers 40 Km^2 (Municipal Council of Nakuru, 1999).

The main economic activities in Nakuru are commerce, industry, tourism, agriculture and tertiary services (Foeken & Owuor , 2000). Most commercial activities are situated in the Central Business District (CBD). Nakuru serves as an agro-based industrial and manufacturing centre due to its rich agricultural hinterland. Additionally, almost 100 agro-industrial institutions exist ranging from food processing to farm machinery assembly plants (Municipal Council of Nakuru, 1999).

3.6.3 Physical characteristics

Being on the floor of the Rift Valley, Nakuru is situated in an area of loose volcanic soils such that during the dry season, the town is engulfed in whirlwinds of dust, giving the town its name (derived from the Maasai dialect meaning “the place of dust”). Nakuru was declared the first Ramsar Site in 1990. Ramsar sites are wetlands of international importance. This means that specific urban development and environmental management interventions are necessary in order to protect this wetland. The altitude of Nakuru ranges from 1,751 to 2,188 metres above sea level as obtained from the digital surface model (DSM).

The volcanic and tectonic activities in Nakuru yielded varying landscape units. These include; Menengai Crater (8060 - 2040m above sea level) to the North, the Bahati and Mau Escarpments to the North East and South West respectively and a number of hills such as the Lion (1780 - 2040m), Neylan (1870 - 1920m), Hyrax (1800 - 1840m) and Honey Moon Hill (1800 - 1840m). These are characterised by steep slopes. At the extreme south, these activities give rise to the Lake Nakuru water catchment at 1758 metres above sea level, which is served by an array of rivers, and natural albeit seasonal drains. The five main rivers draining into the lake include rivers Njoro, Nderit, Lamudiak, Ng’ossor and Naishi. They discharge very low volume of water to the lake due to high seepage through numerous faults found upstream (Municipal Council of Nakuru, 1999).

Nakuru generally has a dry sub-humid equatorial climate and has an average annual rainfall of 950 mm. There are two rainy seasons; long rains which occur between March and May, and short rains between October and December. The average temperatures in Nakuru are 28 degrees Celsius in the dry season and 24 degrees Celsius in the rest of the year.

3.6.4 Urban growth in Nakuru

The urban pattern of Nakuru town and its environs are characterised by intense urban pressures, first along the main highways and through the planned development of sub urban areas. Since 1962 Nakuru population has been growing at the mean annual rate of 5.6%. From a population of 38,181 in 1962, the population reached 47,151 in 1970 (Republic of Kenya, 1970), 92,851 in 1979 (Republic of Kenya, 1981), 163,927 in 1989 (Republic of Kenya, 1994), 289,385 in 1999 (Republic of Kenya, 2000), and 473,288 in 2009 (Republic of Kenya, 2010). By the year 2015, the population is projected to rise to 760,000, which is approximately 50% above the present levels (Mwangi, 2003).

Urban sprawl has a negative impact on infrastructure and the sustainability of cities (UN-HABITAT, 2010). This is exhibited for instance in the increase of transport costs, public infrastructure of residential and commercial development. Most African cities show characteristic patterns of urban sprawl where urban development evolves around the nexus of the main transportation routes, with urban growth tending to grow in sectors emanating from city centres (Mundia & Aniya, 2007). Connected with a fast-growing urban city in Africa like Nakuru is the spontaneous development of slums, a large increase in the number of street children, unemployment and high rates of crime, and strain on existing urban infrastructure and services. Many urban areas are faced with environmental problems like water pollution, uncontrolled waste disposal, bad air quality and noise. With respect to institutional arrangements, the local governments, entrusted with the provision of urban basic infrastructure, have been unable to perform as a result of administrative problems and lack of capability (Obura, 1996).

4 MONITORING LAND-USE CHANGES

4.1 Introduction

Quantitative urban studies are becoming increasingly important for planners knowing that in the year 2015 more than half the global population will be residing in cities (UNECE, 2003). Suitable urban planning ought to be a top priority for future development but unfortunately sound planning has not taken place especially in many African cities as heavy rural-urban migration continues to cause cities to expand at uncontrollable rates (Mundia & Aniya, 2007). As a consequence, the urban population in Africa is increasing at a much faster rate than in the rest of the world, contributing to the augmentation of the existing problems such as unsuitable land-use (Lavalle, Demichili, Turchini, Casals Carrsco, & Niederhuber, 2001). The concentration of population in cities comprises as much as 60% of the total population in most countries. In these immense urban settlements the environmental and social consequences are sometimes disastrous (Barredo & Demicheli, 2003).

Remote sensing techniques have been valuable in mapping urban land-use pattern as well as data sources which aid in the analysis and modelling of urban growth and land-use change (Clarke, Parks, & Crane, 2002). Remote Sensing offers spatially coherent data sets that cover large areas with both high spatial detail and high temporal frequency. These data characteristics are necessary for land-use monitoring, which is an essential element of socio-ecological studies. As urbanisation occurs, changes in land-use accelerate and land making up the natural resource base such as forests and agricultural land, leading to modification and conversion of existing land-uses (Mundia & Aniya, 2006). This is referred to as land take (Tóth, 2012).

We evaluated the spatial dimension of the imageries using Nakuru. The spatial dimension of remote sensing images as assessed by image texture contains information on local spatial structure and variability of land-use categories, and can raise land-use classification accuracies in heterogeneous landscapes (Ghimire, Rogan, & Miller, 2010). Texture information has improved classification accuracy for optical sensors such as the Satellite Pour l'Observation de la Terre (SPOT) High Resolution Visible (HRV) sensor (Franklin & Peddle, 1990), Landsat TM (Chica-Olmo & Abarca-

Hernandez, 2000), Multispectral Electro optical Imaging Scanner (MEIS-II) (Anys, Bannari, He, & Morin, 1994), and airborne multispectral sensors (Franklin, Hall, Moskal, Maudie, & Lavigne, 2000). The optimal window size for texture measurements is highly dependent on the image spatial resolution and the land-use characteristics (Pesaresi, 2000). Normally, window size should be large enough to include the entire texture pattern, and at the same time small enough to include only one land-use type (Dell'Acqua & Gamba, 2006; Pesaresi, 2000; (Puissant, Hirsch, & Weber, 2005). Shaban & Dikshit (2001) computed texture measurements with different window sizes as inputs for urban area classification using SPOT HRV.

Very high resolution SAR sensors are playing an increasingly important role in urban remote sensing due to their ability to operate day and night through cloud cover, recent improvement in data availability and spatial resolution (Rogan & Chen, 2004). Many studies have focused on the frequency and polarimetry of SAR data in land-use classification (Chen, Chen, & Lee, 2003), whereas SAR image texture is found helpful in improving map accuracy, particularly for urban and forest categories (Dekker, 2003).

The study of land-use changes is essential not only for land-use management but also in detecting environmental change and in formulating sustainable development strategies (Barnsley & Barr, 1997). Accurate information on land-use changes is needed for documenting urban growth, making policy decisions and improving land-use planning. Information concerning land-use changes is also required for predictive modelling (Mas, Pérez-Vega, & Clarke, 2012).

The aim of this chapter was to perform different land-use classification using multi-temporal and multi-sensor data to monitor land-use change. We used multi-temporal Landsat images of 1986, 2000 and 2010 for land-use analysis of Nairobi. In the case of Nakuru, we used both optical and SAR datasets. Optical datasets included: Landsat of 1986, 2000 and 2010; Worldview-2 of 2010; and ALOS PALSAR imagery of the year 2010. Image classification was performed on resampled datasets at 12.5 meters and 28.5 meters. Several image classification algorithms were explored and their performance evaluated using accuracies measured such as overall accuracies and kappa coefficient values. Support vector machine (SVM) performed better compared to maximum likelihood classifier (ML) (Mubea & Menz, 2012). Thus combining images from optical and SAR yielded better results in image classification. Land-use change monitoring was achieved by comparing the change between two corresponding years and the result given as a percentage.

4.2 Utility of multi-sensor satellite data

Urban landscapes remain one of the most challenging environments to be analysed from remotely sensed data. They are complex, featuring spatial and spectral heterogeneity and are composed of multi-fold artificial and natural surface types (Herold, Roberts, Gardner, & Dennison, 2004). In a comparative analysis of urban reflectance, Small (2005) concluded that sensors with similar spectral and radiometric properties to Landsat Thematic Mapper (TM) principally comprise a three-dimensional spectral feature space. In such a feature space, linear combinations of spectral end members (high albedo, vegetation and low albedo) cover approximately 98% of the variance contained in an urban scene (Griffiths, Hostert, Gruebner, & Linden, 2010).

Challenges of urban mapping can be solved using more temporal information and data from different sensors. Integrating multi-temporal information helps distinguish urban from non-urban surfaces as urban spectral responses are largely persistent over time compared to non-urban surface phenology (Griffiths, Hostert, Gruebner, & Linden, 2010).

Multi-temporal SAR images have proven to be useful in urban, forest, and agriculture land-use classification (Le Toan, Laur, Mougin, & Lopes, 1989; Pellizzeri, Gamba, Lombardo, & Acqua, 2003; Quegan, Toan, Yu, Ribbes, & Floury, 2000; Schotten , Rooy, & Janssen, 1995). Recent studies report that the integration of optical and SAR data is useful due to their distinct of features. Optical images contain information on surface reflectance and emissivity characteristics, while SAR images capture the structure and dielectric properties of the Earth surface materials (Zhu, Woodcock, Rogan, & Kellndorfer, 2011). Land-use types that are impossible to separate in optical images might be distinguishable with SAR images and vice versa because of the complementary information contained in the two datasets (Amarsaikhan & Douglas, 2004).

Many approaches employing both optical and SAR images have been explored for land-use classification (Amarsaikhan & Douglas, 2004; Blaes, Vanhalle, & Defourny, 2005; Chust, Durcot, & Pretus, 2004; Corbane, Faure, Baghdadi, Villeneuve, & Petit, 2008; Kuplich, Freitas, & Soares, 2000; Michelson , Liljeberg, & Pilesjo, 2000; Shupe & Marsh, 2004; Solberg , Jain, & Taxt, 1994; Waske & Benediktsson, 2007; Zhu, Woodcock, Rogan, & Kellndorfer, 2011). The results from integrating optical and SAR sensors are always significantly higher than those obtained from using an individual sensor, particularly for certain land-uses, such as urban (Corbane, Faure, Baghdadi, Villeneuve, & Petit, 2008; Toll, 1985), agriculture (Blaes, Vanhalle, & Defourny, 2005; Chust, Durcot, & Pretus, 2004), wetlands (Augusteijin & Warrender, 1998; Li & Chen, 2005; Mwita, Menz, Misana, & Nienkemper, 2012), and desert vegetation (Shupe & Marsh, 2004).

Combining multi-spectral imagery with data from the microwave spectral domain has also proven to be a powerful strategy, especially for monitoring urban areas and for overcoming spectral ambiguities (Phinn, Stanford, Scarth, Murray, & Shyy, 2002; Pacifici, Del Frate, Emery, Gamba, & Chanussot, 2008). The combined use of synthetic aperture radar (SAR) and multispectral optical imagery has been successfully used to delineate built-up areas (Gomez-Chova, et al., 2006).

Urban mapping requires the selection of an appropriate scale of observation. This involves a certain trade-off between the richness of detail of very high resolution (VHR) remote sensing imagery and the generalizing nature of moderate to high resolution sensors such as the 30 m of Landsat data (Griffiths, Hostert, Gruebner, & Linden, 2010). The long-term and future data record is an advantage of Landsat data compared to very high resolution sensors (NASA, 2008; Wulder, et al., 2008). Optical and SAR systems operate in different wavelengths, ranging from visible to microwave.

Landsat sensors include MSS (Multi-Spectral Scanner), TM (Thematic Mapper) and ETM+ (Enhanced Thematic Mapper Plus) (properties of Landsat TM and ETM + are shown in appendix 9.1.1). Figure 4-1 illustrates a false colour composite Landsat RGB (red, green and blue bands) and panchromatic band of Nakuru municipality. World view-2 was launched on 8th October 2009. It is the first commercial eight multispectral bands high resolution satellite (sensor). Figure 4-2 illustrates Worldview-2 True colour bands of the central business district (CBD) of Nakuru.

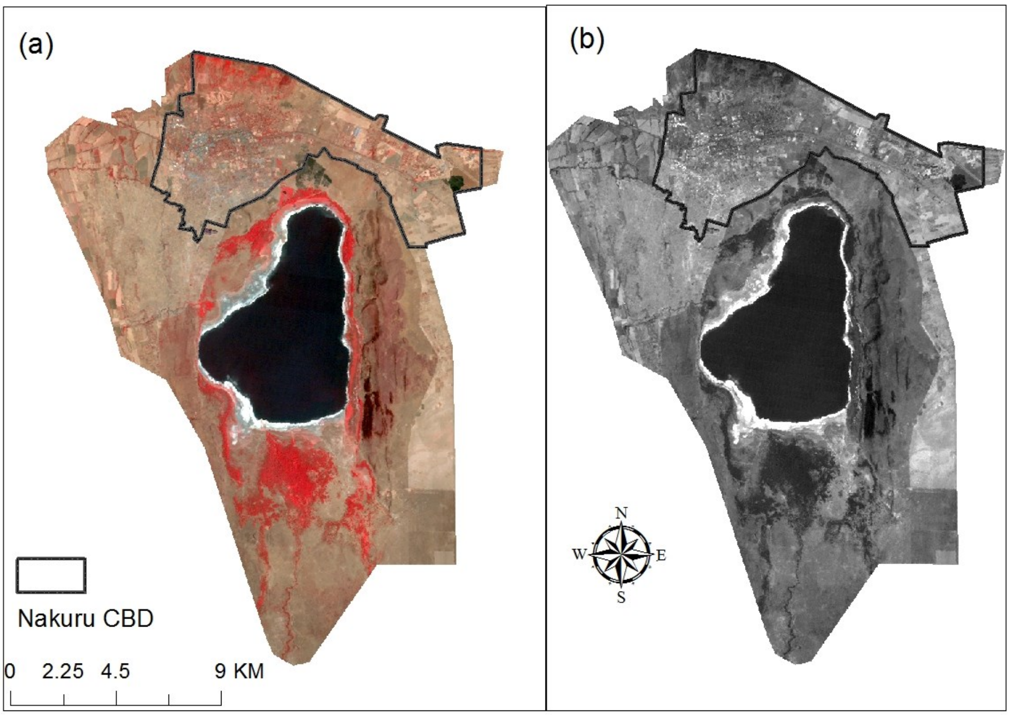

Figure 4-1: (a) False colour composite Landsat TM (Path 169, Row 60) RGB of 1986 for Nakuru municipality (b) Panchromatic band of 1986 for Nakuru Municipality

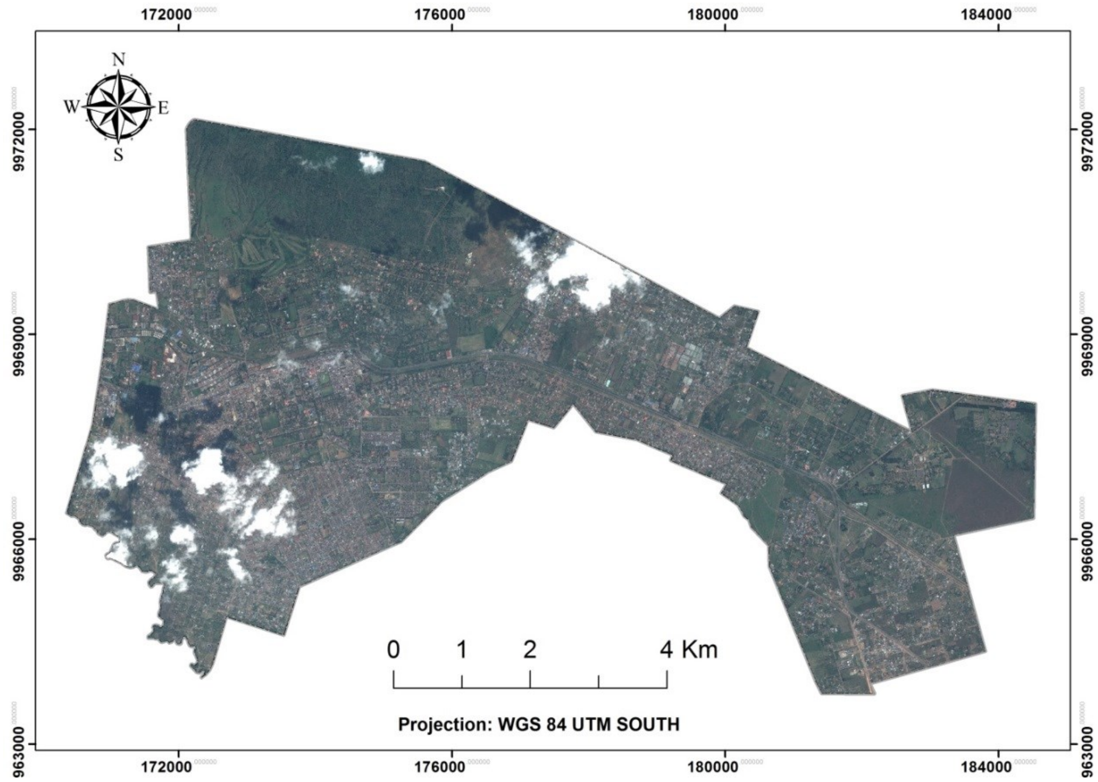

Figure 4-2: Worldview-2 True colour image of year 2010 for Nakuru CBD

Radar wavelength has an ultimate influence on the interaction between the electromagnetic wave and the natural medium (Garestier, Dubois-Fernandez, Dupuis, Paillou, & Hajnsek, 2006). As wavelength increases, surface roughness criteria will also change. In general, more surface features will appear smoother at longer wavelengths than at shorter wavelengths.

The capability to penetrate through precipitation clouds or into a surface layer is increased with longer wavelengths. Typically the penetration is half the wavelength and as wavelength increases and frequency decreases, respectively, the penetration becomes higher (Henderson & Lewis, 1998).

Radar is able to receive and process all four combinations of polarizations: HH, HV, VH, and VV. HH stands for horizontal transmit and horizontal receive, VV stands for vertical transmit and vertical receive, HV stands for horizontal transmit and vertical receive, and VH stands for vertical transmit and horizontal receive. HH and VV are referred to as like-polarized because the transmit and receive polarizations are the same, while HV and VH are referred to as cross-polarized because the transmit and receive polarizations are orthogonal to one another. The channels have varying sensitivities to differentiate surface characteristics and properties. For instance, the dynamic range of the like-polarized module is larger than that of the cross-polarized module for urban areas; this is in contrast to the measurement for forested areas, where the dynamic range of the cross-polarized component is larger than that of the like-polarized component (Dong, Forster, & Ticehurst, 1997).

Multiple polarizations help to distinguish the physical structure of the scattering surfaces e.g. HH vs. VV is used in the alignment with respect to the radar, HV is used in the randomness of scattering for vegetation cover, HH VV phase angle is used for the corner structures and urban land-use mapping. Past studies showed that radar imagery collected using different polarization may provide different and complementary information about the targets on the surface and thus improve the interpretation of different urban features (Dong, Forster, & Ticehurst, 1997). The use of polarimetric datasets for urban analysis has been accelerated in recent years with more and more fully-polarimetric SAR systems being in operation for example Terra SAR-X. Several studies demonstrated that polarimetric datasets have great potential for urban applications Garestier, Dubois-Fernandez, Dupuis, Paillou, & Hajnsek, 2006; Schneider, Papathanassiou, Hajnsek, & Moreira, 2006).

4.3 Land-use change analysis in Nakuru

4.3.1 Data

The approach adopted for the analysis of land-use involved: Landsat images for 1986, 2000 and 2010, Worldview-2; and Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) image for 2010 were selected for the study area. The ALOS PALSAR was at level 1.5 and polarimetric mode, multi-polarized images, HH Horizontal-Horizontal + HV Horizontal-Vertical + Vertical-Horizontal + VV Vertical-Vertical. Nakuru municipality is entirely contained within Landsat TM path 169, rows 60. The Landsat data sets include TM, and ETM+ images. Digital elevation model (DEM) at spatial resolution of 90 meters was obtained from the United States Geological Survey (USGS) and used to pre-process the SAR data. Reference data included a topographic map (scale 1:50,000) and ground truth information about land-use from 50 GPS points which were used for classifier training and accuracy assessment. Stratified random sampling was adopted for selecting samples. The datasets used for land-use change analysis of Nakuru are shown in Table 1.

Table 1: Datasets for land-use change analysis of Nakuru

Data type	Source	Resolution	Application
Satellite imagery	Landsat TM (28.1.1986)	28.5 metres	Land-use mapping
	Landsat ETM+ (27.1.2000)	28.5 metres	
	Landsat ETM+ (30.1.2010)	30 metres	
	World view 2 (2010)	2 metres	
	ALOS (2010)	12.5 metres	
Topographic map		Map scale 1:50000	Geometric correction Ground truthing
GPS points			Ground truthing

4.3.2 Land-use classification

Two approaches were implemented for the land-use classification of Nakuru; Nakuru municipality with six land-use classes (namely urban, water, forest, agriculture, barren land and rangeland) and Nakuru Central Business District (CBD) with three land-use classes (namely urban, forest and agriculture). The three classes were selected for Nakuru CBD since it is the centre of major activities and infrastructure. Several factors were considered during the design of categorization scheme such as the major land-use categories within the research area, disparities in spatial rules of the sensors, and the need to always discriminate land-use classes irrespective of seasonal disparities (Anderson, Hardy, Roach, & Witmer, 1976). See appendix 9.1.2 and 9.1.3 for more information on the land-use classification categories.

Image pre-processing steps for the optical datasets were radiometric and geometric correction as illustrated in Figure 4-3. GPS points were used for image to map registration. UTM 37 South was selected as reference system for the research area. The processing of the SAR data was done using European Space Agency (ESA) NEST SAR Remote Sensing software. Multi-look correction was applied. Radar speckle which appear as grainy "salt and pepper" texture in imagery, was reduced prior to interpretation and analysis using Gamma Map filter with 5 X 5 kernel. The DEM used was an SRTM (Shuttle Radar Topography Mission) and was used to remove relief displacement in SAR data.

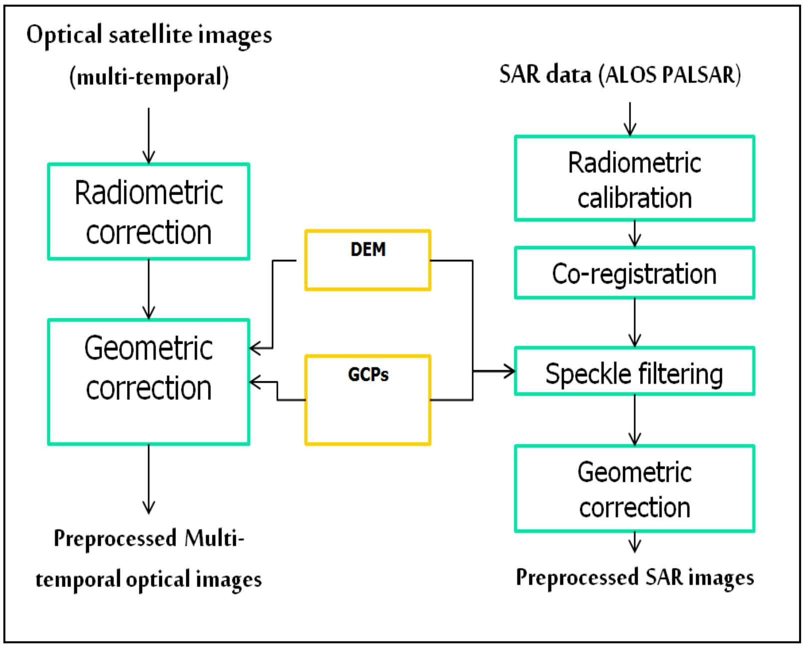

Figure 4-3: Image pre-processing workflow of the multi-sensor satellite data sets

In order to find the optimal spatial resolution scenarios of upscaling and downscaling of the data sets were explored. Upscaling refers to the decrease in spatial resolution while downscaling is the increase in spatial resolution. Scale has several definitions according to Lam & Quattrochi (1992) namely: cartographic or map scale; observational or geographic scale that refers to the size or spatial extent of the study; measurement scale or resolution that refers to the minimum size that can be distinguished; and finally operational scale that refers to the scale at which certain processes operate in the environment.

In a nutshell, scale is the spatial and temporal dimension of the research while at the same time; scale also refers to the spatial extent and frequency that a certain phenomenon or process occurs (Ming, Yang, Li, & Song, 2011). Additionally, scale shows the level on which the object is understood. Hence scale can either be temporal or spatial scale, and of which both were investigated in this research. Combinations of the reflective spectral bands from images (i.e., stacked vector) were used for classification of the 1986, 2000 and 2010 images. The ratio of HH/HV was used for the case of the ALOS PAL-SAR imagery which yields best results for urban areas (Idol, Haack, Sawaya, & Sheoran, 2008; Zhu, Woodcock, Rogan, & Kellndorfer, 2011).

Image processing techniques were applied to the data sets both at spatial resolution of 12.5 meters and 28.5 meters using nearest neighbour interpolation. Therefore the Worldview-2 data was resampled from 0.5 meters (original) to 12.5 meters and 28.5 meters. Landsat was resampled from 28.5 meters (original) to 12.5 meters while ALOS PALSAR was resampled from 12.5 meters (original) to 28.5 meters. The objective was to assess how classification accuracy changes with spatial resolution. Image processing workflow is illustrated in Figure 4-4.

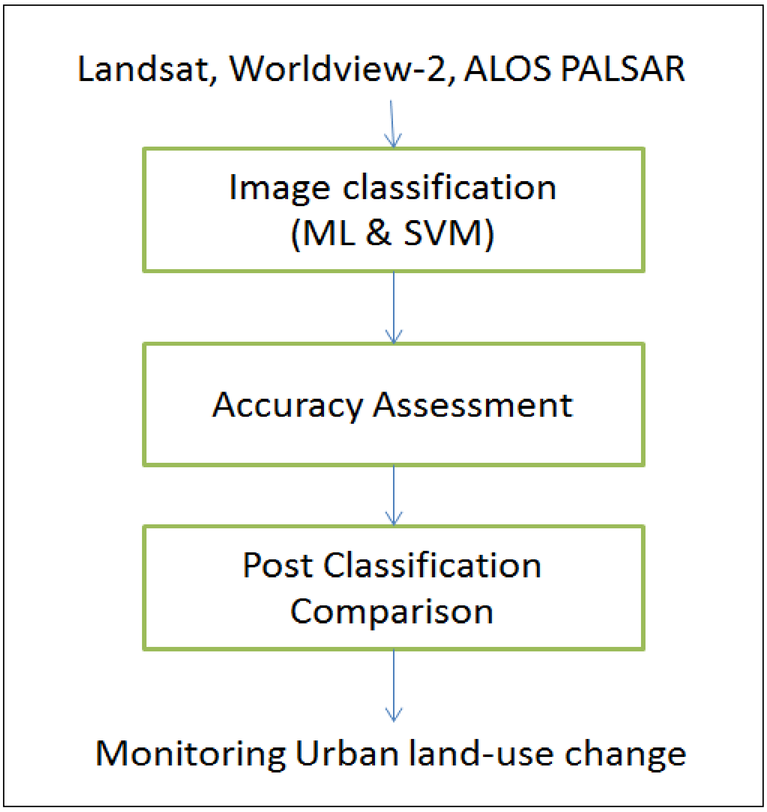

Figure 4-4: Image workflow for classification and change detection of multi-sensor data sets

Training sites representing the land-use classes of interest were collected using the region growing tool in ENVI 4.8. Such sites were homogeneous and extensive to provide excellent statistics. ML was applied to the multi-sensor datasets, and performance assessed using the corresponding confusion matrices. SVM classification in ENVI 4.8 was applied to all the data sets and its performance assessed using confusion matrices. The SVM classifier has four kernels namely linear, polynomial, Radial Basis Function (RBF) and sigmoid. Radial basis function kernel is the default and works well in most situations (Shafri & Ramle, 2009).

SVM is well recognized in the field of machine learning and pattern recognition (Waske & Benediktsson, 2007) and has recently been introduced in context of remote sensing image analysis (Melgani & Bruzzone, 2004). SVM has been applied successfully for classifying multispectral imagery for example in (Huang, Davis, & Townshend, 2002) and outperformed other methods in the very most recent cases. In some studies SVM has been seen to produce higher accuracies than other classifiers, as a maximum likelihood classifier, an ANN and a simple decision tree (Melgani & Bruzzone, 2004).

Different voting schemes for multi class SVMs have been explored (Melgani & Bruzzone, 2004).

Post-classification refinements were enforced to diminish categorization errors as a result of the similarities in spectral responses of certain training classes such as bare fields and urban areas and some crop fields and wetlands. Independent samples of about 100 pixels for each class were randomly selected from each classification category to assess classification accuracies. Confusion matrices as cross-tabulations of the mapped class versus the reference class were used to assess classification accuracies (Congalton & Green, 1999). Overall accuracy, user's and producer's accuracies, and the Kappa statistic were then derived from the error matrices. The Kappa statistic incorporates the off diagonal elements of the confusion matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance. Following the classification of imagery from the individual years, a GIS based multi-date post classification comparison (PCC) change detection strategy was employed to determine changes in land-use in Nakuru. Change detection analysis entailed finding the type, amount and location of land use changes that had taken place.

4.3.3 Results and Discussion

Image classification of Landsat for 1986, 2000 and 2010 with 28.5 meters (original) spatial resolution was successfully performed and the results tabulated in Table 2. SVM produced better results compared to ML for example SVM in 2010 yielded an overall accuracy of 86.96 % compared to ML of the same year with 83.80%. Land-use maps for Nakuru municipality for the three years are illustrated on Figure 4-5.

Table 2: Confusion Matrix for Land-cover classification for Nakuru municipality (Landsat data from 1986, 2000 and 2010)

Method	**Landsat**			
SVM		1986	2000	2010
	Overall Accuracy	93.42%	83.77%	86.96%
	Kappa Coefficient	0.9087	0.7988	0.8393
ML				
	Overall Accuracy	89.00%	82.50%	83.80%
	Kappa Coefficient	0.8527	0.7862	0.8025

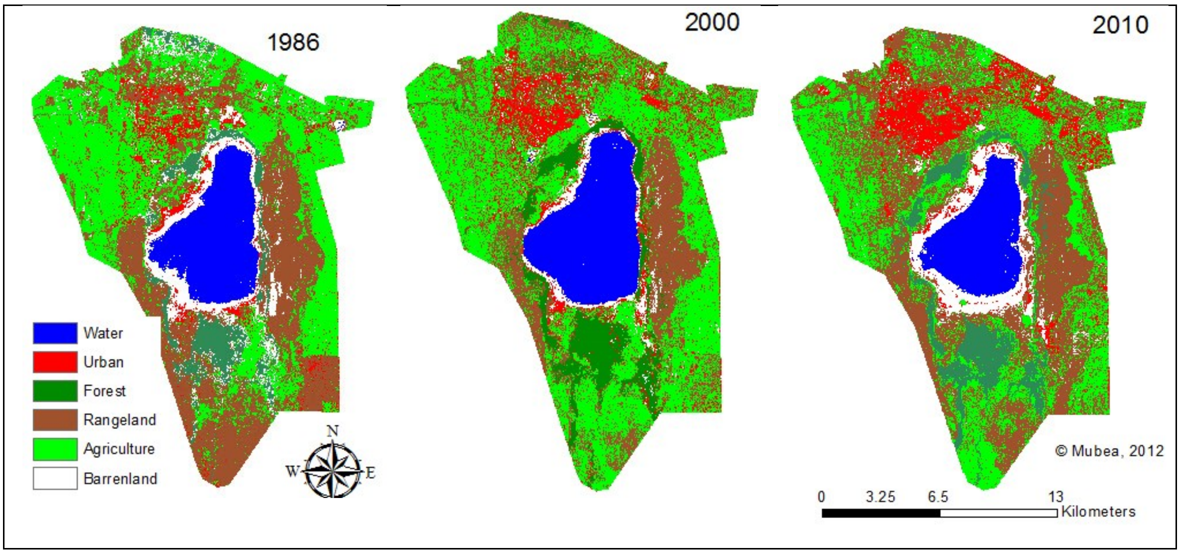

Figure 4-5: Land-use Map for Nakuru Municipality from Landsat for 1986, 2000 and 2010

Furthermore, the Radial Basis Function (RBF) kernel of support vector machine at various percentages was explored. RBF performed best at 0.33 compared to 0.5 and 0.7. The RBF value of 0.33 is the default value in ENVI software. For example the overall accuracy value of 93.42 % was obtained for the year 1986 at RBF value of 0.33 compared to 93.14 % at 0.5 and 93.14% at 0.7. Similarly an overall accuracy value of 83.77% was obtained for the year 2000 at RBF value of 0.33 compared to 82.75% at 0.5 and 82.75% at 0.7.

Land-use summary for Nakuru municipality (using Landsat at spatial resolution of 28.5 meters) was performed in ENVI and results tabulated in Table 3. SVM gave better results compared to ML. For example, looking at the urban class, using SVM growth was from 4.78 km^2 in 1986, 12.73 km^2 in 2000 and 27.84 km^2 in 2010 compared to ML.

Table 3: Land-use estimates for Nakuru municipality using Landsat (28.5 spatial resolution)

	1986		**2000**		**2010**	
Land-use classes (km^2)	**MLC**	**SVM**	**MLC**	**SVM**	**MLC**	**SVM**
Water	33.29	36.95	38.77	40.09	27.25	30.78
Urban	16.65	4.78	26.4	12.73	26.83	27.84
Forest	16.95	20.55	25.77	27.1	21.91	26.93
Barren land	24.69	13.46	9.5	5.98	18.82	19.84
Rangeland	93.63	150.07	70.44	134	111.15	122.57
Agriculture	104.78	64.20	119.12	70.1	84.03	62.03
Total	**290.00**	**290.00**	**29.00**	**290.00**	**290.00**	**290.00**

Next we analysed the upscaling of World view-2 and ALOS for Nakuru CBD which yielded low classification accuracy as shown in Table 4. World view-2 was up scaled from 0.5 to 28.5 meters and ALOS PALSAR from 12.5 to 28.5 meters.

Table 4: Comparison of classification accuracies for the three multi-sensor data sets at 28.5 spatial resolution for Nakuru CBD

Method		Landsat			Worldview-2	ALOS PALSAR
		1986	2000	2010	2010	2010
SVM	Overall Accuracy	96.18%	93.22%	99.51%	76.76%	59.37%
	Kappa Coefficient	0.9343	0.7321	0.9914	0.6358	0.3555
ML	Overall Accuracy	95.24%	93.22%	99.60%	76.76%	18.62%
	Kappa Coefficient	0.9196	0.7321	0.9929	0.6358	0.0000

Land-use summary for Nakuru CBD, using all data sets at spatial resolution of 28.5 meters, was performed in ENVI and results tabulated in Table 5 and Figure 4-6. From Table 5 the respective SVM values of Landsat 2010, Worldview-2 and ALOS PALSAR for the three land-uses were different because of the different sizes of the training polygons and heterogeneity of the individual land-use classes.

