DYNAMIC GEOSPATIAL MODELLING AND SIMULATION OF PREDOMINANTLY INFORMAL CITIES

AN INTEGRATED AGENT-BASED AND CELLULAR AUTOMATA MODEL OF URBAN GROWTH

DEPARTMENT OF LAND ECONOMY

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PREFACE

Declaration

This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except as declared in the Preface and specified in the text.

It is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my dissertation has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text

It does not exceed the prescribed word limit for the relevant Degree Committee.

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Felix S. K. Agyemang

Publications

Portions of this work have been published as follows:

Chapter Four – Agyemang, F. S., & Silva, E. (2019). Simulating the urban growth of a predominantly informal Ghanaian city-region with a cellular automata model: Implications for urban planning and policy. *Applied Geography*, *105*, 15-24.

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ABSTRACT

Dynamic geospatial modelling and simulation of predominantly informal cities: An integrated agent-based and cellular automata model of urban growth

Felix Seberh Kamusu Agyemang

Against the backdrop of urbanization, cities have evolved globally, but more so in Sub-Saharan Africa (SSA) in recent decades. Cities in the sub-region differ in many ways from those in other parts of world. One of the major differences is the overwhelmingly informal nature of urban growth in many cities in SSA, a feature that has regulation and spatial pattern dimensions. These dimensions are, however, less explored in urban modelling research. Cities have not evolved alone, but, alongside with massive evolution in the methods of their abstraction. Cellular Automata (CA) and Agent-Based Modelling (ABM) are two popular techniques that have emerged from this evolution. These models are rarely applied to cities in SSA. After a period of independent applications, there is an increasing recognition that the two approaches are mutually reinforcing, hence are mostly integrated in recent urban growth models. Existing integrated ABM and CA models of urban growth hardly account for the predominantly informal dynamics (unplanned and unregulated growth) that characterise many cities in Sub-Saharan Africa.

Following the above, this research pursues three main objectives: one, simulates the urban growth of a predominantly informal Sub-Saharan African city-region with urban CA; two, examines the evolving urban spatial structure of Sub-Saharan African cities and the relationship with mainstream urban spatial structure models; and, three, develops an integrated ABM and CA model that simulates urban residential growth of a predominantly informal city-region in SSA. In exploring the first objective, diverse spatially explicit datasets are drawn from Accra, and SLEUTH, a dynamic urban CA model, is applied to the Ghanaian city-region. In relation to the second objective, the research draws on wide ranging spatial datasets and combines SLEUTH with urban spatial metrics to analyse the evolving spatial structure of Kumasi city-region (Ashanti region) of Ghana. The third, also the overarching objective, develops *TI-City model* (The Informal City model), an integrated ABM and CA model for simulating urban residential growth of predominantly informal cities in SSA. The model, which relies on spatial and empirical socio-economic datasets in its development, is applied to Accra city-region

The research finds urban growth in both Accra and Kumasi city-region to be highly spontaneous and rapid; and new developments fast turn into urban growth nuclei. It also uncovers that, while Kumasi city-region's urban spatial structure before the turn of the Twenty-first century largely conforms to the traditional monocentric model, it is increasingly becoming deconcentrated and dispersive, which suggests a likely pending phase of coalescence in a stochastic fractal urban growth process. Contrary to what is observed in other parts of the world, the declining monocentricity has not transformed into a polycentric urban structure, rather, urban growth is becoming amorphous. The application of TI-City, the model newly developed by this research, to Accra city-region shows that the model can offer unique insights into the dynamics of urban residential growth in predominantly informal SSA cities. TI-City could, therefore, function as a decision support tool in Ghana and many Sub-Saharan African countries. The research further discusses the implications of the model for theory, urban policy and practice.

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To

My mother, Yaa Adubea (Salamatu Sharif),

For being the great Mum you are.

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List of Acronyms

AB-CA –	Agent-Based-Cellular Automata
ABM –	Agent-based model / Agent-based modelling
ACO –	Ant Colony Optimization
ACR –	Accra City-Region
AHP –	Analytic Hierarchy Process
AI -	Aggregate Index;
ALOS –	Advanced Land Observing Satellite
ANN –	Artificial Neural Network
APS –	Average Patch Size
AREA_MN -	Mean Patch Area;
ASTER –	Advanced Spaceborne Thermal Emissions and Reflections Radiometer
AUC –	Area Under Curve;
AUER –	Annual Urban Expansion Rate
AVNIR-2 –	Advanced Visible Near Infrared Radiometer Type 2
CA –	Cellular Automata
CBD –	Central Business District
CBR –	Case Base Reasoning;
CVCA –	Countervailing Cellular Automata
Diff –	Diffusion
DT –	Decision Tree; FF – Fuzzy Functions
ED –	Edge Density;
ENN_MN -	Mean Euclidean Nearest Neighbour Distance;
ETM –	Enhanced Thematic Mapper
FAR -	Ratio of False Alarms
FoM –	Figure of Merit
FRAC-MN -	Mean Patch Fractal Dimension;
GA –	Genetic Algorithm
GDEM –	Global Digital Elevation Model
GDP –	Gross Domestic Product
GIS –	Geographic Information Systems
GFM –	Gravitational Field Model
GSS –	Ghana Statistical Service
GREDA -	Ghana Real Estate Developers Association
KPCA –	Kernel Principal Component Analysis
LPI –	Large Patch Index;
LSI -	Landscape Shape Index;
LUPMIS –	Land Use Planning and Management Information Systems
LUCC -	Land Use and Land Cover Change
MAPE -	Mean Absolute Percentage Error;
MAR –	Ratio of Missing Warning;
MC –	Markov Chains
MCE –	Multi-Criteria Evaluation
NASA –	National Aeronautics and Space Administration
NDBI –	Normalized Difference Built-up Index
NIR –	Near Infrared
NP –	Number of Patches;
OLI –	Operational Land Imager
PARA_MN -	Mean Parameter Area Ratio;
PCE –	Polynomial Expansion Chaos

PLADJ -	Percent of Like Adjacencies;
PLAND –	Percent of Landscape;
PSO –	Particle Swarm Optimization
RG –	Road Gravity
SA –	Simulated Annealing
SD –	Systems Dynamics
Slp –	Slope
Sprd –	Spread
SSA –	Sub Saharan Africa / Sub Saharan African
SVM –	Support Vector Machine
SWIR –	Shortwave Infrared
TCPD –	Town and Country Planning Department
TM –	Thematic Mapper
UEDI –	Urban Expansion Differentiation Index
UEII –	Urban Expansion Intensity Index
UN –	United Natio

CHAPTER ONE
GENERAL INTRODUCTION AND BACKGROUND

1.1 Introduction

Against a backdrop of rapid urbanization, cities have evolved over the past decades, and so have the methods and techniques for studying them. The objectives of this research are extracted from these two strands of evolution.

The evolution of cities

The second half of the Twentieth century through the Twenty-first century has seen a world that has rapidly urbanized. From being about 70 percent rural in 1930, the world recorded more than five-fold increase in its urban population six decades onwards, accommodating over half of its inhabitants in cities and other urban areas (UN, 2014; Pacione, 2009). Global urban population is further projected to increase by about 2.5 billion by 2050. Sub-Saharan Africa (SSA) has significantly contributed to global urbanization trends in recent decades, but more crucially, the sub-region is expected to play a leading role in future urbanization patterns, at least, in the next three decades. Indeed, the UN, in the 2014 World Urbanization Prospects, projects Africa and Asia to account for about 90 percent of additional urban inhabitants expected by the middle of the century.

Despite the rapidity of Sub-Saharan Africa's urbanization over the past few decades, the majority of its inhabitants still live in rural areas, reinforcing the expectation that the sub-region will dominate future global urbanization trends as there is higher tendency for the phenomenon to continue. This implies that existing large cities in the sub-region are likely to get larger while new cities are formed. Urbanization impacts cities in diverse ways, presenting both opportunities for, and challenges that inhibit growth (El Glaeser, 2011; Baloye and Palamuleni, 2015; Duranto and Puga, 2004; Ravallion et al., 2007; Chen, 2007; Watson, 2009; Eigenbrod et al., 2011). Maximizing the growth opportunities of the ongoing urbanization in Sub-Saharan Africa while ameliorating its negative externalities requires, among others, a thorough contextual understanding of the nature of the phenomenon and the processes that underpin it. However, a thorough review of literature suggests that the sub-region has been peripheral to urban studies, particularly when it comes to modelling and simulation of urban growth dynamics.

A major feature of cities in Sub-Saharan Africa is the highly informal nature of their urbanization (UN-Habitat, 2011; Anokye et al., 2013; Burra, 2004). Unlike in other parts of the world, many cities in the sub-region exhibit overwhelmingly informal characteristics, including the processes of urban growth. Urban growth informality has a spatial dimension, which normally manifests in the form of fragmented and dispersive development patterns (Shuvo and Janssen, 2013), and a planning and regulation dimension, which reflects un-regulated and unplanned nature of growth (Boamah et al., 2012; Lourenço-Lindell, 2004). Many cities in Sub-Saharan Africa manifest both dimensions which present enormous challenges to urban managers and policy makers in the sub-region (Agyemang and Silva, 2019; Korah et al., 2016; UN-Habitat, 2009; Burra, 2004). That notwithstanding, the predominantly informal nature of urban growth in Sub-Saharan African cities is hardly explored in mainstream urban modelling.

As part of their evolution, cities have undergone massive transformation in spatial structure. For many cities in the Global North and several in China and Latin America, the evolution is characterised by a transformation from monocentric urban spatial structure to polycentric patterns (Huang et al, 2017; Liu and Wang, 2016; Aguilar and Hernandez, 2016; Fernandez-Maldonado et al., 2014; Hall and Pain, 2006; Parr, 2004; McMillen and Lester, 2003). Whilst the spatial evolution of cities in the outlined regions have been extensively studied, knowledge about those in Sub-Saharan Africa is extremely limited and peripheral to urban studies. Less is known about whether the evolving spatial structure of Sub-Saharan African cities is explained by mainstream urban spatial structure models or conform to the observed patterns in the Global North. This knowledge gap is significant on its own, but even appears bigger when juxtaposed with the fact that cities in Sub-Saharan Africa are unique in terms of their informal growth and the sub-region in general is also expected to play a lead role in future global urbanization trends.

The evolution of urban modelling approaches

Cities are generally seen as inherently complex as they are characterised by complexity features such as self-organization, emergence, adaptation, chaos, fractal structure and enormous heterogeneity (Batty et al., 2014; Portugali, 2011; Silva et al., 2008; Silva, 2010; Couclelis, 2002; Torrens, 2000; Batty, 1997, 1998, 2007; Batty et al., 1997; White, 1998; White & Engelen 1993). In unravelling the urban complexity, urban modelling approaches have evolved from traditional equation based, statistical, systems and linear approaches (Silva and Wu, 2012; Batty et al., 2012; Wu and Silva, 2010a; Berling-Wolff and Wu, 2004). This evolution is marked by massive progress from an era dominated by aggregate, deterministic, top-down and static models, that mostly treated heterogeneity as noise, to one revolutionized by disaggregate, probabilistic, bottom-up and dynamic models that are increasingly viewed as enhanced ways of abstracting the urban complexity over time and space (Silva, 2012; Wu and Silva, 2010a; Guan et al., 2005; Goldstein et al., 2004; Dietzel and Clarke, 2004a; White and Engelen, 1993).

Cellular Automa (CA) and Agent Based Modelling (ABM) are two major dynamic modelling approaches that have remarkably underpinned many of the new generation of urban models. The two approaches offer modellers unique strengths in abstracting urban systems. CA on the one hand has a huge advantage in modelling spatially explicit phenomenon (Batty, 2012; Portugali, 2011; Wu and Silva, 2010a; Almeida et al., 2003), but it is less powerful in modelling a-spatial dynamics such as behavioural and socio-economic processes, which also form an integral part of urban systems (Zhang et al. 2010; Benenson and Torrens, 2004; Parker et al. 2003). ABM on the other hand presents enormous flexibility in modelling socio-economic and behavioural processes (Chen, 2012; Ettema, et al, 2007) but, unlike CA, is less powerful in abstracting spatial processes (Filatova et al., 2013; Wu and Silva, 2010a, 2010b).

Traditionally, urban modellers employ these two approaches independently (Sethuram, 2008; Silva 2011). However, there has been an increasing recognition in recent decades that independent application of these approaches is insufficient in formalizing the relationship that exist in most urban systems (Shuvo and Janssen, 2013; Wu and Silva, 2009; Parker and Meretsky, 2004; Benenson and Torrens, 2003; Agarwal et al., 2002). Underpinning urban growth, for instance, are complex interactions between socio-economic forces and spatial processes, hence the integration of CA and ABM offers an enhanced platform for developing more powerful urban models. Against this backdrop, there has been a surge in urban growth and land use change models that integrate the two dynamic techniques as reviewed in Chapter two.

The architecture and mechanics, however, of the integrated ABM and CA urban growth models that have been developed so far, hardly accounts for the peculiar urban growth dynamics in many Sub-Saharan African cities. For instance, in most existing models, urban development is undertaken by real estate developers and highly regulated by government, see, for example, Mustafa et al (2017), Tan et al (2015), Dahal and Chow (2014), Jjumba and Dragićević (2012), Wu and Silva (2010), and Li and Liu (2008). In contrast, the overwhelming majority of development in many cities in Sub-Saharan Africa is undertaken by households, normally through self-build techniques (UN-Habitat, 2011; Boamah et al., 2012; Korah et al., 2016; Burra, 2004). Again, the bulk of developments in cities in the sub-region is unplanned and un-regulated (Anokye et al., 2013; UN-Habitat, 2009; Lourenço-Lindell, 2004). For instance, about 70 percent of houses in Ghana are unplanned and built with no authorization from government or an appropriate planning authority (UN-Habitat, 2011). Thus, the aforementioned distinct informal nature of urban growth in many Sub-Saharan African cities, particularly the unregulated dimension, is not captured by existing integrated ABM and CA models.

Generally, dynamic urban models, whether CA, ABM or combination of both, are rarely applied in Sub-Saharan Africa. An extensive review of these models of urban growth and land use change in the subsequent chapter shows how Africa, relative to most parts of the world, is less explored. Policy makers and urban managers in many Sub-Saharan African cities find themselves in extremely difficult position compared to their counterparts in other parts of the world, as they have to, on the one hand, contend with rapid urbanization patterns, while on the other, do not have decision support tools (urban models) that are tailored to the dynamics of their cities.

The above discussion has so far identified three main gaps of interest to this research. These include: the extremely limited application of dynamic CA or ABM models to urban growth in predominantly informal SSA cities; limited knowledge of whether the spatial evolution of SSA cities is explained by existing urban spatial structure models; and non-capturing of peculiar urban growth dynamics of largely informal SSA cities in integrated ABM and CA models.

1.2 Research Objectives and Questions

This research explores the aforementioned gaps by pursuing the following three main objectives.

- Simulate the urban growth of a predominantly informal SSA city with a dynamic CA model;
- Examine the evolving urban spatial structure of SSA cities and the relationship with traditional spatial structure models; and
- Develop an integrated ABM and CA model that account for the peculiar informal dynamics of urban residential development in many SSA cities.

In exploring the objectives, a number of questions are asked. The objectives and their underpinning questions are captured in Table 1.1.

Table 1.1: Research objectives and questions

Objective	Questions
Simulate the urban growth of a largely informal city-region in Sub-Saharan Africa with a dynamic CA model	• Are urban CA models sensitive to predominantly informal urban growth trajectories of SSA cities? • What are the urban planning and policy implications of the informal urban growth trajectories of SSA cities?
Examine the evolving spatial structure of a Sub-Saharan African city-region	• How have SSA cities evolve in spatial structure? • Is the spatial evolution of SSA cities explained by traditional spatial structure models? • What are the urban planning and policy implications of the evolving spatial structure of SSA cities?
Develop an integrated ABM and CA model that simulates urban residential growth of a predominantly informal city-region in SSA.	• How do urban households in SSA cities make location choice decisions? • How can the predominantly un-regulated and unplanned urban growth of SSA cities be modelled with an integrated ABM and CA? • What are the urban planning and policy implications of the integrated AB-CA model of urban growth?

1.3 Summary of methodological approach

Using a case study approach, the research draws on data from two principal regions in Ghana, Accra City-Region and Ashanti Region, to explore the above stated objectives. The rationale behind the selection of these two large and rapidly urbanizing regions is detailed in section 3.2.3 under the methodology chapter. This summarily include their contextual appropriateness, additionality to knowledge, data accessibility. Other subjective reasons such as the author's knowledge of the context and established networks also played a role in selecting the cases.

In exploring the first objective, SLEUTH, the most popular dynamic urban CA model is applied to Accra city-region. The grounds for selecting this model are articulated under section 3.4. Geospatial datasets acquired through classification of LandSat 8 imagery and also from various institutional sources, refer to section 3.6, are used for calibrating the model. A combination of qualitative data from literature and expert validation through key stakeholder consultations are used to validate the calibrated results from SLEUTH.

The second objective is pursued through a combined application of SLEUTH and spatial metrics to the urban spatial structure transformation of the Ashanti Region. The evolving structure is analysed in both administrative district units and bands representing various distances from the Central Business District. Spatially explicit datasets of urban extents and transport networks, accessed through diverse institutions, were used in the analysis.

The third, also the last objective, of the research is executed by using ABM and CA to develop an urban residential growth model based on geospatial and socio-economic datasets from Accra City-Region. The model, built in NetLogo modelling platform, uses bounded rationality, perceived utility maximizing and heuristics to regulate the behaviour of actors responsible for urban development. The behaviour regulation is also anchored on an analysis of households' location choice decisions, which was derived through survey. A combination of visual analysis, comparison of model results with that of SLEUTH calibration for the same area, and opinions of local experts are used to validate the output of model, which is named as "*The Informal City (TI-City) model".*

1.4 Contribution and Innovation of Research

This research is innovative in many ways and makes diverse contribution to knowledge, policy and practice. While the innovation runs through the analytical chapters, only the key ones are outlined below.

First, this research has developed and introduced the "The Informal City (TI-City) model", a new urban residential growth model. The innovativeness of this model fundamentally stems from its capacity to model the micro dynamics of un-regulated and unplanned urban developments in predominantly informal Sub-Saharan African cities. In modelling these peculiar dynamics of informal urban growth, the newly developed model also accounts for the spatio-economic dimensions of the phenomenon. As evident in its application to Accra (see Chapter 7), TI-City's modelling of informal urban residential development is spatially explicit and includes economic, i.e. income characteristics. Thus, not only does TI-City simulate where growth, informal and formal, would occur, but also the income attributes of households that will occupy newly developed areas. So far, TI-City, is the only urban growth model that dynamically simulates the socio-economic and geospatial processes of predominantly informal urban residential development.

Again, the research has offered, by developing TI-City model, a unique methodological approach for modelling predominantly informal cities. The model also stands to offer valuable support to policy makers and urban planners in largely informal cities in Sub-Saharan Africa. The model could, as demonstrated in later parts of Chapter 7, serve as decision support tool, as it can be used to explore different policy interventions.

The research also facilitates unique theoretical insights into the evolution of the spatial structure of SSA city-region and its relationship with traditional spatial structure models. By applying a combination of spatial metrics and dynamic CA model, this research, in Chapter 5, introduces a new approach to studying the evolving spatial structure of SSA cities. The same chapter discusses the exclusive urban planning and policy implications of the massive transformation in the spatial structure of a SSA city.

Furthermore, this research presents, in Chapters 4 and 7, the first dynamic simulation of any Ghanaian city, and in the process, offers exclusive insights in the dynamics of urban growth in the West African country. Despite that Ghana has been a major player in urbanization patterns in SSA, none of its principal cities, regions, city-regions or other settlements has been dynamically modelled or simulated in relation in urban growth.

1.5 Structure of Dissertation

The dissertation is organized into eight chapters. Chapter Two sets the theoretical framework based on extensive review of literature. Among others, the review encapsulates the evolution of urban modelling approaches; foundation of CA and ABM; modifications to urban CA modelling, overview of post 2010 urban CA models; strengths and weaknesses of urban CA modelling; overview of agent-based models of urban growth and land use change; strengths and weaknesses of agent-based models; overview of integrated Agent-Based and Cellular Automata models; the complexity of agent-based-cellular-automata models; location choice factors in agent-based-cellular-automata models of urban growth and land use change; and geographical application of CA, ABM, and integrated agent-based-cellular-automata models.

Chapter Three lays out the methodological framework of the research, by detailing the methods, techniques, datasets and sources employed in answering the research questions. Chapter Four explores the first objective and its related questions, as it simulates urban growth in Accra city-region with an urban CA model and examines the sensitivity of the model to the spatial dimension of informal dynamics in the city-region. The chapter also dissects urban policy implications of the simulated growth.

Chapter Five is devoted to the second objective and its associated questions. This Chapter analyses the evolution of the spatial structure of the Ashanti region of Ghana, used as the case study, and its relationship with mainstream urban spatial models. The urban planning and policy implications of the evolving spatial structure are also discussed in the chapter.

The location choice decisions of urban households in Accra city-region is explored in Chapter Six. This chapter provides critical information required for pursuing the third objective. Chapter Seven directly explores the third objective by developing an urban residential growth model capable of simulating both the spatial and unregulated dimensions of urban development informality in many SSA cities. The research is concluded in Chapter 8, which summarizes the findings, policy and future research implications of the study.

CHAPTER TWO

OVERVIEW OF CELLULAR AUTOMATA, AGENT-BASED, AND INTEGRATED AGENT-BASED-CELLULAR AUTOMATA MODELS OF URBAN GROWTH AND LAND USE CHANGE

2.1 Chapter Introduction

This chapter sets out the theoretical foundations of the research. Themes explored in the chapter include but not limited to: the evolution of urban modelling approaches; foundation of CA and ABM; Cellular Automata in urban modelling; modification to CA urban Modelling; modifications to urban CA, post 2010 review; Strengths and Weaknesses of CA in Urban Modelling*;* Multi-Agent Systems in Urban Modelling; overview of ABM models of land use change; strengths and weaknesses of ABM; integrated Agent-Based and Cellular Automata models; the Complexity of Agent-based-cellular models; location choice factors in agent-based-cellular models of land use change; and geographical application of CA, ABM, and integrated agent-based-cellular-automata models.

2.2 Evolution of Urban Modelling Approaches

Over the years, urban modelling has co-evolved with computing power and technology (Crooks et al., 2007; Dietzel and Clarke, 2007; Dietzel and Clarke, 2004b; Agarwal et al., 2002; Herold et al., 2001; Wegener, 1994). The antecedent of urban/geographical modelling and simulation could be traced to Alan Turing's ideas on the digital computer which he earlier conceived in the 1930s (Turing, 1936) and further developed in 1950 (Turing 1950). Turing's idea which also forms the roots of contemporary artificial intelligence was part of an effort to decode the German enigma code for the World War II (Torrens, 2012). In the 1950s and 60s, the first generation of computational models arrived. Often underpinned by mathematical equations and the theory of gravity, large scale urban modelling, predominantly capturing global processes, dominated the scenes during this generation (Lee, 1994; Berling-Wolff and Wu, 2004; Batty, 2012). Lowry's model of residential location (1964) which integrates equations of spatial interactions within a generic framework of demography and economics is a classic example. Wilson's works on urban systems, land use location and interaction in the 1960s and 70s, for instance, see Wilson (1967), Wilson and Macgill (1979), further illustrates how mathematical formulations contributed to urban modelling in the early decades of post

WWII. A major limitation of the equation based urban models was that they were mainly deterministic and static, often assuming urban systems existed in some state of equilibrium (White & Engelen 1993; Ettema et al., 2007; Silva and Wu, 2012). The land use and transport dominant computational models were initially perceived as vitals tools for guiding urban policy in a period where urban planning was interpreted as a rationally comprehensive activity (Wegener, 1995; Harris 1965).

Rarely were these models operational and the few that were applied exhibited abysmal performances, showing signs of possible abandonment in the 1960s (Berling-Wolff and Wu, 2004). In the 1970s, the large-scale urban models eventually collapsed as Lee's criticisms proved fatal not only for modelling but planning in general (Harris, 1994). In 1973, Lee argued that existing large-scale urban models lacked strong theoretical background and were too coarse, mechanical, expensive and data hungry. These criticisms awakened the senses of urban modellers over a possibly looming future. The demise of the first generation gave birth to a second and subsequent number of generations that have evolved afterwards. Silva and Wu (2012) identifies four subsequent generations: a second, driven by sector specific focus largely transport, and based on non-linear programming technique but also deterministic in nature; a third, which embraces the advancement in computing and data availability to engineer scientific and technocratic sector solutions comprehensible by only equally advanced and expert users; a fourth, which has a wider appeal relative to the third but lacking in knowledge transfer; and a fifth which presents an integrated artificial intelligence system of models with guides that facilitates easy comprehension by non-expert users. CA and ABM are part of the fifth generation (Wu and Silva, 2010b). Heppenstall et al (2012) to outline the evolution of ABMs in addition to articulating their conceptual and theoretical framework. Berling-Wolff and Wu (2004) chronicles the evolution of urban modelling.

2.3 Foundation of CA and ABM

The historical roots of CA and ABM cannot be fully traced without reference to complex systems theory, which emanated from physics and later spread to the social sciences. Crucial to the understanding of complexity is John von Newmann and Oskar Morgenstern (1944) theory of games and economic behaviour which among others, placed emphasis on stochasticity, indeterminism and discrete behavioural nature of systems (Silva and Clarke, 2005), the very characteristics CA and ABM best represent. Physical geography and its related disciplines dominated the early application of complex theory. Batty and Longley's demonstration of cities as fractal entities in 1994 accelerated a wider application of complexity theory in human geography, especially urban systems. Subsequently, a number of studies, including Portugali (2011), Silva (2010), Batty (2007), and Torrens (2000), have depicted various forms of complex behaviour exhibited by cities. Indeed, the general acceptance of urban systems as intrinsically complex opened up the exploration of modelling techniques that better represent the complexity, subsequent to which CA and ABM have emerged.

That said, it is important to point out that, despite the multiplicity of research on complex systems (Casti, 2002; Silva and Clarke, 2005; Batty, 2005, 2007), there is no agreement as to its exact definition (Auyang 1998; Ziemelis and Allen 2001; Batty et al., 2014). That notwithstanding, there appear to be a wider consensus across diverse fields on the principles of emergence, chaos, self-organisation, criticality, adaptation, and irreducibility as features of complexity (Casti, 2002; Couclelis, 2002; Cheng et al., 2003; Silva and Wu, 2012; Batty, 2012). Holland (1998) advanced that the main defining feature of complex systems is emergence, a concept criticised for its subjectivity. Clarke (2018), discusses three aggregate phases of dynamic systems, a key concept of complexity theory. These include: chaos, a stage where no discernible pattern is observable; stability, a phase where a system's relationships are linear, and the overall behaviour of the system is predictable with differential equations; and complexity, which is characterised by a spatio-temporal manifestation of both chaos and stability.

2.4 Cellular Automata in Urban Modelling

A number of contributions have spearheaded the development of CA, including but not limited to: Von Newmann's (1966) exploration of self-reproducing systems, influenced by the work of Ulam (1952; 1961); John Conway's game of life popularised by Gardner (1970) which demonstrated the emergent properties of CA by mimicking human life; Waldo Tobler (1979) introduction of CA in Geography; behavioural characterisation of CA (Wolfram, 1984, 2002); understanding of stochastic properties of automata Kaufmann (1984); Couclelis (1985, 1988, 1989) formalization of the conceptual relationship between CA and complex systems theory; Itamy (1988) integration of CA with Geographic Information System (GIS); Phipps (1989) examination of the communication between cells impacts spatial configuration; development of generic modelling language for CA (Takyeama, 1996; Couclels, 1996); conceptual and theoretical justification(Batty and Longley 1994, Batty and Xie 1994); development of empirical and operational models (Clarke and Gaydos, 1998; White, 1991; White and Engelen, 1994; Silva and Clarke, 2002; Cecchini and Viola, 1990, 1992; Engelen et al., 1997; Portugali and Benenson, 1995, 1997; Clarke et al., 1997; Wu and Webster 1998; Batty et al., 1999; Wu, 1998; Yeh & Li, 1998; Meaille & Wald, 1990); and integration with other urban modelling techniques (Silva et al., 2008; He et al., 2006; Wu and Silva, 2010b; Wang et al., 2007; Li and Liu, 2007; Dahal and Chow, 2014).

2.5 Modification to CA urban modelling

A traditional urban CA is composed of 5 main elements (Liu, 2009; Sudhira et al, 2005; Silva, 2011; Batty et al., 1997): cells, which is used for spatial representation of objects, for instance land parcels; state, which presents a defined attribute or set of conditions of an object, for example, whether a parcel is developed or not, or the type of development – residential, commercial, industrial, open space, etc; neighbourhood, which defines an area within which a cell/parcel influences or is influenced by other cells/parcels; transition rules; which encapsulate the mechanisms or rules that govern the change behaviour of a system; and time. The initial concepts of a conventional CA model were marked by: a regular lattice spatial representation; Moore's 3*3 or Newman's 2*2 neighbourhood size; transition rules largely defined with Logistic Regression models; and mostly, no consideration of global variables that constrain local interactions. However, down the years, as urban CA intensified, the approach has significantly evolved from its initial concepts. Some of the evolution is also attributable to advancement in computational efficiency and technology in general.

Since 2000, a number of studies, for instance, see (Gonzalez et al., 2015; Crooks, 2010; Moreno et al., 2009; Stevens and Dragićević 2007, Stevens et al. 2007), have used irregular polygons to represent spatial objects. Indeed, this is seen as progress, as real-world objects hardly conform to regular structure. Indeed, the popularity of regular lattice structure of CA is more to do with computational efficiency than accurate depiction of geographical objects. Similarly, neighbourhoods considered in CA models have been significantly increased. An example is the work by White (1998), which defines the neighbourhood of a cell to incorporate about 100 surrounding cells.

Furthermore, the transition functions have evolved in several ways, notably: from simple Boolean rules (Couclelis, 1985) to one that captures system-wide dynamic processes including spontaneous and uncoordinated growth (Clarke et al., 1997; Wu, 1996); from spatio-temporally static rules to one that embrace variations in relation to time and space as in the case of SLEUTH model (Clarke et al., 1997); from simple rules that are classically tied to the state of a cell and those within a specified neighbourhood to more complex rules which integrate other factors such as geographical and ecological conditions, accessibility/proximity to urban infrastructural facilities and services, for example railways, roads, etc (Al-Ahmadi et al., 2009; He et al., 2008; Liu et al., 2008; Yang et al., 2008; Li and Yeh, 2004).

Again, several optimization techniques geared at improving the efficiency of CA model calibration have been added. Unlike previously where the calibration of CA models was largely based on heuristics (Wu, 2002), a number of studies (Almeida et al., 2008; Guan and Wang 2005; Pijanowski et al., 2005; Li and Yeh, 2001, 2002; Yeh and Li, 2003) have applied Artificial Neural Network techniques to the calibration of CA for exploring urban systems. Multiple studies (Liu et al., 2014; Clarke-Lauer and Clarke, 2011; Shan *et al.,* 2008; Goldstein, 2004) have also introduced Genetic Algorithm to optimize the calibration of CA models. Also, away from its earlier conceptions where global actions are constrained (Theobald and Gross, 1994), some CA models for example, countervailing cellular automata (CVCA) model by Silva et al (2008), SLEUTH by Clarke et al (1997) make provision for distant actions and global impacts. These evolutionary changes and many others, see, for instance, Wu and Silva, (2010a), have enhanced the attractiveness of CA to many urban and geographical modellers. Sante et al. (2010), reviewed urban CA models. In their work, CA has evolved from its classic conditions in 8 different ways, as summarised below:

- Irregular spatial representation / cell space;
- Non-homogeneous spatial representation, encapsulating variations in cells attributes;
- Expanded neighbourhood;
- Variable neighbourhood;
- Non-linear transition rules;
- Variable transition rules;

- Limits of expansion; and
- Variable time steps

2.6 Modifications to urban CA, post 2010 review

Since Sante et al's (2010) review, dozens of urban CA models have been developed. This section presents a review of these models, capturing not only the modifications to CA's initial conceptions, but also the techniques employed in their development and application. Whilst there are hundreds of studies that involve urban CA since 2010, those included in the review are the ones that modify part(s) of the traditional elements of the approach. This criterion produced 50 models, details of which are presented in table 2.1. The models are largely used to model and simulate urban growth patterns and land use change dynamics. The majority are developed as generic models, but then are applied empirically, normally as a form of model validation – a process discussed in later parts of the section. Despite the attempts at making the models transferrable across diverse geographical areas, most of the generic models are yet to be applied beyond the case studies used either in their development or validation. Several of the models are also developed solely as empirical models, while a few are generic without any empirical application.

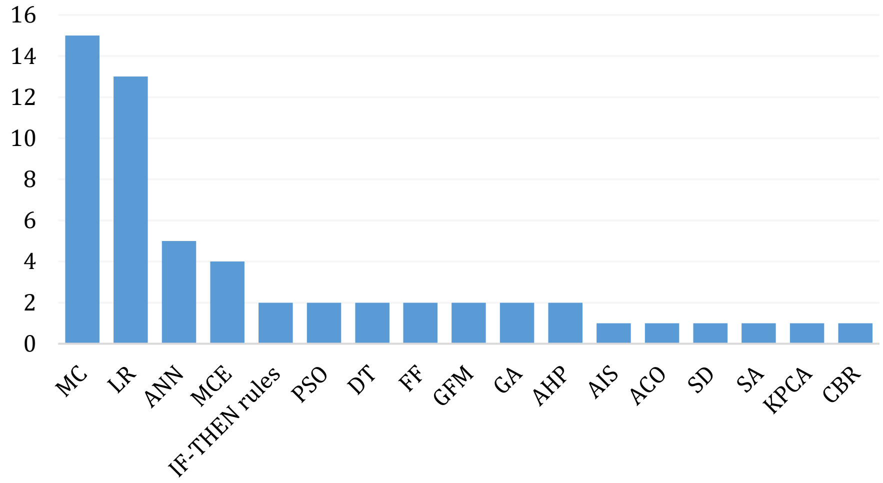
An overwhelming majority of the models are structured on the traditional regular grid lattice, despite the wide acceptance that geographical objects are largely irregular. Also, considering the increasing research on computational efficiency techniques, such as parallel processing (Zhang et al, 2010; Blecic et al, 2013; Blecic et al, 2015; Guan et al, 2016), that considerably improves the previously challenging processing speed of vector files (irregular polygons), it would not have been peripheral to expect a higher usage of irregular cells. A few of the models (Pinto & Antunes, 2010; Ballestores Jr and Qiu, 2012; Barreira-González et al, 2015; Dahal and Chow, 2015) are based on irregular cell space.

The treatment of neighbourhood in the models has been quite traditional, as most employ Moore's 3 * 3 technique (see for example, Liu et al, 2010; Chen et al, 2013; Cao et al, 2014; Yao et al, 2016), and in some cases, for instance, as in Huang et al, 2014, it is expanded to include more cells. That stated, some of the models also make use of different techniques, such as usage of enrichment factor (Liao et al, 2016), distance decay concept (Lauf et al, 2012; Liao et al, 2014; Barreira-González et al, 2015), spatial buffering (Ballestores-Jr and Qiu, 2012), circular neighbourhood (Santé et al, 2013), and variable neighbourhood (Pinto & Antunes, 2010). Dahal and Chow (2015) used 9 neighbourhood types - Adjacency, Extended Adjacency, Restricted topological, Boundary proximity, Centroid proximity, Boundary intercepted buffer, Centroid intercepted buffer, Boundary extent-wide, Centroid extent wide – in an irregular urban CA model.

2.6.1 Transition Rules; techniques applied

The desire to improve the performance of urban CA models has occasioned the application of wide-ranging techniques in the development of transition rules. Figure 2.1 presents these diverse techniques and the frequency of their application. It is important to note that, in most models, two or more different techniques are applied. The variations in techniques combinations are later discussed. About 17 techniques have been applied in the models. Among them are Machine Learning (ML) approaches, such as Artificial Neural Networks and Support Vector Machines (SVM), which have gained popularity as part of increasing application of Artificial Intelligence (AI). These approaches are viewed as an improvement in capturing more complex processes. However, they are also criticized for their complex structure and black box nature (especially ANN). Other techniques, including Analytic Hierarchy Process (AHP), Decision Tree (DT), and Fuzzy Functions (FF) have also been applied to the development of complex rules. Among the techniques, Markov Chains (MC), largely used to generate transition probability maps, has seen the highest application, even more than the traditional Logistic Regression (LR) mechanism. Some optimization techniques, including Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) have also been applied to transition rules.

Figure 2.1: Techniques used in the development of transition rules



MC – Markov Chains; ANN – Artificial Neural Network; MCE – Multi-Criteria Evaluation; PSO – Particle Swarm Optimization; DT – Decision Tree; FF – Fuzzy Functions; GFM – Gravitational Field Model; GA – Genetic Algorithm; AHP – Analytic Hierarchy Process; ACO – Ant Colony Optimization; SD – Systems Dynamics; SA – Simulated Annealing; KPCA – Kernel Principal Component Analysis; CBR – Case Base Reasoning; SVM – Support Vector Machine

2.6.2 Transition rules; combination of techniques

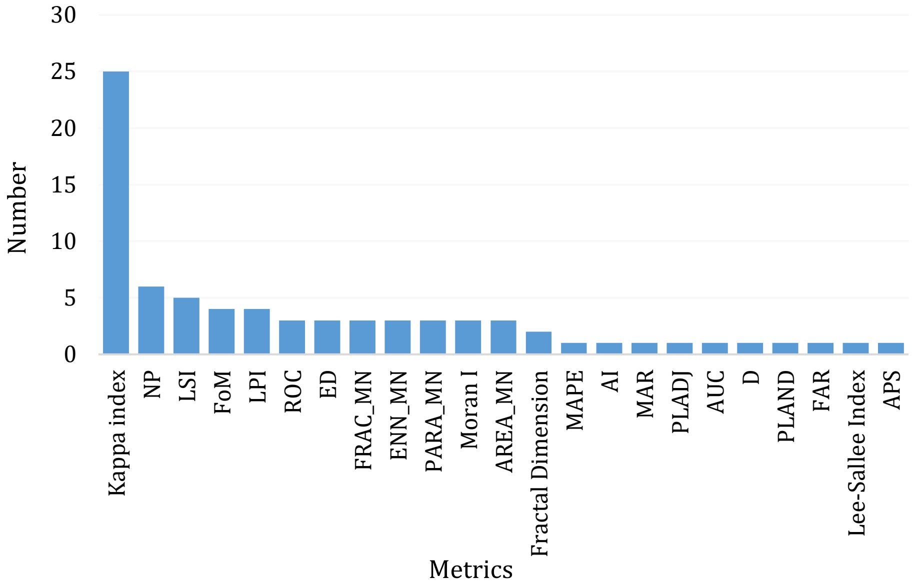
In line with the increasing recognition of the complexity of the systems for which urban CA models are developed, authors hardly rely on singular techniques in the development of transition rules. It is often the case that different techniques are combined, generally with the aim of compensating inherent weaknesses associated with independent application of techniques. About 15 combinations are identified, with the most popular being the joint application of Markov Chains and Multi-Criteria Evaluation techniques. The multi-criteria that is combined with Markov Chains normally includes Analytic Hierarchy Process and fuzzy membership techniques (Mitsova et al, 2011; Moghadam and Helbich, 2013; Vaz and Arsanjani, 2015, Aburas et al, 2017). In the MC-MCE combination, MC is used to generate, quantitatively, the probability of one category, mostly land use type, transitioning to another, while MCE, for instance AHP, is used to integrate and weight various development factors (Arsanjani et al, 2011; Chowdhury and Maithani).

Other combinations include: the usage of LR to weight the influence of spatial and socio-economic variables, while transition probabilities are extracted with Markov Chains (Huang et al, 2014; Liu et al, 2015); Fuzzy Set Theory and Artificial Neural Network, where the latter is used to capture spatio-temporal complexities associated with development forces, while the former is applied to uncertainties (Azari et al, 2016); weighting of factors with LR and integration of urban flows with Gravitational Field Model (Lin and Li, 2015); the use of LR to determine urbanization probability, and Particle Swarm Optimization to derive the best combination and weighting of spatial variables (Rabbani et al, 2012); the quantification of development probability with LR, and optimization of parameters with Simulated Annealing algorithm (Feng and Liu, 2013); the weighting of spatial variables with logistic regression and parameter optimization with Ant Colony (Li et al, 2011); decision tree, used to weight contributions of development factors, and MC, which is applied to extraction of transition probabilities (Al-sharif and Pradhan, 2015); and the usage of landscape expansion index (LEI) to differentiate urban growth types, while case-based-reasoning (CBR) is used to derive variant rules (Liu et al, 2014).

2.6.3 Validation of urban CA models

Validation is one of the most crucial phases of model development. For urban CA models to serve their overarching purpose of informing urban planning and policy decisions, their developers as well as users (for instance urban planners and policy makers) need to be convinced of their accuracy and reliability. In model validation, the question faced by researchers is: does the model do what it intends to do? The predominant approach to answering this question has involved comparison of simulated or modelled output with an actual map. The output that is compared with actual data is mostly derived from modelling or simulation of historical maps and data. The major differences among the models, however, stems from the metrics and indices used as basis for comparing the simulated with the actual. Figure 2.2 captures the wide range of spatial metrics, more than 20, applied to model validation. More than half of the models employ Cohen's Kappa Index (K), generally as part of preparation of confusion matrix. The Kappa coefficient which computes the proportional error reduction attributed to the model in question relative to errors that would arise from a random prediction. The Kappa Index has known limitations, which include: lack of details on location errors, for instance, when a simulated land use type differs from the actual; and quantification errors, an example is when the simulated number of cells/parcels for a given land use does not conform to the number observed in the actual map. In response to these limitations, many studies (for example, Subedi et al., 2013; Ballestores Jr and Qiu, 2012; Rienow and Goetzke, 2015), in addition to Kappa coefficient, also calculate $K_{location}$, which accounts for location errors, and $K_{quantity}$, which considers quantification errors. Metrics, such as fractal dimension, landscape shape index, edge density, aggregation index, number of patches, large patch index, mean euclidean nearest neighbour distance, and mean parameter area ration (Guan et al., 2011, Li et al., 2013; Chen et al., 2013; Santé et al., 2013; Lin et al., 2014) with spatial pattern orientation, have also been used in several models.

Figure 2.2 Metrics used in validation of urban CA models



NP – Number of Patches; LSI - Landscape Shape Index; FoM – Figure of Merit; LPI – Large Patch Index; ED – Edge Density; FRAC-MN - Mean Patch Fractal Dimension; ENN_MN - Mean Euclidean Nearest Neighbour Distance; PARA_MN - Mean Parameter Area Ratio; AREA_MN - Mean Patch Area; MAPE - Mean Absolute Percentage Error; AI - Aggregate Index; MAR – Ratio of Missing Warning; PLADJ - Percent of Like Adjacencies; AUC – Area Under Curve; PLAND – Percent of Landscape; FAR - Ratio of False Alarms; APS – Average Patch Size

Table 2.1: Urban CA modifications; summary of post 2010 review

Author	Phenomenon	Model Type	Cell Type	Neighbourhood	Cell Transition	Calibration	Validation
Pinto & Antunes (2010)	Land use change modelling	Generic with Empirical application	Irregular	Variable circular neighbourhood	Statistical weighting of land use suitability, accessibility and neighbourhood effect	Based on PS algorithm that optimised a modified kappa index	None
Wu et al (2010)	Urban growth simulation	Empirical model	Regular	3 * 3	Based on Regression and ANN technique	Based on ANN	Comparison of simulated map with real map using fuzzy kappa index
Liu et al (2010)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Based on Artificial Immune System (AIS) technique, incorporating planning interventions	Based on AIS	Comparison of simulated output with an actual map using visual inspection and confusion matrix
Guan et al (2011)	Land use change simulation	Empirical model	Regular	3 * 3	Based on MC transition probability matrix and hysteresis rule.	Uses AHP to weight the local importance of indicators	Compares simulated map with actual map using GIS and spatial metrics such as Shape Index and fractal dimension,
Mitsova et al (2011)	Urban growth simulation	Empirical model	Regular	5 * 5	Based on MC transition matrix and MCE that involves fuzzy membership functions	Based on MC and MCE	Pixel by pixel comparison of simulated map with actual using Kappa index
Wang et al (2011)	Factors Selection; land use change	Empirical model	Regular	Radius of 3, 5 and 15 cells from centre cell	Based on "IF-THEN" rules	Based on Rough Set Theory (implemented in Rosetta) involving random sampling approach and GA	Comparison of simulated historical map with actual one using Kappa coefficient
Sang et al (2011)	Land use patterns simulation	Empirical model	Regular	5*5	Combination of MC transition probability matrix and CA	MC is used to extract observed land use transition probabilities, which serves as basis for future quantitative forecast	None

Li et al (2011)	Zoning optimization	Generic with Empirical application	Regular	5*5	Combination of Ant Colony Optimization (ACO) and LR	Based on LR weighting of spatial variables	Cell-by-cell comparison of simulated historical map with actual map. Also, using a utility function, the performance of ACO-CA is compared with that of simulated anealing (SA), iterative relaxation (IR), and density slicing (DS)
Arsanjani et al (2011)	land use change simulation	Empirical model	Regular	3*3, 5*5, 7*7	MCE function integrating MC transition probability matrix and CA conditions	Compares different contiguity filters and hundreds of iterations using Kappa index (location and quantity). Simulated maps are compared with real maps	None
Liu (2012)	Urban growth simulation	Generic with Empirical application	Regular	3*3	Combination of primary rules, which is based on cells sensing their states and that of their neighbours; and secondary rules based on environmental and institutional factors	Assessment of simulated urban accuracy against actual using modified error matrix approach	None
Rabbani et al (2012)	Urban growth simulation	Generic with Empirical application	Regular	11 * 11 Incorporates rasterized vector objects	PSO is used to search for best combination of spatial variable weights; and LR is used to determine cell urbanization probability	Based on PSO technique	Comparison of simulated historical image with actual one using Kappa coefficients
Ballestores Jr and Qiu (2012)	Land use change simulation	Empirical model	Irregular	145 m buffer around the edges of a parcel	Based on Decision Tree (DT) algorithm (J48 classifier)	DT analysis of historical land use changes	Comparison of simulated historical map with actual using confusion matrix, Cohen's kappa coefficient (location and quantity)

Lauf et al (2012)	land use change modelling	Empirical model/generic	Regular	Distance decay concept	Based on System Dynamics (SD) modelling of macro variables, and weighting of spatial variables with Metronamica CA	Based on Differential equations weightings, Optical interpretations, cell and land use transitions analysis	Comparison of integrated SD-CA model, termed with a null model using actual map using kappa coefficients and MAPE
Arsanjani (2013)	Land use simulation	Empirical model	Regular	3 * 3	Based on Markov Chain Probability Matrix	Cross comparison of actual and simulated land use maps	Model is evaluated based on (ROC) values for various variable sets
Wang et al (2013)	Urban Growth simulation	Generic with Empirical application	Regular	Ring neighbourhood with radius = 4	Product of cloud model development probability (two and multi-dimensional), neighbourhood and global factors	Testing of different Hyper-entropy (He) values. Historical modelled urban land is compared with observed using Kappa index	Compares simulated map with actual map using kappa, khisto, kloc and FoM metrics. Also compares Cloud-CA model with Fuzzy-CA and Fuzzy-set-and-monte-carlo-CA models
Feng and Liu (2013)	Land use change modelling	Theoretical with empirical application	Regular	3 * 3	Based on LR weighting of spatial proximity factors, neighbourhood effects, and physical constraints, and Simulated Annealing algorithm.	LR is used to initialize model parameters. Resultant simulated land use is compared with actual land use. Mismatches and disagreements between the maps are reduced with an SA algorithm, which is constructed on MC. Upon trial and error experiments, the SA generates parameters that optimizes the accuracy of the CA model.	Compares SA-CA model with logCA model and a null model using error matrix and error budget indices
Li et al (2013)	Urban growth simulation	Theoretical with empirical application	Regular	unspecified	Based on LR weighting of development forces, and a GA fitness function that incorporates landscape pattern indices.	Based GA fitness function that integrates landscape indicators, percentage of landscape (PLAND), patch metric (LPI) and landscape division (D).	Compares pattern-calibrated GA-CA model with LogCA, and Cell-calibrated GA-CA using landscape metrics, LSI, ED, Aggregation Index (AI), PLAND, LPI and D.

Chen et al (2013)	Urban growth simulation	Generic with Empirical application	Regular	5 configurations (3*3, 5*5, 7*7, 9*9, 11*11)	Based on LR weighting of spatial proximity factors, density of neighbourhood development, and development constraints.	Four-step calibration process: i) estimation of new patch size using power function; ii) LR weighting of spatial factors; iii) sensitivity analysis based on different neighbourhood configurations; and iv) different combinations of dispersion parameters are examined in a trial-and-error approach.	Cell by cell, pattern and fractal comparison of simulated map with actual map using landscape metrics (FoM, NP, LPI, ENN_MN, PARA_MN)
Moghadam and Helbich (2013)	Urban growth simulation	Empirical model	Regular	5 * 5	Based on MCE, comprising of AHP and fuzzy functions, and MC	Comparison of simulated historical map with actual using Kappa index	Comparison of simulated historical map with actual based on Kappa index
He et al (2013)	Modelling of urban landscape dynamics	Empirical model	Regular	3 * 3	Based on Linear regression models, Gravitational Field Model (GFM) - for urban flows - and local neighbourhood factors	Based on Adaptive Monte Carlo Approach	Comparison of simulated historical map with actual using kappa index and Moran I.
Chen et al (2013)	Land cover patterns simulation	Empirical model	Regular	3 * 3	Combination of MC transition probability matrix and neighbourhood conditional probability	MC is used to extract a matrix of observed land use transition probabilities, which serves as basis for future quantitative forecast	Comparison of simulated historical map with actual based on error matrix and kappa coefficient
Feng & Liu (2013)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Kernel Principal Component Analysis (KPCA) technique is used to construct non-linear rules	Based on KPCA analysis of historical data; and trial-and-error operations	Compares KPCA-CA model with a PCA-CA model using Kappa coefficients, producer, user and overall accuracy indexes.

Al-sharif & Pradhan (2013)	Land use change simulation	Empirical model	Regular	5*5	Combination of MC transition probability matrix and CA conditions	Comparison of simulated results from multiple iterations and several neighbourhood filters with actual historical map using Kappa statistical indices.	Comparison of simulated historical map with an actual map using Kappa statistical indices.
Subedi et al (2013)	land use change simulation	Empirical model	Regular	5*5	Combination of MC transition probability matrix and CA conditions	MC extraction of land use transition probability matrix	Comparison of simulated historical map with an actual map using kappa statistical indices ($K_{standard}$, K_{no}, $K_{locality}$).
Santé et al (2013)	Urban growth simulation	Generic with Empirical application	Regular	Circular with radius = 3 cells	Combination of weighted spatial variables with LR	Combination of statistical techniques (for parameter reduction) and GA (for automation of calibration process)	Cell-by-cell comparison of simulated historical map with an actual map using spatial metrics (NP, AREA_MN, ED).
Li et al (2013)	Prediction of illegal development	Empirical model	Regular	unspecified	Integration of ANN and LR	Combination of LR and ANN	Compares integrated CA-ANN model with CA and ANN models using indicators such as MAR (ratio of missing warnings), FAR (ratio of false alarms).
Basse et al (2014)	Land use changes simulation	Generic with Empirical application	Regular	3 * 3	Based on ANN Multi-Layer Perceptron (MLP) with a standard back-propagation learning algorithm	Learning through iterative training and testing of datasets	Compares simulated map with real map using confusion matrix
Liu et al (2014)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Based on integration of Landscape Expansion Index (LEI) and Cased Based Reasoning approach	Unspecified	Simulated patterns from LEI-CA model is compared with actual patterns using confusion matrix, which is computed based on cell-on-cell spatial overlay. LEI-CA model performance is compared with a Logistic CA model.

Liao et al (2014)	Urban expansion simulation	Theoretical with empirical application	Regular	Based on Distance decay. Neighbourhood radius range: 1 - 24 pixels	Based on Neighbourhood Decay (ND), LR weighting of spatial factors, and development constraints.	The cumulative difference between simulated output and sample data is computed. PSO automatically searches for parameter combinations that optimizes transition rules.	Compares simulated map with an actual map using confusion matrix, kappa coefficient, and error budget metrics. PSO-NDCA model results is also compared with that of PSO-CA model.
Lin et al (2014)	Vertical Growth simulation	Empirical model	Regular	10 m radius circular area	Based on "IF-THEN" rules and linguistic variables, guided by the Burgess's concentric zone model	Based on heuristics	Comparison of simulated historical map with actual one based on error matrix (overall accuracy and Kappa index) and fractal dimension
Chowdhury and Maithani (2014)	Urban growth simulation	Empirical model	Regular	Circular, 2*2, 5*5, and 7*7	Based on MC transition matrix; and MCE technique, involving AHP, used to weight and combine economic, topographical, accessibility and urban infrastructure factors.	Based on MCE	Compares simulated historical map with actual one using spatial metrics (FRAC-MN, LSI), and Percentage of Like Adjacencies (PLADJ)
Huang et al (2014)	Land use change simulation	Generic with Empirical application	Regular	Expanded Moore	Combination of MC transition probability matrix and LR weighting of global and local restriction conditions	Unspecified	Comparison of simulated historical map with actual, measuring simulation accuracy and errors
Cao et al (2014)	CA calibration / rural-urban land conversion	Generic with Empirical application	Regular	3 * 3	Based on LR function, optimized with Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)	Based Pareto front-based heuristic search algorithm (NSGA-II)	Compares NSGA-II calibrated model with LR Generic GA calibrated model, and NOE-based GGA calibration approach, using simulation precision, maximum likelihood estimation (MLE), and number of errors (NOE) indexes

Rienow and Goetzke (2015)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Uses Support Vector Machine (SVM), which are based on geophysical, proximity, socioeconomic and demographic variable, to prepare exclusion layer and urban probabilities.	Combines SVM with SLEUTH's brute force calibration technique	Uses metrics such as Area Under Curve (AUC), Kappa, Kloc, Khisto to assess the accuracy of model results
Lin and Li (2015)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Based on LR weighting of spatial proximity variables; intercity urban flow factors weighted with GFM; neighbourhood influence; and geographical constraints	Uses LR to determine the weight of spatial variables, while GFM is used to weight urban flow factors.	Compares CA-weighted-urban-flow model with CA-flow and Log-CA model using FoM and Proportion of urban land change to total.
Barreira-González et al (2015)	Urban growth simulation	Generic with Empirical application	Vector/ Irregular parcells	500 m buffer around a parcel. Distance decay functions to capture effect	Sum product of neighborhood, accessibility, suitability and zoning status	Not specified	None
Feng et al (2015)	Urban growth simulation	Generic with Empirical application	Regular	5*5	non-linear rules based on least squares support vector machines (LS-SVM)	Comparison of different iteration results of LS-SVM-CA with a NULL model, using cell-by-cell (confusion matrix) technique.	Comparison of simulated historical maps by LS-SVM-CA model and log-CA model with an actual map. Performance assessment is based on visual inspection, misses, false alarms, correct rejections, and error budget (quantity errors, allocation errors).

