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February, 2016

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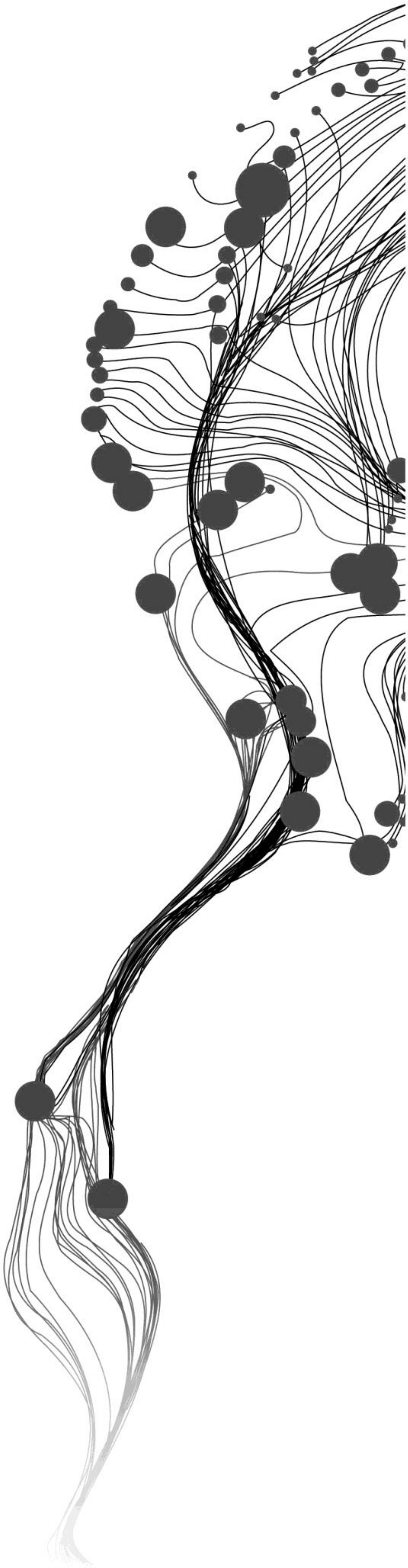

GROWTH AND EVICTION OF INFORMAL SETTLEMENTS IN NAIROBI

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ABSTRACT

Informal settlements (INSEs) in the developing world have been growing, and so has been the need to better their interventions. Earlier work on INSEs indicate that improving our understanding of INSEs' dynamics can assist at providing better interventions. Accordingly, this study employs spatial modelling to understand expansion, densification and eviction of INSEs in Nairobi, a city with over half of its population residing in INSEs. The study uses Google Earth historical imagery to extract outlines of Nairobi's INSEs' at years 2005, 2010 and 2015, and overlays them to identify and quantify change locations. Further, information from literature and key informants is used to identify probable drivers of INSEs change, following which, the strengths of probable spatial drivers are tested in 16 logistic regression models (LRM): 6 for expansion, 9 for densification, and 1 for eviction. The models were tested based on their correct predictions (PCP). Further, usability of the modelling approach was tested by assessing overlay of change probability maps and actual change locations. Subsequently, the study assesses practical applications of modelling results to Management of INSEs in Nairobi.

The study revealed diversity in INSEs, leading to their categorization into *Classic* and *Atypical* INSEs. Within the study period, settlements expanded at a rate of 4.1%, *Atypical* INSEs expanding five times faster than *Classic* INSEs. Likewise, densification was found to be on the rise, with 26% of INSEs area experiencing a shift in density class; *Atypical* settlements densified three times more than *Classic* INSEs. At the same time, eviction happened in 2.5% of combined INSEs' area since 1970, a seemingly minimal proportion but huge in impact to INSEs dwellers. From key informants and literature, *escape from rural vulnerabilities* and *the inability of housing agencies to provide sufficient housing* were found to be the main non-spatial drivers of INSEs growth while *poor land governance* is the top driver for eviction. From the modelling of spatial drivers, PCPs between 68 and 89 were achieved for all models, which literature shows as satisfactory. Despite failure to include some probable drivers because of unreliability of data, the models revealed that *Classic* INSEs are likely to develop *close to rivers, industrial areas*, and the *railway*; while *Atypical* INSEs are likely to develop *close to rivers, main road* and *industrial areas*. Additionally, low, medium and high-density locations are likely to occur close to *rivers, rivers* (again), and *railway* respectively. For eviction, location *close to rivers* and *protected areas* are more likely to be evicted than other locations.

The study recommends application of this modelling approach; this is based on overlay results which had at least 76% of all actual growth locations falling within the *very high probability* quantile. Specific decisions this modelling approach could be used to inform include pro-active provision of services on probable change locations, and identification of low-income housing locations. However, the study shows that Nairobi requires an INSEs' policy that will recognize INSEs into plan making for effective adoption of advanced spatial planning technologies, this modelling approach included. Finally, to overcome the weaknesses of the LRM, the study recommends inclusion of an agent based model in INSEs' modelling, and possible integration of expansion, densification and eviction in one model.

Key words: Informal settlements, change, modelling, drivers, interventions

Dedication:

To my wife, Antonina, and my Son, Tom:

You supported and motivated me all the way

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I owe much to my family: my wife, my son, and my brothers (Magira, Kamithi and Solo). You did not think pursuing studies away from home was a bad idea, yet I would miss a few of your calls to finish a paragraph of this report.

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LIST OF ACRONYMS AND ABBREVIATIONS

ABM	Agent Based Model
AFD	French Development Agency
ASDSP	Agricultural Sector Development Support Programme
CA	Cellular Automata Model
CBD	Central Business District
COHRE	Centre on Housing Rights and Evictions
DEM	Digital Elevation Model
GIS	Geographic Information System
GoK	Government of Kenya
GPS	Global Positioning System
GUO	Global Urban Observatory
IDRE	Institute for Digital Research and Education
INSE(s)	Informal Settlement(s)
ITC	International Training Centre (Faculty of Geo-Information and Earth Observation)
KNBS	Kenya National Bureau of Statistics
KPC	Kenya Pipeline Company
LRM	Logistic Regression Model
NCC	Nairobi City County
NCRM	National Centre for Research Methods
NGO(s)	Non-governmental Organization(s)
OR	Odds Ratio
PCP	Percentage of Correct Predictions
SE	Standard Error
SIDA	Swedish International Development Corporation
SLEUTH	Slope, Land-use, Exclusion, Urban extents, Transport, Hillshade
SPSS	Statistical Package for the Social Science
UPM	Urban Planning and Management
UTM	Universal Transverse Mercator
VHR	Very High Resolution (imagery)
WGS	World Geodetic System

1. INTRODUCTION

Spatial analysis of urban change is a recent development made possible by advancements in the fields of Geo-information science and Earth observation. This section discusses the need to study and model spatiotemporal changes of informal settlements (INSEs). Growth and eviction of INSEs in Nairobi have been selected for a case study. Discussed in this section are the background to the research, research problem, research objectives and questions, and the conceptual framework.

1.1. Background and Justification

Although there lacks an agreement on what exclusively constitutes INSEs – also synonymous to slums in some places, contexts and countries – the term generally refers to locations in urban areas where the poor are concentrated and living in substandard conditions (Huchzermeyer & Karam, 2006; World Bank, 2006). In the cities of the developing world, INSEs are prominent features. The proportions of urban dwellers in INSEs are estimated at one third globally (UN-HABITAT, 2015) and more than a half in Nairobi (Amnesty International, 2009). In these settlements, conditions are harsh, characterized by overcrowding, deficient access to safe drinking water and sanitation, insecurity of tenure and poor housing conditions (Sclar, Garau, & Carolini, 2005). That notwithstanding, accelerated urbanization, which is the principal cause of emergence and expansion of INSEs (Khalifa, 2015; Roy, Lees, Palavalli, Pfeffer, & Sloot, 2014), remains steady. According to Berner (2001), INSEs' growth translates into increased poverty since housing condition is a qualified indicator, factor, and cause of poverty.

Various responses to INSEs exist, notably infrastructural and support services provision, incremental upgrading, tenure and enabling approach, but also eviction and resettlement. Success on these interventions is reported to a certain scale, but limited by their inherent weaknesses and lack of sufficient resources, the approaches have not succeeded in reversing the growth of INSEs. Whereas site and service scheme are noted as being too expensive to be afforded by low-income groups (Khalifa, 2015), for example, slum upgrading projects fail because, besides being too small-scale to satisfy the rising housing demand, they are so poorly monitored to gauge their real impact (Imparato & Ruster, 2003). Eviction is the most unpopular of the approaches, criticized for being insensitive to human rights, against the poor, and unsustainable (COHRE, 2005). Moreover, the Informal City Dialogues (2013) argues that INSEs do not disappear through removal but transformation.

Accordingly, the need to employ approaches that can reverse the negative effects of INSEs in a sustainable manner, or at least contain their deteriorating conditions, has remained constant. The success of these approaches must be based on the understanding that INSEs are complex and highly dynamic. Roy et al. (2014) argue that for governments to understand the consequences of their policies on INSEs, they must consider a multitude of factors and most importantly how the factors interact. In the developing world, INSEs have been studied extensively yet only a few of those studies investigate spatial factors of INSEs change. This has been attributed to unavailability of detailed spatial data e.g. parcel based land information systems (Cheng, 2003), inability or unwillingness by governments to provide resources for spatial planning (Mutisya & Yarime, 2011), and perhaps shortage of expertise in using complex algorithms applied in spatial analysis procedures (Oostrum, 1999). Yet, contemporary interventions for INSEs are largely dependent on spatial data and their analysis methodologies. Realignment of unplanned settlements to a city's spatial grid though limited spatial intervention (Karimi et al., 2007), INSEs inventory and monitoring using remote sensing data and volunteered mapping (Hofmann, Taubenbock, & Werthmann, 2015), and participatory slum upgrading (UN-HABITAT, 2003b), as examples of such interventions, rely heavily on mapping and analysis of spatial data. Establishing where INSEs exists, how they grow and disappear, and the forces behind their change not only gives the understanding of INSEs an additional dimension but is also a starting point towards developing interventions that are more robust. Studies exploring such spatiotemporal dynamics mostly rely on modelling (e.g. Vahidi & Yan, 2014); however, they are few and particularly lacking for big cities with INSEs in Africa e.g. Nairobi.

Spatial modelling and simulation as tools for decision making have been used to understand complex dynamics of INSEs (Roy et al., 2014). This includes providing support for exploring likely land changes under different scenarios (Verburg, Schot, Dijst, & Veldkamp, 2004). Commonly applied techniques in modelling urban growth include: cellular automata modelling (CA) (e.g. Perez, 2014; Shuvo & Janssen, 2013), agent based modelling (ABM) (e.g. Hosseinali, Alesheikh, & Nourian, 2013), logistic regression modelling (LRM) (Xie, Huang, Claramunt, & Chandramouli, 2005), and hybrid modelling which utilizes two or more modelling approaches (e.g. Allen & Lu, 2003; Arsanjani, Helbich, Kainz, & Boloorani, 2012). Based on their relative strengths, these approaches have been used to model growth with promising outcomes. Studies specific to INSEs (e.g. Dubovyk, Sliuzas, & Flacke, 2011) have been affected by unavailability of inaccurate spatial data, often originating from inaccuracies in extraction of settlements from images. This challenge is being overcome by development of slum ontology for INSEs classification (Kohli, 2015) and application of new image analysis techniques such as use of spatial metrics (e.g. Kuffer & Barros, 2011).

Although modelling has been proven worthwhile in understanding INSEs, most cities with sprawling INSEs have not benefited from it, perhaps for the reason that most modelling approaches are relatively new. Hofmann et al. (2015) observe that while modelling can be applied to establish the genesis of INSEs and monitor their daily development, common application has been limited to situational analysis, often with no clear intent to model the future. In Nairobi, spatial studies and plans on INSEs are numerous (e.g. Muungano Support Trust, International, Nairobi, & University of California Berkeley, 2012; Mweni, 2013) but limited to static plans that fail to harness the potentials of dynamic modelling and simulation. Additionally, no studies yet have attempted to model spatial dynamics of eviction. Certainly, the city of Nairobi can immensely benefit from augmented spatial knowledge and change modelling of its INSEs. Sirueri (2015) recommends more research in Nairobi on drivers of INSEs' growth, particularly that which focuses on spatiotemporal components. Consequently, policy makers will be able to tap into this knowledge for informed decision-making.

1.2. Informal Settlements in Nairobi

INSEs in Nairobi existed before 1960, but it was until in the 1960s and 70s – after the exit of the colonial government – that they enlarged, densified and proliferated (Amnesty International, 2009; Pamoja Trust, 2009). Locations occupied by first INSEs included: workers' camps for colonial settlers farms, undeveloped land near big farms, idle government or city council land around industrial areas, relocation sites issued by government to squatters and victims of war, and idle private land (Matrix Development Consultants, 1993). Confronted by the challenges of poor planning and inability to provide affordable housing, the government could not control the expansion of settlements and emergence of new ones, and this led to sprawl of INSEs to riparian reserves, refilled quarries, dump sites and land under high voltage power lines (Pamoja Trust, 2009).

Nairobi experienced a sharp rise in the number of its INSEs in the 1970s. Ngau (2013) attributes this to the influx of people from rural areas to the city triggered by the oil crises that led to the decline of tea and coffee industries in Kenya accompanied by heavy loss of jobs. This growth concerned the government which responded by evicting and demolishing INSEs. Massive eviction happened in 1978 and 1979 but stopped rather abruptly following the death of the then president Jomo Kenyatta – as the government hoped to consolidate citizen support (Amnesty International, 2009; Ngau, 2013). The succeeding government was initially lenient on eviction, a result of which there was unrestrained settlement proliferation; only in 1982, following a failed coup, did the government resumed eviction, the motivation being that INSEs were disorderly for governance (Ngau, 2013). Politically motivated eviction continued amid rising concerns that land recovered from eviction was unjustly taken for personal gains (Pamoja Trust, 2009). NGOs and international development agencies responded by starting advocacy against eviction, and this effectively halted massive eviction towards the year 2000 (Amnesty International, 2009). Since then, resistance to eviction has been heightened but happens at suppressed frequencies. Meanwhile, growth of settlements has continued; in 1998, up to 50% of the city population resided in INSEs which merely occupied 5% of the city's residential land (Matrix Development Consultants, 1998).

Nairobi currently has more than 3.36 million inhabitants (United Nations Development Programme, 2011) and at least 134 INSEs (UNEP, 2006), being home to 60% of its population (UN-HABITAT, 2006). UNDP (2011) projects the city will have a population of 4.9 million at 2020 and 6.1 at 2025. This implies that as many people as the current population of the city will reside in INSEs at 2025. Existing INSEs in the city have a character of diversity in terms of history, spatial extents, densities, social characteristics and also levels of deprivation (Wakhungu, Huggins, Nyukuri, & Lumumba, 2010). Conversely, they are similar in that they lack proper housing, access clean water, sanitation systems, solid waste management systems, adequate community facilities such as educational and health facilities, and residents lack decent means of livelihoods (Mutisya & Yarime, 2011).

1.3. Research Problem

The Informal City Dialogues (2013) notes that despite Nairobi's INSEs being among the most studied in the world, their totality remains elusive. This observation expresses the gap that exists between the available spatial and non-spatial information for the city. The importance of spatial information is further emphasized by Potsius et al. (2010) who argue that location in the form of spatial data is a key enabler for visualizing existing situations, making impacts predictions, improving service delivery and consequently enhancing decision making. Incidentally, gathering of spatial data has been made affordable by availability of imagery from cheaper sources such as Google Earth (Q. Hu et al., 2013). Furthermore, spatial analysis programs are increasingly becoming accessible and are even being complemented by open source software (Ramsey, 2007).

Advanced use of spatial data, for example in modelling, will support planning authorities to understand the complexities of their INSEs (Sietchiping, 2005). Spatiotemporal analysis improves human understanding of the dynamics of INSEs (Dubovyk et al., 2011). For Nairobi, dynamic modelling and simulation will give a deeper and perhaps entirely new meaning to the vast non-spatial data available on INSEs in the sense that patterns of occupation, growth and eviction will be detected and better understood. Additionally, by analysing location characteristics of INSEs, it is possible to establish the driving forces behind their change based on spatial statistics (Lesschen, Verburg, & Staal, 2005)

These drivers are realized by modelling predictors of change, where Xie et al. (2005), for example, outlines land use change drivers in classes of (1) site specific, (2) proximity, and (3) neighbourhood. It is essential for policy makers to establish the extent to which factors under such classes can explain the growth of INSEs in Nairobi, including showing where INSEs may develop in future. Among various urban modelling techniques, a model that has been proven effective in understanding such spatial patterns because of its strength in interpreting occurrence of spatial phenomena is spatial logistic regression (Cheng, 2003). Likewise, assessing spatial and non-spatial drivers of eviction statistically will help in establishing whether location characteristics of INSEs can be linked to the threats of eviction, and to what extents. This knowledge is vital in decision making for better-informed urban management.