Table 5: Land-use estimates for Nakuru CBD (28.5 spatial resolution)

Land-use classes (km^2)	Landsat			Worldview-2	ALOS PALSAR
	1986	2000	2010	2010	2010
	SVM	SVM	SVM	SVM	SVM
Forest	13.3	13.7	10.7	16.1	11.3
Urban	12.4	15.4	22.3	22.3	17.4
Agriculture	32.3	28.9	25.0	19.6	29.4
Total	**58.0**	**58.0**	**58.0**	**58.0**	**58.0**

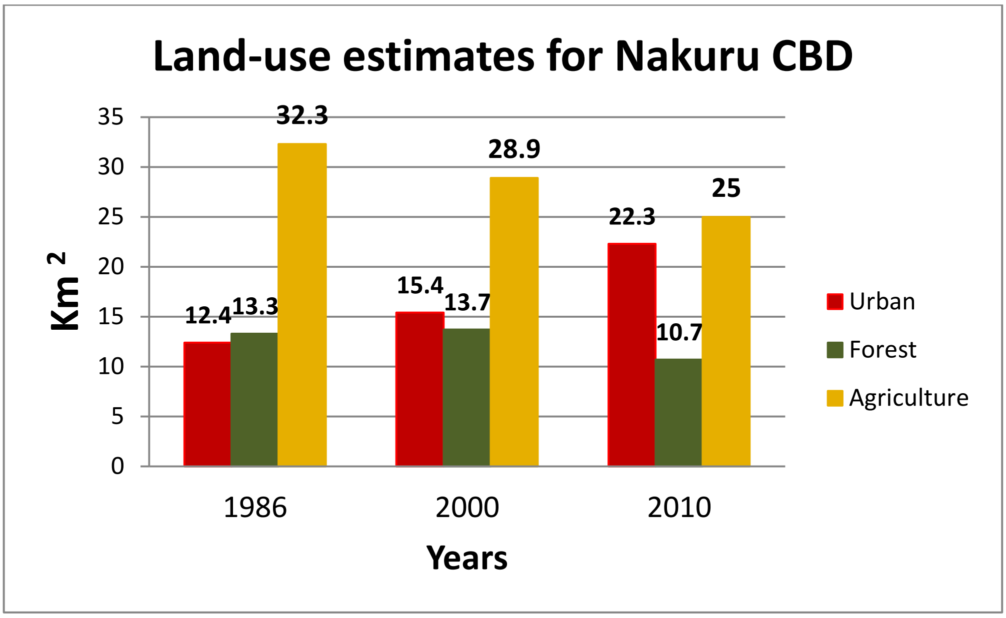

Figure 4-6: Land-use estimates for Nakuru CBD (28.5 metres)

Land-use summary for Nakuru CBD, using all data sets at spatial resolution of 12.5 meters, was performed in ENVI and results tabulated in Table 6. Relatively good values of urban class were achieved using SVM ALOS data as compared to Landsat data and World view-2 at 12.5 meters spatial resolution. Land-use maps for Nakuru CBD are illustrated in Figure 4-7, Figure 4-8, Figure 4-9, Figure 4-10 and Figure 4-11.

Table 6: Land-use estimates for Nakuru CBD (12.5m spatial resolution)

Land-use classes (km^2)	Landsat			Worldview-2	ALOS PALSAR
	1986	**2000**	**2010**	**2010**	**2010**
	SVM	**SVM**	**SVM**	**SVM**	**SVM**
Urban	15.9	18.9	23.3	23.6	27.7
Forest	8.9	9.2	9.7	14.1	7.1
Agriculture	33.2	29.9	25.0	20.3	23.2
Total	**58.0**	**58.0**	**58.0**	**58.0**	**58.0**

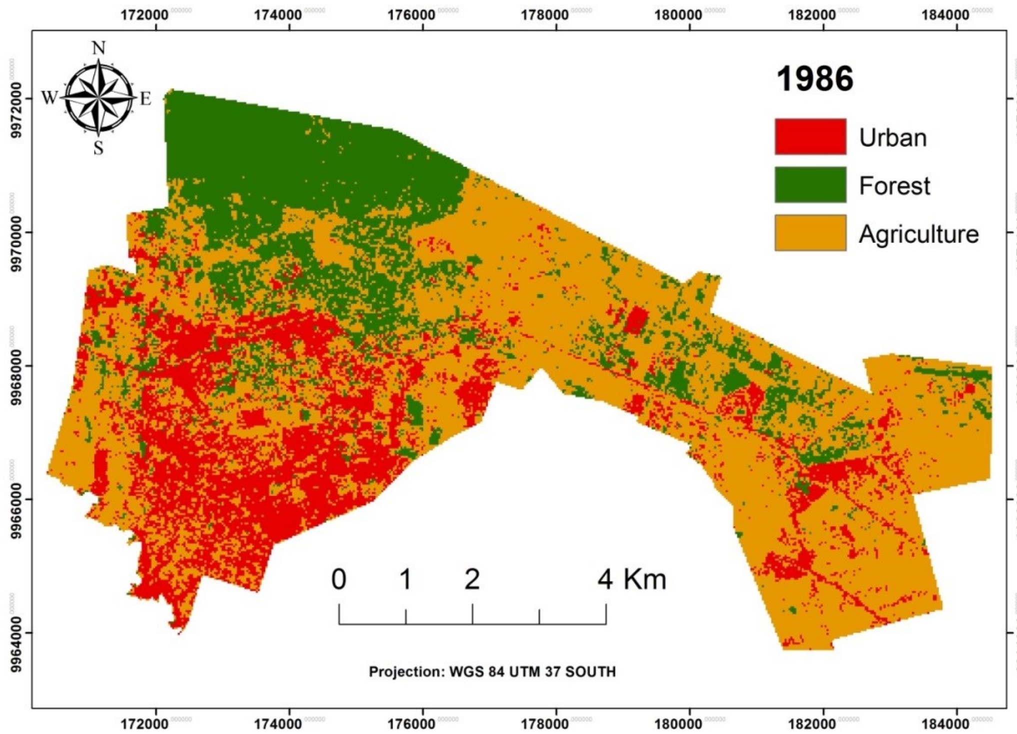

Figure 4-7: Land-use Map for Nakuru CBD using Landsat TM 1986

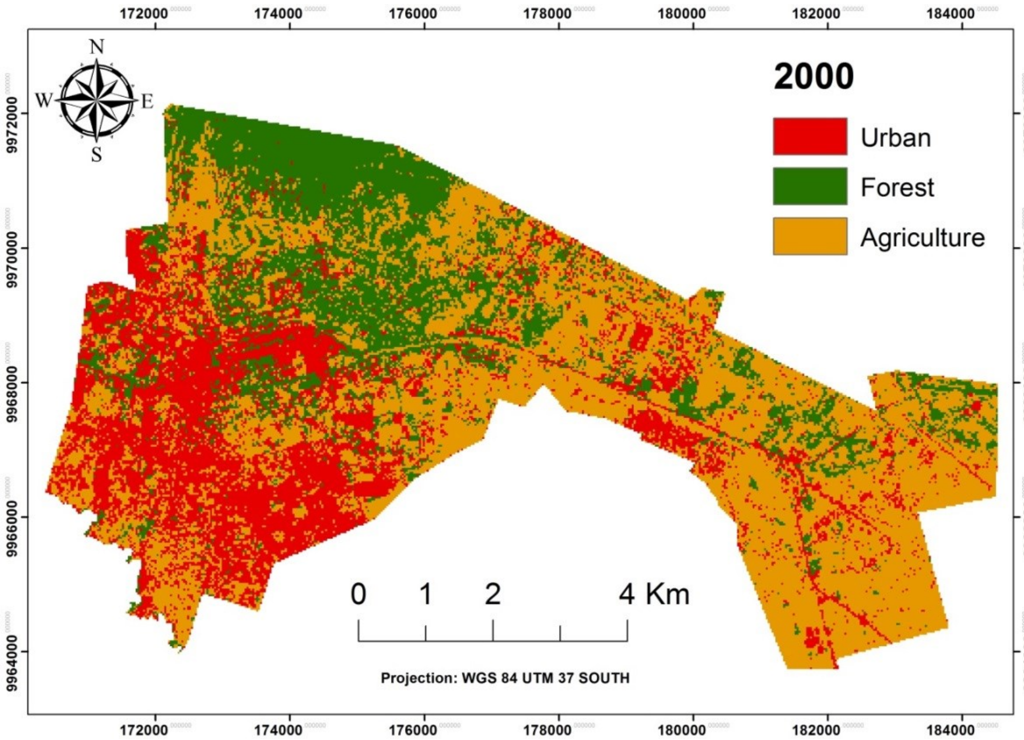

Figure 4-8: Land-use Map for Nakuru CBD using Landsat ETM 2000

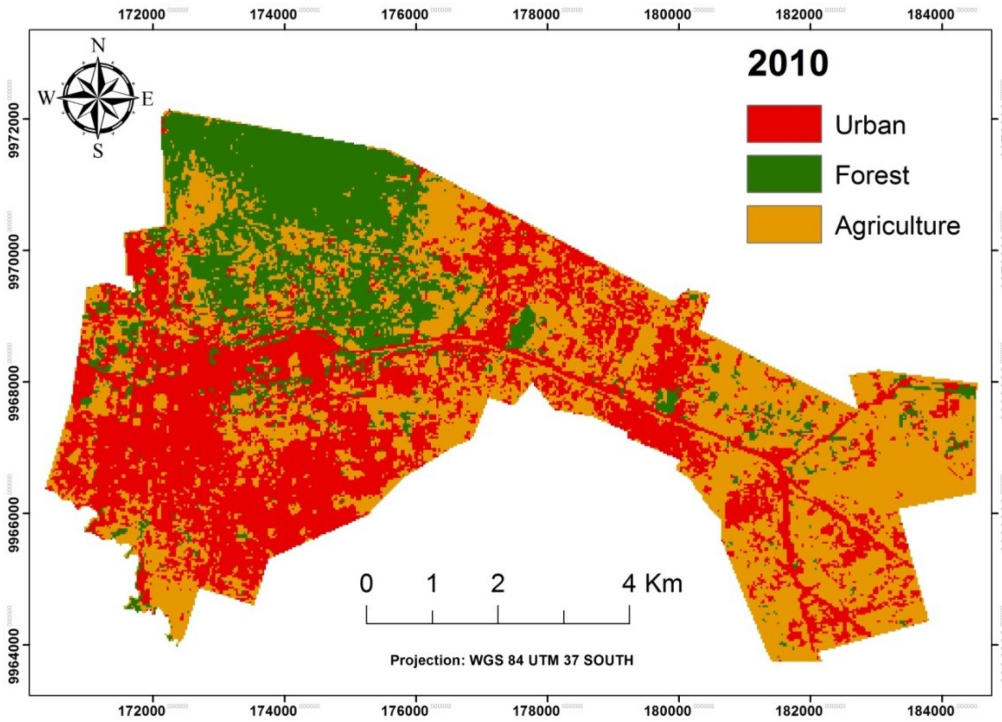

Figure 4-9: Land-use Map for Nakuru CBD using Landsat ETM + 2010

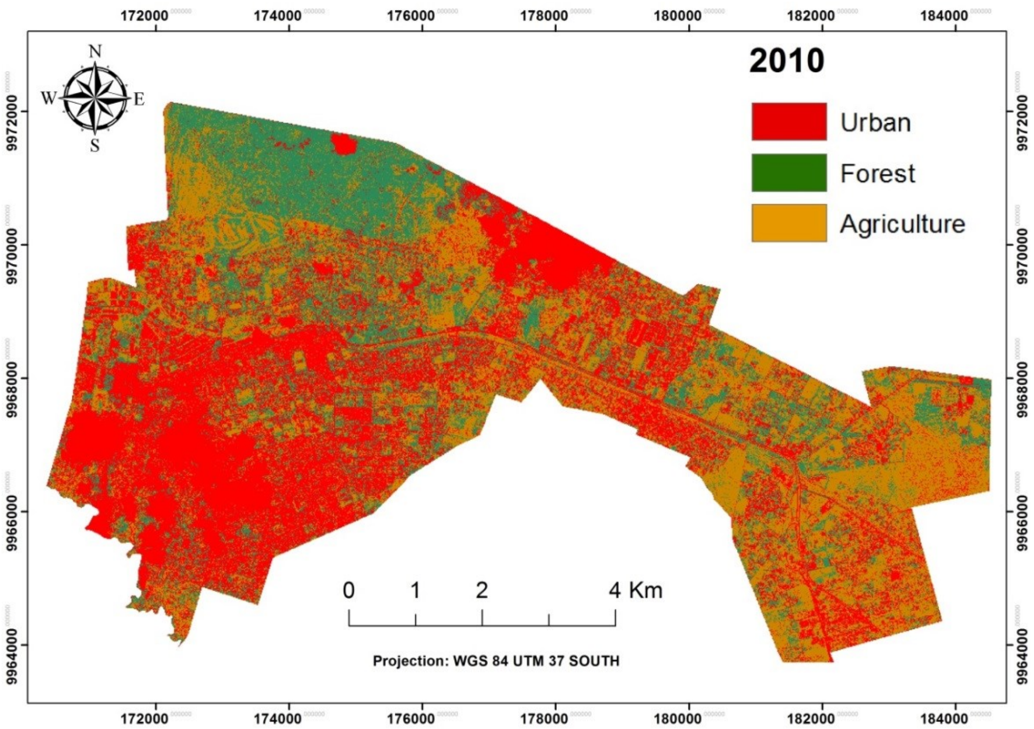

Figure 4-10: Land-use Map for Nakuru CBD using World-view 2 2010

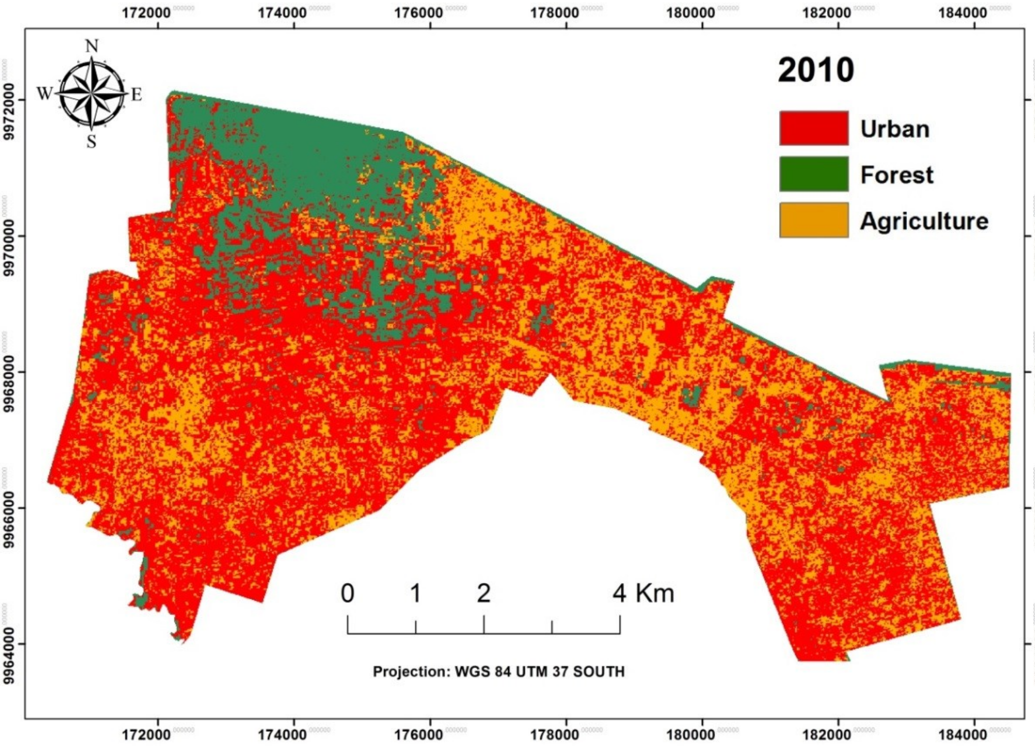

Figure 4-11: Land-use Map for Nakuru CBD using Landsat ETM + 2010 and ALOS

From the Table 7, downscaling of Landsat data sets did not affect classification accuracy. Landsat was downscaled from 28.5 meters to 12.5 meters. For example, the kappa coefficient value of 96.18% in Table 4 for Landsat 1986 classification is close to that one of 96.23% in Table 7 of the same data set classification using SVM.

Table 7: Confusion Matrix for Land-use classification for Nakuru CBD (12.5 spatial resolution)

Method		Landsat			Worldview-2	ALOS PALSAR
		1986	2000	2010	2010	2010
SVM	Overall Accuracy	96.23%	96.91%	99.05%	77.47%	84.09%
	Kappa Coefficient	0.943	0.9507	0.9836	0.6343	0.6878
ML	Overall Accuracy	96.66%	97.09%	98.68%	77.47%	21.00%
	Kappa Coefficient	0.9495	0.9485	0.9774	0.6343	0.0000

The ratio of HH/HV ALOS PALSAR was combined with (bands 2, 3, 4) Landsat 2010 as a layer stack and SVM carried out. The combined ALOS PALSAR (2010) and Landsat (2010) gave better results in terms of classification accuracies. For example an overall accuracy value of 93.64 % and kappa statistic 0.8795 was obtained using the combined Landsat and ALOS PALSAR compared to that of ALOS PALSAR alone 84.09 % and 0.6878 respectively as illustrated on Table 7 using SVM.

Based on the results from the different image classification, land-use change was calculated using post classification technique and results tabled in Table 8 and maps illustrated on Figure 4-12 and Figure 4-13. From Table 8, 6.25 km^2 of land changed to urban land-use from non-urban between the years 1986 to 2000 compared to the value of 19.70 km^2 between the years 2000 to 2010. Non-urban land-use included forest and agriculture land-uses. Thus rapid urban growth has taken place between the years 2000 to 2010 due to urbanization. This has been witnessed by the high population growth (Republic of Kenya, 2000; Republic of Kenya, 2010), and rapid infrastructure developments such as more houses to cater for the growing demand for housing.

Table 8: Land-use change estimates based on post classification comparison

	1986 to 2000	2000 to 2010
Land-use change	**Change (km^2)**	**Change (km^2)**
No change	36.69	23.69
From non-urban to urban	6.25	19.70
from urban to non-urban	8.93	7.75

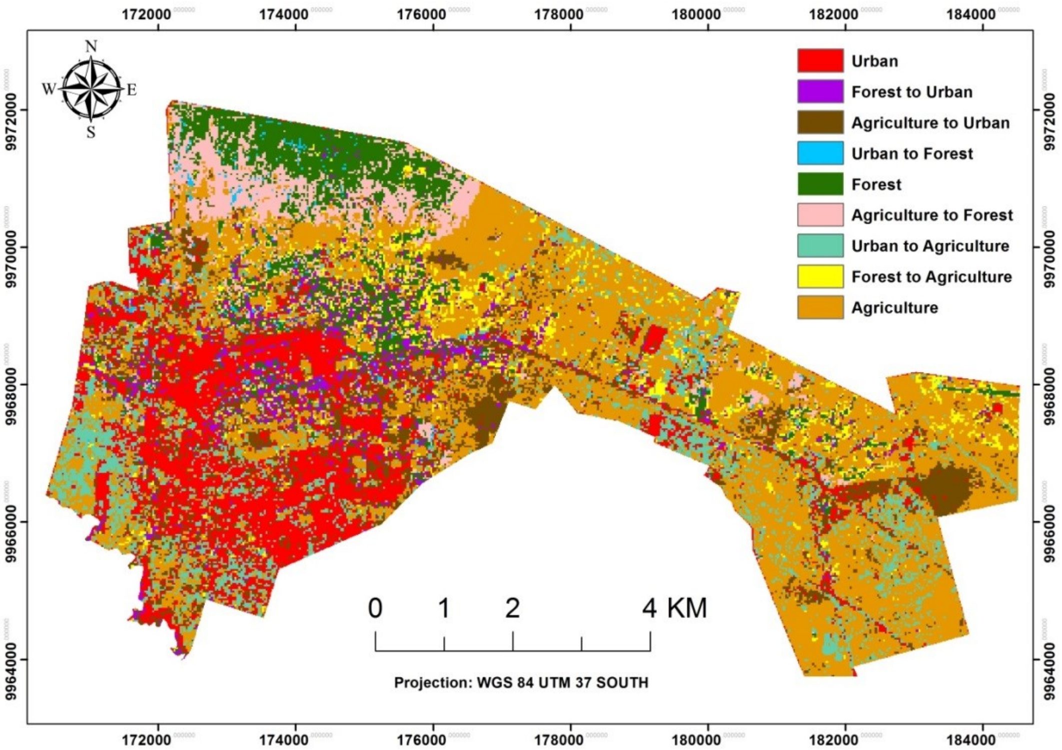

Figure 4-12: Land-use change conversion in Nakuru CBD using Landsat TM (1986) and Landsat ETM (2000)

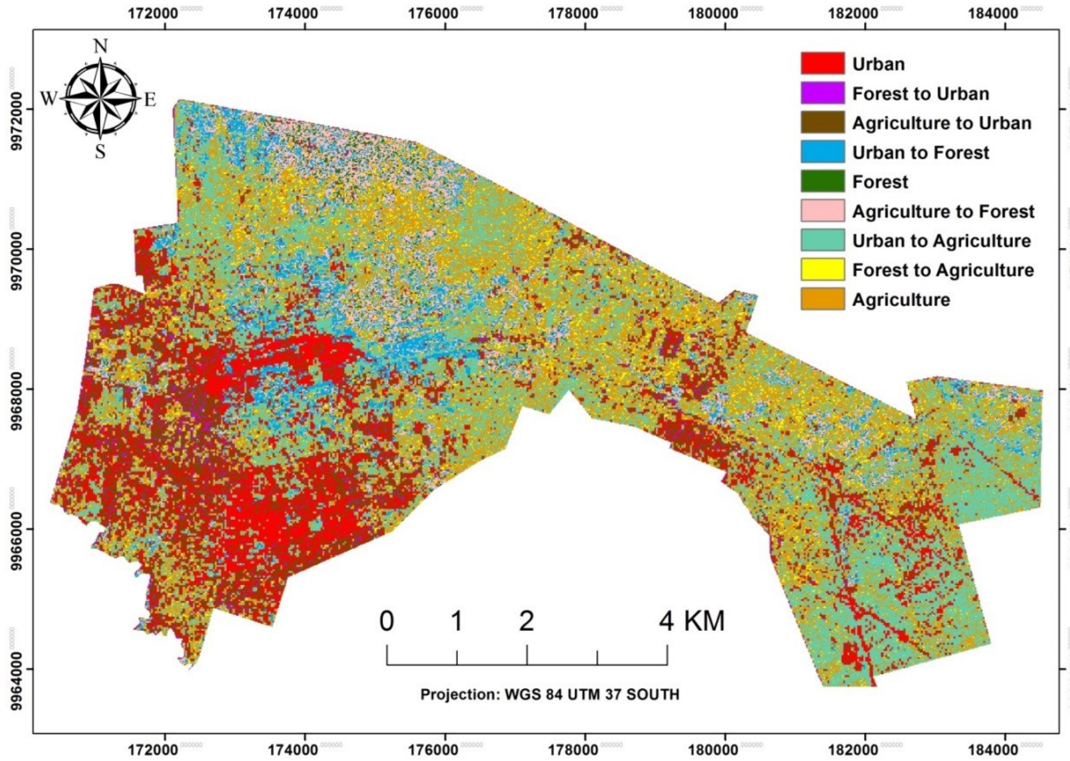

Figure 4-13: Land-use change conversion in Nakuru CBD using Landsat ETM (2000) and ALOS PALSAR (2010)

Monitoring urban land-use and spatial-temporal changes is essential for guiding decision making in resource management. We analysed land-use changes between 1986 and 2010 using multi-sensor satellite datasets. The performances of various classifiers were assessed. SVM algorithm gave better results compared to ML classifier. Image upscaling and downscaling were explored in this research. Downscaling of Landsat data sets did not affect classification accuracy as compared to upscaling of Worldview-2 and ALOS PALSAR datasets. The integration of Landsat and ALOS PALSAR yielded good results compared to when ALOS PALSAR was classified alone. Post classification comparison was performed to determine the land-use changes and conversion.

4.3.4 Factors influencing land-use changes and urban growth

The results from the land-use change analysis for Nakuru indicate that the city has undergone rapid urban growth. This has been attributed to economic growth and rapid urbanisation.

Economic growth

Nakuru has developed rapidly as it lies on the Kenyan-Uganda railway and the Trans-African highway linking the coastal region. It's close proximity to Nairobi, good climate and rich agricultural hinterland has seen the town develop into the fourth largest town in Kenya.

Figure 4-14 shows the main economic activities in Nakuru. Commerce and industry has blossomed along the main transportation corridor. Economic development has led to the development of industries, roll out of residential areas and expansion of built up areas. Poor performance of crops due to changes in local climatic conditions and drought has made more farmers turn into other alternative sources of income such as trade and industry. Such agricultural land has been converted into urban development.

Over the last decades there have establishment of more colleges, universities, banks and big companies such as Geothermal Development Corporation (GDC). This has led to a strain on existing housing and causing a rise in the value of urban land. Only a fraction of the labour force in Nakuru town is actually employed in the formal sector such as in county government administration, industries, schools and parastatals (Mwangi, 2003). Consequently, limited access to formal employment has resulted in the rapid increase of informal trading activities not only in the Central Business District (CBD) but in the residential areas as well (Owour, 2006).

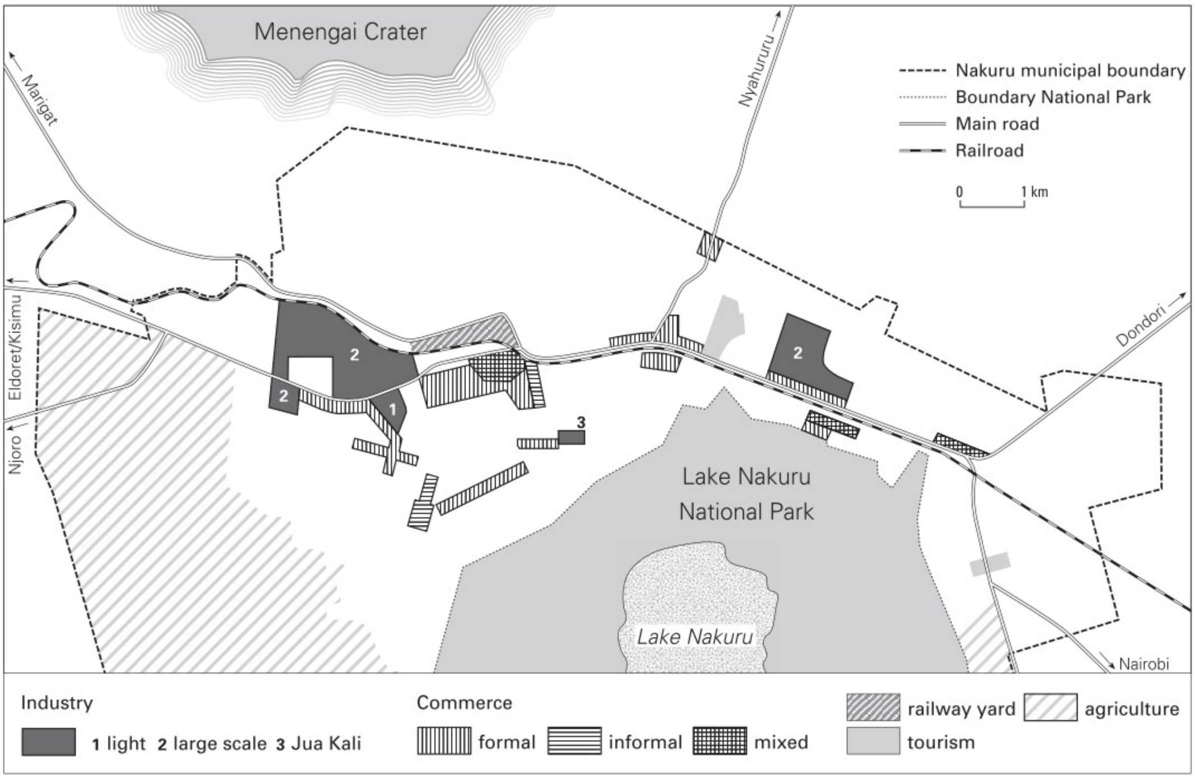

Figure 4-14: Economic structure of Nakuru Municipality (Source: Owour, 2006)

The municipal council of Nakuru is always engaging in battles with hawkers and other small scale traders whom fail to comply with city by-laws. The challenge is providing a common market for small scale traders with adequate facilities such as market stalls, water and sanitation.

Tourism has flourished over the last decades. The presence of key natural features such as Lake Nakuru, the Menengai Crater and archaeological sites like Sirikwa holes and Hyrax Hill have made Nakuru to be a top tourist destination in the country (Mwangi, 2003). The location of Nakuru at the centre of the rift valley has contributed to its success as a tourist destination. The Lake Nakuru National Park has received visitors both domestic and international and the numbers have doubled over the years due the country tourism marketing locally and abroad. Accordingly, more hotels have been built up to accommodate the growing numbers of tourists.

Urbanisation

From a population of 38,181 in 1962 the population in Nakuru has growth up to 473,288 in 2009 (Republic of Kenya, 2010). The rise in population growth has been attributed to natural urban increase, rural-urban migration from the local hinterland and other parts of Kenya and boundary extensions (Owour, 2006).

Housing and real estate has occurred in ad hoc manner in response of high rural urban migration into Nakuru. As a result informal settlements have sprouted on the peripheries of the city so as to cater for the low income and urban poor inhabitants as seen in Figure 4-15. The development of the town's infrastructure and regulatory structures has failed to keep up with the rapid population growth (Owour, 2006). This has resulted in a relatively majority of the population inhabiting in informal, unregulated and poorly serviced settlements.

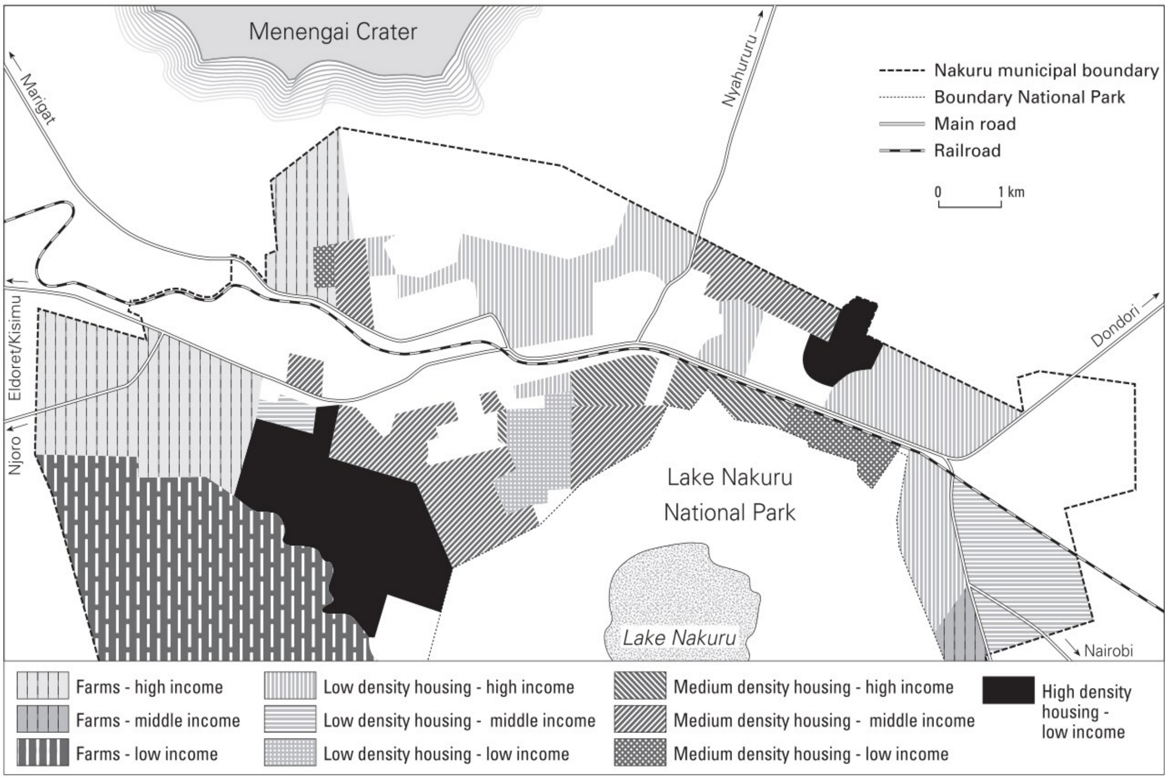

Figure 4-15: Settlement structure of Nakuru municipality (Source: Owour, 2006)

Physical factors

Rapid urban growth has occurred mostly along the transportation corridor of the major highway and railway which links the city to Nairobi and Kisumu. The availability of cheap construction material due to the presence of different volcanic rocks has contributed to the burgeoning of housing and real estate development. Cement and sand are readily available as well cheap labour from low income settlement zones.

From Figure 4-15 we can see that in the southern east part of the city most urban growth has occurred and it is a fairly flat area at average height of 1800 metres above sea level. This area has middle income and high residential houses.

In the northern part of the city towards the west we have high residential areas and it is pretty step at 1,900 metres above sea level. Here construction is limited by the steep slopes but ideal for high income inhabitants who can afford the high prices of land and rent. Low income residential areas including informal settlements are located on the southern western part of the city. The area is fairly flat at an average altitude of 1780 metres above sea level.

4.3.5 Consequences of Nakuru's urban growth

The results from the land-use change analysis of Nakuru demonstrate that major changes have occurred. These significantly diminish the achievement of sustainable development. Urban growth has resulted in reduction of forest and conversion of agricultural land into urban development.

There has been high demand for housing due to high rural urban migration resulting in high prices of land. The house rent has also gone up leading to the flourishing of informal settlements for low income inhabitants. The urban growth has sprout into the edges and into the neighbouring towns as people search for low-priced land for development of homes.

The quality of infrastructure has also decreased with an increase in housing density (Owour, 2006). This is because a high proportion of the population is mainly located in the low-income settlements which offer affordable rent. Nonetheless, there have been high traffic congestions in rush hours.

There has been a strain on the water and sanitation facilities in the city. Some areas have little or no access to piped water and are forced to buy water from water kiosks. In some low income estates bathroom and toilets are communal posing hygiene hazards.