Al-sharif & Pradhan (2015)	Urban growth simulation	Empirical model	Regular	Not specified	Based on combination of Chi-square automatic integration detection decision tree (CHAID-DT), MC transition probability matrix, and CA conditions	Assessment of weights/contributions of urban growth factors with CHAID-DT; and extraction of transition probability with MC	Comparison of simulated map by the integrated CHAID-DT-MC-CA model with an actual map using receiver operating characteristics, and kappa index
Dahal and Chow (2015)	Urban growth simulation	Descriptive	Irregular	Adjacency, Extended Adjacency, Restricted topological, Boundary proximity, Centroid proximity, Boundary intercepted buffer, Centroid intercepted buffer, Boundary extent-wide, Centroid extent wide	Based on LR weighting of spatial variables	LR is used to weight the influence of development factors	Comparison of simulated results from different neighbourhood types with an actual map using metrics such as kappa index, number of patches, average patch size, Lee-Sallee index, Moran's Global I.
Li et al (2015)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Based on LR uncertainty maps; classification and regression tree (CART), and ANN integrated with k-nearest neighbour (k-NN)	Combination of LR and self-adaptive k-NN algorithm	Compares: combined algorithms with single models; and different combination strategies, using ROC metric. Ensemble-CA is compared with Log-CA using Kappa, OA, FoM, NP, LPI, AREA_MN, PARA_MN, ENN_MN, FRAC_AM, and LSI

Vaz and Arsanjani (2015)	Urban growth simulation	Empirical model	Regular	3 * 3	Function involving MC transition probabilities, weights evaluated with MCE (AHP), and neighbourhood influence	Combination of MC, MCE, and text mining	Comparison of simulated land use map with actual, using kappa index
Liu et al (2015)	Urban growth simulation	Empirical model	Regular	5*5	Combination of MC transition probabilities and Auto-LR weighting of spatial variables	Combination of MC and ALR techniques	Comparison of simulated historical map with actual, using kappa index
Chen et al (2016)	Urban growth simulation	Generic with Empirical application	Regular	3 * 3	Uses Cox Regression Model to calculate the development potential of non-urban cells. Uses partial likelihood method to weight factors.	Survival analysis based on censored land use data	Compares simulated values with observed values using landscape metrics (Number of urban patches, Largest-patch Index, mean Euclidean nearest-neighbour distance, mean perimeter-area ratio). Also compares with two other CA models
Liao et al (2016)	Land use change modelling	Empirical model	Regular	Enrichment factor is used to quantify the extent and effect of large neighbourhoods (up to 46 cells radius)	Based on binary logistic weighting of spatial factors and large neighbourhood effects	Compares Log-CA and large neighbourhood log-CA using confusion matrix (calculated overall accuracy and kappa coefficients)	Compares Log-CA and large neighbourhood log-CA using confusion matrix (calculated overall accuracy and kappa coefficients). Comparison reference is an actual map not used in the model development
Azari et al (2016)	Urban growth simulation	Generic with Empirical application	Regular	7*7	ANN, fuzzy set theory, and LR	Based on ANN and fuzzy rules; and testing of different neighbourhood sizes using kappa coefficient.	Simulated maps by CA-ANN-Fuzzy, Log-CA, CA-ANN models are compared with an actual map, using Kappa coefficient

Yao et al (2016)	Urban growth simulation	Empirical model	Regular	3 * 3	Based on PSO and LR technique	PSO algorithm, LR model, heuristics, trials and tests	Comparison of simulations from PSO-CA and LOGIT-CA with actual land use maps, using Kappa index, Moran I, NP, ED, LSI, AREA_MN, FRAC_AM
Aburas et al (2017)	Urban growth simulation	Generic with Empirical application	Regular	5 * 5	Based on combination of MC transition matrix, AHP (for weighting economic, environmental, utility, physical factors); and MC-Frequency Ratio (FR)	Based on MC, AHP; and MC-FR	Comparison of simulated historical image with actual one using ROC and Kappa indexes
Feng (2017)	Land use change simulation	Generic with Empirical application	Regular	5*5	Based on Generalized Pattern Search (GPS) that incorporates Genetic Algorithms	GPS optimization algorithm is used to derive weights of spatial variables and eliminate spatial autocorrelation effects.	Comparison of simulated historical maps by GPS-CA, LR-CA, and NULL models with an observed map using cell-by-cell comparison technique, involving hits, correct rejections, misses and false alarms.

AHP – Analytic Hierarchy Process; LR – Logistic Regression; Log-CA – Logistic Cellular Automata; MC – Markov Chains; MCE – Multi-criteria evaluation;
PS – Particle Swarm; PSO – Particle Swarm Optimization; ROC – Relative Operating Characteristics; SA – Simulated Annealing.

2.7 Strengths and Weaknesses of CA in Urban Modelling

CA has unique qualities which have been proven over the years. Wolfram's 1994 characterization of CA presents all but a few of its strengths encapsulating: clarity in the correspondence between physical and computational processes; simplicity which triggers complexity; ease of computation with absolute precision; possible replication of any physical system and the irreducibility of CA models.

In addition, and perhaps the most popular, is the capability of CA to: model spatio-temporal dynamic processes (Silva et al, 2008; Wu, 1998a; Batty et al., 1997; Openshaw & Openshaw, 1997; Xie, 1996; Wagner, 1995; White and Engelen, 1993) spatially integrate geographical objects and remote sensing data (Portugali, 2011; Piyathamrongchai and Batty 2007; Silva and Clarke, 2005; Batty et al.,1999; Wagner, 1997; Itami, 1994); adapt to changes in rules and integrate with other modelling techniques (Wu and Silva, 2009; Batty, 2007; Sudhira et al, 2005; Manson, 2005; Wagner, 1995); and be visualized (Berling-Wolff and Wu, 2004; White 1997). What appears to be the wider consensus within modelling environment of the advantage of CA over other dynamic models for instance ABM, is the ability to effectively model spatially explicit phenomena (Batty, 2012; Portugali, 2011; Wu and Silva, 2010a; Almeida et al., 2003; Goldstein et al., 2004; Dietzel and Clarke, 2004a; White 1997; Wagner, 1995; White and Engelen, 1993).

There is a similar understanding that CA, relative to some of the dynamic modelling approaches, is less effective in spatially modelling the behavioural and socio-economic decisions which underlay urban systems (Dahal and Chow, 2014; Zhang et al. 2010; Wu and Silva, 2010b; Torrens and Benenson, 2005; Benenson and Torrens, 2004; Parker et al. 2003, 2002). That notwithstanding, CA models continue to offer promising theoretical and empirical insights in addition to informing and shaping policies. As a result, CA has been applied to wide range of urban and environmental issues encompassing but not limited to modelling and simulation of: urban growth (morphology, White and Engelen, 1993; Clarke and Gaydos, 1998; Syphard et al. 2004; Silva and Clarke, 2005; Stanilov and Batty, 2011); land use and land cover changes (Buckley, 1994; Wu, 2002; Dietzel and Clarke, 2004; Tsang and Leung, 2011); migration (Portugali, 1995; Sembolini, 1997); landscape dynamics (Theobald and Gross, 1994; Ervin, 1994); and ecological phenomena (Couclelis; 1998; Green et al., 1990; Silvertown et al., 1992).

2.8 Agent Based Modelling/Multi-Agent Systems in Urban Modelling

Like CA, agent-based models and multi-agent systems trace their origins from complexity science and the works of Von Neumann, Ulam and Conway in the 1950s through the 70s (Clarke, 2018). As a class of computational modelling, agent-based models are primarily set up to model: the behaviour, actions and interactions of individual or collective autonomous agents; and explore how is a system is influenced by agents or their behaviour. ABM is premised on the understanding that systems are composed of autonomous, mobile and heterogeneous actors who interact through time and space, hence an abstraction of their actions, behaviour and decision-making processes could facilitate understanding of the system (Filatova et al 2013; Walsh et al. 2013; Crooks et al., 2007; Matthews et al, 2005; Parker, 2003).

Structurally, a traditional ABM model is composed of four main elements: defined autonomous agents that operate various set scales; an environment, within which agents act, that is influenced by and influences agents; decision-making rules; and procedure for action and interactions (Clarke, 2018). Similar to CA models, ABM also engages the principle of global order emerging from micro/local level interactions among agents and their environment (Torrens and Nara 2007; Holland, 1992). However, despite that CA models and ABMs share several commonalities, there are notable differences between the two. For instance, while CA models are generally concerned with the emergence of macro structure from local interactions and transition rules, ABMs are largely focused on understanding how agent's characteristics, type of behaviour or form of interactions affect an entire system.

Agents in multi-agent systems (MAS) are characterised by set of attributes, including: self-regulation and independence in terms of control over their actions and internal state; ability to set and pursue goals; interaction with other agents within a wider social network; and response and adaptation to their environment (Sudhira et al, 2005; Parker and Meretsky, 2004; Ligtenberg, 2004; Mohamed, 2000; Oliveira, 1999; Green et al., 1997; Ferrand, 1996; Franklin and Graeser, 1996). Agents have been employed in models to represent diverse entities encompassing but not limited to humans, institutions, animals and bio-cells (Agarwal et al., 2002; Janssen and Jager 2000; Conte et al., 1997; Epstein and Axtell 1996).

The development and application of ABMs have become popular in social science and other disciplines over the past decade. While their popularity seems nascent, the application of ABM in social science could be traced as far back as the 1970s to the residential segregation models of Thomas Schelling (1971) and Sakoda (1971). It should, however, be stated that these models were not computational. That notwithstanding, the works demonstrated how global order could emerge from the interactions between autonomous agents and their environment. Subsequent works, such as, the exploration of cooperative strategies through prisoners' dilemma (Axelrod and Dion, 1988), and simulation of social life (Epstein and Axtell, 1996) are among the key early applications of ABM in social sciences.

2.9 Overview of ABM models of land use change

Since taking off in the 1970s and 1980s, hundreds of ABM computational models have emerged, with the rate of development and application considerably increasing over the past decade. In land use change applications alone, dozens of ABMs have been developed. This section presents an overview of 39 ABM computational models of land use change, outlining and summarizing their key characteristics, including phenomenon of investigation, type of model, type of data used, modelling platform, spatial representation, decision-making agents, behavioural regulation, calibration, validation, geographical application and extent of complexity. Figures 2.3 and 2.4, summarise the key characteristics of the models.

Also, in line with the research objectives, the review is presented in two groups based on integration or non-integration of CA. The first group, captured with Table 2.2 and made up of 26 models, refer to ABMs that are not integrated with CA, while the second group, constituted by 13 models captured in table 2.3, integrates CA and ABM. The determination of whether an ABM integrates CA is not straightforward, considering that almost all land use change ABMs have some element of cellular space. For this research, the presence of neighbourhood of interaction within a cellular space is used as the distinguishing factor. Thus, if a model has cellular space but no spatial interaction within a neighbourhood, the model is presented in table 2.2. It should, however, be emphasized the classification only apply to the presentations in the two tables and not the summaries captured by the figures. Below are the summaries of the identifiable characteristics of the models.

2.9.1 Data Sources

A key feature of ABMs and, indeed, the new generation of dynamic urban models is their data intensiveness. Technological advancement, particularly in the field remote sensing, has made available, high resolution spatially explicit datasets that were previously non-existent. Satellite imageries form an important part of the datasets used by about 44 percent of ABMs of land use change. The United States Geological Survey's Landsat images have been particularly dominant in this regard. Beyond remote sensing, technological advancements have produced a new wave of computational efficiency that enable the faster processing of large data. Stemming from this, researchers have been presented with the capacity of combining traditional urban dataset with that of remote sensing. Indeed, conventional data sources, such as census, empirical surveys, cadastral maps, local plans, etc are still useful in the development and application of ABMs. Census and empirical survey data form part of the datasets of about 41 and 36 percent of the models respectively.

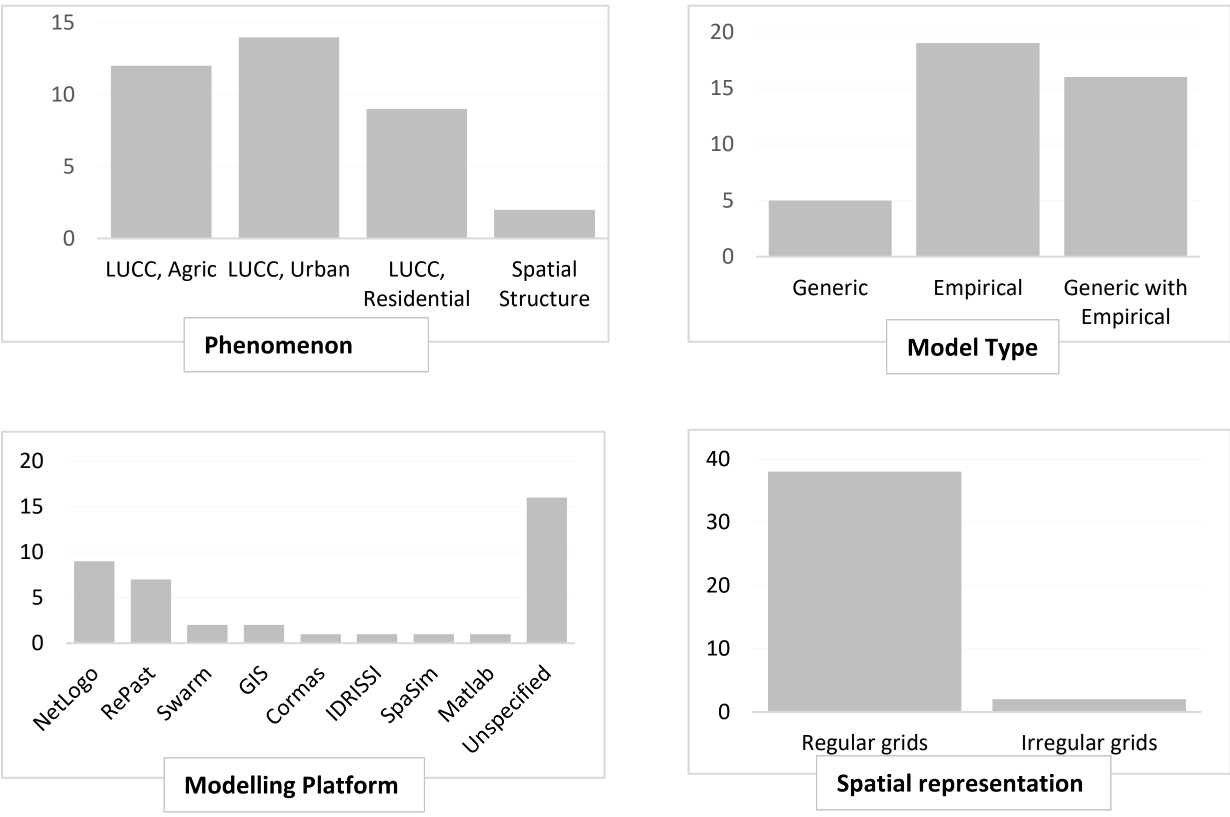
2.9.2 Phenomena of investigation

The land use change phenomenon for which the models are developed and applied are categorised into four groups: one, models focus on urban land use changes; two, models with agricultural land use change focus; three, models primarily concerned with residential/housing changes; and, four, models concerned with spatial structure. More than half of the models are either developed for or applied to urban or agricultural land use changes. Quite a significant number of the models (9) are solely applied to residential aspects of urban life, a while a few (2) are used to explore spatial structure of cities and regions. Loibl and Toetzer (2003) simulation of polycentric development in the Vienna region of Austria is one of few applications of ABM to spatial structure.

2.9.3 Model Type

There is no one way of classifying models, especially ABMs with many defining features. Parker et al.'s (2002) framework for categorising ABMs of land use and land cover change (LUCC) has been adapted for the classification in this research. Their framework includes grouping of ABMs on a continuum that ranges from deductive to inductive, or from theoretical to empirical. In this research, the models are classified into 3 groups, namely, Generic, empirical, and Generic with empirical application. Similar to Parker et al (2002), the definition of theoretical models encapsulates models that are developed largely on deductive reasoning, with generalizable results, i.e. valid beyond a particular case study, whereas empirical models are based on inductive reasoning, with validity of application being case-specific. The third group identifies the theoretical models that are applied to real world case(s). As depicted in Figure 2.3, close to half (19) of the models are empirical; two are generic without empirical application; and the remaining 16 are generic with empirical application. The last group, accounting for 40 percent of the models, underscores the capacity of agent-based modelling in integrating deductive and inductive methodologies, a feature which is seen as a unique strength of the approach (Bithell et al., 2008).

Figure 2.3: Characteristics of ABMs; phenomenon, typology, platform, and spatial representation



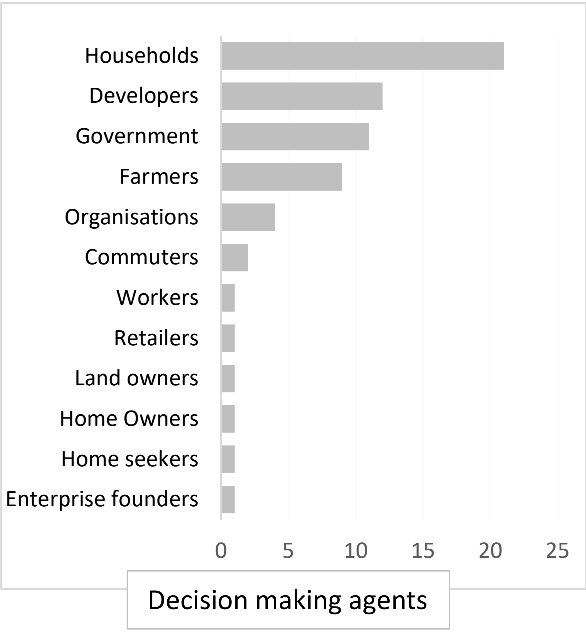
2.9.4 Modelling Platform

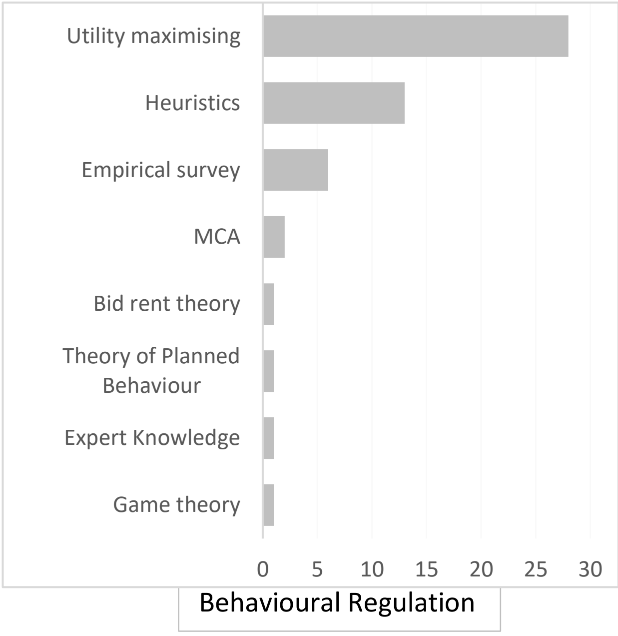
The very nature of ABMs requires a platform that is capable of modelling agents' behavioural actions, interactions and emergent phenomenon. Two of such platforms, NetLogo and Recursive Porous Agent Simulation Toolkit (Repast), have dominated the development of ABMs. Indeed, out of 24 models that specified their modelling platform, two-thirds (16) were developed on the two platforms, with NetLogo being slightly more popular than Repast. Both are open source software and free to access. Their implementation in Java is another common feature. Swarm, an open source software written in Java, has also been employed in the development of ABMs. GIS platforms, such as IDRISI, ArcGIS, QGIS, have also been applied to the development of ABMs. Mostly, the GIS software are used to analyse the spatial dimensions of ABMs, after which results are exported to agent compatible platforms for agents' procedures to be developed.

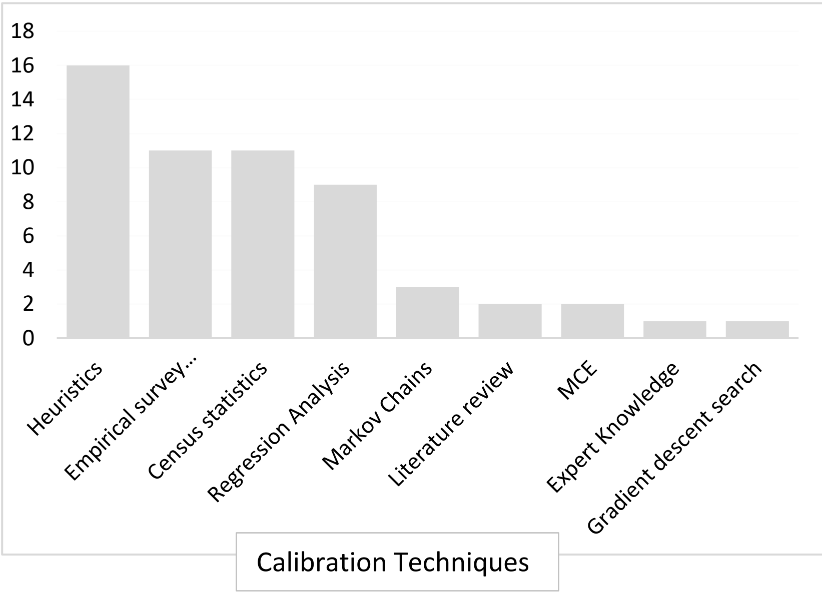
2.9.5 Decision Making Agents

Decision making agents form a key component of urban ABMs, as they are responsible for change in a system. Figure 2.4 partly captures the wide range of actors that have been modelled. The number of decision-making agents employed in a singular model vary from 1 (Deadman et al., 2004) to 8 (Dahal and Chow, 2014), with 3 being the average. The household, used in broad terms in this context to include residents, is the most popular unit of analysis and simulated entity in many of the models. More than half of the models, households are either the main or part of the decision-making agents. The popularity of the household unit is not only restricted to urban ABMs, but also manifests in agriculture-based ABMs. Depending on the objective of the study, households are further classified into distinct sub-groups, normally along the lines of socio-economic and demographic characteristics, including income, age, family size, etc. Developers and government are also frequently modelled as decision making actors. Indeed, many ABMs, especially those that simulates urban growth, have a tripartite structure in terms of decision making, mostly consisting of households, developers and government, see for example (Liu et al., 2006; Li and Liu, 2008; Wu and Silva, 2010). Farmers are also the major decision-making actors of many models, particularly those with agricultural component, for instance, see (Mustafa et al., 2017; Castella et al., 2005; Le et al., 2008). As with households, many studies differentiate farmers based on several characteristics, such as farm size, type of crop grown, etc. Institutions are also major actors of decision making in several models. Other decision-making agents simulated by the various models include, among others, workers, commuters, retailers, enterprise founders, landowners, home owners, and home seekers.

Figure 2.4: Characteristics of ABMs; decision making agents, behaviour regulation and calibration techniques







2.9.6 Behaviour regulation

Understanding the behaviour of decision-making agents is a vital part of ABMs of land use change, and the complexity that characterises human behaviour makes this task daunting. It is therefore not particularly striking that about a quarter (24.52 percent) of models use heuristics to govern the behaviour of decision-making actors. In improving the robustness of models, authors have embraced a number of approaches, some of which are theory driven, whilst others are based on empirical data as captured in Figure 2.4. Urban economics and social behavioural theories have proven quite useful to many modellers. Rationality, bounded rationality, bid rent, theory of planned behaviour, and game theory are examples of socio-economic behavioural theories that have been applied by various models. Indeed, rationality theory, typically captured with utility maximizing functions, is applied in more than half (52.8 percent) of the models, making it the most popular. A fifth of these models apply bounded rationality theory variation, which is normally expressed with random utility functions to overcome some of the weaknesses of rationality theory, such as unrealistic assumption of perfect information. Models also notably regulate the behaviour of agents through an analysis of survey and census data. This approach is especially popular with empirical ABMs.

In most cases, these approaches and others captured in Figure 2.4 are independently insufficient to deal with the complexity that engulfs the behaviour of decision-making agents. As a result, overwhelming majority of studies apply, at least, two approaches to govern the behaviour of agents. The combined application of utility maximizing functions, theory of planning behaviour and genetic algorithm by Wu and Silva (2010) to model urban growth; and the usage of bounded rationality, logistic regression and heuristics by Murray-Rust et al (2013) to model land use dynamic and quality of residential life are few examples. Tables 2.2 and 2.3 have more details of various combinations.

2.9.7 Calibrating ABMs

Model calibration, a mechanism for adapting the model parameters to a specific geographical area, is one of the most crucial aspects of model development. Indeed, the usefulness of a model's output to a case study is largely related to the effectiveness of the calibration process. Calibrating ABMs of land use change is particularly difficult in various ways. First, there is problem of scarcity with regard to the presence of transferrable land use change ABMs. Unlike urban CA, which has several models that have been proven to be geographically transferrable, for example SLEUTH, there are few ABMs with similar records of transferability. Indeed, as pointed earlier, the majority of ABMs are empirical. Thus, calibrating an existing ABM for a case study other than the one used in its development is quite challenging. The transferability challenges associated with ABMs partly stem from the absence of generic calibration methods, as the formulation and parameterization of most empirical models are largely improvised. ABMs tend to have so many parameters making their calibration particularly challenging, as, for instance, issues like high degree of freedom emerge. Searching for best fit spatio-temporal values for human behaviour and socio-cultural systems is quite complicated. Crooks and Heppenstall (2012 p94) captures it this way: *"…many if not most agent-based models suffer from a lack of uniqueness in parameter estimation due to the fact that their assumptions and processes tend to outweigh the data available for a complete assessment of their goodness-of-fit."* There has, however, been notable progress in the calibration of ABMs in recent decades. The use of Genetic Algorithm (GA) to optimize the search for best fit values is gaining popularity in ABMs (Ngo and See, 2012).

Following the above, the use of heuristics, with no proven optimality, has emerged as the most popular ABM calibrating technique as depicted in Figure 2.4. In addition, qualitative approaches, such as, the use of empirical survey, census statistics, expert knowledge and literature review have been deployed in calibrating ABMs. Regression analysis, Markov Chains and gradient descent search are among the few quantitative techniques that have been applied.

2.9.8 Validating agent-based models

Validation is an important stage in model development and application. The accuracy of models is normally measured at this stage. However about 40 percent of the models reviewed are either not validated or do not have such information provided. This finding depicts the challenges that engulfs the validation of ABMs of land use change. There is no consensus on a desirable method of validating ABMs. While the stochastic nature of the models is seen as a strength, see for example Crooks and Heppenstall (2012), it also presents major challenges during validation processes. Heppenstall et al (2012) outline the challenges associated with the validation of ABMs. Some scholars also contend that stemming from their nature, the validation of ABMs should not necessarily follow the methods adopted by other dynamic urban models, such as CA. The validity of ABMs, as argued by these scholars and many others, should go beyond quantification, location and pattern accuracy, which is normally the preoccupation of many dynamic models especially CA models, to encapsulate structural and logical accuracy. Thus, whether the behavioural rules and relationships of an agent-based model makes logical sense is a critical component in assessing the model's validity. A difficulty that arises is that there is no standard method for measuring the internal logical accuracy of models, opening the subject to multiple and, sometimes, non-quantifiable treatments.

Following this measurement difficulty, the validation process of ABMs is still dominated by statistical and spatial metrics that examine quantity, location and pattern accuracies as captured by Tables 2.2 and 2.3. However, the use of qualitative techniques, such as visual assessment of simulated outputs (Loibl and Toetzer, 2003; Huigen et al., 2006; Zhao and Peng, 2007), validation based on opinions of experts (Valbuena et al, 2010), and comparison of simulated output with historical knowledge (Moreno et al., 2007) are also getting popular.

Table 2.2: Summary of review of Agent-based models of land use change

Author(s)	Purpose	Model Type	Modelling Platform	Agent Categories	Spatial/environment Representation	Behaviour Regulation / Analysis technique	Calibration	Validation
Loibl and Toetzer, 2003	Simulation of polycentric development	Empirical		Households (Higher, medium and lower income categories), Weekend-home seekers, enterprise founders	Regular grid 100m	Regression analysis, heuristics; and rationality	Analysis of socio-economic data, heuristics	Visual comparison of simulated output with observed output,
Deadman et al, 2004	Simulation of land use behaviour of farming households	Empirical	REPAST	Household agents	Regular grids (1 ha)	Heuristics	Heuristics and regression equations	Compares simulated land use percentages and standard deviations from LUCITA model with those observed by other studies
Huigen, 2004	Models land use and demographic dynamics (applied to migration and deforestation)	Generic with Empirical application	Mameluke Framework (Extention of Repast)	Heterogeneous actors that is user defined	Regular grids (100m2)	Heuristics	Heuristics, census statistics, and survey	Unspecified
Brown et al, 2004	Evaluate effectiveness of greenbelts	Generic	Swarm	Residents, Service centres	Regular grids	Heuristics, and utility maximizing among randomly selected locations	Heuristics	Examines agreement between results of ABM with that of a mathematical model

Ligtenberg et al, 2004	Models multi-actor decision making	Generic with Empirical application	REPAST	Multi-generic actors. Case study actors: regional authorities, farmers organization and environmentalists' organisation.	Regular grids	Decision theory, intentional model composed of desires, beliefs, values and preferences	Heuristics	None
Castella et al, 2005	land use change simulation	Empirical	Cormas	Farm households, institutions	Regular grids	Participatory survey, role playing game, and heuristics	Participatory survey, role playing game, heuristics	Compares simulated map with observed based on quantity of cells in a land use category
Huigen et al, 2006	Modelling of settling decisions and behaviour	Empirical	Mameluke Framework (Extention of Repast)	Collective household actors; Individual household actors	Regular grids (1 ha)	Heuristics	Heuristics, census statistics, and ethnographic survey results	Visual analysis of simulated output
Brown and Robinson, 2006	Models the effects of residential preference heterogeneity on urban sprawl ABM model	Generic	Swarm	Residents	Regular grids	Maximization of utility among randomly selected locations. Uses Cobb Douglas utility function	Analysis of survey, heuristics	Unspecified
Liu et al, 2006	land use change simulation	Generic with Empirical application	Unspecified	Residents, Developers, Government	Regular grid (100m)	Heuristics, random utility maximizing, Monte Carlo model	Heuristics, analysis of census data, entropy model	Cell-by-cell, and aggregate comparison (Moran I) between simulated image and real-world map.
Yin and Muller, 2007	Simulation of household decision making	Empirical	REPAST	Commuters and Second Homeowners	Regular grids	Heuristics involving development of ranking system based on simple prioritization approach	Heuristics	Compares simulated output with real world observations using visual inspections and metrics, including neighbourhood density, standard

								deviation, RMSE, range, and variance
Evans & Kelley, 2008	Analysis of forest regrowth processes	Empirical		Households	Regular grids	Maximization of expected utility	Gradient descent search, and parameter filling	Calculation of residuals of simulated predictions
Le et al, 2008	Simulation of spatio-temporal dynamics of landscape system (Agric and Ecology)	Generic	NetLogo	Farm Households (3 groups)	Regular grid	Bounded rationality, utility, maximization (modelled with spatial multi-nominal logistic functions) and heuristics		
Bakker and Doorn, 2009	Modelling of land use change (Agric)	Empirical		Farmers (Active, innovative, absentee, old)	Regular grid, 10*10m	Logistic regression	None	None
Valbuena et al	Model land use change at regional scale	Generic with Empirical application	NetLogo	hobby, conventional, diversifier, expansionist-conventional and expansionist-diversifier	Regular Grids	Assignment of probabilities based on expert knowledge, and analysis of survey data	Analysis of cadastral, survey and census data, heuristics	None

Fontaine and Rounsevell, 2009	Simulation of future housing demand	Empirical	NetLogo	Households (singles and couples, all families, all retired)	Regular grids (250*250m)	qualitative analysis, and heuristics	Qualitative and statistical analysis, testing of all combinations of parameter values, heuristics,	Compares results from parameter combinations with observed data using correlation coefficient, statistical analysis of histogram shape, and visual inspections
Bravo et al, 2010	Modelling of Integrated land use and transport interaction	Generic	MATLAB	Households, Individual travellers	Transport network	Logit & entropy models	Heuristics	None
Valbuena et al, 2010	Landscape structure	Empirical	NetLogo	Hobby, conventional, diversifier, expansionist conventional, and expansionist diversifier farmers	Regular grid 1 hectare	Heuristics	Empirical methods including analysis of sample surveys, census data and spatial data	Expert validation (interviews with 5 experts)
Le et al, 2010	Simulation of spatio-temporal dynamics of landscape system (Agric and Ecology)	Empirical	NetLogo	Farm Households	Regular grids	Bounded rationality, utility, maximization (modelled with spatial multi-nominal logistic functions) and heuristics	Analysis of sample data	Empirical validation of sub-models; evaluation of model structure; and behavioural testing. Techniques used include, Standard inferential statistics based on household survey; uncertainty analysis based on computation of mean values of performance indicators of multiple simulations

Valbuena et al, 2010b	Analyse effects of voluntary mechanisms on land use change	Empirical		Crop farm agents, mixed agents large mixed farm agents, and large farm agents	Regular grid	Assignment of probabilities based on empirical data	Analysis of historical data	None
Mialhe et al, 2012	Simulation of Land use patterns	Generic with Empirical application	NetLogo	Farmers (rational, collective minded, boundedly rational), investors	Regular grids	Random functions, heuristics, field survey analysis,	Scenarios testing	Compares simulated output with actual land use patterns using confusion matrix and Cohen's Kappa index
Robinson et al, 2012	Modelling impacts of land system dynamics on human well-being:	Empirical		Residential households, residential developers, non-residential developers	Regular grid	Utility theory, Logistic regression	Computational experiments, LR	None
Murray-Rust et al, 2013	Modelling land use dynamics and residential life quality	Empirical		Residential households, residential developers, non-residential developers	Regular grid	Bounded rationality, LR and heuristics	Multiple regression analysis, computational experiments and heuristics	Compares alternative scenarios with 'business as usual' scenario
Ralha et al, 2013	Simulation of land use change	Generic with empirical application		GRID Manager, Spatial Manager, Transformer Manager, Cell Agent, Transformer Agent (farmers and ranchers)	Regular grid			Compares simulated map with observed map using figure of merit
Arsanjani et al, 2013	Simulation of urban growth patterns	Empirical	Unspecified	Residents, Developers, Government	Regular grids (30m2)	Multi-criteria analysis (MCA) of qualitative survey	MC model and statistical extrapolation	Compares simulated output with actual urban development map using Kappa Index

Tsai et al, 2015	Simulation of land use patterns (Agric)	Generic with empirical application		Agric land owners (Farmers)	Regular grid, 30m	Heuristics, Utility (perceived expected) maximization	Extraction of observed land use transition probabilities with MC; Monte Carlo experiments for uncertainty analysis	Measures the goodness-of-fit between simulated and observed output using Nash–Sutcliffe efficiency index (NSEI)
Li et al, 2018	Residential land growth simulation	Generic with Empirical application		Households, Developers	Regular grid, 50m	Extended reinforced learning algorithm; land utility function,	Theoretical review; RL results	Categorization of predicted output into perfect, close or poor match

2.10 Strengths and Weaknesses of ABM

Similar to CA, ABM has unique advantages which have attracted growing interest in their application. Among others, ABM presents: a platform for integrating human behaviour and decision making into space (Silva, 2011; Wu and Silva, 2010a; Tian et al. 2011; Ligtenberg et al. 2009; Matthews et al. 2007); an avenue for formalizing the interactive relationship among mobile agents and also between agents and their environment (Chen, 2012; Parker et al, 2003); flexibility in capturing heterogeneity through the incorporation of multiple varying actors across multiple scales (Wu and Silva, 2010b; Ettema, et al, 2007; Ligtenberg et al, 2004; Berger et al, 2002); flexibility for incorporating advanced behavioural theories (Ettema, et al, 2007; Berger et al, 2002); an enhanced abstraction of natural systems (Parker and Meresky, 2004; Bonabeau, 2002); and a platform for theory validation and extension (Axelrod and Tesfatsion, 2010).

However, like others, the approach has its own challenges that include: less effectiveness in capturing spatial processes (Filatova et al 2013; Wu and Silva, 2010a, 2010b); complexity (Batty et al., 2012); and high data demand (Ettema et al, 2007). Notwithstanding the challenges, ABM is fast gaining grounds and dominating territories in social science (Janssen, 2005; Batty, 2003; Benenson, 1999; Benenson 1998; Epstein and Axtell, 1996; Epstein and Axtell, 1996), environmental studies (Krzysztof et al., 2005; Kreft et al., 1998) and economics (Filatova et al 2010; Filatova, 2008; Tesfatsion, 2006), among others. The approach has also found widespread expression in many urban studies (Zhang et al, 2015; Arsanjani et al., 2013; Jjumba and Dragićević, 2012; Xie and Fan 2012; Patel et al., 2012*,* Augustijn-Beckers et al., 2011; Benenson et al., 2007; Ligmann and Jankowski, 2007; Milner-Gulland *et al*., 2006) in recent years.

2.11 Integrated Agent-Based and Cellular Automata Models

Traditionally, most models developed in urban, environmental and economic studies examine human behaviour and biophysical phenomenon as separate and distinct variables (Sethuram, 2008; Silva 2011). However, it is increasingly becoming clear across multiple disciplines that, urban systems and processes are embedded with interactive and symbiotic relationships between and among socio-economic and environmental parameters, hence the conventional dichotomization of the two is deemed highly insufficient in the understanding and representation of urban systems (Shuvo and

Janssen, 2013; Wu and Silva, 2009; Wu and Silva, 2010a; Parker and Meretsky, 2004; Benenson and Torrens, 2003; Agarwal et al., 2002). Thus, as dynamic as the new generation of dynamic modelling techniques are, independently, they do not sufficiently capture the dynamism and complexity of the urban system. With ABM's capacity for effectively modelling aspatial - socio-economic – processes (Silva, 2011; Wu and Silva, 2010a; Tian et al. 2011; Ligtenberg et al. 2009; Matthews et al. 2007; Bonabeau, 2002) and CA's strength for representing spatially explicit phenomenon (Batty, 2012; Wu and Silva, 2010a; Almeida et al., 2003; Goldstein et al., 2004; Dietzel and Clarke, 2004a), an integration of the two approaches appears promising in facilitating an enhanced insight into the representation of many systems across multiple disciplines (Li and Liu 2007; Parker, 2005; Parker et al, 2002; Silva, 2011; Silva and Wu, 2010b). The integration has the capacity to mutually reinforce the strengths and overcome the inherent weaknesses of each of the approaches (Nara and Torrens, 2005; Parker et al, 2003).

Silva (2011) pointed out that the future of dynamic modelling partly lies in the full integration of spatial and a-spatial oriented techniques. Not only in urban studies is the integration of spatial and a-spatial dynamics seen as the future to understanding complexity but also in environmental and ecological studies where combination of social-economic and biophysical factors appears to offer more promising solutions (Matthews et al, 2005; Agarwal et al., 2002). Indeed, over the past decade, studies in diverse disciplines have sort to formalize the relationship between a-spatial and spatial processes through an integration of ABM and CA. For instance, in environmental studies, Moreno et al (2007) integrated agents with CA to explore the bio-complexity of deforestation. In urban studies, systems – be it land use change, urban growth, transport, etc – are seen as a product of complex and intricate web of relationships between socio-economic and biophysical factors.

A number of urban studies have contributed to the ABM-CA integration. Nara and Torrens (2005) combined CA and multi-agent systems for simulating inner city gentrification. The authors used CA to build the environmental framework whilst MAS was used to model the decision making of residents and their mobility. Torrens and Nara (2006) again developed a hybridized model which constituted of CA and agents for the testing of hypothesis on gentrification. Wang et al (2007) combined the two approaches to model the behaviour of passengers in terms of organization at a passenger station during peak hours. Manson (2005) blended ABM with CA to model land change in a Mexican region. However, by representing local individuals with population; and social systems with institutions, Manson's integration tended to aggregate heterogeneous actors, one of the pitfalls of traditional large-scale urban models. Parker (2005) highlighted some of the challenges with integrating ABM and CA. Sudhira et al (2005) provided a conceptual framework for combining ABM and CA, especially for simulating urban sprawl dynamics. Li and Liu (2007) merged ABM and CA to model residential development and applied it to a rapidly developing city in South China.

Within the context of urban growth modelling, the works of Wu and Silva (2009, 2010b, 2011) further advanced previous efforts at integrating ABM and CA. In their integrated model, the behaviour of identified heterogeneous actors were modelled with ABM and governed by Genetic Algorithm (GA) and the theory of planned behaviour, while environmental processes were captured with CA. In what can be considered partial integration, Wu and Silva used transition tables and decision matrix to synchronise spatio-temporal processes within the two approaches. Again, the piloting of the model was based on a simplified data for a virtual city as the hybridized model is yet to be tested with any real-world data. Fu et al., (2010) developed a hybridized CA-ABM model for simulating land use change. However, Fu et al.'s model was a departure from the dominant conceptual framework which integrates the spatial and a-spatial strengths of CA and ABM respectively. Their model did not account for socio-economic processes that essentially underlie land use change and urban growth. Thus, their integration was more for computational flexibility and efficiency rather than incorporating socio-economic dynamics into space.

Silva (2011) identified inconsistencies with the data structure of CA – grid/cell/polygon – and ABM – neural nets/decision trees – which poses several limitations to their integration. Silva therefore proposed a new data structure, hexa-dpi which could work as a generic magnetic field for integrating CA, ABM and GA. As part of examining the complexities of cities, Portugali (2011) coined and discussed the term FACS - free agents on a cellular space – which essentially, is a combination of ABM and CA. He further used FACS to explore the emergence of urban culture in self-organising cities. Shuvo and Janssen (2013) fused CA with ABM in modelling informal settlements. Their hybrid model which was applied to Dhaka city focused on modelling non-contiguous urban expansion.

However, non-contiguous urban expansion, which they termed "leapfrog development" is just one of different patterns of growth that cities undergo. Filatova et al. (2013) by examining the prospects and challenges of spatial agent-based models for investigating socio-ecological systems shared some thoughts on the combination of CA and ABM. Dahal and Chow (2014) developed an Agent-Integrated-Irregular- Automata to simulate urban growth in San Marcos. In their model, CA was represented with vector polygons which provided the space over which heterogeneous actors (including households, firms, industries and planners) operated. Whilst their model considered multiple and diverse actors in urban development, the spatial component in the form of neighbourhood influence which is one the major strengths of CA was overlooked in the model. Thus, to borrow the words of Agarwal et al. (2002, p5), the model was spatially representative but not spatially interactive.

A broader overview of urban models that integrate ABM and CA is captured with table 2.3. While there is a plethora of ABMs that have element of cellular space, only a few incorporates the core elements of cellular automata, such as neighbourhood interaction. The overview presented in the table is based on 13 ABMs that, at least, integrates the neighbourhood element of CA. About half of the models are generic with empirical application, whilst around 40 percent are empirical. As with ABMs, the integrated ABM-CA models are largely built on NetLogo and Repast modelling platforms. CA is largely (85 percent) represented as a regular lattice despite the increasing recognition that geographical objects are mostly irregular. Dahow and Chow (2014) and Jjumba and Dragićević (2012) models are the only reviewed ABM-CA models that have irregular spatial structure.

The combination of approaches used to regulate the behaviour of agents in integrated ABM-CA models do not substantially vary from those applied to only ABMs. Utility maximization functions, genetic algorithm, theory of planned behaviour, hierarchical nested choice, and multi-criterial evaluation are some of the popular approaches applied to behavioural regulation in the integrated models.

Table 2.3: Summary of review of integrated Agent-based-cellular-automata models of land use change

Author(s)	Purpose	Model Type	Modelling Platform	CA Representation	Agent Categories	Behaviour Regulation / Analysis Techniques	Calibration	Validation
Dahal and Chow, 2014	Simulation of urban growth scenarios	Empirical	GIS	Irregular parcels, neighbourhood = 200ft	Households, retailers, industries, institutional agents, residential developer, commercial developer, industrial developer, city planner	Utility maximizing	Demographic and real estate data dynamics; Logistic Regression (MCE Techniques)	Compares modelled map with Empirical land-use map and an irregular automata-based map; site-specific-assessment using union overlay algorithm in GIS
Wu and Silva, 2010	Urban growth simulation	Generic	RePast	Variation of Sleuth model	Residents, developers, Government	Utility maximizing, Theory of Planned Behaviour, Genetic Algorithm	None	None
Li and Liu, 2008	Simulation of residential development	Empirical	ARC/INFO	Regular grids	Residents, Developers, Government	Utility maximizing	Logistic regresssion; Saaty Pairwise ranking; MCE techniques; Heuristics	Comparison of simulated output with: actual maps (classified TM Image); and output of CA model by calculating Moran I.

Jjumba and Dragićević, 2012	Modelling of urban Land use change	Generic with Empirical application	JUMP; REPAST	Irregular grids	Household, housing developer, retail developer, industrial manufacturers developer, urban planner	Simple Deterministic Rules	Heuristics; Knowledge-based approach (Expert knowledge)	
Mustafa et al, 2017	Simulation of urban development	Generic with empirical application	Unspecified	Regular Grid (100 * 100m), Moore neighbourhood	Developer, farmer and planning authority	Logit model, Genetic Algorithm, and profit maximization	Logit Model and Markov Chain	Comparison of simulated map with real map using cell-to-cell (CTC) location agreement, and Spatial Metrics (number of patches, mean patch area, area-weighted mean shape index, patch cohesion index)
Torrens and Nara, 2007	Urban gentrification	Generic with Empirical application	NetLogo	Regular grids (25m * 25m)	Residents	Hierarchical nested choice; discrete choice approach, Utility evaluation, and choice likelihood	Adjustments based on Census Statistics, and gentrification theories	None
Shuvo and Janssen, 2013	Simulation of leapfrog development	Generic with empirical application	NetLogo	Regular grid (2*2 m)	Workers	suitability (utility) maximization		None

Tan et al, 2015	Urban growth simulation	Generic with Empirical application		Regular grid (30m)	Government, land developer, land owner	Game theory	Logistic Regression, Delphi Method	Comparison of simulated image with real image using metrics (prod accuracy, user accuracy, overall accuracy and Kappa coefficient). Model accuracy is further compared with that of pure logistic CA model
Tian et al, 2016	Simulation of urban expansion	Empirical	C#.NET of Visual Studio 2010; ArcEngine 10.	Regular (Moore neighbourhood)	Authority Agent, Residential Agents	Dynamic Random-effects Model (DRM) is used to regulate residential agents location decisions	CA and Multi Agent Systems (MAS) weights are selected based on heuristics. Kappa coefficient is used to assess performance of the weights.	None
Lagarias, 2012	Simulation of urban sprawl	Generic with empirical application	NetLogo	Regular grids (Von Newman neighbourhood, and 300m radius neighbourhood)			Comparison of simulated map with actual map using geometrical indexes. Multiple regression model is also used to calibrate socio-economic factors	Comparison of simulated map with actual map using geometrical indexes

Manson, 2005	Land use change simulation	Empirical	C++, IDRISI	Regular grids (28.5 * 28.5 m); neighbourhood = 25 cells	Household, Institution	Multicriteria evaluation, analysis of household survey, Genetic programming	Analysis of census data and household survey, symbolic regression	None
Zhao and Peng, 2007	Simulates spatial suitability of land use change	Generic with empirical application	Unspecified	Regular grids (50* 50 m), Moore neighbourhood	Households, employment, developers,	Bid rent theory	Analysis of historical land use and socio-economic data	Compares simulated output with actual using confusion matrix and visual inspection
Moreno et al, 2007	Models social and environmental complexity of deforestation	Empirical	Galatea agent library and languages; SpaSim	Regular grids, Moore neighbourhood	settlers, government, lumber concessionaires.	Heuristics, logical based model	Heuristics, literature findings	Qualitative comparison of the results with historical knowledge

Although promising, these past attempts at integrating the two approaches in modelling urban growth appear insufficient and limited in relation to the urban system they seek to explore. For instance, most of the integrated CA-ABM models (Dahal and Chow, 2014; Wu and Silva, 2009; Li and Liu, 2007), resident/household and developer actors are treated separately; and development or urban change does not occur without a government agent's approval. Whilst this is apt for explaining the socio-economic and environmental change processes in many developed settings, it is insufficient in accounting for the complex and informal development processes that characterise many developing regions where: resident/household and developer agents are not necessarily separable; and the probability of development taking place is less dependent on a government agent approval (Anokye et al., 2013; Sietchiping, 2004). Even though this might be seen as a mal-functionality of urban planning and management systems, it is intrinsically part of the complexity that engulfs today's urban systems in many developing regions which contemporary urban modelling attempts should not treat as deviation but rather, be more flexible to. Thus, whilst many of the integrated urban growth models are good for the case studies to which they were developed and applied, they are less suitable for replication in other context or theorizing.

2.12 The Complexity of agent-based-cellular models

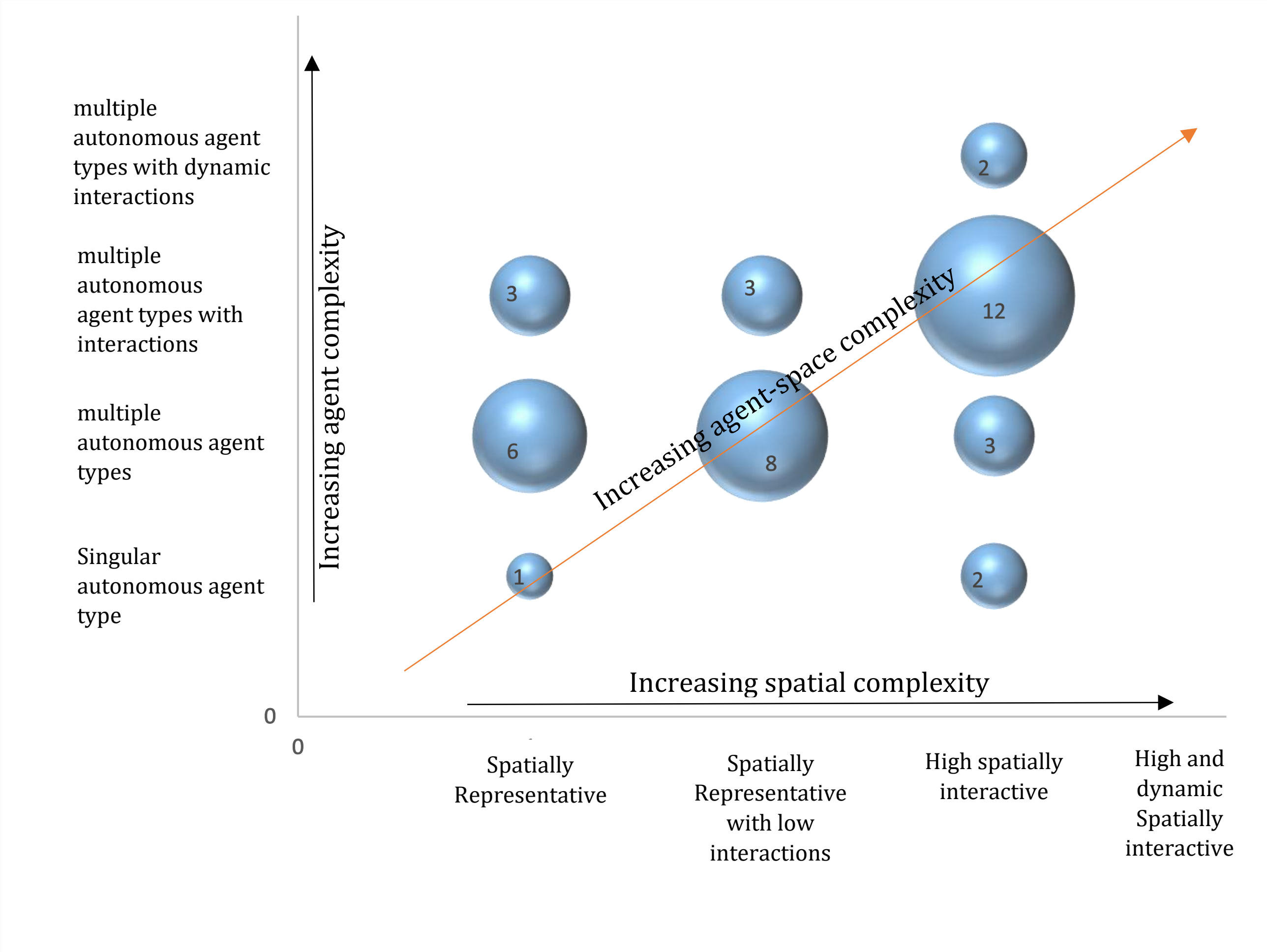
The capability to handle complexity is one of the key features that has attracted cellular automata and agent-based models to many urban modellers. Considering that each has unique strengths for exploring some aspects of complexity, their integration even presents a more powerful mechanism for better modelling and simulating complex urban systems, at least, theoretically. However, beyond the realms of theory, there is little evidence on the complexity progress of the integrated approach. Thus, the question arising here is how complex are agent-based-cellular models of land use change? In exploring this, we have examined the models within a framework of complexity.

As captured earlier, there is no one agreeable definition of complexity, a fact that underscores the challenge with any attempt at classifying the complexity of models. Despite this challenge, however, there are some features of complexity that are recognized by a larger academic community. This study modifies the framework proposed by Agarwal et al, (2001), where complexity of agent-based models was examined on three main dimensions; agent complexity, spatial complexity and temporal complexity. This research modifies the three features into two main dimensions, agents and space, with time being a key defining feature as presented with Figure 2.5 and table 2.4.

In Figure 2.5, the complexity of the agent dimension is captured on the vertical axis, while the horizontal maps the spatial complexity dimension of the models. On the agent axis, complexity increases from bottom to up among four discrete groups: singular autonomous agent type, which highlights models that have only one type of autonomous agents; multiple autonomous agent types, which depicts models with two or more types of autonomous agents but do not capture interactions among the agents; multiple autonomous agent types with interaction, which refers to models with two or more types of autonomous agents that interact; and multiple autonomous agents with dynamic interactions, which absorbs models with two or more autonomous agents that interact in way that is non-linear, at least, with time. Thus, for the last group, which is the highest the complexity ladder, the interactions among agents is not held constant but rather changes with time.

Similarly, on the spatial axis, the complexity of models increases from left to right among four categories: spatially representative; which highlights models that have spatial representation, mostly depicted with cellular grids, but are not spatially interactive; spatially representative with low interaction, which outlines models with minimal spatial interactions, normally captured in form of proximity analysis; high spatially interactive, which refers to models with spatial interactions that go beyond proximity analysis to include other forms of interactions, for instance, neighbourhood interactions; and, highly and dynamically spatially interactive, which outlines models that, in addition to being highly spatially interactive, also capture the temporal non-linearity of the interactions. In other words, for the highest category, the rules of spatial interactions change with time and not held constant.