1.4. Research Objectives and Questions

1.4.1. The Main Objective

The main objective of this research is to augment the knowledge of growth and eviction of INSEs for local planning in Nairobi.

1.4.2. Sub-objectives and Questions

1. To quantify spatial horizontal growth and eviction of INSEs between 2005 and 2015
    - Where are INSEs located in Nairobi?
    - Which INSEs' locations experienced expansion and to what scales?
    - Which INSEs' locations experienced densification and to what scales?
    - Which INSEs experienced eviction and to what scales?
2. To identify the causes of growth and eviction of INSEs in Nairobi
    - What are the driving forces of INSEs expansion?
    - What are the driving forces of INSEs densification?
    - What are the driving forces of INSEs eviction?
3. To assess the impact of modelling outputs to the future management of INSEs in Nairobi
    - Which locations are likely to experience INSEs expansion, densification and eviction in future?
    - Which existing policies relate to management of growth and eviction of INSEs?
    - How have these policies impacted growth and eviction of INSEs in Nairobi?
    - Which policy measures should be taken in regard to growth and eviction of INSEs in Nairobi?

1.5. Conceptual Framework

This section describes the research variables and their conceptual basis. Roy et al. (2014) describe INSEs as complex dynamic systems whose problems cannot be solved by one model. This research is anchored on the premise that a strong understanding of spatial dynamics of INSEs is a prerequisite for informed planning policy. Fragkias and Seto (2007) point out that that understanding urban growth dynamics is key to scientific planning and management. Correspondingly, a vital component of this research is to establish a stable knowledge base of INSEs through understanding their characteristics and change dynamics with an aim of applying them in shaping their future. To achieve this, a comprehensive understanding of INSEs from global to local contexts, which is achieved by through baseline survey enriched with ground data and literature, is desired. Accordingly, understanding dynamics of INSEs change is achieved by an assessment of past and current development trends, often based on the assumption that future trends will not be significantly different from a projection of existing trends.

With a good knowledge base on INSEs and their spatial-temporal dynamics, modelling links the known state and possible futures, offering insights into the opportunities and threats posed by continued trends and also possible intervention. A LRM is used in this study as a filter, able to bring out the very important spatial drivers of change from all probable drivers of INSEs expansion, densification and eviction. Subsequently, probability mapping reveals locations with high probability of converting to INSEs, densifying or getting evicted. As shown in Figure 1, the converge of spatial drivers of change, non-spatial drivers of change and probable locations of change based on modelling outputs, creates improved understanding of INSEs, and that is what policy makers need for decision making on INSEs locations. These decisions could include protecting probable areas or making prior layouts before occupation, which should result in improved INSEs layout plans, and better access for service provision. This cycle could continue (see feedback loop in Figure 1) with policy makers being able to shift what is often seen as spontaneous development into planned development.

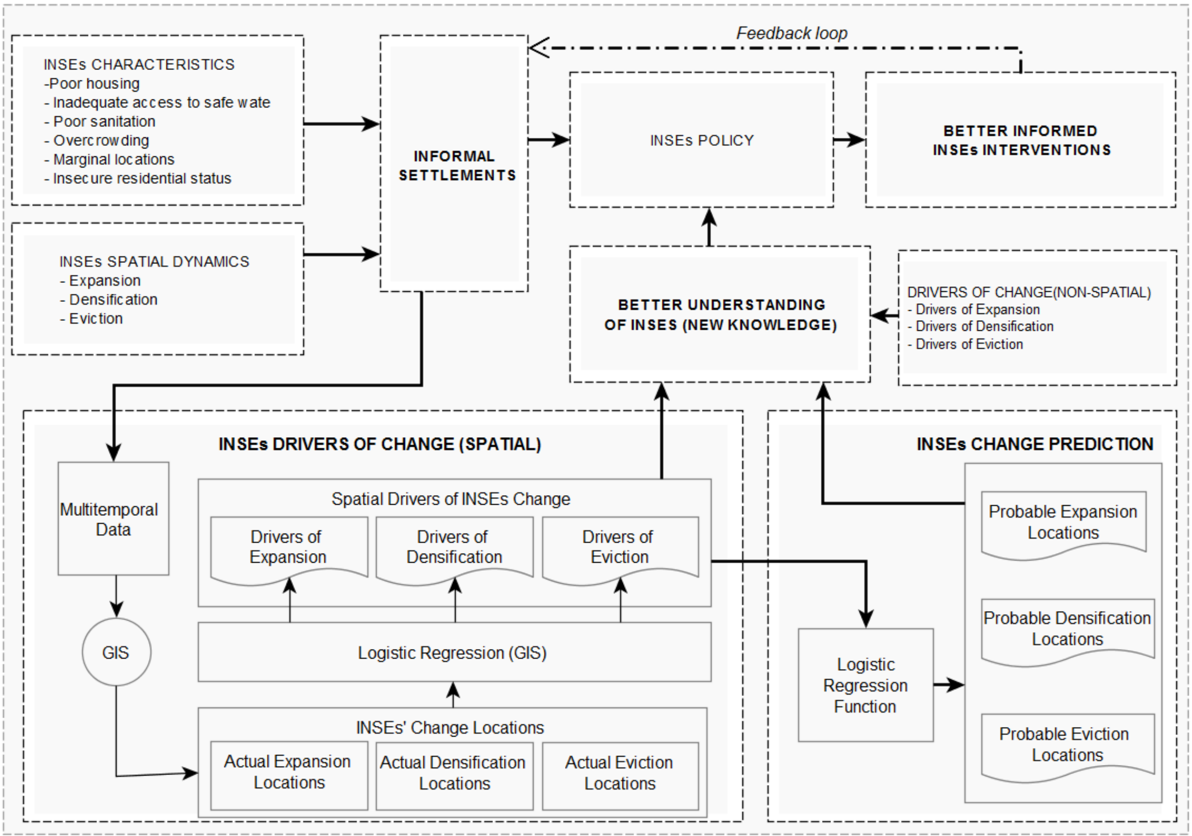


Figure 1: Conceptual framework

1.6. Thesis Structure

This report is organized in chapters. *Chapter 1* provides an introduction where the research background and problem are discussed and the research goal defined as well as the conceptual framework. In *Chapter 2* dynamics of INSEs and theoretical background to the modelling approaches taken in the research are discussed, while in *Chapter 3,* data needs and methods are discussed largely based on literature review. This also includes the methodological framework of the research. *Chapter 4* presents research findings, including output from the applied models, while *Chapter 5* uses the modelling outputs show locations at high probability of experiencing INSEs change. Further, an assessment of INSEs policies in Nairobi is done. A critical discussion of the study, its appraisal on achieving its gaols, and an assessment against related studies, is carried out in *Chapter 6,* while study conclusions and recommendation are presented in *Chapter 7*.

2. INFORMAL SETTLEMENTS DYNAMICS AND MODELLING

2.1. Understanding Informal Settlements

The term "informal settlement" may simply be taken to mean settlements that are not formal or lack legal recognition by authorities. While this is fundamentally true, this concept has been used in many contexts to mean different things. This sub-section discusses the difficulty of defining INSEs, offers a global view of INSEs, and provides the reasons INSEs have continually attracted the attention of policy makers.

2.1.1. Defining Informal Settlements

INSEs are defined not by a single feature but by a combination of characteristics. Accordingly, their names and characteristics vary with contexts, locations, and authors. Concepts used alongside INSEs – either synonymously or with slight shifts in connotation – generally refer to manifestation of urban poverty and social inequality in housing (Majale, 1993). Terms commonly used alongside INSEs include: *unplanned settlements*, which points to lack of site planning and zoning in housing; *squatter settlements*, which emphasizes settlement by people who do not own the land they occupy; *spontaneous settlements*, which underlines absence of government control and aid; *popular settlements*, which explains occupation by low income households; *marginal settlements*, which implies inferior location and role of dwellers in the society; *shanty towns*, which points to poor quality in construction; *transitional settlements*, which implies non-permanence in settlement; and most popularly, among many others, *slums*, which underlines squalor in building and environment (Kuffer, Barros, & Sliuzas, 2014; Majale, 1993; Shrestha, Tuladhar, & Zevenbergen, 2014).

UN-HABITAT (2003) admits the lack of an official definition for INSEs. Common across the definitions of INSEs and related terms is the lack of precision. Definitions often have overlapping aspects, but each will add or remove some elements from another depending on its focus context and assumed points of view (Taubenböck & Kraff, 2014). A functional definition for a study may therefore involve refining proxy indicators from accredited sources to fit the study context. UN-HABITAT (2002), for example, based on an expert group meeting, agreed on indicators and thresholds for defining INSEs as lack of one or more of the following: access to adequate water; access to sanitation facilities; sufficient living area; structurally durable or quality housing; and security of tenure. Similar indicators are applied by the World Bank (2006) who use the terms 'slum' synonymously and also underlines variations in definition from place to place.

For planning purposes, some governments tailor definitions to their local contexts. In South Africa, the department of human settlements has set benchmarks for identification of INSEs as including: inappropriate location, illegality and informality, poverty and vulnerability, restricted public and private sector investments, and social stress (Alhassan, 2013). It is notable that INSEs in regions close to each other are defined with more similar indicators than regions far apart. A contrasting case with less overlap to commonly used indicators in the African regions is of Papua New Guinea where a group of experts' defined INSEs to include locations with: people of the same tribe living in clusters; a self-employed population; overcrowded households; presence of health issues including tuberculosis and human immunodeficiency virus (HIV); and environmental and ground water pollution from human and solid waste among others (World Bank Group, 2014).

2.1.2. A Global Perspective of Informal Settlements

INSEs are a global phenomenon, hosting an estimated 25% of the world's population; even more, the population living in INSEs in Africa is estimated at 61.7% (UN-HABITAT, 2015a). Although there are practical challenges in producing huge-in-scale yet precise statistics, Figure 2 shows what are believed to be estimates of populations in slums (INSEs) worldwide by percentage.

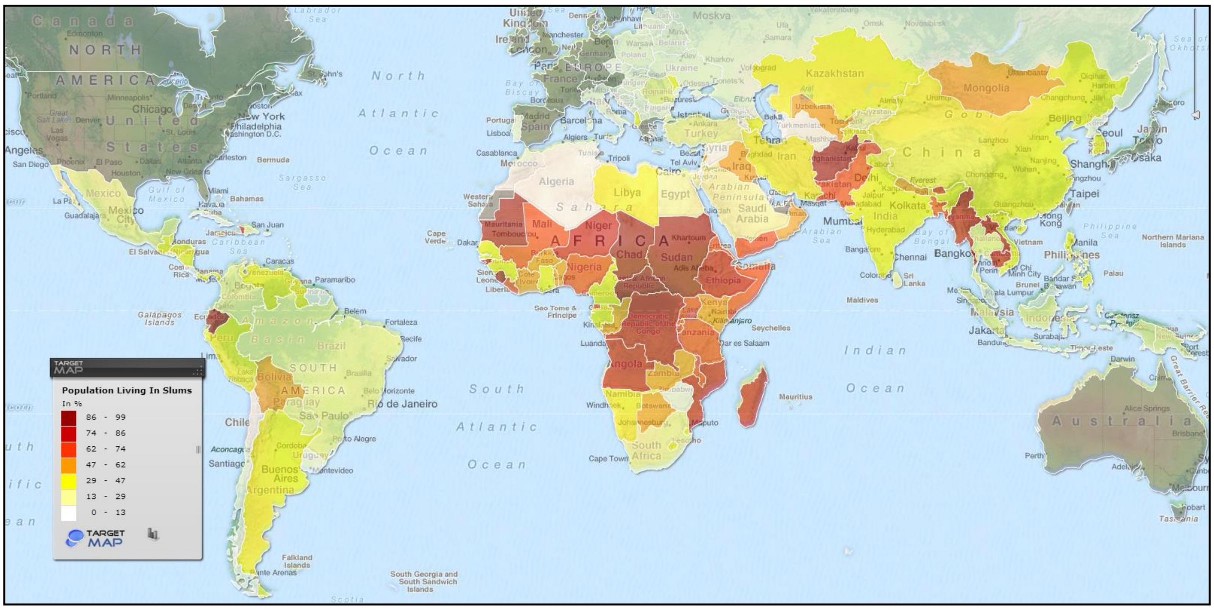


Figure 2: Populations in slums worldwide by country (in %)
Source: TargetMap (2015)

The sub-Saharan African region – which has the highest proportion of INSEs – ranks first in urban growth with estimates indicating an unpresented growth rate of 5% per annum (Kessides, 2005). In this region, notes Enemark, McLaren, and Molen (2009), 90% of new urban growth is in the form of INSEs. Countries with INSE incidences estimated at 83% and above include Angola, Ethiopia, Sierra Leone, Somalia, Benin, Ethiopia, Chad, Guinea Bissau, Mauritania, Niger and Madagascar (Arimah, 2011). Kenya's INSEs population is estimated at 54.7% (GORA, 2015).

2.1.3. Concerns over Informal Settlements

The biggest concern over INSEs today is that they are growing so fast that the population they host may double by 2030 (Hatuka & Saaroni, 2014). While some statistics show a slight decrease in the overall percentage of the population living in INSEs, the absolute number of INSEs dwellers is rising. Majority of INSEs' dwellers are aged between 15 and 24 (UN-HABITAT, 2012), a population valued for its power to shape the future, and at the same time vulnerable to illicit activities while confronted with survival challenges (Tibaijuka, 2005).

Living in INSEs is associated with a host of problems ranging from physical and economic to social. Arimah (2011) describes INSEs proliferation in a city as an expression of social exclusion. For being located in hazardous locations, most settlements are especially prone to impacts of climate change (Enemark et al., 2009). Further, overcrowding increases the risk of spread of communicable diseases such as tuberculosis and meningitis, aided by reduced disease resistance among the inhabitants as a result of unhealthy feeding (Sclar et al., 2005). Where population densities are too high, inhabitants live in life-

threatening conditions, often without the most basic of services (Enemark et al., 2009); Bloom, Canning, and Fink (2008) desribe the enviroment of these settlements as that of fear and hopelessness.
Incidentally, the economic potential of these settlements is high; in INSEs locations, informal economy thrives, and this is where 85% of all new employment around the world occur (UN-HABITAT, 2012). An appreciation of what INSEs hold as well as the risk they pose has made policy makers to view them more positively (Global Urban Observatory, 2003). These two sides of INSEs make it clear that while they are beneficial to growing economies, they are also centres of despondency, and their intervention can only be urgently desired. Apparently, despite the fact that governments will want to benefit from these informal economies through taxation, INSEs exist in locations with no security of tenure, whereby governments consider them illegal and undesirable (Shrestha et al., 2014). From this, it can be deduced that as growth of INSEs continues, a decision between ignoring them because they are illegal and watch them proliferate, and offering them a legal status and starting to intervene on them, starting by offering basic spatial planning support (especially at their establishment), is a big challenge for many governments in the developing world.

2.1.4. Diversity in Informal Settlements

At the global and more abstract level, INSEs have been categorized into *slums of hope* and *slums of despair* to show the divide between those that are progressing and those declining respectively (UN-HABITAT, 2003a). Studies of INSEs not only face challenges at establishing functional definitions for concepts but also at explaining variations between settlements. Even the formal-informal divide in settlements is rarely crisp, with settlements found to exist along a continuum of formality with nebulous transitions. While discussing deteriorating housing conditions in the industrial age Geddes (1915) already categorized settlements as *slums*, *semi-slums* and *super-slums* along a scale of increasing prosperity for their dwellers. Fekade (2000) also noted wide variations in building typologies, population density and other urban characteristics among INSEs, a cause for which he categorized them as the *affluent* INSE, *moderate* INSEs, and the *disadvantaged* INSEs. More recently, Soliman (2004) categorized settlements in Cairo into: *semi-informal* – to include those with legal tenure but land subdivision is not under regulated cadastre; *squatting informality* – to include those whose occupants are not legitimate land owners; and *hybrid informal* – to include individual dwelling units with certain degree of informality and whose land ownership could have been originally legal but transformed partly or fully to illegal configurations.