The price of food has gone up as agricultural produce is fetched from neighbouring towns. The suppliers pass the high transportation costs to consumers translating to high food budget prices for each household. As a result, poor households continue to rent low income houses and dwell in informal settlements so as to survive (Owour, 2006).

4.4 Land-use change analysis in Nairobi

4.4.1 Data

The approach adopted for the analysis of land-use involved: cloud-free Landsat images for 1986, 2000 and 2010. Nairobi is entirely enclosed within Landsat TM path 168, rows 61. The Landsat data sets used included TM, and ETM+ images. Reference data was developed for each of the separate years and then randomly divided for classifier training and accuracy assessment. Ground truth data included a topographic map which was used as reference data for the 1986 and 2000 classifications while GPS points served as reference data for the 2010 classification.

Table 9: Datasets for land-use change analysis of Nairobi

Data type	Source	Resolution	Application
Satellite imagery	Landsat TM (3.5.1986)	28.5 metres	Land-use mapping
	Landsat ETM+ (2.5.2000)	28.5 metres	
	Landsat ETM+ (31.2.2010)	30 metres	
Topographic map		Map scale 1:50000	Geometric correction Ground truthing
GPS points			Ground truthing

4.4.2 Land-use classification

Land-use classification of Nairobi consisted of six land-use classes; namely urban, forest, agriculture, open/transitional areas, water and rangeland. Urban land-use included built-up areas within the research area. Forest included evergreen forest, mixed forests with high densities of trees, little or under-storey vegetation. Open/transitional areas included bare land, exposed areas, quarries and transitional areas. Water included rivers and reservoirs. The sewage treatment plant in Ruai was also captured under water class. Rangeland included bush land and ground layer covered by grass and sparsely disturbed scrub species. The design of the classification scheme involved consideration of factors such as the major land-use groups within the research area, disparities in spatial resolution of the sensors, and the need to always discriminate land-use classes irrespective of seasonal disparities (Anderson, Hardy, Roach, & Witmer, 1976).

Image pre-processing steps for the optical datasets were radiometric correction and geometric correction. GPS points were used for image to map registration. Combinations of the reflective spectral bands from images (i.e., stacked vector) were used for classification of the 1986, 2000 and 2010 images. Training sites representing the land-use classes of interest were collected using the region of interest tool. Such sites were homogeneous and extensive to provide excellent statistics. Support vector machine (SVM) classification was applied to all the data sets and its performance assessed using error matrices. SVM is well recognized in the field of machine learning and pattern recognition (Vapnik, 1998; Schölkopf & Smola, 2002) and has recently been introduced in context of remote sensing image analysis (Huang, Davis, & Townshend, 2002; Foody & Mathur, 2004; Melgani & Bruzzone, 2004). Recently SVM has been found to perform better compared to maximum likelihood classifier (Mubea & Menz, 2012).

Post-classification refinements were enforced to diminish categorisation errors as a result of the similarities in spectral signatures of certain classes. Spatial modeller and additional rule based procedures were adopted to overcome these classification challenges and differentiate between classes.

Independent samples of pixels for each class were randomly selected from each classification category to assess classification accuracies. Error matrices as cross-tabulations of the mapped class versus the reference class were used to assess classification accuracies (Congalton & Green, 1999). Overall accuracy, user's and producer's accuracies, and the Kappa statistic were then derived from the error matrices. The Kappa statistic incorporates the off diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance.

4.4.3 Results and discussion

Land-use summary for Nairobi was performed and results tabulated in Table 10 and Figure 4-16. Land-use maps for Nairobi are illustrated on Figure 4-17, Figure 4-18 and Figure 4-19. The urban/built-up areas increased from 35.16 km^2 in 1986 to 52.50 km^2 in 2000 and 79.38 km^2 in 2010. Forest increased from 62.87 km^2 in 1986 to 71.14 km^2 in 2000 but decreased to 66.86 km^2 in 2010. In areas where forest decreased such land was classified as agriculture or urban due encroachment of the forest.

Agriculture increased from 144.72 km^2 in 1986 to 152.53 km^2 in 2000 but decreased to 148.21 km^2 in 2010. Typical agriculture land-use include small-scale crop gardens and peri-urban agriculture for cultivation, and such land-use was converted to urban land-use namely building up of residential and commercial buildings to cater for the increased urban population in Nakuru. Open/Transition areas increased from 99.54 km^2 in 1986 to 146.94 km^2 in 2000 but decreased to 117.94 km^2 in 2010. Rangeland increased from 361.11 km2 in 1986 to 261.74 km^2 in 2000 but decreased to 257.61 km^2 in 2010. Water increased from 9.60 km^2 in 1986 to 11.15 km^2 in 2000 and increased further to 26.00 km^2 in 2010.

Table 10: Land-use summary and error estimates for Nairobi

Year	1986		2000		2010	
Land-use classes	**Area (km^2)**	**%**	**Area (km^2)**	**%**	**Area (km^2)**	**%**
Urban	35.16	4.9	52.50	7.4	79.38	11.1
Forest	62.87	8.8	71.14	10.0	66.86	9.4
Agriculture	144.72	20.3	152.53	21.4	148.21	20.8
Open/transition areas	99.54	14.0	146.94	20.6	117.94	16.5
Rangeland	361.11	50.6	261.74	36.7	257.61	36.1
Water	9.60	1.3	11.15	1.6	26.00	3.6
Total	**696**	**100**	**696**	**100**	**696**	**100**
Overall Accuracy (%)	92.64		90.9		91.87	
Kappa Coefficient	0.8679		0.8834		0.8953	

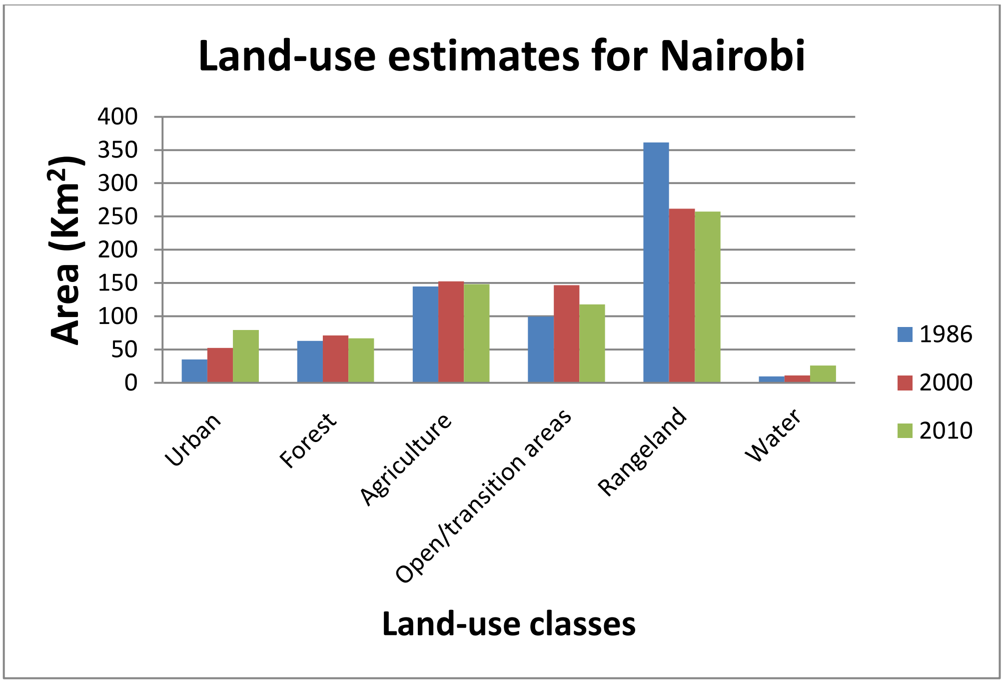

Figure 4-16: Land-use estimates for Nairobi

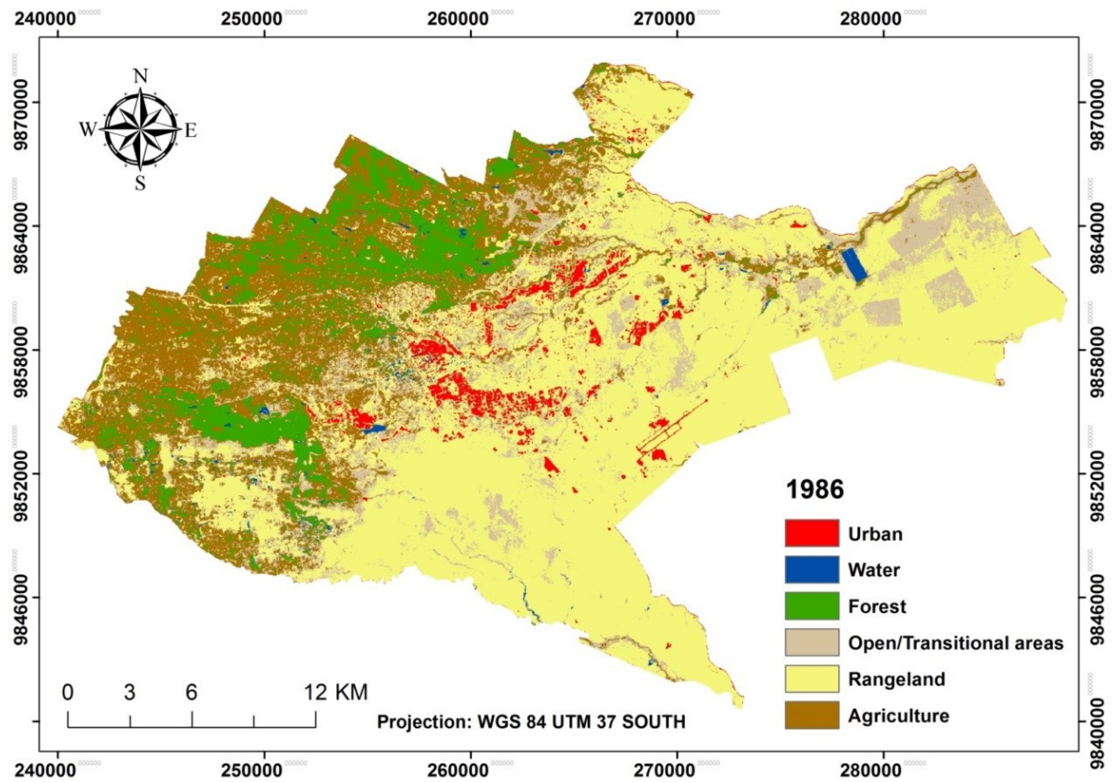

Figure 4-17: Land-use map for Nairobi using Landsat TM 1986

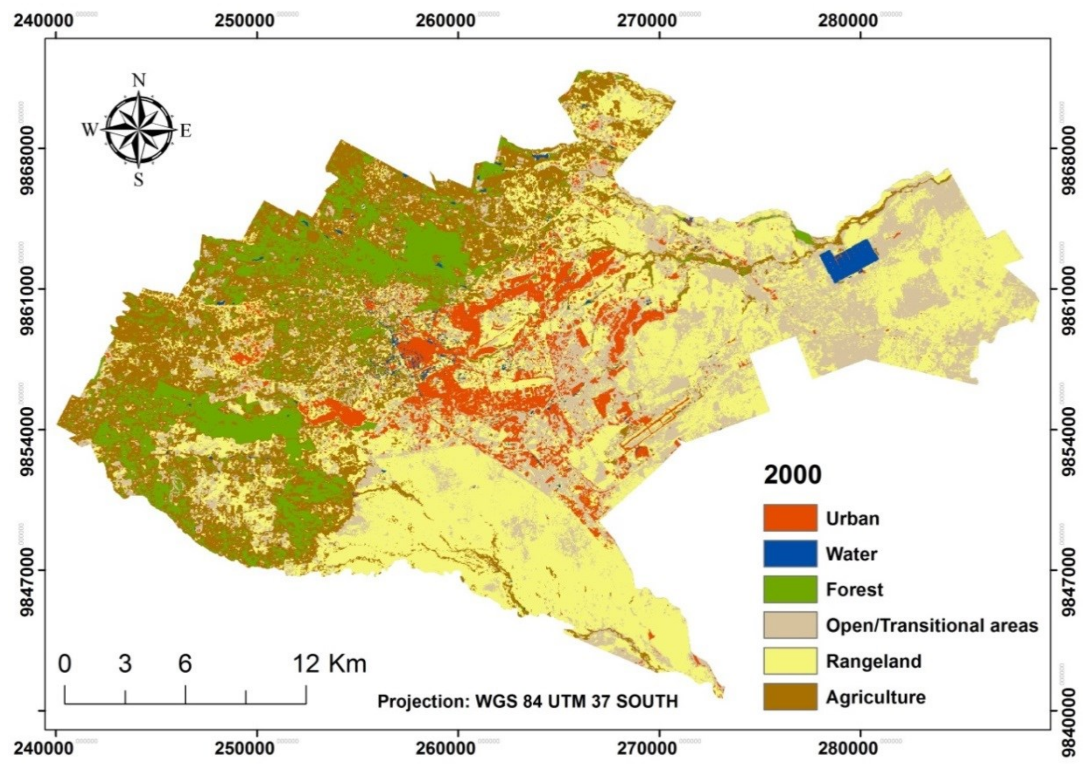

Figure 4-18: Land-use map for Nairobi using Landsat ETM 2000

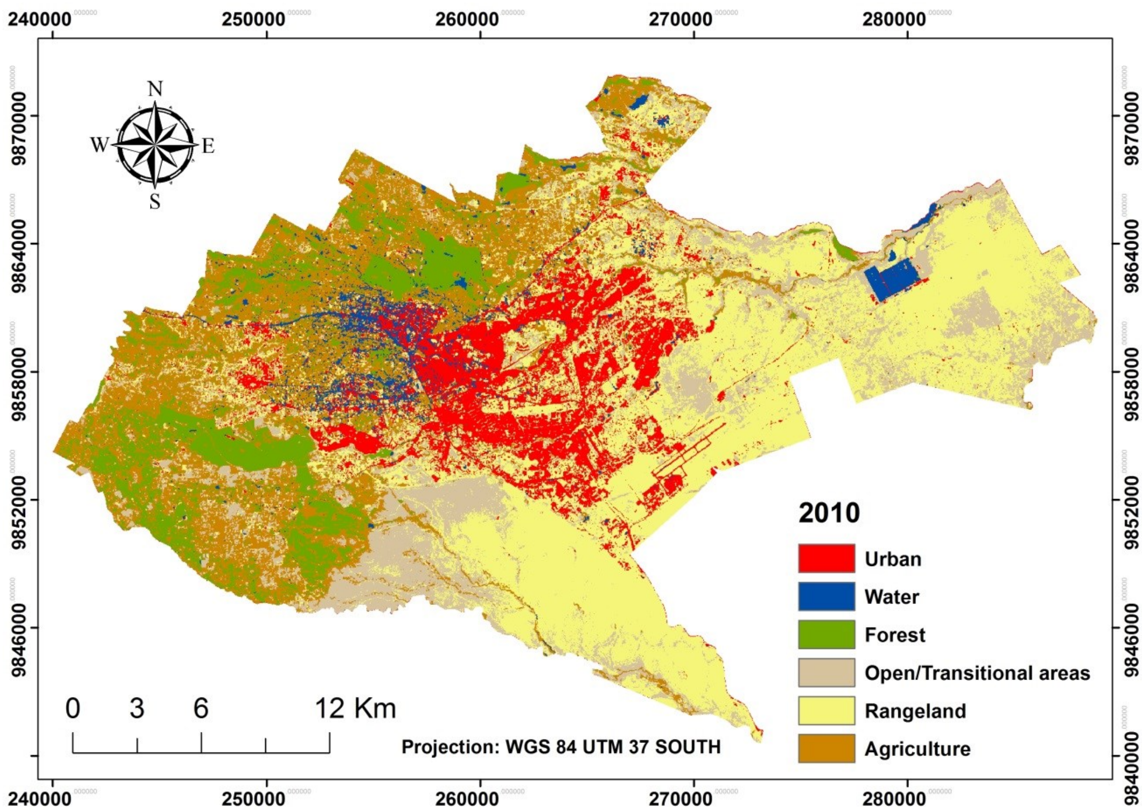

Figure 4-19: Land-use map for Nairobi using Landsat ETM + 2010

4.4.4 Factors influencing land-use changes and urban growth

The results from the land-use change analysis for Nairobi indicate that the city has undergone rapid urban growth. This has been attributed to the fast economic development witnessed over the last decade among other factors such as rapid urban growth, physical factors.

Economic development

Nairobi, with 8.4 per cent of the country's population, accounts for almost 20 per cent of national GDP (UN-Habitat, 2012). Nairobi hosts the Nairobi Stock Exchange which is one of Africa's largest bourses. Several international companies have established their headquarters in Nairobi such as Coca-Cola and Google. United Nations Environment Programme (UNEP) and UN-Habitat have their headquarters in Nairobi.

Over the last few decades transport and communications infrastructures have been developed in Nairobi, with tangible results in terms of efficiency and productivity in various economic sectors. This has been as result of the East African Community

(EAC) enabling a common market for East Africa comprising Kenya, Uganda, Tanzania and Rwanda.

Economic development has led to a boom in industries and consequently expansion of built up areas. Consequently this has also led to the blossom of the real estate and housing as more people migrate into Nairobi in search for jobs and amenities. Nonetheless housing has become expensive resulting in informal settlements and expansion of the city at the fringes where land is slightly affordable.

Small-scale businesses have sprouted sporadically due to lack of employment and hard economic times. This has seen a rise in hawkers fighting battles with the City Council of Nairobi (CCN) as they seek grounds to sell their merchandise. The challenge for CCN has been that of providing market stalls for low income earners as well as regulating business through licences and taxes. However, most hawkers are not able to cope with the taxes and regulations imposed by CCN. Hawkers engage mainly in selling second hand clothes from abroad and groceries.

There has been construction of bypasses and new roads in Nairobi to cope with the high economic growth and traffic congestions witnessed in the rush hours. The bypass roads have been built on the outer rings of the city to minimise traffic coming into the central business district.

Economic development has growth countrywide maintaining a positive growth a GDP of 4.5 % in 2012. Nairobi has become an information and communication technology centre (ICT) hub with the large telecommunication companies such as Orange and Huawei establishing their bases. Tourism has blossomed in Nairobi with the role out of more international flights through Jomo Kenyatta International Airport (JKIA) and the refurbishment of the Nairobi National Park (NNP).

Urban population growth

The population of Nairobi has been increasing from 310,000 in 1960 to 3,138,369 in 2009 (Republic of Kenya, 2010). The rapid population growth has seen an increase in urban population due to rural urban migration. Thus this is responsible for the land-use changes as shown in Figure 4-17, Figure 4-18 and Figure 4-19.

The high population has resulted in high demand for food and subsequent demand for agricultural. However, most agricultural land has been cleared for urban expansion within Nairobi city resulting in import of agricultural produce from the neighbouring towns on the edges of Nairobi such as Naivasha and Kiambu. This has translated into high food prices as sellers pass the transportation costs to consumers.

The existing infrastructure and public services have not expanded at per with the increasing population growth. This has led to a strain on water supply with some residents experiencing water shortages. There have been blackouts due to a high demand for electricity for residential, commercial and industrial use.

The city's wastewater management has not kept up with increasing demands from the growing population and is inadequate to treat the amount of industrial and municipal effluent entering the Nairobi River and other surface waters (UNEP, 2009). Currently the city has only two sewage treatment plants, one in Dandora and the new one in Ruai.

60 % of Nairobi's inhabitants live in informal settlements with inadequate access to quality water and are forced to buy their water at kiosks at a higher price (Engel, Jokiel, Kraljevic, Geiger, & Smith, 2011). This has translated into the lack of access to sanitation resulting in untreated waste and wastewater not only endangering human health, but also deteriorating the river systems.

Nairobi's high population growth has resulted in urban sprawl with emergence of informal settlements and consequently influencing land-use changes. Poor planning coupled with rapid population increase has worsened the existing physical, social, economic and environmental problems.

Physical factors

Urbanisation has occurred on the flat areas in Nairobi. In the eastern part of the city urbanisation has continued unabated with the high rise residential areas being constructed in ecological fragile areas such as Nairobi River. The existing land which was open/transitional areas and rangeland has been converted into urban use with such growth expanding into the surrounding neighbouring towns to the east of Nairobi.

In areas to the west of Nairobi are higher in altitude and predominately high class residential areas. Here expansion has been constrained by steep slopes ranging 1760 metres to 1945 metres above sea level. However, looking at Figure 4-19 we can see that urban growth has replaced forest and agricultural land.

Towards the south eastern part of the city urban growth has been constrained by the boundary of JKIA airport and to the south by Nairobi National Park. The national park serves as a protected area for conservation of wildlife and flora. The park is a big tourist attraction for Nairobi. The area around the airport has been protected from urban development and serves a safety zone and noise corridor for taxing of aeroplanes.

The availability of cheap construction material due to the presence of different volcanic rocks has contributed to the flourishing of housing and real estate. Cement and sand are readily available from the neighbouring towns such as Athi River which are linked by the Nairobi Mombasa highway.

4.4.5 Consequences of Nairobi's urban growth

The analysis of land-use changes in Nairobi reveal that major changes have occurred. These changes pose challenges in the achievement of sustainable development. Hereto, current forest, natural areas and agricultural land have been cleared to pave way for urban development.

Planning of Nairobi has been done in a haphazard manner based on old master plans. New roads have been constructed on existing urban land where residents are either compensated or forcefully evicted since they hold fictitious title deeds. The land-use zone has changed over time with unclear gaps between various land-uses. The expansion of the city has been random and mostly influenced by transportation network and speculation of land prices.

Housing and real estate has blossomed with exorbitant prices being charged. In some cases houses are built on available spaces with little consideration for basic infrastructure and amenities. Nairobi's rapid growth increased the demand for land and led to land speculation, forcing the poor to settle in fragile and unsavoury areas where they face hardships due to a lack of proper housing and public services and where they are vulnerable to environmental change (UNEP, 2009). This has led to emergence of informal settlements adjacent residential areas which are comprise about 60 % of Nairobi's inhabitants.

Urbanisation has occurred in ad hoc manner posing environmental challenges. Some houses are located close to each with inadequate water supply and sanitation services such as seen in informal settlements. There is immense pressure on urban land that even areas prone to flooding or landslides are often built up for residential use (Lamba, 1994).

5 MODELLING URBAN GROWTH

5.1 Introduction

Urban growth is a complicated process involving the spatio-temporal changes of all socio-economic and physical components at different scales (Han, Cao and Imura, 2009). Using models of urban growth this process can be illustrated in a simplified way and be analysed empirically. Numerical simulation models for land-use change comprise highly complex applications that have been developed to solve specific problems in urban areas. Consequently, a majority of these models have been developed at universities and are a result of long-time research (Goetzke & Judex, 2011).

In section 2 we introduced urban growth modelling and cellular automata. A majority of urban growth models as introduced in Chapter two are restricted to simulate changes of one land-use category, which is urban, and that typically just in one direction, which is growth (Goetzke & Judex, 2011). SLEUTH is such a model and is an acronym for “Slope, Land use, Exclusion, Urban, Transport, Hill shade”, as its main input parameters. SLEUTH is a cellular automaton (CA) based urban growth and land-use change model (Clarke, Hoppen, & Gaydos, 1997). The model was initially applied in the United States of America but has also been applied in other regions of the world such as in Europe (Silva & Clarke, 2005), South America (Leão, Bishop, & Evans, 2004), Southeast Asia (Lebel, Thaitakoo, Sangawongse, & Huaisai, 2007) and Africa (Mundia & Aniya, 2007). SLEUTH consists of two components, an urban growth model based on the Clarke Urban Growth Model (UGM) described in Clarke, Hoppen, & Gaydos, (1997) and a so-called Land cover Deltatron Model (Candau & Clarke, 2000) to simulate other land-use changes induces by urban growth. In most of the studies using SLEUTH described in the scientific literature only the UGM component of SLEUTH is applied.

UGM (Urban Growth Model) has been implemented in the modelling platform XULU (eXtendable Unified Land Use Modelling Platform) in a modified way (Goetzke, 2011; Goetzke & Judex, 2011). UGM requires four spatial input parameters namely; a map of urban land-use, transportation, slope and exclusion/restriction. The exclusion layer determines, which areas in the study area cannot be changed (e.g. water bodies or protected areas) or, if not excluded, are by a certain degree resistant against urbanisation. The transportation layer represents the road network in a research area. While SLEUTH needs at least four urban land-use data sets to calculate a set of calibration coefficients (Silva & Clarke, 2002), the modified UGM in XULU only needs a map for the starting year of the calibration phase and a reference map at the end year. The simulated urban area of the end year is compared to the reference map with the Multiple Resolution Validation (MRV) as described in Pontius Jr, Shusas, & McEachern, (2004).

Monitoring of land-use change requires understanding and predicting the dynamic process and spatial patterns of urbanisation at different time periods (Thapa & Murayama, 2012). Thus we modelled urban growth in Nairobi and Nakuru using regionalised UGM in 2010 and 2030. The modelling approach adopted for this research is shown in Figure 5-1. Modelling of Nairobi and Nakuru involved dataset preparation, model calibration and urban growth simulation. Urban growth modelling for Nairobi and Nakuru utilised four data layers namely urban land-use, road layer, slope, and exclusion layer. The urban land-use data for Nairobi and Nakuru for 1986, 2000 and 2010 were extracted from land-use maps as illustrated in section 4. For our UGM we used urban land-use maps for 1986 and 2010 which covered a period of 14 years. The simulation period was from 2010 to 2030 covering a period of 20 years. The urban land-use for 1986 was used to initialise the model during the calibration phase.

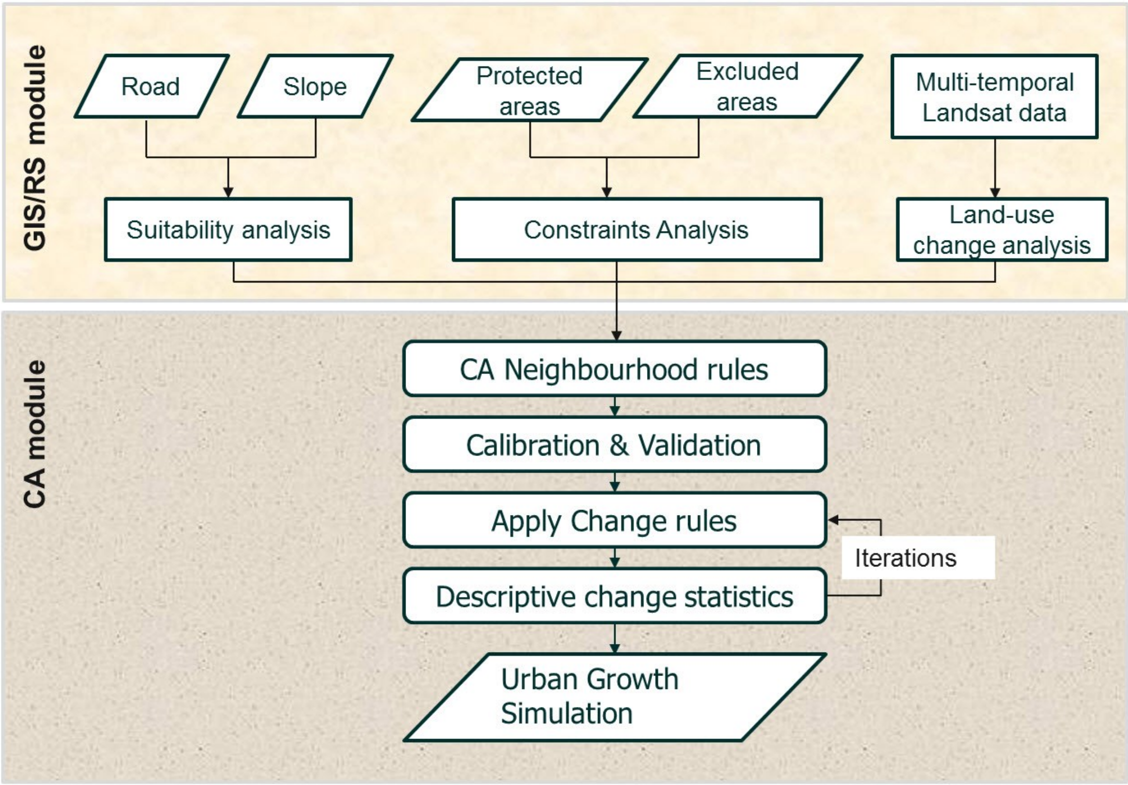

Figure 5-1: Flowchart of urban growth modelling

Calibration is the most crucial step in any modelling application (Clarke, Hoppen, & Gaydos, 1996). In the calibration phase of UGM a brute-force method is used in order to determine five calibration parameters. These parameters control the transition rules that are implemented in the model. A number of Monte-Carlo iterations are performed in the brute-force calibration to obtain the best set of the five calibration parameters. Since testing all possible parameter combinations in Monte-Carlo iterations in a brute-force way would be way too time consuming, calibration is performed in sequential phases ranging from a coarse to a fine calibration (Silva & Clarke, 2002).

The simulation of the three scenarios of urban growth was achieved by varying the protection levels in our exclusion layer. The exclusion later included national parks, public parks, dams, airport and military bases. Scenarios one involved an unmanaged growth with no exclusion layer. Scenario two was based on an exclusion layer with 70 % protection level. Scenario three was based on an exclusion layer with 100 %. At the end of this chapter we compared the urban growth parameters for the two cities; Nairobi and Nakuru.

5.2 The modelling framework (XULU)

Schmitz, Bode, Thamm, & Cremers, (2007) developed XULU (eXtendable Unified Land Use Modelling Platform), a modelling framework that enables model integration and carries out tasks using functionalities such as data storage, input/output methods, editing and visualisation. XULU was first used to compute the future land-use for different scenarios with their specific boundary conditions for a watershed in Benin (Menz, et al., 2010). Therefore, the CLUE-s land-use change model, developed by Verburg et al., (2002) was implemented in the XULU modelling framework.

XULU as a modelling framework has functionalities which include input, output, editing and visualisation. XULU is implemented in Java 1.6 and offers a model independent graphical user interface. The core program contains the fields of data management, input/output routines for data import and export, data structure, memory management and data visualisation as shown in Figure 5-2 (Schmitz, Bode, Thamm, & Cremers, 2007).

At any one time several models can be plugged into the framework at the same time offering the possibility to combine different models and model types. Since all models are based on the same data structures and use the same data pool, the output of one model can be used immediately as input for another model. XULU can be executed in any operating system namely Windows and LINUX.

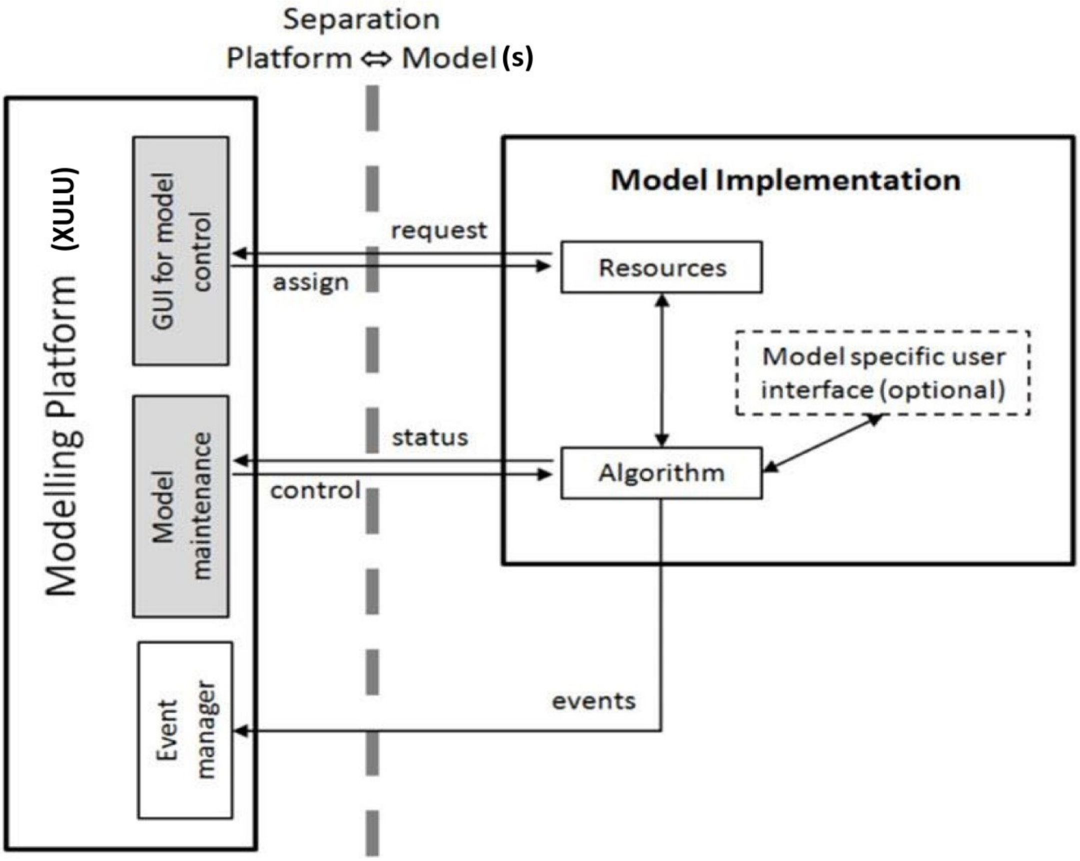

Figure 5-2: Separation of the XULU modelling framework from a certain model implementation

(Source: Goetzke, 2011)

XULU is a stand-alone JAVA application with a user-friendly and clearly arranged graphic user interface (GUI) as shown in Figure 5-3. The user has to load the necessary data objects into the data pool and allocate them to the individual model resources. The following plug-ins for land-use modelling are implemented in XULU: spatial data types for raster and vector data, I/O routines for shape files and different raster types (e.g. ASCII and GeoTIFF) and a layer-based visualisation for raster and vector maps (Schmitz, Bode, Thamm, & Cremers, 2007). Land-use change models are loaded as plug-ins as well. Models that are implemented so far include CLUE-s and the Urban Growth Model UGM (Goetzke & Judex, 2011). As Figure 5-2 shows, a model or any plug-in is separated from the main software. This means that only the specific model algorithm has to be programmed when a model is to be implanted in XULU.

Other plug-ins include a routine to copy results from one model to another and the MRV for evaluating the goodness-of-fit of models.