Figure 2.5: The complexity of Agent-based-cellular models



The interactions among the two dimensions produce a matrix that encapsulates the agent-space complexity of the models. This complexity increases along a diagonal line from bottom to up or left to right. In all, the framework captures 16 discrete classes. It is striking that, while a significant number of the models (19) are highly spatially interactive, the interactions are mainly static, as none of the models fall under the highest spatial complexity category. Similarly, on the vertical axis, despite that a substantial number of the models (18) capture multiple autonomous agent types that interact, the nature of the interactions is largely held constant with time, as only two models are found to be temporally dynamic. Thus, notwithstanding their dynamic nature, integrated agent-based-cellular models of land use change still have a lot of grounds to cover in term of capturing the dynamic temporal complexity of interactions among autonomous agents and space. That stated, there are positives that need highlighting. For example, among the 16 classes, most of the models (12) fall under the second highest agent-space complexity category, which means that not only do the models have multiple autonomous agents that interact among themselves, but are also highly spatially interactive, in terms of exploring complexity. Compared to few decades ago where urban modelling was predominantly based on large scale statistical models that tended to treat heterogeneity as noise, this complexity feature of the agent-based-cellular models cannot be emphasised. The specific models that fall under various classes is presented with table 2.4.

Table 2.4: Complexity of Agent-Based-Cellular Models of Land Use Change

	Spatially representative	Spatially representative with Low interactions	High Spatially interactive	High and dynamic Spatially interactive
Multi-autonomous agents with interactions and dynamic temporal dimension			Huigen, 2004; Huigen et al, 2006;	
Multi-agents with interactions	Arsanjani et al, 2013; Valbuena et al, 2009; Ligtenberg et al, 2004;	Li et al, 2018; Murray-Rust et al, 2013; Robinson et al, 2012	Zhao and Peng, 2012; Wu and Silva, 2010; Dahal and Chow, 2014; Moreno et al, 2005; Jjumba and Dragićević, 2012; Mustafa et al, 2017; Tan et al, 2015; Tian et al, 2016; Manson, 2007; Zhao and Peng, 2007; Liu et al, 2006; Manson, 2005;	
Multi-autonomous agents	Bravo et al, 2010; Valbuena et al, 2010; Mialhe et al, 2012; Valbuena et al, 2010b; Brown et al, 2004; Fontaine and Rounsevell, 2009	Deadman et al, 2004; Bakker & Doorn, 2009; Brown and Robinson, 2006; Castella et al, 2005; Evans & Kelley, 2008; Le et al, 2008; Le et al, 2010; Loibl and Toetzer, 2003	Lagarias, 2016; Ralha et al, 2013; Yin and Muller, 2007;	
Singular autonomous Agent	Tsai et al, 2015;		Torrens and Nara, 2007; Shuvo and Janssen, 2013	

2.13 Location choice factors in Agent-based-cellular models of land use change

Location choice, whether by households seeking a comfortable place to settle, developers searching for the most profitable location to build, or farmers looking for the best area to cultivate, forms an important component of the agent-based-cellular models of land use change. Table 2.5 captures the location choice factors expressed in the reviewed models. The factors could, which are sorted from left to right in order of popularity, can be categorised into: socio-economic; geophysical; and centrality - normally represented with spatial proximity variables. Proximity to roads – be it highways, sub-regional trunk roads or local access – emerged as the most popular factor. Slope, land values, land cover, proximity to school are also among the popular location choice factors.

Table 2.5: Location choice factors employed in agent-based-cellular models of land use change

	Proximity to Roads	Slope	Land Cover	Soil quality /Type	Proximity to River	Land values	Proximity to School	Green space	Topography	Urban density	Proximity Public Transport	Land Zoning	Proximity to CBD	Environmental amenities	Elevation	Proximity Shopping Centres	Noise	Proximity to Railway station	Proximity to Service Centre	Proximity to recreational facility	Proximity to family	Neighbourhood similarity	Neighbourhood Aesthetics	Proximity Health facility	Proximity to Market	Proximity to Cities	Proximity to Airport
Arsanjani et al, 2013						*																					
Bakker & Doorn, 2009	*	*		*																							
Brown and Robinson, 2006																			*			*	*				
Castella et al, 2005			*	*					*																		
Deadman et al, 2004			*	*																							
Fontaine and Rounsevell, 2009;	*									*																	
Huigen et al 2006	*	*		*	*																*						
Le et al., 2008	*	*	*		*																						
Le et al., 2010	*	*			*				*																		
Li et al, 2018	*						*					*	*	*										*			
Liu et al, 2006	*					*	*							*													
Loibl and Toetzer, 2003	*		*			*	*		*											*							
Manson, 2005		*		*						*					*										*		
Murray-Rust, 2013	*		*					*			*					*	*										
Mustafa et al, 2017	*	*										*														*	
Ralha et al, 2013	*				*													*									
Robinson et al, 2012	*		*					*			*				*	*	*										
Yin and Muller, 2007	*							*		*																	
Zhao and Peng, 2012	*	*	*	*							*		*					*									*

* Applied

2.14 Geographical Application of CA and ABM models

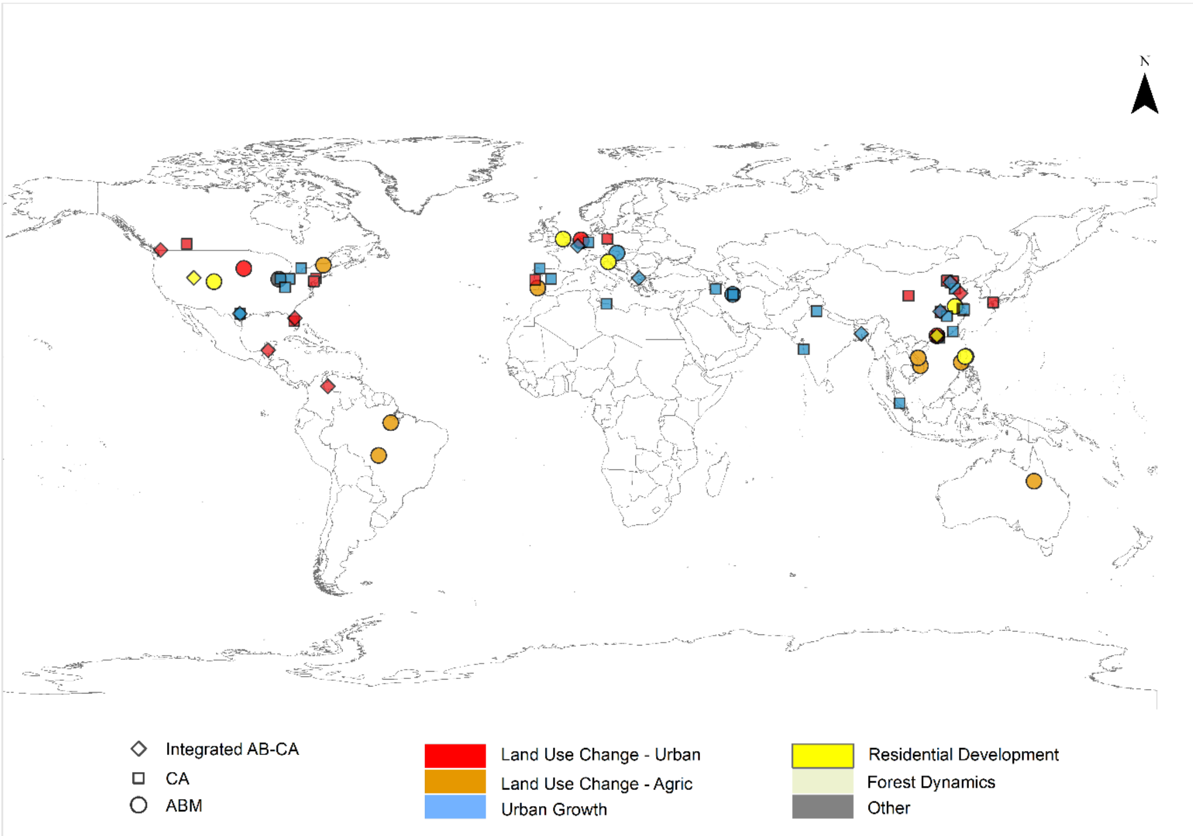
The geographical applications of the models reviewed above, which includes post 2010 CA modifications, ABM and integrated CA and ABM models, is mapped in Figure 2.6. Different shape styles is used to represent the type of model, while colour coding is employed to distinguish the varied purposes for which the models are applied. At a continental level, the distribution pattern in Figure 2.6 shows concentration in three continents, Asia, Europe and North America. This geographical skewness is reflected in the application of the three types of models reviewed. The woefully inadequate application of the dynamic models in Africa, South America and Australia imposing. This is quite alarming, especially for the region of Sub-Saharan Africa, which, in the Twenty-first century has recorded massive urban transformation and still undergoing immense spatial evolution. The paradox of the extremely limited application of dynamic urban models in continents where arguably they are needed most underscores the huge research gap that exist between Africa on the one hand, and essentially, the rest of the world.

Ghana, one the fastest developing economies in Africa could be used to illustrate the lack or extreme inadequacy of dynamic geo-spatial research centres in Sub-Saharan Africa. Even though there are dedicated university research and academic departments on spatial planning and geography, the country is yet to have a centre with advanced expertise in dynamic geospatial modelling and simulation. The picture is hardly different for most of the countries in the sub-region.

This disparity also manifests the skewness in the geographical distribution of research centres that specialize in dynamic geo-spatial analyses. Whilst the United States and Europe have traditionally been the power houses is geospatial research, China has, over the past few decades, also emerged as a focus of research in dynamic modelling and simulation. In the face of globalization and technological advancement, especially regarding the availability of remote sensing data, it is moderate to have anticipated a faster diffusion process in the development and application of dynamic land use change models in Africa. Thus, SSA represents a huge gap as far as the application of dynamic models is concerned.

This gap is significant on its own, but even gets bigger when it is situated, for instance, within the context of the peculiarity of spatial development trajectories of Sub-Saharan African cities. The knowledge and other benefits that comes with the application of the dynamic models in North America, Europe and Asia, are not easily transferrable to SSA owing to significant contextual differences. For instance, the predominantly informal nature of cities in the sub-region is hardly comparable to what is experience by cities in other parts of the world. Indeed, the formalization of urban growth in the integrated CA and ABM models is such that, development is contingent on the approval of a government or local planning authority agent. This framework is fundamentally different in most SSA cities where overwhelming majority of development is informal and emerge spontaneously (UN-Habitat, 2011; Boamah et al., 2012; Anokye et al., 2013). Thus, the huge geographical gap does not only reflect how cities in SSA are less studied, but also expresses the inadequate decision-making support for policy makers and urban managers in the sub-region.

Figure 2.6: Geographical Application of Post 2010 CA modifications, ABM and Integrated CA and ABM models



2.15 Emerging Issues from the review

The highlights from the review are summarized below.

Post 2010 CA modifications

- Most of the models are developed as generic models, but then are applied empirically, normally as a form of model validation.
- Despite the attempts at making the CA models transferrable across diverse geographical areas, most of the generic models are yet to be applied beyond the case studies used either in their development or validation.
- An overwhelming majority of the models are structured on the traditional regular grid cell space, despite technological advancements, particularly in computational efficiency, and the wide acceptance that geographical objects are largely irregular.
- The treatment of neighbourhood in the models has been quite traditional, as most employ Moore's 3 * 3 technique
- Machine Learning (ML) approaches, such as Artificial Neural Networks and Support Vector Machines (SVM), are increasingly being applied to development of CA transition rules.
- Markov Chains (MC), largely used to generate transition probability maps, has seen the highest application, even more than the traditional Logistic Regression (LR) mechanism.
- The combination of techniques to generate CA transition rules, generally with the aim of compensating inherent weaknesses associated with singular techniques, is becoming widespread.
- In validation, more than half of the models employ Cohen's Kappa Index (K), generally as part of preparation of a confusion matrix.

Relating to ABM/MAS

- Satellite images form an important part of the datasets used by about 44 percent of ABMs of land use change.
- About two-thirds of models that specified their modelling platform were either developed with NetLogo or Repast.
- About a third of models employ some form of heuristics as part of the mechanisms used to govern the behaviour of decision-making actors.

- Rationality theory, typically captured with utility maximizing functions, is applied in about 40 percent of the models, making it the most popular.
- Overwhelming majority of studies apply, at least, two different approaches to govern the behaviour of agents.
- About 40 percent of the models reviewed are either not validated or do not have such information provided.

Relating to Integrated ABM-CA

- The combination of approaches used to regulate the behaviour of agents in integrated ABM-CA models do not substantially vary from those applied to only ABMs.
- Utility maximization functions, genetic algorithm, theory of planned behaviour, hierarchical nested choice, and multi-criterial evaluation are some of the popular approaches applied to behavioural regulation in the integrated models.
- Despite that a significant number of the models are highly spatially interactive, the interactions are mainly static, as none of the models fall under the highest spatial complexity category.
- Notwithstanding that a substantial number of models capture multiple autonomous agent types that interact, the nature of the interactions is largely held constant with time.

Relation to Geographical Application of post 2010 CA modifications, ABM and integrated ABM-CA models

- The application of is highly concentrated in Asia, Europe and North America.
- The geographical application of the models is extremely limited in Sub-Saharan Africa.

CHAPTER THREE

BROAD METHODOLOGICAL FRAMEWORK

3.1 Chapter Introduction

This chapter lays down the broad methodological framework for the research, which is structured into two main parts. Each part composes two chapters as presented by Table 3.1. Part 1 explores the first three objectives of the research and is constituted by: Chapter 4, which simulates the urban growth of a Sub-Saharan African city with a CA model and explores the sensitivity of urban CA models to informal growth trajectories; and Chapter 5, which examines the urban spatial structure of Sub-Saharan African cities with CA and spatial metrics, in addition to exploring the urban planning and policy implications of the evolving structure. Part 2 is primarily devoted to the integration of MAS and CA and their application informal urban growth simulation. It is organized into chapter 6, which analyses the location choice decisions of various urban households; and chapter 7, which Integrates MAS and CA to simulate urban growth of a predominantly informal Sub-Saharan African city-region.

This chapter also outlines for the various sections: the geographical areas used as case study; modelling techniques employed; data sources and methods; and data processing and analysis techniques, among others.

Table 3.1: Broad Research Structure

Part	Chapter	Objectives
1: Urban CA, informal urban growth and urban spatial structure of Sub-Saharan African Cities	4: Simulating the urban growth of a predominantly informal Sub-Saharan African city-region with CA	Simulates the urban growth of a predominantly informal Sub-Saharan African city-region with urban CA
		Examines the sensitivity of urban CA models to informal urban growth trajectories
	5: Understanding the urban spatial structure of Sub-Saharan African Cities with	Examines the evolving urban spatial structure of Sub-Saharan African cities and the relationship with mainstream urban spatial structure models

	dynamic urban growth model and spatial metrics	Explores the urban planning and policy implications of the evolving spatial structure
2: Integrated MAS-CA and Informal urban growth modelling and simulation	6: Understanding the location choice decisions of urban households	Examines the locations choice preferences of urban households
	7 Integration of MAS and CA towards the modelling and simulation of informal urban growth	Develops an integrated ABM and CA model that simulates urban residential growth of a predominantly informal city-region in SSA.

3.2 Case study areas

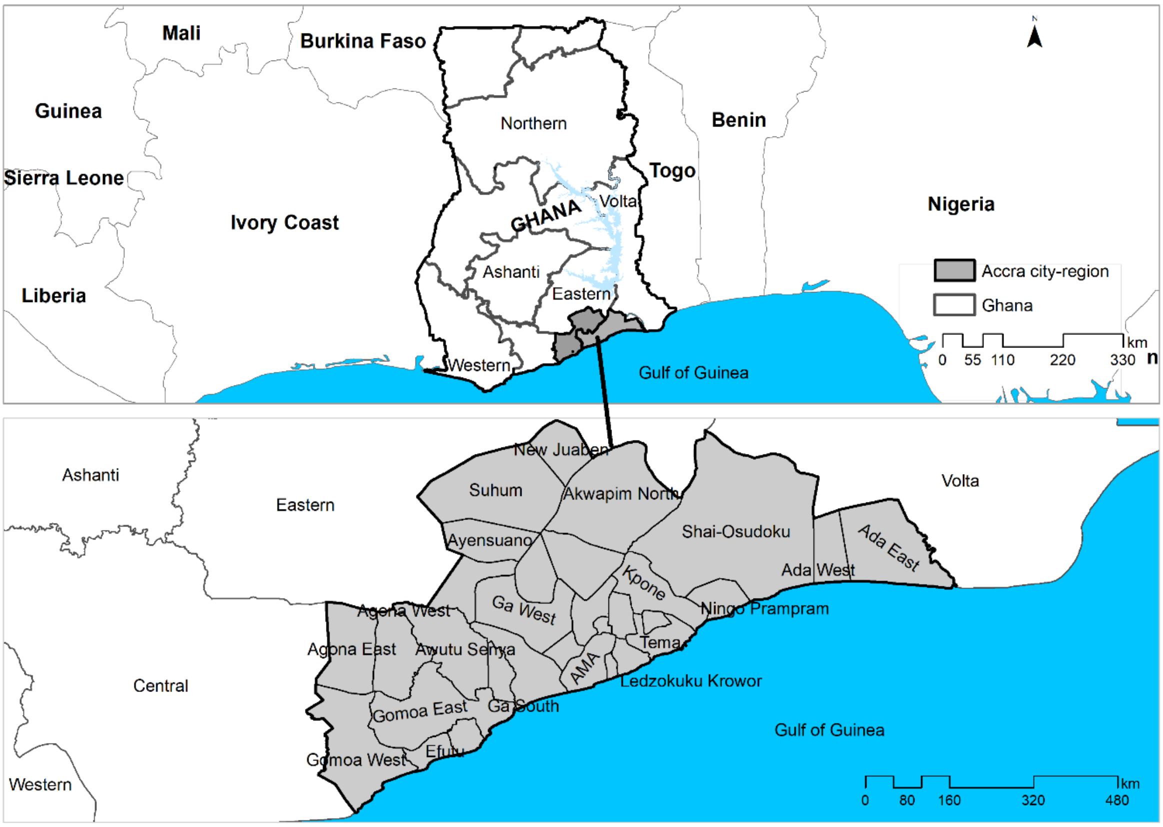
The research draws on data from two Ghanaian regions, Accra City-Region (ACR) and Ashanti region, to pursue its objectives. The rationale behind their selection is discussed under section 3.2.3. The first part of the research uses both regions; Accra city-region for Chapter 4, and Ashanti region for Chapter 5. Section 2, however, is situated only in ACR. Notable demographic and economic characteristics about the regions are subsequently outlined.

3.2.1 Accra City-Region

Accra City-Region (ACR), home of the capital of Ghana, is located in the southern part of the West African Sub-region as presented by Figure 3.1. ACR as delineated in the National Spatial Development Framework (Town and Country Planning Department of Ghana, 2015) spans over a total land area of about 9,600 km^2, covering Greater Accra region and parts of Central, Eastern and Volta Regions. In all, the area extends over 42 districts either in full or in part. However, taking into consideration the feasibility of accomplishing the research within resource constraints, such as time, finance and data availability, required that the area is further downscaled. In scaling down the area for ACR, priority has been given to the districts that constitute the Greater Accra administrative region and those that completely fall within the ACR. Through this mechanism, which also ensured that the contiguous Accra built up extent is captured, 30 districts distributed over three regions, Greater Accra (16), Central (7) and Eastern (7) have been settled on as depicted in figure

3.1[1]. Using GIS techniques, the urban and rural settlements within the selected area of ACR were extracted, enabling the computation of some demographic and economic characteristics drawn from census data for years 2000 and 2010 as shown with Table 3.2.

Figure 3.1: Accra City-Region in regional and national context



The selected ACR covers about 8100 km^2 of land, representing 3.4 percent of the land area of Ghana. The region accommodated approximately 5.5 million people in 2010, which is an increment of about 1.35 million in relation to its total population at the beginning of the twenty-first century. Based on the projections of the TCPD (2015), the population of the area could reach 10 million by 2035. Despite constituting less than 4 percent of Ghana's land area, the region absorbed more than a fifth of the national population in both 2000 (22.03 percent) and 2010 (22.36 percent). The region is

[1] Since 2000, the number and boundaries of districts in Ghana has changed several times; for instance, from 117 in 2000 to 170 in 2010, and 216 in 2012. Indeed, as of the time this report was being finalized, there were an official process underway to further increase the number of districts. The district boundaries used in Fig X, Table X and subsequent district tables and districts relates to number of boundaries of districts as of 2012, which is the most recent available official data from the Ghana Statistical Service.

undergoing rapid urbanization, recording annual urban growth rate of 3.2 percent between 2000 and 2010 – the last intercensal period. Having recorded urbanization levels of 77 and 81 percent in 2000 and 2010 respectively, the selected ACR is the most urbanized region in Ghana. These figures compare strongly with national averages of 44 percent in 2000 and 51 percent in 2010. Indeed, according to projections by the TCPD of Ghana, the selected ACR will be virtually all urban (95 percent urbanization level) by 2035.

The population distribution in ACR ranges from about 37k in Akwapem South in the Eastern region to around 1.66 million in Accra metropolis, which is a core district to not only Greater Accra administrative region, but also the entire functional ACR. Districts such as Ga South (411k), Tema (292k), Ledzokuku Krowor (227k) and Ga West (219k), together with Accra metropolis, form the top five populous districts in the region. At the bottom, Shai-Osudoku (52k), Ada West (59k), and Effutu (68k), Ningo Prampram (70k) along with Akwapem South constitute the 5 least populous districts in the region.

The selected ACR with a GDP size of US$12.6 billion in 2010 is the most economically vibrant region in Ghana. Despite absorbing just about 3.4 percent of Ghana's land mass and slightly above a fifth of the national population, the ACR holds more than a quarter (28.1 percent) of the economy of the West African country. The top three populous districts (Accra metropolis, Ga South and Tema) are also the top 3 economically vibrant districts. Indeed, including Ledzokuku Krowor, the 4 most populous districts are part of the top 5 economies in the city-region. Similarly, 4 of the 5 least populated districts, namely Akwapem South, Shai-Osudoku, Ada West Effutu, make up the bottom 4 economically vibrant areas in the region. Thus, it appears there is a strong correlation between population size and the size of economy as it pertains to ACR.

Table 3.2: Population and Economic Characteristics of Accra City-Region

District	Area (Km2)	Population 2000[2]	Population 2010	Annual Growth Rate 2000 - 2010	GDP (US$ 000)*
Accra Metropolis	141.0	1753608	1665086	-0.5	4,060,523
Ga South	242.2	80383	411377	17.7	922,364
Tema	126.7	282443	292773	0.36	808,821
Ledzokuku Krowor	64.2	67913	227932	12.9	591,128
Ga West	354.0	223285	219788	-0.2	522,828
Gomoa East	485.7	92545	207071	8.4	370,135
Ashaiman	32.5	159582	190972	1.8	459,227
New Juaben	169.1	134424	183727	3.2	422,935
La Dade-Kotopon	18.5		183528		600,504
Ga East	116.8	188913	147742	-2.4	406,426
Akwapim North	652.4	104753	136483	2.7	230,180
Gomoa West	494.0	105617	135189	2.5	202,899
Ga Central	56.3	8790	117220	29.6	269,410
Agona West	265.2	100321	115358	1.4	204,540
La Nkwantanang-Madina	18.0	1551	111926	53.4	303,929
Kpone	237.1	30457	109864	13.7	282,368
Awutu Senya East	86.8	39126	107570	10.6	218,498
Suhum	640.5	134294	91324	-3.8	164,288
Awutu Senya	352.3	82551	87736	0.6	147,416
Upper Akim West	183.0	42231	87051	7.5	131,549
Nsawam Adoagyiri	147.9	54661	86000	4.6	165,033
Agona East	313.6	42884	85920	7.2	135,915
Adentan	75.0	86788	78215	-1.0	239,797
Ayensuano	223.7	36805	76227	7.6	119,186
Ada East	490.4	84739	71671	-1.7	118,810
Ningo Prampram	116.3	15829	70719	16.1	137,412
Effutu	77.0	43128	68597	4.8	114,110
Ada West	159.6	12294	59124	17.0	104,878
Shai-Osudoku	1486.6	95333	52117	-5.9	107,790
Akwapim South	237.9	61683	37501	-4.9	70,016

* At current price

[2] Many of the districts were non-existent as of year 2000, hence the associated population has been extrapolated through a process that includes: disaggregating districts' population into settlements based on district boundaries of 2000 and spatial distribution of urban and rural settlement; and subsequent aggregation of settlements' population using the district boundaries of 2012. Thus, the actual 2000 population for the districts may slightly differ. The extrapolation is to help readers have a broad sense of the historical population dynamics.

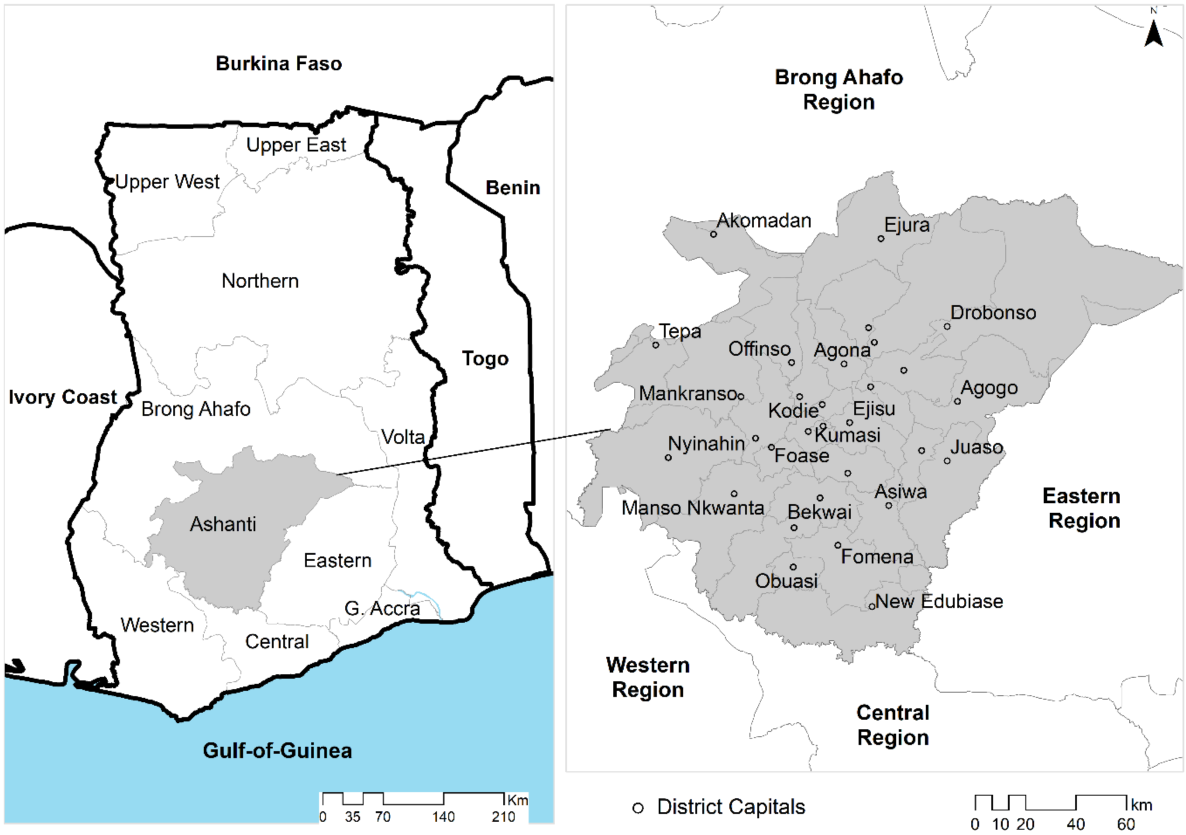
3.2.2 Ashanti Region

The Ashanti region, with a tropical rainforest ecology, is located in the mid part of Ghana, bounded by: Brong Ahafo region to the north; Central region to the south; the Eastern region to the east; and Western region to the West as depicted in Figure 3.2. The region extends over 24,379 km2 of land that encompasses 30 administrative districts[3]. It has been the most populous administrative region in Ghana from 1960 when it absorbed about 1.1 million people through 2010 when it accommodated around 4.78 million inhabitants (Ghana Statistical Service, 2012). Thus, whilst it occupies only a tenth of the national land area, it absorbs, at least, a fifth of Ghana's population. The TCPD of Ghana projects the region to account for about 7 million people by 2035 (TCPD, 2015).

The region has also been conceptualized as a functional city-region that primarily revolves around Kumasi, its principal city, and other major urban centres, including Obuasi, Mampong and Konongo. The region has generally grown steadily in the past decades, but particularly rapid over the first decadal interval of the twenty-first century when it added around 1.2 million people. The rapidity of the overall population growth is also reflected in the annual growth rate of 4.6 percent between 2000 and 2010. Also, the region has considerably urbanized over the past 5 decades, having increased its urbanization level from just about a quarter in 1960 to around 60 percent in 2010. Having recorded urban annual growth rate of 4.5 percent between 2000 and 2010, the region's urbanization level is expected to reach 83 percent in 2035.

[3] The comment in footnote 2 applies.

Figure 3.2: Ashanti region (KCR) in geographical context



Population distribution in the region ranges from about 1.7 million in Kumasi Metropolis, the capital, to around 28k in Sekyere Afram Plains North. The population is heavily concentrated in few districts. For instance, the top 5 populous districts, namely Kumasi metropolis, Asokore Mampong (304k), Obuasi Municipal (168k), Atwima Nwabiagya (149k) and Ejisu Juaben (143k), which collectively hold less than 7 percent of the land, absorbs over half (52 percent) of the population. Along with Sekyere Afram Plains North, districts such as Offinso North (56k), Bosome Freho (60k), Sekyere East (62k) and Sekyere Afram Plains (65k) constitute the 5 least populated areas. In terms of land area, however, Sekyere Afram Plains North dominates with a share of 14 percent.

On the economic front, the Ashanti region is the second most economically vibrant region in Ghana. In 2010, the region's GDP amounted to 8.3 billion, representing close to a fifth of the national GDP. GDP distribution in the region is largely skewed towards the densely populated areas, such as: Kumasi metropolis, which holds approximately 40 percent of the wealth; Asokore Mampong, which accounts for 6.4 percent; Obuasi Municipal, which absorbs 3.9 percent; Atwima Nwabiagya, which constitutes 3.23 percent; and Amansie

West, which generates 3.21 percent of the GDP. Thus, 4 out of the 5 most populous districts are part of the top 5 economies in the region. Similarly, the least populated areas in the region generates the least of the GDP as depicted by Table 3.3.

Table 3.3: Population and urbanization characteristics of districts in Ashanti Region

District	Area	2000	2010	AGR 2000 - 2010	GDP, 2010 (US$ 000)*
Kumasi Metropolis	214.3123	1181872	1730249	3.89	3,347,721
Asokore Mampong Municipal	23.91995	-	304815	-	540,522
Obuasi Municipal	220.6952	144708.9	168641	1.54	323,462
Atwima Nwabiagya	579.1589	89371.61	149025	5.25	271,447
Ejisu Juaben	582.699	123878.8	143762	1.50	244,739
Afigya Kwabre	409.4224	50485.81	136140	10.43	232,174
Amansie West	1230.684	108312.4	134331	2.18	269,331
Ahafo Ano South	1190.404	140348.5	121659	-1.42	174,878
Atwima Mponua	1882.3	146458.8	119180	-2.04	181,960
Bekwai Municipal	535.3498	80257.99	118024	3.93	186,560
Asante Akim South	1154.147	96040.04	117245	2.02	184,156
Kwabre East	122.9902	150493.7	115556	-2.61	197,416
Adansi South	1328.606	143413.7	115378	-2.15	188,184
Adansi North	853.9148	87909.43	107091	1.99	159,790
Ahafo Ano North	593.3224	70916.73	94285	2.89	137,438
Afigya Sekyere	416.902	70490.39	94009	2.92	129,976
Bosomtwe /Atwima / Kwanwoma	422.6066	81848.81	93910	1.38	168,049
Amansie Central	849.5462	94266.36	90741	-0.38	139,455
Atwima Kwanwoma	251.5218	65203.21	90634	3.35	161,133
Mampong Municipal	670.448	69912.59	88051	2.33	136,897
Ejura Sekye Dumase	1340.67	81871.64	85446	0.43	135,571
Offinso Municipal	585.6718	69962.8	76895	0.95	120,479
Asante Akim Central Municipal	300.426	53864.88	71508	2.87	123,108
Sekyere Central	1632.232	49650.46	71232	3.68	106,993
Asante Akim North	1126.721	70114.93	69186	-0.13	102,211
Sekyere Afram Plains	576.943	53407.95	65402	2.05	103,938
Sekyere East	239.245	40123.26	62172	4.48	99,445
Bosome Freho	569.0633	50465.6	60397	1.81	89,078
Offinso North	945.7467	65768.92	56881	-1.44	81,328
Sekyere Afram Plains North	3529.351	69469.86	28535	-8.51	51,566

*GDP is current price level

3.2.3 Why the Study Area?

The selection of the two regions was premised on a number of interrelated factors outlined below.

Appropriateness to the phenomenon of interest

One of the key considerations for selecting the study areas is the presence of rapid and informal urban growth. As aforementioned, not only are ACR and Ashanti region the two most populous regions in Ghana, but they are also the top urbanized areas in the West African country. ACR and Ashanti region, with 4.47 million and 2.89 million urban dwellers respectively, absorbed almost 60 percent (59.1) of Ghana's urban population in 2010. The selected ACR urbanized at annual rate of 3.2 percent between 2000 and 2010 and is projected to be a meta city-region with a population of 10.05 million by 2035 (TCPD, 2015). Ashanti region's urbanization has even been more rapid, as discussed under section 3.2.2. Its urban population is expected to reach 6.9 million in 2035.

The two most economically productive areas in Ghana also accounted for close to half (47 percent) of the national GDP. The combination of rapid urbanization and economic development in the two regions have resulted in massive urban spatial growth over the few decades. What is, however, crucial about the monumental urban growth is its informal and unregulated characteristics. Indeed, various studies, for example, see UN-HABITAT (2011), Boamah et al (2012), Korah et al (2016), have outlined the informal nature of an overwhelming majority of developments in Ghana. In the estimation of the UN-HABITAT, not less than 70 percent of developments in Ghana occur without authorization by the government, which is represented by the planning system. This informality does not only relate to developments by households, but also those undertaken by institutions/organizations such as real estate developers (Anokye et al., 2013). These characteristics of the two regions fits the objectives of the research, particularly regarding the modelling and simulation of informal urban growth.

Cases yet to be explored

Despite the increasing popularity of dynamic urban modelling and simulation, there is no existing study that models or simulates the urban growth of any Ghanaian city. Situating this against the backdrop of the massive and informal nature of urbanization taking place in Ghana, especially as evidenced by ACR and the Ashanti region, presents two geographical areas that are in need or urgent research attention. For the purpose of uncovering new knowledge with regards to the performance of dynamic urban modelling techniques such as CA and ABM in predominantly informal urban settings the two regions make a suitable case. The two also fit in well with the research objective of informing urban planning and policy in SSA through the development and application of planning decision support models.

Data Accessibility

Refined models normally go in tandem with refined data as the latter constitute a vital component in the construction of the former. Indeed, over the years, the development and application of dynamic urban models – which are mostly data hungry – have been largely influenced by the availability of data. It is therefore less surprising that a region, such as West Africa, with severe challenges of data paucity, is hardly explored when it comes to the development and application of dynamic urban models is concerned.

This research is also data intensive. For instance, the application of CA model and the development of an integrated ABM and CA model do not only require enormous diverse spatial data, but also great depth of a-spatial datasets, including socio-economic and demographic data. Initial checks with the Town and Country Planning Department of Ghana through existing networks – another contributing factor – revealed the availability of many of the required spatial datasets for ACR and the Ashanti region. This information played a vital role in the final selection of the two case areas.

Knowledge of the Context and Influence of Networks

As identified from Chapter Two in the review of cellular automata and agent-based models of land use change, the development of transition rules, calibration and validation, particularly for ABMs, requires rich and diverse datasets some of which are simply non-existent. As a result, most urban models employ some form of heuristics in their development and application. This research also relies on some heuristics as part of the development, calibration and validation of the models, especially the integrated ABM and CA model in Chapter 7. A good knowledge and understanding of the study areas is therefore vital to this research.

Having lived and schooled in the Ashanti region for about 13 years, I have witnessed and, some ways, participated in the urban growth that has taken place in the region. Similarly, I lived in Accra and worked with the TCPD Head Office for, at least, 2 years, an experience that did not only improve my understanding of the Ghanaian planning system, but also shaped my knowledge of the complex urbanization and development processes in Ghana. My knowledge of the local context also helped with the acquisition of some of the vital datasets, as I knew where to get what. For instance, the integration of ABM and CA required, in addition to spatial datasets, extensive socio-economic data that had to be collected through survey, a method that requires good knowledge of the context not only for its administration, but also its design. prior to that, with the design of instruments and tools such as questionnaires and interview guides. Again, not only is information about data availability critical, but its accessibility. Besides, in many developing countries, personal and informal networks tend to be efficient in accessing data compared with going through formal institutional channels. My networks in ACR and the Ashanti region proved valuable in accessing some of the key components of the research.

3.3 Data and Methods for Part 1

Part 1 of this report constitutes, as outlined above, Chapter 4, which simulates the urban growth of a predominantly informal Sub-Saharan African city-region; and Chapter 5, which explores the evolving spatial structure of Sub-Saharan African cities and their relationship with mainstream urban geography models. These chapters collectively engage three main techniques, including: the application a CA model (for both chapters); expert validation of the applied CA model (for chapter 4); and application of a set of spatial metrics (for chapter 5). Further details about these techniques are provided below.

3.4 Application of an urban Cellular Automata; selecting a model

A number of CA urban growth models exist. Sante et al. (2010) in their review of CA models classified more than 30 cellular automata models of urbanization. Silva and Wu (2012) provides a comprehensive review of 64 urban models, many of which are based on cellular automata. Chapter two of this research reviews 50 post 2010 CA models of land use change. One of the most well established and used CA model is SLEUTH (Chaudhuri and Clarke, 2013). In addition to its widespread recognition, the selection of SLEUTH is premised on several factors that include the following.

- The capacity to simulate diverse urban growth patterns such as spontaneous, new spreading centres, edge and road-influenced growth (Clarke et al., 1997; Jantz et al, 2010; Bihamta, 2015). Indeed, the geographical differences in urban growth patterns, for instance, between Sub-Saharan Africa and other regions, largely account for the exploration of the extent to which the model could function in areas that have not been applied. It is therefore essential that a model that is flexible to several growth patterns is considered.
- Ability to simulate emergent phenomenon (Silva and Clarke, 2005), a central feature of complexity (Iltanen, 2012).
- In built Self-modification function.
- Widespread application to similar studies across the globe, for instance, (Clarke and Gaydos, 1998; Syphard et al.,2011) in North America; (Leao et al., 2004) in South America; (Silva and Clarke, 2002, 2005; Henriques, 2010) in Europe; (Huang et al., 2008; Xi et al., 2008) in Asia; and (Azaz, 2004; Watkiss, 2008) in Africa.
- Openly accessible codes (http://www.ncgia.ucsb.edu/projects/gig/index.html) which facilitates modification for other purposes. For instance, Houet et al. (2016) modified the source codes for a non-path dependent model. Within the context of this research, the codes will guide the re-implementation of the model in a multi-agent enabling platform.
- Less difficulty in data accessibility: In spite of its fairly large data requirements, SLEUTH input data normally exist in multiple sources including governmental and research institutions (Leao et al., 2004) in the form of historical maps or processed remotely sensed images.
- Long range forecasting: Various studies have demonstrated the robustness of the model in forecasting into distant future including a 70-year interval (Goldstein et al., 2004).

3.5 SLEUTH Model

There is an existing body of literature on SLEUTH – for example, see Jantz et al (2004), Silva and Clarke (2005), Dietzel and Clarke (2007), Chaudhuri and Clarke (2013), Sakieh et al (2016) – hence this section offers a summarised description of its functionality. SLEUTH, which was first introduced 2 decades ago, derives its name from the required input data; slope, land use, exclusion, urban, transport and hillshade (Clarke et al., 1997). The model serves two main purposes; the simulation of urban growth and land use change. SLEUTH has four growth rules (spontaneous growth, new spreading centres, edge growth, and transport influence development. These are controlled by five parameters or coefficients: *dispersion*, which accounts for the dispersive and random nature in the distribution of urban pixels; *breed*, which determines the probability that a newly and isolated urbanized pixel becomes a new centre of growth; *spread*, which controls the extent of expansion from the edges of existing urban clusters; *slope, which* affects the likelihood that urbanization occurs on steep slopes; and road gravity, which determines the degree to which roads influence the urbanization of cells. To better depict the typical S-curved urban expansion rate, SLEUTH has an internal self-modification function that dynamically adapts the model to new conditions of boom and bust (Silva and Clarke, 2002; Dezhkam et al. 2014). When the model encounters high growth, the parameters are multiplied by a greater than 1 multiplier. Similarly, when the model encounters little growth, a less than 1 multiplier is applied to the control parameters.

The parameters have possible values that ranges between 0 and 100. The exact value of a parameter depends on the patterns of historical urban expansion of a geographical area, which is derived through calibration. Calibrating the model is one of the most important stages in the application process, as it is the avenue for adapting the model's parameters to the unique historical growth patterns of a geographical area. In determining the best fit parameter values for a geographical area, SLEUTH employs a rigorous brute force calibration process that has 3 main stages; coarse, fine, and final, see Jantz et al (2004), Silva and Clarke (2005) and Jantz et al (2010) for more. At each calibration phase, different combinations of parameters values are tested, with each model run representing a unique combination. There is a Monte Carlo stochastic algorithm in SLEUTH that generates multiple simulations, which are averaged to constitute a model run.

As the calibration process moves from coarse to final, the set of parameter values that best explain the growth trajectory of the area in question are refined. For instance, at the coarse stage, the model generates thousands of runs to test the entire range of possible values (0 – 100) for each parameter. Each run produces a simulated urban expansion for a historical year, which is compared with the real-world urban expansion (accessed from satellite imagery), using the model's inbuilt metrics described in Table 3.4. The metrics generate, for each run, best fit values that explain the goodness of fit of the simulated data (from the parameters combination) with the actual. The model runs are sorted with an Optimal SLEUTH Metrics (Dietzel and Clarke, 2007), which is the product of the metrics described in table 3.4, and the parameters values for the top three are selected. The selected values form a new and refined range of parameters that are subsequently tested in the next calibration phase known as *fine* calibration. The same process is followed, and the parameters of the top three runs are selected for further refining in the *final* calibration. After the final calibration, which conforms to the procedure outlined, the parameters for the top sorted run is used for the prediction of urban growth. More information about the calibration processes for ACR and Ashanti region are provided under Chapters 4 and 5 respectively.

Table 3.4: SLEUTH metrics for assessing the goodness of fit of simulated output in calibration stage

Metric	Description
Compare	Comparison between modelled final urban extent to real final urban extent
Population	Least squares regression score for modelled urbanization compared to actual urbanization for the control years
Edges	Least square regression score of modelled urban edges against the urban edges of control years
Clusters	Least squares regression score for modelled urban clustering compared to known urban clustering for the control years
Slope	Least squares regression of average slope for modelled urbanized cells compared to average slope of known urban cells for the control years
X-mean	Least squares regression of average x_values for modelled urbanized cells compared to average x values of known urban cells for the control years

Y-mean	Least squares regression of average y_values for modelled urbanized cells compared to average y_values of known urban cells for the control years

Source: Adapted from Dietzel and Clarke (2007)

3.6 Data sources for SLEUTH calibration

For both Chapter 4 and 5, SLEUTH is applied to urban growth simulation, which, unlike land use simulation, require only 5 input datasets; slope, exclusion, urban, transport and hillshade. Thus, for this research, land use input layer is not required. The input datasets for ACR and Ashanti region were accessed through multiple sources, such as, the Forestry Commission of Ghana, TCPD of Ghana, United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA) as shown in Table 3.5.

The urban extents data of both regions relating to 1990, 2000 and 2010 epochs were accessed through the TCPD. These datasets, however, originally emerged from the Forestry Commission's project of mapping forest cover and carbon stock that was undertaken in 2013 as captured in box 1. The 2015 urban extent data for the Ashanti region was obtained from the Ashanti regional TCPD through the Ashanti Region Spatial Development Framework project that took place in 2015/2016.

The transport layers for the two regions of comprise trunk roads for 1990 and 2012. For the latter, data was accessed from the TCPD through the Land Use Planning and Management Information System (LUPMIS), while that of 1990 was extracted from Very High Google Earth Image. The exclusion layer, representing areas resistant to development, constitutes forest and game reserves, water bodies and national parks, all of which were accessed from the TCPD through the LUPMIS database.

Table 3.5: Data required and sources

Data	Source
Urban extents (1990, 2000 and 2010) for ACR and Ashanti region	Forestry Commission of Ghana (2015); TCPD (2015)
Ashanti region urban extent for 2015	Ashanti regional TCPD (2015)
ACR urban extent for 2015	Author's classification of LandSat 8 imagery
Transport (trunk roads)	TCPD (2015) / Google Earth
Exclusion (forest reserves, game reserves national parks, water bodies)	TCPD (2015)
Slope and Hillshade	NASA (2016) – 30m ASTER GDEM

Box 1: Description of spatial data from the Forestry Commission of Ghana

The Forestry Commission of Ghana (2013) undertook a project on mapping the forest cover and carbon stock of Ghana in 2012. The project as part of its deliverables classified satellite data for 1990, 2000 and 2010 into six land uses, settlement (built - up), crop land, forest cover, wet land, grass land and others for the entire Ghana.

For 1990 and 2000 classifications, Landsat Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper (ETM) images, both with spatial resolution of 30m were used respectively, whereas Advanced Land Observing Satellite (ALOS) Advanced Visible and Near Infrared Radiometer type 2 (AVNIR-2) images with 10m spatial resolution were used for the 2010 epoch. Prior to classification, the images were processed for geometrical corrections. The project used a GIS software to classify the imageries into the six land uses mentioned above. Ground verification was undertaken after the classification using 2,213 locations across Ghana, a significant number of which fall within the two study areas. Based on the ground truthing, the identified anomalies were rectified. After the final classification, there was an overall accuracy of 83 percent. Settlement cover and wetlands, the two land use types of interest to this research recorded producer accuracies of 99.65 and 99.35 percent respectively. For user accuracy, the same figure (99.35 percent) was recorded for wetland, while 85.50 percent was recorded for settlements. For more details, see Forestry Commission of Ghana (2013).

3.5.1 Classification of Satellite Data

As indicated in table 3.5, ACR's 2015 urban extent data was based on a satellite data classified by this research. First, Landsat 8 OLI/TIRS image (path 193, row 56) with spatial resolution of 30m was accessed in 2015 from the USGS as a standard product. The image was geometrically referenced to the coordinate system, WGS 1984, UTM Zone 30N. Comparing the satellite imagery with very high resolution Google Earth imagery for the same area, it was realized that the image's cloud cover, which was around 7 percent, was mainly in non-built-up areas. Using QGIS software package, atmospheric corrections in relation to cloud cover and sun elevation were undertaken on the bands by converting digital numbers to reflectance values. To enhance the identification of built-up areas, a Normalized Difference Built-up Index (NDBI) was computed, the formula for which is found below.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \qquad (3.1)$$

Where, SWIR is shortwave infrared and NIR, near infrared. Combining the NDBI image with natural band colour combination and a very high resolution 2015 Google Earth image, training samples were selected for the classification. Using maximum likelihood classification function in QGIS, the Landsat image was classified into three distinct land use classes: built-up (for the urban extent layer), water (used as part of the exclusion layer) and non-built-up. To ensure consistency with the previously classified dataset, the Forestry Commission (2013) definition for settlement cover (built-up) was used. Thus, built-up cover is defined to include all developed lands with varying uses, such as residential, commercial, educational, industrial, transport, etc. The classification of non-built areas followed standard typologies to include any land other than built-up and water. This includes forest land, grass land, croplands, bare lands, etc. Still within QGIS, and using 250 random points from Google Earth imagery, 82 percent overall classification was achieved.

3.6 Expert Validation of Calibrated CA model

A key part of Chapter 4 involves exploration of the capacity of urban CA models to model and simulate informal urban growth trajectories. This is pursued in three ways, including: comparison of the calibrated results for ACR with findings from existing literature on the context; situating the calibrated results within an international context; and seeking expert opinions on the calibrated results. The opinions were sought from two groups of experts – urban planning professionals and academics – through meetings. The first meeting, held on 26th July 2016 at the Town and Country Planning Department Head Office in Accra, comprised mainly of spatial planning practitioners that included the National Director and Senior Planning Officers from the TCPD Head Office, Greater Accra Regional TCPD Director, and Planning Officers from the various districts within ACR. The second meeting, which took place on the 27th July 2016 at the Department of Planning, Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, involved academics specialised in urban planning.

3.7 Application of Spatial Metrics

In Chapter 5, a set of spatial metrics are used along with SLEUTH to analyse the evolving spatial structure of a SSA city. Over the years, various spatial metrics have been developed and applied spatial structure, see, for instance, Reis et al., (2016). Three main spatial metrics, namely, annual urban expansion rate (AUER), urban expansion intensity index (UEII) and urban expansion differential index (UEDI) are applied in this research. The selection of these metrics is largely influenced by their proven capacity to quantify spatio-temporal patterns of urban growth, for example, see Hu et al (2007), Li et al (2010), Lu et al (2014), Acheampong et al (2016). The metrics rely primarily on the urban extent data for the Ashanti region described in section 3.5. Further details about the metrics are provided under section 5.2 of Chapter 5.

3.8 Methods and Data for Part 2

Part 2 focuses on the integration of ABM and CA in simulating urban growth in an informal context. Prior to the integration, which is captured in Chapter 8, the location choice decisions of urban households are analysed in Chapter 7. In the conceptual framework presented in Chapter 8, the integrated model comprises two main parts; multi-agent and spatial systems. In the multi-agent system, captured with ABM technique, the decision-making processes and behaviour of actors responsible for urban development are modelled. The development processes and interactions in the spatial system, on the other part, is formalized with urban CA modelling approach.

Pursing the overall objective of this part of the research requires understanding the location choice decisions of urban development actors such as households, real estate developers and government. In Ghana, unlike most of the other contexts for which integrated AB-CA models have been developed and applied, overwhelming majority of developments are undertaken by households. Whilst developments by real estate institutions have notably increased over the past few decades, particularly in ACR, they still represent a minute proportion (less than 15 percent) of the overall supply. Small scale and incremental development process by households is still the main driving force of urban growth in Ghanaian cities. To understand how household actors make location choice decisions, primary data was collected from sampled households.

3.9 Sampling of Households

A number of activities were undertaken prior to the sampling of households. These include, among others, the determination of sample size, design of survey instruments, recruitment and training of field assistants and piloting of questionnaires. A copy of the household questionnaire is presented in the Appendix.

3.9.1 Determination of Sample Size

This research samples 800 households, a size determined through the equation:

$$n = \frac{NY}{(Y + N - 1)} \tag{3.2}$$

Where, n is the household sample size; N is the total number of households; and is given by the equation below.

$$Y = \frac{{Z_a}^2\big(p\ (1 - p)\big)}{x^2} \tag{3.3}$$

Where, Z_a is 1.96, the critical value of normal distribution at 95 percent confidence level; p is the sample proportion (estimated at 0.5); and x is the margin of error, which is 3.5 percent.

In equation 3.2, the number of households in ACR is estimated as:

$$N = {}^{P}\!/_{h} \tag{3.4}$$

Where, P is the total population (5,515,808), and h is the average household size in ACR, which is 3.9 according to the Ghana Statistical Service (2012). Thus, there are about 1,414,310 households in ACR. Substituting all the values into equation 3.2 generates a sample size of 784 households. To cater for possible non-responses, a total of 800 households were sampled.

3.9.2 Sampling techniques

The research adopted two main sampling techniques; cluster and systematic. Starting with the former, the sample size of 800 households was distributed among the major suburbs in the city-region. The distribution of the sample size was based on the proportion of the city-region's household population absorbed by the districts of the various suburbs. In addition to being population hotspots, the suburbs, presented with Table 3.6, were selected largely according to economic characteristics, particularly the spatial manifestation of dominant income class. The selected suburbs/clusters, which includes predominantly low-income areas (such as Nima), mainly high-income areas (such as Airport residential), and middle-income areas (such as Achimota), reflect the diversity in income distribution in the city region. The suburbs were also selected to include newly and fast developing areas, such as Kasoa, Pokuase, Amasaman, that present an opportunity for interviewing households that have made recent location choice decision. Location also played a role, as the suburbs were selected in a way that the major parts of ACR were covered.

Table 3.6: Selected Clusters and Household Sample Sizes

Suburb	Number of Households Sample Sizes	Suburb	Number of Households Sample Sizes
Abeka	25	La	20
Achimota	35	Labone	15
Adenta	20	Lapaz	25
Airport Residential	15	Madina	30
Amanfrom	20	Malam	20
Amasaman	20	Mamprobi	15
Ashongman	30	Mataheko	20
Bubuashie	20	Nima	60
Dansoman	25	Nungua	25
Dome	25	Osu	25
Dzorwulu	20	Pokuase	20
East Legon	25	Tema	50
Kaneshie	35	Teshie	25
Kasoa	50	Ashaiman	30
Kwabenya	40	Ridge	15

Having selected the clusters/suburbs and distributed the sample size among them, systematic sampling technique was used, albeit loosely, to access the households. Not more than one household was selected from a house. For many of the clusters, especially those with operational street/house numbering system, a house was first randomly selected from a list of house numbers. In slum areas, like Nima, where house numbering system is essentially non-existent, the clusters were loosely divided into mini blocks/sites. A block is randomly selected and one of the houses within is chosen. In houses that have two or more households, the first household that enumerators come across upon entering is chosen. Arrangements are then made to meet the household head for a possible interview. Upon meeting the household head, initial questions are asked to make sure that the person has either moved houses before or plans to move to a specific place. Persons that did not meet this criterion were not interviewed, since they had not made location choice decision. Upon selecting the first house and a household, a loosely defined interval, ranging from 10 to 30 houses for the various clusters, was applied in the selection of the subsequent houses and households. In all, 800 interviews were started, but 790 were successfully completed.

3.9.3 Survey Instruments, Piloting, Recruitment and Training of Enumerators

Semi-structured questionnaires and interview guides were used as the main survey instruments in collecting the household data. These instruments were piloted with 9 households, after which they were modified. Field assistants, consisting mainly university students and graduates, were recruited and trained. The training, which took place on the 31 August 2016 at the Head Office of the Town and Country Planning Department of Ghana, involved 13 field assistants. As part of the training, the enumerators were taught how to collect the geographical coordinates with their mobile phones. Thus, the longitudes and latitudes of each sampled house were collected.

3.4 Other Data Sources

In addition to household data, Part 2 uses a number of institutional datasets accessed from various sources as captured in Table 3.7. Besides, since this part of the work integrates ABM and CA, the spatially explicit datasets employed in the CA application in Part 1, especially for the ACR, are also used heres.

Table 3.7: Data and Sources for Part 2

Data	Source
Land Values	Ghana Lands Commission Department
Population / Demographic Characteristics	Ghana Statistical Service
Structure Plans	Town and Country Planning Department
Transport Network	Town and Country Planning Department

3.5 Analysing Household Data

After its collection, the household data was edited, collated and coded into the Statistical Package for Social Scientist (SPSS) software. In addition to performing descriptive statistics, the data was exported into R statistical package for further exploration. In R, logistic regression functions were used to analyse the location choice preferences of various households. GIS techniques were also used to analyse some of the household datasets that needed to be processed spatially. The longitude and latitude coordinates that were picked up with mobile phones proved helpful in this area. NetLogo modelling platform was used to develop the integrated ABM and CA model, drawing on results of the analysis performed in SPSS, R and ArcGIS.