Others researchers have identified unique types of settlements and emphasized the need to study them separately, for example, the back-shack dwellings in south Africa (Lemanski, 2009). In less spatial terms, other parameters such as levels of income have been used to show variability in settlements (Majale, 1993).

In Nairobi the only documented attempt to classify INSEs was done by Etherton (1971) who, under the concept *uncontrolled development*, categorized settlements into 4 categories: *semi-permanent rural*, *semi-permanent urban*, *temporary urban*, and *temporary and semi-permanent infills*. This categorization was based on layout and construction, location, public utilities, population density, land tenure, employment and commercial activities, and cultivation. Such a classification may not be suitable for Nairobi today as the city image has changed immensely, with what was rural being largely urban, or at least rurban.

2.2. Changes in Informal Settlements

INSEs experience changes in their physical and non-physical fabric. This could range from very rapid to very slow changes. Discussed in this section is only physical changes of INSEs. Case studies show that the processes of INSE change are hard to generalize (Pamoja Trust, 2009). Fekade (2000) argues that INSEs develops linearly through the stages of *starting*, *booming* and *saturation*. Along this perspective but with more details, Sliuzas (2004) discusses the process of INSEs development on unoccupied land as involving appearance, expansion, shrinking, disappearance, and densification. The building process is summarized in Figure 3. The driving forces of change for a settlement determine the speed at which each stage evolves to another.

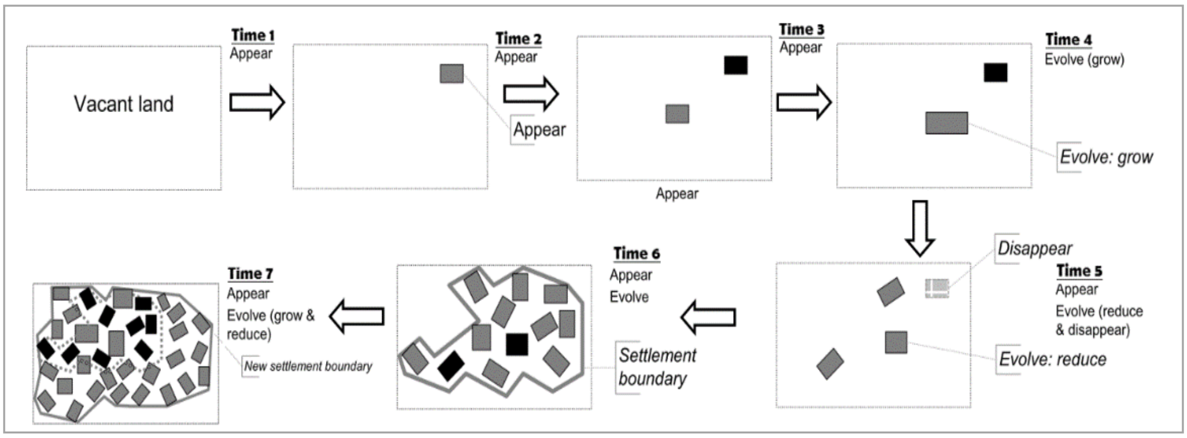


Figure 3: INSE formation processes (Adapted from Sliuzas, 2004)

These stages can be generalized into growth (to include appearance, expansion and densification) and eviction (to include shrinking and disappearance). Abebe (2011) discusses three phrases of INSEs growth as infancy, consolidation and saturation. At infancy, available agricultural or unoccupied land is converted to residential use by low-income groups; at consolidation, also booming stage, up to 80% of land is occupied by housing; and at saturation, there are additional construction in vertical growth and infill of unoccupied spaces. Sartori, Nembrini and Stauffer (2002) explores the limit of densification where they note that beyond a density of 2000 persons per square hectare, only vertical growth is possible. They give this as the reason population of Kibera INSE has only minimally increased since year 2000. Densification of INSEs through vertical growth has been widely reported in other parts of the world (e.g. India (Gill & Bhide, 2012)), but rarely in Africa. However, Abebe (2011) expresses the need for its investigation.

Shrinking and disappearance of INSEs are broadly as a result of natural disasters or human intervention (Sliuzas, 2004). General causes of shrinking and disappearance include: population migration, forced eviction, government relocations, transformations such as settlement upgrading, natural disasters e.g. flooding and earthquakes, and human disasters such as fire and conflicts (UN-HABITAT, 2003b). Profiles of INSEs in Nairobi show their shrinking and disappearance happen majorly a result of forced eviction (Matrix Development Consultants, 1998; Pamoja Trust, 2009).

2.3. Drivers of INSEs' Spatial Change

Fernandez (2011) argues that changes to INSEs "do not just happen", implying existence of numerous driving forces behind location and patterns of their establishment. While there is considerable discussion in literature on what these forces are, Arimah (2011) admits the lack of comprehensive understanding on what drives growth and proliferation of INSEs in developing countries. The discussion in this section utilizes literature in an attempt to understand what drives INSEs growth and eviction.

2.3.1. Drivers of INSEs' Growth (Expansion and Densification)

There are spatial and non-spatial forces of INSEs growth. The UN-HABITAT (2003) views rapid urbanization as the main trigger force behind emergence and growth of INSEs. In line with this, Ali and Sulaiman (2006) state that informality in settlements begins when urban populations grow without commensurate supply of housing, where Brueckner and Lall (2015) and Khalifa (2015) relate this shortage to the inability of housing markets to provide adequate accommodation at the rates of urbanization. The main reasons for urbanization include low income from agriculture; escape from rural poverty, vulnerabilities and economic downturns; better job prospects in urban areas; and the belief by rural residents that cities can offer better living in terms of better-quality transport, communication and education among other life support services (City Alliance, 2014; Mutisya & Yarime, 2011; Wakhungu et al., 2010).

Also widely discussed as driving INSEs growth is poor governance (City Alliance, 2014; Olajuyigbe, Popoola, Adegboyega, & Obasanmi, 2015). It is argued that most governments respond slowly to urbanization, ignore INSEs, fail to create or implement pro-poor policies, and are reluctant to provide security of tenure which would motivate dwellers to invest in improving their homes (Payne, Durand-lasserve, & Payne, 2012).

Spatially, Xie, Huang, Claramunt, and Chandramouli (2009) and Ahmed & Bramley (2015) argue that each human settlement is unique and is therefore impossible to have a set of growth factors universally fit for all contexts. In studies, factors of INSEs growth have been generated case by case through literature and knowledge enrichment from local experts, and then tested using urban growth models (Abebe, 2011; Dubovyk et al., 2011). Nevertheless, for a firm theoretical basis in urban growth studies, there have been attempts to scope the factors of urban growth. Sietchiping (2005), for example, classifies factors specific to INSEs in the categories of physical, economic and social cultural. In an alternative approach, Xie et al. (2005) classifies growth factors into site specific, proximity and neighbourhood characteristics; this approach has been adopted in this study for the reason that it can represent drivers of Nairobi INSEs better than other classifications.

Table 1 show the drivers that have been investigated in INSEs modelling studies. Re-categorizing drivers from different sources into this framework of specific-proximity-neighbourhood characteristics conceivably presents the challenge of ambiguity. Placement has been done on the principle of best fit.

Sietchiping (2005) and Global Urban Observatory (2003) discusses these factors in a global context, and do not employ a modelling approach to rank their influence. The three other cases listed uses modelling approaches, where they establish that drivers can have a negative or a positive effect to INSEs growth. Dubovyk et al. (2011) found *population density*, *slope* and *proximity to undeveloped land* as the strongest factors for INSEs expansion in Sancaktepe, all with a positive effect to expansion; Abebe (2011) found *proximity to roads* and *proximity to existing INSEs* (with negative effect to INSEs expansion) and *proportion of undeveloped land* (with a positive effect to expansion) as the three strongest drivers of expansion in Dar es Salaam; and Shekhar (2012) found out that *proportion of surrounding undeveloped land* and *proximity to existing INSEs* are the most influential drivers of expansion in Pune, both positively correlated to INSEs expansion.

On densification, Fekade (2000) argues that location advantage, availability of urban services and facilities are the most critical drivers. Abebe (2011) has modelled densification in Dar es Salam and found *population density* and *distance to rivers* (with a positive influence), *distance to the CBD* and *major roads* (with a negative influence) as the major spatial drivers of densification.

Table 1: Summary of drivers of INSEs growth from literature

Source:	Sietchiping (2005)	Global Urban Observatory (2003)	Dubovyk et al. (2011)	Abebe (2011)	Shekhar (2012)
Study	*Developing countries' Slum Dynamics Modelling*	*State of INSEs Report (General)*	*INSEs Modelling in Istanbul*	*Modelling INSEs Growth in Dar es Salam*	*Modelling probable INSEs Drivers in Pune*
Site-specific	-	• -	• Population density	• Population density	• Population density
	• Topography • Low lying areas & wetlands • Marginal, less valuable land (e.g. dumpsites)	• Areas at risk of flooding • Hazardous locations • - Rural fringe of the city	• Slope	• Slope • Environmental hazard locations	• Relief/slopes
	• Spatial Planning policies	-	-	-	--
Proximity	• Proximity to transport networks (roads)	• Proximity to wide street reserves • Proximity to railway tracks	• Proximity to roads	• Proximity to roads	• Proximity to transport networks (rivers and railway)
	• Proximity to rivers/riverbanks	• Proximity to riparian reserves	-	• Proximity to rivers • Proximity to the ocean	• Proximity to riverbanks and canals
	• Proximity to source of income (industrial areas, market places)	• -	• Proximity to industrial areas	-	• Proximity to job locations (industries)
	-	• Proximity to the CBD (on sites awaiting development)	• Proximity to CBD	• Proximity to CBD and sub-centres & satellite centres	-
Neighbourhood characteristics	• Interaction with exiting informal settlements	• Proportion of surrounding formal residential land uses	-	• Proportion of INSEs in the surrounding & planned residential land	• Close interaction with old INSEs
	-	-	• Proportion of surrounding urban land	• Proportion of urban land in the surrounding	-
	• Surroundings unexploited plots	-	• Proportion of surrounding undeveloped land	• Proportion of undeveloped land in the surrounding	• Undeveloped land neighbourhoods
	-	• Proportion of transportation land uses in the surroundings	-	-	-

2.3.2. Drivers of INSEs' Eviction

Eviction happens in complex environments, often characterized by politics, disagreements, resistance, stand-offs, destructions and chaos (COHRE, 2005; Pamoja Trust, 2009). Many attribute eviction to poor land governance, citing lack of transparency, equity, accountability, pro-poor legislation, rule of law and participation in land management (Shrestha et al., 2014; Tibaijuka, 2005; UN-HABITAT, 2015a). There is a strong political dimension in INSEs eviction; in Nairobi, case by case details implicate high ranking state official in irregular land acquisition and allocation (Amnesty International, 2009; InformalCity, 2015; UN-HABITAT, 1996).

Further, projects of city image restoration have led to massive evictions. Generally, governments perceive INSEs as landscape eyesores, havens for criminals, and a health hazard, reasons for which they have been evicted by city authorities prior to international events or visits by important personalities, or merely to make the city attractive (Arimah, 2011; Huchzermeyer & Karam, 2006). A *Classic* example of an eviction whose end was only to clear informality from the city is *Operation Murambatsvina* (operation drive out rubbish) in Zimbabwe where a politically motivated eviction led to loss of homes for 700,000 people in only 6 weeks (Schöpfer, Tiede, Lang, & Zeil, 2007). Additionally, eviction are initiated by governments as a way of ensuring safety for their citizens. Settlements under high-voltage power lines, along flight paths, within railway reserve, and those in areas prone to hazards of flooding and land-slides have faced eviction or at least treats from city management authorities (Pamoja Trust, 2009; Roy et al., 2014).

Spatially, among the drivers of eviction is infrastructure development; this often happens when governments are set to make up for city infrastructure backlog through construction of wide roads and drainage systems (UN-HABITAT, 1996). Other city development projects that have led to massive loss of homes include expansion of railway reserves and environmental health restoration projects like river clean ups (Pamoja Trust, 2009).

No research yet have investigated the strengths of the above-discussed spatial drivers through modelling. As a result, this study gathers probable drivers for modelling majorly from key informants and non-modelling discussions in literature. Matrix Development Consultants (1993) and Pamoja Trust (2009) have profiled INSEs in Nairobi case by case where they discuss: first, location characteristics of evicted INSEs such as land tenure and their level of encroachment into infrastructure networks and riparian reserves; second, INSEs proximity characteristics such as their distances to prime lands, neighbourhood characteristics, distances to transport networks and also CBD; and third, INSEs characteristics such as resident population, age, area and density; and future development plans. This is a good baseline for eviction spatial modelling.

2.4. Modelling Informal Settlements Dynamics

Urban modelling aims at creating functions and processes to generate spatial structure that can enable location data to be tested against prediction (Batty, 2009). Of the dynamics of INSEs, modelling efforts have been concentrated on growth with most studies employing widely known urban growth models. Some of these are discussed below.

2.4.1. Modelling Growth of Informal Settlements

The approaches for modelling INSEs are similar to those applied in modelling urban growth. They are numerous and have been classified according to their characteristics, methodologies and application areas (Rui, 2013). Cheng (2003) discusses the main urban modelling approaches as: ABM, CA, chaotic and catastrophe modelling, fractal based modelling, artificial neural network based modelling, and spatial statistics modelling. Modelling objectives and relative strengths and weaknesses of these models determine the best one for use in any particular case.

A favourable way to model land use change is by LRM (Z. Hu & Lo, 2007; Xie et al., 2005) This model has been chosen for this research because it is comparatively stronger in modelling urban spatial dynamics; allows deeper understanding of forces driving growth; is spatially explicit; is suitable for multi-scale analysis; has less computational calibration; and can incorporate human drivers beyond biophysical variables (Cheng & Masser, 2003; Dubovyk et al., 2011).

2.4.2. Logistic Regression Modelling

Regression involves extraction of empirical relationships' coefficients from observations (Xie et al., 2005). To investigate drivers of urban growth, LRM statistically quantifies the relationships between urban land use locations and their likely forces of growth. This approach has been used to model general urban growth (e.g. Allen & Lu, 2003; Hu & Lo, 2007; Nduwayezu, 2015) and also growth of INSEs (e.g. Abebe, 2011; Dubovyk et al., 2011). Allen and Lu (2003) however note that the success of a LRM can range from 30 to 90%, arguing that case-specific characteristics, selected land use categories, and size of study area among others are responsible for the huge variability.

However, unlike rule-based simulations such as CA, LRM is noted to lack temporal dynamics (Hu & Lo, 2007). Researchers have used hybrid models, for example, logistic regression-based Cellular Automata to compensate for the deficiency of individual models, the limitation of LRM being its inability to quantify spatiotemporal changes (Munshi, Zuidgeest, Brussel, & van Maarseveen, 2014). LRM is nevertheless strong in that it can be used to predict future development through analysis of past trends (Dendoncker, Rounsevell, & Bogaert, 2007).

2.4.3. Logistic Regression Modelling Inputs

Primary spatial LRM inputs include multi-temporal data, predictor variables, and computer applications.

a) Multi-temporal data

This data is largely extracted from imagery through classification. Images may be acquired from different satellite systems e.g. Landsat, SPOT or MODIS and may require radiometric, geometric and atmospheric correction before classification (Bakx et al., 2012). During classification, expected challenges while using pixel based classification methods may include "salt and pepper" effects (Bakx et al., 2012). Additionally, the spectral properties of INSEs overlaps with those of other built-up areas, a phenomenon currently being overcome by employment of improved techniques of image analysis such as object oriented image analysis (Kohli, Warwadekar, Kerle, Sliuzas, & Stein, 2013). In the absence of VHR multi-temporal imagery for Nairobi, data for this study has been generated from Google Earth based on the idea of Hu et al. (2013). The technique used is visual image interpretation.

Visual image interpretation

This is an intuitive approach for extracting data from remote sensing imagery relying on human vision and ability to relate colour and patterns on image to real world features (Baks, Janssen, Schetselaar, Tempfli, & Tolpekin, 2012). Image interpreters need to be well trained and with local knowledge about the study location (Isa Baud, Kuffer, Pfeffer, Sliuzas, & Karuppannan, 2010). Interpretation is based on hue, elevation, shadow, texture, pattern, shape, size and association, and depending on the familiarity of the interpreter to the image location, interpretation can either be spontaneous or by logical inference (Baks et al., 2012).