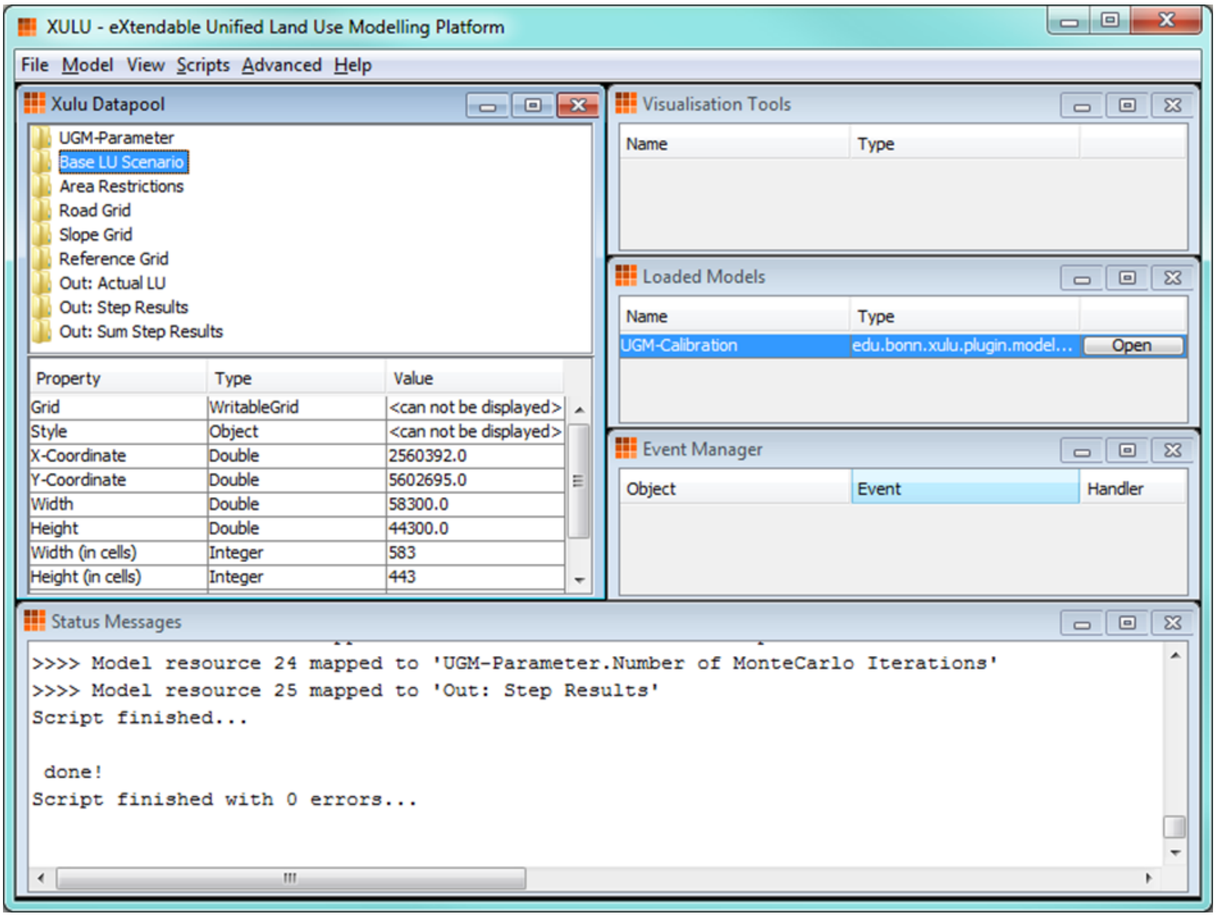

Figure 5-3: The main window of the XULU modelling platform

5.3 Model Parameters and Growth Types

Urban growth model begins with historical data and other biophysical factors which served as inputs into our UGM. The CA model randomly selects potential cells for urbanisation and the transition rules evaluate the properties of the cell and its neighbours. For example this is demonstrated by the probability that a given cell is selected and whether it is urban or non-urban, as well as its slope value and proximity to a road. The CA knows only two states: 1 = urban/built-up and 0 = non- urban/non-built-up.

The number and location of the randomly selected cells is controlled by the growth parameters. UGM uses five parameters (whose values range from 0 and 100) to simulate urban growth with a set of transition rules. They include: dispersion, breed, spread, slope resistance and road gravity. Dispersion determines the dispersiveness of the outward distribution and controls the number of pixels that are selected randomly for possible urbanisation. Breed refers to the probability that a newly generated settlement starts its own growth. Spread controls how much existing settlements radiate. Slope resistance influences the likelihood of growth on steep slopes. Road gravity influences the creation of new centres along roads. We used starting values of 1, 50 and 100 for each parameter so as to achieve a coarse calibration.

Urban growth modelling leads to simulation of four types of urban land-use change (Mundia & Aniya, 2007). These include spontaneous growth, new spreading centres growth, edge growth, and road-influenced growth. These growth types are applied sequentially each year during each growth step and are controlled through the interactions of the five growth parameters. These growth parameters determine the probability of any chosen location becomes urban or non-urban. Table 11 shows the summary of growth types simulated by our UGM and illustrates the contribution of each parameter as well as when combined with others and several different growth processes (Jantz, Goetz, & Shelley, 2004). Figure 5-4 shows the growth types simulated by UGM. Supplementary illustrations on urban growth types are shown in appendix 9.2.1.

Table 11: Summary of growth types simulated by the UGM model

Growth cycle order	Growth type	Controlling parameter (s)	Summary description
1	spontaneous	dispersion	Randomly selects potential new growth cells.
2	new spreading	breed	Growing urban centres from centre spontaneous growth.
3	edge	spread	Old or new urban centres spawn additional growth.
4	road-influenced	Road gravity, dispersion, breed.	Newly urbanized cell spawns growth along transportation network
Throughout	slope resistance	slope	Effect of slope on reducing probability of urbanisation.
Throughout	excluded layer	user-defined	User specifies areas resistant or excluded to development.

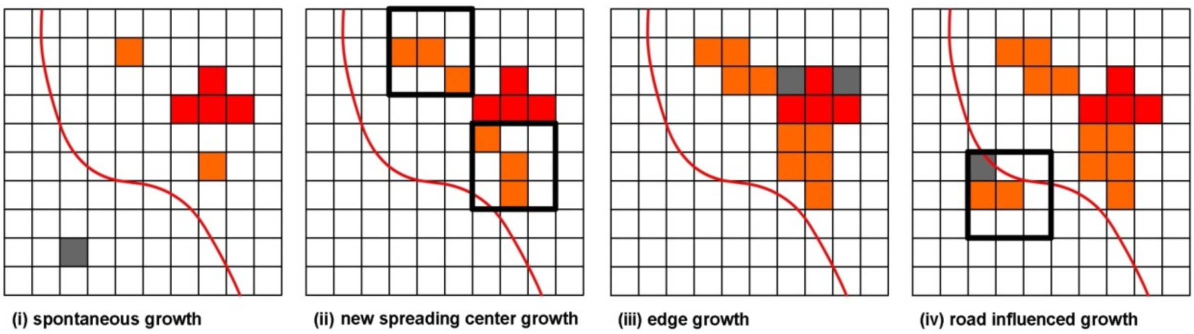

Figure 5-4: Growth types simulated by the UGM model

(Source: Rienow et al., (2011)

Spontaneous growth occurs when a randomly chosen cell falls in a suitable location for urbanisation at the boundary of an existing settlement, simulating the fragmenting influence urban areas have on their surroundings (Clarke & Gaydos, 1998). The dispersion parameter determines the probability that a non-urban cell will be urbanised.

New spreading centre growth produces new urban centres by generating neighbouring urban cells around areas that have originated from spontaneous growth. The breed parameter governs that a pixel produced through spontaneous growth also undergoes new spreading centre growth.

Edge growth is the outward growth experienced in old or new urban centres. It is determined by spread parameter and influences the possibility of a non-urban cell in becoming urbanised.

Road-influenced growth results in spread of new urban cells emerging on road networks. It is influenced by breed parameter in areas where new growth is observed due to establishment of new roads. Furthermore road-influenced growth is influenced by road gravity parameter where growth of urban centres occurs within a certain radius to the proximity of roads. Dispersion parameter also influences road-influenced growth when the model searches randomly on where to place an urbanised cell with a search distance along a road.

The slope parameter influences growth tremendously. Areas with high slope value will experience less urban growth whiles reality flat areas attract most urban growth. Thus suitable areas with relatively flat or gentle slopes will attract high urban growth. The value of slope was set at 15 % in our model according to previous studies by Goetzke (2011).

The exclusion layer significantly controls urban development. The percentage of exclusion used is used in simulating scenarios of urban growth. Ideally sustainable development is possible to simulate with an exclusion layer which has national parks, water resources, researved areas such as cementaries, military bases and airports. In this research we explored three scenarios of urban growth.

5.4 Model calibration

Model calibration was performed using a brutal force Monte Carlo calibration technique for Nairobi and Nakuru respectively. This method uses the first starting image of urban extent (in our case 1986) and applies an initial set of control parameters. Thus, the model is able to approximate the observed data. The technique simulates the iteration of components of CA, that is, time, space, state, transition rules and neighbourhood.

The initial set of control parameters include slope, spread, dispersion, breed and road whose values were varied between 1 and 100. Thus, calibration was performed in four stages. The first stage was coarse calibration and we assigned values between 1 and 100 in order to get an approximate set of parameters. The second, third and fourth stages were fine calibration and were obtained using increments of 25 such as 1, 25, 50, 75 and 100. This aimed at obtaining the best set of model parameters which mimic reality. Simulated urban growth was a result of an interaction of the five model parameters and resulted in various urban growths as seen in Table 11.

The calibration was a vigorous exercise aimed at determining whether a given cell is urban or non-urban with various model parameter combinations as shown in Figure 5-4. This was achieved using various metric measures such as pixels, edges, and clusters. The calibration using Monte Carlo predictions computed the averages across multiple runs to ensure robustness of the solutions.

Our two cities exhibit different and unique characteristics. Thus Monte Carlo calibration was done separately for each city. Finally, we achieved predicted urban growth for our cities. The next step was validation of our results using multiple resolution validation method (MRV) as explained in section 5.5.

5.5 Model validation

It is difficult to test the accuracy and efficiency of land-use models. Nevertheless, different model users have different ways of assessing land-use models. Whereas there is a group of model users who wish to make predictions as accurate as possible, another group emphasises on the ability of a model to support the general knowledge of processes and mechanisms of land-use change (Pontius Jr & Malanson, 2005).

The method of multiple resolution validation (MRV) was used in a comparison of land-use models in which the tests were conducted in seven laboratories with 13 applications, 9 different models and in 12 study areas (Pontius Jr, et al., 2008). This was the first time that a consistent method for model validation was applied. MRV technique is described in detail for the comparison of categorical land-use data by Costanza (1989) and Pontius Jr, Huffaker & Denman (2004). It takes into account the magnitude as well as the position of change. Typically maps are compared pixel-wise. A limitation of the method is that it does not consider neighbourhood effect. This causes a problem for land-use modelling, because models rarely target the exact position of real change, nevertheless they serve as agents for representing patterns of change. At a pixel-by-pixel analysis every pixel is calculated as an error, where the model map does not exactly fit with the reference map. In MRV technique four neighbouring pixels are averaged stepwise. Thus with every step the length of the pixel side increases by the factor two. The amount of correct pixels increases in every step, until in the last step when the whole research area is inside of one big pixel and both location agreement and location disagreement approach 0 (Goetzke & Judex, 2011). The MRV technique was incorporated in UGM.

Since a research area is normally not a perfectly square, every cell has to be weighted according to its fraction in the larger framework. The weight *Wn* results from the number of smaller cells that make up a larger cell. Equation 1 shows the agreement *Fg* between the maps *R* (reference) and *S* (simulation) at resolution *g*, where every cell *n* has the weigh *Wn*. *Rnj* (*Snj*) is the fraction of class *j* in grid cell *n* of the reference map *R* (or simulation map *S*) and *Ng* is the number of grid cells in the given map resolution. With Equation 2 the overall agreement for every resolution can be calculated as follows (Pontius Jr, 2000):

Equation 2

$$F_g = \frac{\sum_{n=1}^{Ng}\left[Wn\sum_{j=1}^{J} MIN(Rnj, Snj)\right]}{\sum_{n=1}^{Ng} Wn}$$

The weighted average of each resolution was used since it is useful to look at a measure of agreement that combines all resolutions. Thus the higher resolutions gain a higher weight and coarser resolutions gain a lower weight, but without ignoring them. Here the following Equation 3 taken from Costanza (1989) was used:

Equation 3

$$F_t = \frac{\sum_{g=1}^{n} F_g e^{k(g-1)}}{\sum_{g=1}^{n} e^{k(g-1)}}$$

Where *Ft* is the weighted average over all resolutions, *Fg* the measure of agreement at resolution *g*, and *k* is a constant. Together with this exponentially less weight is given to the agreement at coarser resolutions. The constant *k* gives subjectively more weight to the higher or coarser resolution. If $k = 0$ all resolutions have the same weight, if $k = 1$ only the first resolution levels are considered. To assess land-use patterns Costanza (1989) proposes a value of $k = 0.1$, which we retained.

In order to evaluate model results with the technique described above, three datasets are necessary: a reference map of time 1, a reference map of time 2 and a simulation map of time 2. The reference map of time 1 is the initial point for modelling, that is, land-use map of 1986 and at the same time serves as a Null-model, which is the assumption that no change has taken place. Therefore, the reference maps of t1 and t2 are compared. To evaluate the model result, the simulation map of t2 is compared with the reference map of t2.

We performed four iterations for the calibration of our UGM. The first calibration was coarse which began with the values of 1, 25, 50, 75, and 100 for each of the five parameters. A good set of five parameters were selected based on the best MRV obtained. For the subsequent iterations we used narrow range of values within the best set of parameters obtained. On the fourth calibration we obtained the best set of parameters that best fit the historical data and used them to forecast urban growth in 2010 and 2030.

We used Pontius Jr, Huffaker & Denman (2004) method to validate our results. We compared the simulation model with a null model. The null model obtained used the 2010 reference map as the prediction for 2010. We used the UGM script for model calibration and validation as shown in appendix 9.2.2.

5.6 Scenarios of urban growth

Scenarios use words, numbers and graphics to describe how future events could unfold, and suggest lessons on how to direct the flow of events towards sustainable pathways and away from unsustainable ones (City Council of Nairobi, 2007). Thus scenarios enable us make wise decisions enabling plausible success stories in the future. The use of scenarios to address land-use changes have become useful tools in the assessment of land-use dynamics (Verburg, Schulp, Witte, & Veldkamp, 2006). This approach is required to anticipate the consequences of various development scenarios. However scenarios are not predictions but rather they are an approach to help manage decisions based on the interpretation of qualitative descriptions of alternative futures translated into quantitative scenarios (Petrov, Lavalle, & Kasanko, 2009).

There is need for such scenarios to be integrated in land legislation. Several policies and strategies have been formulated by various national and regional governments in order to minimise the negative impacts caused by improper urban developments (Zhang, Ban, Liu, & Hu, 2011). Nevertheless, such policies are not well defined in the context of Kenya. Thus, exploring various scenarios by predicting future urban land-use patterns under different ‘’what-if’’ conditions can help in the management of urban expansion and change as well as in the development of alternative plans before irreversible transformations occur (Conway & Lathrop, 2005). This paradigm can help Kenya to manage its resources sustainably.

Usually baseline predictions have been used in simulating urban growth other than scenario based studies as seen in Clarke & Gaydos (1998). Furthermore, the scenarios developed have focused on specific development strategies in specific cities such as seen in Conway & Lathrop (2005) whom modeled the ecological consequences of four land-use policy scenarios in New Jersey, USA. In our research we conducted urban growth scenarios of two cities in Kenya using UGM. The simulation of future urban growth scenarios and the related environmental assessments can therefore assist policymakers in evaluating alternative development schemes, and can form a basis for urban planning policy recommendations for sustainable city development (Zhang, Ban, Liu, & Hu, 2011).

The Government of Kenya formulated Kenya Vision 2030 (Government of Kenya, 2007). This was an attempt at maximum protection of natural resources so as to ensure sustainable development is attained in the year 2030. Cities in Kenya have undergone rapid urbanisation as people migrate into cities in search of employment and better amenities. Thus this gave us the motivation to investigate scenarios of urban growth in Nairobi and Nakuru simultaneously. Nairobi is Kenya's capital city. Nakuru is the fourth largest city in Kenya. Currently there are a few studies on scenario-based urban growth simulation in Nairobi and almost none for Nakuru. Nevertheless, Mundia & Aniya (2007) used SLEUTH to model urban growth in Nairobi. This is the first time that UGM has been used to model urban growth in the context of African cities. At this time, we made an assumption that there will be stable economic and political conditions up to the year 2030.

In order to test the usefulness of the urban growth modelling and to provide a coherent and alternate framework for the policy makers, we explored three scenarios in the modelling process. First scenario depicts an unmanaged growth with no restriction on environmental areas, such as forest, agriculture and wetland. Thus urban growth continues with the historical trend of land transition and permits future urban growth allocation without any constraint.

The second scenario assumes a managed growth with moderate protection. Here the exclusion layer included government buildings and forest cover. Cities in Kenya have undergone rapid urbanisation due to high rural to urban migration as people search for employment and social amenities (Mundia & Aniya, 2005). There has been significant effect to preserve forest cover in Kenya under the Forest Act, 2005 (Laws of Kenya, 2012).

The third scenario simulates a managed growth with maximum protection on forest, government reserved areas, government buildings, military bases, airports, and urban green. Government reserved areas include parks, cemeteries.

We used the UGM resource mapping script shown in appendix 9.2.3 to simulate the three urban growth scenarios using the best model parameters obtained after model calibration and validation. The script was applied respectively for each city. The input parameters varied included the best model coefficients of slope, breed, spread, dispersion and road as well as the simulation periods up to the year 2030.

5.7 Scenarios of urban growth in Nakuru

5.7.1 Data

The urban growth modelling of Nakuru utilised land-use classification information for the years 1986, 2000 and 2010 as well as other biophysical data. A Digital Surface Model (DSM) at spatial resolution of 30 metres was obtained from Intermap Technologies and was used as an input parameter for urban land-use modelling yielding slope information. Road network data for Nakuru was obtained from Nakuru municipality and comprised all the roads within the city. An exclusion layer was obtained from Nakuru municipality and comprised of government property buildings and other land marked as reserved.

Inputs for UGM included land-use datasets (1986 and 2010), slope data, exclusion data and road data for Nakuru CBD as shown in Table 12. Urban land-use data for 1986 (Figure 5-5) was used as the base data for modelling while land-use data for 2010 (Figure 5-6) were used as the reference grid. The land-use maps used satisfied the minimum accuracy requirement of 85 % stipulated in Anderson classification scheme (Anderson, Hardy, Roach, & Witmer, 1976). The land-use data has been reclassified to a binary map showing only urban and non-urban land-use. Slope data was derived from Digital Surface Model of Nakuru at 30 metres spatial resolution. Exclusion data included areas within Nakuru where development is restricted e.g. government buildings and property. Road data included all road networks in Nakuru CBD and the major roads where given a higher weight for the purposing of modelling. Most development is likely to occur along the major roads in Nakuru.

Table 12: Data for urban growth modelling of Nakuru

Data layer	Source	Description	Resolution
Urban extent	Land-use map	Urban extent extracted from land-use map for 1986, 2000 and 2010	30 metres
Slope	DSM	Derived from Digital Surface Model	30 metres
Exclusion	Topographic map	Vector coverage of protected areas	
Road	Road network	Vector coverage of classified roads	

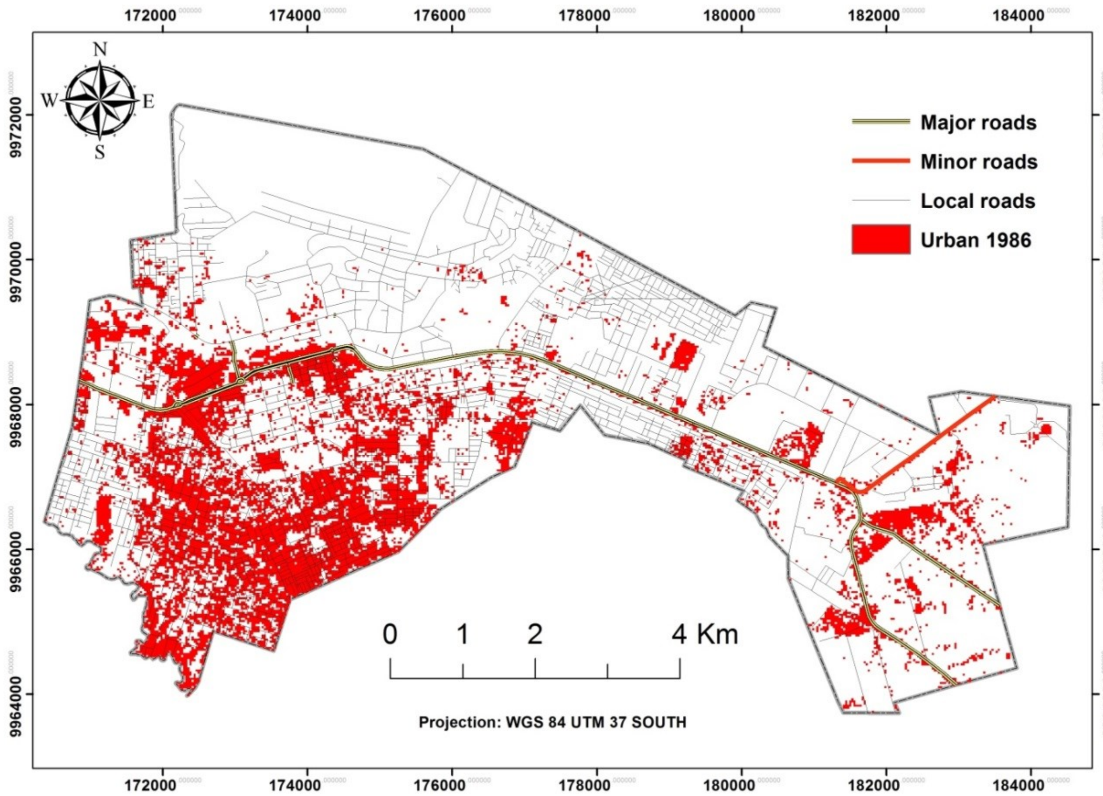

Figure 5-5: Urban extent in Nakuru (1986)

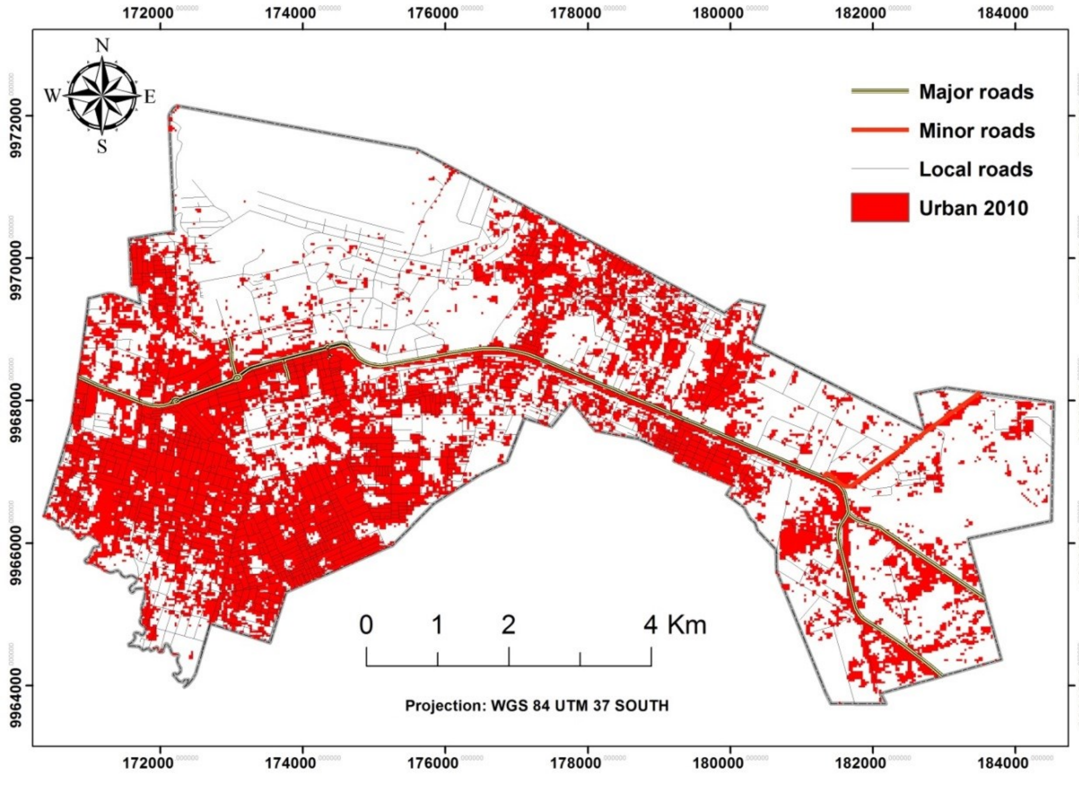

Figure 5-6: Urban extent in Nakuru (2010)

UGM operates in two steps. Firstly, the model was run using default parameters of slope, breed, dispersion, road and spread. This was done in order to get a view of where the appropriate values lie before model calibration. Model calibration was done successfully in four sequences from coarse to fine calibration while the parameters were varied. The MRV method was used to achieve the optimal parameterisation for our model during the calibration phase as well as for the validation of the model results.

5.7.2 Modelling of urban growth in Nakuru

Modelling of Nakuru utilised urban extents extracted from land-use maps for 1986 and 2010 as inputs. Other layers used included slope, areas excluded from development and road network. The road layer included three weight values of 100, 50 and 25 (Silva & Clarke, 2005). A weight value of 100 was assigned to class A roads (International trunk roads), 50 was assigned to class B and C roads (National Trunk Roads), and 25 was assigned to local streets (Minor roads). The road classification in Kenya is explained in Wasike (2001). Thus a road with a value of 100 has the highest potential of attracting urban growth compared to a local street with a value of 25.

Three scenarios were explored in the modelling process. First scenario depicts an unmanaged growth with no restriction on environmental areas, such as forest, agriculture and wetland. The second scenario assumes a managed growth with moderate protection. Here the exclusion layer included government buildings and forest cover. The forest cover is currently protected under the Forest Act, 2005 (Laws of Kenya, 2012). The third scenario simulates a managed growth with maximum protection on forest, agricultural areas, and urban green. Best model parameters for UGM using the three scenarios were evaluated based on the weighted average calculated with the MRV using land-use 2010 as reference grid as shown in Table 13.

Table 13: Best model parameters obtained for Nakuru

	Model parameters					
Scenario	**Slope**	**Spread**	**Dispersion**	**Breed**	**Road**	**Weighted value**
1	50	3	100	100	100	0.8396
2	6	6	60	65	10	0.8448
3	1	6	60	65	60	0.8442

In the first scenario, best model parameters were obtained using land-use dataset with slope at 50, spread at 3, dispersion at 100, breed at 100, road at 100 and a weighted value of 0.83959. In the second scenario, best model parameters were obtained using land-use dataset with slope at 6, spread at 6, dispersion at 60, breed at 65, road at 10 and a weighted value of 0.84488. In the third scenario, best model parameters were obtained using land-use dataset with slope at 1, spread at 6, dispersion at 60, breed at 65, road at 60 and a weighted value of 0.84415. From all the three approaches we can conclude that the calibration of the UGM resulted in an agreement of approximately 84% for the built-up / non-built-up categories between the reference map of 2010 and the map of 2010 fitted with the model. The weighted average shows that 84% were modelled correctly. The null correct percentage value shows the proportional similarity between urban growth reference map of 2010 and the simulated urban growth maps in 2010.

In summary the exclusion layer was varied so as to arrive at the three scenarios. These scenarios in turn can be viewed as scenarios which can show the regional and urban planners the consequences of different planning actions. The model parameters observed in Table 13 show slight similarities in the values between scenarios two and three but none for scenario one.

Scenario one illustrates unmanaged growth as shown in Figure 5-7 and Figure 5-8. In scenario two and three we have managed growth with different values of the exclusion layer as shown in respectively. Scenario two has an exclusion layer of 70 % where government buildings and forest cover were included as shown in Figure 5-9 and Figure 5-10. Scenario three has an exclusion layer of 90 % where government buildings and forest, agricultural areas, and urban green were included as shown in Figure 5-11 and Figure 5-12.

The influence of slope in urban growth was at a minimum in scenario two and three with values of 6 and 1 respectively whereas it was high in scenario one with a value of 50. Thus we can observe growth in steep slopes where we have forests in scenarios one. The influence of road parameter in urban growth was highest in scenario at a value of 100, moderate in scenario three with a value of 60, and lowest in scenario two with a value of 10.

The highest weighted value was obtained in scenario two at 0.8448 and scenario three at 0.8442. However, scenario three presents maximum protection of resources which will in turn ensure sustainable development is achieved and a plausible development agenda. Thus this implies that scenario three gives the best model parameters for the urban growth model of Nakuru.

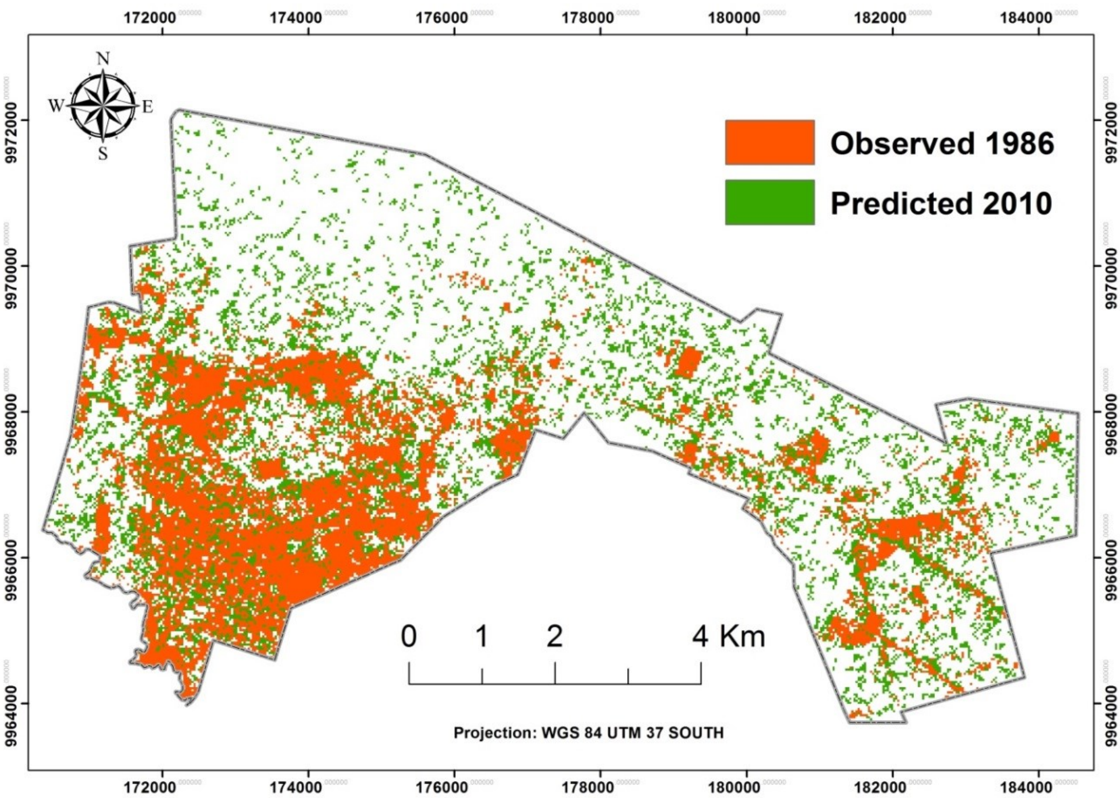

Figure 5-7: Urban growth simulation in 2010 in Nakuru (scenario one)

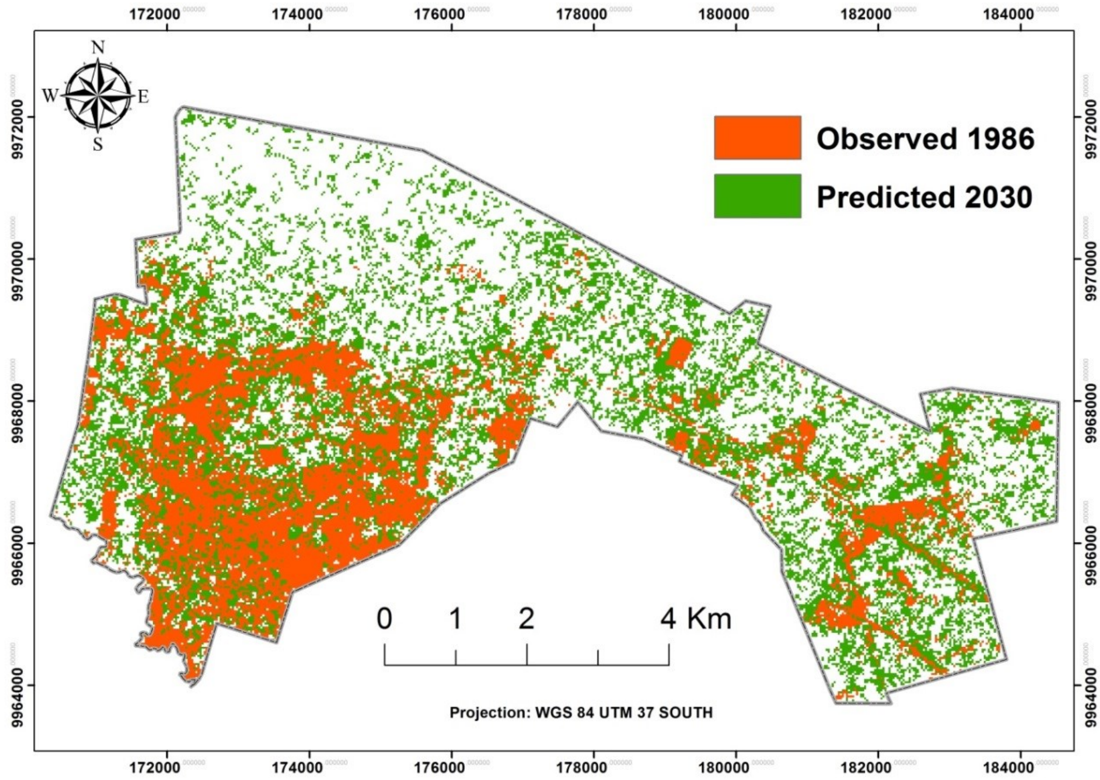

Figure 5-8: Urban growth simulation in 2030 in Nakuru (scenario one)