CHAPTER FOUR
SIMULATING THE URBAN GROWTH OF A PREDOMINANTLY INFORMAL SUB-SAHARAN AFRICAN CITY-REGION WITH A CELLULAR AUTOMATA MODEL: IMPLICATIONS FOR URBAN PLANNING AND POLICY

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4.1 Introduction

The rapid urbanization that has characterized many cities, especially those in the Global South, has gained global recognition and occupied centre stages of urban academic discourse. The phenomenon, which is on-going, is expected to generate additional 2.5 billion urban dwellers by 2050, out of which Africa and Asia are projected to account for about 90 percent (UN, 2014). While urbanization presents socio-economic opportunities that cannot be discounted, its associated challenges, including environmental degradation, urban poverty, overcrowding, etc cannot be overemphasized. Understanding the likely spatio-temporal manifestation of the expected urban population boom is vital to maximizing its opportunities, while ameliorating potential challenges to sustainable development.

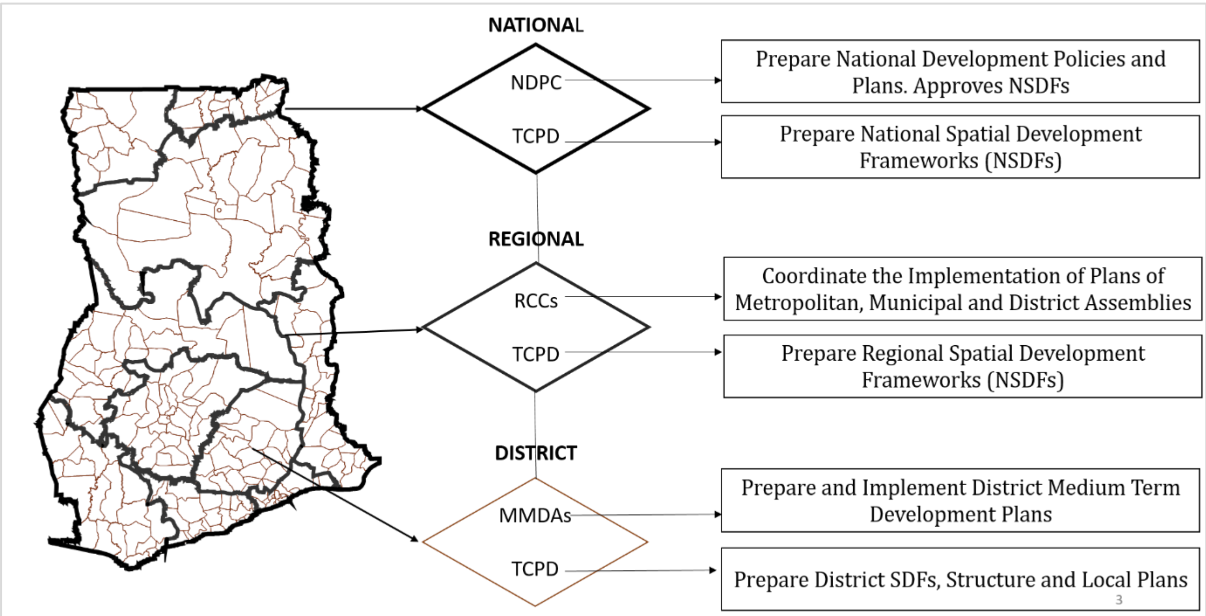
Post-independence Ghana exemplifies the massive urbanization that has characterized many countries in sub-Saharan Africa in recent decades. Since the turn of the twenty-first century, the West African country has changed its status from predominantly rural to urban, gaining about 7 million additional urban dwellers (Ghana Statistical Service, 2013). Stemming from the rapid pace of urbanization, Ghana's urban population of around 15 million is projected to reach 30 million by 2035 (Town and Country Planning Department of Ghana, 2015). The monumental urban growth manifest across diverse spatial scales, the governance of which is shown in Figure 4.1. In particular, growth is highly reflected in the principal cities including Accra, the capital, which has transformed to a city-region that holds more than 5 million people and is projected to be a metacity by 2035 (Agyemang et al, 2017). While the ongoing urbanization in Ghana appears too imposing to be pushed to the peripheries of urban studies, there is no study that simulates the future urban growth of any Ghanaian city. Existing urban policies that are expected to shape future urbanization patterns are less informed by robust research evidence of likely urban growth outcomes. Therefore, as one of two-fold objectives, this chapter simulates the future urban growth patterns of a Ghanaian city-region with a Cellular Automata (CA) model and examines the implication for urban policy.

A major distinguishing characteristic of the spatial growth of Ghanaian cities is their highly informal and un-regulated nature (UN-HABITAT, 2011; Boamah, 2012; Anokye et al., 2013; Korah et al, 2016). This feature sets up the platform for further exploring the sensitivity of CA models to predominantly informal urban growth trajectories, a theme that is not sufficiently covered by existing CA literature, and which forms the second objective of this chapter. Over the past few decades, CA has emerged as one of the major dynamic, bottom-up modelling approaches that have remarkably underpinned many urban growth models. Indeed, stemming from its parsimonious structure and flexible adaptation to evolution, CA has been one of the most robust modelling techniques for simulating urbanization trends and patterns (Sante et al, 2010; Aburas et al., 2016). In some cases, for example, see Shafizadeh-Moghadam et al (2017a), the approach has been found to increase the prediction accuracy of models.

CA has been applied in diverse ways to urban model development and application. From places being selected as test cases for exploring geographically borderless CA research, see Berberoglu et al (2016), Liao et al (2016), Shafizadeh-Moghadam et al (2017b), to the approach being used to solve place specific problems, the global coverage of CA has fast expanded. The wide-ranging geographical applications encompass the continent of North America (Clarke et al., 1997; Syphard et al., 2011), South America (Leao et al, 2004; Almeida et al., 2008), Asia (Feng et al., 2015; Bihamta et al.,2015; Wagner et al., 2016), Europe (Silva and Clarke, 2002; Stanilov and Batty, 2011; Gounaridis et al., 2018), Africa (Okuashi et al, 2012; Okuashi et al, 2012; Mubea et al, 2015) and Austalia (Liu et al, 2014b). A common feature, however, of the above cited CA literature and dozens of others, for instance over 60 studies reviewed by Chadhouri and Clarke (2013), is their application to contexts where urban development is highly regulated and formalized. While in many parts of the world urban development is planned, regulated and formalized, in others, like Ghana, development is overwhelmingly informal (UN-HABITAT, 2011; Boamah, 2012; Anokye et al., 2013). Thus, despite the existing large and still growing literature base of CA, a question which warrants further examination is, are urban CA models sensitive to predominantly informal urban growth trajectories?

Following the above, this chapter pursues two-fold objectives: one, simulates the urban growth of a Ghanaian city-region with urban CA model, drawing implications for urban policy; and, two, examines the sensitivity of CA models to highly informal urban growth trajectories. The CA model, SLEUTH, is subsequently calibrated for Accra City-Region (ACR). There are dozens of CA models that have been developed for urban growth simulation (Sante et al, 2010; Aburas et al., 2016). The selection of SLEUTH is premised on a number of factors, including the model's capacity to simulate many diverse growth patterns (Jantz et al, 2010; Bihamta, 2015), application to many different parts of the globe (Chadhouri and Clarke, 2013), self-modification function (Silva and Clarke, 2005), fairly accessible data (Leao, 2004), and openly accessible codes.

Figure 4.1: Spatial Governance Structure of Ghana



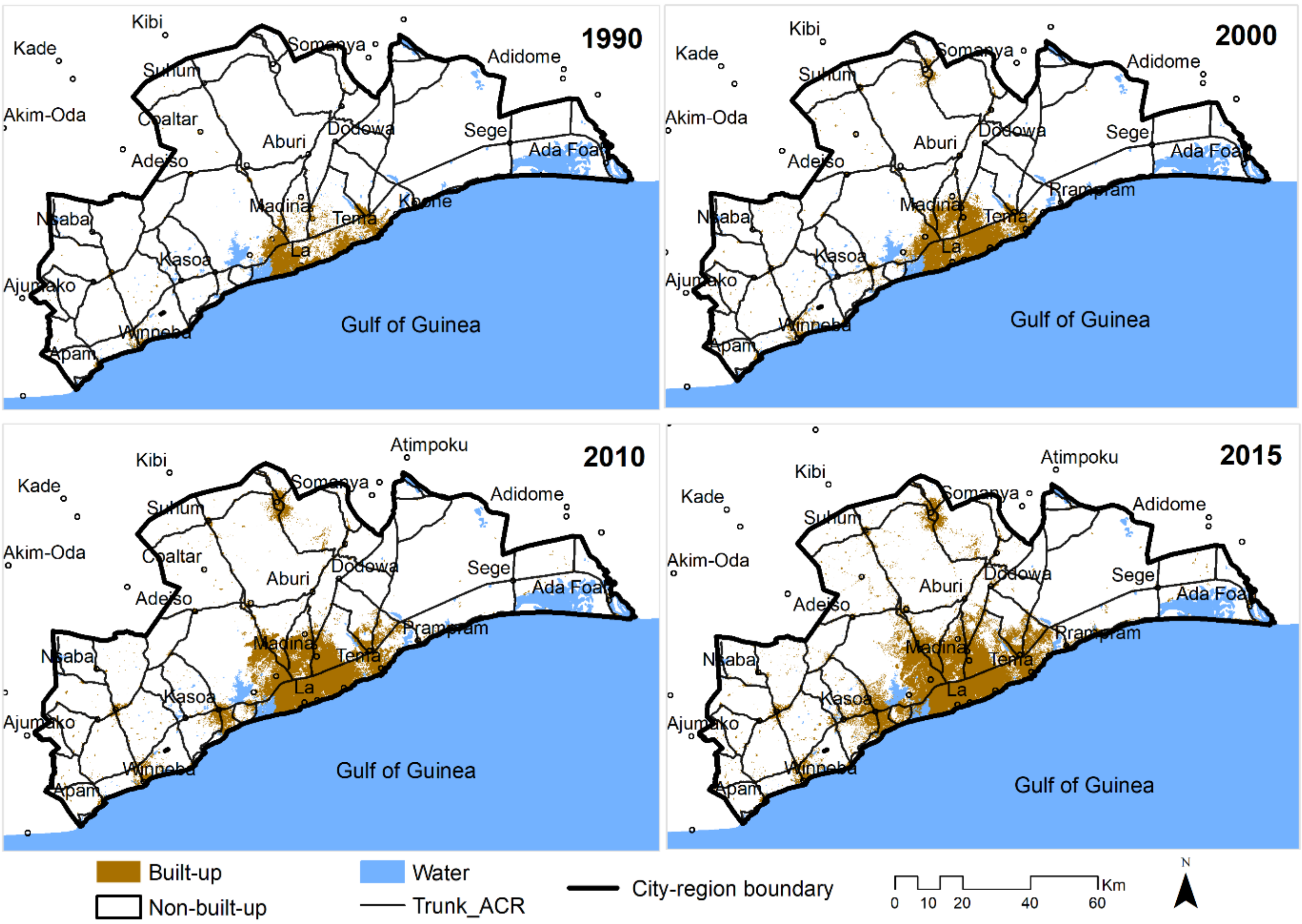
Source: Agyemang et al (2017)

4.2 Brief Characteristics of Accra City-Region

Accra City-Region (ACR), formed around the capital of Ghana, Accra, is selected as case study. The population and economic characteristics of the city-region is captured under section 3.2.1 of Chapter 3. Summarily, the selected city region covers land area of about

8,100km^2, and is the most urbanized as well as economically vibrant region in the West African country. In 2010, ACR absorbed around 5.5 million people in 2010 of which 81 percent lived in urban areas. Based on projections by the Town and Country Planning Department of Ghana (2015), the city-region's population could reach 10 million by 2035. Despite accounting for less than 4 percent of Ghana's total land area, the city-region absorbs more than a quarter of the national GDP. ACR has also undergone massive urban expansion over the past two and half decades. Between 1990 and 2015, the size of built-up extent more than quadrupled. Figure 4.2 shows, broadly, the historical landcover classification for the area.

Figure 4.2: Historical landcover map of Accra City-Region



4.3 Calibrating SLEUTH for ACR

Modelling with CA is now very popular, and one of the most well established and used models is SLEUTH (Chaudhuri and Clarke, 2013). In addition to its widespread recognition, the selection of SLEUTH is premised on several factors, including: capacity to simulate many diverse urban growth patterns (Jantz et al, 2010; Bihamta, 2015); self-modification function (Silva and Clarke, 2005); open access codes; and fairly accessible data (Leao, 2004). There is an existing body of literature on SLEUTH – for example, see Jantz et al (2004), Silva and Clarke (2005), Dietzel and Clarke (2007), Chaudhuri and Clarke (2013), Sakieh et al (2016) – hence this section offers a summarised description of its functionality. A detailed description of SLEUTH as well as the basis for its selection is captured under Sections 3.4 and 3.5 of Chapter 3.

Calibrating the model for Accra city-region followed the traditional calibration of SLEUTH described above. For instance, with coarse calibration, the input data were processed into 200m spatial resolution with 536 rows and 886 columns. The entire range of parameter values (between 0 and 100) were tested. By specifying Monte Carlo iterations of 5, the model generated 3,124 runs, which were subsequently sorted by the Optimal SLEUTH Metrics (OSM). The associated coefficients of the selected top 3 runs as shown in Table 4. 1 were then used to refine the parameters values for the next phase, *fine* calibration. This process was repeated for *fine* and *final* calibration phases. The top run from the *final* calibration was used to predict the urban growth for the city-region.

Table 4.1: Top 3 runs from coarse calibration of SLEUTH

Run	OSM	Compare	Pop	Edges	Cluster	Slope	Xmean	Ymean	Diff	Brd	Sprd	Slp	RG
1625	0.1239	0.240	0.937	0.849	0.905	0.914	0.947	0.828	50	75	1	1	1
1630	0.1239	0.240	0.937	0.849	0.905	0.914	0.947	0.828	50	75	1	25	1
1635	0.1239	0.240	0.937	0.849	0.905	0.914	0.947	0.828	50	75	1	50	25
1640	0.1239	0.240	0.937	0.849	0.905	0.914	0.947	0.828	50	75	1	75	25
1645	0.1239	0.240	0.937	0.849	0.905	0.914	0.947	0.828	50	75	1	25	1
1575	0.1049	0.249	0.964	0.880	0.995	0.947	0.824	0.638	50	50	75	1	1
1580	0.1049	0.249	0.964	0.880	0.995	0.947	0.824	0.638	50	50	75	25	1
1585	0.1049	0.249	0.964	0.880	0.995	0.947	0.824	0.638	50	50	75	50	1
1590	0.1049	0.249	0.964	0.880	0.995	0.947	0.824	0.638	50	50	75	50	1
1595	0.1049	0.249	0.964	0.880	0.995	0.947	0.824	0.638	50	50	75	25	1
2875	0.0937	0.240	0.994	0.935	0.712	0.986	0.818	0.730	100	75	1	1	25
2880	0.0937	0.240	0.994	0.935	0.712	0.986	0.818	0.730	100	75	1	25	1
2885	0.0937	0.240	0.994	0.935	0.712	0.986	0.818	0.730	100	75	1	50	1
2890	0.0937	0.240	0.994	0.935	0.712	0.986	0.818	0.730	100	75	1	75	1
2895	0.0937	0.240	0.994	0.935	0.712	0.986	0.818	0.730	100	75	1	50	25

RG: Road Gravity

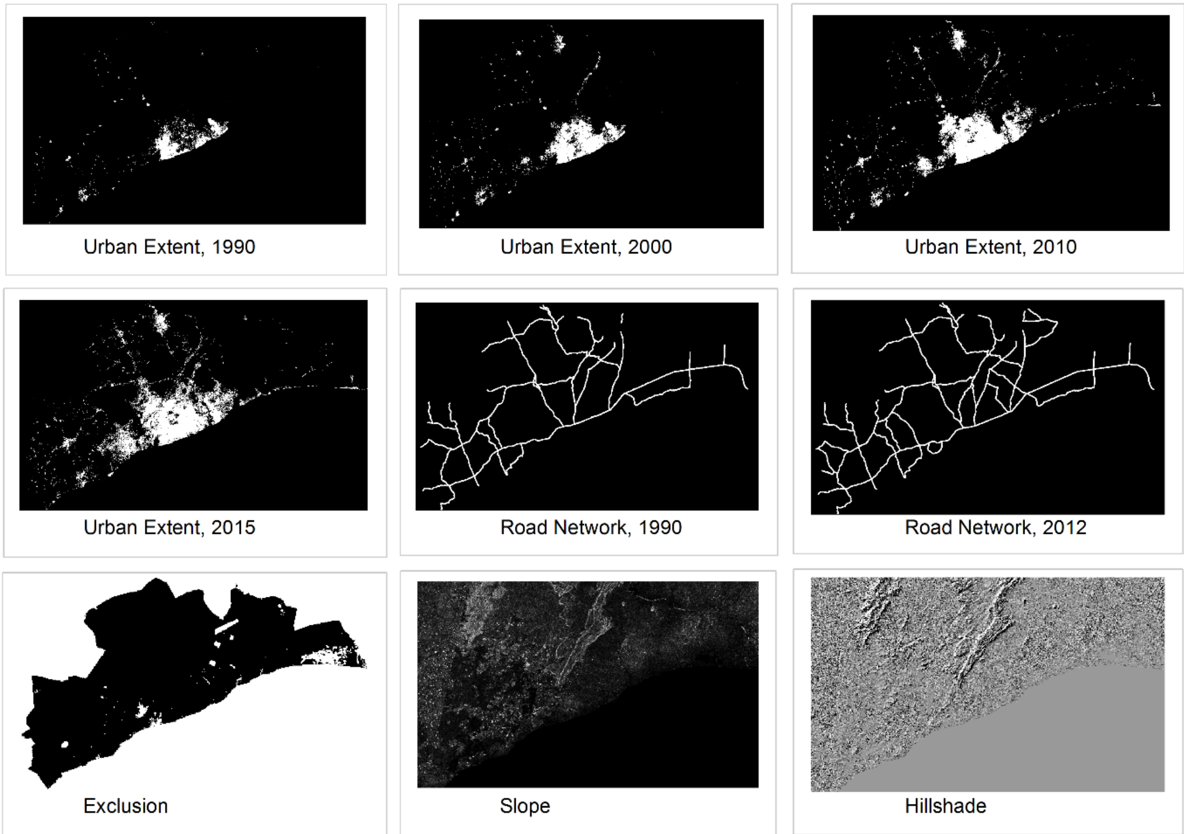
SLEUTH produces two types of outputs, image and statistical. The image output shows the probability level of each pixel being urban. The statistical output, however, includes 13 metrics, 2 of which generate data about cells that are predicted to be urban. These two metrics, known as "pop" (as in population) and "area", count the number of pixels that have probability level of 1 or 100 percent. Both categories of outputs are presented: the image output, depicted by figure 4.3, which displays the different predicted probabilities; and statistical output, represented by figure 4.4 that shows, for each year, the land area predicted to be completely (100 percent) urban.

4.4 Data and Sources

For urban growth simulation, 5 input data – slope, exclusion, urban, transport and hillshade required. The datasets and their sources are described under Section 3.6 of Chapter 3. In summary, the required datasets were accessed through multiple sources, such as, the Forestry Commission of Ghana, Town and Country Planning Department (TCPD) of Ghana, National Aeronautics and Space Administration (NASA), and existing academic publications as shown by table 3.5. The urban extent datasets are based on classification of Landsat imageries. The 1990, 2000 and 2010 epochs were classified by TCPD (2015) while that of 2015 was classified by this research. The transport layer comprises of trunk roads for two epochs, 1990 and 2012. For the latter, data was acquired from the TCPD through the Land Use Planning and Management Information System (LUPMIS), while that of 1990 was extracted from Very High Google Earth Image.

Using Geographic Information System (GIS) techniques, the urban extent and transport layers were processed as binary files, where cells are assigned with values of either 1 or 0, representing presence of urban/road or absence of same, respectively. The exclusion layer was also processed as binary, where all cells resistant to development are assigned a value of 100, while those available for development are coded as 0. Still using the GIS technique, the GDEM data is converted to percent slope. The input data are subsequently stretched and saved as 8-bit greyscale gif files, all with same extent in terms of number of rows and columns, enabling their readability by the model. Figure 4.3 shows the processed input gif files.

Figure 4.3: Processed input data of Accra City-Region



4.5 SLEUTH coefficients for Accra city-region

Results from the brute force calibration of SLEUTH for Accra city-region is summarized in table 4.2. After *coarse* and *fine* calibration phases, the coefficients that best explain the historical trajectory of the city-region were substantially refined for *dispersion* and *breed,* narrowing their ranges to 10. In contrast, the range for *spread* coefficient (60) was not as refined. The best fit values for *slope* and *road gravity* were moderately refined to 0 – 30, and 0 – 20 respectively. The resulting coefficients from the *final* and *forecasting* calibration phases can be classified into two groups; those that are close to 100, which is the highest possible value; and the ones that are close to 1, the lowest possible value. *Spread* (95), *breed* (83), and *dispersion* (76) fall into the first group, while *slope* (11) and *road gravity* (10) coefficients are within the latter.

Table 4.2: Calibration coefficients of SLEUTH for Accra City-Region

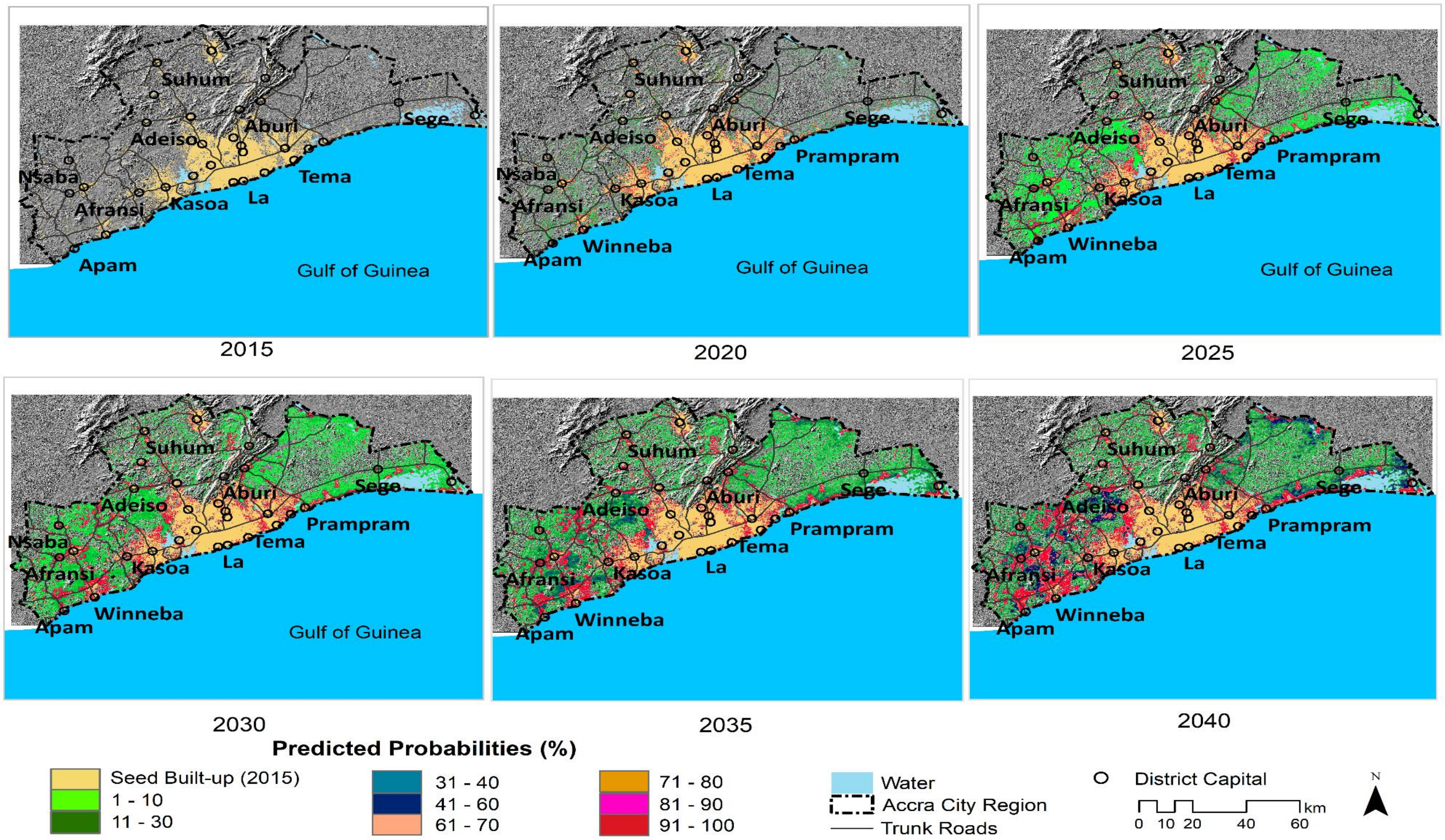
	Coarse Calibration		Fine Calibration		Final Calibration		Forecast	
Parameters	Range	Step	Range	Step	Range	Step	2000	2015
Dispersion	0 – 100	25	50 – 100	10	50 – 60	2	66	76
Breed	0 – 100	25	50 – 75	5	55 – 65	2	71	83
Spread	0 – 100	25	0 – 75	15	15 – 75	12	82	95
Slope	0 – 100	25	0 – 75	15	0 - 30	6	24	11
Road Gravity	0 – 100	25	0 – 25	5	0 - 20	4	7	10

4.6 Simulated urban growth of Accra city-region

The best fit coefficients derived from the brute force calibration are used to predict the urban growth of Accra city-region from 2015 to 2040. A 5-year interval images have been selected and presented with Figure 4.4. Colour coding is used to differentiate the seed year urban extent from predicted ones. In addition, the colours are used to distinguish between the probability levels of pixels predicted to be urban. The predicted images exemplify a pattern whereby the probability of a pixel being developed increases with increasing time span. For instance, most of the green pixels in 2025, which represent areas with just about 10 percent probability level of being converted to urban, changes to one of the colours of blue, deep blue, orange and red in the subsequent years, especially 2040, signifying an increment in urbanization likelihood. Even though the model's capturing of socio-economic and behavioural factors is more implicit, one could, generally, relate to this pattern, considering the context. In Ghana, this reflects the dominant incremental building process adopted by majority of households.

In addition, the predicted urban expansion is largely skewed towards the western parts of Accra, where there are rapidly urbanizing suburban centres, such as Weija, Kasoa and Nyanyano. This is also a reflection of the trend scenario that depicts westerly urban expansion over the past two and half decades. Indeed, the meetings with key local stakeholders revealed how development was planned Easterly in 1990 but was predominantly Westerly by 2015. The 1990 structure plan of Accra shows that the western parts of the city-region was largely planned as vegetation. Unlike the structure plan, the model simulates more growth to the West, which better reflects the actual growth trajectory of the city-region.

Figure 4.4: Simulated urban expansion of Accra City-Region, 2015 – 2040



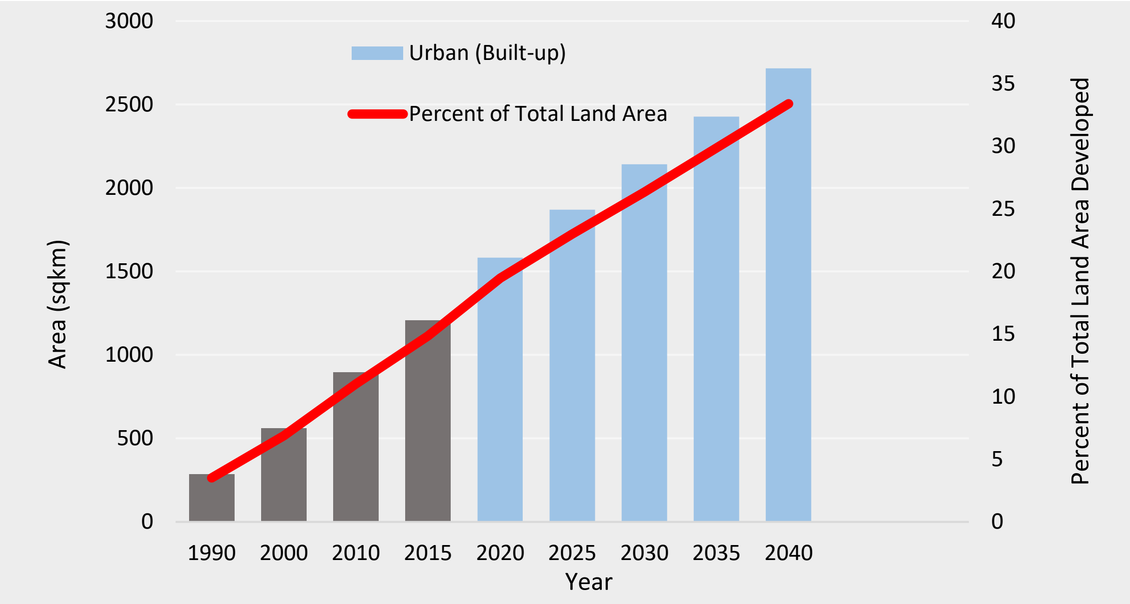
4.7 Quantification of urban growth of Accra city-region; historical and predicted

Figure 4.5 shows the urban growth of Accra for both historical and predicted years. In 1990, less than 5 percent of the total land area of ACR was urban. However, during 2010, the city region expanded rapidly at an annual rate of 6.9 percent, increasing the proportion of land under built-up from 3.5 to 7 percent. The rapidity of this annual rate of urban expansion becomes more visible when juxtaposed with that of Greater Kumasi Sub-region - the second largest urban centre in Ghana, which expanded at an annual rate of 4.7 percent (Acheampong et al., 2016) during a similar period, 1986 – 2001.

The rapid expansion in built-up area continued in the first decade of the twenty-first century, albeit at a slightly reduced pace (4.8 percent). During this decade, the proportion of land under built-up increased to 11 percent. Quite recently, between 2010 – 2015, the rapidity of urban expansion increased, as annual urban expansion rate soared to 6.1 percent, resulting in an upsurge in the proportion of land that is built-up from 11 to 15 percent. Over the 25-year period (1990 – 2015), the city-region recorded a significantly high annual urban expansion rate of 5.9 percent that reflected in a sharp rise in urban land from less than 5 to 15 percent of the total land area. In absolute terms, about 920 km^2 of land were built between 1990 and 2015. Thus, the city-region's urban extent more than quadrupled within a period of 25 years.

Based on the trend scenario, the city-region's built-up area is predicted to account for more than a fifth (22 percent) of the total land area by 2025. This is expected to further increase to a little above a quarter (26 percent) and 30 percent by 2030 and 2035 respectively. By 2040, around a third of the total land area is predicted to be built-up. Thus, the built-up extent of Accra is expected to more than double by 2040.

Figure 4.5: Urban Growth of Accra, Historical and Predicted (1990 – 2040)



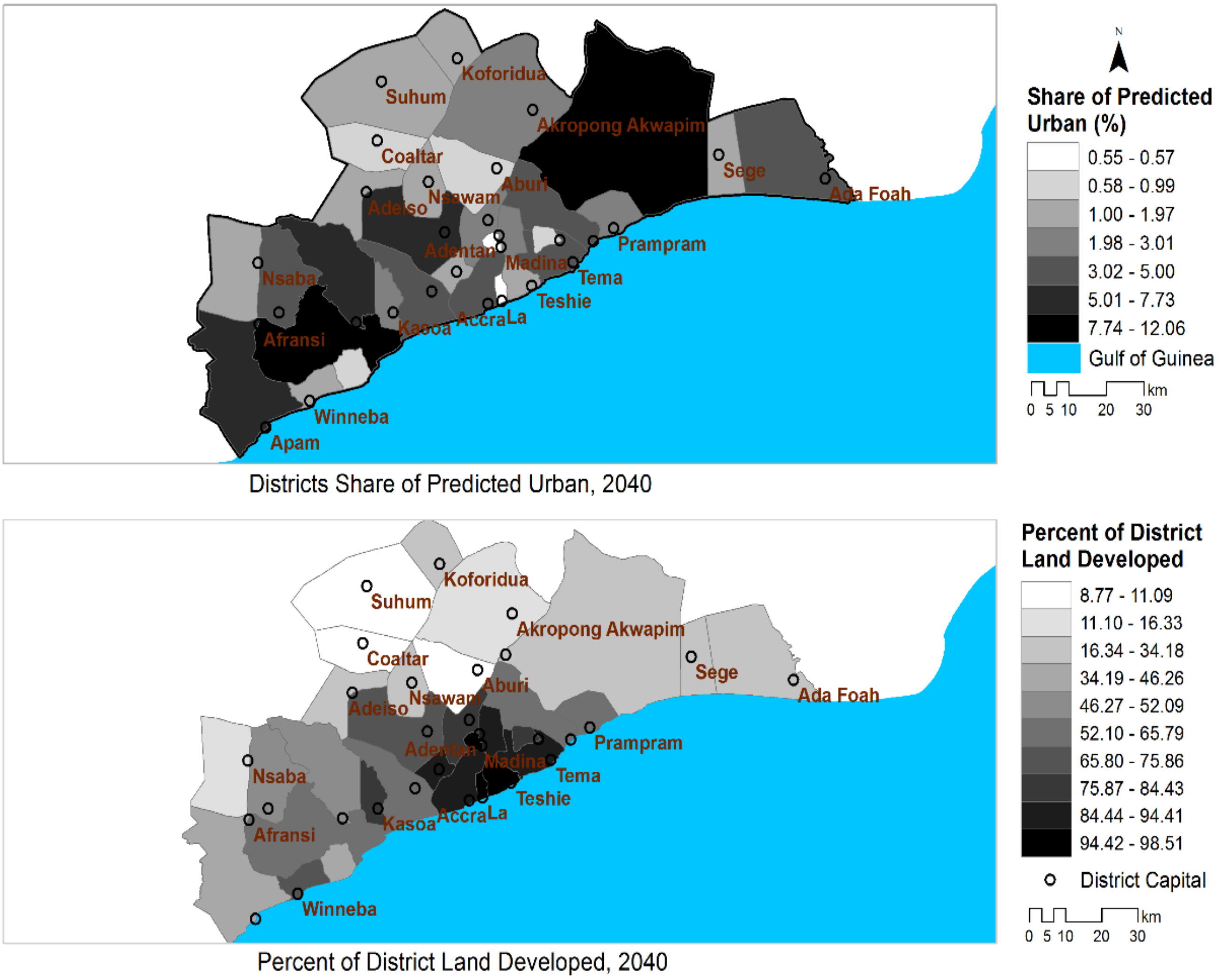
4.8 Spatial Dynamics of Simulated Urban Expansion

The simulated urban expansion for 2040 has been disaggregated into districts for further analysis. Two indicators are subsequently explored: first, each districts' share of the simulated urban expansion is analysed; and, second, the percentage of districts' land simulated as urban is examined. As shown with Figure 4.6, districts' share of simulated urban growth ranges from approximately 0.5 percent in La Nkwantanang to 12 percent in Shai-Osudoku. Gomoa East (9.3 percent), Ga West (7.7 percent), Gomoa West (6.4 percent) and Awutu Senya (5.7 percent) are among the top 5 districts in terms of size of predicted urban expansion. Affirming earlier observation that growth is predicted more to the west, the top five districts, except Shai-Osudoku, are to the West of Accra. However, it must be acknowledged that the measure is quite crude, as land area differs among districts.

Following the above, the second indicator highlights the extent to which districts are predicted to be urban by 2040. The proportion of districts' land areas predicted as urban varies from 8.8 percent in Suhum to 98.5 percent in Ledzokuku Krowor. In all, seven districts, Ledzokuku Krowor, La Dade-Kotopon, La Nkwantanang-Madina, Tema, Ga Central, AMA and Adentan are simulated to reach, at least, 90 percent built-up levels. Thus, these districts, largely constituting the core of Accra, will have, at most, only a tenth of their lands available for further development.

For these districts, redevelopment and vertical expansion may well be the only option of development. Other eleven districts – Ashaiman (84 percent), Ga East (83 percent), Awutu Senya East (81 percent), Efutu (76 percent), Ga West (70 percent), Kpone (66 percent), Ningo Prampram (64 percent), Gomoa East (61 percent), Ga South (59 percent), Awutu Senya (52 percent) and Agona West (52 percent) are predicted to be, at least, half built by 2040. Thus, about 18 districts, which is more than half of the total number of districts in the city-region, will have, at the minimum, 50 percent of their lands under built-up. Only five districts – Agona East, Akwapim North, Ayensuano, Akwapim South and Suhum – are expected to be less than 20 percent developed. Based on the trend scenario, these districts might be the areas available for further expansion from 2040.

Figure 4.6: District Dynamics of Simulated Urban Growth in Accra City Region



4.8 The uniqueness of Accra City-Region's growth trajectory and the sensitivity of SLEUTH

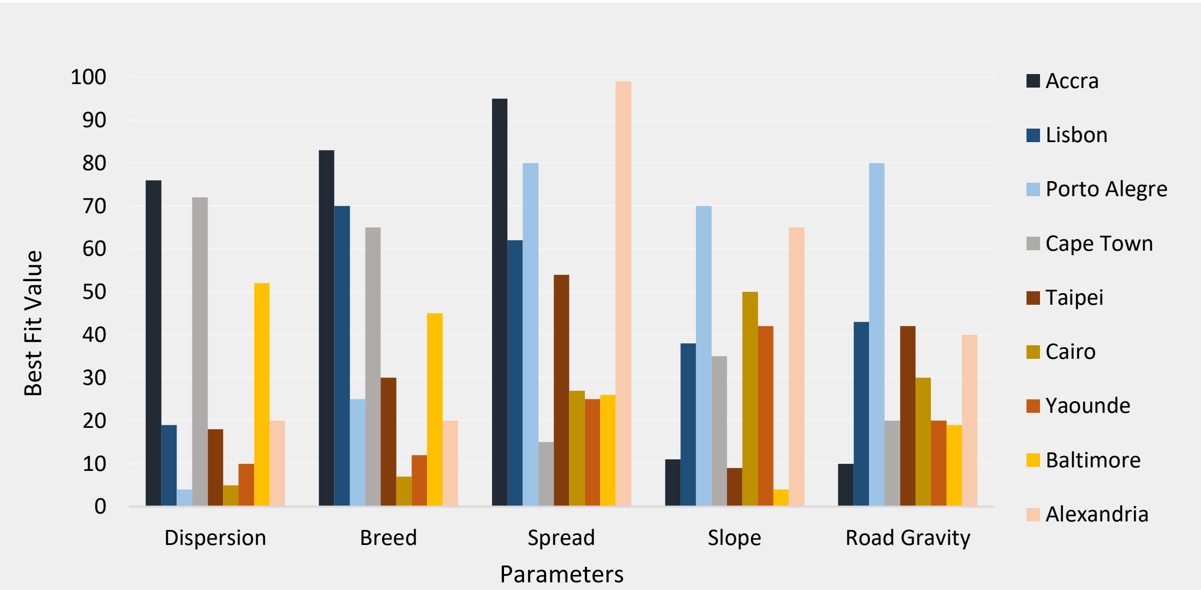
The growth of Ghanaian cities is distinctively informal and un-regulated (Acquah Harrison, 2004; UN-HABITAT, 2011; Boamah et al, 2012; Anokye, et al., 2013; Agyemang et al., 2019), hence it is expected that the results from SLEUTH reflects this uniqueness, especially if the model is sensitive to informal urban growth. In exploring whether SLEUTH captures this trajectory, and to facilitate global insights, the calibrated results for the ACR is juxtaposed with that of African cities – Cape Town (Watkiss, 2008), Yaounde (Sietchiping, 2004), Cairo (Abd-Allah, 2007), Alexandria (Abdou-Azaz, 2004) – where the model has been applied, and 4 cities - Baltimore (Jantz et al, 2004), Tapei (Sangawongse, 2005), Porto Alegre (Leao et al., 2004), and Lisbon (Silva and Clarke, 2002) – from other parts of the world. Cities, like Baltimore, with different growth trajectories have been included to aid the discussion of SLEUTH sensitivity to the differences in growth trajectories. Thus, if the model is sensitive to informal urban growth, it is expected that the results for ACR is substantially and meaningfully different from that of cities with more formalized urban growth trajectory. Another feature of the cities selected, is the application of SLEUTH to urban growth.

As expected in a highly informal context, Accra City-Region recorded, among the selected cities, the highest values for *dispersion* and *breed* coefficients as depicted in Figure 4.7. The unparalleled *dispersion* and *breed* coefficients do not only underscore the spontaneous nature of the city-region's growth, but also highlight the high contagion effect of new developments. In addition, edge expansion in Accra, captured by *spread* coefficient, is massive, and only toppled by that of Alexandria. Comparatively, the three expansive parameters cast an image of a city-region that is fast and randomly consuming space. Also, these results reflect, on the one hand, the extent of informal and leapfrog development in Accra, and, on the other, points to the weaknesses in the planning system regarding the management of the city-region. Indeed, this is consistent with existing studies, including (Acquah-Harrison, 2004; UN-HABITAT, 2011; Boamah et al, 2012; Anokye, et al., 2013) that allude to the spontaneous and unguided nature of urban expansion in Accra and Ghana in general. This also reflects the sensitivity of the model to the spatial dimension of informal growth trajectory of Accra city-region.

Besides, our meeting with key stakeholders in the city-region also offer some insight into the high level of spontaneity and the rapid formation of new spreading centres. Various district planning officers explained how medium and large-scale real estate developments, which have proliferated in Accra (Agyemang and Morrison, 2018), develop in peri-urban areas that are distant from the contiguous Accra built-up. This happens as developers seek to avoid high land values that are associated with lands within the city or close to built-up areas. The leapfrogged large-scale developments then become new centres of attraction, around which other developments begin to occur. Thus, aside being consistent with findings from existing studies, the values recorded for the three coefficients are also explained by the experiences of the local experts.

On the flipside, Accra recorded relatively low road gravity coefficient (11), indeed, the lowest among the selected cities. Two main explanations can be offered. One, the low road gravity coefficient could be the result of a situation where development first occurs based on other factors – like land values – and, subsequently, a road is engineered. Cobbinah et al (2018) found evidence to this effect. The authors indicated that, in some parts of Accra, households develop first and later make amends towards accessibility. Situating this within a broader transportation and land use studies, lies a case where the latter precedes the former. The second explanation is that, the low coefficient could have stemmed from the limitation with the transport data used in calibrating the model. As mentioned earlier, in the absence of thorough transport network data, trunk roads were used. By using very detailed historical local level road data, the coefficient could change significantly. Against this backdrop, the road gravity data should be interpreted cautiously.

Figure 4.7: Accra City Region's Historical Growth Parameters in International Context



4.9 Implications for urban planning policy and practice

The results from the model presents to the fore, diverse issues that do not only affect urban planning policy, but also its practice in Ghana and other sub-Saharan African countries with informal and unguided urban growth.

Urban cellular automata could offer valuable planning decision support, even in informal settings: The results from the calibration, which is affirmed by the knowledge of key planning stakeholders, points to the sensitivity of the CA model to locally specific development trajectory, especially the spatially fragmented informal developments. Again, the consistency of the derived coefficients with existing literature communicates the contemporary relevance of CA urban models, even in Ghana, where development is more informal. Unlike the 1990 structure plan of the local planning authority, which expected more growth in the Eastern parts of the city, the model simulates large growth in the Western areas. As earlier indicated, the historical trajectory of the city shows, contrary to the projections in the structure plan, more growth occurred in the West. The unexpected westerly growth is largely unplanned and unregulated, presenting diverse challenges to urban management and sustainability in the city-region. A case could be advanced that the planners may have made better predictions if they had access to dynamic urban models. In brief, even in contexts as predominantly informal as ACR, CA models, such as SLEUTH, could serve as decision support tools in the development of urban policies.

Need to build a stronger, proactive and functional spatial planning system: The nature of spontaneous, unguided and dispersive development, captured by the model, highlights the urgent need for the spatial planning system of Ghana to be repositioned and strengthened. Even though the local planning stakeholders appreciated the problem of unguided urban expansion, its sheer magnitude and the likely future effects predicted by the model, was far greater than they envisaged. For instance, based on the trend scenario, about a third of the total area of ACR is predicted to be developed by 2040. Considering that not all the remaining 66 percent is buildable, for example, water areas, critical slopes, forest and game reserves, the actual space that will be available for development is likely to be far less. Thus, the ability of future generation to also find space for development beyond 2040 will be severely jeopardized if existing trends continue. Stemming from this, the need for building a stronger, proactive and functional planning system is non-negotiable.

Every single development counts; one new house fast becomes a new growth nucleus: Against the backdrop of an overwhelmingly dispersed and spontaneous nature of growth, the *breed* coefficient provides further information as to what happens to the new developments that randomly emerge in undeveloped areas. Majority of the spontaneously emerged buildings trigger new developments in their surroundings, and, in the process, form new growth nuclei. The extremely high contagion effect posits several implications for urban planning policy in the city-region. It will be important for the planning system to treat every new development as a potential centre, and swiftly address them. For instance, if a single building emerges in an area classified as ecologically sensitive, the planning system would stand a better chance of success by addressing the challenge at its infant stage, than wait for a new informal growth centre to emerge. Thus, the options are, address a single unguided development today, or wait till tomorrow and pay heavily for an entire informal centre.

Target pressure areas: While there is general threat to sustainable development in the city-region, the impact varies with districts. There are districts that will virtually have no space for expansion by 2040. These include, Ledzokuku Krowor, La Dade-Kotopon, La Nkwantanang-Madina, Tema, Ga Central, AMA and Adentan, which are predicted to have, at least, 90 percent of their lands to be developed. Thus, while it is important to have a more guided urban expansion across the city-region, it is particularly urgent in these districts. Besides, districts, such as Ashaiman, Ga East, Awutu Senya East, Efutu, Ga West, Kpone, Ningo Prampram, Gomoa East, Ga South, Awutu Senya and Agona West, should be put on spatial planning alert, as they are predicted to have, at least, 50 percent of their lands developed by 2040. It is also worth noting that the pressure areas could differ depending on the criteria for classification. For instance, if districts are classified based on the extent of ecological threats posed by the simulated urban growth, new pressures areas may emerge. This simulation, however, is important in terms of offering the avenue for estimating likely future threats and identifying areas that will be most affected.

Support densification and consolidation: Lastly, in addition to developing a more proactive spatial planning system, the results from the model underscores the need for urban planning policy to support densification. Far from the existing trend scenario, promoting a more sustainable urban expansion will require significant reduction in the parameter values of *dispersion, breed* and *spread*. This calls for compactness, consolidation and densification, where development largely occur in spaces within already built-up areas, or through high density (re)developments, all of which the spatial planning system has an important role to play. However, the pursuit of densification, should not be oblivious to the existing mixed social acceptability of high-rise buildings in some metropolitan cities of Ghana, see, for instance, Agyemang et al. (2018).

4.10 Limitations

The simulation approach adopted has some limitations that need to be recognized. The spatial resolution used for the simulation (100m * 100m) generally appears coarse, more so when the average residential plot size in Ghana is about 30m * 21m. However, the sheer size of the city-region meant that further increasing the resolution by way of reducing the parcel size would not only negatively affect computational efficiency, but also model performance. Thus, it is worth noting that the coefficients may slightly change when actual plot sizes are used. That stated, the results are consistent with findings from existing literature as discussed above. The high computational requirement is one of the general limitations of predictive urban CA models compared to traditional large-scale statistical models. That said, the computational efficiency of CA models, especially SLEUTH, is fast improving, so it is foreseeable that it will soon be computationally efficient to run high spatial resolution simulations for large regions. For example, Şalap-Ayça et al., (2018) has proposed Polynomial Expansion Chaos (PCE), a meta-modelling approach, as a computational efficient way of analysing spatial uncertainty and sensitivity in CA modelling and simulation.

Urban CA modelling is also known for its limitation in explicitly modelling socio-economic and behavioural processes. SLEUTH does not directly model the behaviour and interactions of actors responsible for urban growth, such as residents, developers and government. It is largely owing to this that studies that simulate urban growth through the explicit actions of urban actors, normally do so by combining CA with other techniques, such as agent-based modelling, see for example (Dahal and Chow, 2014; Mustafa et al., 2017). That notwithstanding, the spatial processes modelled by SLEUTH captures, albeit implicitly, the actions of urban actors and the influences of socio-economic variables. Also, while CA is particularly effective at modelling global order through local interactions, it is generally not known to be strong in quantifying transition probabilities among various land uses. Stemming from this, most studies with focus on quantifying transitions among classes, traditionally integrate CA with other techniques, for instance, Markov Chains (Moghadam et al., 2013; Aburas et al., 2017; Ghosh et al., 2017) and Random Forest algorithms (Gounaridis et al., 2018). However, as mentioned earlier, SLEUTH, the model applied in this chapter, has inbuilt statistical metrics and a self-modification function that support the quantification of transitions.

4.11 Chapter Conclusion

Over the past few decades, urbanization has been particularly rapid in sub-Saharan Africa. Ghana, which is undergoing massive urbanization, is characterised by unique urban growth trajectory, where development is more informal, unguided and spontaneous. Also, despite their huge popularity, knowledge regarding the sensitivity of urban CA models to predominantly informal and less regulated urban growth trajectory is quite limited. The chapter has pursued two objectives: a simulation of urban growth of Accra city-region up to 2040, drawing implications for urban policy; and, an exploration of the sensitivity of the CA model to informal growth trajectory.

The calibration results indicate high level of spontaneous development, rapid formation of new centres, and fast edge expansion in the city-region. These characteristics are found to be consistent with, findings from existing literature, and local knowledge of key planning stakeholders, including district planning officers. Going forward, it is imperative for urban planners and policy makers in Ghana to recognize the need for: a stronger, proactive and functional planning system; treating every new spontaneous and informal development as a potential threat; targeting of pressure areas regarding availability of land for further urban expansion; and promoting urban densification. In addition, CA models are found to be sensitive to informal urban growth trajectories, hence could offer valuable planning decision support, even in contexts like Ghana, where development is overwhelmingly informal and random.

CHAPTER FIVE

UNDERSTANDING THE URBAN SPATIAL STRUCTURE OF SUB-SAHARAN AFRICAN CITIES USING THE CASE OF URBAN DEVELOPMENT PATTERNS OF A GHANAIAN CITY-REGION

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5.1 Chapter Introduction

Over the past few decades, urbanization has dominated debates across diverse platforms. The heightened interest is against the backdrop of a world that has not only rapidly urbanized but is further projected to be more urban-centric in the next few decades (Glaeser, 2011). The United Nation's *World Urbanization Prospects* (UN, 2014) presents some notable statistics regarding the rapidity and extent of global urban transformation. Between 1950 and 2014, the world's urban population increased from 30 to 54 percent, which in absolute terms reflects an additional 3.2 billion urban inhabitants, while another 2.5 billion is expected by 2050. Despite that more than half of the world's population are urban dwellers, Africa has a chunk (about 60 percent) of its inhabitants living in rural areas, implying that there is a higher tendency for urbanization to continue in the continent in the coming decades, as people migrate from countryside areas to cities. Indeed, majority of today's urbanization is occurring in the Global South, with Africa and Asia projected to account for about 90 percent of the expected urban population in 2050 (UN, 2014).

The ongoing urbanization has several implications, including, inter alia, the formation of new cities and expansion of existing ones to megacities. As cities expand, they evolve spatially and functionally in terms of structure. For many cities in the Global North, the evolution is, in essence, characterised by transformation from Alonso-Mills-Muth's monocentric urban form to polycentric patterns (Kloosterman and Musterd, 2001; Parr, 2004; Hall and Pain, 2006). Large cities, including Ile-de-France in France (Guillain et al 2006), and Chicago and Illinois in the United States (McDonald, 1987; McMillen and Lester, 2003) are only a few of many Global North cities that have undergone this transformation. There has also been a growing number of studies in recent decades, for instance, see Garcia-López & Muñiz (2010), Dong (2013), Angel and Blei (2016), that allude to a further shift in the urban structure of some Western cities from polycentric to dispersive patterns. The spatial evolution from monocentricity to polycentricity is also observed in some large and medium-size metropolitan areas in the Global South, especially in China (Zhou and Ma, 2000; Liu et al, 2011; Liu and Wang, 2016; Huang et al, 2017), and in Latin America (Suarez and Delgado, 2009; Fernandez-Maldonado et al., 2014; Aguilar and Hernandez, 2016).

However, while sub-Saharan Africa has been dominant in urbanization of the twenty-first century, research into the spatial evolution of cities in the sub-region, unlike the aforementioned regions, is still in infant stages. Meanwhile, the rapid urbanization trends in Africa presents to the fore, several critical urban issues to diverse stakeholders, including scholars and policy makers. First, from an academic standpoint, is the spatial evolution of African cities explained by mainstream urban structure models, or are different set of models required to account for the transformation? This question forms the first theme of inquiry through which this research seeks to facilitate understanding into the evolving urban structure of Sub-Saharan African cities.

Over the years, a number of models have been developed to abstract the spatial structure of cities. Von Thunen's (1826) bid rent theory lays the foundation for many urban geography models that followed, including Alonso-Mills-Muth's monocentric city (Alonso, 1964; Mills, 1967; Muth, 1969), and the polycentric city model. Other popular urban form models include, Burgess's concentric zone (1925), cental place theory (Christaller, 1933; Losch, 1938), sector model (Hoyt, 1939), multiple-nuclei (Harris and Ullman, 1945), and constrained dispersion model (Angel and Blei, 2016). There are also a number of studies and models on landscape patterns that relate to peri-urbanization and urban-rural land use changes, for example, see Díaz-Palacios-Sisternes et al (2014) and Salvati (2014). For this study, however, three main models (monocentricity, polycentricity and dispersiveness) that characterise the major features of urban spatial structure models are used as references for results comparison and discussion. The results are also situated within the two-phased urban growth process theory of diffusion and coalescence (Dietzel et al., 2005; Martellozo and Clarke, 2011), which cities tend to exhibit as part of a stochastic fractal urban growth process (Batty et al., 1989; Batty and Longley,1994).

Second, from policy perspective, the formulation of effective urban policies – that maximizes the socio-economic opportunities of urbanization and minimizes its negative externalities – require, among others, a comprehensive understanding of urban growth trajectories and spatial structure of geographical areas. Indeed, land use and transport policies that work in a monocentric city, may perform poorly in a city with a polycentric structure (Angel and Blei, 2016). As a result, this research further explores the urban planning and policy implications of the evolving spatial structure of a Sub-Saharan African city. Thus, twofold objectives are pursued by this chapter: one, an examination of the evolving spatial structure of an African city-region and its relationship with mainstream urban geography models; and, two, an exploration of urban planning and policy implications of the spatial transformation.