Baud et al. (2010) note that while this approach is labour intensive, especially while extracting detailed information for a large area or multiple time periods, it is often more reliable that semi-automated techniques as it can zoom to clusters of different sizes. Sliuzas (2004) finds the method preferable when objects of interest on images are smaller than pixel sizes, but cautions that combining digitized features from different interpreters may increase errors due to human subjectivity. Data gathered in this approach are validated by *ground-truthing* surveys, which serve to identify doubtful locations on map and to gather accuracy assessment test data. The study of Baud et al. (2010) in Delhi, for example, used 39 sites selected by random stratified sampling, and in 4 classes achieved an accuracy of 90%. It should be noted that accuracy will increase as the number of classes are reduced (Baks et al., 2012).

Change detection

This can been done directly from unclassified images by methods such as image differencing and image regression, or from classified images though methods such as post-classification comparison in which images of different dates are classified separately and compared (Rashed & Jurgens, 2010). An alternative method is GIS-based approach in which maps are overlaid, allowing visualization and quantification of change (Alkema, Bijker, Sharifi, Vekerdy, & Verhoef, 2012).

b) Predictor Variables

Also independent variable, this is a variable used in regression to predict another variable (Field, 2009). LRM uses GIS based predictors, being probable drivers of change gathered from literature and key informants (as discussed in Section 2.3). The model can take multiple variables which can either be continuous or categorical (Xie et al., 2005). Important to note is that predictor variables must not show dependency on each other as that may lead to unreliable parameter estimation and a false conclusion on the hypothesis (Jesshim, 2003). In the outputs of the LRM, the significance and the strength of each independent variable to predict the dependent variable is presented statistically.

c) Computer Application

Important software applications for LRM modelling include GIS, statistical software e.g SPSS and Imagine (Cheng, 2003), and image classification and processing software such as Erdas Imagine, ENVI and Idrisi (Rashed & Jurgens, 2010). Huang and Sin (2010) recommend use of *change analyst*, a GIS extension that combines all the processes of logistic regression including making prediction of change locations.

2.4.4. Modelling Eviction of Informal Settlements

Existing studies on eviction (e.g. Amnesty International, 2009; Megebhula, 1994; Schöpfer et al., 2007) have discussed eviction in its broader context, without attempting to separate spatial and non-spatial drivers of eviction. Consequently, modelling studies with dedicated interest in eviction are non-existent, at least in literature.

2.5. Policy and Informal Settlements

INSEs' intervention policies started in the 1950s and 60s, a time when state of INSEs got increased attention from urban researchers and policy makers. Before this time, governments perceived INSEs as temporary situations with no serious threat to long term urban development (Sietchiping, 2005). Responses have changed from time to time, with governments being forced to acknowledge that INSEs emerge as a result of failed policies (Fekade, 2000). Notable responses by governments include demolition and replacement of INSEs by public houses in the 1950s and 60s; provision of loans for housing and urban infrastructure (site and service) in the 70s; slum upgrading in the 80s; enabling strategies and security of tenure in the 90s; and *cities without slums* (CWS) action plans in the 2000s (Abbott, 2002; Amnesty International, 2009; Sietchiping, 2005).

Substantial criticism has been given to each of the aforementioned approaches. In the assessment of Hatuka and Saaroni (2014), these policies are mostly ineffective and slow in providing intervention. More critically, the UN-HABITAT (2003a) contends that the problem of INSEs are so superficially understood that applied interventions only tackle the symptoms rather than their underlying causes. The supply of housing in the 1960s, for example, could not satisfy the ever growing demand for housing, and neither could the site and service approach in the 60s be sustained as it depended heavily on unsustainable funding from external sources (Fekade, 2000). For slum upgrading, concerns raised are plentiful, most of them being around the issues of low supply against high and rising demand, slow implementation, progressively shrinking budgets, fast deterioration of upgraded housing, and gentrification brought about by the fact that living in the upgraded localities is beyond means of the poor (Berner, 2001; Imparato & Ruster, 2003). The latest initiative of *cities without slums* is commended for recognising poverty as the root cause of INSEs growth. Criticism of this approach is based on the fact that poverty is not the only cause of INSEs growth; the approach is unlikely to have significant and practical impact; the measures of improved life conditions are hard to define; and that it does not prescribe measures to stop emergence of new settlements (Sietchiping, 2005).

The general discussion on INSEs' interventions is extensive. A recent publication by Gouverneur (2015) discusses how to make future INSEs sustainable. The author urges planners to focus on all issues of urban development including balanced land uses, energy efficiency, water management, mobility, food security, community participation, good governance, productivity, competitiveness, and creation of identity and sense of place. Other experts urge governments to first legitimize INSEs through provision of services, security of tenure and development of sound policies (Payne et al., 2012; Shrestha et al., 2014; USAID Land Tenure and Property Rights, 2015). This multifaceted discussion converges at affirming the observation by Fekade (2000) that there is no single way of solving challenges of INSEs.

2.6. Growth and Eviction Policies for Nairobi – A historical Perspecive

Policy interventions for INSEs in Nairobi largely conform to the trends discussed in Section 2.5. Nairobi's settlements' pattern was shaped by the British colonial government when it developed the masterplan for the city in 1948 with an intent of segregating its population racially (Ngau, 2013). In the subsequent governments, city authorities failed to recognize INSEs in planning and provision of services, a result of which there was extreme inequality (Maina, 2013). A metropolitan growth strategy aimed at decentralizing the city functions where housing would be moved to the city satellite towns was developed in 1973, but the plan lacked funding as the city was then in debt (Ngau, 2013). Radical actions not entrenched in legal policy were taken in the late 1970s where the government massively demolished INSEs as a measure to *clean* the city (Ngau, 2013; Pamoja Trust, 2009). While an explicit government policy on INSEs is yet to be developed, various interventions projects triggered by funding opportunities from external sources have been initiated. For example, the Structural Adjustment Programmes (SAP) loan from World Bank in 1980 went to several development projects, housing included (Ngau, 2013). Numerous small-scale donor funded projects have been implemented in Kibera, Mathare and other locations.

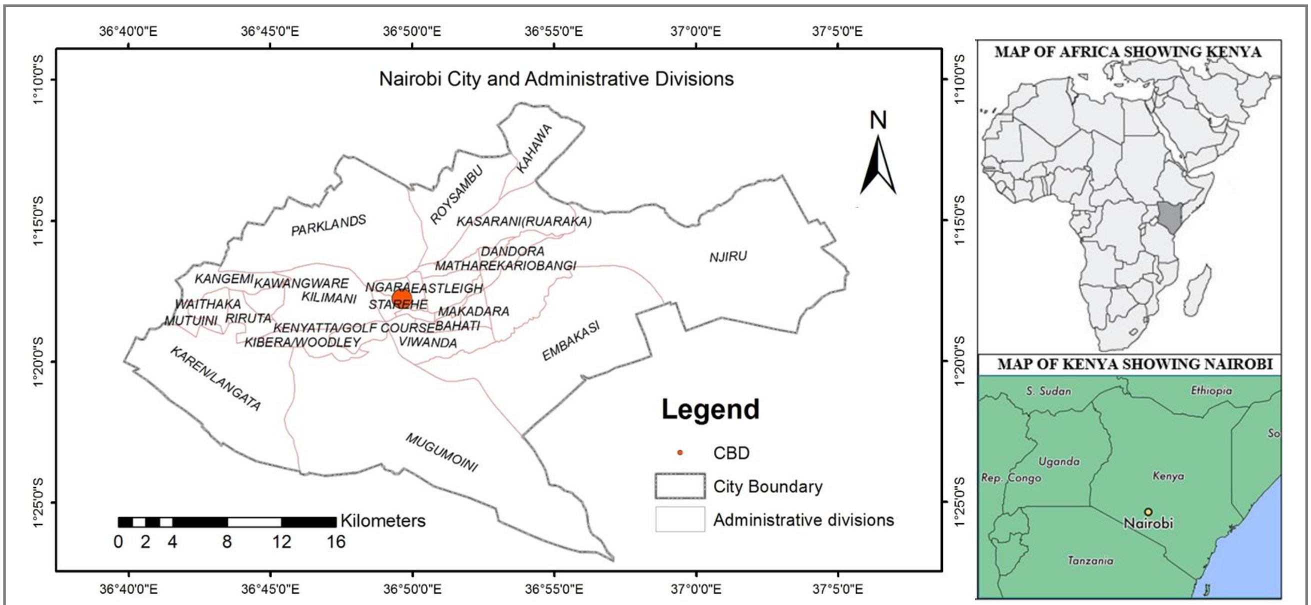
Legislations that would curb proliferation of INSEs are within the broader framework of city planning and have only been minimally dedicated to INSEs. Examples include: the introduction of the Department of Urban and Regional Planning in the University of Nairobi at 2003, launching of Kenya's Vision 2030 at 2008, creation of a new National Land Policy in 2009, and the preparation of Nairobi master plan in 2010. As regards eviction, only little progress has been made principally due to political sensitivity of the matter (Betzema, 2013). A draft anti-eviction and resettlement guidelines bill outlining clear procedures and conditions for eviction was developed in 2012, and the campaign for it to become law is ongoing (ESRC, 2012).

3. STUDY AREA, DATA AND METHODS

Discussed in this section are data, their processing and their application in the study. Also discussed is the study area, and how it relates with INSEs. Additionally, the overall study approach, data collection methods, and details of the modelling are discussion under the methods section.

3.1. Study Area

Nairobi is the capital city of Kenya in East Africa. Its CBD's geolocation is 1.2833^{o} South and 36.8167^{o} East (Figure 4). The city has a tolerable climate, and its elevation is between 1600 to 1850 metres above sea level (JICA, 2014). Elevation increases from east to west (see Figure 37) The city's area has expanded from 18 km^2 in 1898, to 696 km^2 in 1963, with its metropolitan region being 32,000 km^2 (APHRC, 2002). The rainfall for the city ranges between 639 to 899 mm, while annual temperature varies from 10^{o} to 29^{o} Celsius (ASDSP, 2015). Administratively, Nairobi has 8 divisions (Kibera, Pumwani, Makadara, Dagoretti, Embakasi, Central, Westlands and Kasarani), 46 locations and 135 sub locations.



Data source: Maplibrary (2015)

Figure 4: Location of study area

Nairobi existed before the colonial government as a major trading centres for local communities (APHRC, 2002). At 1899, Nairobi gained prominence when the colonial government made it an administrative headquarter following the completion of Mombasa-Nairobi railway (JICA, 2014). Its population has changed from 8,000 in 1901, to 118,000 in 1948, to 343,500 in 1962, to 827,000 in 1979, to 2.14 million in 1999, then to 3.13 million in 2009, and it is currently estimated at 3.4 million (City Population, 2015).

As earlier noted, the settlement pattern of Nairobi is a reflection of the settlement footprints created by colonial government. The natives were considered temporary residents of the city and were settled in camps on low-quality land, mostly near industrial areas and agricultural farms so as to provide labour for the city's production industries (Olima, 2001). The building density map in

Figure 5 shows the big contrast in density between locations; areas in red are mostly INSEs.

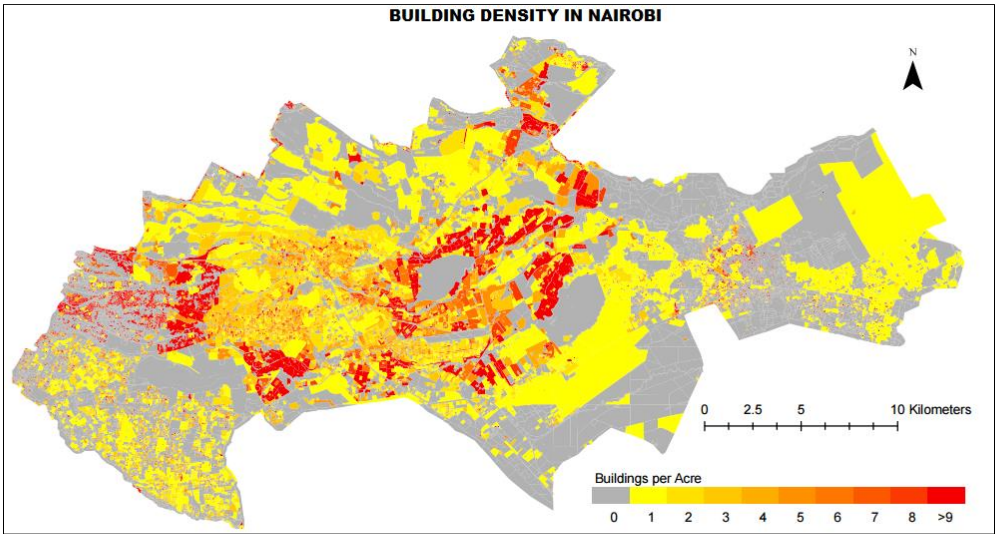


Figure 5: Building density in Nairobi
Adapted from NairobiGISmaps (2015)

About half of Nairobi's land is on residential use; other prominent land uses in the city include industrial, commercial, education and protected areas. Among the protected green areas are three forests (Karura, Ngong and Nairobi Arboretum) and a 117 KM_2 national park located at the southern part of the city. The agricultural land use which was prominent in the 1970s is fast reducing as it is converted to residential use to satisfy the rising housing demand triggered by urbanization (ASDSP, 2015). A land use map is shown in Figure 6. Landlessness is high, particularly among the urban poor. Historical land injustices, land grabbing and influx of job-seeking, semi-skilled rural-urban migrants are top causes of landlessness (ASDSP, 2015).

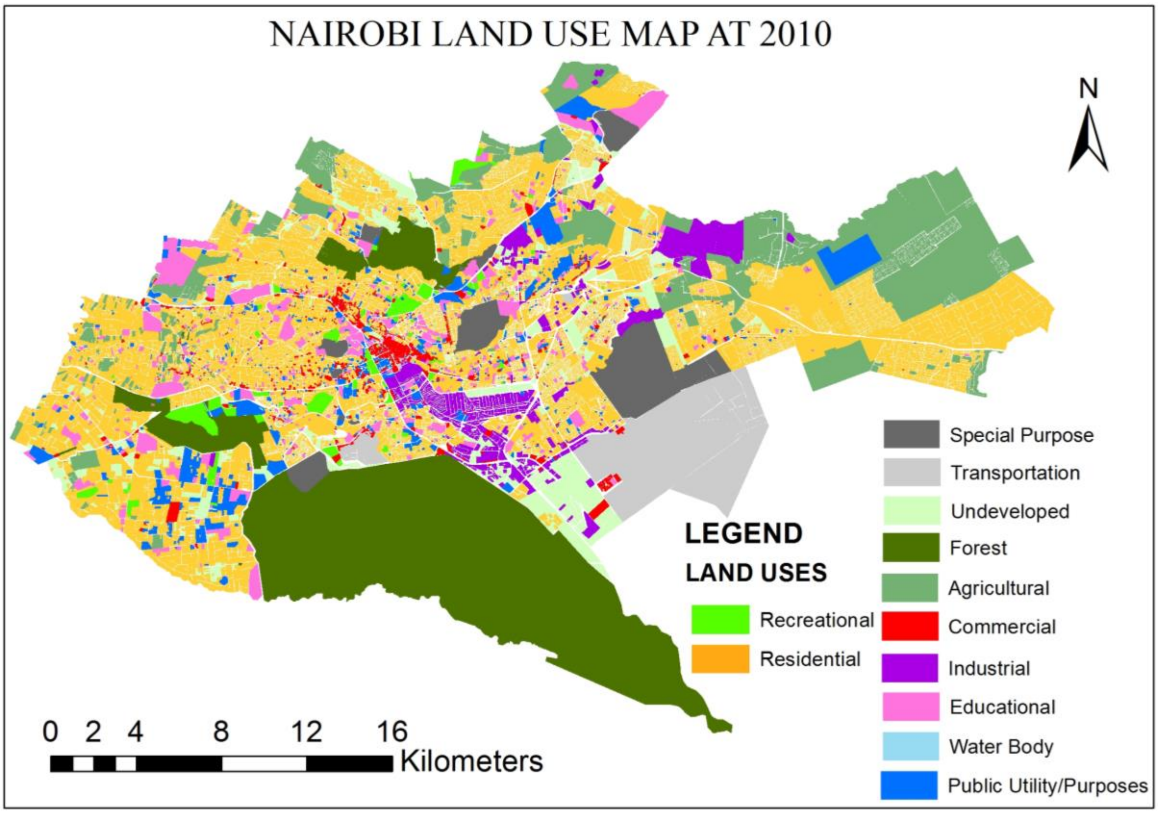


Figure 6: Nairobi land use map

3.2. Data and Methods Overview

Key stages in the study included review the necessary literature; preparation of datasets; quantification of INSEs' temporal changes; modelling expansion, densification and eviction; probability mapping; and integration of findings with INSEs policy for Nairobi. Specific data needs were derived from individual modelling sub-processes, which included expansion, densification and eviction modelling. These processes are shown in Figure 7, and their links explained in Section 3.2.2.