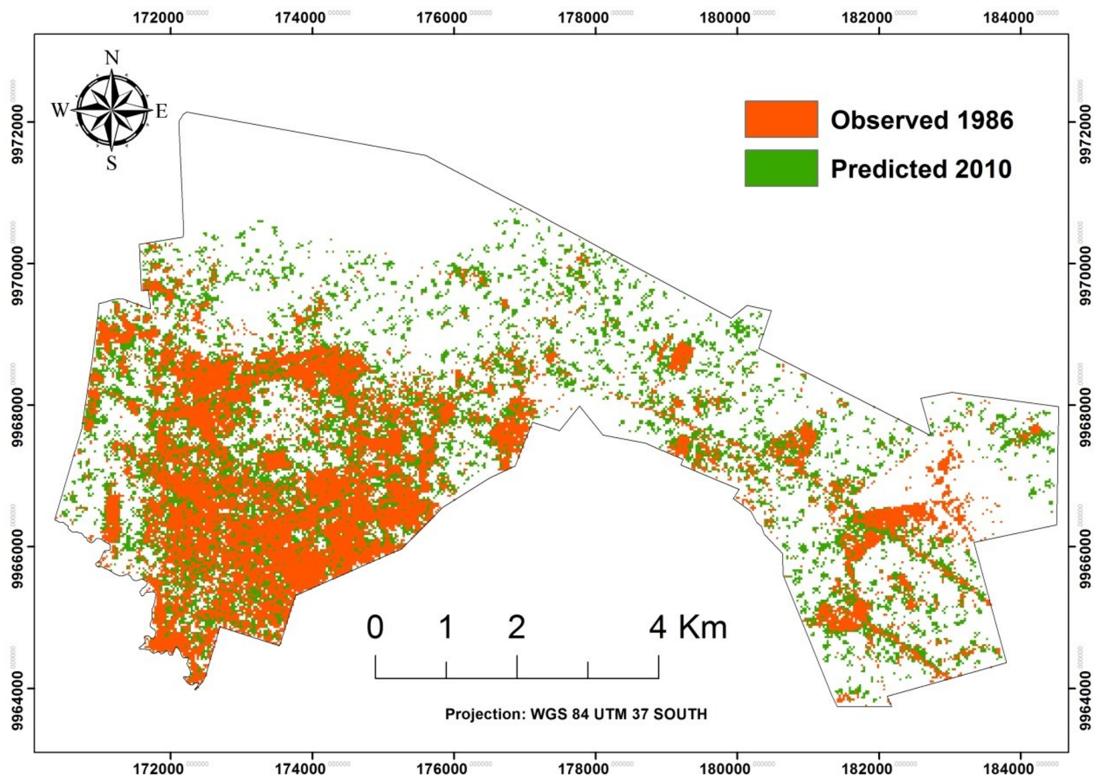

Figure 5-9: Urban growth simulation in 2010 in Nakuru (scenario two)

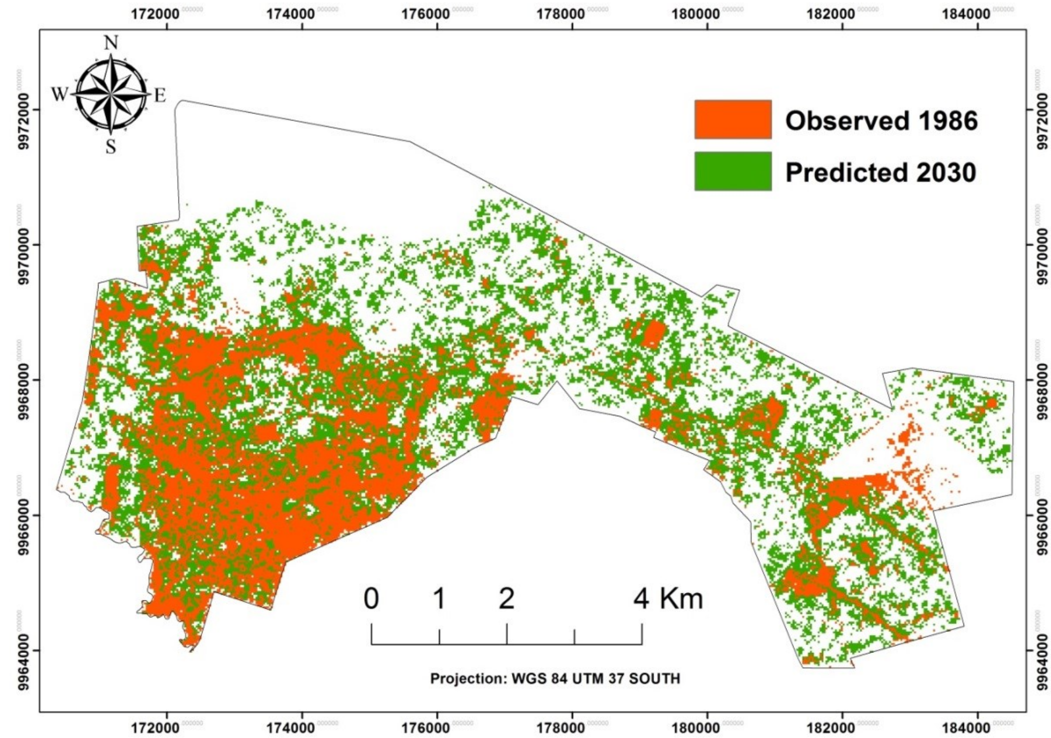

Figure 5-10: Urban growth simulation in 2030 in Nakuru (scenario two)

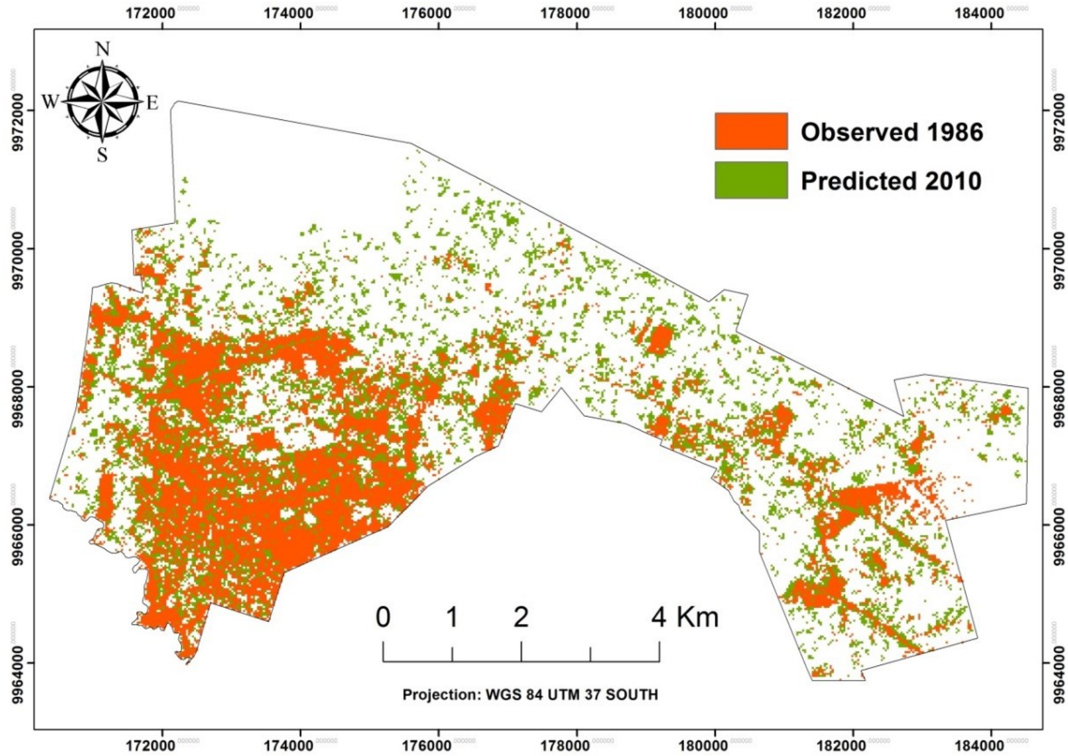

Figure 5-11: Urban growth simulation in 2010 in Nakuru (scenario three)

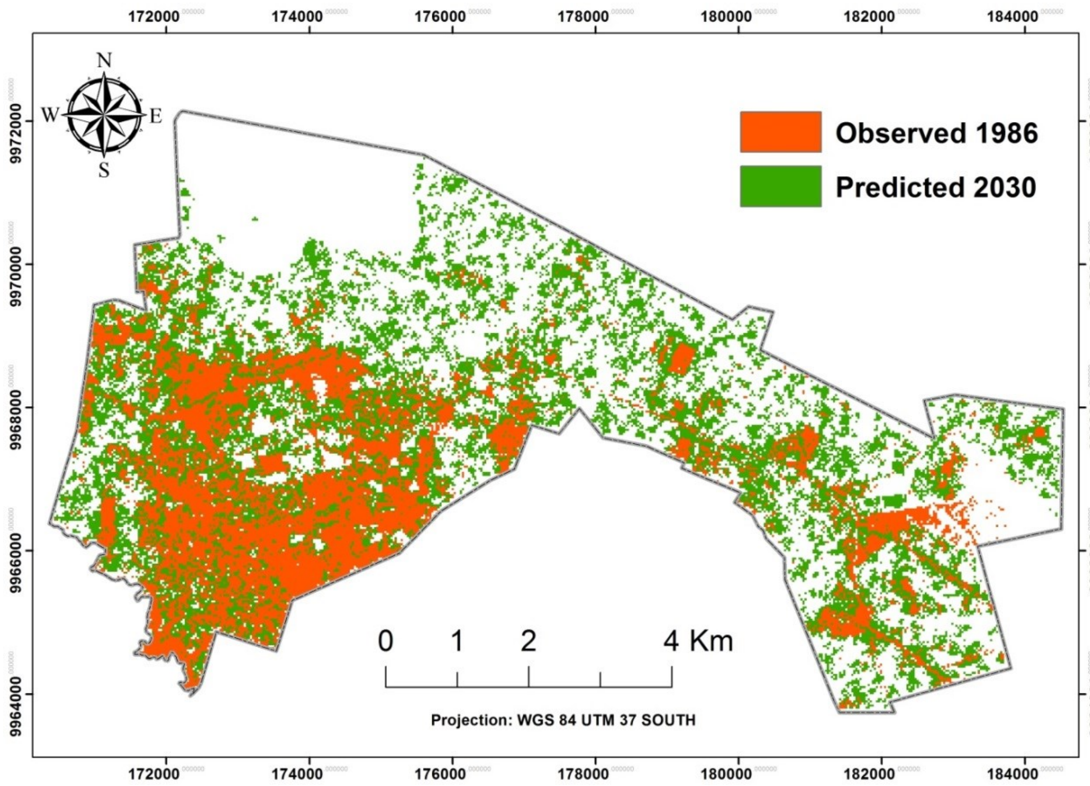

Figure 5-12: Urban growth simulation in 2030 in Nakuru (scenario three)

An evaluation of the three scenarios was conducted as shown in Table 14. The simulated urban growth values of scenario one, two and three were 22.15 km^2, 21.21 km^2, and 21.33 km^2 in 2010 and 29.65 km^2, 28.41 km^2, and 29.42 km^2 in 2030 respectively. The values of 22.15 km^2 in scenario one in 2010 and 21.33 km^2 in scenario three in 2010 were close to the actual urban growth value of 22.3 km^2 obtained from land-use classification.

Table 14: Model evaluation for Nakuru

Year	**2010**			**2030**		
Scenario	1	2	3	1	2	3
Actual Urban (km^2)	22.3	22.3	22.3			
Simulated Urban (km^2)	22.15	21.21	21.33	29.65	28.41	29.42
Error (%)	-0.67	-4.89	-4.35			

In order for an urban growth model to be convincing to land managers and policy makers, more work has to be done other than calibration. Simulation of urban growth ought to be done after successful validation of the model with an independent dataset. Therefore, we carried out the prediction of land-use in 2030, starting with the year 2010 for all scenarios using land-use 2010 as reference data during the UGM calibration. The expansion of urban land-use (built-up areas) was modelled with the UGM with the same model parameters obtained in the 1986-2010 calibration as shown in Table 13.

Consequently the simulated urban land-use estimates achieved using the calibrated UGM for Nakuru in scenario one indicates that urban land-use increased from 22.15 km^2 in 2010 to 29.65 km^2 in 2030. In scenario two, urban land-use increased from 21.21 km^2 in 2010 to 28.41 km^2 in 2030. In scenario three, urban land-use increased from 21.33 km^2 in 2010 to 29.42 km^2 in 2030. Adopting scenario three to advice policy makers on simulation of urban growth, the simulated urban growth in the year 2030 will be approximately 29.42 km^2.

We conducted two map comparisons in Erdas imagine 2011 model maker for scenario three. According to Pontius Jr (2008) there are three possible two-map comparisons namely observed change, prediction change and prediction error. Observed change compares the reference map of time 1 and the reference map of time bearing in mind the dynamics of the landscape. Prediction change compares between the reference map of time 1 and the prediction map of time 2 and thus revealing the behaviour of the model. Prediction error compares between the reference map of time 2 and the prediction map of time 2 and thus ascertains the accuracy of the prediction. In our case time 1 referred to as the year 1986 and time 2 as the year 2010.

The observed change in urban land-use between 1986 and 2010 is illustrated on Figure 5-13 and Figure 5-14. Here we have observed built gain of 13.41 km^2, observed built persistence of 8.77 km^2, observed non-built persistence of 31.98 $Km^2$and observed built loss of 3.59 km^2 obtained from the observed map of the year 2010. Observed built gain refers to areas which we converted into urban land-use in the year 2010. Observed built persistence refers to areas that remained as urban land-use in the year 2010. Observed non-built persistence refers to areas which remained as non-built in the year 2010. Observed built loss refers to areas which were converted to non-built in the year 2010.

The predicted change in urban land-use between 1986 and 2010 is illustrated on Figure 5-15 and Figure 5-16. Here we have predicted built gain of 8.94 km^2, predicted built persistence of 12.39 km^2, and predicted non-built persistence of 36.58 km^2 obtained from the predicted map of the year 2010. Predicted built gain refers to areas which were converted into urban land-use in year 2010. Predicted built persistence refers to areas that remained as urban land-use in year 2010. Predicted non-built persistence refers to areas which remained as non-built in the year 2010.

The predicted error in urban land-use between 1986 and 2010 is illustrated on Figure 5-17 and Figure 5-18. Here we can see four categories: non-built observed and built predicted of 8.28 km^2; built observed and built predicted of 13.02 km^2; non-built persistence and non-built predicted of 27.41 km^2; and built observed and non-built predicted of 9.20 km^2 obtained using the observed map of the year 2010 and the predicted map of the year 2010. A question here arises on whether the model predicts the year 2010 accurately. The total disagreement between the maps is discussed in Pontius Jr (2004). The two most important components are quantity disagreement (i.e., net change) and location disagreement (i.e., swap change), which sum to the total disagreement (Pontius Jr., 2008). Quantity disagreement can be obtained using spatial analyst tools in ArcGIS so as to get the size in kilometres squared for each category as seen in Table 14. In our case we have simultaneous built gain of 13.41 km^2 and built loss of 3.59 km^2 as most of the observed change is quantity disagreement and thus our gain of built is larger than the loss of built by 9.82 km^2. Location disagreement can be resolved by rearranging the pixels spatially within one map so that its agreement with the other map is as large as possible, Pontius Jr (2008). Thus, our UGM for Nakuru predicts the year 2010 accurately since our gain of built is larger than the loss of built.

The regionalised cellular automata, UGM, performed well using urban land-use 2010 as reference data. Since the base year period 1986 to 2010 was a difference of 24 years this perhaps gives a better simulation later into year 2030 which is a 20 year period from the year 2010. Scenario three was selected as the best approach to ensure sustainable development is achieved. Thus the likelihood of new settlements or built-up areas in Nakuru CBD was obtained at a weighted value of 0.8442. Thus, new areas are likely to be developed for residential and commercial uses, which lie in proximity to roads. Such growth could be as a result of high rural urban migration in Nakuru as new people move into Nakuru in search for employment, social amenities and business opportunities.

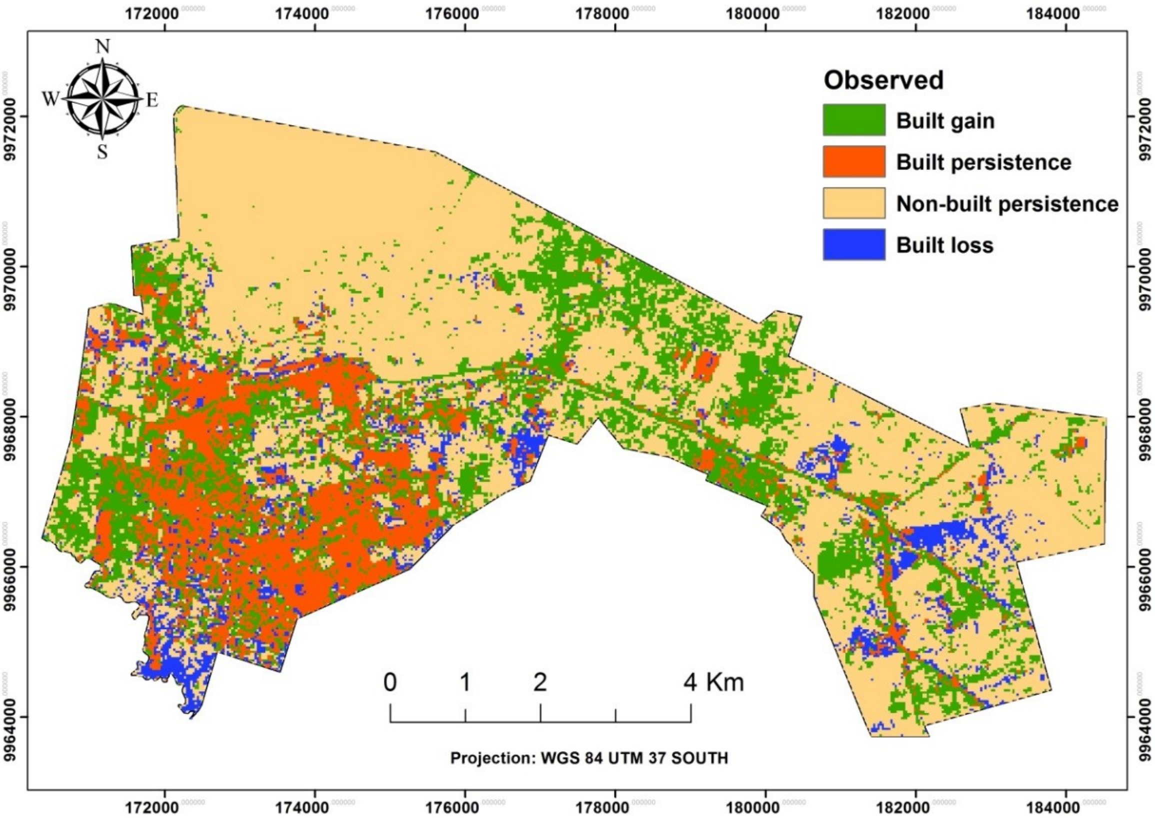

Figure 5-13: Observed change 1986 – 2010 in Nakuru

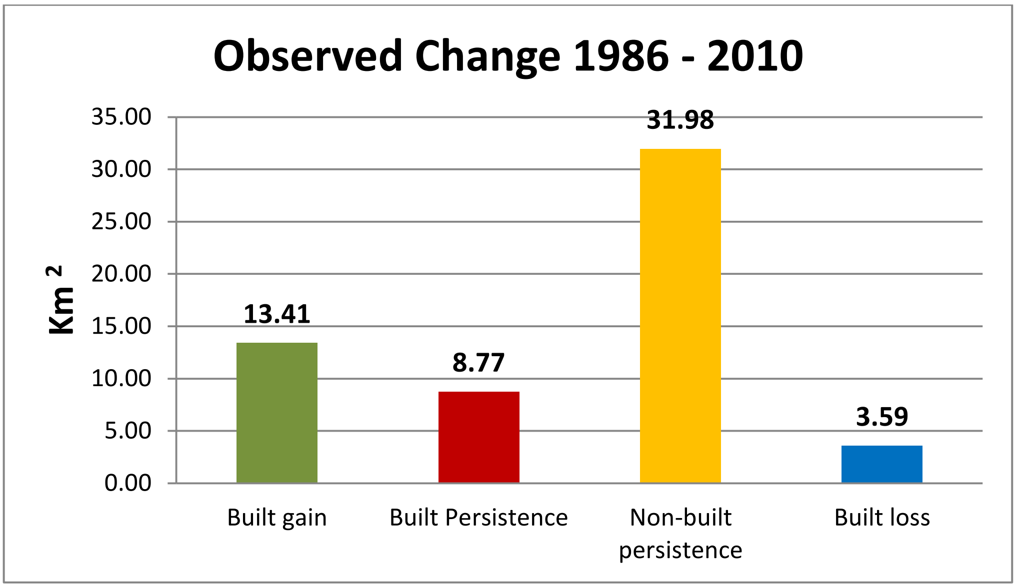

Figure 5-14: Estimates of observed change 1986 – 2010 in Nakuru

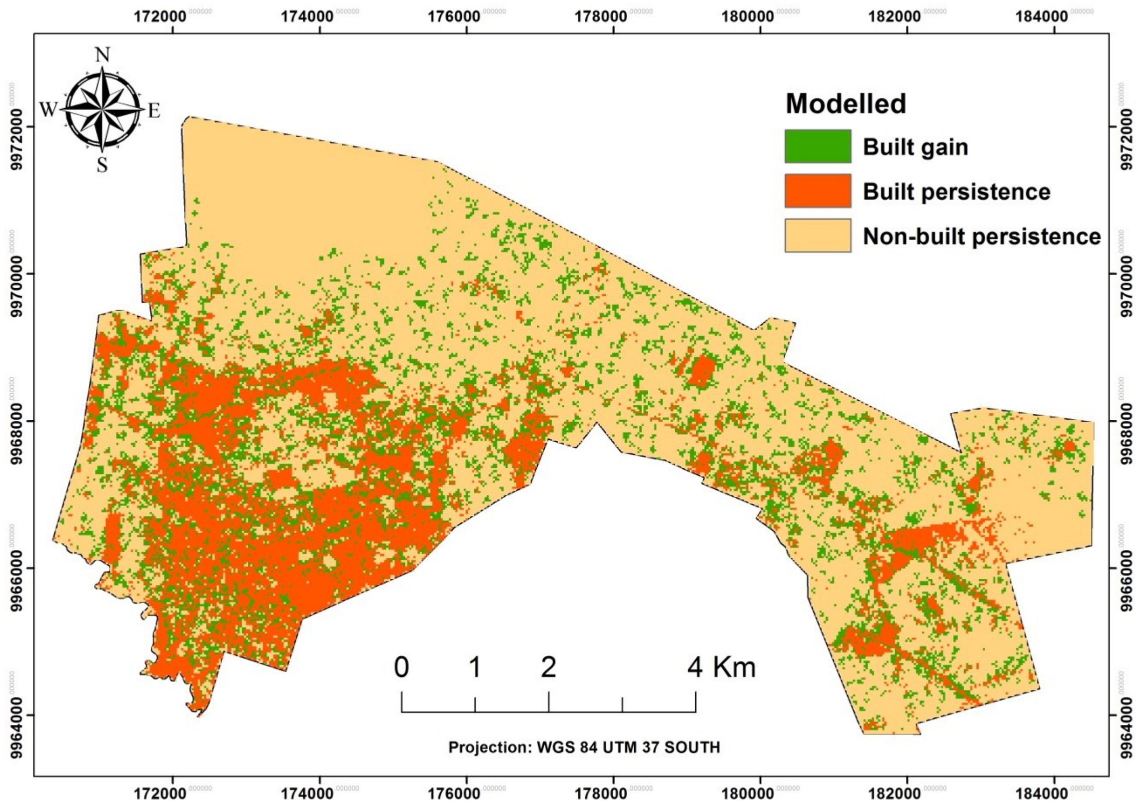

Figure 5-15: Predicted change 1986 – 2010 in Nakuru

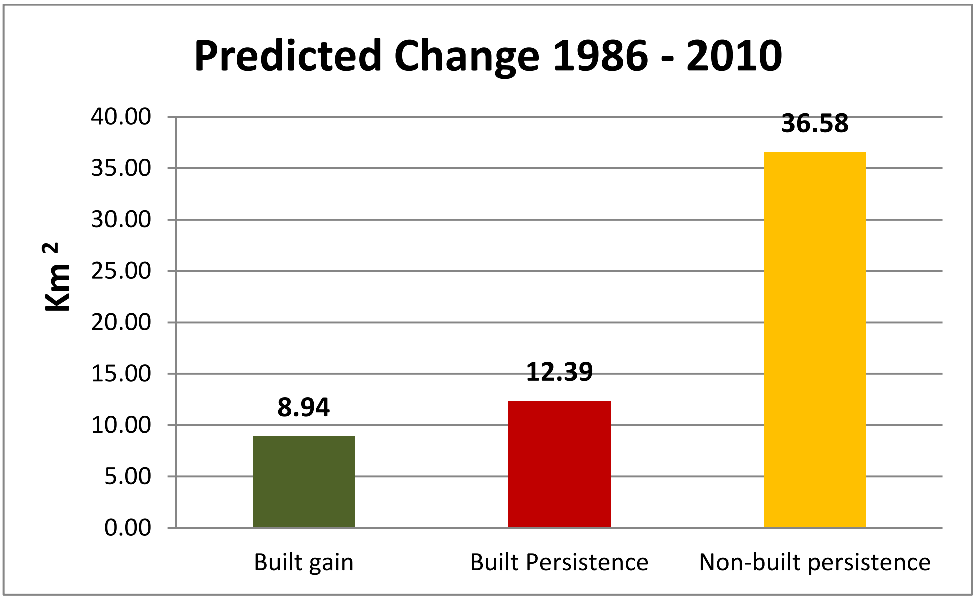

Figure 5-16: Estimates of predicted change 1986 – 2010 in Nakuru

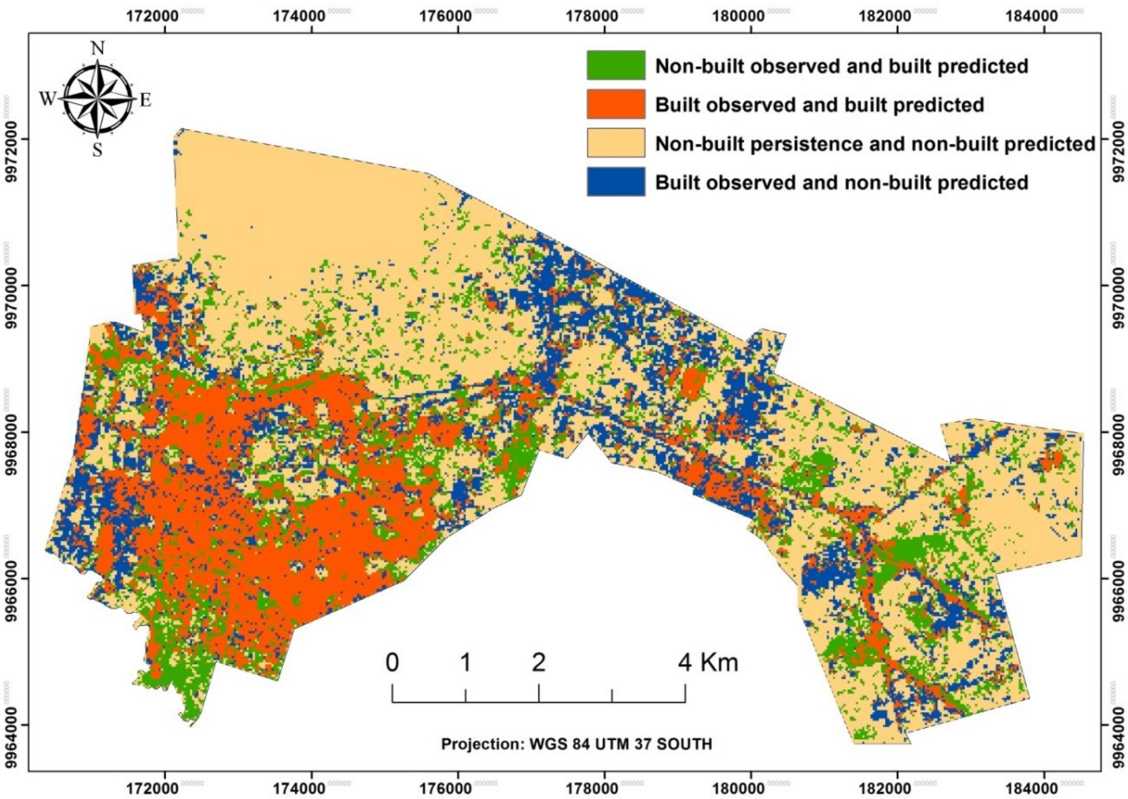

Figure 5-17: Predicted error 1986 – 2010 in Nakuru

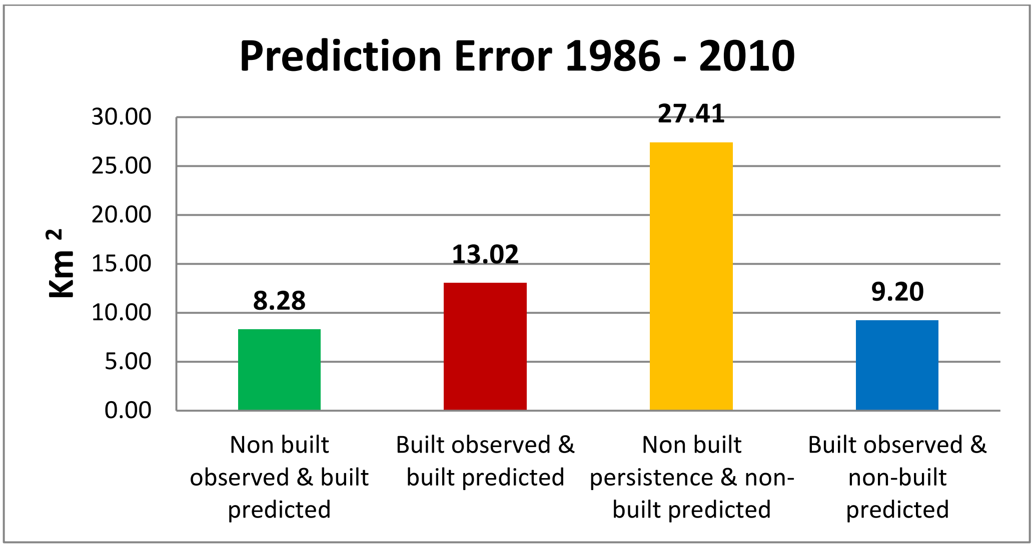

Figure 5-18: Estimates of predicted error 1986 – 2010 in Nakuru

Using scenario three we generated the urbanisation probability map for Nakuru as shown in Figure 5-19 using 100 Monte Carlo simulations (see appendix 9.2.4). High urbanisation within the range of 85 – 100 % is located near Nakuru CBD and is composed of residential areas. High urbanisation tends to occur along roads such as along the major roads and local roads leading to house dwellings. High urbanisation of 85 – 100 % tends to occur in fairly low altitude as shown in Figure 5-20. Relative high urbanisation of 60 – 85 % occurs adjacent to high urbanisation areas followed by 38 – 60 % urbanisation areas. Comparatively low urbanisation of 15 – 38 % comprises of industrial zones, education institutes and urban agriculture areas.

Low urbanisation in the range of 0 – 15 % is located in the forest area and military base to the east side of Nakuru, and these areas were excluded from urban growth modelling. Other areas excluded from modelling included the state house and reserved land by the government.

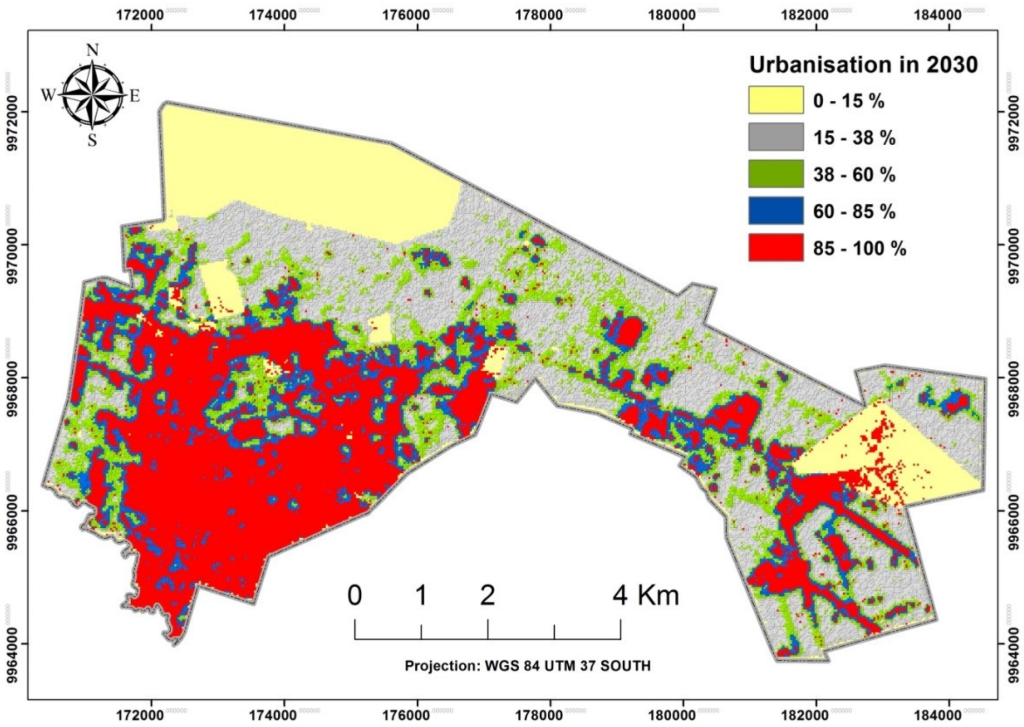

Figure 5-19: Urbanisation probability map for Nakuru

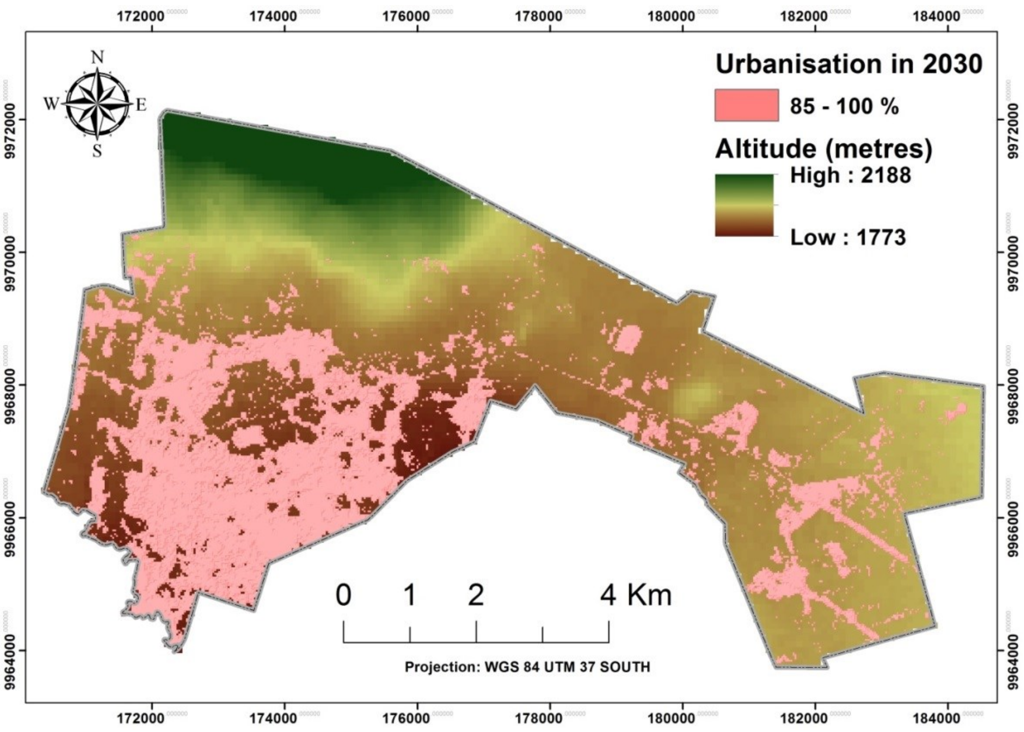

Figure 5-20: Urbanisation probability map for Nakuru showing high urbanisation areas

The modelled urban growth for Nakuru between 2010 and 2030 will be 32%. The value was obtained as follows:

$$Urban\ growth\ = \frac{Simulated\ Urban\ \ in\ 2030 - Urban\ \ in\ 2010}{Urban\ \ in\ 2010}\%$$

$$Urban\ growth\ = \frac{29.42 - 22.30}{22.30}\%$$

$$Urban\ growth\ in\ Nakuru\ =\ 32\ \%$$

5.8 Scenarios of urban process in Nairobi

5.8.1 Data

The model process utilised information from land-use classification in the years 1986, 2000 and 2010 as well as other biophysical datasets as shown in Table 15. A Digital Elevation Model was obtained from SRTM and used to yield slope information for our model. Road network data for Nairobi was obtained from Nairobi City Council and comprised all the roads within the city. An exclusion layer was obtained from Survey of Kenya and comprised of government property buildings and other land marked as reserved.