Ghana is one of the countries that epitomizes the massive urbanization that has occurred in Sub-Saharan Africa over the past few decades. Principal cities, such as Accra and Kumasi, have evolved spatially to form mega city-regions, for instance, see Agyemang et al. (2017). The urban transformation in Kumasi city-region, which largely encapsulates the Ashanti region (TCPD, 2015), is used as a case study. Kumasi, the principal city of the city-region, and one of the largest and rapidly urbanizing metropolitan centers in Ghana and West Africa, forms the main unit of analysis. The region accommodates about 5 million people, majority (60 percent) of whom live in Kumasi and other urban areas (GSS, 2012). Although the study of spatial transformations has engaged diverse methodologies, most (see Fernandez-Maldonado et al., 2014; Aguilar and Hernandez, 2016; Angel and Blei, 2016; Huang et al, 2017) rely on data on distribution of economic activities and commuting patterns. In this chapter, urban spatial structure is analysed from the perspective of spatial development patterns, which is one of the ways of exploring urban structure evolution, for example see Angel (2012).

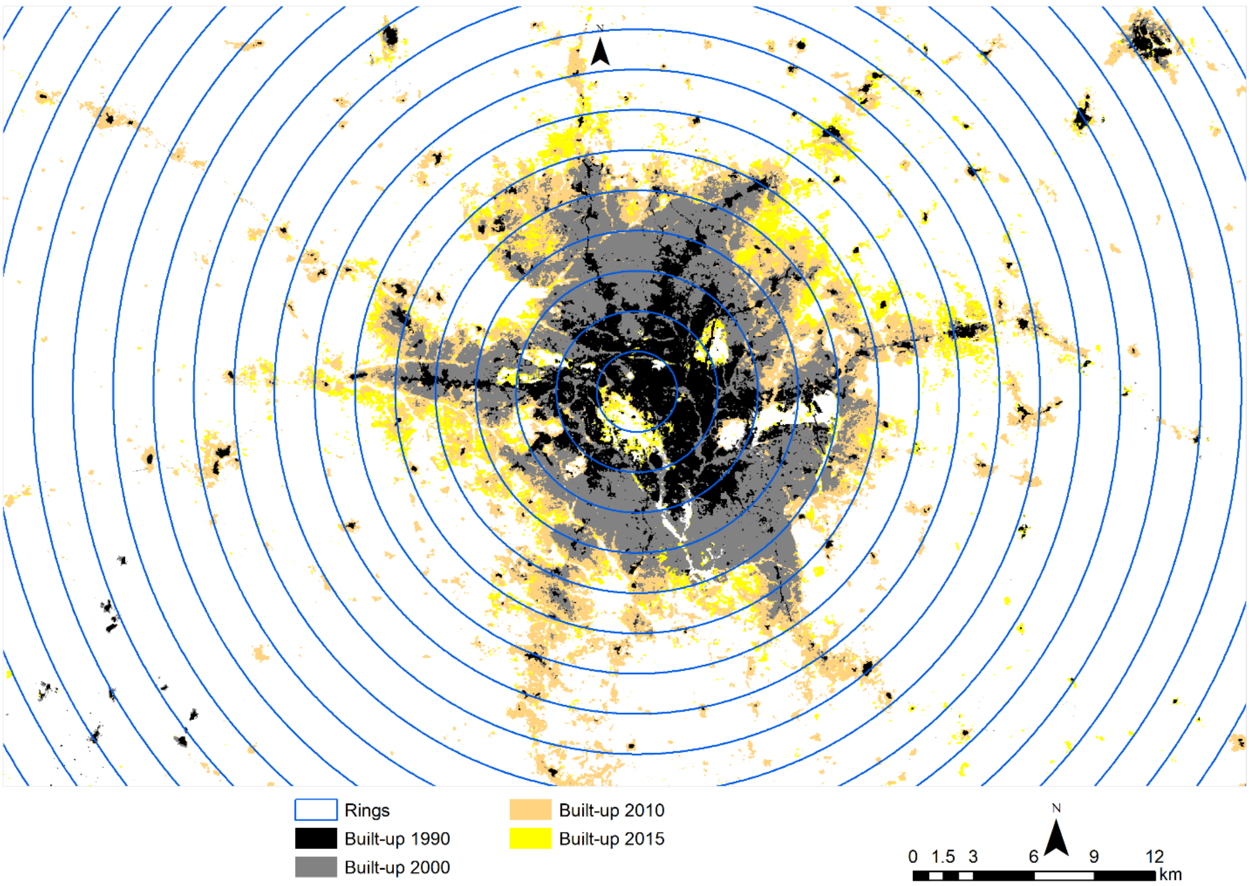
The urban transformation in the city-region between 1990 and 2015 is analysed using two main approaches: one, the application of urban spatial metrics; and, two, the calibration of an urban Cellular Automata (CA) model. Using the Central Business District (CBD) of Kumasi metropolis as a reference point, zones, representing distances from the CBD, are created. The intensity and magnitude of urbanization in each of the zones are analysed with the spatial metrics, while an urban CA model, SLEUTH (Clarke et al, 1997) is used to characterise the growth trajectory in terms of extent of randomness, contagiousness, and influence of transport and slope.

5.2 Assessing urban development patterns

Urban development patterns are analysed in relations to zones, which represent administrative district units and distances from the CBD. In creating distance zones, GIS techniques are used to construct multiple buffer rings around the CBD of the city-region as shown in Figure 5.1. The rings range from 2km to 160km, with 2km increments. Each increment represents a unique zone that is treated independently. For example, after constructing the first 2km ring, the next delineated ring is 2km to 4km, followed by 4km to 6km, continuing in that order. Thus, a 2km ring is not treated as part of a 4km ring, and the two are not analysed as parts of a 6km ring. Upon creating the rings, GIS techniques are further used to quantify the amount of urban land absorbed by each.

Spatial metrics are then used to analyse the patterns of urban development. Spatial metrics and their application to urban issues have heightened over the past few decades (Reis et al, 2016). Among many purposes, various spatial metrics have been used to analyse urban spatial structure (Kuffer and Barros, 2011; Cochran and Brunsell, 2017). This study draws on three spatial metrics, urban expansion intensity index (UEII), urban expansion differentiation index (UEDI) and annual urban expansion rate (AUER), to analyse urban development patterns in Kumasi city-region. In addition to the usage by recent similar studies (Li et al., 2010; Lu et al., 2014; Acheampong et al, 2016), the capacity of these metrics to quantify spatio-temporal patterns, in terms of intensity and rapidity of urban development in various zones, suits the objective of the study. The metrics employed in the study are further described below.

Figure 5.1: Kumasi Built-up and Rings



Annual Urban Expansion Rate

The Annual Urban Expansion Rate (AUER) of a spatial unit computes the average rate at which built-up lands of the spatial unit changes annually (Acheampong et al., 2016). This can be expressed as:

$$AUER_i = \left[\left(\frac{BA_i^{t_2}}{BA_i^{t_1}}\right)^{\frac{1}{t_2-t_1}} - 1\right] \times 100 \qquad 5.1$$

Where: $BA_i^{t_2}$ *and* $BA_i^{t_1}$ represent built-up land area of spatial unit i for time t_2 *and* t_1 respectively.

Urban Expansion Intensity Index

The Urban Expansion Intensity Index (UEII) computes the annual average growth in built-up lands of a spatial unit, normalized by the total land area of the unit. In other words, it refers to the proportion of the annual average change in built-up lands relative to the land area of a spatial unit (Lu et al., 2014). This is expressed mathematically as:

$$UEII_i = \frac{BA_i^{t_2} - BA_i^{t_1}}{TLA_i \times \Delta t} \times 100 \qquad (5.2)$$

Where; $BA_i^{t_2}$ and $BA_i^{t_1}$ are the sizes of the built-up land area of spatial unit i at time t_2 and t_1 respectively; and TLA_i represents the total land area of unit i and Δt is the time period.

Urban Expansion Differentiation Index

Urban Expansion Differentiation Index (UEDI) is defined by the rate of urban expansion of a spatial unit standardized by the rate of urban expansion of the bigger spatial unit in which it is contained (Hu et al., 2007; Li et al., 2010) This enables the comparison of growth in different spatial units contained by the bigger spatial unit. Mathematically, this is expressed as:

$$UEDI_i = \frac{\left|BA_i^{t_2} - BA_i^{t_1}\right| \times BA^{t_1}}{\left|BA^{t_2} - BA^{t_1}\right| \times BA_i^{t_1}} \tag{5.3}$$

Where: $BA_i^{t_2}$ and $BA_i^{t_1}$ represent built-up land area of unit i at time t_2 and t_1 respectively; and BA^{t_2} and BA^{t_1} indicate built-up land area of the bigger region of unit i (the entire study area) at time t_2 and t_1 respectively.

5.3 Characterizing spatial development patterns with SLEUTH urban growth model

While the aforementioned metrics aid the quantification of spatio-temporal patterns of urban growth, they are, like many other spatial metrics, static in nature. As a result, we have, in addition, calibrated a dynamic urban growth CA model, SLEUTH (Clarke et al, 1997; Chauduri and Clarke, 2013) for the city-region. The calibration of the model provides additional information pertaining to urban growth trajectory, such as: extent of dispersion and spontaneity; emergence of new spreading centres; expansion from existing clusters; and influence of transport and slope. Refer to Sections 3.4 and 3.5 for detailed description of SLEUTH.

SLEUTH's conventional brute force calibration mechanism was followed. The mechanism mainly involves 3-stage sequential process; *coarse, fine and final* (Silva and Clarke, 2002; Sakieh et al, 2016). At coarse calibration, all possible range of parameter values (1 – 100) were tested in multiple (thousands) different combinations. The results were sorted with an Optimal SLEUTH Metrics (Dietzel and Clarke, 2007) and the top 3 runs are selected. The values within the range of the top 3 results were subsequently tested in the next calibration phase, *fine.* Like the previous stage, the top 3 runs from this calibration phase formed a new range that was subsequently tested in the next (*final)* phase. At the final phase, the top run was selected, and its associated parameter values represent the best fit coefficients for the city-region. The top 3 runs from the calibration phases are presented in Table 5.1.

Table 5.1 SLEUTH's top three calibration results for KCR

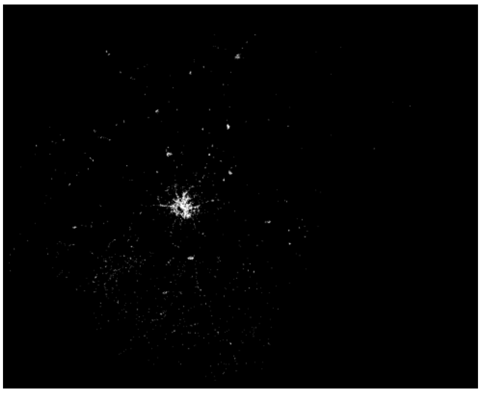
	Run	OSM	Product	Compare	Population	Edges	Cluster	Size	Leesale	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	Dispersion	Breed	Spread	Slope	RG
Coarse	3102	0.202	0.008	0.280	0.969	0.9999	0.876	0.250	0.259	0.902	0.640	0.995	0.944	0.966	0	100	100	100	1	50
	3103	0.191	0.020	0.274	0.966	0.9997	0.877	0.703	0.258	0.898	0.610	0.999	0.916	0.963	0	100	100	100	1	75
	3079	0.189	0.001	0.260	0.992	0.9948	0.818	0.036	0.259	0.943	0.597	0.978	0.973	0.990	0	100	100	75	1	100
Fine	7709	0.202	0.011	0.276	0.989	0.9968	0.834	0.318	0.258	0.938	0.648	0.978	0.970	0.987	0	100	100	95	1	100
	7740	0.202	0.014	0.278	0.976	0.9998	0.859	0.429	0.258	0.914	0.637	0.991	0.955	0.973	0	100	100	100	1	50
	4865	0.201	0.023	0.280	0.975	1.0000	0.863	0.703	0.259	0.910	0.647	0.992	0.946	0.972	0	90	95	90	1	100
Final	6343	0.204	0.018	0.278	0.977	0.9999	0.871	0.543	0.258	0.914	0.640	0.989	0.952	0.974	0	98	100	94	2	60
	5951	0.204	0.018	0.279	0.976	0.9999	0.870	0.543	0.258	0.915	0.640	0.992	0.946	0.974	0	98	98	96	2	100
	6166	0.203	0.026	0.279	0.977	0.9999	0.864	0.779	0.258	0.916	0.643	0.990	0.951	0.975	0	98	99	96	2	90

5.4 Data

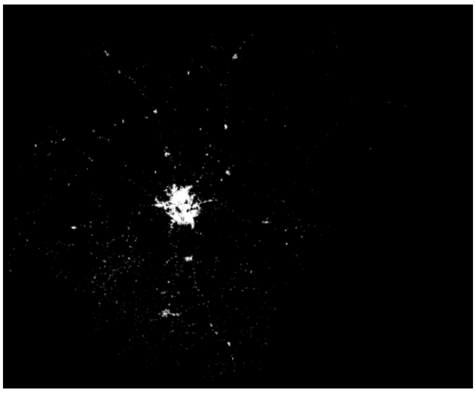
The study relied on a wide range of spatially explicit dataset, including data on urban extent of 1990, 2000, 2010 and 2015; trunk roads for 1990 and 2012; slope; and areas resistant to development such as wetlands, forest and game reserves. These were acquired from multiple sources as acknowledged in Figure 5.2.

Figure 5.2: Spatially explicit input dataset

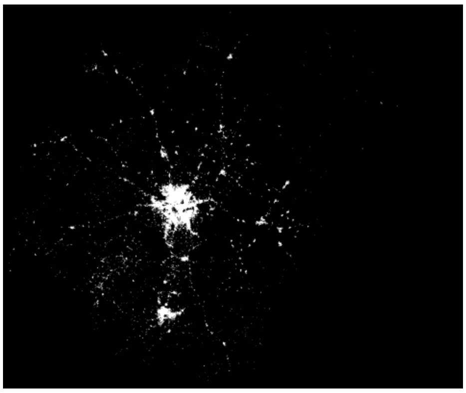
Urban extent, 1990



Urban extent, 2000

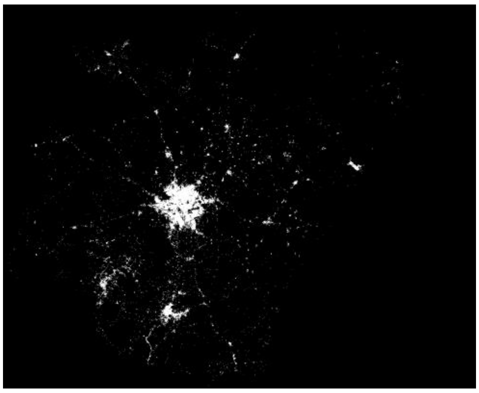


Urban extent, 2010



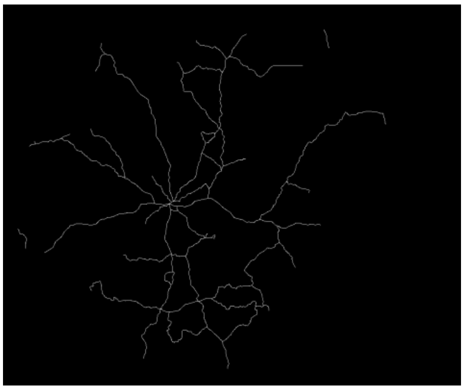
Source: Processed from classified Landsat data by TCPD

Urban extent, 2015

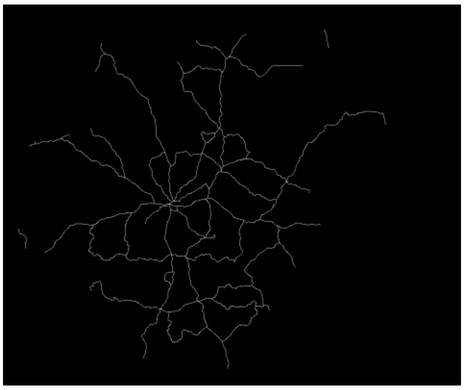


Source: Processed from classified Landsat data

Trunk Roads, 1990

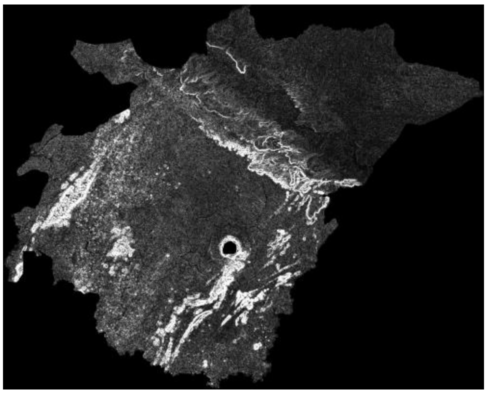


Trunk Roads, 2012



Source: Processed from TCPD data

Slope, 2015



Source: Processed from NASA 30m ASTER GDEM

5.5 Patterns of historical urban expansion

Ashanti region has recorded massive urban expansion over the past few decades. Table 5.2 presents basic facts about the expansion. As of 2015, about 4 percent of the total land area was built, which, when viewed nominally, does not appear massive. However, when situated within the context of the rapidity of expansion that has taken place over the past two and half decades, the figure is quite striking. For instance, from 153 km^2 in 1990, the extent of urban land area more than sextupled to 943 km^2 in 2015, and, in the process, recorded annual expansion rate of 7.5 percent. Considering that, in 1990, less than a percent (0.63) of the total land area was urban, the rise to 4 percent over a 25-year period could only be considered massive. That notwithstanding, the region's urban growth is occurring at a decreasing rate as annual expansion rate decreased from of 8.9 percent in 2010 to 5.4 in 2015.

The dynamics of urban expansion at the district level presents a more refined image. The impact of the expansion is particularly severe in the core areas. For instance, while core districts such as Asokore Mampong and Kumasi Metropolitan Assembly (KMA) were, at least, 90 percent urban in 2015, the more peripheral ones such as Sekyere Central and Sekyere Afram Plains North had less than one percent of their lands under built-up.

However, the rate of urban expansion has been quite high in almost all the districts. Over the 25-year period, Bosome Freho's 3.9 percent was the least annual urban expansion rate that was recorded. As depicted in Table 2, from 1990 to 2015, 12 districts - Asante Akyim North, Obuasi Municipal, Sekyere Afram Plains, Atwima Kwanwoma, Bosomtwe Atwima Kwanwoma, Sekyere Central, Sekyere Afram Plains North, Afigya Kwabre, Kwabre East, Atwima Nwabiagya, and Ejisu Juaben – recorded an annual urban expansion rate above 10 percent.

Temporally, urban growth was rapid in the core districts between 1990 and 2000. KMA, Kwabre East and Obuasi Municipal, recorded significantly high urban expansion rates as shown in Table 2. However, over the subsequent periods, more physical development occurred in the surrounding districts and even farther into the hinterlands. This, in terms of spatial development patterns, depicts suburban and peri-urban growth. Thus, the cities and towns in the core areas expanded into outlying areas. Indeed, between 2000 and 2010, Asante Akim North, Sekyere Afram Plains, and Sekyere Central, which could be described as peripheral districts, emerged the top three rapidly expanding districts, as each recorded at least, 28 percent annual urban expansion rate. During the same period, the core districts, KMA and Asokore Mampong substantially declined in their rate of expansion. KMA, for instance, dropped from 9.6 percent to 1.3 percent between the first two decades. The pattern of suburban and peri-urban growth continued in the last 5-year interval, as annual expansion rates further declined in the core while stabilizing and increasing in the peripheral and hinterland districts. The decline in urban expansion rates in the core districts may be explained by the seemingly non-availability of land to be observed by the growth and as such the peripheral districts serves as recipient of the influx.

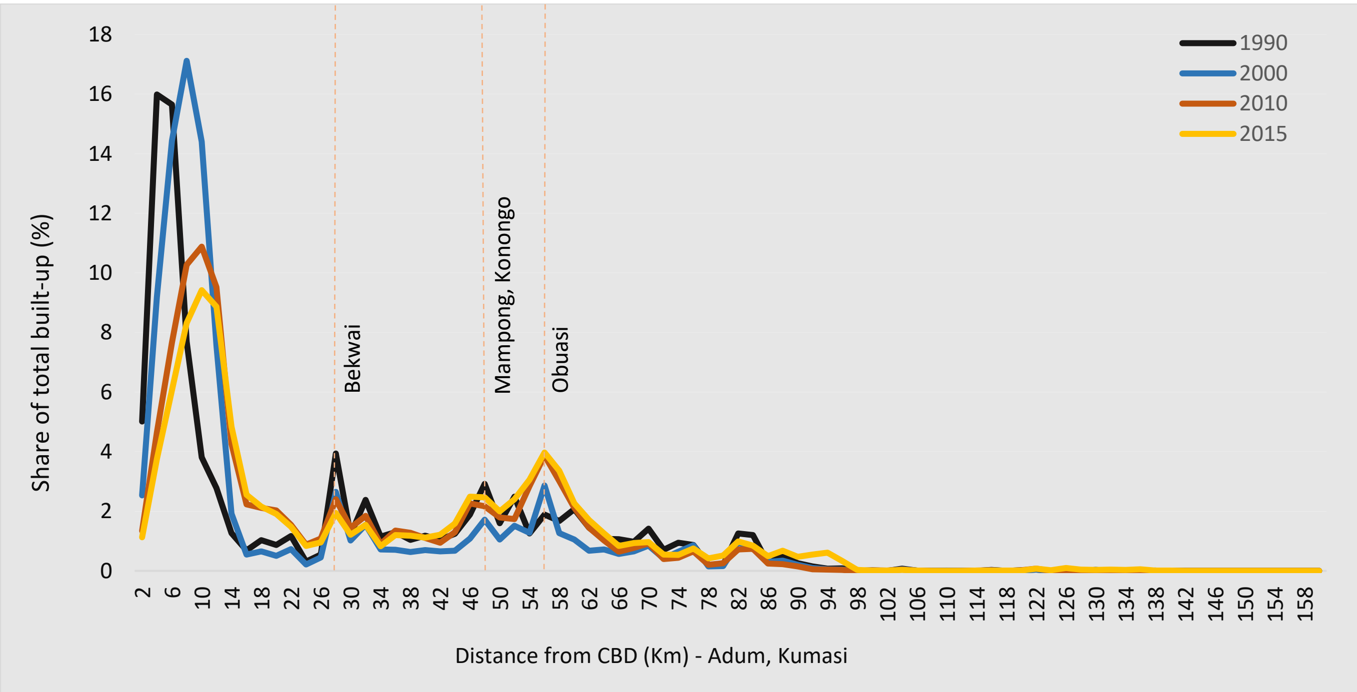
Table 5.2: Urban Expansion in Ashanti Region

Administrative Unit	Total Land Area	Urban Land (km^2)				Percent of Land Urban				Annual Urban Expansion Rate			
		1990	2000	2010	2015	1990	2000	2010	2015	1990 to 2000	2000 to 2010	2010 to 2015	1990 to 2015
Kwabre	123.0	3.3	18.2	33.1	45.4	2.69	14.84	26.95	36.93	18.64	6.15	6.51	11.05
Asokore Mampong Municipal	23.9	6.9	15.6	20.7	21.9	28.69	65.03	86.37	91.53	8.52	2.88	1.17	4.75
Obuasi Municipal	220.7	1.7	11.4	59.6	70.5	0.79	5.16	27.01	31.95	20.63	17.99	3.42	15.94
KMA	214.3	63.4	158.4	180.1	189.6	29.60	73.90	84.01	88.46	9.58	1.29	1.04	4.48
Amansie West	1230.7	12.3	15.7	33.1	75.3	1.00	1.27	2.69	6.12	2.48	7.76	17.87	7.53
Atwima Kwanwoma	251.5	1.5	10.2	40.7	47.7	0.60	4.04	16.20	18.97	20.95	14.89	3.21	14.79
Atwima Nwabiagya	579.2	4.5	16.0	44.8	58.2	0.78	2.77	7.74	10.06	13.49	10.83	5.39	10.77
Afigya Kwabre	409.4	3.1	17.0	35.6	44.6	0.77	4.15	8.69	10.90	18.37	7.67	4.64	11.19
Ejisu Juaben	582.7	3.4	6.7	31.0	42.9	0.59	1.16	5.32	7.36	6.96	16.49	6.74	10.63
Asante Akim North	1126.7	0.4	0.6	8.5	26.0	0.04	0.06	0.76	2.31	3.92	29.87	25.02	17.89
Bosomtwe Atwima Kwanwoma	422.6	1.2	11.2	30.4	36.4	0.29	2.66	7.20	8.61	24.79	10.48	3.65	14.52
Adansi South	1328.6	4.1	5.9	8.7	24.6	0.31	0.44	0.65	1.85	3.65	3.94	23.14	7.40
Adansi North	853.9	5.0	7.5	14.4	23.8	0.59	0.88	1.69	2.79	4.15	6.68	10.59	6.42
Sekyere Afram Plains	576.9	0.3	0.4	5.4	11.7	0.06	0.07	0.94	2.03	3.02	28.85	16.67	15.50
Amansie Central	849.5	4.4	5.2	15.2	23.1	0.52	0.61	1.78	2.72	1.73	11.29	8.81	6.88
Offinso North	945.7	1.3	3.3	8.8	17.7	0.14	0.35	0.93	1.87	9.50	10.27	14.90	10.87
Mampong Municipal	670.4	3.0	3.3	8.9	12.7	0.45	0.49	1.33	1.90	0.85	10.50	7.39	5.93
Afigya Sekyere	416.9	2.4	2.8	9.0	11.4	0.57	0.68	2.16	2.73	1.81	12.32	4.77	6.50
Asante Akim Central Municipal	300.4	1.6	2.7	13.6	15.1	0.52	0.90	4.52	5.01	5.72	17.46	2.08	9.50
Sekyere East	239.2	1.7	3.1	9.6	10.5	0.70	1.31	4.02	4.37	6.45	11.90	1.70	7.61
Offinso Municipal	585.7	4.6	6.9	17.2	18.9	0.79	1.17	2.94	3.23	4.08	9.63	1.91	5.82
Ejura Sekye Dumase	1340.7	4.0	5.4	7.8	11.5	0.30	0.41	0.59	0.86	3.05	3.74	7.99	4.30
Atwima Mponua	1882.3	3.3	7.8	12.9	17.3	0.17	0.41	0.69	0.92	8.99	5.25	6.03	6.89
Bosome Freho	569.1	2.1	2.5	4.2	5.5	0.37	0.44	0.74	0.97	1.65	5.41	5.55	3.92
Bekwai Municipal	535.3	5.7	10.6	27.3	28.5	1.07	1.99	5.09	5.32	6.35	9.87	0.86	6.61
Sekyere Afram Plains North	3529.4	0.5	0.8	1.5	7.1	0.01	0.02	0.04	0.20	5.48	6.55	37.01	11.60
Sekyere Central	1632.2	0.3	0.5	5.8	8.4	0.02	0.03	0.36	0.51	4.17	28.08	7.47	13.85
Asante Akim South	1154.1	2.9	3.8	14.9	16.2	0.25	0.33	1.29	1.40	2.68	14.62	1.64	7.08
Ahafo Ano North	593.3	0.9	2.0	6.8	7.2	0.14	0.34	1.15	1.21	8.85	13.03	1.06	8.88
Ahafo Ano South	1190.4	3.2	4.1	12.6	13.1	0.27	0.34	1.06	1.10	2.44	11.88	0.88	5.79
Ashanti Region	**24379**	**153.2**	**359.7**	**722.3**	**942.9**	**0.63**	**1.48**	**2.96**	**3.87**	**8.91**	**7.22**	**5.48**	**7.54**

5.6 Spatial development patterns of Kumasi City-Region, 1990 – 2015

Figure 5.3 shows the distribution of urban development in relation to distance from the main city centre or CBD. The distribution represents the share of the city-region's total built-up land absorbed by the different rings. In addition to the regional capital, Kumasi, which is also the second capital of Ghana, the region has several notable urban settlements, including Obuasi, Mampong, Konongo and Bekwai. While the CBD in figure 3 refers to the city centre of Kumasi, the centres of the settlements mentioned above are also annotated. At city scale, a highly monocentric spatial structure that is spreading out and becoming less concentrated over time is observed. In 1990, a fifth (21 percent) of the region's built-up land was within 4 km distance from the CBD. More than a third (35.6 percent) of built-up land can be found when distance is increased to 6km, while majority (51 percent) is absorbed within 12 km. The overwhelming concentration of development in the immediate surroundings, reflects the dominance of the CBD and the monocentricity of development distribution. The spatial structure in 2000 was monocentric as well, though the proportion of development absorbed within 6 km radius from the CBD decreased to about a quarter (26 percent). The decrement, however, was accounted for by the next 2 km radius (6 to 8 km from the CBD), which absorbed around a sixth of built-up land. In general, 43 percent of the region's urban land was contained within 8 km, while the majority (57 percent) was absorbed by 10 km distance from the CBD.

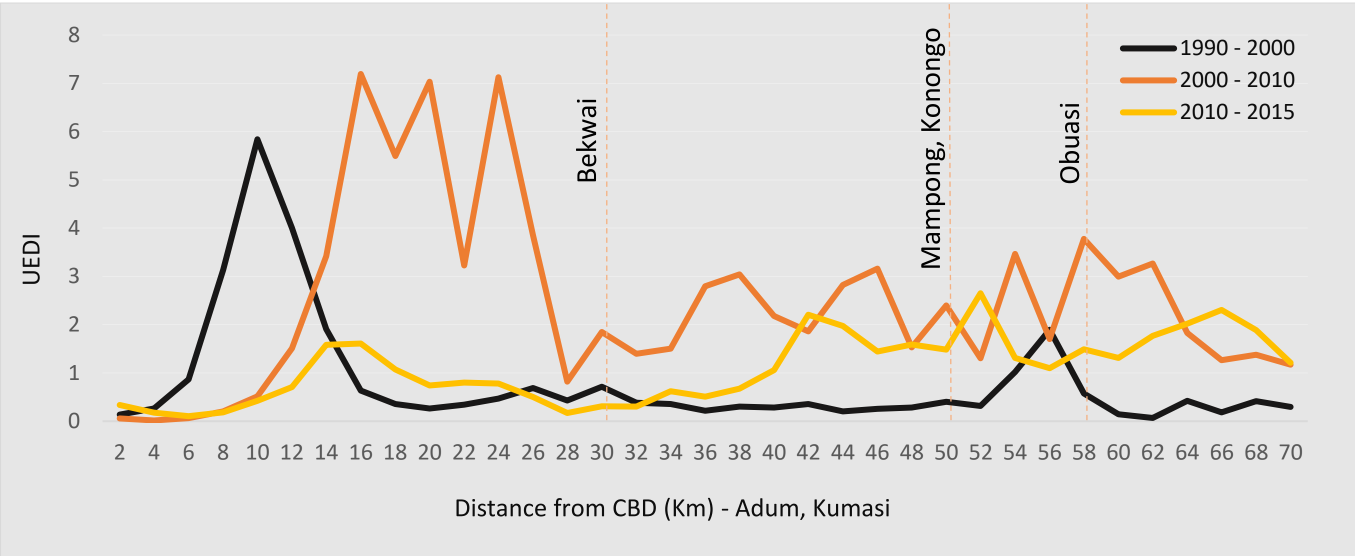
Figure 5.3: Share of total built-up land and distance from the CBD



The first decade of the twenty-first century saw a decline in the monocentric nature of urban distribution as development spread farther out from the CBD and its immediate surroundings. In 2010, the 6, 8 and 10 km zones only absorbed 13, 23 and 34 percent of built-up land respectively. Unlike the previous decades, it is until 16 km distance from the CBD that the majority (51 percent) of urban land is found. The spreading out of development appears to continue into 2015, as the proportion of built-up land within 6 km decreased to 10 percent. The 8 and 10 km zones also dropped in share of built-up by 5 and 6 percentage points respectively, while the majority (50.5 percent) of urban lands is not found until 22 km distance from the CBD. Compared with 1990, the first distance from the CBD within which more than half of urban developments is found increased by 10 km (12 to 22).

To better present the picture of the spreading out and de-concentration of development, historical UEDI of the various zones as shown in Figure 5.4 is presented. During the last decade of Twentieth Century, the highest rate of annual urban expansion occurred between 8 and 10 km from the CBD, as the zone recorded UEDI of around 6. Development was predominantly concentrated within this area, giving the UEDI curve its monocentric and unimodal shape. Generally, the area between 7 and 15 km distance from the CBD expanded rapidly than the entire region. Beyond 15 km, the rate of urban expansion considerably declined to below 1 UEDI, meaning the region, as a whole, grew faster than this area. Development further shifted outwards between 2000 and 2010, as the area between 16 and 25 km distance from the CBD recorded the highest UEDIs. The slowest urban expansion for the decade occurred within the immediate surrounding areas (10 km) of the CBD, with the zone recording UEDI that is less than 1. Contrary to what is observed in the previous decade, there were multiple concentrations of urban expansion between 2000 and 2010, reflecting a multi-modal UEDI curve. The spreading out of development continued in the last period (2010 – 2015), as the previously multiple peaked UEDI curve flattened out. Dominant peaks are hardly identifiable. Except for 12 to 14 km zone, urban expansion was generally low in the area within 40 km distance from the CBD.

Figure 5.4: UEDI and distance from the CBD



5.7 Urban growth patterns in local administrative boundaries

The patterns of urban growth have been examined for districts, which are the local planning administrative units. Here, the results for two metrics, UEII and UEDI, are mapped with Figures 5.5 and 5.6 respectively. The grouping of UEII in Figure 5.5 follows conventional classification method that categorises the values into 5 groups (Ren et al. 2013); very low (below 0.28), low (0.28 to 0.58), medium (0.59 to 1.04), high (1.05 to 1.92) and very high (above 1.92). Detailed results are additionally presented in Table 5.3.

Generally, the intensity of urban expansion in the region, has been increasing over the years. This is expressed in increasing UEII scores as seen appendix Table 5.3. At the same time, the differences among districts in terms of growth intensity appears to be evening out over the years. Typified by a declining UEII coefficient of standard deviation (2.6764 - 1.4508 - 1.2895) for the three historical periods urban development is getting less concentrated in few districts and more dispersed, reinforcing earlier observation of a declining monocentric spatial structure. There are also spatial nuances to the UEII scores that require highlighting. Between 1990 and 2010, few districts, mainly the urban core and immediate surrounding districts, dominated the UEII scores as shown by Figure 5.5. KMA, Asokore Mampong, urban core districts, recorded the highest UEII scores. Kwabre East, Afigya Kwabre and Atwima Kwanwoma, neighbouring districts of KMA, together with Obuasi municipal, another core district, constituted the other four dominant districts.

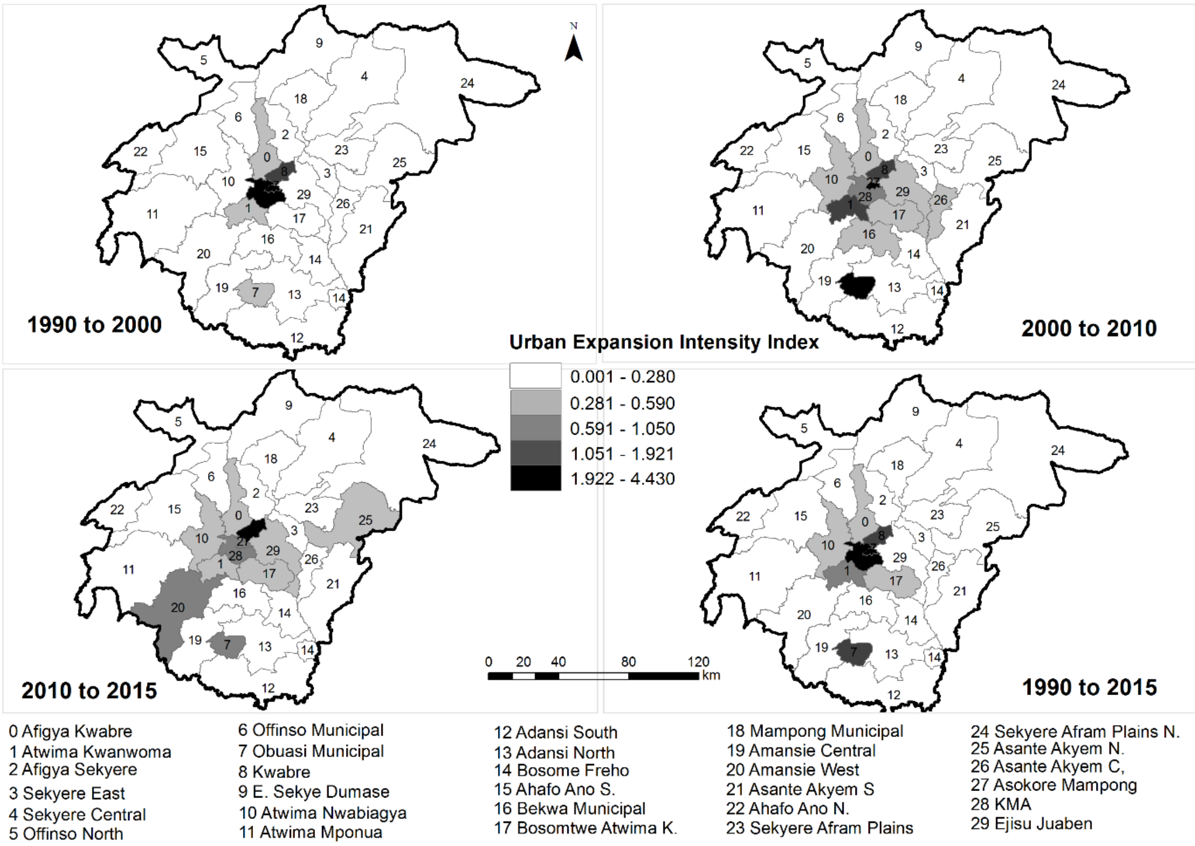
Table 5.3: Urban Expansion Intensity and Differentiation indices, 1990 - 2015

District	Urban Expansion Intensity Index				Urban Expansion Differentiation Index			
	1990 - 2000	2000 – 2010	2010 - 2015	1990 - 2015	1990 - 2000	2000 - 2010	2010 - 2015	1990 – 2015
Afigya Kwabre	0.3383	0.4539	0.4426	0.4054	3.2650	1.0844	0.8336	2.5573
Atwima Kwanwoma	0.3438	1.2155	0.5549	0.7347	4.2310	2.9841	0.5609	5.9104
Afigya Sekyere	0.0111	0.1486	0.1134	0.0866	0.1459	2.1794	0.8583	0.7428
Sekyere East	0.0607	0.2711	0.0706	0.1468	0.6447	2.0608	0.2879	1.0199
Sekyere Central	0.0010	0.0328	0.0310	0.0197	0.3741	10.7950	1.4203	4.7779
Offinso North	0.0210	0.0582	0.1872	0.0691	1.0978	1.6447	3.2825	2.3667
Offinso Municipal	0.0387	0.1766	0.0582	0.0977	0.3653	1.4953	0.3243	0.6039
Obuasi Municipal	0.4373	2.1841	0.9898	1.2465	4.1004	4.1960	0.6000	7.6408
Kwabre	1.2151	1.2110	1.9971	1.3699	3.3569	0.8098	1.2131	2.4739
Ejura Sekye Dumase	0.0105	0.0180	0.0548	0.0224	0.2598	0.4401	1.5343	0.3614
Atwima Nwabiagya	0.1985	0.4970	0.4641	0.3710	1.8892	1.7833	0.9821	2.3081
Atwima Mponua	0.0238	0.0275	0.0467	0.0298	1.0133	0.6621	1.1134	0.8315
Adansi South	0.0134	0.0209	0.2392	0.0616	0.3198	0.4678	5.9938	0.9626
Adansi North	0.0295	0.0804	0.2208	0.0881	0.3719	0.9028	2.1418	0.7263
Bosome Freho	0.0066	0.0304	0.0460	0.0240	0.1319	0.6884	1.0159	0.3132
Ahafo Ano South	0.0074	0.0713	0.0095	0.0333	0.2025	2.0560	0.1468	0.5989
Bekwai Municipal	0.0913	0.3107	0.0446	0.1697	0.6312	1.5521	0.1433	0.7671
Bosomtwe Atwima K.	0.2368	0.4541	0.2830	0.3330	6.0534	1.6950	0.6435	5.5645
Mampong Municipal	0.0039	0.0838	0.1137	0.0579	0.0652	1.7006	1.4023	0.6243
Amansie Central	0.0096	0.1172	0.1876	0.0882	0.1385	1.8982	1.7204	0.8293
Amansie West	0.0277	0.1416	0.6859	0.2049	0.2059	1.1031	4.1745	0.9969
Asante Akim South	0.0077	0.0963	0.0219	0.0460	0.2249	2.8916	0.2770	0.8795
Ahafo Ano North	0.0193	0.0811	0.0124	0.0426	0.9910	2.3850	0.1772	1.4320
Sekyere Afram Plains	0.0019	0.0865	0.2182	0.0790	0.2576	11.5191	3.8038	6.9328
Sekyere Afram Plains North	0.0009	0.0020	0.0319	0.0075	0.5235	0.8795	12.5300	2.8196
Asante Akim North	0.0018	0.0700	0.3104	0.0908	0.3475	12.5483	6.7257	11.6824
Asante Akim Central	0.0386	0.3618	0.0980	0.1798	0.5519	3.9674	0.3548	1.6806
Asokore Mampong	3.6332	2.1347	1.0315	2.5135	0.9397	0.3257	0.1955	0.4249
KMA	4.4298	1.0113	0.8896	2.3544	1.1105	0.1358	0.1733	0.3858
Ejisu Juaben	0.0566	0.4161	0.4097	0.2710	0.7124	3.5735	1.2615	2.2306
Ashanti Region	0.0847	0.1487	0.1810	0.1296	1.0000	1.0000	1.0000	1.0000
Coefficient of Standard Deviation	2.6764	1.4508	1.2895	1.7078	1.2823	1.1783	1.3856	1.1144

The first decade of the twenty-first century saw the intensity of development shifted into the surrounding areas of core districts. Indeed, KMA, which recorded the highest UEII score in the previous decade, dropped to fourth, as urban expansion intensified in neighbouring districts, such as Atwima Kwanwoma, Kwabre East, Afigya Kwabre, Ejisu Juaben and Bosometwe Atwima Kwanwoma. Obuasi municipal, unlike KMA and Asokore Mampong, rather increased its UEII during this period. One of the possible reasons for Obuasi's departure from the other two core districts could be availability of more space for inward expansion. For instance, as of 2000, just about 5 percent of the land area of Obuasi Municipal was built, a proportion which is substantially lower than those of KMA (73 percent) and Asokore Mampong (63 percent). The booming of large-scale mining activities in the area is another factor that could explain Obuasi's trend over this period.

The intensity of expansion over the last 5 years increased significantly in some of the peripheral districts, while reducing, albeit slightly, in the suburban areas. Amansie West and Asante Akyem North are two notable peripheral districts that markedly increased their UEII scores. Thus, expansion further continued from the suburban districts into farther outlying areas. Obuasi Municipal also declined in intensity during this period. Together with a reducing coefficient of standard deviation, the patterns over the periods affirm the observation that urban expansion intensity is becoming more widespread than concentrated.

Figure 5.5: Urban Expansion Intensity Mapping

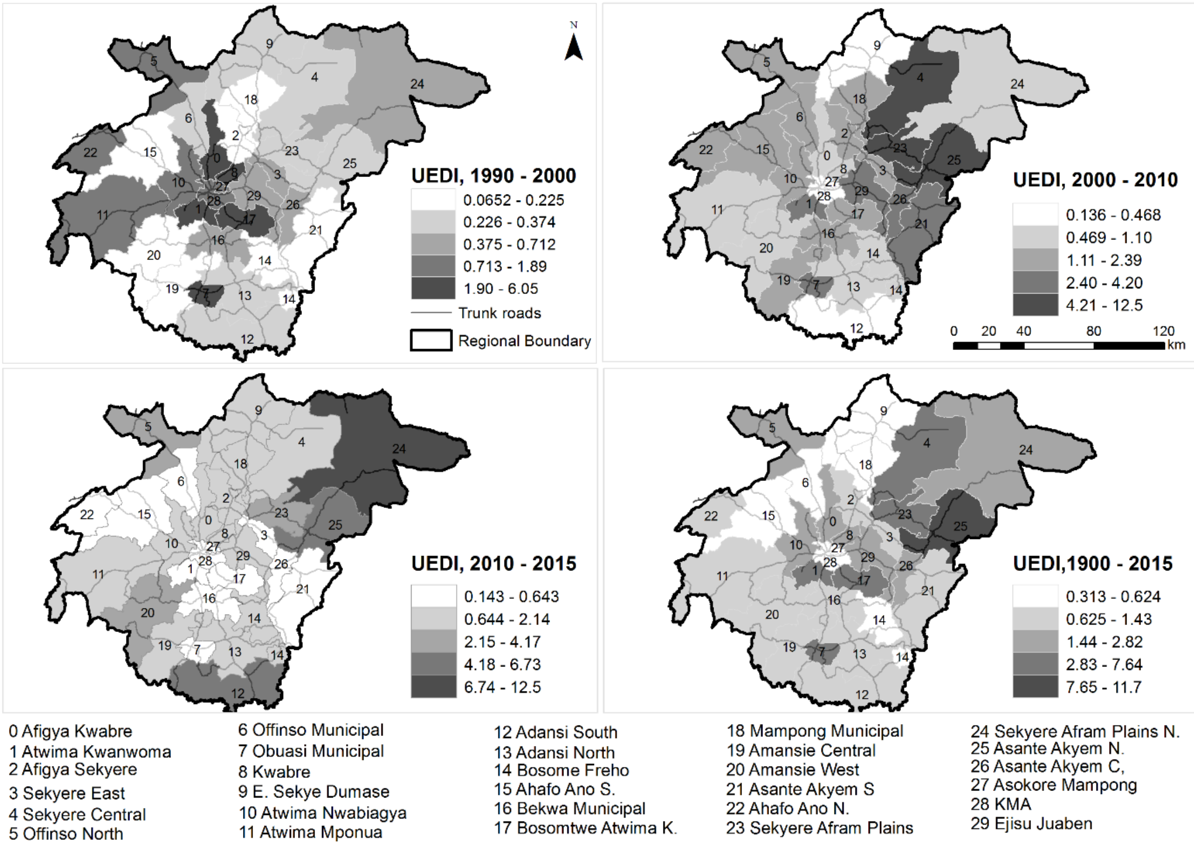


By standardising annual urban expansion rates of districts by that of the region, the second metric, UEDI, provides basis for determining actual growth hotspot. The mapping of the scores, as presented by Figure 6, follows Jenks natural break classification function (Jenks, 1963) in GIS. Consistent with results from UEII, the spatio-temporal patterns emerging from UEDI scores depict peri and suburbanisation, and dispersion into peripheral areas. However, there are some temporal differences that require further expatiation.

Unlike the UEII scores where the expansion of the core cities into surrounding districts is visibly expressed in the decade after 2000, UEDI results suggest the trend started even earlier. Between 1990 and 2000, higher UEDI scores were recorded in suburban districts that surround core districts (KMA and Asokore Mampong). Even so, the core areas were also part of the growth hotspots in the decade. Thus, the Greater Kumasi Sub-Region (GKSR), a functional area that encompasses KMA, Asokore Mampong and their neighbouring districts, featured significantly in the region's urban expansion.

However, between 2000 and 2010, the core areas, notably, KMA and Asokore Mampong dropped in UEDI score as urban growth soared in farther outlying districts. The trend of urban expansion shifting from core cities to hinterlands intensified during this period. The interval between 2010 and 2015 saw urban growth occurring more in the peripheries, whilst expansion in the GKSR and its neighbouring districts dropped. The outward expansion saw fringe districts, such as Sekyere Afram Plains North, Offinso North, Amansie West and Adansi South emerge as growth hotspots. In contrast to what is observed in the previous decades, urban expansion considerably slowed down in Obuasi Municipal as it recorded significantly low UEDI score.

Figure 5.6: Urban Expansion Differentiation Mapping



5.8 SLEUTH results on urban growth trajectory of the city-region

The calibrated results from SLEUTH is shown in Table 5.4. The region registered an extremely high dispersion coefficient (97), indicating high level of spontaneity in urban growth over the 25-year period. Thus, development randomly occurs in the region and almost every developable land has equal likelihood of being developed. Randomly urbanized parcels fast turn into new growth nuclei, as very high *breed* coefficient (96) is generated. Similarly, the region recorded substantially high *spread* coefficient (94), which depicts rapid expansion from the edges of existing urban clusters. Collectively, they cast an image of a region that is experiencing massive urban expansion that is rapid, dispersed and uncontrolled.

In addition, major transportation networks, like trunk roads seems to exert significant influence on the pattern of expansion as road gravity coefficient of 60 is recorded. Indeed, a superimposition of trunk roads on the urban extents affirms this as the shape of the former could be observed in the latter. Unlike roads, slope has a very low weight on the probability of a parcel being developed. In other words, with coefficient of 2, the likelihood of urbanization is less affected by a rise in local slope. This may be explained by the relatively flat terrain in the study region.

Table 5.4: Summary of calibration values

	Coarse		*Fine*		*Final*		Selected Results
Parameter	Range	Step	Range	Step	Range	Step	
Dispersion	0 - 100	25	75 - 100	5	90 – 100	2	97
Breed	0 - 100	25	75 - 100	5	95 – 100	1	96
Spread	0 - 100	25	75 - 100	5	90 – 100	2	94
Slope	0 - 100	25	0 – 25	5	0 – 10	2	2
Road Gravity	0 - 100	25	50 - 100	10	50 – 100	10	60

5.9 Emerging Issues

The results present to the fore a number of issues regarding the evolving spatial structure of the city-region. In addition to outlining them, this section discusses the implication for urban planning and policy.

Declining monocentric urban spatial structure

In the early decades, especially 1990, the urban spatial structure of the city-region largely conformed to the monocentric model described in Alonso (1964), Mills (1967) and Muth (1969). As Figure 3 depicts, in 1990, an overwhelming majority of built-up areas were concentrated within the city centre and its immediate surroundings. The city centre, Adum, which is not only the administrative capital of the Ashanti region, but also the commercial and transportation hub of the region and entire country, absorbed more than a third of the region's built-up area within 6 km. Thus, the monocentric model could be applied to the urban structure of the Ashanti region as of 1990 and 2000. This finding is similar to the observation of Oduro et al. (2014) who studied Greater Kumasi Sub-Region. The monocentricity, however, as Figure 5.3 would suggest, has been in sharp decline since the turn of the Twenty-first century. Urban growth is spreading farther out, and development is getting less concentrated. Indeed, the differences among districts within the region, in terms of urban growth intensity, is declining over the years, as typified by decreasing UEII coefficients of standard deviation. While the city centre is still slightly dominant, the monocentric model could hardly be applied to the recent urban structure of the region. The urban de-concentration in the region is rather akin to what Glaeser and Kolhase (2004) observed in US, where decreasing transport cost triggered urban dispersion. The proportion of workers in Ghana with access to motorized transport has increased significantly over the past couple of decades. For the first time, in 2012, almost half of workers commuted to work with a motorized transport (GSS, 2013). The decreasing urban concentration seems to reflect the increase in access to motorized transport.

Urban growth is becoming dispersive and amorphous

The spreading out of development from the urban centre and its environs, and the declining monocentricity have triggered an increasing amorphousness in spatial development patterns, especially since 2000. This pattern is observed by the different methods engaged by the study. First is the results of the relationship between UEDI spatial metric, which shows actual hotspot in terms of growth, and distance from the CBD. Depicted by Figure 5.4, there is a trend of a shift from a more concentrated urban growth to unconstrained dispersion. The decade to the twenty-first century was characterised by an overwhelming concentration of development, largely within 6 and 12 km zones from the CBD, with the UEDI curve having a dominant singular peak. Between 2000 and 2010, development was concentrated in several areas, notably, 14 – 16 km zone, 18 – 20 km zone, and 22 – 24 km zone from the city centre. Each zone represents a peak on the UEDI curve. However, contrasting these observed peaks, urban growth in the period after 2010 displays the absence of a dominant zone, as the peaks in UEDI curve virtually disappears. In other words, there is no marked difference among the zones in terms of rapidity of urban growth. Thus, the relationship between UEDI and distance from the CBD manifests a shift from high concentration to virtually no concentration. Post 2010 urban growth in Kumasi city-region has been unguidedly dispersive. The pattern of unconstrained dispersion, i.e development occurring everywhere in the region, can be interpreted as a form of amorphousness

Also affirming this observation, is the calibration results from SLEUTH CA model. As presented in Table 5.4, there is high level of spontaneity in the urban growth of the region. The recorded dispersion coefficient of 97, which is the highest in Africa as far as the application of SLEUTH is concerned – see the calibration results from Sietchiping (2004), Abdou-Azaz (2004), Abd-Allah and Mohammed (2007), Watkiss (2008) – brings into focus the excessive randomness of development in the city-region. This spontaneity also speaks to the dispersive and amorphous nature of urban growth, as spatial development seems to occur everywhere in the region. That notwithstanding, it is important to point out that the shift towards amorphousness does necessarily imply that the urban structure of the region fits the maximum disorder model as described by Angel and Blei (2016). In the case of the disorder model, there are no centripetal and centrifugal forces. However, similar to *dispersion,* the city-region recorded high coefficients for *breed* (96), *spread* (94) and *road gravity* (60), showing high level of contagiousness and influence of transport. Thus, the notion of the absence of centripetal and centrifugal forces does not hold in the region, hence while the urban spatial structure is becoming amorphous, it does not equate maximum disorder. The direct transformation from monocentricty to dispersiveness and seemingly amorphousness is quite unique relative to what is observed in other parts of the world. As mentioned earlier, the spatial transformation of many cities in the Global North, Asia and Latin America is marked by a shift from monocentric to polycentic urban form. Even though some US cities are becoming dispersive, they, unlike what is being experience in Kumasi City-Region, first evolved from monocentricity to polycentricity.

The dispersiveness of the city-region's spatial transformation can be situated within the phased oscillation theory (Dietzel et al., 2005; Martellozo and Clarke, 2011), which describes a two-staged process of urban growth. In the first phase, marked as diffusion stage, cities undergo a period of dispersion characterised by a shift in urban growth from high density areas (normally the urban core) to regions of low density. This is followed by the second period, termed the coalescence phase, where dispersed urban patches and clusters merge to constitute a mega urban region. Diffusion and coalescence are intrinsic parts of the stochastic fractal urban growth process described by (Batty et al., 1989; Batty and Longley, 1994). The results, which points to dispersive transformation, suggests that Kumasi city-region is in the diffusion stage. This also implies, a priori, the city-region's dispersed urban growth will eventually coalesce. The commencement of this phase depends on, among others, how long the diffusion stage will last, a duration which can be influenced by urban policy. Thus, the amorphous pattern is a phase transition of a fractal urban growth process that awaits a period of coalescence.

Weak planning system, influential transport

Underpinning the dispersiveness and high spontaneity of growth trajectory is institutional malfunctionality, especially on the part of the planning system, which has been largely redundant in managing urban growth. A number of studies (for instance, see UN-HABITAT, 2011; Boamah et al, 2012; Korah et al, 2016) have pointed to how majority of developments in Ghana occur without the requisite planning permission. Indeed, in addition to unauthorized low-scale development by households, some real estate companies develop large scale housing units without appropriate planning authorization (Anokye et al., 2013). The spontaneous proliferation of large-scale developments is also deducible from the work of Agyemang and Morrison (2018) who mapped the spatial distribution of mega residential developments in Accra. Thus, the evolution of the urban spatial structure is more led by the urban market, and less guided by the planning system.