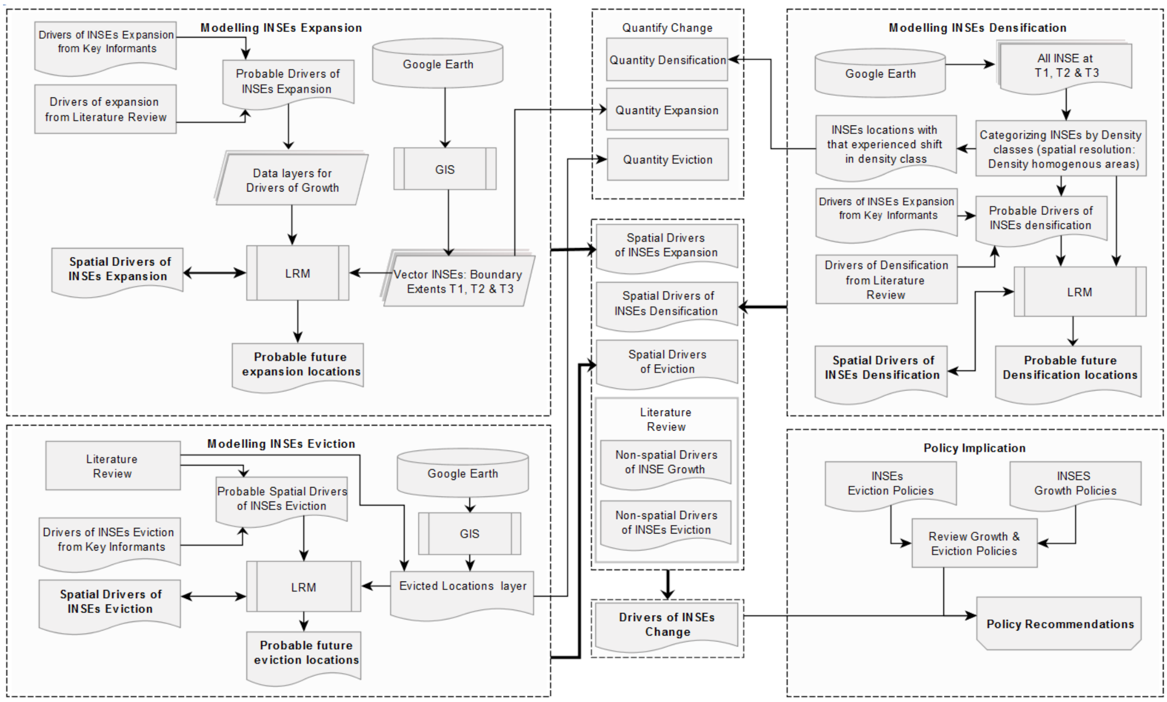


Figure 7: Flow chart of study methodology

3.2.1. Setting Modelling Environment

The study modelled expansion, densification and eviction separately. Based on data availability and review of related studies (e.g. Dubovyk et al., 2011), 3 modelling time steps were chosen at intervals of 5 years as: 2005 (T_1), 2010 (T_2), 2015 (T_3)[1]. All models were done by binary logistic regression in GIS environment but complemented by spatial statistics. In this environment, all data were adjusted to raster format – being the standard LRM data type. Cell resolution was set at 10*10 because INSEs in Nairobi only occupy 5% of the city landscape and are widely spread out (see Figure 15) that bigger cells sizes would have reduced precision at both quantification of spatial change and modelling. Further, all data were set to Transverse Mercator projection, WGS_1984_UTM_Zone_37S, being the commonly used projection for Nairobi.

For expansion modelling, reference is made to Section 4.1 where study findings led to categorization of INSEs in Nairobi into *Classic* and *Atypical*, the reason for which expansion modelling was done for the two INSEs typologies in three time steps, giving 6 models. Densification was modelled based on low, medium and high-density classes for three time steps, giving 9 models. Note that the study has not aligned densification models along the two INSEs typologies as this would have created 18 models, splitting the study area into locations too small for representative results. Eviction, being different from expansion and densification in that it incorporates all known cases of eviction since 1970s, was done in one integrated

[1] Between modelling time steps, time periods are defined as: P_1 – between year 2005 and 2010; and P_2 – between 2010 and 2015

model because interest areas are small and scattered that categorizing them on a temporal scale would have reduced their proportional sizes too small for any statistically reliable and generalized conclusions.

3.2.2. Summary of Modelling Processes

The modelling process started by locating INSEs in the city and characterizing them by typologies and densities (for T_1, T_2 and T_2). Overlaying these three INSEs layers produced statistics on expansion, densification and eviction locations. The trend was then analysed spatially and statistically to respond to study *objective 1*. Under each modelling sub-process, the first action was to gather data from literature and key informants, particularly probable drivers of change. In expansion modelling, the drivers were tested statistically in the LRM against *Classic* and *Atypical* INSEs locations. The important drivers were then used to show locations with high probabilities of converting to INSEs, following which the usefulness of the results in policymaking was assessed. Similarly, probable drivers of densifications were tested by LRM, and the strongest drivers used to map probability of locations to densify, results for which was also adopted to inform policymaking. A similar process for eviction was carried out. Finally, an assessment of existing policy for Nairobi's INSEs was made, leading to a discussion on how the modelling process is relevant to INSEs management. These processes respond to study *objective 2* and *3*.

3.3. Data Needs

This study has used secondary and primary data gathered in three main phases: (1) exploration of existing data; (2) extraction of data from imagery, and (3) data authentication and fieldwork. Details on these phases are discussed below:

3.3.1. Review of Existing Data

Non-spatial data were sourced from literature as has been discussed in chapter 2. On the other hand, spatial data came from different sources as: (Table 2).

Table 2: Existing data

	Data	Year	Format	Sources
1	INSEs for Nairobi	2015	Vector (shp)	ITC archive data
2	Railway	2010	Vector (shp)	ITC archive data
3	CBD	2010	Vector (shp)	ITC archive data
4	Rivers	2010	Vector (shp)	Pamoja Trust
5	Roads	2010	Vector (shp)	Pamoja Trust
6	Land use Map, 2010	2010	Vector (shp)	NairobiGISmaps (2015)
7	DEM, 30 metres resolution	2011	Vector (tif)	http://www.jspacesystems.or.jp/ersdac/GDEM/E/index.html
8	Business centres	2015	Vector (shp)	World Resource Institute (2015), updated in Google Earth
9	City Boundary	2011	Vector (shp)	World Resource Institute (2015)
10	City Sub-locations	2011	Vector (shp)	World Resource Institute (2015)
11	Population for sub-locations	2009 and 1999	Statistics (shp)	Kenya National Bureau of Statistics (2010)
12	Imagery for city	2005, 2010, 2015	Imagery (shp)	Google Earth
13	Built-up layer	1990, 2000 and 2014	Raster (tif)	Global Human Settlement Layer (GHSL – Landsat)

The ITC archive data has been used in a previous study in Nairobi by Sirueri (2015). The accuracy of this data was assessed by overlaying them with Google imagery and carrying out geo-reference checks. Visually satisfactory overlay match was realized in vector layers for INSEs, Railway, CBD, Rivers, Roads, Land use, business centres, city boundary, and built-up layer. Data for sub-locations showed a slight offset to the right, probably caused by a differences in datum and map projections during data creation (ESRI, 2015b), and this was adjusted manually by shifting to layer.

3.3.2. Extracting Data from Imagery

Multi-temporal INSEs data (INSEs' boundaries at 2005, 2010 & 2015) were extracted from Google Earth through on-screen digitizing with object identification elements being hue, elevation, shadow, texture, pattern, shape size and association (discussed in Section 2.4.3). Classes of interest were *Classic* INSEs and

Atypical INSEs, and based on literature (Sartori et al., 2002), local knowledge, and information from key informants, rules for discriminating these classes in the Google image were set as: (Table 3)

Table 3: Criteria for on-screen digitizing

		Level 1	Level 2	
No.	**Elements**	**Discriminating INSEs from Other built-up**	**Discriminating *Classic* from *Atypical* INSEs**	**Discriminating *Atypical* from *Classic* INSEs**
1	*Hue*	Silver and brown structures (tin roof & soil) Absence of variety in roof paints	Almost complete absence of green spaces within the settlements	Presence of some green spaces within the settlement
3	*Texture*	Rough-striped texture (iron-sheet roofs)	-	-
4	*Shadow*	Very short or no shadow (one level development)	-	-
5	*Pattern*	Irregular spacing between structures	Irregular street layout & Mixture of structures with different sizes and exist in an irregular manner	Some discernible basic street pattern Structures with almost similar sizes, often in a regular layout within clusters
6	*Shape*	Simple rectangular structures (simple geometry)	Simple geometry with roof overlaps and wavy edges	Simple but crisp roof geometry, especially rectangles
7	*Size*	Presence of small structures & Narrow streets or lack of streets	A wide range of structure sizes from very small to large	Even sized structures, particularly within clusters
8	*Association*	Structures joined to each other & Lack of regular brown and green spaces between structures	Very compact; paths between structures rarely visible	Lesser compact, with visible pathway between structures & May exist between formal development

a) On-screen Digitizing and Limitations

Based on the criteria presented in Table 3, an existing layer of Nairobi INSEs' outline from ITC achieves was overlaid with Google Earth base map for year 2015 and boundaries updated. Accordingly, this layer was further overlaid with Google base map at year 2005 and 2010 and revised to produce new feature files. An example of a digitized section of Nairobi is shown in Figure 8. This was done by one interpreter (author) for data consistency.

The challenge of uncertainly was encountered, with locations hard to classify being marked for ground verification. However, due the scale of the city, locations with uncertainly were sampled and those with similar characteristics classified on inference. Seven (7) locations were visited and used to updated 16 locations of with uncertainties. Locations associated with this challenge were mostly at the city periphery, on what was formerly agricultural fields but now urban. These locations appeared to be at the middle of formal-informal settlements' continuum (see example in Figure 9). Clarity was achieved with the help of physical planning experts, and classification done based on the criteria outlined in Section 4.1.

An additional limitation to this exercise has been expressed by Kohli (2015) who notes that authorities, researchers, key informants and local people may have different perceptions on settlement' boundaries; while some consider open spaces between a settlements as part of INSEs, for example, others does not. Limited by time, this study did not define INSEs with the resident community, and therefore used the INSEs' boundary limits visible from imagery or as adjusted based on the opinion of key informants. Therefore, locations that are undeveloped but considered part of a settlement by residents are left out of this study.

Figure 8: Vector data generation from Google Earth

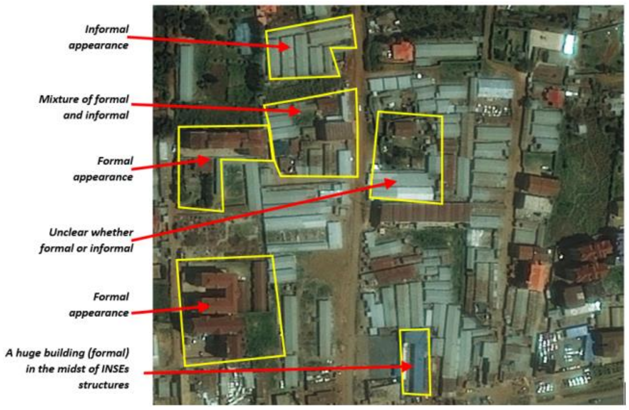


Figure 9: A map of an area with mixed development (formal & informal)

b) Ground-Truth Data

The validity of the digitized data was tested during fieldwork. Within the extents of INSEs' layer for 2015, 100 random points were generated in GIS. The decision to limit sample points to the digitized location was informed by the fact that Nairobi is spatially vast, and with INSEs being only 5% of it, sample points over the whole city would very likely dedicate only 5% of fieldwork effort to the locations of interest. To ensure randomness in distribution, minimum distances between points were set at 500 metres, a measurement set based on effect-checking on different measurements. Further, to overcome the insecurity challenge of travelling around INSEs with huge digital equipment (as these locations often have high crime rates (Wakhungu et al., 2010)), the study area was divided into 10 clusters based on proximity of settlements, and A3-size maps printed for each cluster (see Figure 10). During field visit, locations were tracked using a handheld GPS complimented by manual map-navigation.

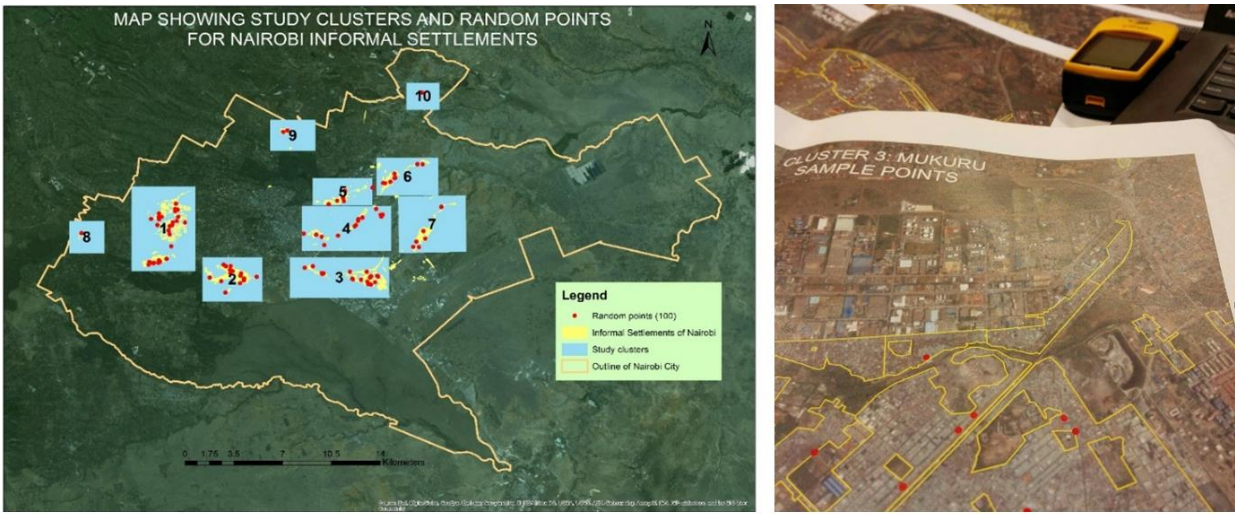


Figure 10: INSEs cluster used during fieldwork (left); and image at fieldwork (right)

The reason for *ground-truth* data validation was to check whether all digitized locations were INSEs, and that *Classic* and *Atypical* INSEs were rightly classified. Therefore, for each ground sample point, characteristics that define the type of settlements were checked. They included: land tenure, roof coverage, water connection, sanitation system, electricity, nature of building, and layout pattern. Based on this, statistics on correct classifications was produced. A screenshot of the field visit form is in Figure 36 (Appendix B).

3.3.3. Key Informants

The selection of key informants was based on the criteria applied by Thapa and Murayama (2010) which limits informants to persons with university degrees and an evident track record in the subject area. Additionally, this study considered only informants actively involved in INSEs studies in Nairobi. In this regard, targeted respondents were from the planning department of Nairobi City County Government, physical planning firms, NGOs dealing with INSEs, institutions of higher learning, and slum dwellers organizations. The study targeted a minimum of 10 respondents. Twenty-five (25) respondents were identified, and contacted by e-mail prior to fieldwork, where 15 confirmed availability for an interview during fieldwork. At the time of data analysis, only 10 had either been reached for interview or responded to the study questionnaire, three of whom were not part of the original number; they were admitted to the study in a snowball approach (Kumar, 2011). The qualifications of the respondents are in Table 24 (Appendix A).