Inputs for UGM included land-use datasets (1986 and 2010), slope data, exclusion data and road data for Nairobi. Urban land-use data for 1986 (Figure 5-21) was used as the base data for modelling while urban land-use data for 2010 (Figure 5-22) were used as the reference grid. The land-use maps used satisfied the minimum accuracy requirement of 85 % stipulated in Anderson classification scheme (Anderson, Hardy, Roach, & Witmer, 1976). The land-use data has been reclassified to a binary map showing only urban and non-urban land-use. Slope data was derived from Digital Elevation Model of Nairobi at 30 metres spatial resolution. Exclusion data included areas within Nairobi where development is restricted e.g. government buildings and property. Road data included all road networks in Nairobi and the major roads where given a higher weight for the purposing of modelling. Most development was likely to occur along the major roads in Nairobi.

Table 15: Data for urban growth modelling of Nairobi

Data layer	Source	Description	Resolution
Urban extent	Land-use map	Urban extent extracted from land-use map for 1986, 2000 and 2010	30 metres
Slope	DEM	Derived from Digital Elevation Model	30 metres
Exclusion	Topographic map	Vector coverage of protected areas	
Road	Road network	Vector coverage of classified roads	

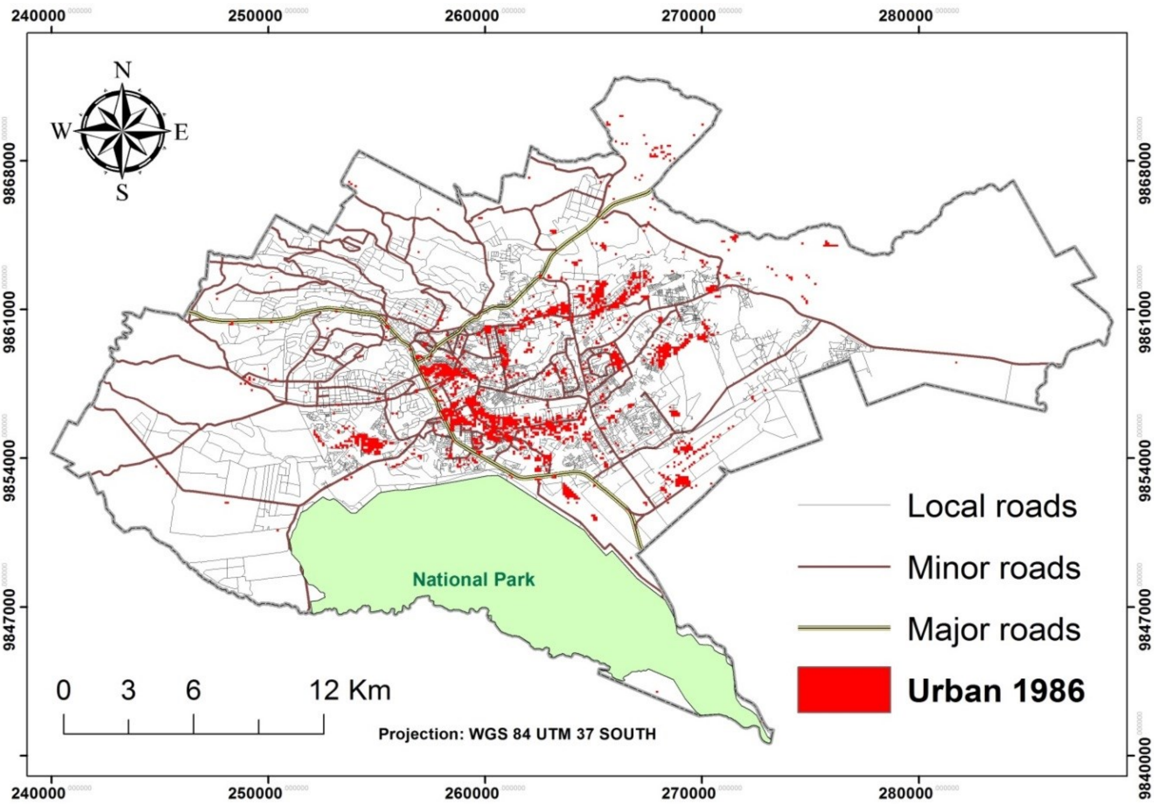

Figure 5-21: Urban extent in Nairobi (1986)

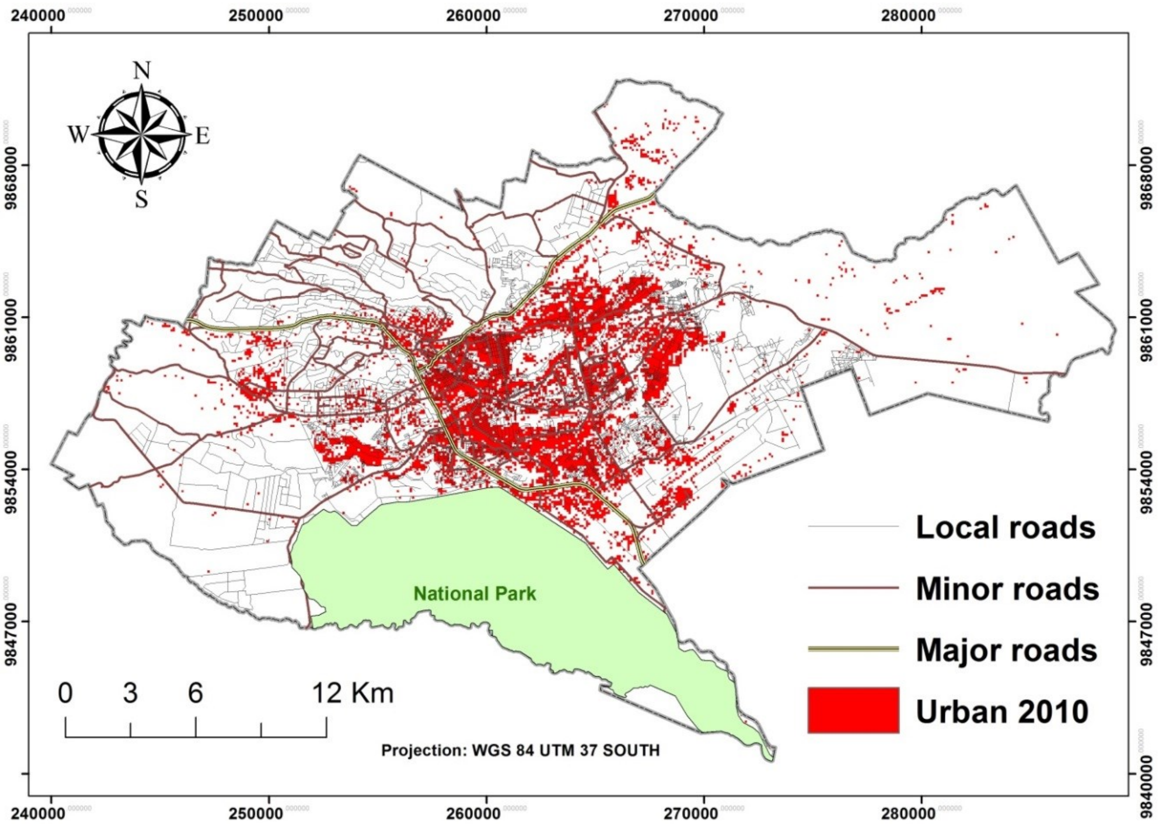

Figure 5-22: Urban extent in Nairobi (2010)

Model calibration of UGM involved running the model using default parameters of slope, breed, dispersion, road and spread. The default parameter values are 1, 50 and 100. Model calibration was done iteratively in four sequences from coarse to fine calibration as the parameters were varied. The MRV method was used to achieve the optimal parameterisation for the UGM during the calibration phase as well as for the validation of the model results (Pontius Jr, Huffaker, & Denman, 2004).

5.8.2 Modelling of urban growth in Nairobi

First scenario depicts an unmanaged growth with no restriction on environmental areas, such as forest, agriculture and wetland. The second scenario assumes a managed growth with moderate protection (70 %) on national park, forest, military base and airport. The last scenario simulates a managed growth with maximum protection (100 %) on forest, national parks, parks, golf courses, dams, military base and airport.

Modelling of Nairobi utilised urban extents extracted from land-use maps for 1986 and 2010 as inputs. Other layers used included slope, areas excluded from development and road network. Calibration was done using land-use 2010 as a reference grid. Best model parameter for UGM was evaluated based on the weighted average calculated with the MRV using land-use 2010 as reference grid. The road layer included three weight values of 100, 50 and 25 (Silva, 2005). A weight value of 100 was assigned to class A roads (International trunk roads), 50 was assigned to class B and C roads (National Trunk Roads), and 25 was assigned to local streets (Minor roads). The road classification in Kenya is explained in Wasike (2001). The exclusion layer included forest cover and urban green areas within the research area. Urban green areas refer to natural vegetation and gardens both public and private within a city.

Table 16: Best model parameters obtained for Nairobi

Scenario	Model parameters					Weighted value
	Slope	Spread	Dispersion	Breed	Road	
1	50	25	1	50	75	0.9449
2	52	25	1	50	25	0.9470
3	52	27	1	52	2	0.9477

Table 16 shows the final model coefficients obtained after successful calibration of UGM for the three scenarios. We can see the values as follows: slope at 50, spread at 25, dispersion at 1, breed at 50, road at 75, and a weighted value of 0.9449 for scenario one; slope at 52, spread at 25, dispersion at 1, breed at 50, road at 25, and a weighted value of 0.9470 for scenario two; and slope at 52, spread at 27, dispersion at 1, breed at 52, road at 2, and a weighted value of 0.9477 for scenario three. We adopted scenario three since it will ensure sustainable development is met in the future.

An evaluation of the three scenarios was conducted as shown in Table 17. The simulated urban growth values of scenario one, two and three were 82.87 km^2, 76.61 km^2, and 73.14 km^2 in 2010 and 141.72 km^2, 127.96 km^2, and 118.35 km^2 in 2030 respectively. The values of 73.14 km^2 in scenario three in 2010 was close to the actual urban growth value of 79.38 km^2 obtained from land-use classification. The urban growth simulation maps for the three scenarios are illustrated in Figure 5-23, Figure 5-24, Figure 5-25, Figure 5-26, Figure 5-27 and Figure 5-28.

Table 17: Model evaluation for Nairobi

Year	2010			2030		
Scenario	1	2	3	1	2	3
Actual Urban (km^2)	79.38	79.38	79.38			
Simulated Urban (km^2)	82.87	76.61	73.14	141.72	127.96	118.35
Error (%)	4.40	-3.49	-7.86			

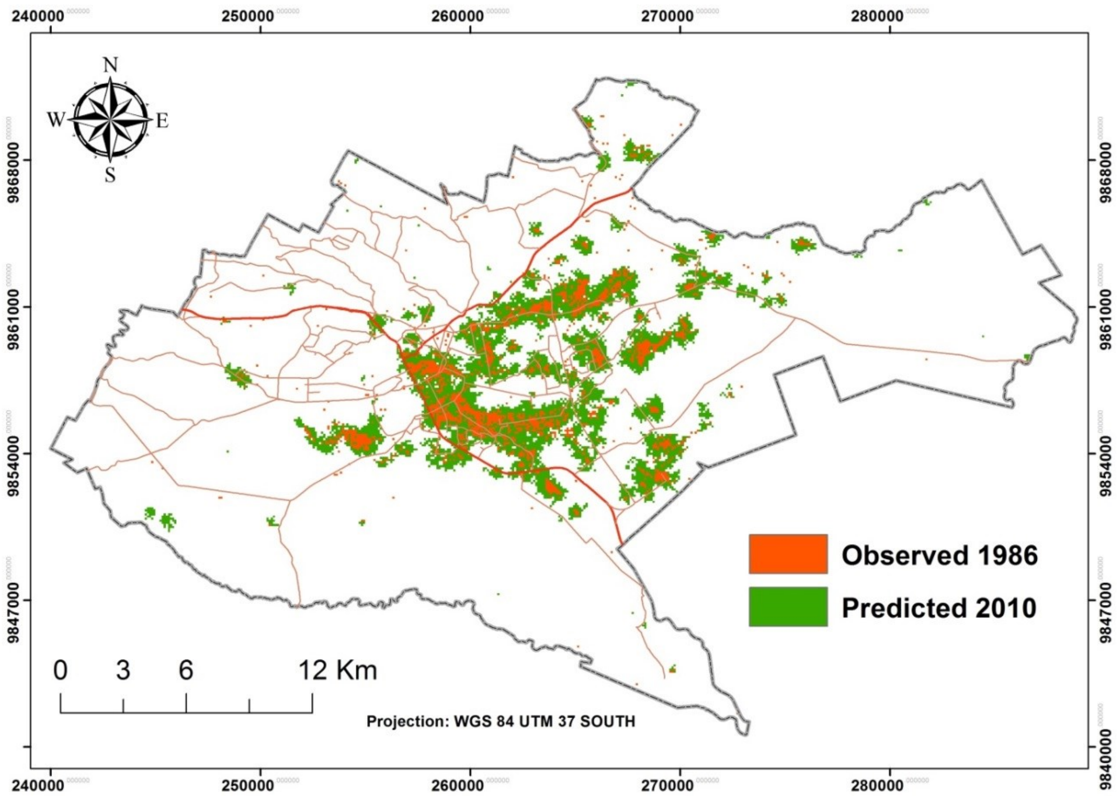

Figure 5-23: Urban growth simulation in Nairobi in scenario one (2010)

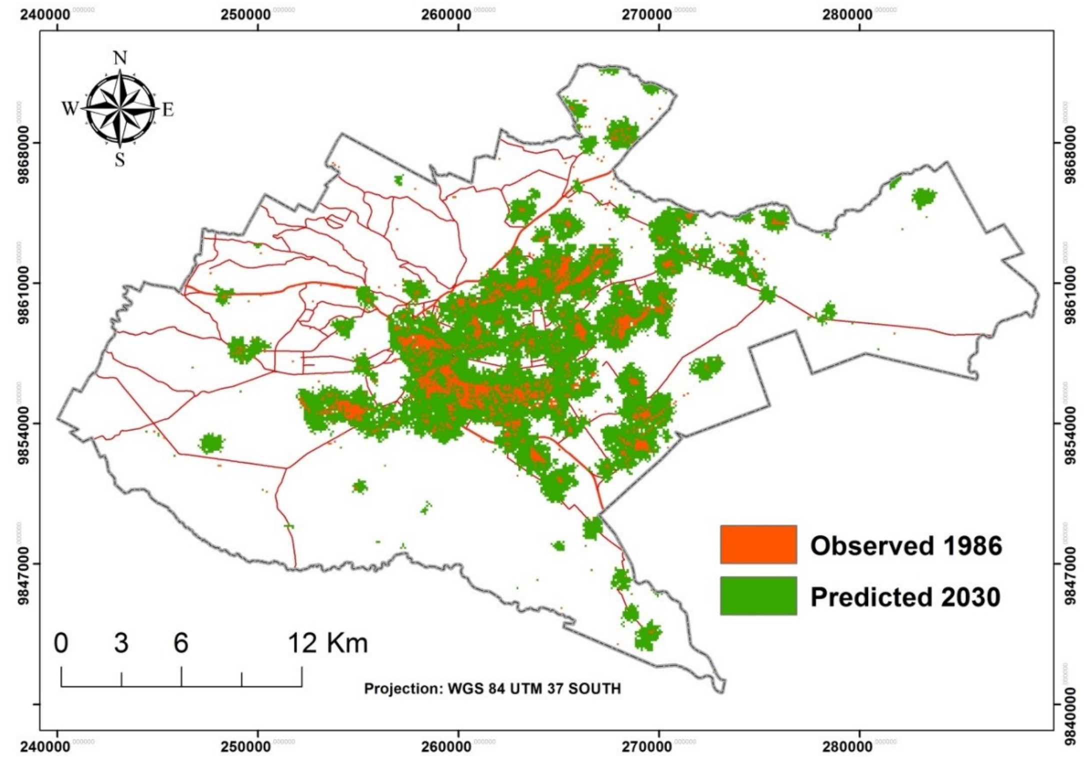

Figure 5-24: Urban growth simulation in Nairobi in scenario one (2030)

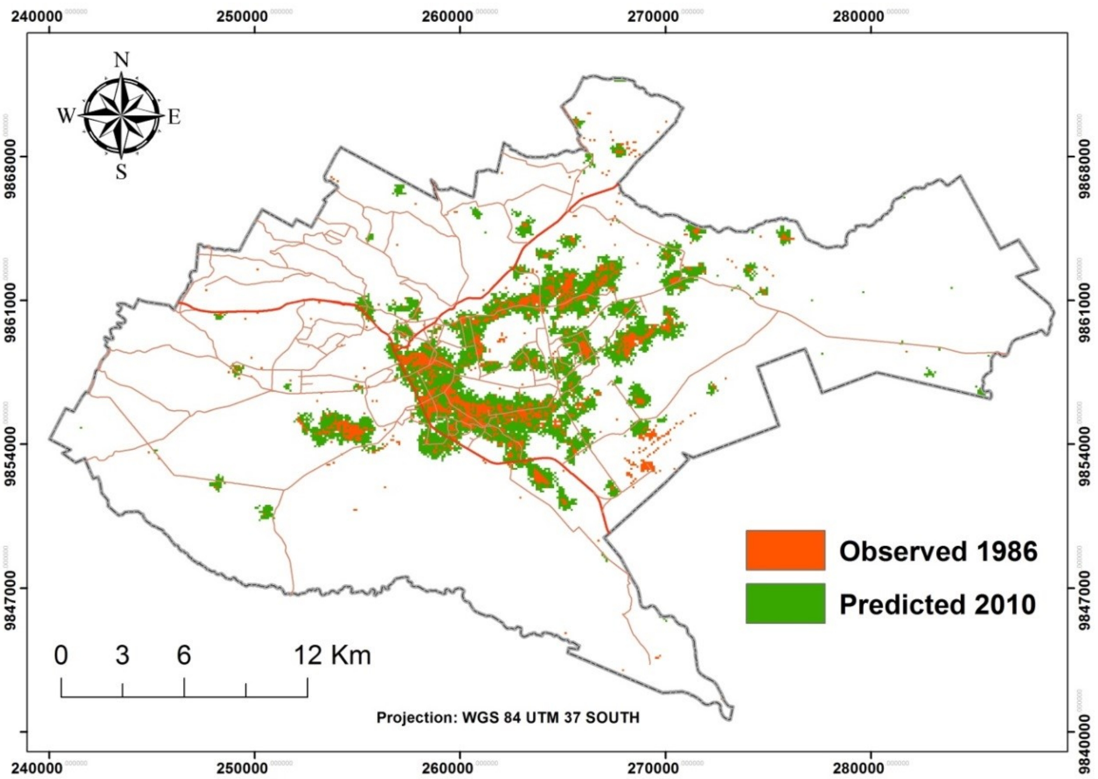

Figure 5-25: Urban growth simulation in Nairobi in scenario two (2010)

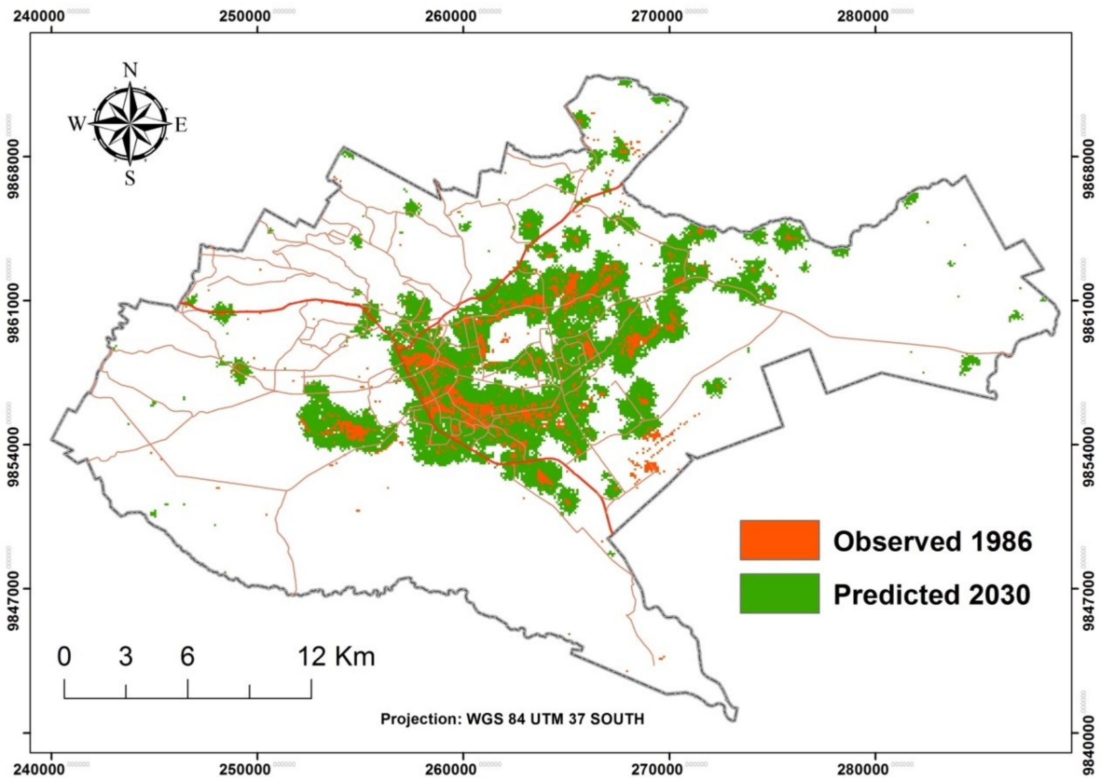

Figure 5-26: Urban growth simulation in Nairobi in scenario two (2030)

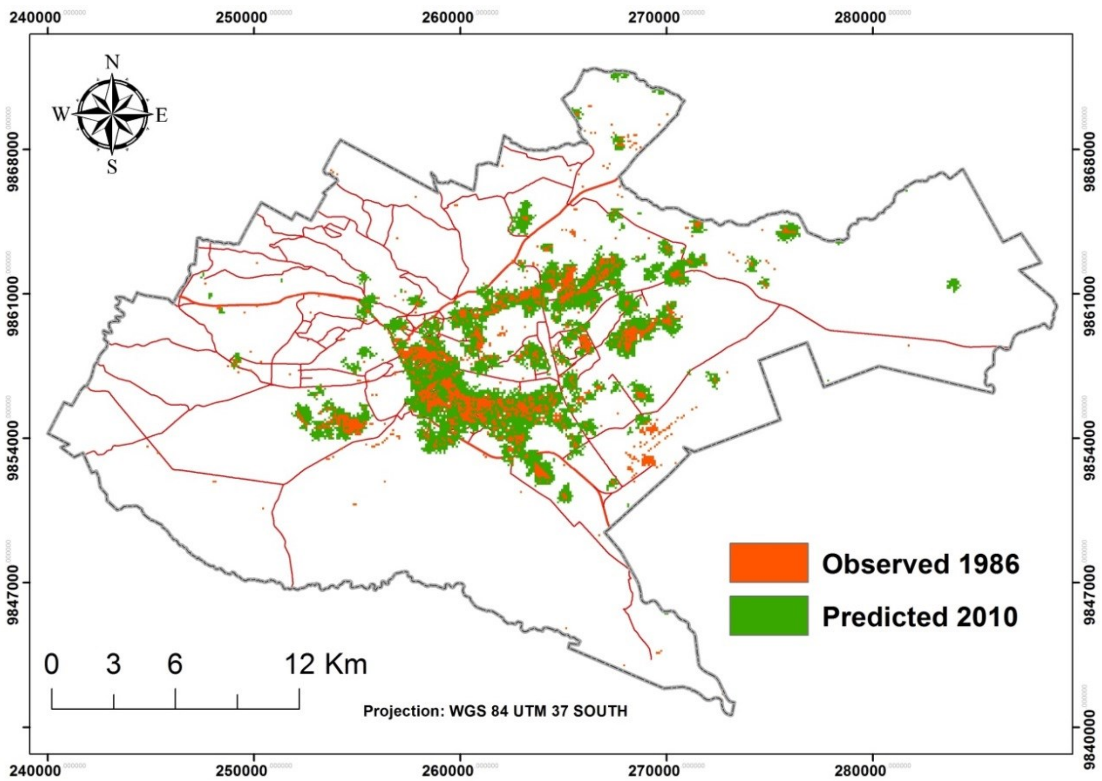

Figure 5-27: Urban growth simulation in Nairobi in scenario three (2010)

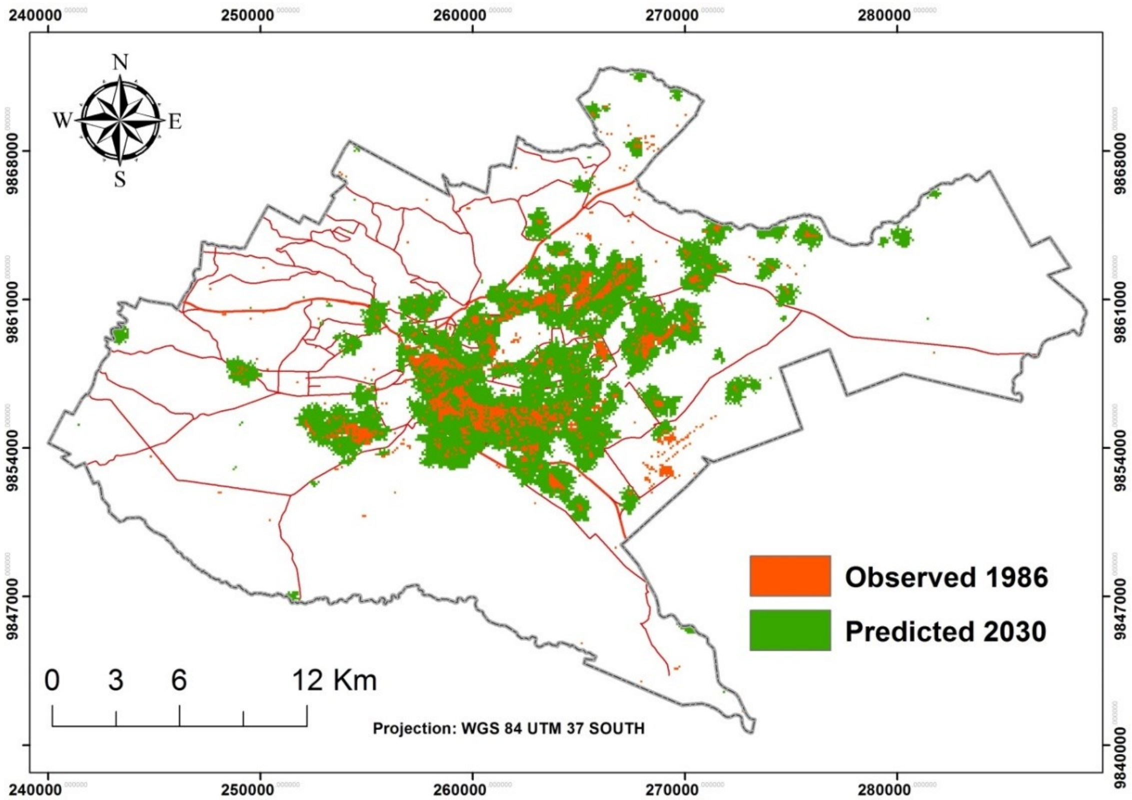

Figure 5-28: Urban growth simulation in Nairobi in scenario three (2030)

We conducted two map comparisons in Erdas imagine 2011 model maker for scenario three for the city of Nairobi. According to Pontius Jr (2008) there are three possible two-map comparisons namely observed change, prediction change and prediction error as described above in urban growth modelling of Nairobi (See section 5.7.2).

The observed change in urban land-use between 1986 and 2010 is illustrated on Figure 5-29 and Figure 5-30. Here we have observed built gain of 65.25 km^2, observed built persistence 17.80 km^2, observed non-built persistence of 607.19 km^2 and observed built loss of 3.41 km^2 obtained from the observed map of the year 2010.

The predicted change in urban land-use between 1986 and 2010 is illustrated on Figure 5-31 and Figure 5-32. Here we have predicted built persistence of 73.79 km^2 and predicted non-built persistence of 620.51 km^2 obtained from the predicted map of the year 2010.

The predicted error in urban land-use between 1986 and 2010 is illustrated on Figure 5-33 and Figure 5-34. Here we have: non-built observed and built predicted of 57.95 km^2; and built observed and built predicted of 40.99 km^2 obtained using the observed map of the year 2010 and the predicted map of the year 2010. Our UGM for Nairobi predicts the year 2010 accurately since our gain of built is larger than the loss of built as seen in Figure 5-30.