In contrast to the planning system exerting virtually no control over urban development, transport appears quite influential in directing growth. In other words, transport influences development better than the planning system. This has wide-ranging implications; one of them being a reconceptualization of transport. Beyond just serving as accessibility and means of mobility, transport presents the planning system a powerful tool for managing urban growth. In overcoming its peripheral influence, urban planning policy in the region could strategically rally around the strengths of transport network, at least as a starting point. Thus, as much as possible, the design of transportation network and their construction should reflect the envisaged urban structure.

Spatial development path is inefficient and unsustainable

The spontaneity in development trajectory and the amorphousness of the evolving spatial structure cast an image of a city-region that is charting an inefficient and unsustainable urban development path. The nebulous nature of growth has wide ranging adverse implications on policy formulation and urban management in the region. For instance, with development occurring essentially everywhere, providing transport infrastructure and other utilities will be cost ineffective. Besides, energy inefficiency hovers around, as, stemming from the urban structure, there are more motorized trips by fewer people. The resultant increase in pollution, and the fast depletion of vegetative cover owing to the dispersiveness of growth, does not only complicate an already daunting urban management task, but also challenges the liveability and attractiveness of the region. A swift policy decision that strengthens the planning system in the management and guidance of spatial development patterns could prove decisive in averting the inefficient path that the city-region is currently charting. One of the policies could be the pursuit of urban compactness, which ought to recognize and manage the mixed social acceptance (Agyemang et al., 2017) of high-rise buildings in the region.

5.10 Chapter Conclusion

Against the backdrop of rapid urbanization that has characterised SSA in recent decades, many cities in the sub-region have undergone massive spatial transformation. Studies show that, in other parts of the world, largely the Global North, China and Latin America, urban transformation has seen the spatial structure of cities evolve from traditional monocentric to polycentric patterns. However, while urbanization in the twenty-first century is particularly massive in SSA, there is very limited knowledge on the extent to which the spatial evolution of cities in the sub-region conforms to or is explained by mainstream urban spatial structure models. Subsequent to this, the chapter examines the spatial evolution of a SSA city and its relationship with existing urban geography models; and further discusses the implications for urban planning and policy. While there are many ways of studying urban structure evolution, this chapter examines the phenomenon from the perspective of spatial development patterns. Spatially explicit data is drawn from the Ashanti Region of Ghana, one of the most populous regions in West Africa. The region, also referred to as Kumasi City-Region, hosts Kumasi, a principal metropolitan city in Ghana, which forms the main unit of analysis. Upon categorizing the city-region into zones that represent distances from the CBD of Kumasi, the study relies on a number of spatial metrics and an urban cellular automata model, SLEUTH, to analyse spatial development patterns in each of the zones.

The results show that, the spatial structure of the city-region in 1990 essentially conforms to the traditional monocentric model. However, subsequent to that, urban growth is increasingly getting deconcentrated, dispersive and amorphous. Linking this finding to the phase oscillation urban growth theory points to a pending coalescence phase in a stochastic fractal urban growth process. The spatial transformation in the city-region does not conform to the traditional trend of transition from monocentricty to polycentricty that is observed in many cities in the Global North, China and Latin America. That mentioned, it is important to point out that this finding is coming out of an analyses of spatial development trends. While this morphological perspective is an important starting point, additional studies that examine urban spatial structure in functional terms are required. The results further indicate high level of randomness in urban development patterns, casting an image of a city-region that is charting an inefficient and unsustainable spatial development path. Urban scholars would have to transcend the frontiers of existing urban structure models to better depict the spatial evolution of SSA cities like Kumasi City-Region, while Policy makers need to reposition the Ghanaian planning system to be more influential on development patterns.

CHAPTER SIX

UNDERSTANDING THE DYNAMICS OF LOCATION CHOICE DECISIONS OF URBAN HOUSEHOLDS

6.1 Introduction

This chapter, as one of two chapters of Part 2, is primarily allocated to understanding the dynamics of location choice decisions of urban households. For general physical, economic and population characteristics of Accra city-region, see Section 3.2.1 of Chapter 3. A number of objectives are explored here. These include examining the location decision-making processes of urban households; understanding how different urban households make prioritize different location choice factors; and quantify the weights assigned to development factors by urban households. Thus, the chapter investigates the following questions:

- What processes do various households undergo in making a location choice decision;
- Do different agents prioritise different location factors differently; and
- What quantifiable weights do different agents assign to different location choice factors?

By exploring the above stated questions and objectives, the chapter zooms into key features for developing the parameters of the model, which is captured in Chapter 7. For instance, out of dozens of location choice factors, the decision on what factor to include in the model development needs to go beyond heuristics and be grounded in hardcore empirical evidence. This is particularly so, given that the research is situated within Sub-Saharan African context, a region that has largely been peripheral to mainstream urban modelling, hence have less existing theoretical evidence to tap into.

Again, and more specifically, by exploring the decision-making processes of different urban households and their prioritization of diverse location choice factors, the chapter provides useful data for calibrating and operationalizing the model. Moreover, through the derivation of weights assigned to different location choice factors by different households, the chapter provides a foundation for computing and evaluating the suitability of each available land parcel for households with different characteristics. This enables the transformation of qualitative attributes regarding location choice decisions to quantifiable weights, thereby enabling their integration into the computational model. For instance, in real world, households normally consider multiple factors when choosing a place to live. The importance of the factors tends to differ to different households, in which case the quantification of weights helps in computing the different utilities of a location to different households.

Besides, by exploring into depth the location choice dynamics of urban households in a Sub-Saharan African context, the chapter contributes to the discourse on existing theories of location choice and models of urban spatial structure, especially regarding their transferability to the sub-region. The chapter also outlines some of the urban planning and policy implications of the location choice dynamics.

6.2 Basic Demographic Characteristics of Households

Gaining an insight into the basic demographic characteristics of the respondents is vital as it serves as the basis for differentiating the household agents. Key characteristics that have been considered include gender, age, marital status, highest educational level attained, household size, number of children in household, employment status and income.

The survey recorded high participation, as out of the 800 sampled respondents and attempted interviews, 790 were successfully completed, forming a response rate of 98.8 percent. Since participation was solely discretional, respondents, having started the interviews, had the option of opting out if they found it necessary. This was the case of the 10 interviews that were partially completed. These interviews have been excluded from the analysis. Again, it should be noted that, in some cases, the total respondents fall short of 790. This is as a result of respondents opting not to answer a particular question, or a question not being applicable to a particular respondent.

The majority of the respondents are males, constituting almost two-thirds (64 percent) of the total sample size. This follows a major feature of the population considering that the respondents are heads of households and for a typical traditional home in Ghana males are largely the de facto heads. If the respondents had been residents in general, but not necessarily heads of households, then the male skewness would have been a deviation, since the general population is slightly dominated by females as reported by the GSS (2012). However, as mentioned earlier, even for a household dominated largely by females, in most instances, the only male present who might be the father, normally assumes the headship role. This is a feature that is not dominantly shared by contemporary cities in the Global North, hence reiterating the need for such analysis in building models that also account for the peculiar socio-cultural characteristics in sub-Saharan Africa.

The age of respondents ranges from 22 to 89. Table 6.1 categorizes the age into various cohorts and shows their frequency and percentages. Table 6.2 also presents basic quantitative and descriptive facts about the overall age distribution. The average age, using mean measurement, is 41, whilst the median age is 39. The difference between the two measurements is quite marginal (only 2 years) and, indeed, it would not be a deviation to consider the average as 40.

Table 6.1: Age Characteristics of Respondents

Age Cohort	Number	Percent
20 - 24	17	2.2
25 - 29	123	15.6
30 - 34	131	16.7
35 - 39	130	16.5
40 - 44	112	14.2
45 - 49	90	11.5
50 - 54	62	7.9
55 - 59	56	7.1
60 - 64	33	4.2
65 +	32	4.1
Total	786	100.0

From Table 6.1, about a sixth of the respondents (16.7 percent) are within their early thirties (30 – 34) and a similar proportion (16.5 percent) fall into the other half of thirties (35 – 39). Thus, the thirties cohort constitutes a third (33.2 percent) of the sampled respondents, which is the highest of the distribution. The forties cohort absorbs the second highest of the distribution, which is about a quarter (25.7 percent). The youngest cohort (20 – 24) absorbed the least of the respondents (2.2 percent), followed by the oldest category (64 +) which constituted 4.1 percent. If one, however, considers the entire cohort of twenties (20 – 29), it accounts for a significant proportion (17.8 percent) of the respondents. Thus, the number of young heads of households (those under age 30) is quite sizeable. This is not surprising, considering that Greater Accra Region is the main destination of migrant population from across the country, who are largely young adults either seeking greener pastures or access to better educational and other socio-economic facilities.

Table 6.2: Descriptive characteristics of Age distribution

	Number of people in household	Number of children in households	Age
Mean	4.05	1.26	41.25
Median	4.00	1.00	39.00
Std. Deviation	2.682	1.379	11.857
Minimum	1	0	22
Maximum	26	10	89

6.3 Marital Status of households

Marital status is one the major characteristics that, quite often, inform people's location choice decisions. Table 6.3 depicts the distribution of respondents' marital status. The majority, about 60 percent, are married while an additional 12 percent are in consensual relationship. Thus, about 72 percent of the respondents have partners. The 28 percent that are single can be further categorised into two main groups: respondents who have never married at all, constituting 18 percent; and those who have married before (10 percent).

Table 6.3 Marital Status of Respondents

Marital Status	Frequency	Percent
Married	471	59.8
Never Married	141	17.9
Divorced	34	4.3
Consensual relationship	95	12.1
Widow	47	6.0
Total	788	100.0

6.4 Number of children in households

The presence of children (under age 18) in households and their number features that have potential of influencing location decisions. The distribution of these two variables, which have been categorised into 5 groups, over the sampled respondents is shown by Table 6.4. About 40 percent of households do not have a child. The remaining 60 percent have children numbers that range from 1 to 10. Only one household has the maximum number. Majority of households (56 percent) have 1- 3 child/ren while 5 percent have from 4 to 6 children. The average number of children from both mean and median measurements is 1.

Table 6.4: Number of Children in Households

Number of children in household	Frequency	Percent
0	301	38.1
1 – 3	444	56.2
4 – 6	40	5.1
7 – 9	4	.5
10	1	.1
Total	790	100.0

6.5 Household Size

As with the variables presented above, the size of one's household could affect where the person decides to live or build. Table 6.5 presents the varying sizes of sampled households. The household size ranges from 1 to 26. Single person households constitute just 12 percent of the total sample, while households made of up 2 to 3 members account for about a third of the sample. Majority of households (45 percent) have 4 to 6 members. Indeed, the average household size by both mean and median measurement is 4. Big size households, as in those with 10 or more members, form 3.1 percent of the sample, which is the least proportion.

Table 6.5: Household Sizes

Household Size	Frequency	Percent
1	95	12.1
2	108	13.7
3	151	19.2
4 – 6	354	45.0
7 – 9	54	6.9
10 - 15	20	2.5
16 +	5	.6
Total	787	100.0

6.6 Educational Level

The potential role educational level could play in location decision cannot be overemphasized. Prior to exploring any empirical relationship between the variable and location selection, the highest educational levels attained by the sampled respondents is briefly discussed. Table 6.6 shows the distribution of various educational levels attained. A dominant majority of respondents have attained some form of formal education, as the opposite, those without any, account for only 3 percent. However, what differs largely is the level of education attained by those who have been to school. The highest of level of education attained by most of the respondents (42 percent) is second-cycle qualification. Quite a significant proportion of the sample (30 percent) have been educated up to the tertiary level, which, in Ghana, encompasses certificates issued by universities, technical universities (formerly polytechnics) and training colleges. For about a fifth of the respondents, junior high school is their highest level of education attained.

Table 6.6: Highest Level of Education Attained by Respondents

Level attained	Frequency	Percent
Tertiary	240	30.5
Secondary	334	42.4
Junior High	148	18.8
Primary	41	5.2
Never	24	3.0
Total	788	100.0

6.7 Employment Status of households

So far, the variable presented are socio-demographic in nature. Whilst it is necessary to uncover the diversity in socio-demographic characteristics of household agents, understanding the economic dynamics and heterogeneity that define the location decisions of households, is fundamental to the research. Following this, a number of economic variables, including employment status of sampled heads of households are discussed briefly under this section. About 90 percent of the respondents are directly employed, either as employees or self-employers as shown in Table 6.7. The latter makes up more than half of the sample (52 percent). Thus, there are more self-employed heads of households than households who are employees of others. This is expected, particularly when situated within the context of a typical Sub-Saharan

African setting dominated by a large informal private sector, which is made up of wide array of small-scale self-employers. Students, apprentices and casual workers collectively form about 4 percent of the household heads.

Table 6.7: Employment of status of Respondents

Employment Status	Frequency	Percent
Employee	300	38.0
Self-employed without Employees	272	34.4
Self-employed with employees	138	17.5
Apprentice	11	1.4
Student	11	1.4
Casual Worker	10	1.3
Unemployed	48	6.1
Total	790	100.0

6.8 Income Distribution

Income is a fundamental if not the most important differentiation variable of the research. Indeed, its role in location choice decision cannot be overemphasized. Table 6.8 categorises income into 10 groups and show their distribution among the sampled respondents. Monthly income, expressed in Cedis, is first presented, followed by annual computations (also in Cedis), and a sub-sequent conversion of the latter to Pound Sterling to help orient the international reader.

Table 6.8: Income Distribution among Respondents

Monthly Income (GHC)	Annual Income (GHC)	Annual Income (£)[4]	Frequency	Percent
< 150	<1800	< 301	7	1.0
150 - 400	1800 – 4800	301 – 802	89	12.3
500 - 1000	6000 – 12000	1003 – 2007	278	38.5
1100 - 1500	13200 – 18000	2207 – 3010	102	14.1
1600 - 2500	19200 – 30000	3211 – 5017	125	17.3

[4] The bands under annual income (GHC) is a direct conversion of the primary bands, which is monthly income. The conversion to Pounds Sterling is based on annual income (GHC) bands, using the exchange rate of the Bank of Ghana as of Friday, September 17, 2017, which is GHC1: £0.17

2600 - 3500	31200 – 42000	5217 – 7023	54	7.5
3600 - 5000	43200 – 60000	7224 – 10033	45	6.2
5100 - 7500	61200 – 90000	10234 – 15050	10	1.4
7600 - 10000	91200 – 12000	15251 - 20067	9	1.2
> 10000	> 120000	> 20067	4	.6
Total			723	100.0

Table 6.9, which takes off from Table 6.8, further categorises income into three broad groups, i.e. low, medium, and high. Majority of the respondents (38.5 percent) earn between approximately £1,000 and £2,000 annually, whilst only 4, constituting 0.6 percent earn more than £20,067 a year. A percent of the respondents has annual income less than £300, and 13 percent receive a maximum of £800. About 83 percent of the household do not receive more than £5,000 annually and 9 out of 10 earn below £7,000 a year. These figures only cast nominal impressions. To have a better picture of the income distribution, consider the following; an annual rent for a single bedroom in Accra ranges from around £200 in deprived neighbourhoods to about £600 in standard areas – with fairly good roads and clean surroundings.

Having collapsed the bands into three major income groups, the distribution as captured in table 6.9 shows that about half of respondents (52 percent) are low income earners, while close to 38 percent can be classified as middle-income earners. High income earners make up just about 9 percent of the respondents.

Table 6.9: Broad Income Groups Distribution

Group	Frequency	Percent
Low	374	51.7
Middle	281	38.9
High	68	9.4
Total	723	100.0

6.9 Factors Affecting Location Choice Decisions

Having examined the characteristics of the respondents, this section and subsequent ones directly explore the main objectives of the chapter, which includes understanding how location decisions are made. In an attempt at unravelling the myriad of factors that influence people's decision to select a particular place for occupation, the respondents are asked a number of questions pertaining to their location decisions. Specifically, they are asked about the specific factors that were considered before their selection of their current place, which is the place they lived at the time of the interview. Respondents had no limit as to the number of factors they could list. The question only applies to respondents who have moved places. Table 6.10 presents basic statistical information about the wide array of factors that informed respondents selection of their current place.

Table 6.10: Location Choice Factors Considered by Households

Location Choice Factor	Number of times selected	Percent of all selections	Percent of Sampled Households
Land Values	398	11	53
Distance to Work Place	370	10.2	49.3
Neighbourhood Environmental Quality	287	7.9	38.2
Distance to School	283	7.8	37.7
Distance to Road	257	7.1	34.2
Population Density	243	6.7	32.4
Family Networks	241	6.6	32.1
Neighbourhood Development Status	229	6.3	30.5
Land Ownership	202	5.6	26.9
Distance to Suburb Centre	201	5.5	26.8
Distance to Market	192	5.3	25.6
Distance to CBD	164	4.5	21.8
Distance to Health Facility	109	3	14.5
Religious Networks	100	2.8	13.3
Ethnic Networks	99	2.7	13.2
Planning Scheme[5] Availability	89	2.4	11.9
Slope	40	1.1	5.3
Land Registration Status	38	1	5.1
Elevation	27	0.7	3.6

[5] Planning scheme refers to a local plan or sector layout prepared by a local planning authority

Distance to Shopping Mall	22	0.6	2.9
Distance to Airport	21	0.6	2.8
Distance to Rail Station	9	0.2	1.2
Distance to Parks and Gardens	6	0.2	0.8
Distance to Rivers	6	0.2	0.8
Total	3633	100	483.8

About 95 percent of the respondents, representing 751 heads of households, have changed places, meaning they have made a location decision regarding their current place. In all, 24 different factors influenced the location decisions of the households, and, on the average, a household considered about 5 different factors. Land values emerged as the most influential as more than half (53 percent) to respondents considered it. This is followed closely by proximity to place of work, which partly informed the location decision of approximately half of the respondents (49.3 percent). Proximity to school and neighbourhood environmental quality comes as third and fourth respectively, with each having been considered by about 38 percent of households. Proximity to roads (34.2 percent), population density (32.4 percent), and family networks (32.1 percent) partly influenced the location decision of, at least, a third of the respondents.

Neighbourhood development status, which refers to whether or not surrounding parcels are developed, is also influential as it informed the location decision of close to a third of households (31 percent). Proximity to suburb centres (26.8 percent), markets (25.6 percent), and land ownership status were considered by at least a quarter of the respondents.

Religious and ethnic networks, factors that are quite rare to find as drivers of location decisions in many cities in the Global North, emerged as quite influential, accounting for the location choice of about 13 percent of households. Most of the existing urban growth or location choice models reviewed in Chapter 2 hardly take into consideration such factors, hence their transferability to cities and regions in Sub-Saharan Africa is quite limited.

Two factors, availability of planning scheme and land registration status, were also considered by a section of the respondents. These factors could provide insights into the willingness of people to comply with development/building regulations as specified by the planning system. The law governing spatial planning in Ghana, as with many countries across the world particularly, the Global North, requires that development permit be requested and approved by a local planning authority before any development occurs. How does this point relate to the two factors mentioned in the paragraph? For a local planning authority to issue a development permit, it is required that the land should not only have a planning scheme and be zoned for the purpose for which the permit is sought, but, also be registered. Thus, without checking the boxes for the two factors, one cannot secure a development permit.

Having this in mind, prior to selecting a parcel of land for development, households that do not consider these factors are more likely to develop without a permit relative to those that consider them, other things being equal. Just about 12 percent of the respondents considered availability of planning scheme, and even smaller proportion (5 percent) considered land registration status. This is consistent with earlier findings, for instance, by (UN-HABITAT, 2011; Anokye et al., 2013) that majority of development in Ghana take place without the consent of a local planning authority.

Distance to rivers (0.8 percent), proximity to a park or garden (0.8 percent), proximity to rail station (1.2 percent), proximity to airport (2.8 percent), and proximity to shopping mall (2.9 percent) constitute the bottom five influential factors of location choice. One would have expected that, distance to rail station, which is normally a major mode of transport, would have been more influential. However, when situated within the local context where rail system is largely dysfunctional, the finding is not a deviation from the reality.

6.10 Relationship Between Households' Attributes and Location Choice Consideration

Do different agents prioritize different location choice factors differently?

Having examined, from the previous section, myriad of factors that inform location choice decisions, this section explores the second question of the chapter, which is, do different agents prioritize different location factors differently? In other words, is there a relationship between households who share certain unique characteristics and the factors they consider in selecting a location to live. The differentiation of households follows the socio-economic and demographic features such as, income, presence of children, marital status, etc. that have been presented earlier. The importance of this question, regarding its role in the model development and calibration, as well as the theoretical and policy relevance have been articulated in the chapter introduction. In exploring the question further, let us start from equation 6.1, which expresses location selection as a function of wide range of location choice factors.

$$y = f(X_1, X_2,..X_n) \tag{6.1}$$

Where, y is location selection; and X_1, X_2, and X_n are the location choice factors.

In making location decisions, there are two outcomes or choices, which is either a place is selected or not. A binary logistic regression function has been used to explore relationships in terms of odds ratios between the location selection of various households and each of the diverse location choice factors. Mathematically, the logistic function is expressed below.

$$\boldsymbol{P(Y) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n \in_n)}}} \tag{6.2}$$

Where, P(Y) is the probability of the dependent variable Y, which is dichotomous, occurring; X_1, X_2, and X_n[6] are the independent variables; and *β_1, β_2, and β_n* are the coefficients the independents variables respectively. Substituting the location choice factors into equation 6.2, the equation can be rewritten as:

$$\boldsymbol{P(S_i) = \frac{1}{1 + e^{\substack{-(\beta_0 + \beta_1 Land\ Value + \beta_2\ Proximity\ to\ School + \\ \beta_3 Proximity\ to\ Road + \beta_4 Proximity\ to\ health\ facility + \\ \beta_5\ Proximity\ to\ Suburb\ Centre + \beta_6 Proximity\ to\ CBD + \\ \beta_7 Proximity\ to\ Market + \beta_8 Proximity\ to\ Shopping\ Mall + \\ \beta_9 Proximity\ to\ Airport + \beta_{10} Proximity\ to\ Rail\ Station + \\ \beta_{11} Proximity\ to\ Park\ and\ Garden + \beta_{12} Proximity\ to\ river + \\ \beta_{13}\ Population\ density + \beta_{14} Slope + \beta_{15} Elevation \\ + \beta_{16} Availability\ of\ Planning\ Scheme + \beta_{17} Land\ Ownership\ Status + \\ \beta_{18}\ Land\ registration\ status + \beta_{19} Neighbourhood\ development\ status + \\ \beta_{20}\ Neighbourhood\ environmental\ quality + \beta_{21} Family\ networks + \\ \beta_{22} Religious\ networks + \beta_{23} Ethnic\ networks + \\ \beta_{24} Proximity\ to\ Place\ of\ Work)}}}} \tag{6.2}$$

Where, $\boldsymbol{P(S_i)}$ is the probability (P) of location (S) being selected by a household with characteristic i. It is treated as a dichotomous variable. Thus, there can only be two outcomes, either selected or not selected. As a result, characteristic (i), which is very important as it represents the attribute of interest, assumes only one characteristic for each given expression.

[6] The predictors including the proximity variables are based on the responses from households, hence has the weakness of being perceptional.

For instance, i cannot be equal to income status and presence of children at the same time. If i equals presence of children, the dependent variable is interpreted as, the probability of households with children selecting a place relative to households without children.

Other categorical variables that have more than two states are aggregated or recoded as binary variables. Income is a typical example. Each of the three cohorts outlined in Table 6.9 is treated independently as a binary variable. Thus, the location decision of households with high income is examined exclusively, likewise those with middle or low income. Explaining this further, let's consider a situation where i = low income. In such an instance, the response variable will be interpreted as the probability of households with low income selecting a place, relative to those not classified as low income.

6.10.1 Location Choice Selection of Low-Income Earners

Table 6.11 presents the results from the logistic function, which explores the relationship between location selection of low-income earners and various location choice factors. A significant relationship is found for 8 of the factors at 95 percent confidence level. The direction of the relationship for five of the factors, i.e. proximity to work, proximity to major road, proximity to suburban centres, proximity to market, and population density is positive, while that of proximity to school, shopping mall, and slope are negative.

Table 6.11: Location Choice Selection of Low-Income Households

Location Choice Factor	B	S.E.	Sig.	Exp(B)
Land Values	.005	.286	.987	1.005
Proximity to school	-2.410	.285	.043*	.090
Proximity to road	.687	.280	.014*	1.989
Proximity to health facility	-.326	.420	.438	.722
Proximity to suburban centre	2.354	.798	.003**	10.523
Proximity to CBD	-.463	.366	.206	.630
Proximity to Market	.889	.385	.021*	2.432
Proximity to shopping mall	-2.331	1.114	.036*	.097
Proximity to Airport	-1.360	.963	.158	.257
Proximity to rail station	.894	1.604	.577	2.446
Population Density	.856	.337	.011*	2.354
Slope	-1.488	.625	.017*	.226
Elevation	-.845	.704	.230	.430
Availability of planning scheme	.210	.445	.637	1.234
Land ownership type	.049	.304	.871	1.051
Land registration status	-.405	.551	.462	.667

Extent of neighbourhood development	-.359	.309	.246	.699
Neighbourhood environmental quality	-.035	.293	.904	.965
Family network	.535	.275	.052	1.708
Religious network	-.122	.504	.809	.885
Ethnic network	.582	.363	.108	1.790
Proximity to place of work	1.113	.299	.000***	3.044

From Table 6.11, proximity to work is more likely (OR = 3.04) to influence a place being selected by low income households. The relationship is quite strong, considering that $p < 0.001$, and it is the only factor that is statistically significant even at 99 percent confidence level. This could be explained by the sensitivity of low-income earners to transport, as captured by, for instance, traditional urban economics theories, particularly, Alonso's bid rent as applied to residential location. Since transport cost, arising from commuting, increases with increasing distance between home and place of work, low-income households prioritize proximity to place of work as a cost saving measure. Indeed, by far, this relationship is not surprising when it is examined within the local context. As with many cities in Sub-Saharan Africa, traffic congestion in the city of Accra is massive, and access to commercial transport is a daunting daily task, especially during peak periods. For those who either do not own or have access to private cars, a segment of the population that constitute the majority, mobility becomes extra difficult, more so when the distances are longer, hence the significant relationship.

Furthermore, proximity to road is more likely (OR = 1.99) to influence the location selection of low-income households. This buttresses the point about the sensitivity of low-income earners to transport. To cut down on transport cost, which is a necessity for low-income households, preference is not only given to proximity to place, but also proximity to road. Another rationale that emanates from the survey is the economic advantages most roads presents. In Accra, like many cities in Sub-Saharan Africa, hundreds of thousands of people earn living through the informal sector that principally include footloose trading along major roads. Thus, for significant proportion of households, largely low-income earners, proximity to a major road is synonymous to proximity to source of income.

Related to the point above, proximity to suburban centre (OR = 10.5) and market (OR = 2.4) are more likely, respectively, to influence a place being selected by low income households when making location choice decision. Suburban centres in Accra and other parts of Ghana serve as major employment hubs for many households employed by the informal economy. These centres, which have lorry terminals, tend to function as agglomeration points for intra and inter-city transport, hence present huge informal economic opportunities. Markets play a similar for many households that do not have access to formal economic opportunities. It is therefore, not unexpected that, proximity to, suburban centres and markets seems to play a major role in the location decisions of low-income households.

In a similar vein, high population density more likely (OR = 2.35) to influence a place being selected by low income households. Some of the respondents explained that, high population density is conducive for informal economic activities, as it provides the market for petty trading. However, living in highly dense areas involves trade-offs, like exposure to diverse forms of urban pollution and crime. Indeed, in Accra, slum areas such as Nima, tend to be the highly dense areas. The trade-offs involved offer a more plausible rationale behind the relationship observed. In essence, low income households are more willing to embrace urban pollution and high crime tendency as a price for access to market opportunities.

In addition to these factors, at 90 percent confidence level, a statistically significant relationship is observed between the location choice decision of low-income households and family networks as depicted by Table 6.11. In terms of odds ratio, family networks are more likely (OR = 1.7) to influence a place being selected by a low-income household. From the survey, consideration of family networks manifests in various ways, including the availability of lands owned by the family; physical presence of people from one's nuclear or extended family or presence of people known by and recommended by family members. Accessibility to lands owned by one's family or by a member of the family normally comes at much reduced cost relative to general market prices, at times they are accessed at no direct cost. Besides, the presence of family members in a neighbourhood or people recommended by them, provides some sense of communal security and other forms of social capital, particularly in times of distress. Many low-income households rely on these networks to maximize their utility in an otherwise inhibiting land market. Stemming from these, it is not surprising that the results attest a positive relationship, albeit at 90 percent confidence level, between the location selection of low-income households and the presence of family networks.

6.10.2 Location Choice Decision of High-Income Earners

For high income earners, three location choice factors; neighbourhood environmental quality, proximity to place of work, and proximity to school are statistically significant at 95 percent confidence level as presented by Table 6.12. Out of the three, positive correlation exists for two, neighbourhood environmental quality and proximity to school. The results depict that the presence of quality environment is 5.1 times as likely to influence the location selection of high-income households. In Ghana, like many other countries, areas with high quality environment tend to be expensive relative to poor environmental areas. The mechanism behind that normally stems from the interaction of market forces of demand and supply. Almost everyone wants to live in a good environment, but its supply is highly limited, particularly in Accra. Price and income emerge as the determinants of accessibility to the limited high-quality environment. The observed relationship between the location selection of high-income households and neighbourhood environmental quality relationship is therefore not unexpected. Quite surprisingly, proximity to school is more likely to be considered by high-income households.

Table 6.12: Location Choice Selection of High-Income Households

Location Choice Factor	B	S.E.	Sig.	Exp (B)
Land Values	.082	.758	.914	1.085
Proximity to school	2.847	.828	.001	17.243
Proximity to road	.753	.672	.263	2.123
Proximity to health facility	-.635	.948	.503	.530
Proximity to suburban centre	-.278	.866	.748	.757
Proximity to CBD	-1.994	1.399	.154	.136
Proximity to market	.543	.947	.566	1.721
Proximity to shopping mall	.063	1.286	.961	1.065
Population density	-.965	.862	.263	.381
Slope	1.884	1.251	.132	6.578
Elevation	-1.419	1.043	.173	.242
Availability of planning scheme	.769	1.718	.655	2.157
Land ownership type	.832	.715	.244	2.298
Land registration status	.861	1.087	.429	2.365
Extent of neighbourhood development	.291	.691	.674	1.337
Neighbourhood environmental quality	1.643	.725	.023	5.171
Family network	-.019	.703	.978	.981
Religious network	.330	1.284	.797	1.391
Proximity to place of work	-2.715	1.104	.014	.066

In contrast, a negative relationship is found between the location selection of high-income households and proximity to place of work. The odds ratio from the logistic function shows that, proximity to place work is about 15 times unlikely to influence a place being selected by high-income households. This observation is in consonance with traditional urban economics theories that depicts urban spatial structure where the urban core is occupied by low-income households who are more sensitive to transport cost, whilst high-income households enjoy the greenery in the suburban areas with less concerns about transport cost to the CBD.

For some of the other factors, though the relationships are not statistically significant, the direction is worth taking note of. For instance, the relationship between the location selection of high-income households and factors such as population density, proximity to suburban centre, and proximity to CBD appears negative. One feature common to these factors is that, they either characterise existing core urban areas or emerging ones, and, in Ghana, such areas tend to be polluted, particularly by noise. On the other hand, the direction of the relationship for factors such as availability of planning scheme, land registration and ownership status, which, as argued earlier, are proxies for determining the willingness to undertake unauthorised development, is positive. However, it is important to re-emphasize that these relationships are not statistically significant.

6.10.3 Location Choice Decisions of Married Household Heads

The results from the logit function between the marital status of household heads, i.e. married or not married, and the location choice factors are presented with Table 6.13. A statistically significant relationship is found between a place being selected by a married household head and six of the independent variables; proximity to school, land ownership type, land registration status, neighbourhood environmental quality, population density, and family network. For two of the factors; population density and family network, the relationship with being married is negative, while that of the remaining four are positive.

High population density is less likely (OR = 0.38) to influence a place being selected by a married household head. A major reason emanating from the survey that explains this, is accessibility to privacy. Married household heads appear to prioritize privacy with their partners, hence generally live in areas with low population density. Following a similar path, family network is less likely (OR = 0.98) to influence a place being selected by married heads of households. Thus, married people seem to be influenced by desire for privacy from their family, particularly extended type. Some of the married respondents held the view that living away from parents and other extended family members is important for the success of their marriage, as geographical distance serves as a physical barrier against unnecessary intrusion. This finding resonates with the context, especially within the purview of increasing urbanization and its associated urbanism, which includes a shift from a more rural based extended family ties, to a predominantly nuclear and closed urban family system.

Table 6.13: Location Factors Consideration of Married Household Heads

Location Choice Factor	B	S.E.	Sig.	Exp(B)
Land Values	.279	.170	.101	1.322
Proximity to school	.639	.166	.000	1.895
Proximity to roads	-.165	.171	.335	.848
Proximity to health facility	.201	.263	.446	1.223
Proximity to suburban centre	.062	.202	.757	1.064
Proximity to CBD	-.238	.209	.255	.788
Proximity to market	.397	.208	.056	1.487
Proximity to shopping Mall	-.455	.526	.387	.635
Proximity to Airport	-.512	.563	.363	.599
Proximity to rail station	-.337	.833	.686	.714
Proximity to parks and gardens	.583	1.077	.588	1.792
Population density	-.398	.191	.038	.672
Slope	.863	.416	.108	2.370
Elevation	-.446	.458	.331	.640
Availability of planning scheme	.381	.257	.139	1.463
Land ownership type	.579	.199	.004	1.785
Land registration status	1.611	.579	.005	5.009
Extent of neighbourhood development	.347	.199	.081	1.415
Neighbourhood environmental quality	.412	.176	.020	1.510
Family network	-.635	.164	.000	.530
Religious network	-.187	.243	.441	.829
Ethnic network	-.155	.299	.603	.856
Distance to place of work	-.212	.174	.223	.809

In contrast to the direction of the above relationships, proximity to school is more likely (OR = 1.89) to influence a location being selected by married people. Indeed, this relationship is also statistically significant at 99 percent confidence level ($p < 0.01$) as shown in Table 6.13. As part of planning for their future, married couple consider the education of their children or those they anticipate having.

Neighbourhood environmental quality is more likely (OR = 1.5) to influence a place being selected by married people. Once again, the role played by the presence of children, can hardly be overlooked here. When married people are making location choice decisions, they are in effect deciding for their children, both present and unborn, hence tend to be keen about the suitability of the location for these children. Thus, the observed relationship is less surprising.

Similarly, the location choice of married heads of households seems to be influenced, positively, by land management factors such as land title registration status and ownership type. In terms of odds ratio, the former is about 5 times likely to influence a place being selected by married people. As advanced earlier, the consideration of these two factors, together with that of availability of planning scheme, facilitates insights into the likelihood of the occurrence of unauthorized development. Besides, the tendency of losing a development or land to litigation is quite minimized for the acquisition of registered lands. Thus, it appears married people are not only more cautious about the legal security of their developments, but also likely to have the major required documentation for securing development permit. That said, it is worth highlighting that, at this point, there is no direct evidence that married people, relative to those unmarried, do secure planning permission prior to development. This clarification is particularly important, considering that the relationship between marital status and consideration of availability of planning scheme, though positive, is not statistically significant.

6.10.4 Location Choice Decisions of Households with Children

As advanced earlier, presence of children is one of the key socio-demographic variables of interest, and this subsection looks into the relationship between the location selection of households with children and various location choice factors. The results, which is presented with Table 6.14, indicate a statistically significant relationship between the dependent variable and six of the location-choice factors, including proximity to school, land values, population density, neighbourhood environmental quality, family network, and land registration status.

Table 6.14: Presence of Children and Location Choice Factors

	B	S.E.	Sig.	Exp(B)
Land Values	.539	.194	.005	1.715
Proximity to school	2.412	.251	.000	11.156

Proximity to road	.050	.196	.800	1.051
Proximity to health facility	.237	.311	.446	1.267
Proximity to suburban centre	-.282	.232	.223	.754
Proximity to CBD	.022	.234	.925	1.022
Proximity to market	.263	.236	.264	1.301
Proximity to shopping mall	-.361	.604	.550	.697
Proximity to airport	.700	.661	.290	2.013
Proximity of rail station	-.642	.349	.066	.526
Proximity to parks and gardens	-1.146	1.275	.369	.318
Proximity to rivers	-.833	1.069	.436	.435
Population density	-.534	.218	.014	.586
Slope	.234	.480	.626	1.264
Elevation	-.314	.514	.542	.731
Availability of planning scheme	1.613	1.292	.212	5.020
Land ownership type	.208	.237	.380	1.231
Land registration status	2.286	.826	.006	9.838
Extent of neighbourhood development	.084	.228	.714	1.087
Neighbourhood environmental quality	.638	.209	.002	1.892
Family network	-.439	.187	.019	.645
Religious network	.134	.272	.621	1.144
Ethnic network	.624	.291	.032	1.866
Proximity to place of work	.143	.197	.467	1.154

As with that of married heads of households, the direction of the relationship here is negative for two of the factors, family networks and population density. Generally, it is quite ironic that the presence of family is not positively influencing the location choice of households with children. However, situating it within the context, where the predominantly extended family system appears to be shifting to a more closed and nuclear family ties, one could make meaning out of the results. In recent times, a typical urban or modern[7] household in Ghana is normally constituted by a couple or unmarried partners with a child or two. As earlier indicated, such

[7] Here, modern is used mildly to depict the shifting trend.

households tend to prioritize their privacy, particularly from extended family members. By living farther from the extended family, the nuclear families use distance to limit possible intrusions by the former, hence the observed negative relationship. It is along similar lines, i.e. prioritizing privacy by staying away from highly dense areas, that informs the indirect relationship between households with children and population density.

In contrast to the two, proximity to school, neighbourhood environmental quality, land values and land registration status positively influences the location choice of households with children relative to those without. Proximity to school is more likely (OR = 11.16) to influence the location selection of households with children. The rationale behind the prioritization of proximity to school is quite straightforward. This is a case where parents or guardians attach much premium to the education of their children in terms of physical accessibility to schools. Similarly, as part of safety considerations, households with children are more particular about the environmental quality of the neighbourhoods they select. The odds ratio shows that neighbourhood environmental quality is more likely (OR = 1.9) to influence a place being selected by households with children.

Uncovering the rationale behind the relationship with the remaining two factors – land values and land registration status – seems complex. Starting with the latter, it appears households with children are more risk conscious when it comes to the legal security of their homes. As mentioned earlier, developing on an unregistered land is unlawful, hence such developments could be demolished even though it rarely happens. Indeed, in theory, development permit cannot be secured for lands that are unregistered. However, one should not lose sight of the fragile nature of development control regulations in Ghana, which allows overwhelming majority of development to take place without planning permit. That notwithstanding, the risk that ones' home could be demolished appears to weigh heavily on households with children.

Besides, it is also the case that acquisition of registered lands is less susceptible to ownership litigations. An ugly but common feature of the Ghanaian land market, particularly in Accra and major cities, is multiple sale, which refers to an instance where a parcel of land is sold to two or more people. Such cases are more associated with unregistered lands. Thus, by prioritizing land registration status, households with children, also reduces the risk of losing their homes to land litigations.

For land values, the rationale emerges from affordability considerations. Indeed, by considering land values, households measure the affordability of the lands in relation to their purchasing power. The results indicate that land values are more likely (OR = 1.72) to influence a place being selected by households with children.

6.10.5 Location Choice Decisions of Household Heads with Degree

Conceptually, education, particularly the formal type, is expected to impact the decisions and choices of people who access it. Does it also affect location decisions, or in other words, is there a relationship with the location selection of people with a certain level of education, and some location choice factors? The location decisions of households' heads with degree, relative to those without, is explored with a binary logistic function, and the results presented with Table 6.15.

Table 6.15: Household Heads with Degree and Location Choice Factors

Location Factor	B	S.E.	Sig.	Exp(B)
Land values	.065	.284	.820	1.067
Proximity to school	-.160	.311	.607	.852
Proximity to road	.913	.310	.003	2.492
Proximity to health facility	.285	.419	.498	1.329
Proximity to suburban centre	-.657	.361	.068	.518
Proximity to CBD	-.193	.347	.578	.824
Proximity market	-.700	.355	.049	.497
Proximity to shopping mall	1.051	.635	.098	2.861
Proximity to airport	-.579	1.146	.613	.560
Proximity to park and garden	-.760	1.365	.578	.468
Population density	-.244	.318	.442	.783
Slope	-.129	.527	.807	.879
Elevation	-.313	.380	.410	.731
Availability of planning scheme	1.134	.414	.006	3.109
Land ownership	-.045	.284	.875	.956
Land registration status	.655	.374	.080	1.926
Neighbourhood development status	.138	.289	.634	1.147
Neighbourhood environmental quality	.217	.289	.452	1.242
Family network	-.312	.308	.311	.732
Religious network	-.017	.628	.978	.983
Ethnic network	-.105	.422	.803	.900
Proximity to place of work	.712	.423	.092	2.038

At 95 percent confidence level, statistically significant relationship is found between the location selection of household heads with degree and three of the location-choice factors; availability of planning scheme, proximity to road and proximity to market. The relationship is positive for the first two, i.e. planning scheme and road proximity, and negative for proximity to market. In terms of odds ratio, availability of a planning scheme is more likely (OR = 3.1) to influence a place being selected by household head with a degree. This seems to suggest that as more people attain degree, the planning system is more likely to be effective, at least, in terms of awareness creation.

The inverse relationship between attainment of degree and consideration of proximity to market appears to stem from the negative externalities that comes with market places. Most of the market places in Accra and other parts of Ghana are largely informal and noisy, unlike those in Western cities. While the economic opportunities associated with markets attract some households, its pollution also repels others, which seems to include household heads with degree.

6.11 Emerging Issues

A number of issues emerge from the analyses above. These include but not limited to the following:

- Proximity to place of work is about 3 times as likely to influence a place being selected by low-income household.
- Proximity to major road is about twice as likely to influence a location being selected by a low-income household.
- Low-income households are about Suburban centres and markets are about 10 and 2.5 times as likely to influence a place being selected a low-income household.
- High population density is about twice as likely to influence a location being selected by a low-income household.
- Neighbourhood Environmental quality is about five times as likely to influence a place being selected by a high-income household;
- High population density is about 1.5 times less likely to influence a location being selected a married head of household.

- Presence of family is about twice less likely to influence a place being selected by a married household head.
- Proximity to school is about twice more likely to influence a location being selected by a married head of household.
- Land title registration status is about 5 times likely to influence a place being selected by a married household head.
- proximity to school is about eleven times more likely to influence a place of selected by household with children.
- Availability of planning scheme is about three times more likely to influence a location being selected by household head with a degree.

CHAPTER SEVEN

MODELLING AND SIMULATING URBAN RESIDENTIAL GROWTH IN INFORMAL CITIES WITH AN INTEGRATED AGENT BASED AND CELLULAR AUTOMATA MODELLING TECHNIQUES

7.1 Introduction

Agent-based modelling and Cellular Automata have emerged as dynamic modelling techniques, particularly in the era of new generation of urban models. Their appeal, which appears to be increasing in popularity, cut across multiple disciplines. However, the approaches have recognizable inherent weaknesses as highlighted in Chapters 1 and 2. For instance, ABM with its enormous strength in modelling behavioural and socio-economic relationships, has some limitations with directly abstracting spatially explicit relationships (Filatova et al 2013; Wu and Silva, 2010a). Similarly, while urban CA technique is noted for modelling spatially explicit interactions, it is less powerful in modelling behavioural and socio-economic relationships (Dahal and Chow, 2014; Zhang et al. 2010; Wu and Silva, 2010b; Torrens and Benenson, 2005).

In an attempt to compensate for these inherent weaknesses, many urban modellers integrate the two approaches. Indeed, there is a growing popularity of urban growth and land use change models that integrate agent-based and cellular automata (Shuvo and Janssen, 2013; Wu and Silva, 2009). The integration of the two approaches is widely viewed as a more a realistic way of abstracting complex urban systems (Mustafa et al, 2017; Silva, 2011; Li and Liu 2007; Parker, 2005; Nara and Torrens, 2005; Parker et al, 2003). In other words, the combination of the techniques is seen as an avenue for developing robust urban models that can serve as better decision support tools for policy makers and urban managers. Stemming from this, multiple urban growth and land use change models have been developed in recent decades through the integration of the two approaches. Chapter 2 provides a review of many of these integrated models.

A shortfall of these models, however, is that while they offer valuable insights as decision support tools, they are largely limited in their ability to explicitly capture the dynamics of urban development in predominantly informal cities, especially those in Sub-Saharan Africa. The principles, mechanics and relationships that underpin the existing integrated urban growth models principally reflect the nature of urban development in cities of the Global North and some in the Global South. The mechanics of the existing models, for example, see (Mustafa et al, 2017;

Tian et al, 2016; Tan et al, 2015; Dahal and Chow, 2014), is such that development is undertaken by real estate developers based on authorization by government or a local planning authority. In sharp contrast, for many cities in Sub-Saharan Africa, development is predominantly informal as highlighted in Chapters 4 and 5. The informality in this context is not only a description of spontaneous or dispersive developments, but primarily, a reflection of the predominantly un-authorized, un-regulated and unplanned nature of developments (UN-HABITAT, 2012; Burra, 2004; Lourenço-Lindell, 2004). Thus, informal urban growth has spatial pattern and regulation / legality dimensions. Some of the existing dynamic models, for instance, the integrated ABM and CA model of Shuvo and Janssen (2013) and SLEUTH CA model of Clarke et al. (1997), capture the spatial pattern dimension of informality (Agyemang and Silva, 2019). SLEUTH has a parameter for controlling the extent of dispersiveness or spontaneity, while Shuvo and Janssen's model for Dhaka simulates non-contiguous development pattern. However, when it comes to the un-authorized and un-regulated aspects of development, none of the existing models captured this essential dimension of informal urban growth.

The weaknesses of existing integrated ABM and CA models in capturing un-regulated aspects of informal urban growth adversely impact policy formulation and theory development. Regarding policy, the benefits meant to be derived from existing models as decision support tools is significantly inhibited. For instance, one of the major challenges that confront city managers and urban planners in Sub-Saharan Africa is dealing with un-regulated developments. As indicated above, existing urban ABM and CA models offer very less in this regard. Theoretically, the existing models are not strongly grounded to facilitate insights into the dynamics of un-regulated developments. Thus, while existing dynamic ABM and CA models could offer some policy and theoretical insights, there is even more grounds to cover in modelling the dynamics of informal urban growth as witnessed by many Sub-Saharan African cities.

This limitation with existing dynamic models is significant on its own, but more so when juxtaposed with the reality that Twenty-first century urbanization has been particularly imposing in Sub-Saharan Africa. Indeed, together with Asia, Sub-Saharan Africa is expected to account for about 90 percent of the anticipated 2.5 billion global urban population increase by 2050 (UN, 2014). In addition to many of its cities undergoing rapid urbanization, Sub-Saharan Africa still has majority of its population living in rural areas, meaning the urbanization trends in the sub-region is likely to continue in the next decades. The ability to comprehensively model and simulate the informality that characterises urban growth in the sub-region will be vital in managing the expected massive urban transformation. Against this backdrop, this chapter develops *TI-City* (The Informal – City) model, an integrated ABM and CA model that simulates urban residential growth in a predominantly informal cities in Sub-Saharan Africa. This objective is anchored on the question: how can predominantly informal (un-regulated and unplanned) urban growth be modelled with an integrated ABM and CA approach? In addition, the chapter discusses the urban planning and policy implications of the simulated urban residential growth.

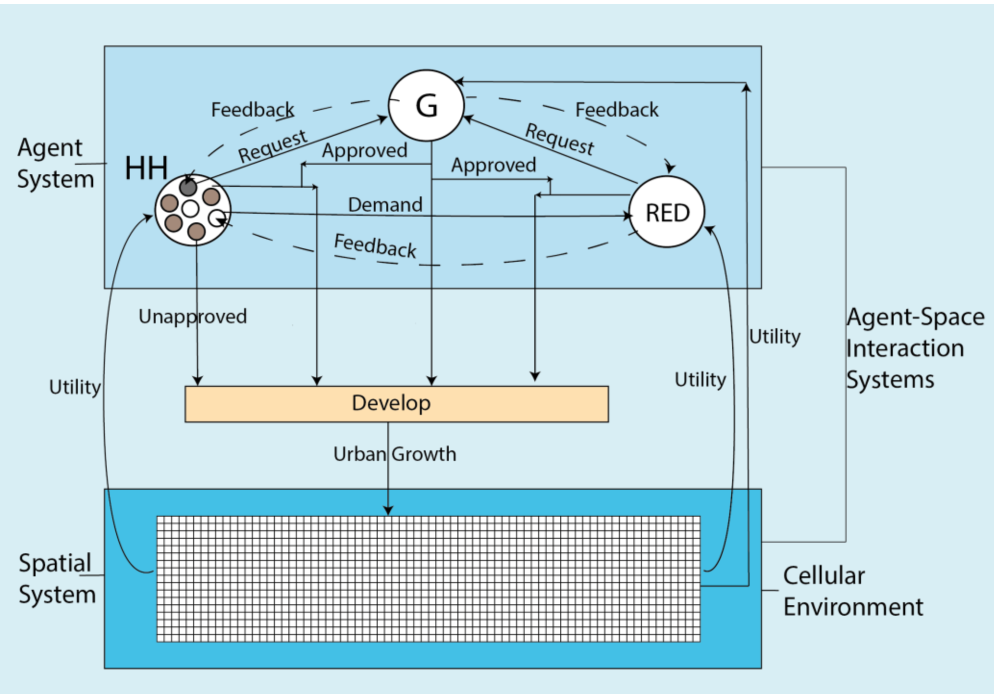
Ghana, one of the fast-growing economies in Sub-Saharan Africa, shares most of the spatial trends that characterises many cities in the sub-region. Ghana has undergone rapid urbanization over the past few decades, which is reflected in population boom and spatial transformation of its principal cities such as Accra, Kumasi, Sekondi-Takoradi, etc (Agyemang et al., 2019; Town and Country Planning Department of Ghana, 2015; Ghana Statistical Service, 2013). Accra city-region in particular has spearheaded the urban transformation processes that has taken place in the West African country (Agyemang et al, 2017). Chapter 3 highlights the major urbanization characteristics of the city-region. One of the dominant features of the city-region's urban transformation is the predominantly informal nature of development, a feature outlined in Chapter 4 that also attracts the focal lens of this Chapter. The spatial informality of the city-region manifests in both development patterns, as simulated in Chapter 4[8], and un-regulated and unplanned nature of developments as alluded to by (UN-Habitat, 2011; Anokye et al., 2013). This Chapter primarily models the latter dimension of informality by drawing on data from Accra city-region. Thus, through an integration of ABM and CA techniques, this Chapter develops an empirical model (TI-City) capable of simulating predominantly informal urban residential growth.

[8] The difference, however, between the focus of this Chapter and that of Chapter 4 is that, while the latter explores informality from the perspective of spatial development patterns, the former directly models the un-authorized and un-regulated dimension of the phenomenon.

7.2 Model Conceptual Framework

The conceptual framework of the model, presented with Figure 7.1, is developed to reflect the nature of urban residential growth in Ghana, particularly Accra city-region. There are notable differences between the dynamics of urban development in Ghana and those observed in other contexts, especially the Global North. Significant part of the differences stem from the varying contextual roles played by even similar identifiable agents. For instance, unlike in many Global North cities and regions where houses are demanded by households but supplied by real estate developers, the overwhelming majority of housing developments in Ghana are demanded and supplied by households. Through low scale and incremental building processes, households have delivered a chunk of the housing stock in Ghana (UN-HABITAT, 2011, Boamah et al., 2012). Also, unlike in many Global North countries where development is contingent on authorization by government or a local planning authority, the majority of housing developments in Ghana are undertaken without any authorization (Anokye, et al., 2013; UN-HABITAT, 2009, 2011; Acquah-Harrison, 2004).

Figure 7.1: TI-City model conceptual framework



HH: Households G: Government RED: Real Estate Developers

The conceptual framework is composed of three main systems, namely, spatial system, agent systems and agent-space interaction systems. These are further described under the model development section. The framework identifies three urban actors / agents that are responsible for urban residential growth. These are households, real estate developers and government. These agents, who interact among themselves and with their environment, play various roles. Household agents undertake majority of developments and provide demand signals; real estate developer agents undertake development; and government agent regulates development. The agents interact among themselves and the spatial system. The interactions among agents include the following:

- A fraction of household agents demand housing from real estate developer agents;
- Real estate developer agents pick market signals from a fraction of household agents;
- Real estate developer agents request government agent for development permit;
- Government Agent approves or disapproves the development request from Real estate agents; and
- A fraction of household agents requests development permit from government agent.

The interaction between agents and spatial environment include:

- Household agents search for suitable place to build and live;
- Estate developer agents search for suitable for suitable to build and sell; and
- Government agent regulates development to an extent.

7.3 Model Development

Following the conceptual framework, the development of the model is categorised into three parts, which are the spatial environment, agent system, and agent-space interaction system. These are subsequently described.

7.3.1 Spatial Environment

The spatial environment, also representing the supply side of the model, is captured with a cellular automata technique. The study area is first standardized into regular 200m * 200m cells, with each representing a parcel of land. It should be stated that this cell size is bigger than actual average plot size in the ACR, which is around 30m * 21m. The bigger plot size is to enhance computational efficiency, given the large spatial extent of the study area, which is over 8000 km^2.

The attributes for each parcel in relation to various spatially explicit variables that influence development are subsequently computed. The spatial variables considered in the model include land values, land title registration status, extent of neighbourhood development, population density, slope, exclusion, and centrality of parcels, which is gauged with proximity to amenities such as trunk road, basic school, suburban centre, market, shopping mall, health facilities, CBD, and attractive suburbs.

In computing land values attributes, data on prices of lands in the study area, ranging from 2005 and 2015, area was accessed from the Ghana Lands Commission (GLC). The vector point type data was converted to polygon using Thiessen polygon interpolation method in GIS, and subsequently to raster to match the cellular spatial structure. A summary of spatially explicit attributes and how they are generated is presented with Table 7.1.

Table 7.1: Outline of spatially explicit development factors

Spatially Explicit Factor	Data source and treatment
Land values	Land price data from GLC, interpolated with Thiessen Polygon
Land title registration	Combination of limited land title registration data sketch map by experts at GLC and Town and Country Planning Department (TCPD)
Extent of neighbourhood development	Count of cell neighbours that are built-up
Population density	Census tract data from Ghana Statistical Service (GSS)
Slope	Percent slope generated from resampled ASTER GDEM data
Exclusion	TCPD data of water areas and wetlands
Proximity to trunk road	
Proximity to school	
Proximity to suburban centres	
Proximity to CBD	
Proximity to shopping centre	Normalized Euclidean distances from cells to amenities and centres. Data on distribution of amenities is accessed from TCPD.
Proximity to market	
Proximity to attractive neighbourhoods	
Proximity to health facility	

The computation of land title registration status attributes of parcels was more challenging, as data available is extremely limited. While it is a recognizable fact that most land titles in the study area are un-registered, there is very little data regarding the title registration for specific lands. To acquire sufficient data, a team of experts at the Ghana Lands Commission and Town and Country Planning Head Offices were contacted. The team, based on their long-standing practical knowledge of the context, produced a sketch for the study area regarding areas that are most likely to be registered. The sketch was rasterized in GIS to conform to the data structure.