The key-informants questionnaire, which was also the interview schedule (Appendix A), gathered data on spatial and non-spatial drivers of expansion, densification and eviction. Pre-determined responses were provided on a *likert*-scale with 4 levels as: (1) very strong driver; (2) strong driver; (3) weak driver and (4) not a driver. The questionnaire gave provision for additional responses and ideas. Weights along the *likert*-scale (Table 11) were used to rank responses. A value averaging between 0 and 0.5 was considered to be for *not a driver*, from 0.5 to 1.5 for *weak driver*, from 1.5 to 2.5 for *strong driver*, and from 2.5 to 3 for *very strong driver*. Therefore, with ten respondents, rating from the summations were computed as: 0 to 5 – *not a driver*; 5 to 15 – *weak driver*; 15 to 25 – *strong driver*; and 25 to 30 – *very strong driver*. Responses from key informants and their weights based on this scale are in Appendix G.

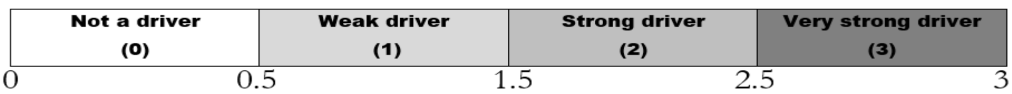


Figure 11: Likert scale for drivers rating

Further to ranking responses, all drivers identified by key informants and with available spatial data were incorporated into the LRM. A comparison of the drivers from key informants and modelling process was done at the end of the modelling process.

3.4. Methods for Change Quantification

Change statistics were computed in GIS by overlay analysis. INSEs layers for T_1, T_2 and T_3 were reclassified in a way that their code summation after a union analysis produced unique codes able to explain transformation of every location from T_1 to T_3 through T_2 based on a three digit code (see Table 4 and Table 5).

Table 4: INSEs change analysis codes

	Classic Codes	*Atypical* Codes
INSEs 2005	100	200
INSEs 2010	010	020
INSEs 2015	001	002

Table 5: INSEs change quantification code interpretation

Code	Interpretation	Code	Interpretation
111	*Classic*: No change from T_1 to T_3	222	*Atypical*: No change from T_1 to T_3
011	*Classic*: Growth at T_1	022	*Atypical*: Growth at T_1
001	*Classic*: Growth at T_2	002	*Atypical*: Growth at T_2
100	*Classic*: Evicted at T_1	200	*Atypical*: Evicted at T_1
010	*Classic*: Growth at T_1 & Evicted at T_2	020	*Atypical*: Growth at T_1 & Evicted at T_2
110	*Classic*: Evicted at T_2	220	*Atypical*: Evicted at T_2
101	*Classic*: Evicted at T_1 but returned at T_2		

The proportion of the city's built-up area under INSEs in percentage was computed as: (Equation 1)

$$P_{T1} = \frac{A_{T1}}{A_B} * 100 \tag{1}$$

Where P_{T1} is the proportion of INSEs at T_1, and A_{T1} is the area of INSEs at T_1, and A_B is the total built-up area of the city.

Expansion of INSEs from T_1 to T_2 and T_3 in percentage was computed based on: (equation 2) (Central Statistics Office, 2015).

$$P_C = \left(\frac{I_{CP} - I_{PP}}{I_{PP}}\right) * 100 \tag{2}$$

Where P_C is the percentage INSEs expansion, I_{CP} is the INSEs area for current period, and I_{PP} is the INSEs area at the previous period.

Annual INSEs expansion (by percentage) was computed by dividing the area of accumulated growth between T_1 and T_3 by study the period in years and making it a fraction of INSEs area at T_1: (Equation 3)

$$P_{C(A)} = \left(\frac{I_{T3} - I_{T1}}{Y_{T3} - Y_{T1}}\right) / I_{T1} * 100 \tag{3}$$

Where $P_{C(A)}$ is annual INSEs expansion in percentage, I_{T3} and I_{T1} are INSEs areas at T_3 and T_1 respectively, and Y_{T3} and Y_{T1} are time (years) for INSEs T_3 and T_1 respectively.

Similarly, for densification and eviction, change between modelling time steps was computed first by summing up the area of locations that experienced change, presenting it as a fraction of total INSEs area, and converting it to percentage (Equation 4).

$$P_{D/E} = \frac{I_{D/E}}{I_{PP}} * 100 \tag{4}$$

Where $P_{D/E}$ is the percentage of densification or eviction (depending on which is being computed); $I_{D/E}$ is the INSEs area that experienced densification or eviction between two time steps, and I_{PP} is the INSEs area at the base year.

3.5. Defining Models and their Variables

To generate results for expansion modelling (2 typologies for 3 time steps), densification (3 density classes for 3 time steps) and eviction, a total of 16 models was set up, where a naming convention was developed for convenient reporting. The convention combined the feature being modelled, model class and year as M(model), C(class), Z (year). Feature labels were $_{EX}$ for expansion, $_{DE}$ for densification, and $_{EV}$ for eviction. Classes under expansion were $_{CL}$ for *Classic*, and $_{AT}$ for *Atypical*; while classes under densification were $_{L, M}$ and $_{H}$ for low, medium and high respectively. Accordingly, the year of the models were labelled as *05*, *10* and *15* for 2005, 2010 and 2015 respectively. Models named by this convention are listed in Table 31, Appendix H.

Dependent variables were binary for all models. The two categories were *INSEs locations* and *other built-up areas* for expansion models; *densified location* and *other INSEs locations* for densification models; and *evicted location* and *other INSEs locations* for eviction models. Classifying density classes into low, medium and high density from imagery was based on visual interpretation. Estimated roof coverage of <30% was taken as low-density; between 30 and 60% as medium-density and >60% as high-density. These classification boundaries were set with key informants, where computation of percentage roof coverage (PRC) is based on Equation 5 (Sliuzas, 2004).

$$\text{PRC} = \frac{\text{sum of roof area}}{\text{area of settlment}} * 100 \tag{5}$$

Probable drivers included in the models combined spatial driver from key informant and literature. Expansion and densification had similar probable drivers, but different from eviction (Table 6). Variables from key informants that were dropped from the model for lack of reliable data included land tenure and land value under expansion and densification, and proximity to prime investments for eviction.

Table 6: Probable factors of expansion, densification and eviction

Model Type	**No.**	**Site-specific characteristics**	**No.**	**Proximity characteristic**	**No.**	**Neighbourhood characteristics**
Expansion and densification	X_1	Slope	X_3	Distance to industrial areas	X_9	Close interaction with undeveloped land
	X_2	Population density	X_4	Distance to rivers	X_{10}	Close interaction with INSEs land uses
			X_5	Distance to roads	X_{11}	Close interaction with commercial land uses
			X_6	Distance to railway	X_{12}	Close interaction with planned residential land uses
			X_7	Distance to CBD	X_{13}	Close interaction with transport land uses
			X_8	Distance to business centres		
Eviction	E_1	Population density	E_4	Distance to rivers	E_8	Distance to business centres
	E_2	Existence on rail wayleave	E_5	Distance to protected areas (environmentally sensitive)	E_9	Proportion of commercial land in the neighbourhood
	E_3	Existence on road reserve	E_6	Distance to protected areas (government)	E_{10}	Proportion of INSEs in the neighbourhood
			E_7	Distance to CBD		

In expansion and densification modelling, under site-specific characteristics were *slope* (X_1) and *population density* (X_2). The DEM was used to generate slope value while population census data for years 1989, 1999 and 2009 were used to establish the population change trends. At the spatial units of sub-locations, growth rates for each spatial units were calculated and used to project populations exponentially for the modelling periods 2000, 2005 and 2015 based on equation 6 (Wou.edu, 2015).

$$\text{N} = \text{N}_0 \text{ (e) kt} \tag{6}$$

Where e is the exponential constant (2.71828), N is future value; N_0 is present value, k is the rate of increase, and t the number of years in which growth is measured.

For proximity characteristics, Euclidean distances were used, with maps for *distance to industrial areas* (X_3), *distance to rivers* (X_4), *distance to roads* (X_5), *distance to rail* (X_6), *distance to CBD* (X_7) and *distance to business centres* (X_8) produced at the modelling resolution of 10*10. Spatial units for Euclidean maps were kilometres.

Under neighbourhood characteristics, the effect of neighbourhood interaction was created by use of focal statistics (ESRI, 2015c). Effects of various neighbourhood windows were tested by comparing their neighbourhood influence and actual growth on locations. Optimal neighbourhood interactions was set at 90 metres, implemented on a 9*9 moving window, inputs being binary maps for neighbourhood factors (set at 1 for location of interest and 0 for other location). Output maps cell values ranged from 0-81 and were standardized for use in the LRM. Factors under this category include: *proportion of surrounding undeveloped land* (X_9), *proportion of surrounding INSEs* (X_{10}), *proportion of surrounding commercial land* (X_{11}), *proportion of surrounding planned residential areas* (X_{12}), and *proportion of surrounding transport land uses* (X_{13}). Not to be confused with *distance to railway* and *roads*, X_{13} has transport related land uses including bus stops, airports, rail stations and land reserved for future transport uses.

In eviction modelling, under site-specific characteristics, *population density* was treated differently because eviction (and also densification) analysis was limited to INSEs locations, where majority of settlements barely extends outside one sub-location. Using sub-location densities would therefore have led to much generalization, effectively ignoring density variations within settlements. Consequently, INSEs locations were mapped and analysed by their density classes (low, medium and high) at their respective modelling time step for densification, and at their time of eviction for eviction locations. Under proximity characteristics, *existence of INSEs on road* and *railway reserves*, binary maps (reserve and other locations) were created, the reserve being 60-metre buffer strips along the roads and railway. The buffer width was based on planning standards in the Physical Planning Act (GoK, 2012b). *Distance to protected areas* were generated on Euclidean distances. Other variables in the eviction model correspond to those in expansion and densification models.

3.6. Logistic Regression Modelling

3.6.1. Process Summary

For each of the 16 models in the study, the regression analysis was run separately. However, a generalized process is summarized in Figure 12.

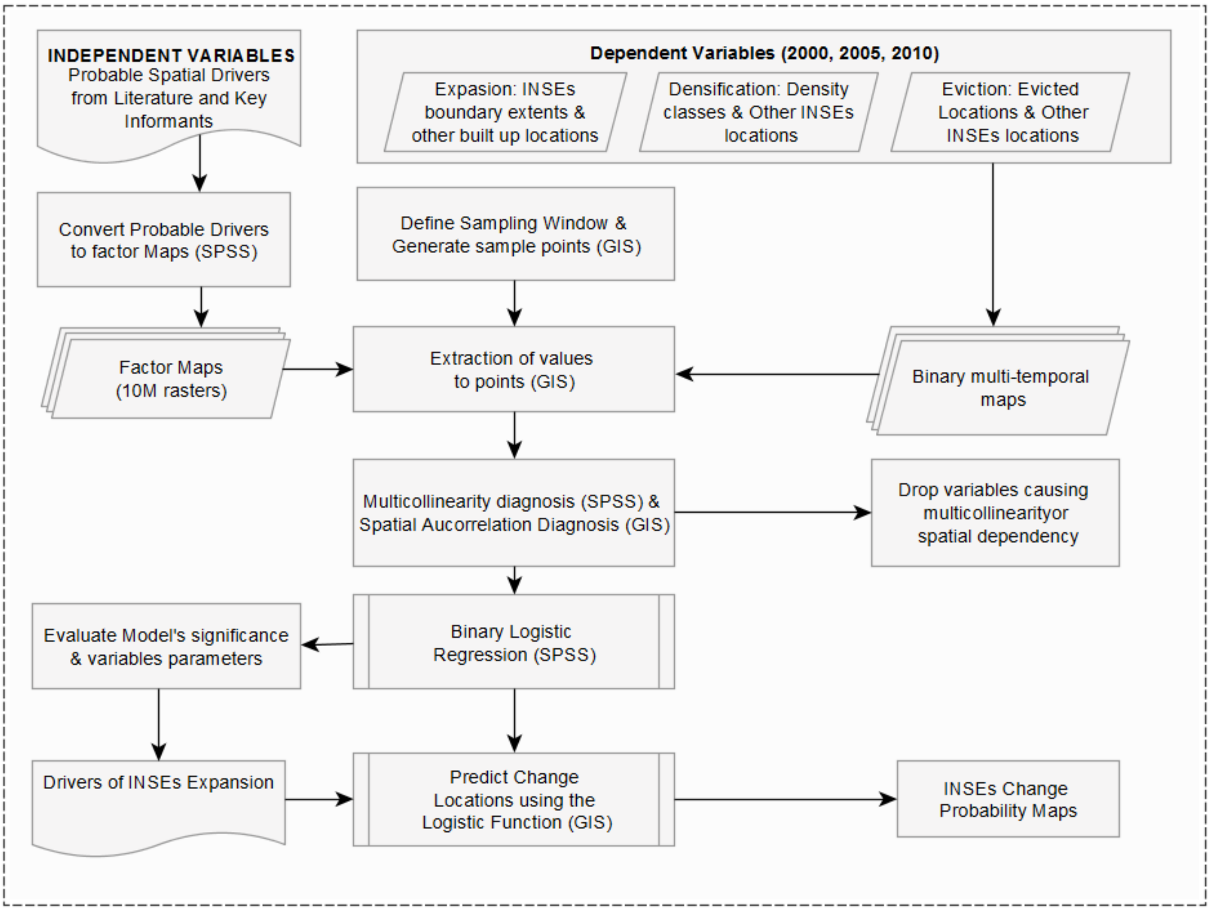


Figure 12: The LRM process

The process involved rasterization of independent variables, production of factor maps, generation of sample points, and extraction of values from all variables to the points. The points' layer was then moved to a statistical program (SPSS), from where tests for multicollinearity, spatial autocorrelation and endogeneity were carried out. Independent variables found to cause either multicollinearity, spatial autocorrelation or endogeneity were eliminated, and logistic regression analysis carried out on the rest. The regression output was interpreted and variables ranked by their strengths based on odds ratios. Subsequently, significant variables were used to produce probability maps, which were then overlaid with land use maps to further spatial analysis.

3.6.2. Sampling

Masser and Cheng (2003) observe that LRM models develop spatial dependency as a result of sampling; random sampling has been found to cause such spatial interdependency, which has been improved by employing other methods as stratified random sampling and also increasing distances between sample locations. These approaches have relative weaknesses e.g. stratified random sampling may lead to loss of information. Noting that spatial autocorrelation is subject to distance decay, Huang et al. (2009) recommend use of regular sampling technique of non-overlapping windows. In this method, smaller windows increases the sample size which is compliant to the needs of the maximum likelihood methods of LRM. In different studies (e.g. Dubovyk et al., 2011; Huang et al., 2009; Nduwayezu, 2015), appropriateness of sampling windows have been tested starting from small windows of 3*3, 5*5 and 7*7. In this study, non-overlapping square windows of 3, 5 and 7 cells were used to generate sample points, and their performance tested.

3.6.3. Testing Multicollinearity

Multicollinearity happens when two or more predictor variables of a regression model have a strong correlation (Field, 2009). If present, it creates bias while interpreting the influence of explanatory variables (Qian & Ukkusuri, 2015). The SPSS diagnostic variance inflation factor (VIF) is the most used method for testing multicollinearity because is able to capture more subtle forms of linear relationships (Field, 2009). Qian and Ukkusuri (2015) propose a two-step check of multicollinearity: Calculate Pearson's moment correlation and eliminate variables with coefficients greater than 0.7; then, compute tolerance and VIF following ordinary least square (OLS) analysis and eliminate variable with VIF values of more than 10. (Jesshim (2003) informs that a tolerance value of less than 0.1 can be taken to indicate multicollinearity. Computing tolerance (*T*) values for the *i*th factor is shown in equation 7, while VIF, which is the reciprocal of the tolerance value is shown in equation 8 (PennState Science, 2015). An R_K of 0 means no correlation between that factor and the remaining independent variable, and this will give a VIF_K of 1 (NIST, 2015).

$$T = 1 - R_k^2 \tag{7}$$

$$VIF_K = \frac{1}{1-R_K^2} \tag{8}$$

Where *T* is tolerance factor, *K* is the factor, and $R^2{}_k$ is what is obtained in its regression on the remaining predictors.

Multicollinearity is solved by combining highly correlated variables through principal component analysis or removing one or more predictor variables (NIST, 2015); the latter approach has been applied in this study.