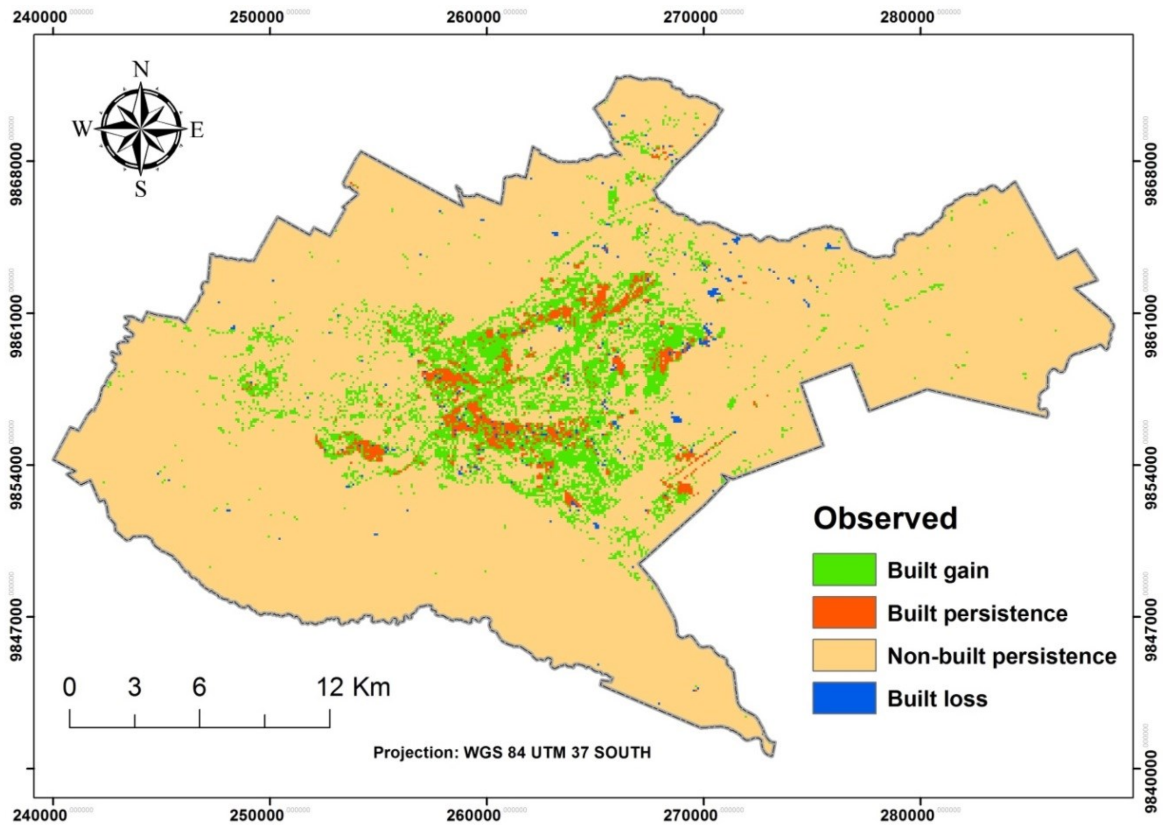

Figure 5-29: Observed change 1986 – 2010 in Nairobi

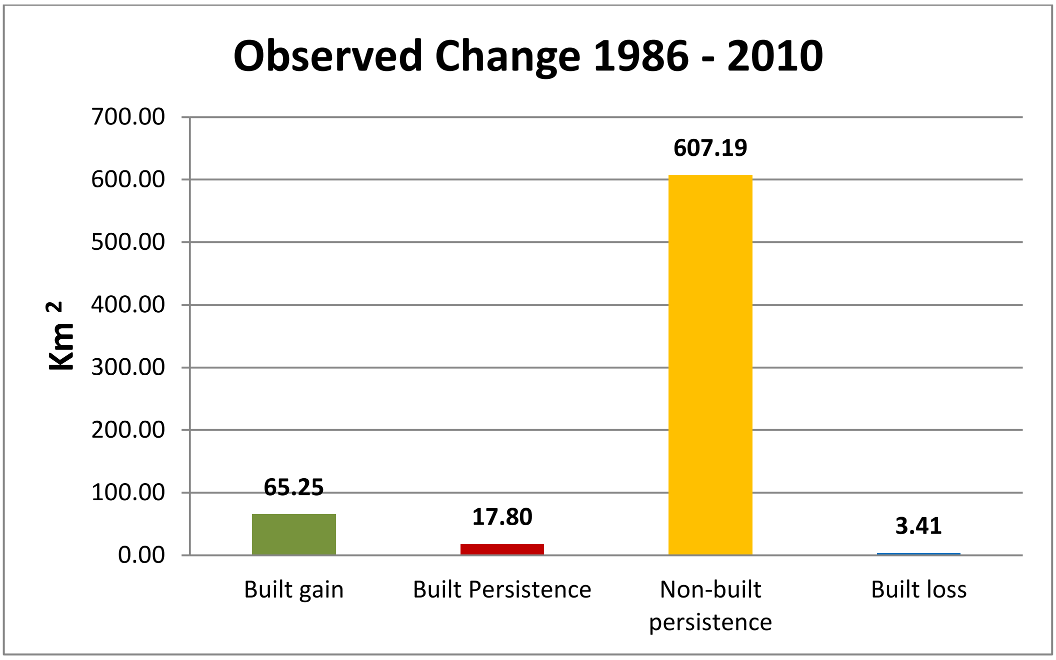

Figure 5-30: Estimates of observed change 1986 – 2010 in Nairobi

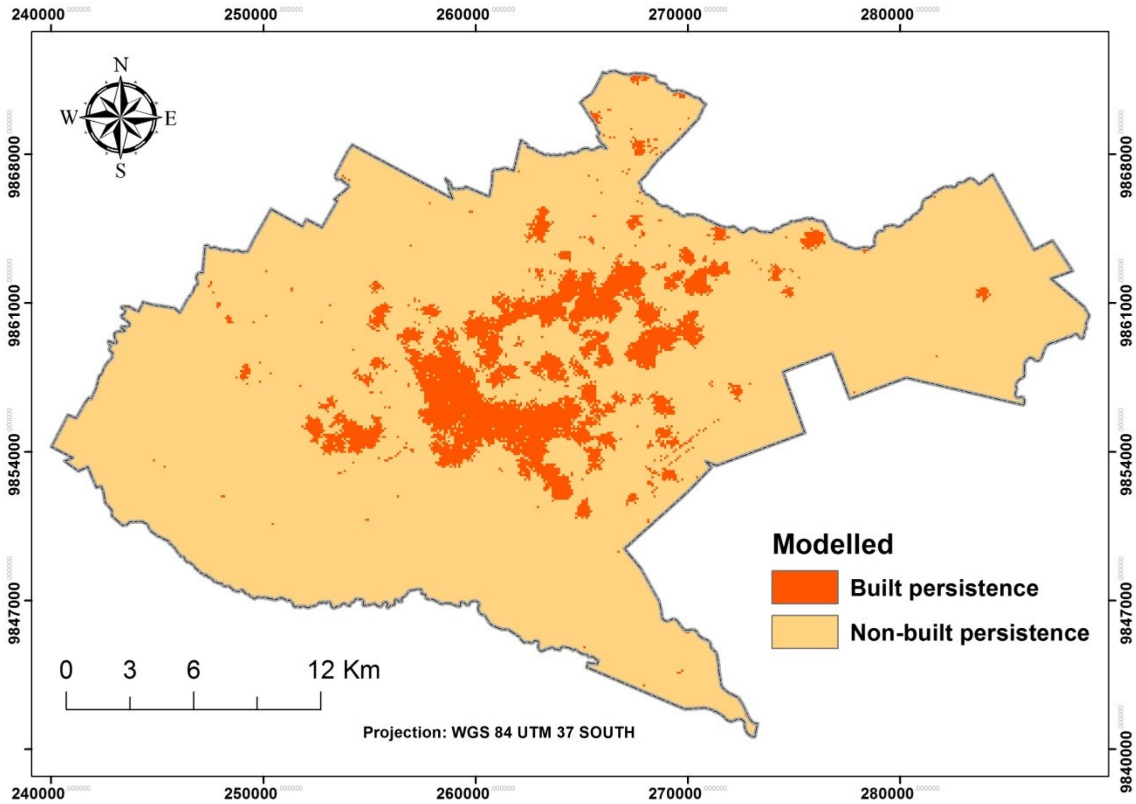

Figure 5-31: Predicted change 1986 – 2010 in Nairobi

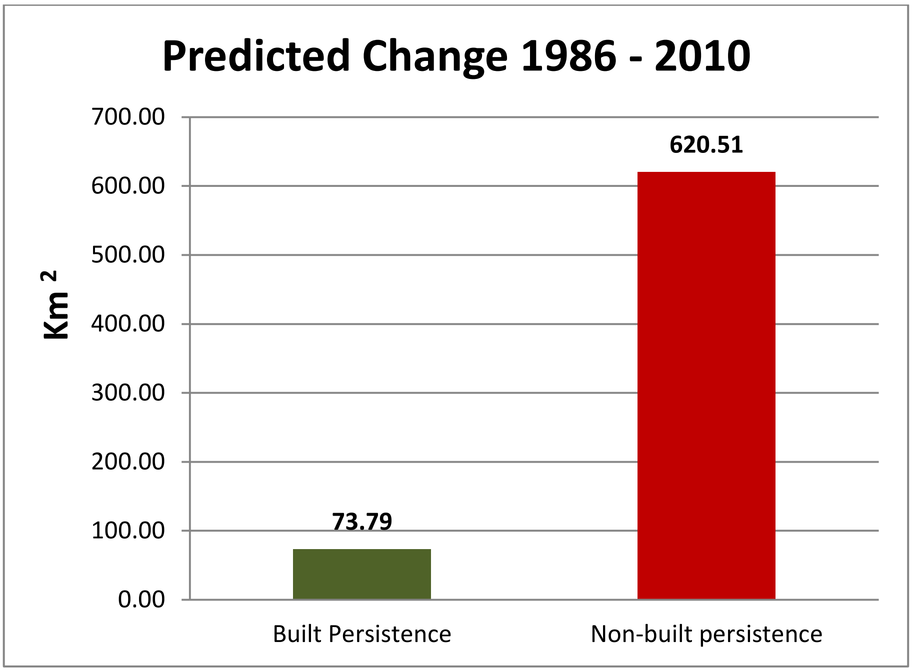

Figure 5-32: Estimates of predicted change 1986 – 2010 in Nairobi

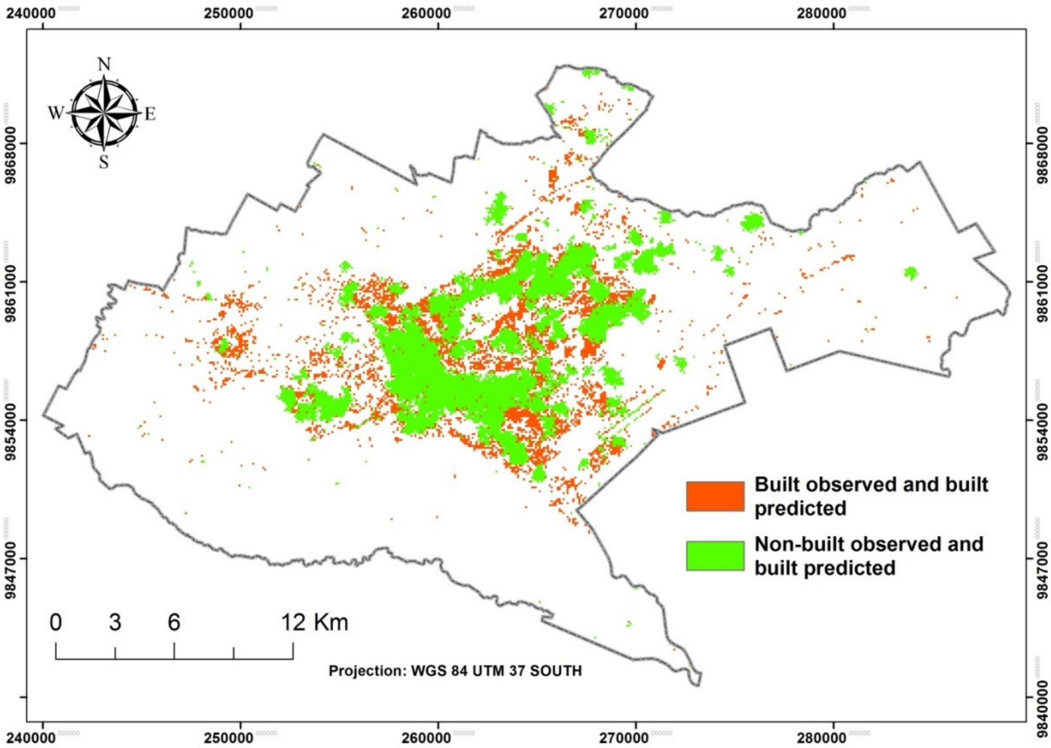

Figure 5-33: Predicted error 1986 – 2010 in Nairobi

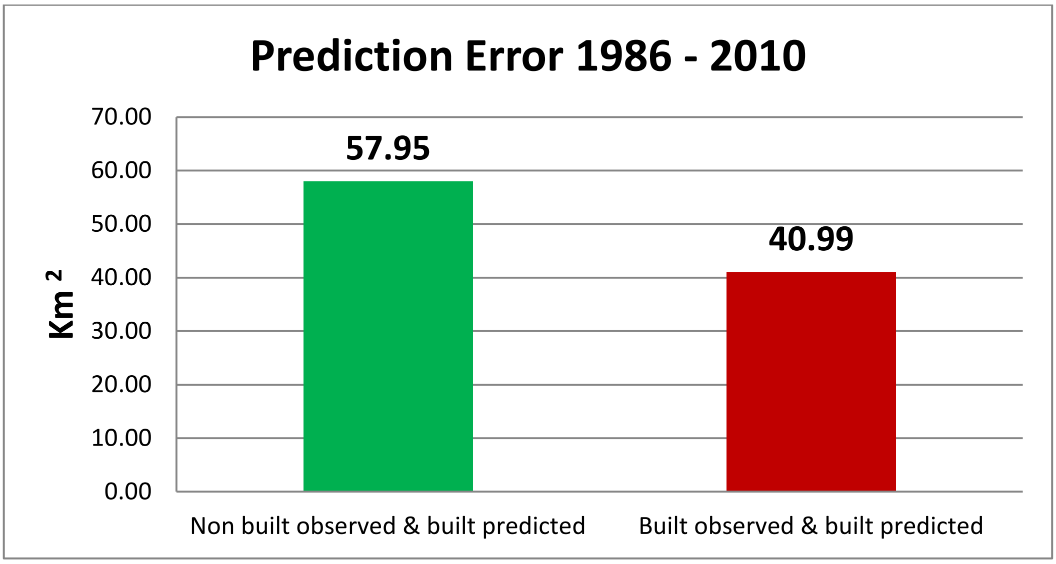

Figure 5-34: Estimates of predicted error 1986 – 2010 in Nairobi

In order for an urban growth model to be resourceful to various stakeholders such as policy makers and urban planners, simulation of urban growth has to be performed after calibration. Scenarios three was selected as the best plausible cause for urban planning management. Thus the likelihood of new settlements or built-up areas in Nairobi was obtained at a weighted value of 0.9477 as per scenario three. This indicates that new urban growth is most likely to be caused by breed (at 52), i.e. probability that a newly generated settlement starts its own growth, then followed by slope (at 52) influenced growth and spread (at 27), and finally followed by road and dispersion as least likely factors for new urban growth. Thus, this implies that new areas are developed for residential and commercial uses, which lie in proximity to roads. Such growth could be as a result of high rural urban migration witnessed in Nairobi as new people move immigrate in search for employment, social amenities and business opportunities.

Using scenario three we generated the urbanisation probability map for Nairobi as shown in Figure 5-35 using 100 Monte Carlo simulations (see appendix 9.2.4). High urbanisation within the range of 85 – 100 % is located near Nairobi CBD. Furthermore, high urbanisation tends to occur along roads such as along the major roads and local roads leading to housing developments. This area includes residential areas and industries. Comparative high urbanisation of 60 – 85 % occurs adjacent to high urbanisation areas followed by 38 – 60 % urbanisation areas. Moderately low urbanisation of 15 – 38 % comprises of new housing developments which are occurring adjacent to high urbanisation areas.

Low urbanisation in the range of 0 – 15 % consists of reserved areas such as Nairobi national park, parks, JKIA airport, military air base, Nairobi sewerage treatment plant which were excluded from urban growth modelling. Additionally, the low urbanisation area also includes high steep areas to the west of Nairobi city, and open/transitional areas to the east of Nairobi.

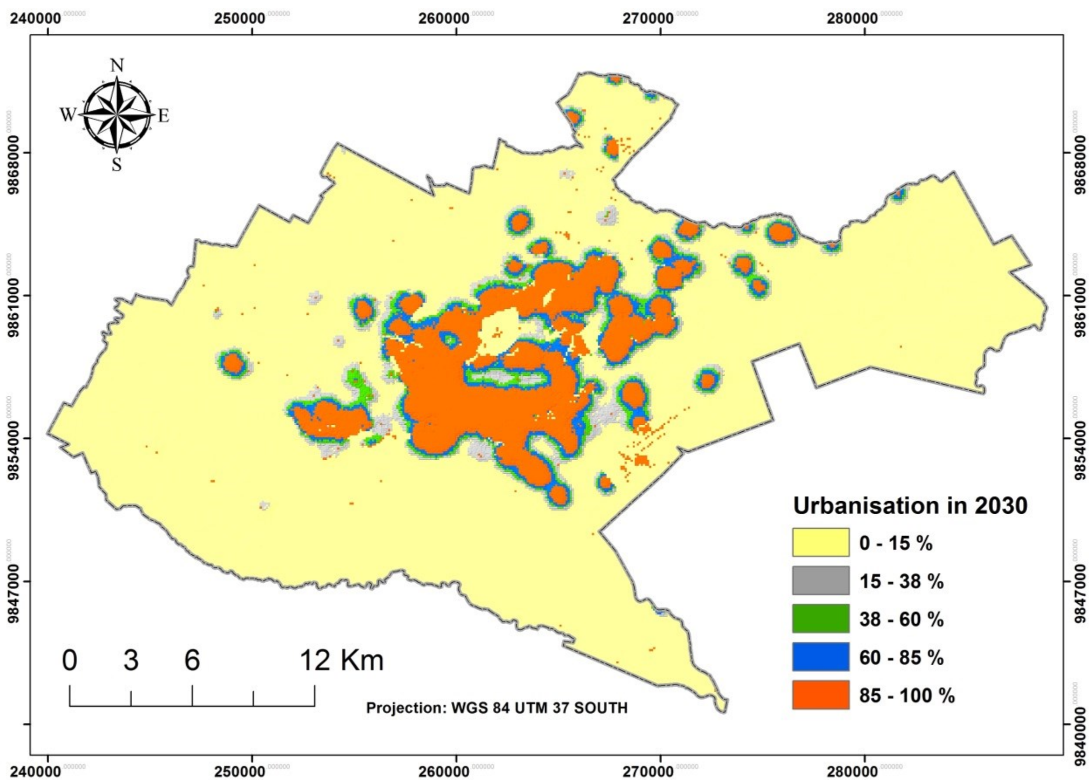

Figure 5-35: Urbanisation probability map for Nairobi

High urbanisation of 85 – 100 % tends to occur in fairly low altitude near the CBD as shown in Figure 5-36. Urbanisation is inhibited towards the west side of Nairobi which is fairly high at an average of 1900 metres above sea level. Here land values are relatively high leaving the land only to high income earners who can commute long distances to the CBD.

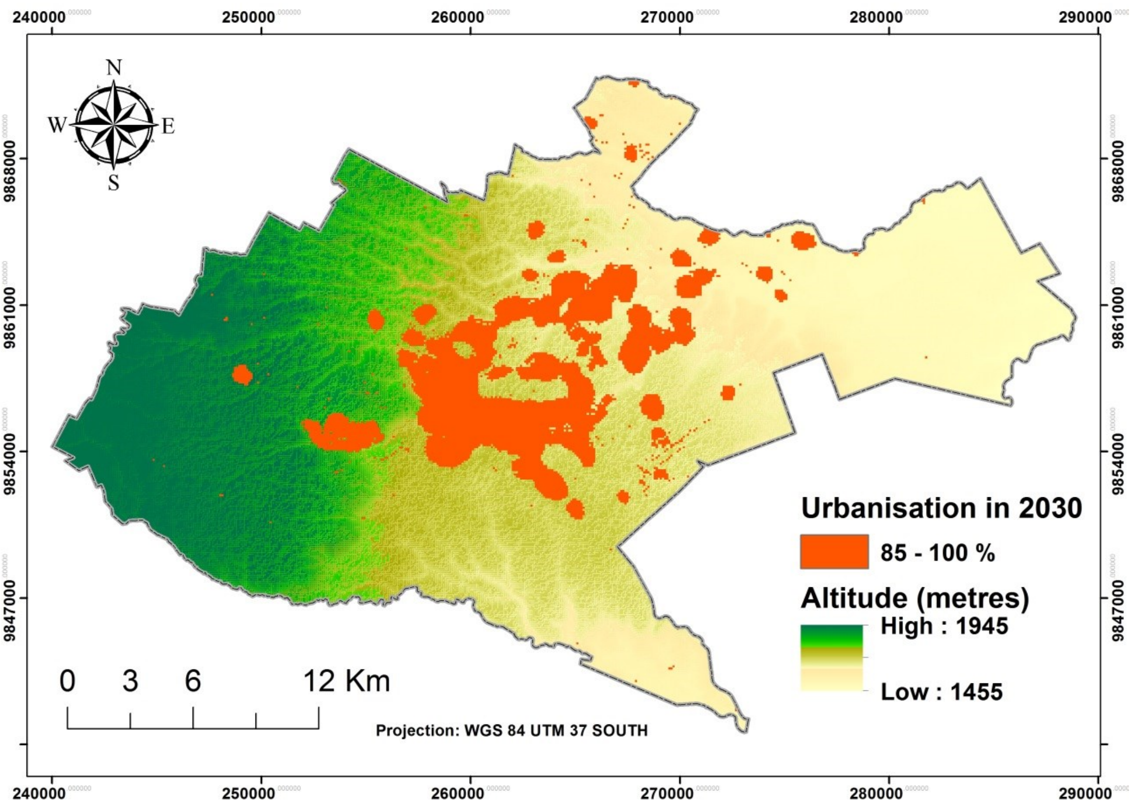

Figure 5-36: Urbanisation probability map for Nairobi showing high urbanisation areas

The modelled urban growth for Nairobi between 2010 and 2030 will be 49 %. The value was obtained as follows:

$$Urban\ growth\ = \frac{Simulated\ Urban\ \ in\ 2030 - Urban\ \ in\ 2010}{Urban\ \ in\ 2010}\%$$

$$Urban\ growth\ = \frac{118.35 - 79.38}{79.38}\%$$

$$Urban\ growth\ in\ Nairobi\ =\ 49\ \%$$

5.9 UGM comparison

We compared UGM modelling for Nairobi and Nakuru using values from the scenario three respectively as shown in Figure 5-37. In both cases we can see that the values for breed were at least above 50 with 52 for Nairobi and 65 for Nakuru. As we can recall from Table 11 breed refers to the probability that a newly generated settlement starts its own growth, thus we can conclude it is a major parameter influencing urban growth in Nairobi and Nakuru. Yet, breed is also used in road influenced growth and this is confirmed in the case of Nakuru with a road parameter value at 60.

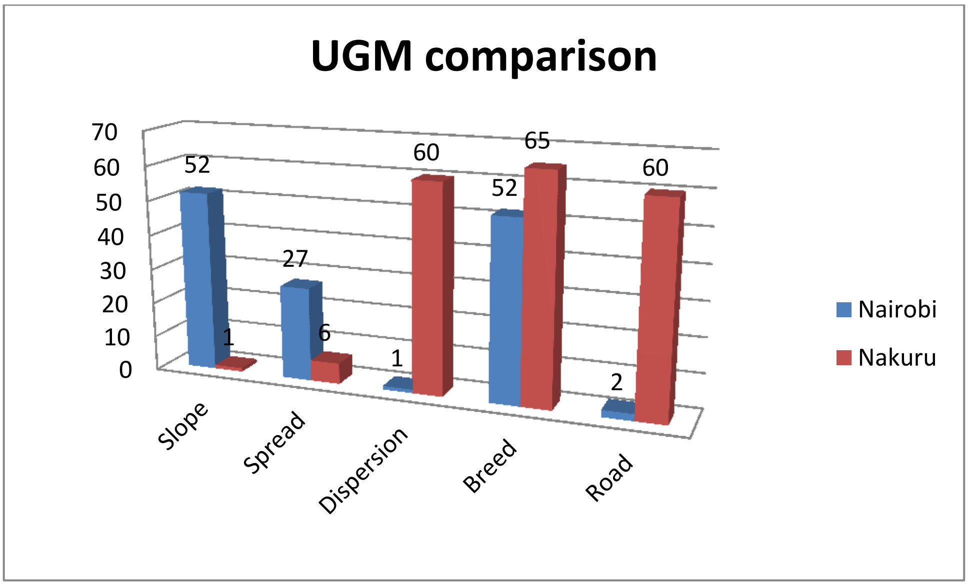

Figure 5-37: UGM comparison for Nairobi and Nakuru

Closely observing the UGM parameters for Nairobi we can see that slope at 52 and breed at 52 were the greatest contributors of urban growth while dispersion at 1 and road at 2 being the least. Spread was a moderate factor at 27 indicating that urbanised centres generate urban growth in their neighbourhoods and surroundings. From Figure 5-36 we can see that the altitude for Nairobi ranges from 1455 to 1945 metres above sea level with most urbanisation occuring around the central business district and in relatively low areas. All the same slope was one of major contributor in urban growth modelling of Nairobi alongside breed. Dispersion and road were least contributors of urban growth suggesting that growth was not random as per definition of dispersion from Table 11 and not enitrely road influenced. Accordingly, urban growth was systematic alongside other residential areas including informal settlements. We can also note that road was least contributor to urban growth modelling in Nairobi compared to the other model parameters.

Similarly, dispersion at 60, breed at 65 and road at 60 were the major contributors for ubran growth in Nakuru with slope at 1 and spread at 6 being the least. Thus we can see that urban growth was random in Nairobi with a high dispersion value as well as spontaneous growth with a high value of breed parameter. Additionally, urban growth was also influenced by road with a high value of road parameter. Breed was also noted to influence growth on road. Spread was a least contributor at value 6 to urban growth demonstrating that urbanised centres are least likely to simulate urban growth in their neighbourhoods. Thus urban growth in Nakuru was unanimously spontaneous, random and road influenced as we can see from Figure 5-19 and Figure 5-20. The main parameters which can give an idea of urban sprawl phenomenon are breed, dispersion and spread; but even the road disposition and the resultant accessibility have influence upon it. (Caglioni, Pelizzoni, & Rabino, 2006). Nakuru has undergone more urban sprawl compared to Nairobi as we can see from Figure 5-37 with the highest values of breed, dispersion and road being observed.

Hence, we can conclude that in both cities at least breed was a major contributor to urban growth. The question on whether the model parameters are correlated and if their variation influences urban growth arose. Thus, the UGM comparison for both cities was the impetus for investigating the influence of the model parameters individually as addressed in section 6.

The modelled urban growth between 2010 and 2030 for Nairobi is 49 % while that of Nakuru is 32%. Thus, we can conclude that Nairobi will experience rapid urban growth compared to Nakuru. This can be attributed to the fact that Nairobi is currently the capital city of Kenya serving as an administrative, political and judicial centre.

6 SPATIAL EFFECTS OF VARYING MODEL PARAMETERS

6.1 Introduction

We tested the spatial effects of varying model coefficients namely spread, dispersion, breed, slope and road in Nairobi. This aided in understanding the land-use system dynamics in our research area. The results obtained indicate that varying model coefficients leads to urban growth in different directions and magnitude. This information is useful to planners and policy makers indicating areas which require infrastructure and amenities so as to ensure sustainable development is realised.

6.2 Model parameter variation

In order to explore spatial effects of our UGM, we conducted combinations and permutations according to the Equation 4 for Nairobi city. The value of runs for each combination was obtained where *n* is the number of parameters which was five and *r* is the parameters to be maintained constant. We obtained five sets for the first combination, ten sets for the second combination, ten sets for the third combination, five sets for the fourth combination, and one set for the fifth combination.

Equation 4

$$\frac{n!}{(n-r)\,(r!)}$$

In total we obtained 31 simulated urban growth maps. In order to evaluate spatial effects, we used the Map Comparison Kit (MCK) software (Visser & de Nijs, 2006) to generate kappa statistics (*K*) using the predicted map of 2010. Hagen (2002) describes *K* statistics and additional statistics within *K* including *K*histo and *K*location.

K is a measure of similarity between two maps based on a contingency table ((Foody, 2004; Visser and de Nijs, 2006). *K* is defined according to Equation 2 where P (A) is the proportion of cases in agreement (i.e., correctly allocated) and P (E) is the proportion of agreement that is expected by chance:

$$\boldsymbol{K = \frac{P(A) - P\ (E)}{1 - P(E)}}$$

Equation 5

*K*location is a measure of the similarity of the spatial allocation of categories of the two compared maps (Pontius Jr, 2000). P (max) gives the maximal similarity that can be found based upon the total number of cells allocated to each category. *K*location is calculated according to Equation 3:

Equation 6

$$\boldsymbol{K = \frac{P(A) - P\ (E)}{P(max) - P(E)}}$$

*K*histo is a measure of the quantitative similarity of the two compared maps (Hagen, 2002). Thus *K*histo makes it possible to express *K* as a combination of similarity in quantity and location as shown in Equation 4:

Equation 7

$$\boldsymbol{K = \frac{P(max) - P\ (E)}{1 - P(E)}}$$

6.3 Results

The model parameters were varied by + 1 and their simulated urban growth obtained so as to explore the influence of each model parameter. We used the best model parameters obtained using UGM for Nairobi (scenario three) as tabulated in Table 16 with a simulated urban growth of 73.14 km^2. A total of 31 simulations were conducted and the results of the five combination sets tabulated in Table 18, Table 19, Table 20, Table 21, and Table 22. We used *K* for map comparison.

Table 18 summarizes the 1st combination. In this combination, the four best parameters were each varied by a value of +1, with one parameter remaining constant (shown in bold in Table 18). The simulated urban growth figures all exceed the 73.14 km^2 figure obtained using the best model parameters (Table 16). The highest spatial effect is realized in Set 5, where the slope value is held constant while the other values were varied. In Set 5, urban growth = 79.99 km^2, with the lowest resultant *K*histo value of 0.950. Again, the *K*histo measure makes it possible to express *K* as a combination of similarity in quantity and location. The lowest spatial effect (75.77 km^2) with the highest *K*histo value (0.980) was observed in Set 4, where the road value was held constant while the others were varied.

Table 18: Model parameter variation in 1st combination

Simulation using urban land-use classification of 2010 as reference									
Set	**Model parameters**					**Simulation (km^2)**	**Kappa statistics**		
	Spread	Dispersion	Breed	Road	Slope		K	*K*location	*K*histo
1	**27**	2	53	3	53	76.99	0.740	0.762	0.971
2	28	**1**	53	3	53	76.76	0.751	0.772	0.973
3	28	2	**52**	3	53	78.71	0.739	0.770	0.959
4	28	2	53	**2**	53	75.77	0.737	0.752	0.980
5	28	2	53	3	**52**	79.99	0.741	0.780	0.950

Table 19 shows the 2nd combination in which the three best parameters were varied by +1 and two parameters (shown in bold in the table) remained constant. Again, simulated urban growth values are uniformly greater than the 73.14 km^2 figure predicted using the optimal model parameters (Table 16). Set 8 yielded a value of 73.31km^2 with a high *K*histo value of 0.999. This value is quite close to the simulated urban growth value of 73.14 km^2, indicating a minimum of spatial effect in this model. The highest spatial effect (79.14 km^2) and lowest *K*histo value (0.954) was observed in Set 14, in which the slope and breed parameters were held constant while the others were varied.

Table 19: Model parameter variation in 2nd combination

Simulation using urban land-use classification of 2010 as reference									
Set	**Model parameters**					**Simulation (km^2)**	**Kappa statistics**		
	Spread	Dispersion	Breed	Road	Slope		*K*	*K*location	*K*histo
6	**27**	**1**	53	3	53	74.06	0.747	0.752	0.993
7	**27**	2	**52**	3	53	76.73	0.745	0.766	0.973
8	27	2	53	2	53	73.31	0.739	0.740	0.999
9	**27**	2	53	3	**52**	76.06	0.749	0.766	0.978
10	28	**1**	**52**	3	53	78.01	0.755	0.783	0.964
11	28	1	53	2	53	73.93	0.759	0.764	0.994
12	28	**1**	53	3	**52**	78.23	0.745	0.774	0.962
13	28	2	**52**	**2**	53	77.02	0.737	0.759	0.971
14	28	2	**52**	3	**52**	79.41	0.744	0.780	0.954
15	28	2	53	**2**	**52**	74.03	0.753	0.758	0.993

Table 20 summarizes the 3rd combination, where the two best parameters were varied by +1 and the other three parameters remained constant (again shown in bold). Again, the simulated urban growth values are greater than the 73.14 km^2 figure obtained using best model parameters as shown in Table 16. Set 19 yielded a simulated urban growth value of 73.16 km^2 with a high *K*histo value of 0.996. This simulated urban growth value is very close to the figure of 73.14 km^2 produced by the original calibrated UGM model. Thus, varying two model parameters -- Dispersion (at 2) and Slope (at 53) -- in Set 19 yields a good fit curve for urban growth modelling along with the least spatial effect. In contrast, Set 20 yielded the highest spatial effect (77.32 km^2) with a low *K*histo value (0.985). These figures result from varying Dispersion at 2 and Slope at 52 (rather than 53 as in Set 19).

Table 20: Model parameter variation in 3rd combination

Simulation using urban land-use classification of 2010 as reference									
	Model parameters						**Kappa statistics**		
Set	Spread	Dispersion	Breed	Road	Slope	**Simulation (km^2)**	*K*	*K*location	*K*histo
16	**27**	**1**	**52**	3	53	74.08	0.752	0.757	0.993
17	**27**	**1**	53	**2**	53	72.68	0.759	0.761	0.996
18	**27**	**1**	53	3	**52**	75.09	0.749	0.760	0.985
19	**27**	2	**52**	**2**	53	73.16	0.750	0.750	1.000
20	27	2	52	3	52	77.32	0.742	0.766	0.969
21	27	2	53	2	52	73.28	0.743	0.743	0.999
22	28	**1**	**52**	**2**	53	72.94	0.757	0.758	0.998
23	28	**1**	**52**	3	**52**	76.93	0.743	0.765	0.972
24	28	**1**	53	**2**	**52**	75.19	0.764	0.776	0.985
25	28	2	52	2	52	73.92	0.762	0.767	0.994

Table 21 shows the 4th combination where the single best parameter was varied by +1 while keeping the other four parameters constant (shown in bold). The simulated urban growth values are greater than the value of 73.14 km^2 obtained using best model parameters (Table 16). Set 26 yielded a value of 73.18 km^2 with the highest *K*histo value of 1.000. The 73.18 km^2 value was closest to the simulated urban growth value of 73.14 km^2. Varying only the Slope parameter in set 26 yielded the least spatial effect. It is useful to compare these results with those produced in Set 30 in which only the Spread parameter was varied. Set 30 yielded the highest spatial effect; an indication of the sensitivity of our UGM in modelling urban growth.

Table 21: Model parameter variation in 4th combination

Simulation using urban land-use classification of 2010 as reference									
	Model parameters						**Kappa statistics**		
Set	**Spread**	**Dispersion**	**Breed**	**Road**	**Slope**	**Simulation (km^2)**	*K*	*K*location	*K*histo
26	**27**	**1**	**52**	**2**	53	73.18	0.758	0.759	1.000
27	**27**	**1**	**52**	3	**52**	74.70	0.751	0.760	0.988
28	**27**	**1**	53	**2**	**52**	75.70	0.749	0.763	0.981
29	27	2	52	2	52	73.74	0.752	0.755	0.995
30	28	**1**	**52**	**2**	**52**	76.48	0.757	0.776	0.975

Table 22 shows the 5th combination under which all of the best parameters were varied by a value of +1. The simulated urban growth value produced by this combination was 77.29 km^2 with a *K*histo value of 0.969. This growth value significantly exceeds the 73.14 km^2 figure yielded by using best model parameters. It is clear that varying all parameters affects our UGM significantly.

Table 22: Model parameter variation in 5th combination

Simulation using urban land-use classification of 2010 as reference									
	Model parameters						**Kappa statistics**		
Set	Spread	Dispersion	Breed	Road	Slope	**Simulation (km^2)**	*K*	*K*location	*K*histo
31	28	2	53	3	53	77.29	0.736	0.760	0.969

In this research we explored the spatial effects of varying the UGM model parameters and the results indicate the sensitivity of our UGM in urban growth modelling. Varying at least one model parameter while leaving the other parameters constant had a significant effect on the resulting simulated urban growth values. The highest spatial effect obtained was 79.99 km^2 (Table 18) while the lowest value derived was 73.16 km^2 (Table 20). The value of 79.99 km^2 was obtained as the Slope parameter was held constant while the others were varied. The value of 73.16 km^2 was obtained by holding Spread, Breed, and Road parameters constant while varying Dispersion and Slope. In addition, examining Table 21 shows that the value of 73.18 km^2 was the second lowest value obtained for spatial effect. This figure was obtained by varying the Slope parameter and holding the other parameters constant.

Analysis of the lower spatial effect values (73.16 km^2 from Table 20 and 73.18 km^2 from Table 21), shows that these results are produced by holding Spread, Breed and Road parameters constant. This suggests that these three model parameters are closely correlated in the production of similar amounts of urban growth cells. Model sets yielding a low spatial effect and those with a high spatial effect are shown in Table 23 and Table 24.

From Table 19, Table 20 and Table 21 it is clear that maintaining constant values for Dispersion and Slope at a minimum yielded high spatial effects (78.23 km^2, 76.93 km^2 and 76.48 km^2). As the value of the Road parameter was increased we observed in all simulations increasing urbanisation of more accessible areas. This connection to the road network is evident with equal growth rates (due to the values of the other parameters), an effect observed by Caglioni, Pelizzoni and Rabino (2006).

Figure 6-1 shows the urban growth simulations for the 31 Sets. Again, the simulated urban growth value of 73.14 km^2 was produced by UGM using the best model parameters (Table 16). Figure 6-1 shows that Set 19 produced an urban growth value of 73.16 km^2, the closest to that produced by the UGM (also in Table 20).