The generation of parcels attributes regarding the extent of neighbourhood development is based on Moore's 3 * 3 neighbourhood range. For each cell, the number of neighbours that are built-up are counted and assigned as an attribute. Regarding slope, the 30m ASTER GDEM data used in Chapters 4 and 5 is also used here. The data is resampled in GIS to match the selected cell size and percent slope is computed. The exclusion attribute follows SLEUTH's concept, which refers to areas that are resistant to development. Areas classified as excluded include, water and wetlands.

Regarding spatial proximity attributes, data on distribution of the various amenities were accessed from Ghana TCPD Head Office. For places of work, dominant employment centres, which happen to be suburban centres and the CBD, were used as proxies. Euclidean distances from cells to the amenities and centres were computed in GIS. To improve computational efficiency, the distances were standardized to 0 – 1 as shown with figure 7.2. For factors that lower values are generally preferable, for instance, proximity to suburban centres, schools, roads, etc, the following equation is used.

$$N_{i(x,y)} = \frac{\gamma_{i(x,y)} - \gamma_{i(min)}}{\gamma_{i(max)} - \gamma_{i(min)}}, \qquad 0 \leq N_{i(x,y)} \leq 1 \qquad 7.1$$

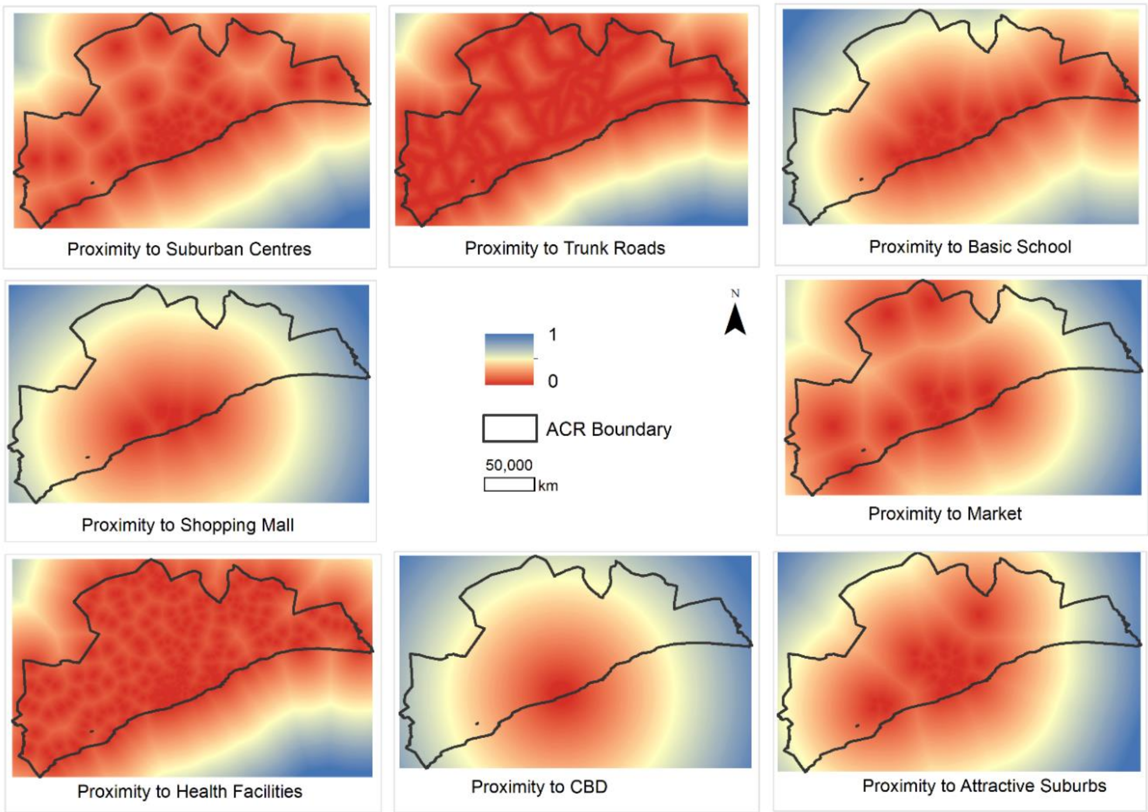
Where $N_{i(x,y)}$ is the normalized index of factor i at location(x, y); $\gamma_{i(x,y)}$ is the value of factor i at location(x, y); $\gamma_{i(max)}$ and $\gamma_{i(max)}$ are the maximum and minimum observed values respectively of factor i in the entire study area.

For factors that higher values are generally favourable, the normalization equation follows:

$$N_{i(x,y)} = \frac{\gamma_{i(max)} - \gamma_{i(x,y)}}{\gamma_{i(max)} - \gamma_{i(min)}}, \qquad 0 \leq N_{i(x,y)} \leq 1 \qquad 7.2$$

This maintains consistency in terms of the order of favourability of values. Thus, closer the normalized factor to 0, the higher the favourability.

Figure 7.2: Standardized spatial proximity variables



7.3.2 Suitability of Parcels

An important component of the spatial environment is determining the physical suitability of cells for development. SLEUTH's handling of suitability is adapted. Using NetLogo modelling platform, three variables, namely, critical slope, slope coefficient and exclusion are combined to generate a suitability attribute. Critical slope is the percent slope value beyond which development cannot occur. Parcels that fall above the critical slope are normally too steep to be physically developed or restricted from development as a matter of policy. Slope coefficient determines the extent to which development patterns are influenced by slope. Critical slope and slope coefficient are represented with sliders that can be adjusted to between 1 and 100.

7.3.3 Capturing informal development dynamics into the spatial system

Modelling informal urban growth, a central piece of this research, requires a good understanding of the phenomenon, particularly the underlying mechanisms. In unravelling the dynamics of informal developments in Ghana, a team of experts, made up of Senior Planning Officers at the TCPD Head Office, were consulted. Underpinning informality are a number of land and institutional factors, principal among which include land titling and registration complications, problems with enforcement of development rules and regulations, and corruption.

The laws governing spatial development in Ghana requires every development to be authorized by government, normally represented by local planning authorities. In applying for development permit, the laws require that, among others, the applicant proves official ownership of the parcel land to be developed. This proof requires providing evidence of official title registration. The challenge, however, is that Ghana, like many developing countries in Sub-Saharan Africa, has a major problem with land title delineation and registration, stemming partly from its dominant customary land ownership system. The vast majority of lands do not have their titles assigned and registered, hence makes it virtually impossible to demonstrate the official proof of ownership required by the laws. In essence, a planning permit cannot be secured for developing on lands with titles unregistered. Thus, developments that occur on informal lands ends up being unauthorized (informal).

Another central requirement of development permit is that proposed developments must conform to the zoned land use type as expressed in a local plan. For example, if a residential development is proposed for an area not zoned for same purpose, it will not be authorized. Thus, developments that do not conform to zoned land use types are mostly informal.

Connecting the aforementioned factors, is institutional weaknesses in the enforcement of development and spatial planning laws. Whilst it is a requirement that every development be first authorized by an appropriate local planning authority, most occur regardless, without any punitive consequences. The majority of households hardly consider the land registration status or the designated land use type of a parcel prior to development.

In capturing these processes that trigger informal development, the model assigns to each parcel, an informality attribute. This attribute determines whether a parcel is liable to informal development. Parcels susceptible to informal development, assigned informality attribute of 1, are either unregistered with regard to their titles, or not zoned for residential development. The scale of informality, in terms of the number of informal parcels that available for development, depends on the efficacy of law enforcement or development management measures and physical factors, which are controlled government or local planning authority. The section on government agent provides further details the scale has been captured in the model.

It should also be emphasized that, while the majority of informal residential developments occur on informal lands – lands with unregistered titles or not zoned for residential purpose – some also occur on formal lands, which are lands registered and zoned for residential purposes. Factors that account for the latter include, delays in securing planning permission, recalcitrance and corruption. Stemming from data paucity, the model does not capture informal developments that occur on formal lands.

7.3.4 Agent System

The agent system, which is also the demand side of the model, is abstracted with an agent-based modelling technique. Following the conceptual framework and using NetLogo, three autonomous agent types, i.e. households, real estate developers and government are created.

7.3.5 Government Agent

Government is represented by the local planning authority, which is in charge of urban growth management. As part of this mandate, the local planning authority enforces development control regulations. The extent to which the behavioural actions of household and RED agents are affected by regulations depends on the level of enforcement by government agent. To account for this, an informality coefficient is introduced into the model. The coefficient, represented with a slider that ranges from 0 to 100, reflects the extent or strength of enforcement of development control measures. The closer the coefficient to 100, the higher the strength of enforcement and the lower the probability of development occurring on informal lands. If, for instance, informality coefficient is 10, it means about 90 percent of informal lands, will be available for development.

7.3.6 Household Agents

As stated above, development is largely undertaken by households. Household agents have income attribute, which specifies their level of income. Based on the income levels, household agents are further classified into three groups; low-income, middle-income and high-income. The number of household agent that can operate the in the model can range from 100 to 100,000. Similarly, the disaggregation of household agents into income groups is flexible to adjustments, with the use of sliders. The behaviour of households is regulated by the theory of bounded rationality. The agents make location choice decisions based on the perceived utility of parcels, which are not necessarily optimal. This research adapts the additive form of the utility function employed by (Brown et al., 2008; Dahal and Chow, 2014). The perceived utility is given as:

$$U_{a(x,y)} = \left(\sum_{i=1}^{n} (\gamma_{i(x,y)})^{\omega_{ia}} \right) + \varepsilon, \quad 0 < \varepsilon \leq 0.1 \qquad 7.3$$

Where, $U_{a(x,y)}$ is the utility of agent a at location (x, y); $\gamma_{i(x,y)}$ is the value of factor i at location (x, y); $\omega_{ia}$is the weight agent a assigns to factor i; and n is the number of spatially explicit development factors, which are the proximity variables outlined in Table 7.2. and extent of neighbourhood development; and ε is randomly generated in NetLogo. The random variable is important as it emphasizes the rather perceptive nature of the utility, which may not equate actual utility.

The weight assigned to a factor denotes the importance level of the factor to a specific household agent. This varies with income status. The weights are derived empirically through the household survey described in Chapter 3. As part of the survey, heads of households who have made location decision ranked, on a scale of 1 to 10 where 10 is highly influential, the extent to which each factor affected their location choice. The mean score for each factor is cross tabulated with income status, and the results, representing the weights used in the model, is presented with table 7.2.

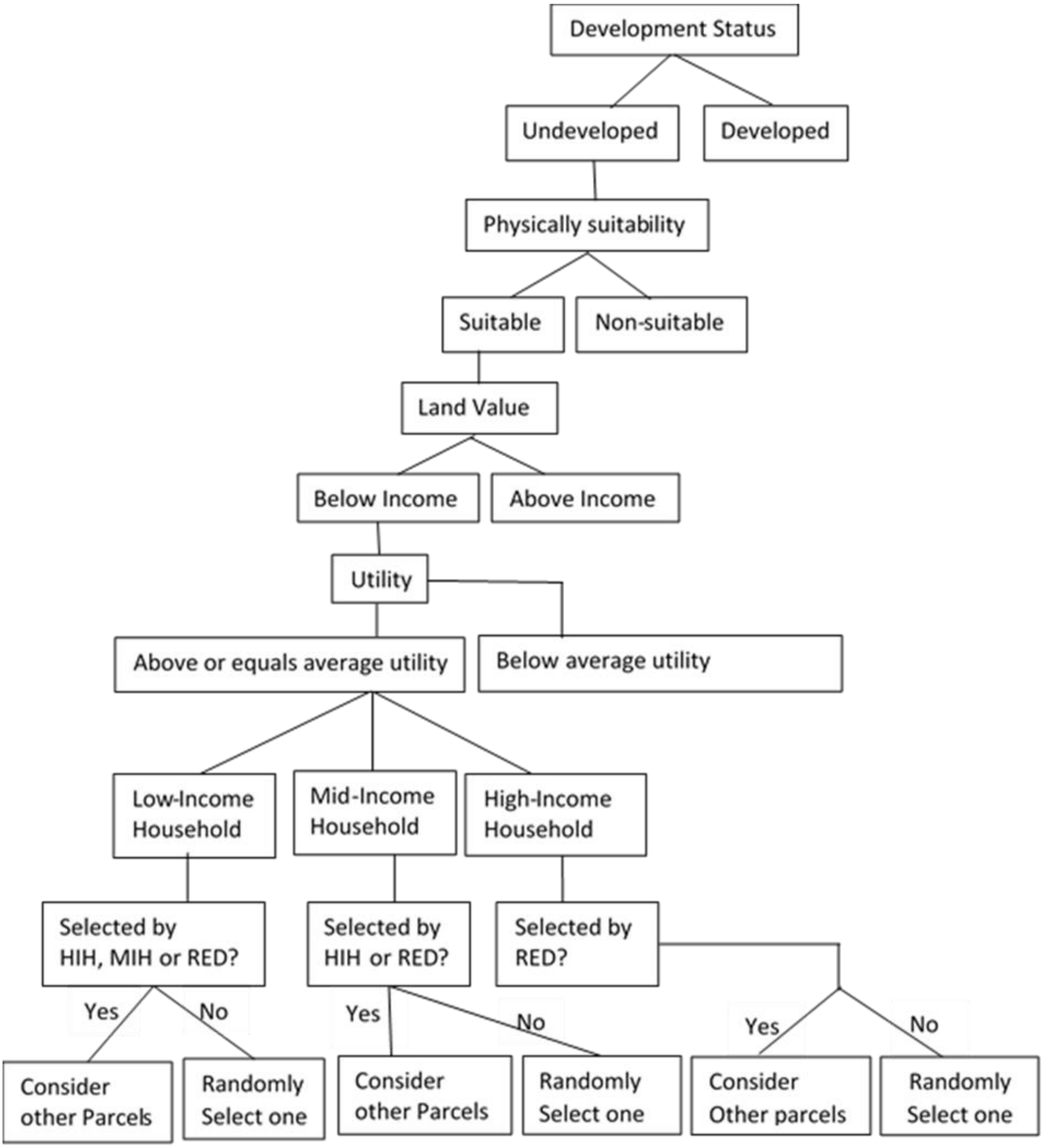
Table 7.2: Households weighting of development factors

Factor	Weight		
	Low-Income	Mid-Income	High-Income
Proximity to road	8	5	3
Proximity to school	2	4	4
Proximity to suburban centres	10	4	2
Proximity to CBD	5	3	2
Proximity to shopping centre	4	4	5
Proximity to market	6	4	2
Proximity to attractive neighbourhoods	2	8	10
Proximity to health facility	1	1	1
Extent of neighbourhood development	7	6	5

7.3.7 Decision making structure of household agents

The model allows a number of household agents to enter the land market annually and search for a place for developing. The exact number of agents is determined by the user. Like in real life, agents with different income status can enter the market simultaneously. Upon entering the market, household agents undertake a number of actions in selecting a place to develop. These behavioural actions are captured with the decision tree presented in Figure 7.3. Prior to describing the figure, it is worth highlighting that, as a measure of parsimony, the model does not allow a household agent to select more than one parcel. Also, household agents cannot redevelop parcels that are already developed. The degree to which households follow development and spatial planning regulations depends on the strength of enforcement by government agent.

Figure 7.3: Household agents location choice decision tree[9]



Household agents only search for lands that are not developed. The search is further reduced to lands physically suitable for development, which encapsulates parcels that are below the critical slope and also not classified as wetland. The scope is further limited to lands whose prices are within the income levels of agents. However, it should be mentioned that this is a simplified

[9] It applies the same way to informal lands. However, the availability and quantity of informal lands in the market is solely determined by the extent of government regulation of development as described under section 7.3.3.

measure, as in real life, particularly in the context of the study area, some households squatter on lands that are beyond their affordability. The available parcels, which are the ones agents can afford, are grouped, based on their perceived utility, into two: above or equal to average utility of parcels; and below average utility. Agents consider the former. This non-optimization treatment of utility mimics what transpires in real-life where households, partly as a result of information limitations, do not optimize utility. The common practice, however, in making location choice decisions, is that households normally have areas they prefer to avoid and those want to consider. In the model, areas to avoid are parcels with perceived utility below the average utility, whilst the areas to consider are those above average utility. Household agents randomly select one of the considered parcels. This randomness in the final selection of parcels and the perceived nature of utility are key stochastic elements of the model. If two or more household agents select the same parcel, the one with the highest income wins. Similarly, if a household agent and real estate developer agent clash on a parcel, the latter wins.

7.3.8 Real Estate Developers

In this context, RED agents are defined to encapsulate institutions and corporate entities that undertake medium to large-scale developments for commercial purposes. RED agents supply residential developments to a fraction of middle and high-income households. Accordingly, RED agents are further categorised into mid and high end. The model provides room for specifying the number of RED agents, which can range from 10 to 1000, in addition to disaggregating them to the two typologies (mid and high-end developers). In making location choice decisions, RED agents attempt to maximize profit / utility to the extent of information available. This follows the utility equation for household agents, except that the development factors are weighted differently. The weights used in the model, which are shown in Table 7.3, were derived from a consultation with the management of Ghana Real Estate Developers Association (GREDA). The minimum and maximum weights are 1 and 10 respectively.

Table 7.3: RED weighting of development factors

Factor	Weight	
	Mid-end RED	High-end RED
Proximity to attractive neighbourhood	7	10
Proximity to road	8	8
Proximity to school	5	5
Proximity to suburban centres	7	7
Slope	7	5

RED agent goes through a process in selecting a place for development. This is similar to that of household agents captured in Figure 7.3. Unlike household agents who select individual parcels, RED agents select areas, which are made up of nine parcels, which a parcel and its neighbours. As with household agents, RED only follow development and spatial planning regulations to extent of the efficacy of enforcement by government agent. RED agents are assumed to have a competitive edge over households. As a result, if an area selected by RED agent includes a parcel that has been selected by a household agent, the parcel is won by the former. If a mid-end and high-end RED select the same area or parcel, the latter wins the competition.

7.3.9 Dynamic treatment of neighbourhood

Neighbourhood is treated dynamically in the model. As development process is initiated and agents make location choice decisions, the utility and land values of parcels are updated based on a neighbourhood relationship. As the updating occurs, cells change their status in relation to the two variables to reflect the characteristics of the agent type predominantly found in a neighbourhood. For instance, if an undeveloped cell, with low land values and below average high-income household utility, has three or more neighbouring cells occupied by high-income household agents, the cell in question updates itself by increasing its high-income utility above average and land value to range of high income. Thus, stemming from neighbourhood effect, the parcel will no longer be affordable to low income households, and will now be attractive to high-income earners. If the cell already has high land value and above average high-income utility, it will maintain its values. In a similar vein, if an undeveloped parcel, with a below average low-income household utility and high land value, has three or more neighbours occupied by low-income households, the parcel in question changes its low-income utility to above average, while its land value is decreased to within low-income range. The parcel then becomes available for consideration for low-income households, while being unattractive for those with high income.

This neighbourhood effect also applies to developments by RED agents. If, for instance, a vacant parcel, with low land value and below average middle or high-income utility, has three or more neighbours selected by RED agents, the parcel increases in land values and utility in a way that it becomes attractive to middle and high-income households. If the RED utility for this parcel is below average, it increases to above average, boosting its attraction to RED agents. This treatment of neighbourhood reflects what happens in real world property values change based on surrounding characteristics.

7.4 Model output metrics

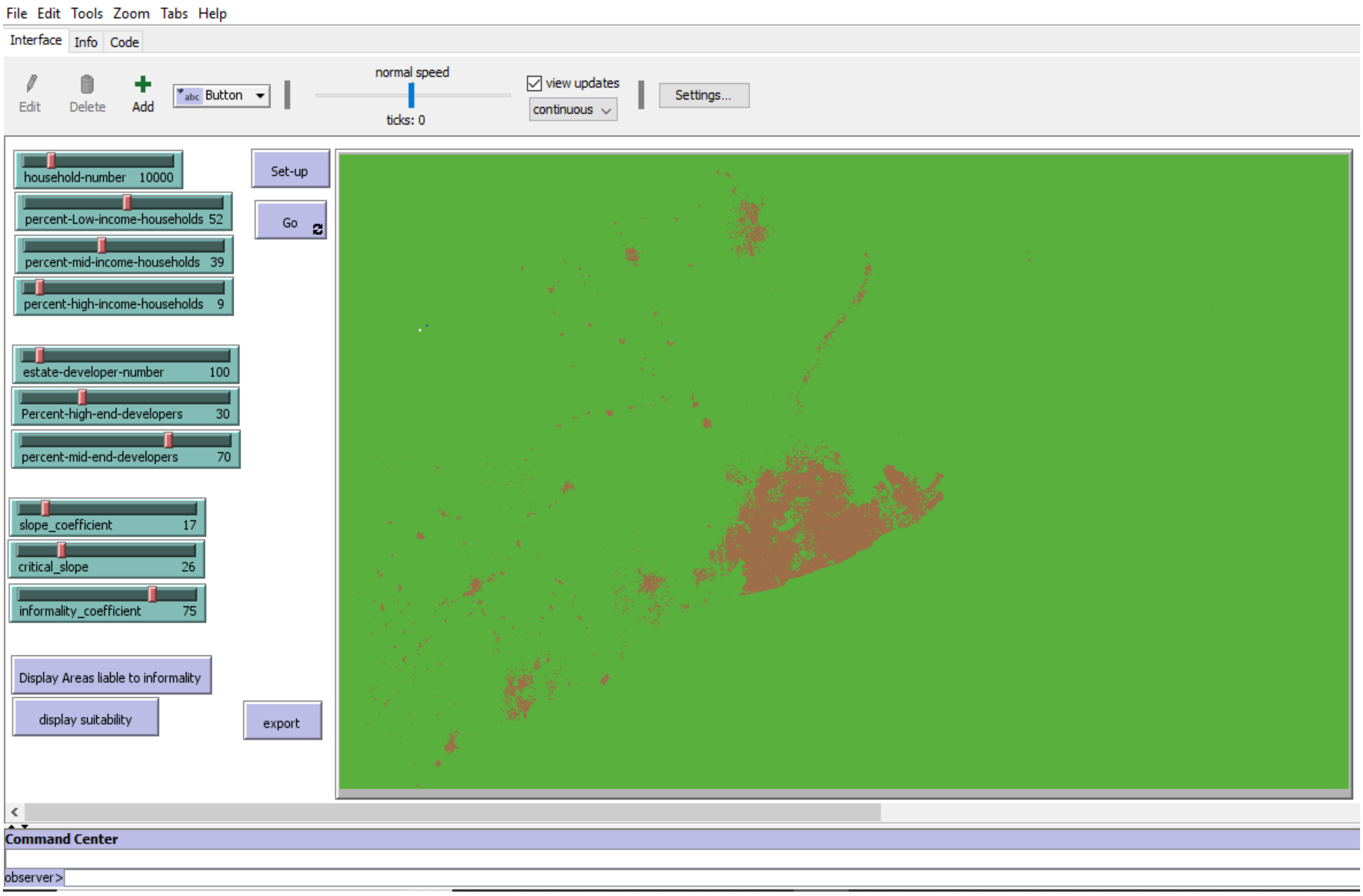
The model uses 8 metrics to further characterise simulated outputs. These are: percent informal, which quantifies the proportion of all new developments that are informal; contribution to informality, which measures the contribution of each income group towards new informal developments; income type informality, which computes, for each income group, the proportion of new developments is informal; percent edge growth, which quantifies the proportion of new developments that occur on the edges of existing urban areas; percent spontaneous; which calculates the proportion of new developments that are dispersive; new spreading centre, which generates the rate at which new centres emerge for new developments; linear growth, which computes the rate at which new developments occur in the neighbourhood of transport networks; and percent urbanized, which quantifies the proportion of land area developed. It is important to highlight the emergent way that the model treats various urban growth patterns, such as dispersiveness, edge growth, new spreading centres and transport growth.

7.5 Model calibration and validation

Validation is one of the critical stages in model development as it serves as a platform for assessing a model's performance and effectiveness. As highlighted in Chapter 2, the validation of agent-based models, which in most instances require comprehensive and rich micro level data, is generally challenging. Further complicating this challenge is when the process takes place in a context that has considerable data challenges. Notwithstanding this challenge, a number of steps has been taken to validate the model.

Prior to applying it to any future simulation, the model has been used to simulate the historical residential growth of ACR, specifically from 2000 to 2010. This requires calibrating the model to depict the characteristics of residential growth of the study area during the period. The calibration largely involves adjusting the values of the parameters found on the model interface, which is presented with Figure 7.4. The calibration is premised on a combination of the empirical analysis undertaken in Chapter 6, national census data and other secondary sources.

Figure 7.4: TI-City model Interface



Household population and income group disaggregation

The number of household agents to be simulated is one of the key parameters of the model. It affects the number of parcels that are developed by households, since each agent exclusively settles on one parcel. The number, which is subsequently distributed over the simulated period, is given by the formulae:

$$N = \frac{HP_2 - HP_1}{T} \qquad 7.4$$

Where, N is annual number of households to be simulated; HP_1 is total number of households at simulation starting year; HP_2 is total household population at simulation end year; and T is the simulation time range (in years). Household population for 2000 and 2010 were derived from Ghana Statistical Service's 2000 and 2010 national census respectively. Substituting the values into the equation generates an initial number of 46,728 households to be simulated. This figure, however, does not take into consideration the extent to which plot sizes are enlarged in the model as described in section 7.3.1. Thus, directly using the initial number will significantly overstate the developed land area. To account for this, the figure is normalized by the scale factor used in the enlargement of the parcel size. This leads to a final figure of 922 households to be simulated annually between 2000 and 2010.

Another parameter is the distribution of household agents by income class. Again, combining the results of the empirical survey with census figures, the following proportions are used: low income (60 percent); mid income (32 percent); and high income (8 percent).

The number of RED agents to be simulated is also a calibrated parameter. Based on estimates by Ghana Real Estate Developers Association (GREDA), there were about 100 developers in the city-region as of 2000. The majority (about 60 percent) target middle-income households, while the remaining 40 percent serve high–income earners.

Informality coefficient, which determines the extent of government enforcement of development regulations and the degree of availability of informal lands for development, is one of the key parameters that requires calibration. As advanced earlier, overwhelming majority of developments in Ghana are un-regulated (UN-Habitat, 2011). Based on the opinions of Senior Planning Officers at the Ghana TCPD Head Office, the informality coefficient was set at 90. Critical slope (25) and slope coefficient (15) were set using the values derived from SLEUTH in Chapter 3. To test how randomness, particularly regarding the location choice decisions of agents, affect the model's output, multiple (4) runs were simulated from the same calibration.

7.6 Results from calibrated runs, 2000 – 2010

The results from the simulated runs are compared in two ways: one, key metrics are used to analyse the runs as shown with Figures 7.5, 7.6, 7.7, 7.8 and 7.9; and, two, output maps are juxtaposed for visual analysis as depicted with Figures 7.10 and 7.11. For most of the metrics, the differences in the runs over the 10-year period appear negligible. For instance, all the runs simulate, in relation to new developments in 2010, about 65 percent informality level; approximately 83 percent level of spontaneity; around 77 percent rate of formation of new spreading centres; and approximately 17 percent level of edge growth. The annual results of the runs, however, is a bit more nuanced, but even so, the differences are slight. Linear growth captured the highest variations, which does not exceed 5 percentage points.

Fig 7.5: Percent Informal

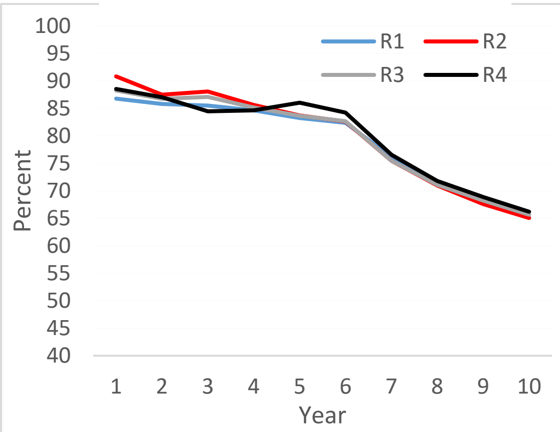


Fig 7.6: Edge growth

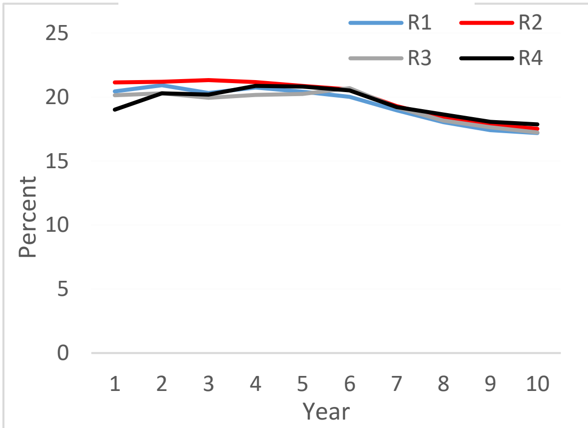


Fig 7.7: Spontaneous Growth

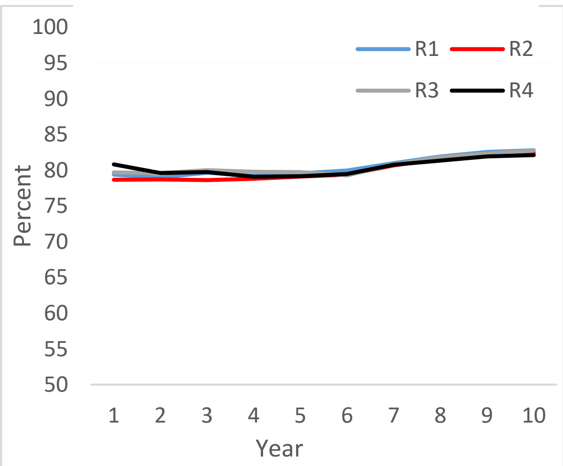


Fig 7.8: New spreading centres

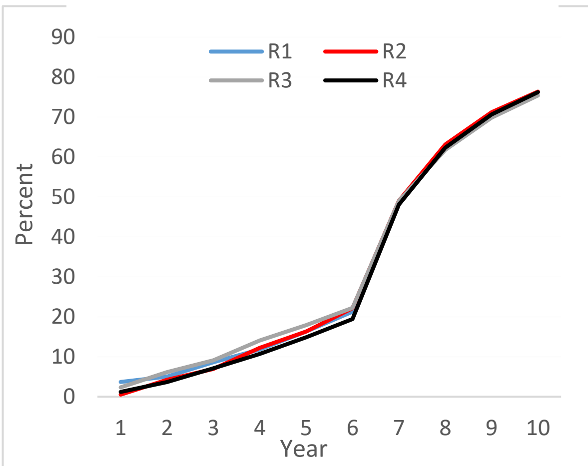
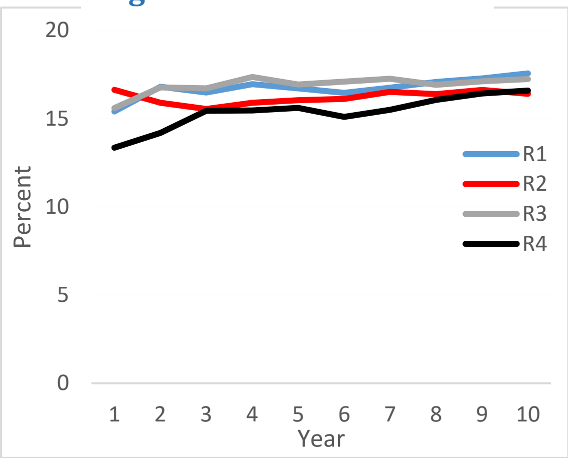


Fig 7.9: Linear Growth



As with the output metrics, the runs are closely similar in the spatial distribution of simulated residential growth. Figure 7.10 shows the spatial distribution of simulated growth by income classification. All the runs simulate more low-income development in the western parts of the city-region, particularly Kasoa and Awutu Breku enclave. Some concentrations are also simulated to the North, specifically along the Amansaman and Nsawam trunk road, by each run. The runs are also much alike in the simulated spatial pattern of middle and high-income residential developments.

The similarities among the runs continues with the spatial pattern of the simulated informal developments. As presented with Figure 7.11, each simulates informal development to occur predominantly at Kasoa, Awutu Breku area to the West; Prampram area to the East; Amasaman Nsawam area to the North; and Dodowa area to the North East. Thus, notwithstanding the internal randomness of the model, the outputs of iterations or different runs are highly similar. Following this, any of the runs could be randomly selected for further validation. Stemming from the study's interest in informal development, run 4, which simulates the highest level of unauthorized development (66 percent) is selected for subsequent validation analysis.

Figure 7.10: TI-City's simulation of urban residential growth by income status in ACR, 2000 - 2010

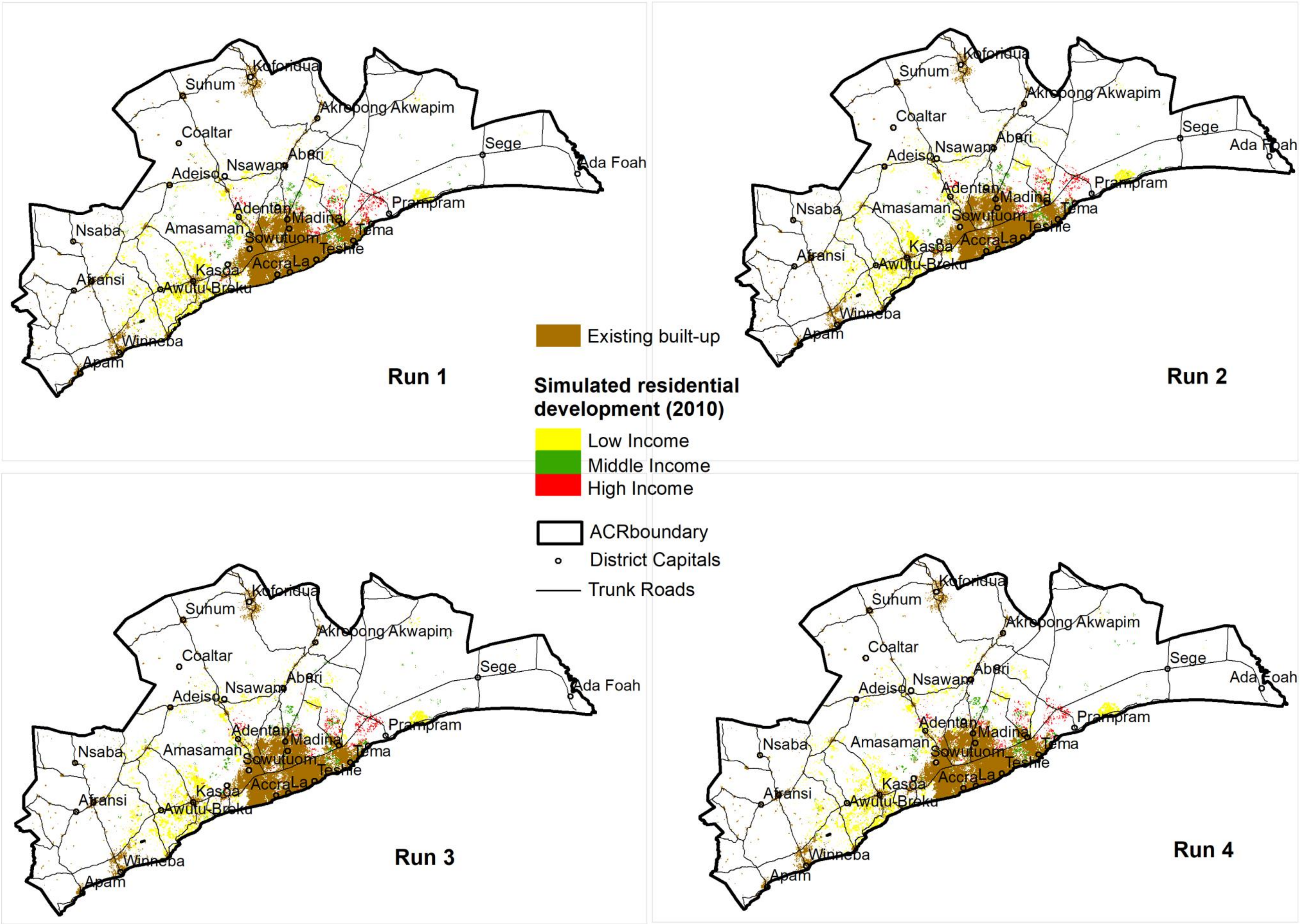
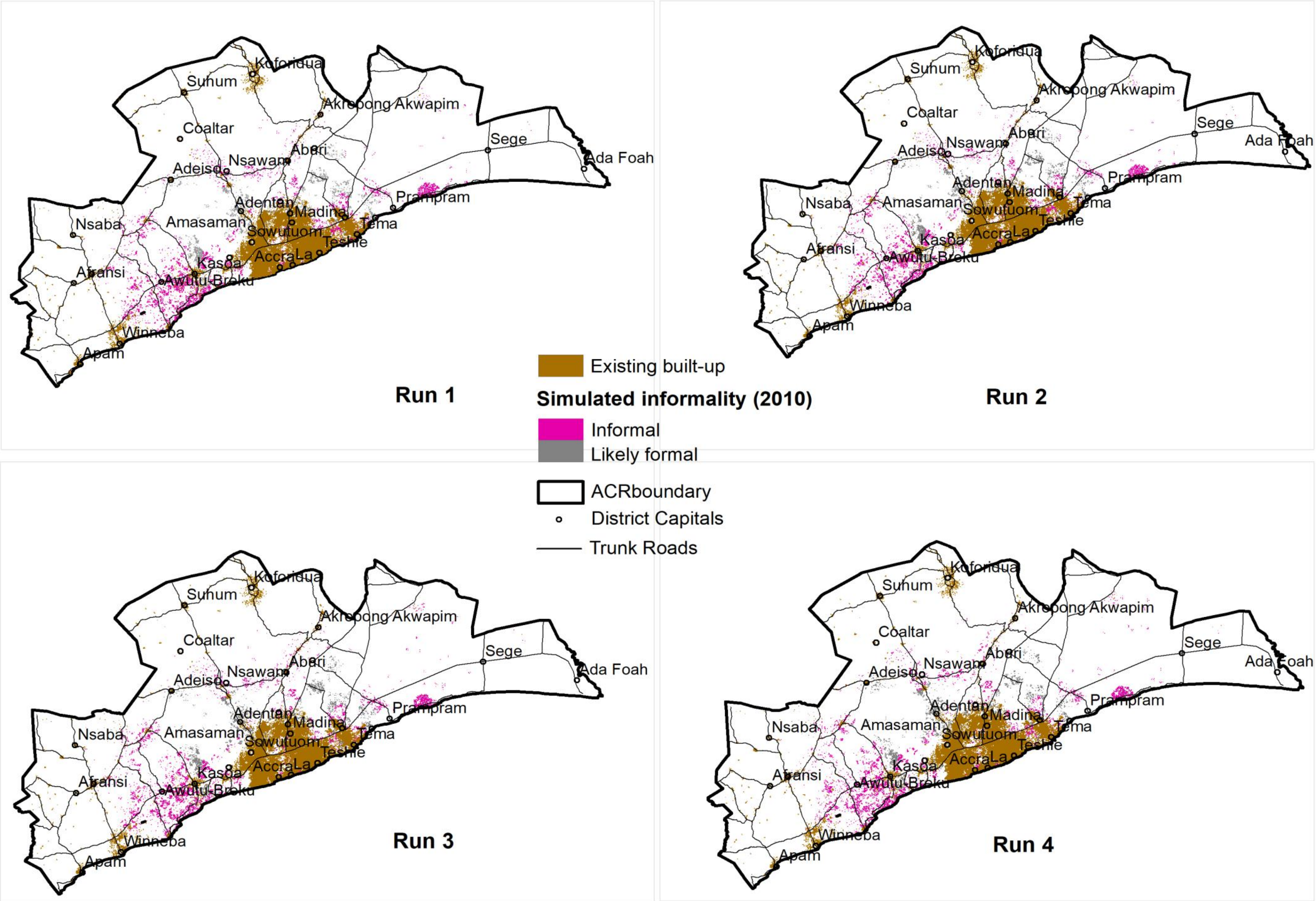


Fig 7.11: TI-City's simulation of urban residential growth by formality status in ACR, 2000 - 2010



7.7 Sensitivity of Model Parameters

The parameter values from the calibration above are adjusted as part of sensitivity testing of the model. There are thousands of different ways of adjusting the parameter values in Tables 7.2 and 7.3. Considering the empirical nature of the model, the analysis of the survey data represents the best fit solution for the city-region. However, increasing the transferability of the model to different case studies would require a systematic testing of all possible combinations of parameter values and selecting the best solution. Integrating optimization algorithms that search for best solution will be vital to the model in the future. For now, to illustrate that changes in parameter values affect the output, three different combinations are additionally explored and shown in Figure 7.12 and Figure 7.13. These include: T1, which is the combination from Tables 7.2 and 7.3; T2, which reduces low-income households' weighting of proximity to suburban centres to 1, while leaving all other values unchanged; T3, which reduces proximity to roads weighting by low-income households to 1, while keeping all other values constant; and T4, which reduces proximity to suburban centres, roads and extent of neighbourhood development to 1, while leaving other values unchanged.

Low-income households account for most (about 60 percent) of the development in the model, hence the decision to adjust theirs. That notwithstanding, stemming from the dynamic nature of the model, for instance, the neighbourhood interactions, the changes also affect other agent categories. Proximity to suburban centres, roads and extent of neighbourhood development represent the top 3 weighted factors by low-income households. Spontaneous patterns, depicted in Figure 7.12, and spatial distribution of development by income, shown in Figure 7.13 are used as examples to illustrate the sensitivity. It is worth highlighting that this is no systematic sensitivity testing, as there are about thousands of different combinations as indicated above.

Figure 7.12 shows a significant increase in spontaneous growth in T2, T3 and T4, but more so in T2 and T4. Similarly, Figure 7.13 shows overwhelming increase in the dispersiveness of low-income in T2 and T4. Combination T3 also substantially increases the dispersion, albeit not as massive as seen in T2 and T4. This indicates the weighting of the factors, at least the top three, matters. In other words, the model is sensitive to changes in parameter values, reinforcing the importance of integrating optimization search algorithms going forward.

Figure 7.12: Parameter change and spontaneous growth

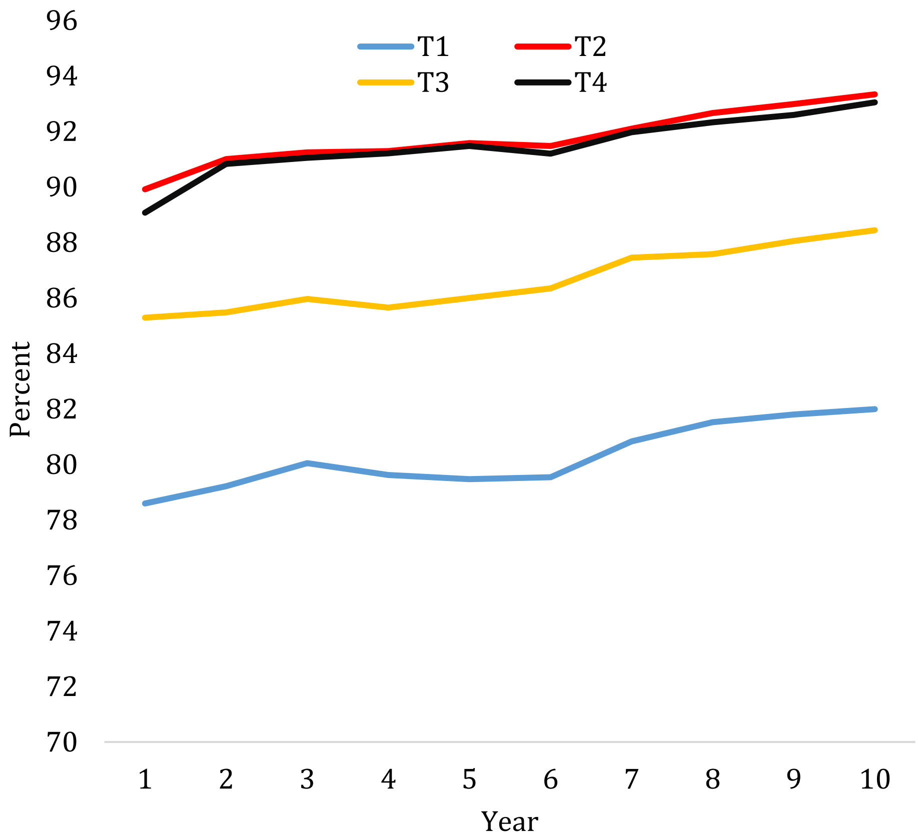
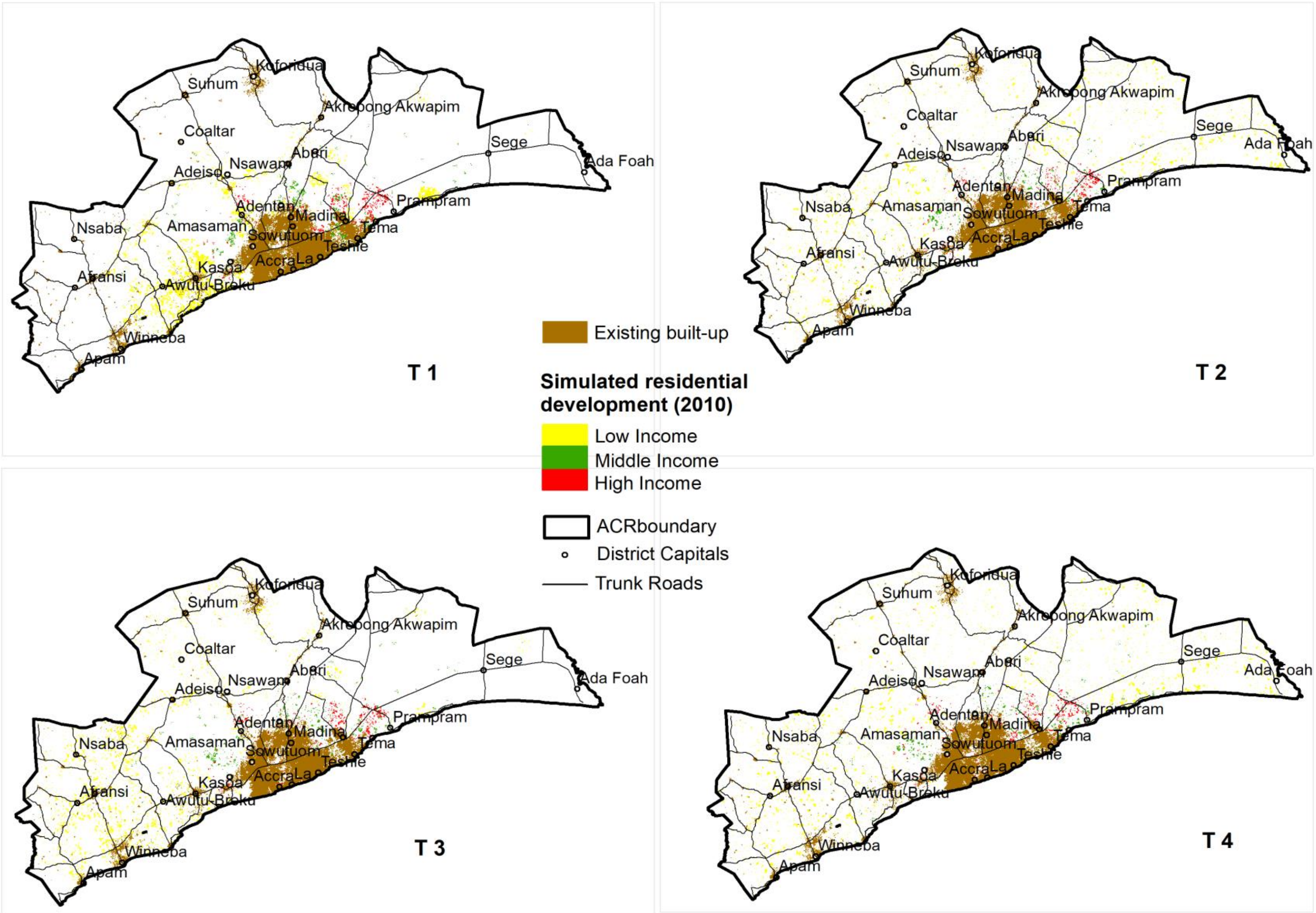


Figure 7.13: Comparison of different parameter values



7.8 Validating TI-City model

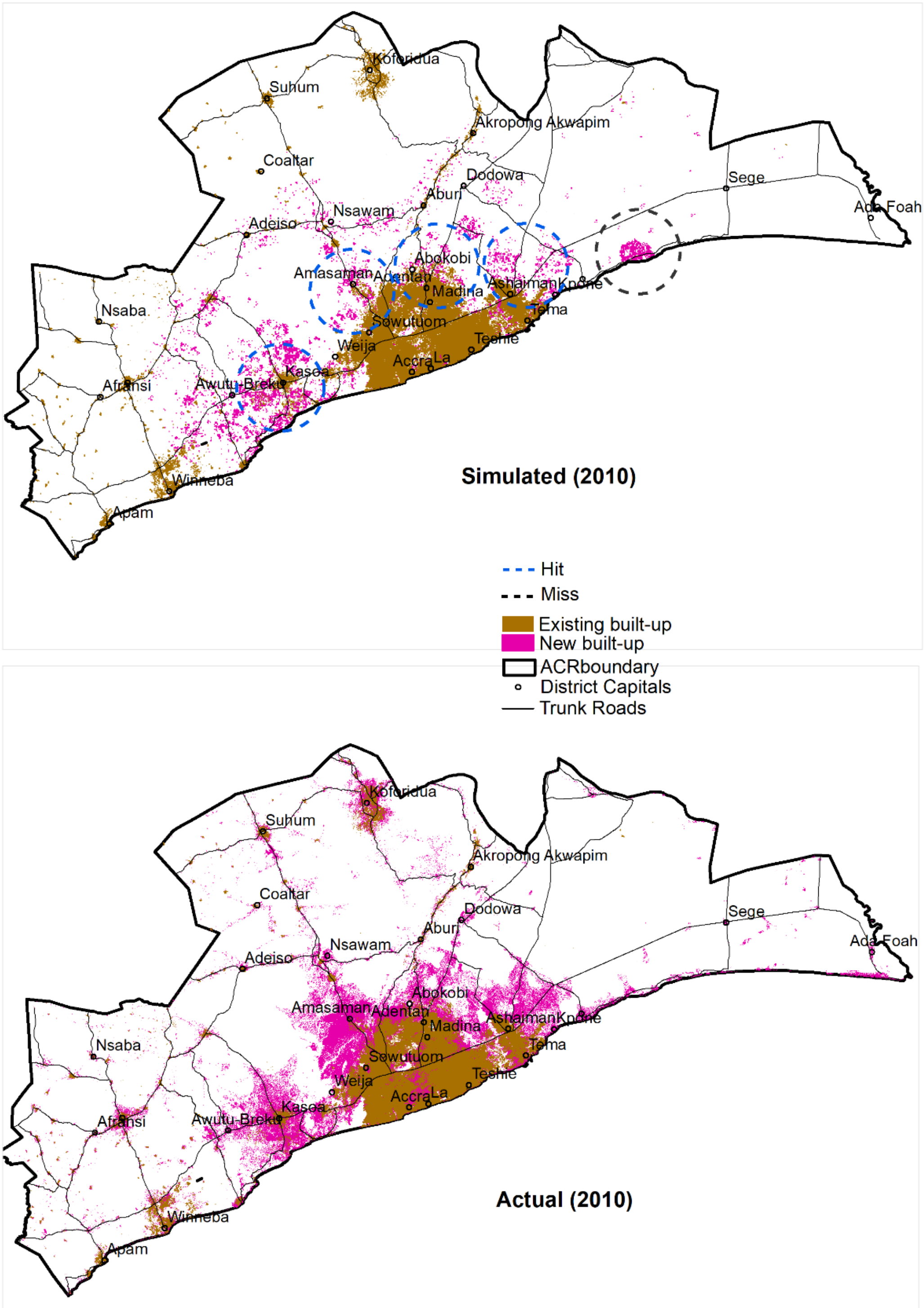
The validation of the model incorporates a three-step analysis of simulated historical output. First, broad patterns from the simulated historical map for 2010 is visually compared with existing land cover maps for the same year. Second, results from the model's key metrics are compared with those derived from the calibration of SLEUTH model. Lastly, experts familiar with development dynamics of the study area are engaged to analyse the accuracy of simulated metrics for which there is inadequate real-world data to enable other forms of comparison.

7.8.1 Visual comparison of simulated output with actual map

Visual comparison of outputs is mainstream technique in validating models, see, for instance, (Feng et al., 2015; Liu et al., 2010; Zhao and Peng, 2007; Huigen et al., 2006). Pursuant to this technique, the simulated historical map of 2010 is juxtaposed with an actual map as presented with Figure 7.14. It is important to highlight that the new developments in 2010 are solely residential for the simulated map, whilst that of the existing map encapsulates all land uses in built-up areas. Thus, the two maps are not identical in their composition, a fact that makes the technique of broad visual comparison of spatial patterns more suitable. If there was an existing and accessible data of residential developments in 2010, the study could have embraced a micro level validation approach, such as cell by cell comparison of maps.

It can be observed in Figure 7.14 that the locational patterns of newly simulated residential developments between 2000 and 2010 is similar to actual developments patterns in the same period. The areas that are similar (hits) are highlighted in red dotted circles, and those that are dissimilar (misses) are circled with dotted black lines. Like the existing map, the model simulates concentrations of new developments in the peri-urban areas, particularly to the West (Kasoa and Awutu-Breku surroundings); the North along two major routes, namely Amasaman-Nsawam and Madina-Aburi trunk roads; and the East (Tema enclaves). A notable miss of the model is the prediction of concentration in the peripheral eastern part of the city-region. The area has relatively low land values, is gently sloped and close to a suburban centre. These potentially explain the emergent phenomenon in the East. In general, the model's performance in predicting development direction is good.

Fig 7.14: Comparison of simulated historical output with existing urban growth



7.8.2 Comparison of TI-City's metrics output with SLEUTH calibration results

The second layer of validation is based on a comparison of the output of some of TI-City's metrics with that of SLEUTH. As explained earlier, TI-City adapts, particularly in its spatial system, some of the characteristics of SLEUTH model. Following this, 4 of the 8 metrics of TI-City (spontaneous growth, new spreading centre, linear and edge growth) are also found in SLEUTH. Only edge growth, out of the 4 metrics, is not directly comparable as it is set up differently in TI-City. Table 7.4 juxtaposes the results of the two models in relation to the comparable metrics. The use of SLEUTH calibration results as a reference point of validation stems from the widely recognised robustness of the brute force technique it adopts. It must be emphasised, however, that the comparison is rather broad, as the underlying land use data not identical but similar. SLEUTH calibration is based on classified LandSat data that includes are types of built-up land uses, whereas TI-City only simulates residential development.