3.6.4. Testing Endogeneity

This problem emerges when a correlation exists between the dependent variable and a model's error term i.e. the part of the model that is not explained by the independent variables (Lewbel, 2004). Causing this could either be omitted variables or simultaneity, where X causes Y, or Y causes X (Freedman & Berk, 2008). Avery (2005) states that the problem is often overlooked while building statistical models and can result to incorrect regression coefficients and also multicollinearity, biasing interpretation of the H_0 and increasing type II errors. Endogeneity is detected from model's coefficients, which becomes larger than true values. Field (2009) notes that large coefficients inflate standard errors, which may result to *Wald statistics* (discussed in Section 3.6.7) being underestimated.

3.6.5. Testing Spatial Autocorrelation

Spatial autocorrelation tests how similar objects are to the nearby objects, and is its absence in modelling creates more robust and replicable results (IDRE, 2016). An appropriate tool for testing spatial interdependency is the *Moran's I* (Overmars, De Koning, & Veldkamp, 2003). This tool is an inferential statistic interpreted in the context of H_0 that states: attributes analysed have complete spatial randomness on the study area (ESRI, 2015a). *Moran's I* values ranges from -1 to 1, with zero showing randomness (true to H_0), values towards -1 showing a tendency toward dispersion and 1 towards clustering (both false to H_0) (Li, Calder, & Cressie, 2007). At significant p-values (i.e $p<0.05$) H_0 is rejected. Similarly, when transformed to z-scores, *Moran's I* values smaller than -1.96 or greater than 1.96 will indicated significant spatial autocorrelation when $\alpha=0.05$ (ESRI, 2015a). Equation 9 is for *Moran's I* (Cliff, 1980). Each models' *Moran I* was computed on LRM residuals in GIS for each sample point.

$$I = \frac{N}{\Sigma_i \Sigma_i w_{ij}} \frac{\Sigma_i \Sigma_i w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\Sigma_i (X_i - \bar{X})^2} \tag{9}$$

Where *N* is the number of spatial units; *I* and *j* are indexing for the spatial units; *X* is the variable of interest and $\overline{X}$ is its mean; and w_{ij} is a matrix element of spatial weights.

3.6.6. Principles of Logistic Regression

Also logit model, this model uses statistical analysis to establish relationship among variables where dependent variables are binomial or multinomial (Christensen, 1989). This model allows prediction of outcomes using predictor variables which can either be categorical or continuous. The methods uses odds (Equation 10) to deal with the binary structure, where Y=1 is an expression of probability of an even occurring (P), and Y≠1 an expression probability of an even not occurring (1 - P) (Lesschen et al., 2005).

$$\text{odds} = \frac{P}{1 - P} \tag{10}$$

In the logistic regression approach, the odds are transformed to natural logarithms, producing a variable that varies from negative infinity to positive infinity, as expressed in Equation 11 (Lesschen et al., 2005).

$$\text{logit } Y = \text{In}\left(\frac{P(Y=1)}{1-P\ (Y=1)}\right) \tag{11}$$

As the odds decrease from 1 towards 0, the logit of Y becomes negative; conversely, it becomes positive and increasingly large as the odds increases from 1 to infinity. This transformation to natural log is used as alternative input for the dependent variable to solves the problem of estimated probability exceeding maximum and minimum possible values for the probability (Moore, McCabe, & Craig, 2009). Thus, the equation of the dependent and independent variables in a multiple logistic regression becomes: (Equation 12).

$$\text{logit}(Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k \quad (12)$$

Where α is constant; $\beta_1, \beta_2 \ldots \beta_K$, coefficient of predictors; and $X_1, X_2, \ldots X_k$, their predictors.

When the logit function is converted to the odds by exponential, it produces the probability function, P(Y=1). This is expressed in equation 13 (Lesschen et al., 2005).

$$P(Y=1) = \frac{e^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)}}{1 + e^{(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)}} \quad (13)$$

Where e is natural logarithm base; α, intercept at y-axis; *β*, regression coefficients, and X predictor variables.

3.6.7. LRM Output Variables

LRM produces multiple coefficients for both model performance and contribution of variables to the model. Evaluating alternative measures provide an opportunity to assess the strength of the model, variables, and sensitivity when a variable in included or excluded. Utilized output variables in this research include:

Variables' coefficients (b)
This variable will show how much change the dependent variable should have when the predictor variable increases by one, while assuming other variables remain constant (Field, 2009). They are computed using maximum likelihood estimator (Overmars et al., 2003). The value may be positive or negative, where an increase in the predictor variable will translate into an increase in the probability of change for positive coefficients, and a decrease for negative coefficients (Masser & Cheng, 2003).

P-values
LRM output variables are interpreted either to accept or reject the H_0 whose expression is that there is no significant relationship between the dependent and the independent variables in the model. P-values (probability of H_0 being true) is assessed against a significant level alpha (α) to find evidence against null hypothesis. When p-values are lower than alpha (α), the H_0 is rejected, and when p-values are higher than α, the H_0 is accepted (Bland & Altman, 1995). This is also the basis for dropping variables from the model.

Wald statistics
These statistics are used to give the individual contribution of each variable in the model (Field, 2009). Wald statistics have a chi-square distribution and will tell whether the coefficient for each predictor is different from zero, and thus having a significant contribution to the model. Wald is computed as: (equation 14)(Moore et al., 2009).

$$\text{Wald} = \frac{b}{\text{SE}_b} \quad (14)$$

Where *b* is the coefficient of the predictor and SE_b its standard error

Pearson's chi-square
These values are also used to check models' goodness of fit by comparing frequencies observed with frequencies that would be expected by chance (Field, 2009). The chi-square is used as a basis for judging the H_0. When there is significant difference between the expected frequencies and the observed, then the H_0 is rejected. Its computation is as: (equation 15) (Field, 2009).

$$\chi^2 = \sum \frac{\left(\text{observed}_{ij} - \text{model}_{ij}\right)^2}{\text{model}_{ii}} \qquad (15)$$

In which X^2 is the chi-square, and i and j the rows and the columns in the contingency table respectively.

Odds Ratio (O.R)
These are the exponentiation of the variables' coefficients. The values are used to give the odds that an outcome increases or decreases when there is a unit change in associated variable (NCRM, 2015). A value of 1 will show no change in the odds after a unit increase in the independent variable, more than 1 will show an increase in the odds, and a value less than 1, a decrease in the odds (Christensen, 1989). This measure has been used in the research to rank the drivers of change.

Percentage of Correct Prediction (PCP)
This measure assesses the utility of a LRM by giving a percentage of the correctly predicted cases based on the full logistic function. PCP of the model is based on the contingency table showing the cases that were 1 and predicted to be so; 0 and predicted to be so, 1 and predicted to be 0; and 0 predicted to be 1 (NCRM, 2015).

Standard Error
These values have been used to show standard errors associated with the coefficients, and are of use in forming confidence interval for parameters. Dividing parameter estimates by the standard error gives t-values (Field, 2009). In the output table in this research, associated errors are shown alongside variables coefficients.

Log likelihood
These values are also useful in checking the model's performance (Lesschen et al., 2005). The statistics give an indication of unexplained information after a model fit (Field, 2009). This translates into large values for a poor model and low values for better models. Equation 16 (Field, 2009) shows how log likelihood values are derived. Application for *log likelihood* is often for comparing a model with another other, or checking how additional variables improve the model. The latter is done by subtracting the new models value from the baseline model (Field, 2009).

$$\text{log-likelihood} = \sum_{i=1}^{N} \left[Y_i \ln(P(Y_i)) + (1 - Y_i)\ln(1 - P(Y_i))\right] \qquad (16)$$

In which $P(Y_i)$ is the probability of occurrence for Y_1

3.7. Probability Mapping

After identification of the drivers of change and their influence statistically, probability mapping was done with an objective of showing locations with higher likelihood of developing INSEs in future. This is done based on the probability function in Equation 17 (Field, 2009), which is in principle similar to Equation 13.

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots + b_n X_{ni})}} \quad (17)$$

To test reliability of the probability mapping, probability values for maps generated from 2005 and 2010 models were extracted to sample points generated on real growth (expansion and densification) locations at period 1 (2005-2010) and period 2 (2010-2015) respectively. This was then visualized by box and whisker plots in order to show distribution of probability values on growth locations. Further, probability maps were reclassified into quantiles (5 quantiles to represent very high, high, medium, low and very low probability values), and statistics of expansion and densification locations in each quantile produced. This tests the hypothesis that growth locations for time *T* are to be found within the very high probability map locations showed by the model of time *T-1*, where *1* is a modelling time step.

Accordingly, the very high probability locations for the models in 2015 are used to show on the land-use map of the city the locations at very high probability of converting to INSEs or experiencing densification of INSEs. Characteristics of these locations are discussed, and further adopted for use in the discussion on policy formulation and future INSEs management.

4. RESULTS

This chapter presents the findings related to the following subjects: description of INSEs in Nairobi, ground-truth findings, quantification of INSE's changes and their drivers as gathered from key informants and as realized from the modelling processes.

4.1. Variations in Nairobi's INSEs

From literature, imagery examination and fieldwork, significant variations in Nairobi's INSEs were noted, resulting to their categorization into two Typologies, named *Classic* and *Atypical* INSEs[2] by this research. Locations with a *Classic* character have what many studies (e.g. GUO, 2003; UN-HABITAT, 2003b; World Bank, 2006) qualify as informal settlements by all their proxy indicators. They include lack of enough living space, spatial planning, proper sanitation, access to water, durable housing and security of tenure. Other INSE locations show a character towards formality but are below the threshold of formal settlements – where this study takes formal settlements as settlements that do not show the qualities of INSEs aforementioned. Named *Atypical* settlements for the reason that they are not *typical* INSEs, these settlements have a mix of overcrowded (3 people per habitable room (GUO, 2003)) and not overcrowded dwellings; show basic spatial layout; have basic sanitation facilities; and possesses some form of security of tenure. In essence, levels of deprivation[3] are higher in *Classic* than in *Atypical* settlements. Criteria for separating these typologies is set as: (Table 7)

Table 7: Defining *Classic* and *Atypical* INSEs

Defining Elements	INSEs *Classic*	INSEs *Atypical*
Housing	Shanty/shack housing	Semi-permanent housing/ more durable housing
Layout	Haphazard layout, with no clear street layout	Exhibits basic planning efforts e.g. some streets network is identifiable from images
Housing/Roof density	Very high density (when fully occupied - mostly more than 70% roof coverage on land)	Lower density than *Classic* (roughly 50-70%), with some green spaces
Community and utility services	Very poor drainage and sanitation	Some drainage and sanitation efforts but not to the required standards
Land tenure	Virtually no security of tenure	Legal Tenure/Formal permit/formal recognition

On imagery, elements to discriminate *Classic* from *Atypical* INSEs are discussed in Section 3.3.2b. Examples of digitized *Classic* and *Atypical* INSEs on imagery and their corresponding photos are in Figure 13. It is noted that, with local knowledge, the two typologies could be identified by spontaneous recognition on image and in the field.

4.1.1. Ground-truth Findings

Results from field data on ground-truth points (only generated on INSEs locations) showed that 97% of the locations were correctly classified as either *Classic* or *Atypical* INSEs. This was based on the ground-truth checklist (Figure 36 in appendix B & explained in Section 3.3.2). The 3% ground locations wrongly classified were at a section of Mukuru settlement where roof pattern is very regular, making what is *Classic* settlement appear as *Atypical*. During fieldwork, it was established that the settlement was very dense and congested, with very poor services and housing quality. Data on that location were rectified.

[2] Type 1 and Type 2 INSEs are alternative names for *Classic* and *Atypical* INSEs respectively

[3] Based on slum dwellers' five deprivations in UN-HABITAT, (2014)

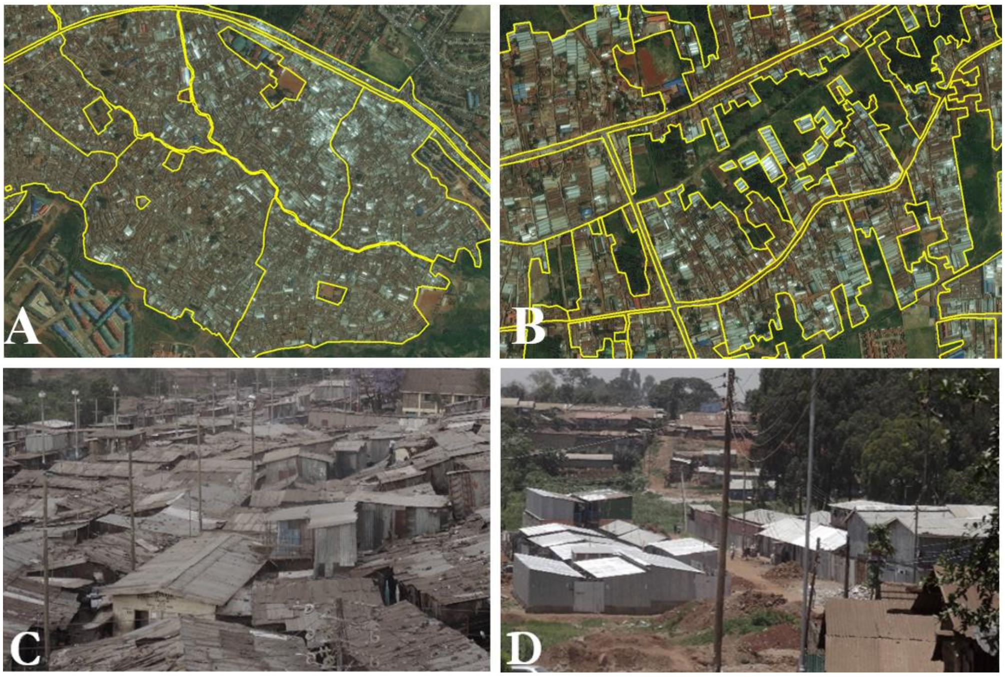


Figure 13: *Classic* INSEs' imagery (A) & photo (C); and *Atypical* INSEs' imagery (B) and photo (D)

4.2. Locating INSEs

Figure 14 shows location of INSEs in Nairobi by typology at year 2015 as generated from on-screen digitizing (INSEs at 2005 and 2010 are in Figure 38, Appendix D). A total of 153 settlements were identified, but found to vary extensively in size that reporting based on their number could result to misrepresentation. Results show that *Classic* settlements are located more at the central and northern parts of city while *Atypical* INSEs are at the western and middle-eastern parts of the city.

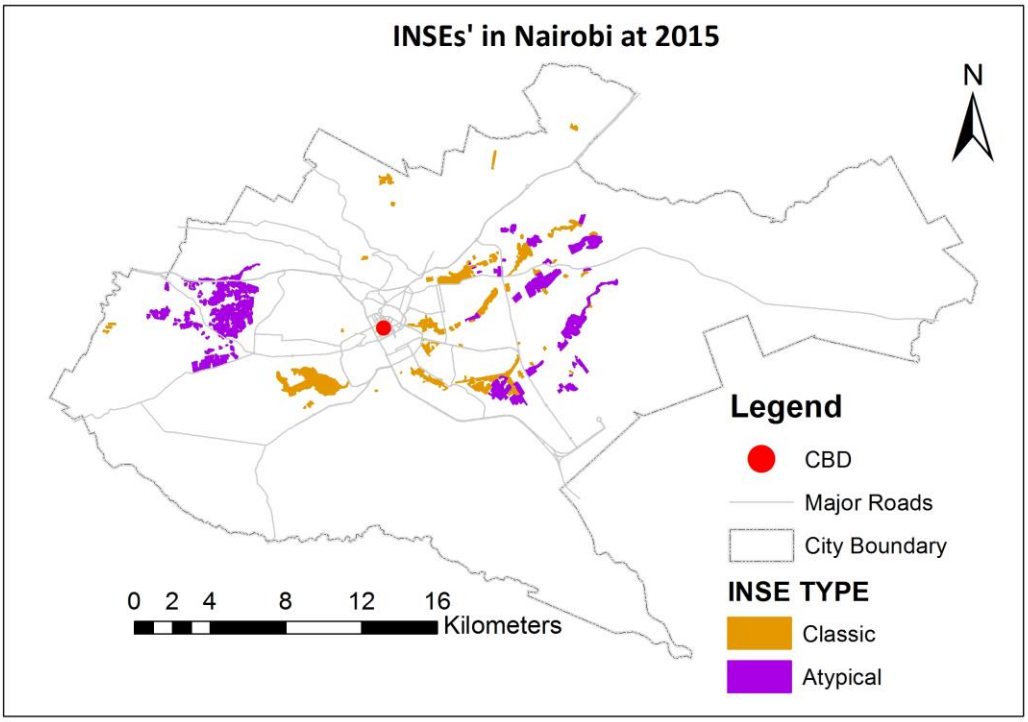


Figure 14: Locations of INSEs by typology

While excluding the southern part of the city, which is a protected national park, only the far eastern part is without patches of INSEs. Incidentally, the far eastern part (Njiru district) had not been part of the city before 1963 (Pamoja Trust, 2009), and is also the farthest district from the CBD. It is dry compared to the other parts of the city, well known for quarrying activities and is out of the city's intense-activity regions (JICA, 2014).