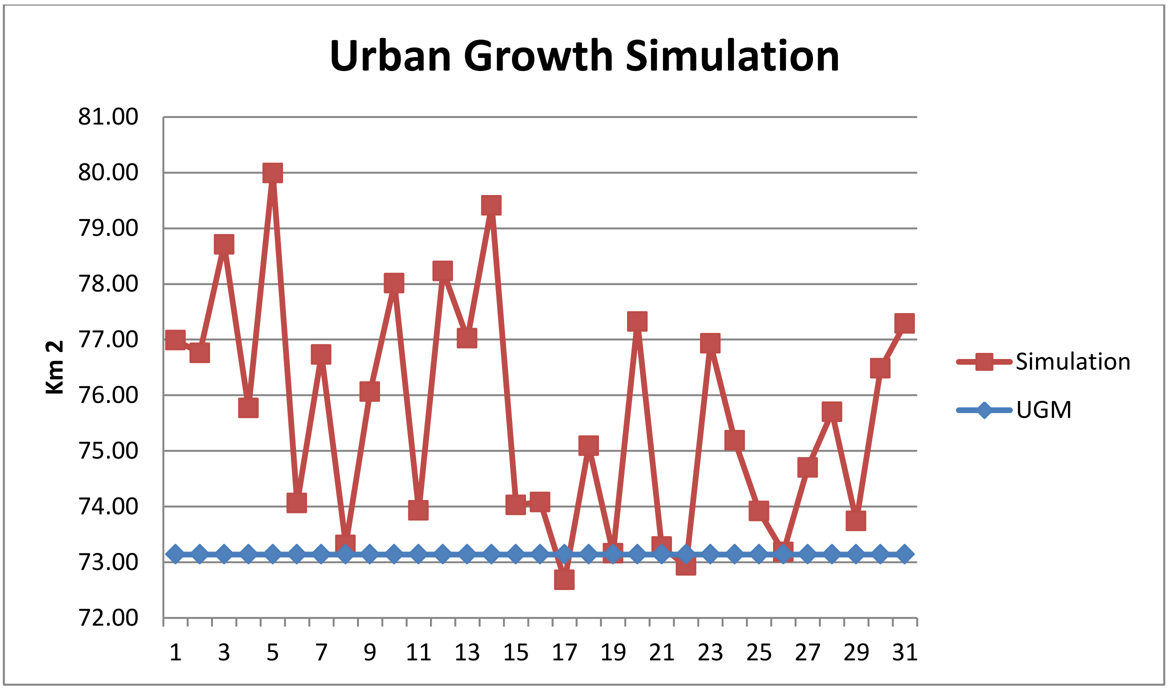

Figure 6-1: Urban Growth Simulation

Figure 6-2 shows the *K* and *K*location values for the 31 simulations. In Set 24 model parameters of Dispersion, Road and Slope were held constant. Set 24 had the highest *K* value of 0.764 indicating the high spatial effect associated with this Set (75.19 km^2). In set 31 all model parameters were varied and Set 31 yielded the lowest *K* value (0.736) along with a high spatial effect of 77.02 km^2. High *K* values indicate low similarity between the maps and therefore a high spatial effect. In Set 10 two model parameters -- Dispersion and Breed -- were kept constant. Set 10 generated the highest *K*location value of 0.783; this is indicative of the high spatial effect, measured at 78.01 km^2. In set 8 where the two parameters of Spread and Road were kept constant, both a low *K* value and a low spatial effect (73.31 km^2) were produced. High *K* and *K*location values describe low similarity between the maps and indicate high spatial effects.

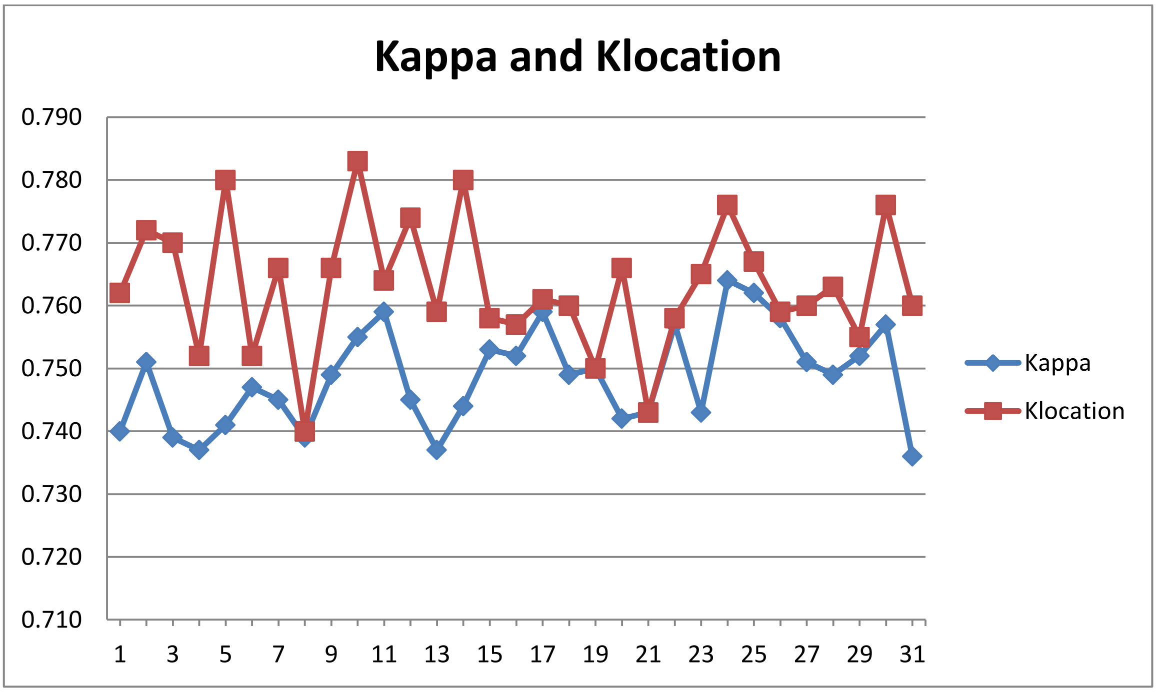

Figure 6-2: *K* and *K*location values for urban growth simulation

Additionally, Figure 6-2 shows that low *K* and *K*location values were observed in Sets 8 and 9; 0.739 in Set 8 and 0.740 in Set 9, with the lowest *K*location value being observed in Set 8. In these two Sets only the Spread model parameter was held constant. Set 31 yielded the lowest *K* value at 0.736.

Figure 6-3 shows the *K*histo values for the 31 simulations. The highest value of *K*histo (1.000) was obtained in both Set 19 and in Set 26. In Set 19 three model parameters (Spread, Breed, and Road) were kept constant, In Set 26 four parameters (Spread, Dispersion, Breed and Road) were held constant. This high *K*histo value indicates the lowest spatial effect. In set 5, where a single parameter (Slope) was kept constant, the lowest *K*histo value of 0.950 was produced, indicating the highest spatial effect observed at 79.99 km^2. High *K*histo values indicate a high degree of similarity between the maps in terms of quantity and location of predicted urban growth and indicate the lowest spatial effect.

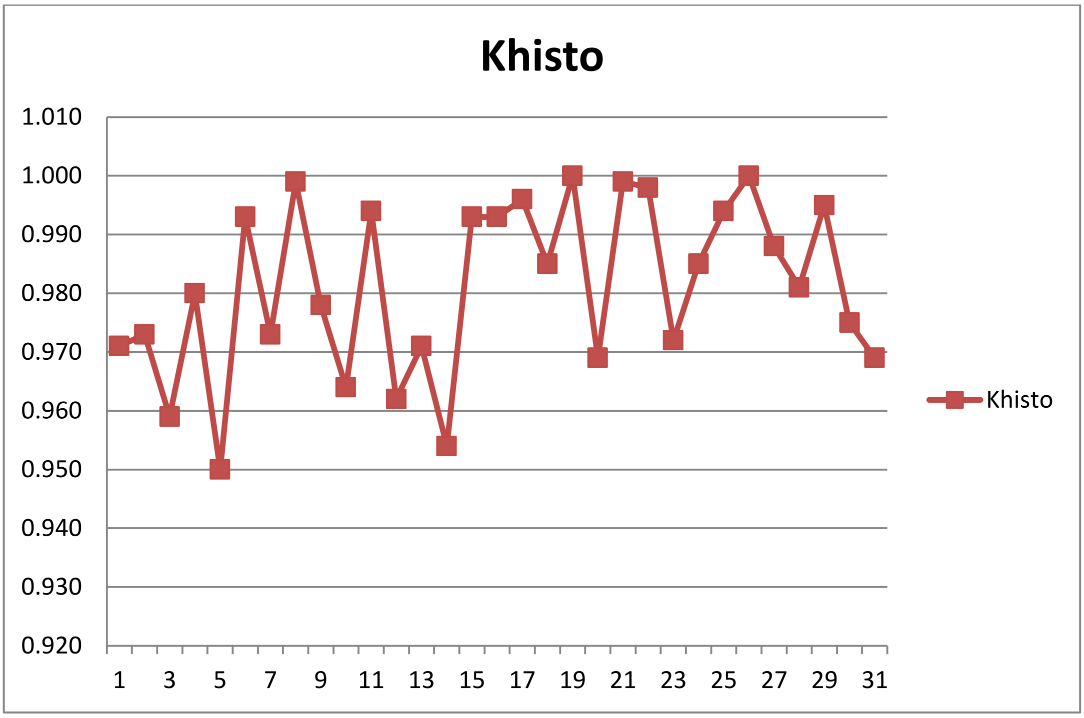

Figure 6-3: *K*histo values for urban growth simulation

Table 23 presents the set of parameters that yielded the minimum urban growth levels and indicate low spatial effect. The lowest spatial effect of 73.16 km^2 is indicated by the highest *K*histo value of 1.000. It is clear that maintaining the values of the Spread, Breed and Road parameters leads to a low spatial effect and indicates that these three model parameters are highly correlated. The growth types predicted were: new spreading growth as a result of Breed; edge growth as a consequence of Spread; and road-influenced growth as a result of the Road parameter.

Table 23: Model parameter sets with low spatial effect for UGM of Nairobi

Simulation using urban land-use classification of 2010 as reference									
	Model parameters						**Kappa statistics**		
Set	Spread	Dispersion	Breed	Road	Slope	**Simulation (km^2)**	*K*	*K*location	*K*histo
4	28	2	53	**2**	53	75.77	0.737	0.752	0.980
8	**27**	2	53	2	53	73.31	0.739	0.740	0.999
19	**27**	2	**52**	**2**	53	73.16	0.750	0.750	1.000
26	**27**	**1**	**52**	**2**	53	73.18	0.758	0.759	1.000

Table 24 presents the set of parameters that produced the maximum urban growth levels. Maintaining only the Slope parameter and increasing the values of the other four parameters resulted in a high spatial effect at 79.99 km^2 along with the lowest *K*histo value of 0.950. However, holding the Dispersion, Breed and Road parameters constant while varying the other two parameters produced a low spatial effect (76.48 km^2) with a high *K*histo value of 0.975. This suggests that the Dispersion, Breed and Road model parameters are moderately correlated, but less so than the Spread, Breed and Road model parameters (see Table 23).

Table 24: Model parameter sets with high spatial effect for UGM of Nairobi

Simulation using urban land-use classification of 2010 as reference									
	Model parameters						**Kappa statistics**		
Set	Spread	Dispersion	Breed	Road	Slope	**Simulation (km^2)**	*K*	*K*location	*K*histo
5	28	2	53	3	**52**	79.99	0.741	0.780	0.950
14	28	2	**52**	3	**52**	79.41	0.744	0.780	0.954
20	**27**	2	52	3	52	77.32	0.742	0.766	0.969
30	28	**1**	**52**	**2**	**52**	76.48	0.757	0.776	0.975
31	28	2	53	3	53	77.29	0.736	0.760	0.969

Maintaining Spread, Breed and Slope constant resulted in the lowest spatial effect value of 73.16 km^2 (Table 23) with the highest *K*histo value of 1.000, as illustrated in Figure 6-4. The highest spatial effect of 79.99 km^2 (Table 24) with the lowest *K*histo value of 0.950 is mapped in Figure 6-5. Figure 6-4 and Figure 6-5 both include the 2010 simulated urban growth map and the simulated spatial effect map.

Additionally, statistics from Figure 6-4 and Figure 6-5 including the four map categories are shown in Table 25.

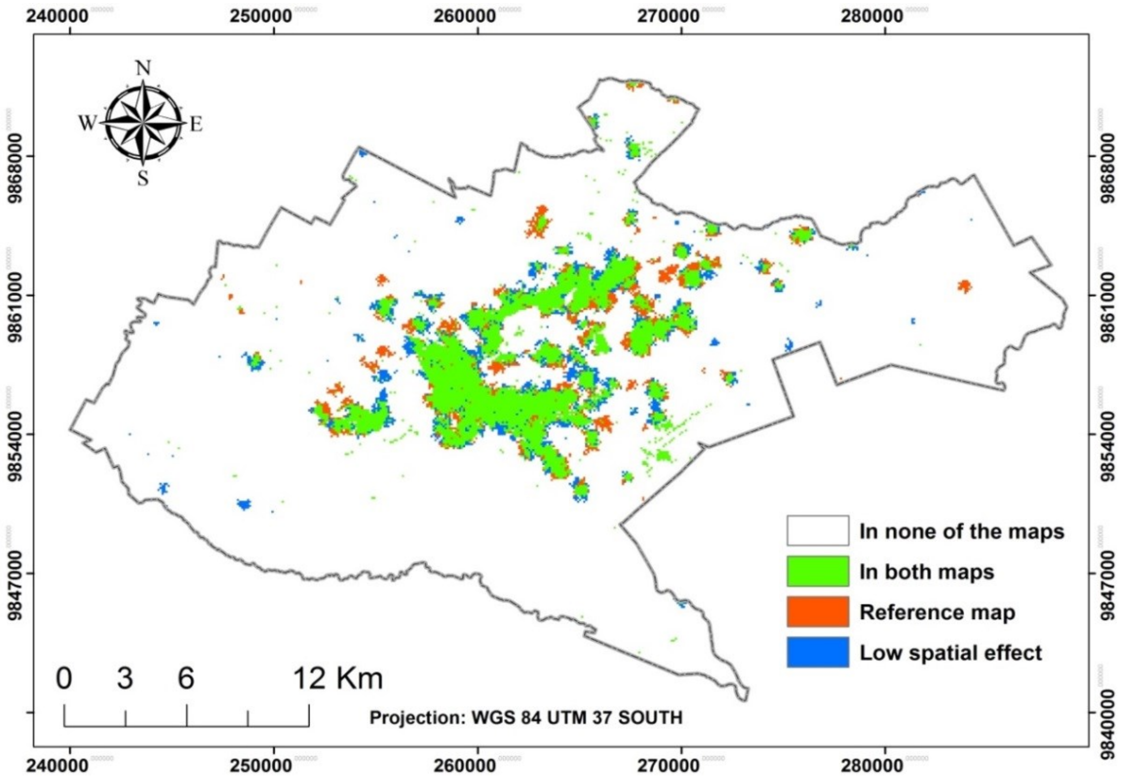

Figure 6-4: Lowest spatial effect based parameters values obtained from set 19

(See Table 23)

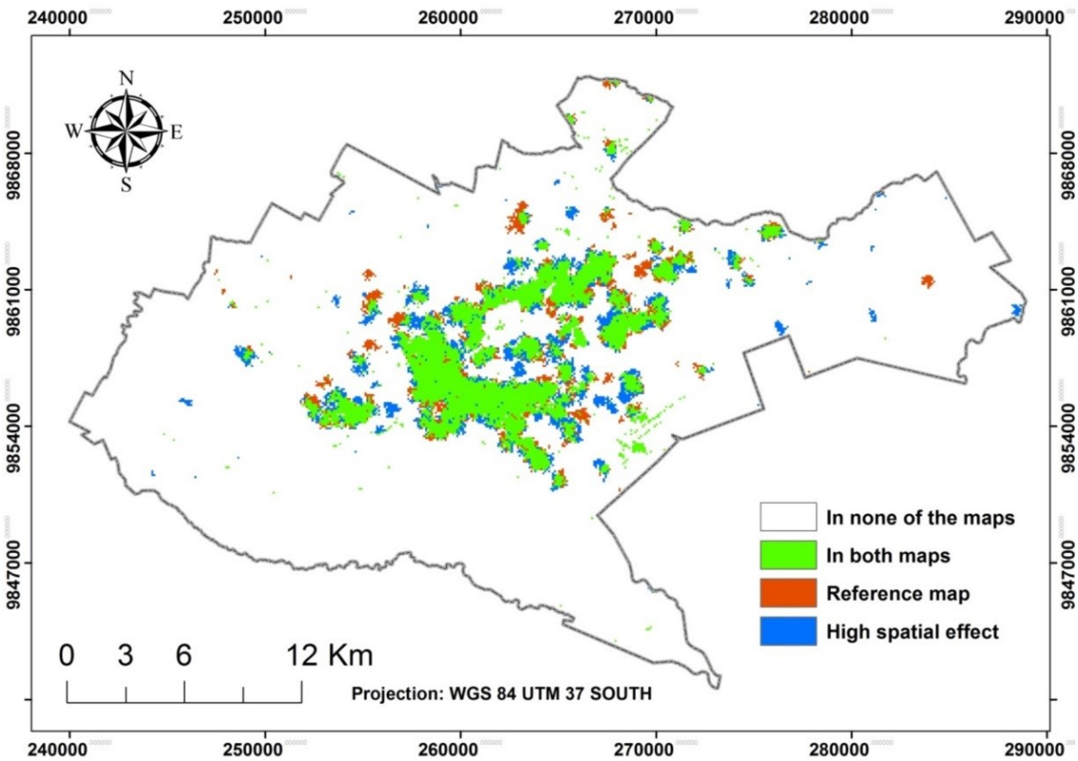

Figure 6-5: Highest spatial effect based parameters values obtained from set 5

(See Table 24)

Table 25: Statistics of spatial effect maps

		Lowest Spatial Effect	Highest Spatial Effect
Category	**Description**	**Area (km ^{2})**	**Area (km ^{2})**
1	In none of the maps	604.78	600.1
2	In both maps	56.78	58.93
3	Reference map	16.38	14.21
4	Spatial effect	16.38	21.06

From Table 25 it can be seen that for the lowest spatial effect case identical values are present for Categories 3 and 4. In the highest spatial effect case the values for Categories 3 and 4 differ significantly; 14.21 km^2 for Category 3, and 21.06 km^2 for Category 4. The values for Categories 1 and 2 are quite similar. Examining the spatial effect as shown in Category 4, reveals a difference of 4.68 km^2 (16.38 km^2 and 21.06 km^2), confirming the sensitivity of our UGM.

These results can help regional and urban planners to understand the implications of varying the parameters in the Urban Growth Model. This can allow planners to simulate differing future urban growth scenarios by incorporating varying combinations of model parameters. Higher spatial effects in model outputs translate to simulations with increasing urban sprawl. Lower spatial effects translate to less urban sprawl simulation. This information can be effective in the design of “smart” cities, which is a vital research agenda in modern urban planning.

7 SUMMARY AND CONCLUSIONS

The modelling of urban growth and prediction of future growth has been the goal of many urban planners in the 21st century. Nairobi and Nakuru as major cities in Kenya were used as examples of fast expanding African cities to analyse the dynamics of land-use changes between 1986 and 2010, and to simulate urban growth into 2030 using a regionalised urban growth model (UGM). We used multi-temporal Landsat images of 1986, 2000 and 2010 to quantify changes in land-use changes within the research period. Furthermore, we explored the use of multi-sensor data in monitoring land-use in Nakuru. SAR data improved our classification results. Moreover, we conducted supervised classification using support vector machine (SVM) which performed better than maximum likelihood classification as noted in Chapter 4. Land-use statistics revealed that substantial changes have taken place as a result of rapid urban growth. At times there is no recent timely land-use information in Kenya. In this research remote sensing techniques were effective in obtaining historic as well as recent information on land-use.

This research revealed that UGM can be used for predicting future urban growth in both cities. Inputs for our model included information from land-use of 1986 and 2010 as well as other data namely slope, road data and exclusion layer. The slope data was generated from digital elevation model for Nairobi and digital surface elevation model for Nakuru. The exclusion layer defined areas where development is controlled.

Model calibration and validation were done simultaneously in XULU. The Monte Carlo iterative method was applied in the UGM calibration. The MRV technique was applied in model validation phase. The model results were compared with the null model. Kenya plans to achieve Vision 2030 in the year 2030 and is to be implemented in successive five-year Medium Term plans having started with the period 2008 – 2012. Thus to achieve the economic and social strategy there is need for land-use simulation in order to cater for the increased economic growth which translates to an increase for housing and urbanisation.

Accordingly in order to predict alternative urban growth patterns for Nairobi and Nakuru, we formulated three scenarios namely; unmanaged, managed and maximum protection. These scenarios were an attempt to model urban growth based on historic urban patterns as well as what is ideal for sustainable urban planning. We used our UGM to come up with three scenarios for the year 2010 and 2030. The results obtained indicate urban growth dynamics for different time periods up to the year 2030 for both cities. Scenario three was selected as plausible cause of action for sustainable planning of our cities with maximum protection on resources. Here the assumption was that we have stable economic and political conditions up to the year 2030. Hence, we observed that our model was suitable in simulating various scenarios and can be used as planning tool. Scenario one indicated a situation where there is lack of a comprehensive plan and can lead to unsustainable urban growth.

Simulated urban growth results for the year 2030 indicate that there is the need for strategic planning under different scenarios so as to control the expansion of built-up areas. There is need for appropriate measures to control the high rural urban migration into Kenyan cities in consideration to the existing demography, economic and social as well as physical constraints. The accuracy of our model was resolved by using Monte Carlo calibration technique. The urban growth values (scenario three) obtained using MRV techniques indicated accuracies of approximately 85% as the minimum for land-use classification as stated in Anderson et al., (1976). We obtained urban growth values of 95% for Nairobi and 84 % for Nakuru.

Closely comparing the UGM parameters for out two cities we observed that breed was a major parameter influencing urban growth in both cities. Breed contributes to road influenced growth and this was confirmed in the case of Nakuru. Slope and breed were the greatest contributors of urban growth modelling in Nairobi. Breed, dispersion and road were the major contributors of ubran growth in Nakuru. Nakuru was noted to have undergone more urban sprawl compared to Nairobi.

Additionally, we observed that Nairobi and Nakuru will undergo rapid growth of 49 % and 32 % respectively between the years 2010 and 2030. Hence, Nairobi is likely to experience more rapid urban growth compared to Nakuru. Nairobi serves as the capital city of Kenya and attracts more population as people come in search of employment and social amenities.

Different UGM parameter combinations were explored and spatial effects of urban growth obtained for Nairobi city. Each model parameter influences urban growth independently. However, several model parameters were observed to be highly correlated namely; spread, breed and road. The lowest spatial effect was achieved by at least maintaining spread, breed and road while varying the other parameters. The highest spatial effect was observed by at least keeping slope constant while varying the other four parameters. We also used kappa statistics to compare the simulation maps. High values of Khisto indicate high similarity between the maps in terms of quantity and location thus indicating the lowest spatial effect obtained.

Thus our cellular automata model represents a worthwhile approach for regional planning as it is able to simulate complex behaviour. The model provided a good guide to the spatial growth of Kenyan cities illustrating areas which can be expanded under different scenarios. This can help cities to manage their resources efficiently and sustainably. Thus cellular automata are a worthwhile approach for regional modelling of African cities such as Nairobi and Nakuru. This provides opportunities for other cities in Africa to be studied using UGM and its adaptability noted accordingly.

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9 APPENDICES

9.1 Appendix 1: Monitoring land-use

9.1.1 Landsat TM and ETM spectral and spatial properties

Band	Landsat 4/5 Spectral (_m)	TM Spatial (m)	Landsat 7 Spectral (_m)	ETM Spatial (m)	Utilization
Blue	0.45-0.52	30	0.45-0.52	30	Water mapping, vegetation identification
Green	0.52-0.60	30	0.52-0.60	30	Green reflectance from vegetation
Red	0.63-0.69	30	0.63-0.69	30	Chlorophyll absorption, vegetation identification
Near Infrared	0.76-0.90	30	0.76-0.90	30	Biomass, water distribution
Middle Infrared	1.55-1.75	30	1.55-1.75	30	Vegetation moisture, snow/cloud identification
Thermal Infrared	10.40-12.50	120	10.40-12.50	60	Thermal mapping, plant heat stress
Middle Infrared	2.08-2.35	30	2.08-2.35	30	Hydrothermal mapping
Panchromatic	n/a	n/a	0.50-0.90	15	

9.1.2 USGS Land-use classification system for use with Remote Sensor Data

Level I	Level II
1. Urban or built-up land	11 Residential 12 Commercial and service 13 Industrial 14 Transportation, communication, and utilities 15 Industrial and commercial complexes 16 Mixed urban or built-up land 17 Other urban or built-up land
2. Agricultural land	21 Cropland and pasture 22 Orchards, groves, vineyards, nurseries, and ornamental horticultural areas 23 Confined feeding operations
3. Rangeland	31 Herbaceous rangeland 32 Shrub and brush rangeland 33 Mixed rangeland
4. Forest land	41 Deciduous forest land 42 Evergreen forest land 43 Mixed forest land
5. Water	51 Streams and canals 52 Lakes 53 Reservoirs 54 Bays and estuaries
6. Wetland	61 Forested wetland 62 Non-forested wetland
7. Barren land	71 Dry salt flats 72 Beaches 73 Sandy areas other than beaches 74 Bare exposed rock 75 Strip mines, quarries, and gravel pits 76 Transitional areas 77 Mixed barren land
8. Tundra	81 Shrub and brush tundra 82 Herbaceous tundra 83 Bare ground tundra 84 Wet tundra 85 Mixed tundra
9. Perennial snow or ice	91 Perennial snowfields 92 Glaciers

The table above is on USGS land-use classification system for use with remote sensor data and is adopted from Anderson, Hardy, Roach, and Witmer, (1976).

9.1.3 Representative Image Interpretation Formats for various Land-use Classification Levels

Land-use Classification Level	Representative Format for Image Interpretation
I	Low to moderate resolution satellite data (e.g., Landsat MSS data)
II	Small-scale aerial photographs; moderate resolution satellite data (e.g., Landsat TM data)
III	Medium-scale aerial photographs; high resolution satellite data (e.g., data acquired by commercial high resolution systems)
IV	Large-scale aerial photographs

The table above is on representative image interpretation formats for various land-use classification levels as borrowed from Anderson, Hardy, Roach, and Witmer, (1976).

9.2 Appendix 2: Urban growth modelling

9.2.1 Urban growth types

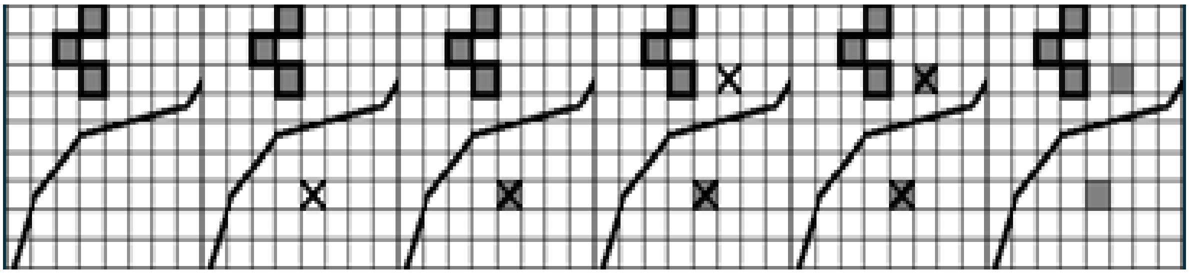

Figure 9-1: Illustration of spontaneous growth

(Source: www.ncgia.ucsb.edu/projects/gig)

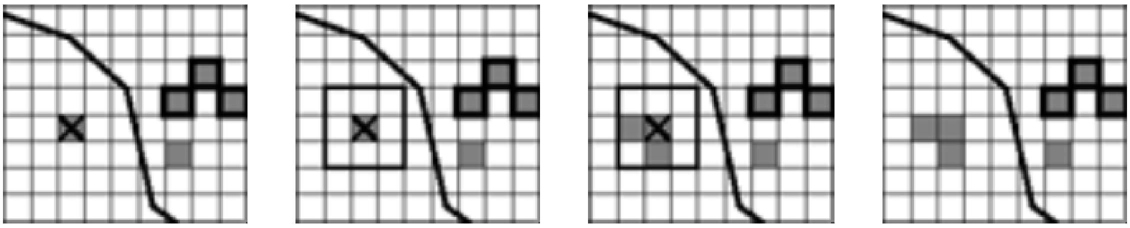

Figure 9-2: Illustration of new spreading centre growth

(Source: www.ncgia.ucsb.edu/projects/gig)

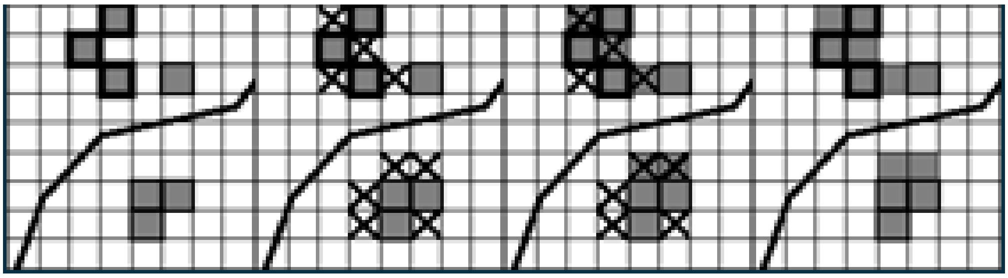

Figure 9-3: Illustration of edge growth

(Source: www.ncgia.ucsb.edu/projects/gig)

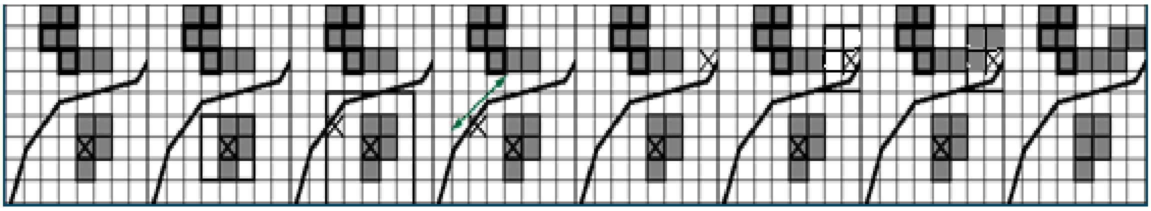

Figure 9-4: Illustration of road-influenced growth

(Source: www.ncgia.ucsb.edu/projects/gig)

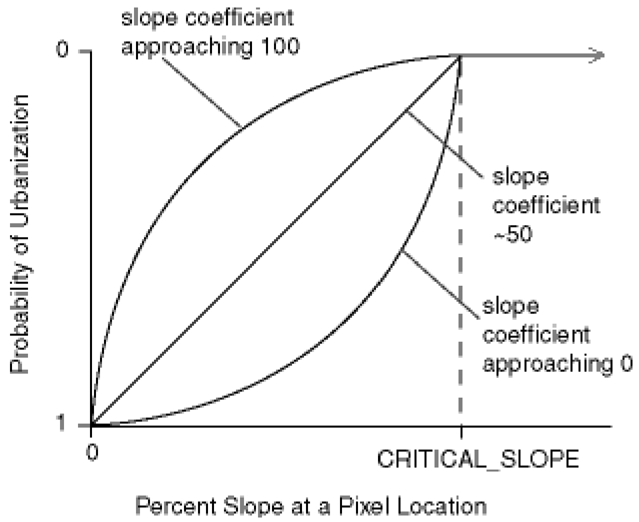

Figure 9-5: Influence of slope on urban growth modelling

9.2.2 UGM Calibration Resource Mapping script

```
UGM-Parameter.Step Count
Base LU Scenario.Grid
Out: Actual LU.Grid
Area Restrictions.Grid
Road Grid.Grid
Slope Grid.Grid
Reference Grid.Grid
UGM-Parameter.Spread Coefficient Start
UGM-Parameter.Spread Coefficient Step
UGM-Parameter.Spread Coefficient End
UGM-Parameter.Dispersion Coefficient Start
UGM-Parameter.Dispersion Coefficient Step
UGM-Parameter.Dispersion Coefficient End
UGM-Parameter.Breed Coefficient Start
UGM-Parameter.Breed Coefficient Step
UGM-Parameter.Breed Coefficient End
UGM-Parameter.RoadGravity Coefficient Start
UGM-Parameter.RoadGravity Coefficient Step
UGM-Parameter.RoadGravity Coefficient End
UGM-Parameter.Slope Coefficient Start
UGM-Parameter.Slope Coefficient Step
UGM-Parameter.Slope Coefficient End
UGM-Parameter.Critical Slope
UGM-Parameter.Number of MonteCarlo Iterations
Out: Step Results
```

From the script above, someone can see the implementation of the start, intermediate and end points for model parameter values between 1 and 100 (Goetzke, 2011). For example, in first phase of calibration the values are 1, 50 and 100 with subsequent increments of 25 or lesser to achieve fine calibration of UGM. We used this script to achieve calibration of our two UGM models for Nairobi and Nakuru.

9.2.3 UGM Resource Mapping script

```
UGM-Parameter.Step Count
Base LU Scenario.Grid
Out: Actual LU.Grid
Area Restrictions.Grid
Road Grid.Grid
Slope Grid.Grid
UGM-Parameter.Spread Coefficient
UGM-Parameter.Dispersion Coefficient
UGM-Parameter.Breed Coefficient
UGM-Parameter.RoadGravity Coefficient
UGM-Parameter.Slope Coefficient
UGM-Parameter.Critical Slope
Out: Step Results
```

From the script above, someone can see the simulation of urban growth using the best model parameters obtained using Monte Carlo calibration and MRW validation (Goetzke, 2011). The Base LU Scenario.Grid represents the starting year e.g. 1986. The Area Restrictions.Grid represents the exclusion layer with areas excluded from development. The Road Grid.Grid represents road network layer used. The Slope Grid.Grid represents the slope data adopted. We used this script to obtain urban growth maps for all scenarios using different model parameters.

9.2.4 UGM Resource Mapping Monte Carlo

```
UGM-Parameter.Step Count
Base LU Scenario.Grid
Out: Actual LU.Grid
Area Restrictions.Grid
Road Grid.Grid
Slope Grid.Grid
UGM-Parameter.Spread Coefficient
UGM-Parameter.Dispersion Coefficient
UGM-Parameter.Breed Coefficient
UGM-Parameter.RoadGravity Coefficient
UGM-Parameter.Slope Coefficient
UGM-Parameter.Critical Slope
UGM-Parameter.Monte Carlo
Out: Step Results
```

From the script above, someone can see the Monte Carlo simulation for urban growth using 100 iterations (Goetzke, 2011). We used this script to obtain high potential urbanisation maps as shown in Figure 5-19, Figure 5-20, Figure 5-35 and Figure 5-36.