As with SLEUTH, TI-City simulates highly spontaneous development pattern in the city-region, with both recording high values in the dispersion parameter as shown in Table 7.4. Similarly, IT-City's simulation of high formation of new spreading centres is akin to that of SLEUTH. Lastly, both models simulate generally low figures for linear growth or road influenced development. Thus, TI-City's simulated results in terms of spatial patterns, is comparable to that of the popular dynamic SLEUTH model.

Table 7.4: Comparison of TI-City metrics results with SLEUTH

Metrics	TI-City model	SLEUTH model
Spontaneous Growth (Dispersion)	83 percent	76
New spreading centre (Breed)	78	83
Linear Growth (road influenced)	17 percent	10

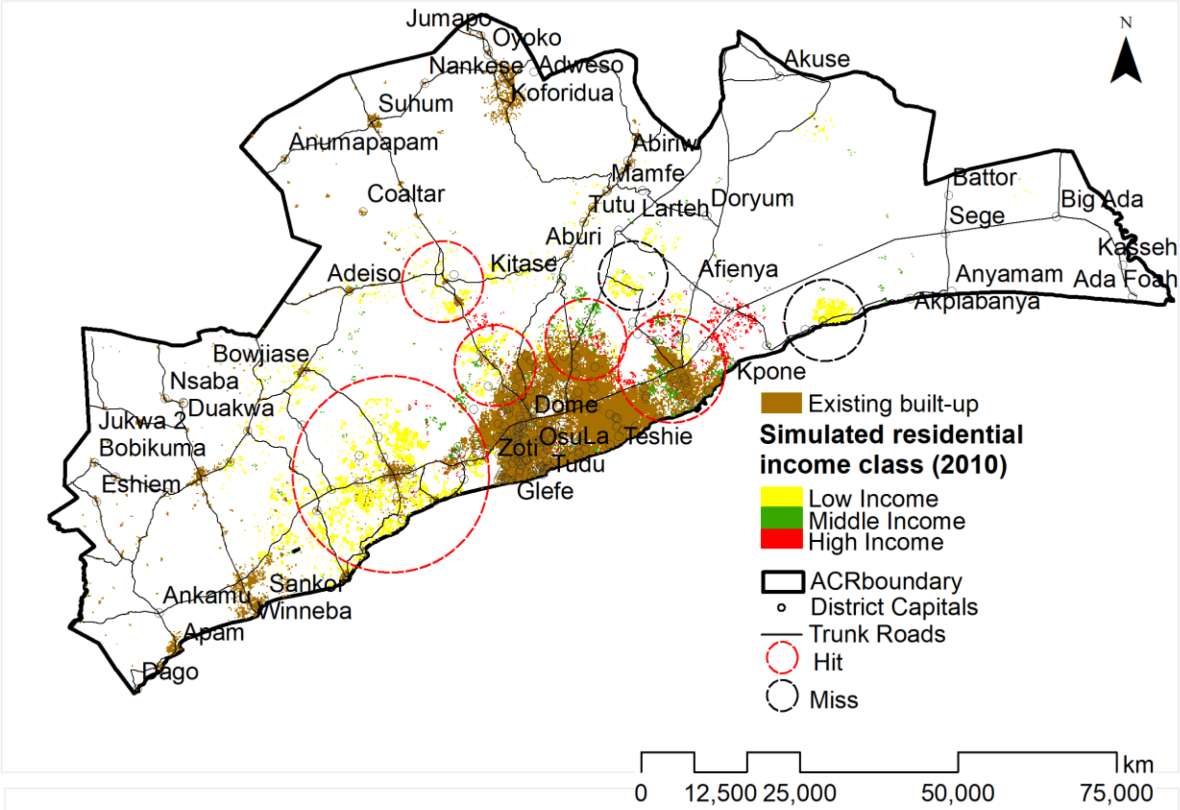
7.8.3 Validation by experts

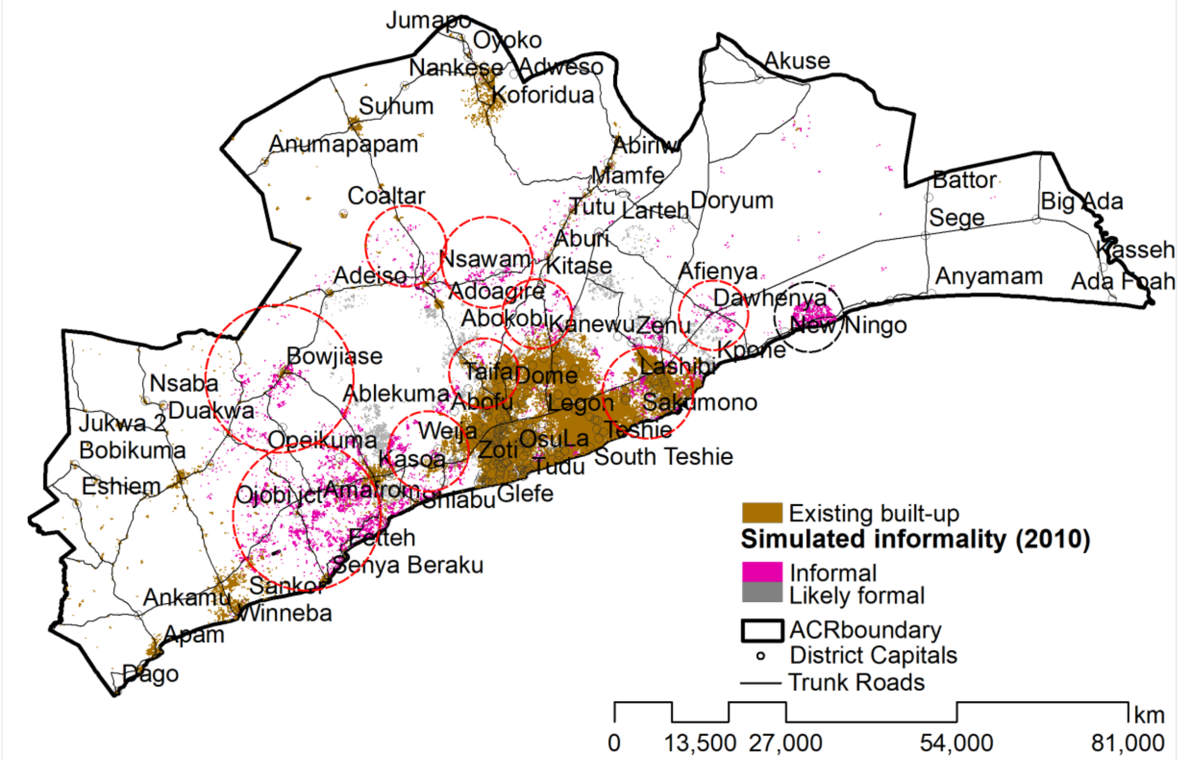
Having analysed the model's simulated spatial development patterns in the first two approaches, the last layer of the validation process focuses on the simulated income and informality dynamics. A direct way of validating this aspect of the model would involve comparing the simulated income and informal development distribution for 2010 to an actual map for the same year. However, owing to data paucity, especially regarding spatially explicit income distribution, this approach cannot be pursued. The research embraced an alternative validation technique that involves seeking the opinions of experts, a technique which is not unpopular, for example, see (Valbuena et al, 2010; Jjumba and Dragićević, 2012). The experts consulted include, Senior Planning Officers at the TCPD head office and Spatial Planning Officers of districts in the city-region. Based on expert opinions, the simulated map of income distribution, presented with Figure 7.15, has been classified into hits, which refers to areas largely simulated more accurately, and misses, referring to areas less accurately predicted.

As can be observed from Figure 7.15, most of the simulated low and middle income areas are seen by the experts to be more accurate. Two simulated concentrations are seen as less accurate in terms of their income dynamics. Notably, the simulated high-income concentration at Dawhenya in the East, was neither classified as hit or miss. This is as a result of differing opinions of experts of the dominant income characteristics of the area. While, some see it as predominantly high-income area, others consider the area largely middle class. In general, majority of the simulation was viewed as more accurate.

The experts were also highly impressed with the simulation of informal developments. The overwhelming majority of new developments classified as informal, were seen to be accurately simulated. It was also indicated that some the areas not simulated as informal are actually informal. This was expected, as TI-City largely models land related aspects of informality. As stated in section 7.3.3, there are instances, albeit less pervasive, where informal development occurs on formal lands. These instances are not captured by the model, hence the designation of areas as likely formal, implying that some could actually be informal.

Figure 7.15: Analysis of TI-City's simulated historical output





7.9 Simulation of residential growth in Accra city-region, 2015 – 2035

Following the three-step validation process, the future residential growth of Accra city-region is simulated with the model based on existing trend scenario. The simulation starts from 2015 through 2035, and it is presented with two maps: Figure 7.16 which depicts the spatial patterns of simulated developments by informality status; and Figure 7.17, which shows the distribution of new developments by income class. Both figures contain four maps, each representing the output of five-year simulation interval. The model generates annual cumulative outputs, but the four maps are selected to simplify the visualization process.

Some of the model parameters were adjusted to suit the simulation. About 600 households are simulated annually, a number derived from the equation below:

$$N = \frac{HP_2 - HP_1}{T \times AHH \times K} \qquad 7.5$$

where, N is number of household agents to be simulated annually; HP_2 is projected number of households for 2035; HP_1 is number of households at simulation seed year (2015); T is simulation period; K is the factor by which the model enlarges average parcel size; and AHH is average number of households per house. AHH also accounts for the fact that not all households undertake residential development, as some, for instance, rent while others live with their family members. N is subsequently distributed over income groups based on the analysis of the empirical household survey in Chapter 6.

The model also simulates 200 estate developers over the two decades. This figure was generated by applying an annual growth rate of 2.2 percent on the number of estate developers that existed in 2015 as mapped by Agyemang & Morrison (2018). The annual growth rate was based on 2000 and 2015 figures of developer institutions as estimated by GREDA and Agyemang & Morrison respectively.

As part of the trend scenario, informality coefficient is kept at 90, which is the rate used in the historical calibration. Similarly, other parameters such as slope and critical slope follow the figures described in Chapter 4 (section 4.5).

Fig 7.16: Simulated urban residential growth by informality status in Accra city-region, 2020 -

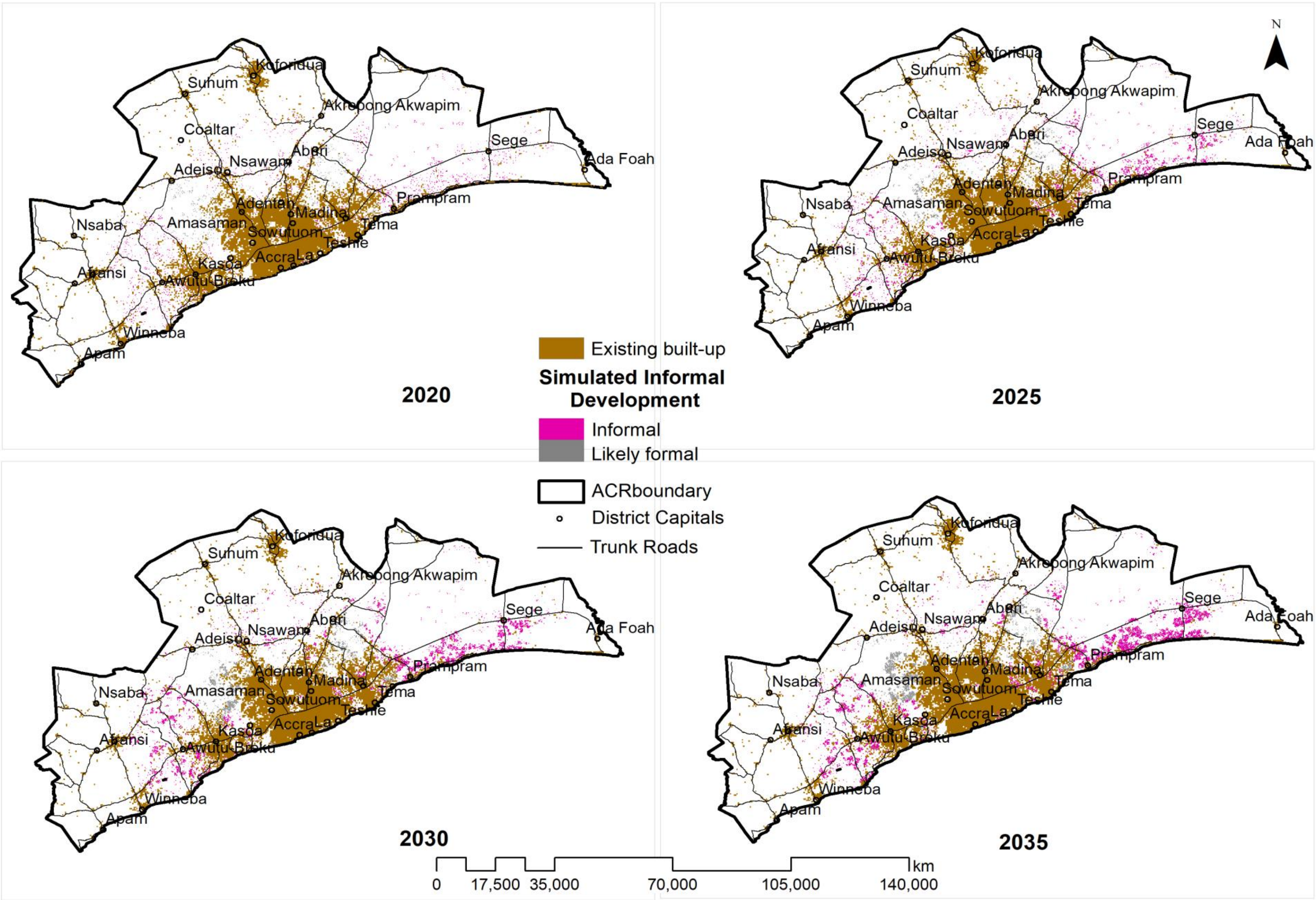
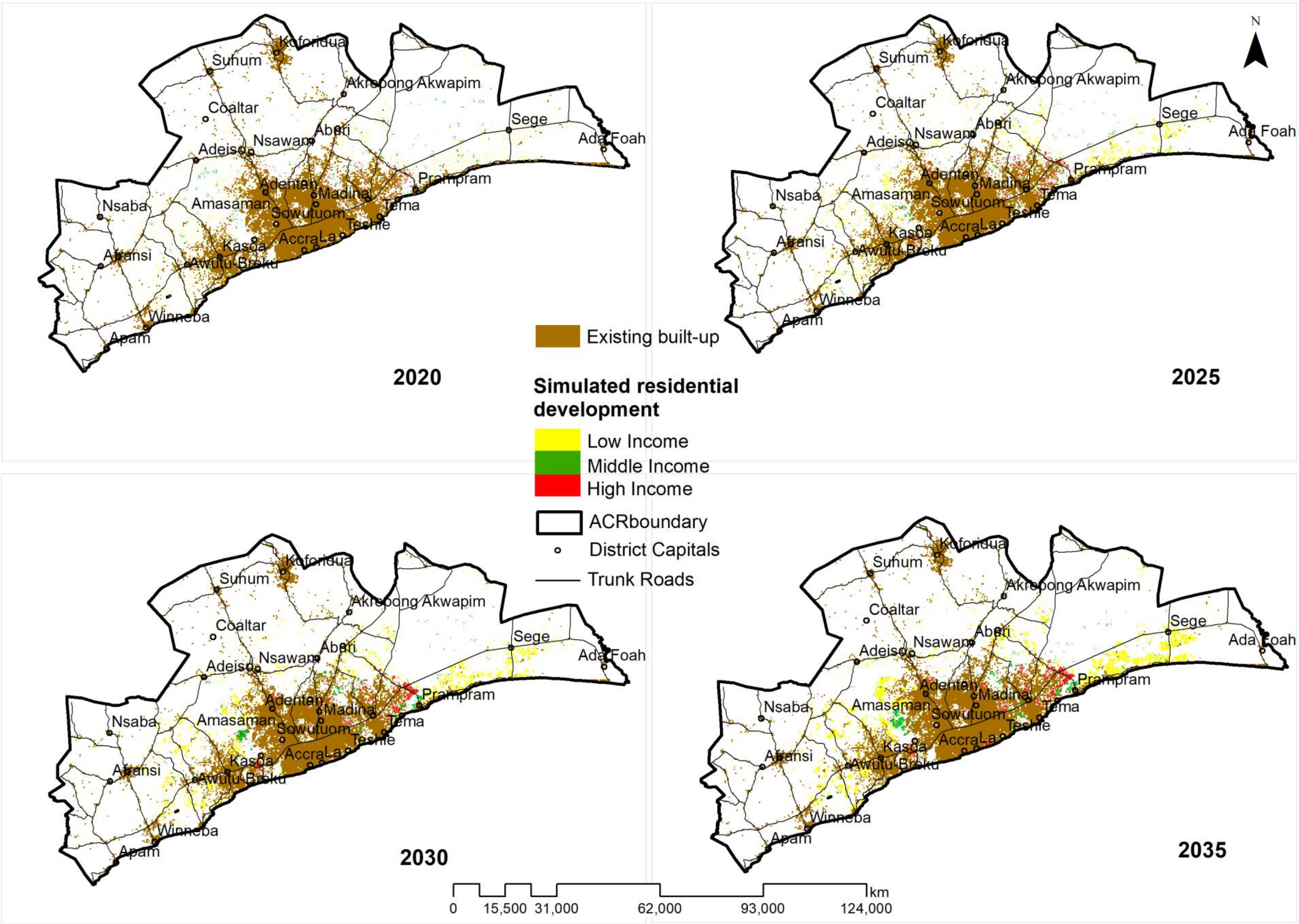


Figure 7.17: Simulated urban residential growth by income status in Accra city-region, 2020 - 2035



The model simulates about 20 percent of ACR's land area to be developed by 2035. This figure could be higher if other non-residential land uses are included in the simulation. The city-region is expected to grow in multiple directions, but particularly in the peri-urban areas to the West, in the area between Awutu-Breku, Winneba and Afransi; the North-West (western parts of Amasaman); the East, along Tema, Prampram and Sege corridor; and North-East (Dodowa enclave) as shown in Figures 7.16 and 7.17. Some consolidated is also expected to occur, for instance, in areas such as Tema, Ga West, etc.

About two-thirds (65 percent) of new residential developments expected to occur by 2035 is simulated to be informal as depicted in Figure 7.19. Most of the informal developments are predicted in the Eastern and Western peri-urban areas of the city-region as shown in Figure 7.16. The income characteristics of simulated informal developments are presented with Figure 7.20, which shows that low-income developments will account for about 82 percent of the former.

Further analysis of informal developments, as depicted in Figure 7.19, reveals that about 70 percent of low-income developments are simulated to be informal. Also, more than half of middle-income developments are predicted to be informal. Only high-income development is simulated to be less than half (48 percent) informal, but even so, very close to the middle line.

The majority of low-income development is expected to occur largely in peri-urban areas to the East (between Prampram and Sege), West and North-Western parts of the city-region. Middle and high income developments, however, appear to occur more in-between built-up areas, with the latter being mainly visible in the East, while the former is concentrated in both eastern and western parts.

Spatial development patterns are simulated to be highly spontaneous, as 78 percent of new development are expected to occur outside the neighbourhood of existing built-up areas of the simulation start year. Figures 7.16 and 7.17 reflects the dispersive nature of simulated growth. Majority of dispersive developments turn into new spreading centres and influence growth in their neighbourhoods, as shown by Figure 7.21. About 22 percent of new development is predicted occur at the edges of existing built-up areas (those that existed in 2015). Linear growth is slightly low, with about 12 percent of new developments simulated to occur within the neighbourhoods of trunk roads. This proportion, however, could increase if access and neighbourhood roads are included in the simulation.

Fig 7.18: Percent of land area

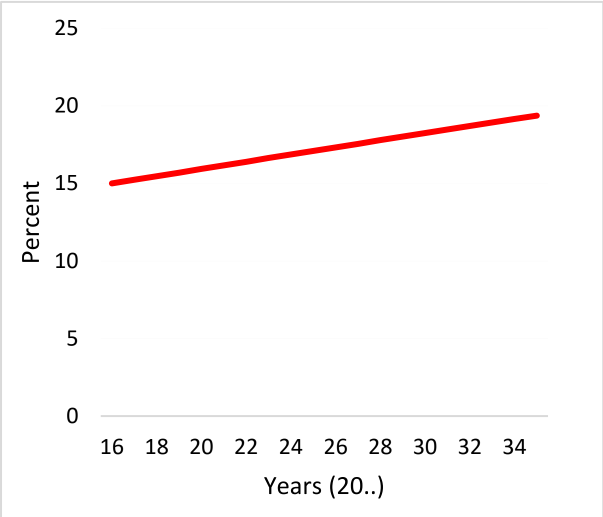


Fig 7.19: Percent Informal

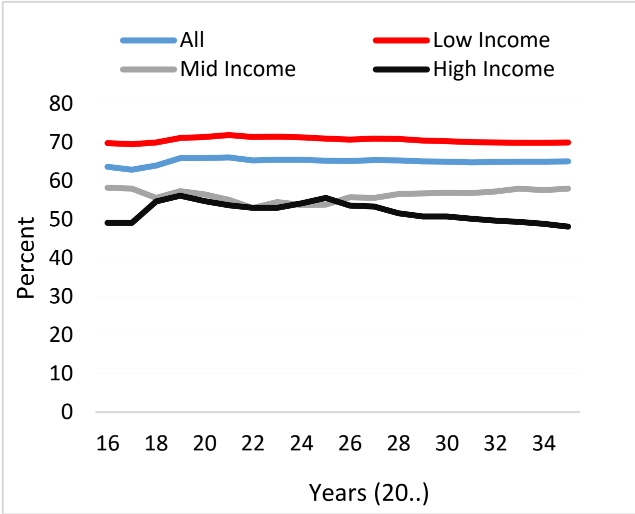


Fig 7.20: Contribution to informal development

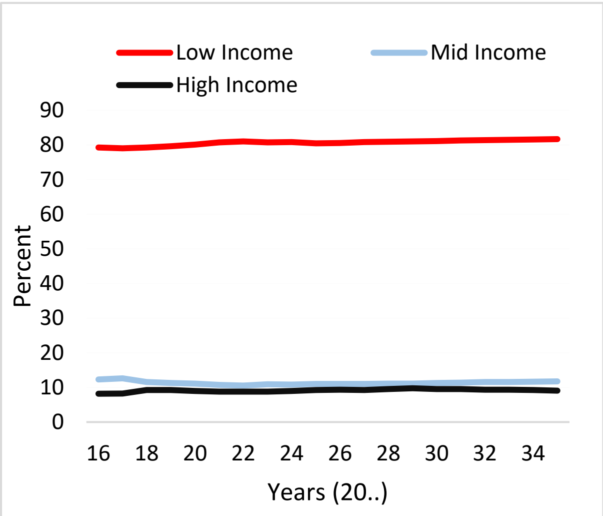
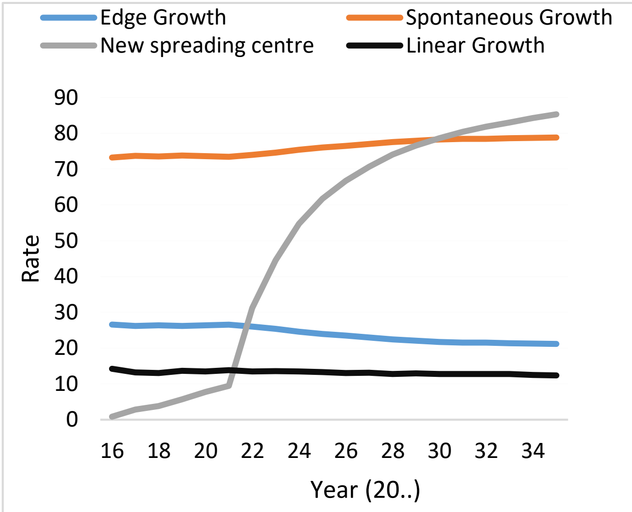


Fig 7.21: Spatial Patterns



7.10 Reflections on TI-City and its simulation results

The implications of TI-City model and its simulation results are discussed under this section. The first three points relate to the model in general, while the last two outlines specific policies based on the simulated output.

TI-City offers unique insight into modelling the dynamics of residential growth in predominantly informal Sub-Saharan African cities

As outlined in Chapter 2, there are dozens of existing urban growth models that integrate CA and ABM approaches. Whilst the majority do not reflect the unique growth dynamics of many Sub-Saharan African cities, there are some that are, to a limited extent, applicable to the urban growth trajectories of cities in the sub-region. SLEUTH is an example of the latter group as demonstrated in Chapters 4 and 5. However, none of the existing urban growth models, including those that could be limitedly applied to cities in Sub-Saharan Africa, explicitly models the un-regulated and unplanned dimension of urban growth informality. In addition, the models hardly capture the self-build dynamics where majority of households supply their own housing needs, hence do not rely on developer institutions. Self-build is also an identifiable feature of cities in Sub-Saharan Africa. Not only does TI-City explicitly models largely un-regulated residential growth, but it also has the capacity to model the dynamics of self-build phenomenon. These unique functionalities of the model have been demonstrated in this chapter, with the simulation of residential growth in Accra city-region.

TI-City facilitates understanding into the economic dynamics of informal developments

The application of the model to ACR simulates, besides spatial patterns of informal developments, the income characteristics of future urban residential developments. This insight can be useful to policy formulation, management of informal cities and development and testing of theories. For example, on the policy front, policy makers could use the information on the contributions of income groups towards informal developments, to design a more targeted economic policy that best addresses the informality challenge. Academics could also use the model to explore relationships, for example, between income class movements and informal developments.

TI-City could function as a decision support tool in Ghana and many Sub-Saharan African countries

The discussion above underscores the role TI-City model can play in the management of ACR and other principal cities in Ghana. Indeed, this section subsequently outlines some policy implications of the simulated residential development. Beyond the baseline trend simulation, the model also provides a platform for examining the impacts of diverse urban policy scenarios, thereby leading to an informed decision making. For instance, a government agent can compare and contrast the impacts of, on the one hand, a policy that prioritizes urban development regulation, with, on the other, one that raises the income of the bottom third households.

The model also holds promising prospects in terms of serving as a decision support tool in other Sub-Saharan African countries. While the informality dimension is based on development dynamics in Ghana, many of the key parameters can easily be calibrated, mainly through the adjustment of sliders, for other cities in sub-region. For instance, the population and economic distribution of households and developer institutions, as well extent of government agent regulation are flexible to be calibrated based on the peculiar dynamics of a city.

Policies that improve the income status of households are likely to reduce the extent of urban informal developments

As earlier outlined, a minimum of two-thirds of new residential development in 2035 is simulated to be informal, and low-income households contribute about 82 percent of this figure. Indeed, around 70 percent of new developments by low-income households are predicted to be informal, comparing with 58 and 48 percent for middle and high income households' developments. Thus, rate of occurrence of informal developments reduces as with higher income class. This seems to suggest that, one of the ways policy makers and managers of ACR could tackle the urban informality challenge is to promote economic policies that can cause upward income class movements. Given a well-defined regulatory policy framework context, interventions that particularly target and significantly improve the economic status of low-income households can substantially reduce the occurrence of informal developments.

Strengthening the planning system

The strength of enforcement of development regulations is a key parameter that influences the extent to which informal development occurs. The relationship is indirect; the higher the strength of enforcement, the lower the tendency for urban actors to undertake informal developments, and vice versa. Evidence of this is found in Ghana where the spatial planning system appears weak in regulating development. As indicated earlier, several studies, including (UN-HABITAT, 2011; Anokye et al., 2013), have described how the majority of urban development take place without any authorization by planning system. Strengthening the spatial planning system is a vital prerequisite to enhancing urban growth management and addressing the challenge of informal developments.

7.11 Limitations of TI-City Model

As a new and unique model, TI-City has a number of limitations that require further work. These are briefly described below.

The model in its current state does not, as mentioned earlier, capture the growth or change dynamics of non-residential land uses. One of the future goals is to further develop TI-City as an urban growth model that, in addition to capturing residential growth process, can also model and simulate other land uses such as commercial, industrial, mix-uses, etc.

The modelling of informal development is localized to an extent as it largely follows the Ghanaian context. Whilst most of the parameters of TI-City can be easily calibrated for other cities across the globe, the dimension on informal development is modelled after the peculiar informal dynamics in Ghana. This means that applying the model to informal developments in cities outside Ghana would require some modifications or adjustments of the informal parameters.

In addition, the modelling of informality does not capture the susceptibility of formal lands to informal developments. As stated earlier, even though informal developments in Ghana predominantly occur on informal lands, there are instances where it also occurs on formal lands. The factors that inform the latter situation include, among others, long delays in processing development permit applications, corruption, and attitudinal problems, for instance, sheer recalcitrance. These variables are not currently modelled by TI-City.

Also, stemming from data scarcity, the research could not pursue a cell-based validation approach. A cell by cell validation would have offered, in addition to the broad pattern-based perspective, an insight into the model's performance at the highest spatial resolution. Pursing this approach requires, however, same resolution existing spatial data for which the model's simulated output could be compared. As outlined under earlier sections, such datasets, for example, the distribution of residential developments by income class at parcel level scale, does not exist in Ghana.

The aforementioned limitations present to the fore, the need for further work in expanding the capacity of the model. Having said that, TI-City in its current state offers diverse contributions, including its capacity to serve as a decision support tool in Ghana and other Sub-Saharan African cities.

CHAPTER EIGHT
CONCLUSION

8.1 Chapter Introduction

This chapter summarizes key issues that have emanated from the research. These issues are presented under the three main tasks performed in exploring the research objectives, including the simulation of urban growth in a predominantly informal SSA city-region with a dynamic CA model; analysis of the evolving urban spatial structure of an SSA city-region; and the development of an integrated ABM and CA model for simulating urban residential growth in largely informal cities in SSA. The chapter ends with identification of potential areas for further research.

8.2 Emerging issues from the simulation of urban growth in a predominantly informal Sub-Saharan African city-region with a dynamic CA model

Urban cellular automata could offer planning decision support, even in informal settings

As evident in Chapter 4, the results from the application of SLEUTH to Accra city-region, which is supported by knowledge of key planning stakeholders from the context, points to the potential sensitivity of urban CA modelling to locally specific development trajectories, particularly the spatial dimension of informal urban growth. This suggests that, even in settings as highly informal as Accra city-region, urban CA models, such as SLEUTH, could facilitate useful insights in the development of urban planning policies.

Need to build a stronger, proactive and functional spatial planning system in Ghana

The spontaneous and dispersive nature of urban growth captured by the model highlights the urgent need for the spatial planning system of Ghana to be repositioned and strengthened. The trend scenario simulation from Chapter 4 predicts about a third of the total area of Accra city-region to be developed by 2040. Considering that not all the remaining 66 percent is buildable, as some are, for example, water areas, forest reserves, game reserves or beyond critical slopes, the actual space that will be available for development will be far less. Thus, sustainable development is under real and serious threat in the city-region. The need for building a stronger, proactive and functional planning system is non-negotiable.

Every single development count; one new house fast becomes a new growth nucleus

The results from the calibration of SLEUTH indicates that, not only is urban development in Accra city-region dispersive, but it is only highly contagious. Majority of spontaneous new developments trigger other developments in their surroundings, and in the process form new urban growth nuclei. This means that it is important for the planning system to treat every new spontaneous development as a potential centre, and swiftly address them. For instance, if a single building emerges in an area classified as ecologically sensitive zone, the planning system would stand a better chance of success by addressing the challenge at its infant stage, than wait for a new informal growth centre to emerge.

Target pressure areas

Despite the general threat to sustainable development in Accra city-region, there are also varying impacts among districts. Districts such as Ledzokuku Krowor, La Dade-Kotopon, La Nkwantanang-Madina, Tema, Ga Central, AMA and Adentan, which are predicted to have, at least, 90 percent of their lands to be developed, will virtually have no space for expansion by 2040. Thus, while it is important to have a more guided urban expansion across the city-region, it is particularly urgent in these districts. Also, districts, such as Ashaiman, Ga East, Awutu Senya East, Efutu, Ga West, Kpone, Ningo Prampram, Gomoa East, Ga South, Awutu Senya and Agona West, should be put on spatial planning alert, as they are predicted to have, at least, 50 percent of their lands developed by 2040. It is also worth noting that the pressure areas could differ depending on the criteria for classification. For instance, if districts are classified based on the extent of ecological threats posed by the simulated urban growth, new pressures areas may emerge.

Support densification and consolidation

In addition to developing a more proactive spatial planning system, the calibration results in Chapter 4 underscores the need to support compact development in Accra city-region. Departing from the existing trend scenario, promoting a more sustainable urban expansion will require significant reduction in the parameter values of *dispersion, breed* and *spread*. This calls for compactness, consolidation and densification, where development largely occur in spaces within already built-up areas, or through high density (re)developments, all of which the spatial planning system has an important role to play. However, the pursuit of densification, should consider the existing mixed social acceptability of high-rise buildings in some metropolitan cities of Ghana, see, for instance, Agyemang et al. (2018).

8.3 Emerging issues from the analysis of the evolving urban spatial structure of a Sub-Saharan African city-region

Declining monocentric urban spatial structure

In the early decades, especially 1990, The analysis in Chapter 5 suggests that the urban spatial structure of Kumasi city-region (Ashanti Region), the case study area, largely conformed to the monocentric model described in Alonso (1964), Mills (1967) and Muth (1969). The monocentricity, however, as again suggested by the Chapter, has been in sharp decline since the turn of the Twenty-first century. While the city centre is still slightly dominant, the monocentric model could hardly be applied to the recent urban structure of the region. The urban de-concentration in the region is rather comparable to what Glaeser and Kolhase (2004) observed in US, where decreasing transport cost triggered urban dispersion. The proportion of workers in Ghana with access to motorized transport has increased significantly over the past couple of decades. For the first time, in 2012, almost half of workers commuted to work with a motorized transport (GSS, 2013). The decreasing urban concentration seems to reflect the increase in access to motorized transport.

Urban growth is becoming dispersive and amorphous

Chapter 5 further suggests that the spreading out of development from the city centre and its environs, and the declining monocentricity have triggered an increasing amorphousness in spatial development patterns, especially since 2000. The Chapter also indicates, however, that the shift towards amorphousness does necessarily imply that the urban structure of the Ashanti region fits the maximum disorder model described by Angel and Blei (2016). The direct transformation from monocentricty to dispersiveness and seemingly amorphousness is quite unique relative to what is observed in other parts of the world. As mentioned earlier, the spatial transformation of many cities in the Global North, Asia and Latin America is marked by a shift from monocentric to polycentic urban form. Even though some US cities are becoming dispersive, they, unlike what is being experienced in Kumasi City-Region, first evolved from monocentricity to polycentricity.

The city-region is charting an inefficient and unsustainable spatial development path

The spontaneity and amorphousness of the evolving spatial structure of the Ashanti region cast an image of a region that is charting an inefficient and unsustainable urban development path. The nebulous nature of growth has wide ranging adverse implications on policy formulation and urban management. For instance, with development essentially occurring everywhere, the provision of transport infrastructure and other utilities will be highly inefficient. This also implies there will be more motorized trips by fewer people. The resultant increase in pollution, and the fast depletion of vegetative cover owing to the dispersiveness of growth, does not only complicate an already daunting urban management task, but also challenges the liveability and attractiveness of the region. Similar to the recommendation in Chapter 4, a swift policy decision that strengthens the planning system in the management and guidance of spatial development patterns could prove decisive in averting the inefficient path that the city-region is currently charting.

8.4 Issues emerging from the development of an integrated ABM and CA model for simulating predominantly informal residential growth in Sub-Saharan African cities

TI-City model offers unique insight into modelling the dynamics of residential growth in predominantly informal Sub-Saharan African cities.

Whilst there are dozens of existing urban growth models that integrate CA and ABM approaches, none of them explicitly models the un-regulated and unplanned dimension of urban growth informality. In addition, the models hardly capture the self-build dynamics, a common practice in many SSA cities, where majority of households supply their own housing needs, hence do not rely on developer institutions. Not only does TI-City explicitly models largely un-regulated residential growth, but it does so by integrating the dynamics of self-build phenomenon. These unique functionalities of the model have been demonstrated in Chapter 7, with the simulation of residential growth in Accra city-region.

TI-City model facilitates understanding into the economic dimension of informal developments

The developed TI-City model also simulates, besides spatial patterns of informal developments, the income characteristics of future urban residential developments. This insight is useful for policy formulation, testing of theories and management of informal cities and development. For instance, policy makers could use the information on income characteristics of informal developments to design a more targeted economic policy that best addresses the informality challenge. Academics could also use the model to explore relationships, for example, between income class movements and informal developments.

TI-City could function as a decision support tool in Ghana and many Sub-Saharan African countries

The modelling and simulation in Chapter 7 indicates that TI-City model can play a useful role in the management of ACR and other principal cities in Ghana. Beyond the baseline trend simulation, the model provides a platform for examining the impacts of diverse urban policy scenarios, which can be used to make informed decisions. For instance, a government can compare and contrast the impacts of, on the one hand, a policy that prioritizes urban development regulation, with, on the other, one that raises the income of the bottom third households. This capacity of TI-City is in line with the new roles expected of urban models, which is to explore diverse future scenarios, see for example Wilson (2016).

TI-City model also has the potential of serving as a decision support tool in other Sub-Saharan African countries. Although the informality dimension of the model is based on development dynamics in Ghana, many of the key parameters can easily be calibrated, mainly through the adjustment of sliders, for other cities in the sub-region. For instance, the population and income distribution of households and developer institutions, as well extent of government regulation, can easily be calibrated for other cities.

Policies that improve the income status of households are likely to reduce the extent of urban informal developments

The simulation in Chapter 7 suggests a minimum of two-thirds of new residential development in 2035 to be informal, and low-income households will contribute about 82 percent. Indeed, as further outlined in the Chapter, around 70 percent of new developments by low-income households are predicted to be informal, comparing with 58 and 48 percent for middle and high income households' developments. This indicates that, a way of tackling the urban informality challenge is for policy makers to promote economic policies that can cause upward income class movements. Interventions that particularly target and significantly improve the economic status of low-income households can substantially reduce the occurrence of informal developments.

8.5 Reflections on Methods and Data

The methods and data employed in the research can be improved in various ways. One is the calibration of TI-City model. While the calibration method based on analysis of empirical survey works best within the context, particularly given the enormous resource constraints, a more optimized approach will facilitate the transferability of the model to other case studies. Optimization techniques that search for best fit parameterization through the testing of virtually all possible solutions – thousands in this case – will further strengthen the model's calibration. Genetic Algorithm is an example of such techniques that could be integrated into the model in the future.

The analysis of the evolving spatial structure of Kumasi city-region in Chapter 5 is based on urban development patterns. However, there are alternative and more popular approaches to examining spatial structure. These include the use of data on commuting patterns, intercity transport, anonymized call details records (CDRs) and other functional spatial interactions. Such datasets are extremely difficult to access if not non-existent in Ghana. That said, it is important to continue to explore the possibility of accessing and applying these datasets in future works.

This research emphasizes the need for socio-economic data with geospatial dimensions that cut across national, regional, local scales. In particular, high resolution (parcel scale) data on land values, income, density and other demographic characteristics are vital for the development of dynamic and sophisticated decision support tools such as urban models. The Ghana Statistical Service could also make use of the proliferating Computer Assisted Personal Interviewing (CAPI) platforms in the conduct of the upcoming census. Most of these platforms, for instance, the World Bank's Survey Solution App, are not free to access but more important, facilitate efficient collection of socio-economic data with geospatial dimensions.

8.6 Potential areas for further research and conclusion

In addition to the methodological, policy and theoretical contributions, the output of this research points to areas that need further exploration. One, there is the need to expand TI-City model to account for many of the diverse informal development processes across Sub-Saharan Africa. Many of the informal dynamics modelled in this research are shared by many cities in SSA. However, there are also nuances of the phenomenon that vary among cities in the sub-region. This means that supporting many policy makers and urban managers in the sub-region will require further research to expand the geographical coverage of this study in modelling informal development dynamics in SSA.

Besides, multiple future scenarios could be explored and simulated. At the moment, the simulations are based on trend scenarios, which provide useful insights as indicated in the work, but the model has the potential to do more. For instance, the impacts of existing plans and urban policies being considered by policy makers could be simulated in future work.

In addition, modelling the processes of unplanned and unregulated informal development on formal lands is an area that could be explored by further research. While the majority of informal development occur on informal lands, which is captured by this this research, there are also instances where it occurs on formal lands. The forces behind the latter case is not explicitly modelled by this research.

Similar to the first point, even though Ghanaian cities share many of the urban growth characteristics of cities in SSA, more research is needed to examine the extent to which the evolving spatial structure of cities in other countries in the sub-region conforms to or deviates from what is observed by this study.

Also, this research uses, as earlier stated, urban development patterns to analyse the evolving spatial structure of a Sub-Saharan African city-region. There are, however, alternative methodological approaches such as the use of commuting data and other functional networks for analysing urban spatial structure. It will be interesting to know whether a different approach will change or support the findings of this research.

Having pointed out the areas that need further research, it is worth concluding the study by recapping the objectives accomplished, which encompasses, the simulation of the urban growth of a largely informal Sub-Saharan African city-region with a dynamic CA model; testing the sensitivity of urban CA modelling to locally specific growth trajectories; analysing the evolving spatial structure of a Sub-Saharan African city; and developing an integrated ABM and CA model that simulates predominantly informal (unplanned and unregulated) urban growth trajectories.

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APPENDIX

Household Survey Questionnaire

UNIVERSITY OF CAMBRIDGE

Contact: Felix Agyemang,
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For this study, data from participants will be used to analyse how different category of households prioritize various location factors and how that can be used to build agent-based computational model. The information provided will be used for this purpose only and participation is absolutely discretional. Thank you for your time.

Consent to interview? Yes [ ] (Continue) No [ ] (Thank the respondents and discontinue)

Date: ______________________ Questionnaire No: __________

Suburb: ______________________ Area: ______________________

Street Name & No: ________________ House No: ________________

Longitude: ______________________ Latitude: ________________

Section 1: Basic Information *Section 2: Household Characteristics*

Section 3: Housing Characteristics *Section 4: Location Choice Decisions*

SECTION 1: BASIC INFORMATION

1. Gender: ☐ Male ☐ Female 2. Age: ________________

3. Marital Status

☐ Married ☐ Never Married ☐ Divorced

☐ Consensual Relationship ☐ Widowed

4. Highest Educational Level attained:

☐ Tertiary ☐ Secondary ☐ Junior High

☐ Primary ☐ Never been to school

5. Nationality:

6. Ethnicity:

☐ Akan ☐ Ga-Dangme ☐ Ewe

☐ Guan ☐ Gurma ☐ Mole-Dagbani

☐ Grusi ☐ Mande ☐ Other (specify)

7. Religion:

☐ Pentecostal/Charismatic ☐ Protestant ☐ Catholic

□ Other Christian □ Islam □ Traditionalist
□ No Religion □ Other (Specify)

8. Employment Status:
□ Employee □ Self-Employed without employee(s)
□ Self-employed with employee(s) □ Apprentice □ Student
□ Casual Worker □ Unemployed □ Other (Specify)

9. Primary Employment:____________________________________

9b. Location of Primary Employment:__________________________

Town:_________________ Suburb:_________________

street address ____________________________________

10. Secondary Employment:____________________________________

10b. Location of Secondary Employment:__________________________

Town: ____________________ Suburb ____________________

street address ____________________

11. How much do you earn monthly? ____________________________________

SECTION 2: HOUSEHOLD CHARACTERISTICS

1. How many people are in your household?________________

2. How many children (< 18 years) are in the household? ________________

3. Age of youngest child in the household: ________________

4. Age of Eldest child in the household: ________________

5. How many children are in **basic** school?________________

5b. What is the location of the schools? (Town, Suburb, street address)

No:	Age of Child	Location of School			Level of School
		Town	Suburb	Street Address	

5c. On the average, how many minutes does it take for the children to get to school?________________

What type of transport do the children use to get to school?
□ Car (private) □ Car (Commercial) □ Motorbike
□ Cycling □ Walking

6. How many children are in **secondary and tertiary schools**? ______________

6b. What is the location of the schools? ______________

No:	Age of Child	Location of School			Level of School
		Town	Suburb	Street Address	

7. How many members of your household work? ______________

8. How many people cater for the finances of your household? ______________

9. What is their relationship with you and what is their estimated month earning?

Relationship	Monthly Earning

10. How many households are in the house? ______________

11. On the average, how many people are in each household? ______________

12. How many rooms does your household occupy? ______________

13. What floor does your household occupy? ______________

SECTION 3: HOUSING CHARACTERISTICS

1. Type of house:
□ Detached □ Semi-Detached □ Flat/Apartment
□ Compound □ Improvised Home (kiosk, container, tent)
□ Other (Specify)

2. State of House:

□ Completed □ Uncompleted

3. How old is the house? ______________

4. Who owns the house?
□ Self □ Household member □ Relative not household member
□ Other private Individual □ Private institution/agency
□ Government □ Other (Specify)

5. What is your occupancy status?
☐ Owner Occupied ☐ Renting ☐ Rent-free
☐ Perching ☐ Squatting ☐ Other (Specify)

5b. If renting, how much rent do you pay in a month? ______________

6. How long have you stayed in the house? ______________

7. Type of residency:

☐ All year round ☐ Seasonal

7b. If seasonal, which other place do you live?

Country, City: ____

8. How many rooms are in the house? ______________

9. Number of floors: ______________

10. How many people are in the house? ______________

11. Land values/price in the area:

Now: ______________ 5 years ago ______________ 10 years ago ______________

SECTION 4: LOCATION CHOICE DECISIONS

1. Has your household ever lived at a different place? ☐ Yes ☐ No

*If yes, answer questions **2** to **13**. If no, continue from question **14***

2. Where did your household live previously?

Suburb, area, street, House Number: ________________________________

At the time:

3. What was your marital Status?

☐ Married ☐ Never Married ☐ Divorced

☐ Consensual Relationship ☐ Widowed

4. How many persons were in the household? ______________

5. How many children were in the household? ______________

6. How many children were in basic school? ______________

7. How many children were in post basic school? ______________

8. What was your employment status?
☐ Employee ☐ Self-Employed without employee(s)
☐ Self-employed with employee(s) ☐ Apprentice ☐ Student
☐ Casual Worker ☐ Unemployed ☐ Other (Specify)

9. What was your housing occupancy status at the time?

□ Owner Occupied	□ Renting	□ Rent-free
□ Perching	□ Squatting	□ Other (Specify)

10. What was your monthly income level at the time?______________________

11. What factor(s) made you select this place? *You can tick many*

□ Land values	□ Distance to School
□ Distance to major roads	□ Distance to health facilities
□ Distance to Suburb Centre	□ Distance to CBD
□ Distance to market centres	□ Distance to Shopping Mall/Centre
□ Distance to airport	□ Distance to railway station
□ Distance to parks and gardens	□ Distance to rivers
□ Population Density	□ Slope
□ Elevation	□ Availability of planning scheme
□ Land ownership status	□ Land Registration Status
□ Neighbourhood Development Status	□ Neighbourhood environmental quality
□ Family networks	□ Religious networks
□ Ethnic networks	□ Others (Specify)

12. Rank the factors in order of importance as to how they affected your decision to settle at this place?

□ Land Price	□ Distance to School
□ Distance to major roads	□ Distance to health facilities
□ Distance to Suburb Centre	□ Distance to CBD
□ Distance to market centres	□ Distance to Shopping Mall/Centre
□ Distance to airport	□ Distance to railway station
□ Distance to parks and gardens	□ Distance to rivers
□ Population Density	□ Slope
□ Elevation	□ Availability of planning scheme
□ Land ownership status	□ Land Registration Status
□ Neighbourhood Development Status	□ Neighbourhood environmental quality
□ Family Networks	□ Religious Networks
□ Ethnic Networks	□ Others (Specify)

Using the scale below, answer question 13
Scale: 0 to 10, where:
0: No Influence ***10: Extremely influential***

13. Assess the level of influence of the following factors on your decision to settle at this place:

Land values
No influence Extremely influential

0	1	2	3	4	5	6	7	8	9	10

Distance to School

0	1	2	3	4	5	6	7	8	9	10

Distance to major roads

0	1	2	3	4	5	6	7	8	9	10

Distance to Shopping Mall/Centre

0	1	2	3	4	5	6	7	8	9	10

Distance to CBD

0	1	2	3	4	5	6	7	8	9	10

Distance to Suburb Centre

0	1	2	3	4	5	6	7	8	9	10

Distance to health facilities

0	1	2	3	4	5	6	7	8	9	10

Distance to market centres

0	1	2	3	4	5	6	7	8	9	10

Distance to railway station

0	1	2	3	4	5	6	7	8	9	10

Distance to airport

0	1	2	3	4	5	6	7	8	9	10

Distance to rivers

0	1	2	3	4	5	6	7	8	9	10

Population Density

0	1	2	3	4	5	6	7	8	9	10

Slope

0	1	2	3	4	5	6	7	8	9	10

Elevation

0	1	2	3	4	5	6	7	8	9	10

Availability of planning scheme

0	1	2	3	4	5	6	7	8	9	10

Land ownership status

0	1	2	3	4	5	6	7	8	9	10

Land Registration Status

0	1	2	3	4	5	6	7	8	9	10

Neighbourhood Development Status

0	1	2	3	4	5	6	7	8	9	10

Neighbourhood environmental quality

0	1	2	3	4	5	6	7	8	9	10

Family Networks

0	1	2	3	4	5	6	7	8	9	10

Religious Networks

0	1	2	3	4	5	6	7	8	9	10

Ethnic Network

0	1	2	3	4	5	6	7	8	9	10

14. Do you have plans of moving to another place within the next 10 years?

☐ Yes ☐ No

*If yes, answer questions **15 to 18** else, continue with question **19***

15. Where are you moving to? ____________________

16. What factor(s) made you select the place? *You can tick many*

☐ Land values
☐ Distance to major roads
☐ Distance to Suburb Centre
☐ Distance to market centres
☐ Distance to airport
☐ Distance to parks and gardens
☐ Population Density
☐ Elevation
☐ Land ownership status
☐ Neighbourhood Development Status
☐ Family networks
☐ Ethnic networks
☐ Distance to School
☐ Distance to health facilities
☐ Distance to CBD
☐ Distance to Shopping Mall/Centre
☐ Distance to railway station
☐ Distance to rivers
☐ Slope
☐ Availability of planning scheme
☐ Land Registration Status
☐ Neighbourhood environmental quality
☐ Religious networks
☐ Others (Specify)

17. Rank the factors in order of importance as to how they affected your decision to choose the place?

- ☐ Land values
- ☐ Distance to major roads
- ☐ Distance to Suburb Centre
- ☐ Distance to market centres
- ☐ Distance to airport
- ☐ Distance to parks and gardens
- ☐ Population Density
- ☐ Elevation
- ☐ Land ownership status
- ☐ Neighbourhood Development Status
- ☐ Family Networks
- ☐ Ethnic Networks
- ☐ Distance to School
- ☐ Distance to health facilities
- ☐ Distance to CBD
- ☐ Distance to Shopping Mall/Centre
- ☐ Distance to railway station
- ☐ Distance to rivers
- ☐ Slope
- ☐ Availability of planning scheme
- ☐ Land Registration Status
- ☐ Neighbourhood environmental quality
- ☐ Religious Networks
- ☐ Others (Specify)

Using the scale below, answer questions X to X.
Scale: 0 to 10, where
0: No Influence ***10: Extremely influential***

18. Assess the level of influence of the following factors on your decision to choose the place:

Land values
No influence Extremely influential

0	1	2	3	4	5	6	7	8	9	10

Distance to School

0	1	2	3	4	5	6	7	8	9	10

Distance to major roads

0	1	2	3	4	5	6	7	8	9	10

Distance to Shopping Mall/Centre

0	1	2	3	4	5	6	7	8	9	10

Distance to CBD

0	1	2	3	4	5	6	7	8	9	10

Distance to Suburb Centre

0	1	2	3	4	5	6	7	8	9	10

Distance to health facilities

0	1	2	3	4	5	6	7	8	9	10

Distance to market centres

0	1	2	3	4	5	6	7	8	9	10

Distance to railway station

0	1	2	3	4	5	6	7	8	9	10

Distance to airport

0	1	2	3	4	5	6	7	8	9	10

Distance to rivers

0	1	2	3	4	5	6	7	8	9	10

Population Density

0	1	2	3	4	5	6	7	8	9	10

Slope

0	1	2	3	4	5	6	7	8	9	10

Elevation

0	1	2	3	4	5	6	7	8	9	10

Availability of planning scheme

0	1	2	3	4	5	6	7	8	9	10

Land ownership status

0	1	2	3	4	5	6	7	8	9	10

Land Registration Status

0	1	2	3	4	5	6	7	8	9	10

Neighbourhood Development Status

0	1	2	3	4	5	6	7	8	9	10

Neighbourhood environmental quality

0	1	2	3	4	5	6	7	8	9	10

Family Networks

0	1	2	3	4	5	6	7	8	9	10

Religious Networks

0	1	2	3	4	5	6	7	8	9	10

Ethnic Network

0	1	2	3	4	5	6	7	8	9	10

Permitting

19. What are some of the difficulties in securing building permit?

19b. How long will you wait for a building permit decision? Or do you have building permit already?

20. Expenditure pattern (Only answer if Question X is not answered)

Item	Monthly Expenditure (GHC)
Food	
Accommodation	
Transport	
Education	
Health	
Utilities	
Clothing	
Miscellaneous	
Saving	

Additional Questions

1. Were you born at his place or you migrated? ☐ Born at the Place ☐ Migrant

1b. If migrant, where were you born?

2. Does the house have the following? *Tick the box if it has*
☐ Septic Tank ☐ Sewage System
☐ Electricity

3 Have you ever considered the following? *Tick the box if you have*
☐ Solar Panel ☐ Wind energy
☐ biogas ☐ biomass

3b. If you ever considered any of the above, what actions did you take?
Solar Panel:
……
……
Wind energy:
……
……
Biogas:

……
……
Biomass:

……
…..
4. If the house is multi-storey, does it have elevator? □ Yes □ No

4b. Does the elevator work at all times? □ Yes □ No

5. If you had to develop which land cover type will you build on? *You can tick many*

□ Forest □ Agricultural lands
□ Grassland □ Wetlands
□ Bare land

5b. Why will you build on that land cover type?
……
……
……………………………………..

6. If the place you could afford was a nature reserve, will you build?
□ Yes □ No
6b. Give reason(s) for your answer in 21.
……
…….

7. In your opinion, what is the right way to increase housing?
□ Densification of existing developed area
□ Expansion of existing built-up area
8. Do you like to live in high-rise buildings?
□ Yes □ No
8b. Give reason(s) for your answer to question
……
…………………
8c. What is the highest floor that you are willing to live?
……………………………………………………

Modified Questions

Bands for Income
Section 1 q11. How much do you earn monthly? In cedis
□ < 150 □ 150 to 400
□ 500 – 1,000 □ 1,100 – 1,500
□ 1,600 – 2,500 □ 2,600 – 3,500
□ 3600 – 5,000 □ 5,000 – 7,500
□ 7500 – 10,000 □ >10,000

Section 2 q5c: What type of transport do the children use to get to school?

□ Car (private) □ **Bus (Commercial)** □ **Mini bus (Commercial)**
□ Motorbike □ Cycling □ Walking