4.3. Identifying Change Locations and Extents

4.3.1. Expansion

INSEs' areas at year 2005, 2010, and 2015 were 1,302, 1,673 and 1,840 Ha (approx.) respectively. Against the built-up area of 2005 (41,647 Ha), 2010 (42,079 Ha) and 2015 (42,218 Ha) these areas are estimated at 3.1%, 3.9% and 4.3% respectively. This is translated to mean that as the built-up area expands, INSEs are gaining prominence on the built-up landscape. Figure 15 presents the result of an overlay analysis, showing expansion locations in P_1 and P_2. Expansion statistics of *Classic* and *Atypical* INSEs from 2005 to 2015 through 2010 are summarized in Table 8.

Table 8: INSEs expansion statistics

	Classic (area)	*Atypical* (area)	Total (area)	Increase in *Classic*	Increase in *Atypical*	Total Increase	Average Expansion per year
INSEs at 2005 (Ha)	660.7	641.3	1302.0	-	-	-	
INSEs at 2010 (Ha)	727.5	945.6	1672.8	66.8	304.1	370.8	74.2
INSEs at 2015 (Ha)	743.1	1096.7	1839.7	15.6	151.3	166.9	33.4
Percentage increase in P_1				10.1%	47.4%	28.5%	5.7%
Percentage increase in P_2				2.1%	16.0%	10.0%	2.0%
Percentage increase for combined P_1 and P_2				12.5%	71.0%	41.3%	4.1%

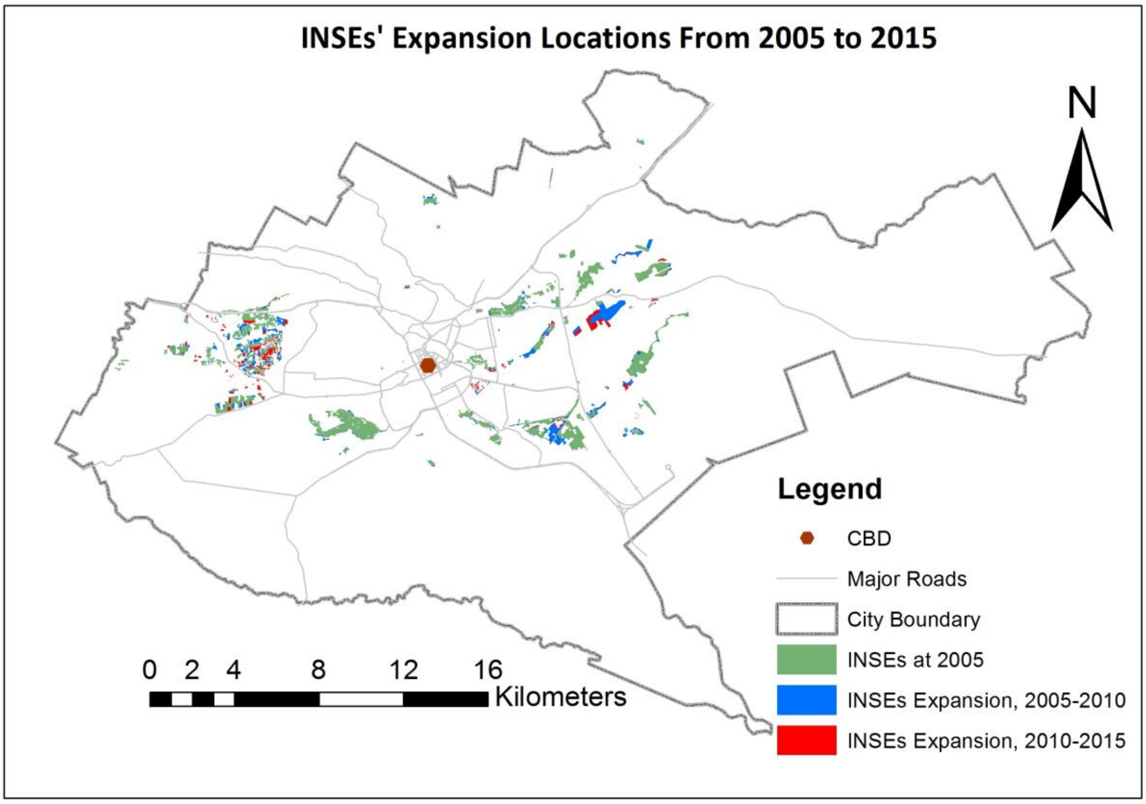


Figure 15: INSEs locations by typology in 2005, 2015 and 2015 and their overlay

The ratios of *Classic* against *Atypical* INSEs are 50.7/49.3 in 2005; 43.5/56.5 in 2010; and 40.3/59.7, an indication of higher rate of growth for *Atypical* INSEs relative to *Classic*. Key informant No. 3, using the example of Kibera settlement, informed that expansion will be unlikely for *Classic* INSEs, especially those near the CBD as these locations are constrained from expansion by neighbouring land uses. In terms of percentage expansion, the trend shows *Atypical* INSEs expanding at least 300% faster than *Classic* (Figure 16).

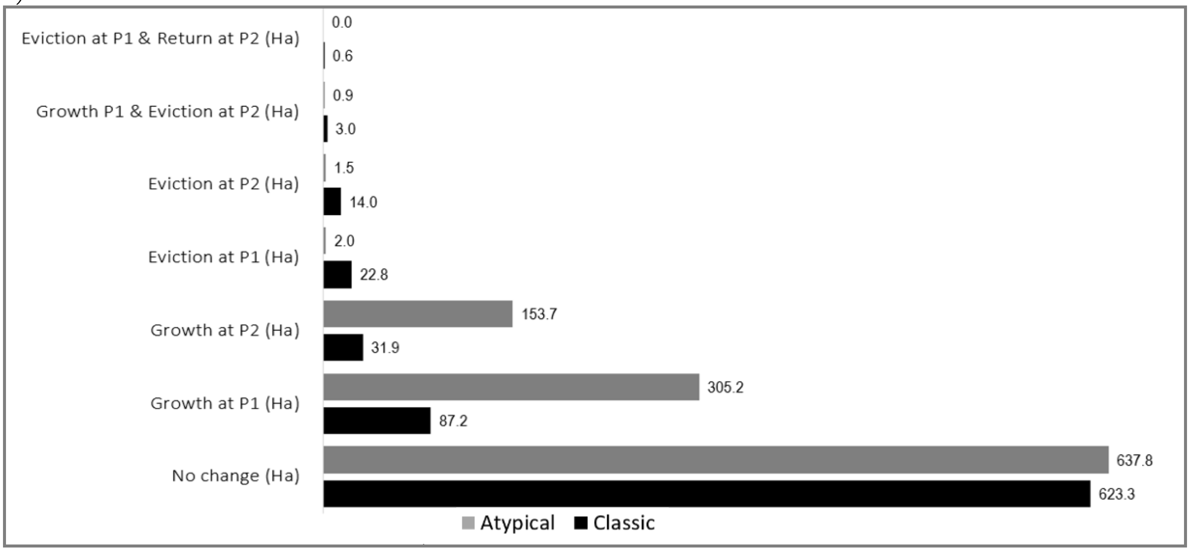


Figure 16: INSEs expansion and eviction statistical summary (2005-2015)

Apparently, INSEs expansion was lesser in P_2 than P_1 for both typologies, which translates into growth at a reducing rate. Figure 16 provides a detailed expansion (also eviction, which is discussed in the next sub-section) analysis across the three time steps. The fact that there are locations that experienced growth in P_1 and eviction in P_2 totalling to 3.8 Ha shows that eviction has been happening alongside expansion, and there is need to look at how the two processes relate.

4.3.2. Densification

Figure 17 provides a general overview of densities at the three modelling time steps. In P_1 and P_2, the areas of low-density reduced by 85% and 26%; the medium-density increased by 103% and reduced by 18%; and the high-density class increased by 8% and 53% respectively. Note, low-density areas are diminishing, implying either their conversion to other densities or eviction. Meanwhile, medium-density is showing an increase in P_1, and a decrease in P_2, which means it first gained area from low-density in P_1 but lost to high-density in P_2. The high-density area is consistently on the rise, and this is evidence of rising densification.

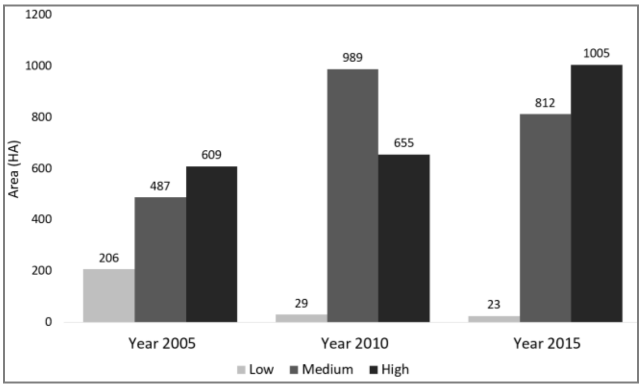


Figure 17: Density profiles of INSEs at 2005, 2010 and 2015

Locations that had a shift in density class from either low to medium or high between the three study time steps were 32 (homogenous) locations, with 15 densifying in P_1 only, 14 in both periods, and 3 in P_2 only (see Table 25 in Appendix E). Figure 18 shows the densified INSEs mapped based on density class change, and Figure 19 shows densification statistics by INSEs typology.

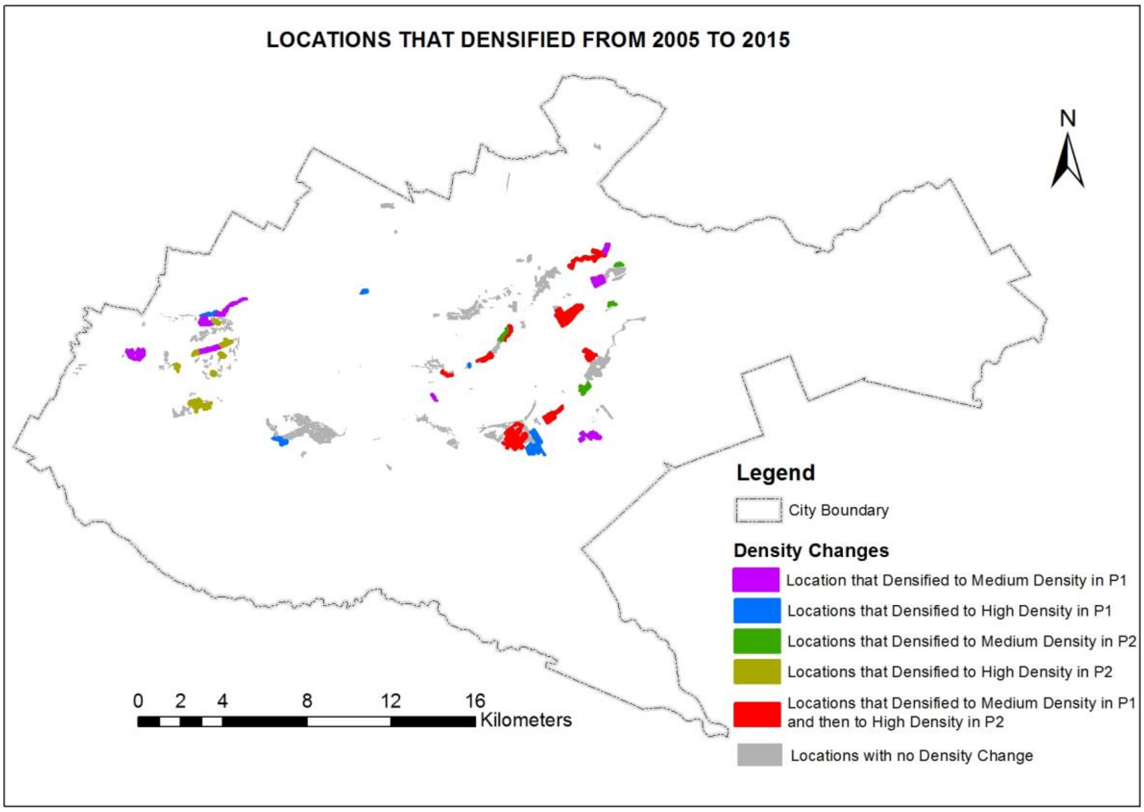


Figure 18: Locations that densified in P_1 and P_2

Note: *Densifying to medium-density in P_1 (2005-2010) implies that the locations had low-density, or did not exist as INSEs at 2005; to high-density in P_1 implies the location had low or medium-density, or did not exist as INSEs at 2005; to medium-density in P_2 (2010-2015) implies the location had low-density or did not exist as INSEs at year 2010; and to high-density in P_2 implies the location had low or medium density, or did not exist as INSEs at year 2010.*

In total 480 Ha (26% of total INSEs area at 2015) experienced some form of densification, 218 Ha densifying at both periods, 174 Ha in P_1 only and 88 Ha in P_2 only. Similar to expansion, densification is happening at a reducing rate. By typology, 34% of all densification (124 Ha) occurred in *Classic* INSEs and 66% of all densification (356 Ha) occurred in *Atypical* INSEs. This is translated to mean that *Atypical* INSEs are 3 times more likely to densify than *Classic* INSEs.

Accordingly, locations that densified to medium-density in P_1 and then to high-density in P_2 had the greatest proportion of densification, out of which *Atypical* settlements densified more than *Classic*. Additionally, *Atypical* settlements lead in all categories of densification, which Pamoja Trust (2015) attributes to availability vacant spaces in them which allows densification to occur.

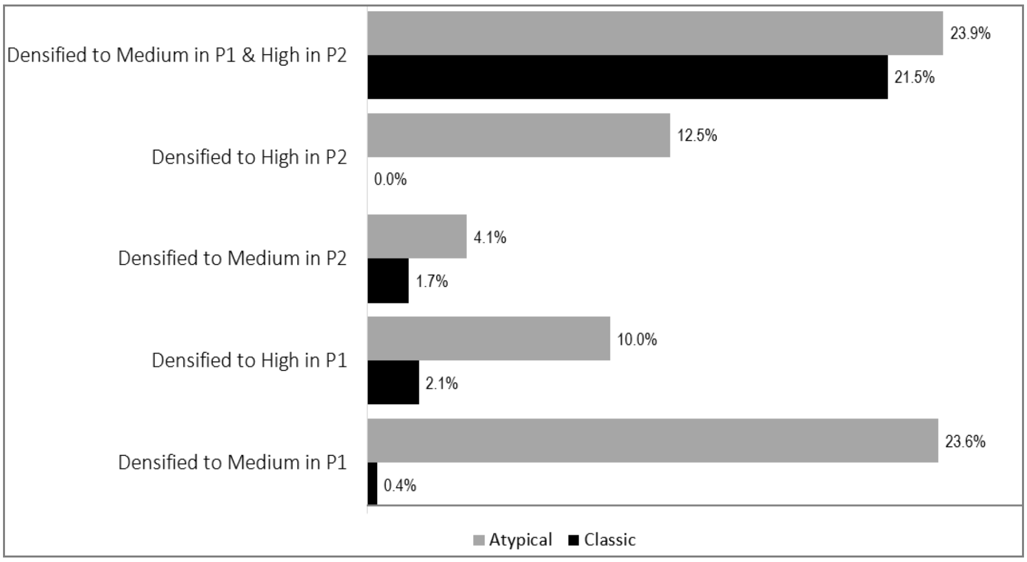


Figure 19: Density change distribution by INSEs typology

4.3.3. Eviction

Spatial change and Extents

From spatial anaysis, accumlated evicted area was 46.3 Ha (approx.) which is 2.5% of total INSEs land. Overlay anaylsis in this study is however done on data 5 years apart, which implies that setttlments that got evicted and established within this period are left out (see example in Figure 22). Of the total evicted area, eviction on 40.3 Ha happened on *Classic* INSEs, effectively showing that *Classic* INSEs are 10 times likely to be evicted than *Atypical*. Figure 20 show locations on map where eviction happened.

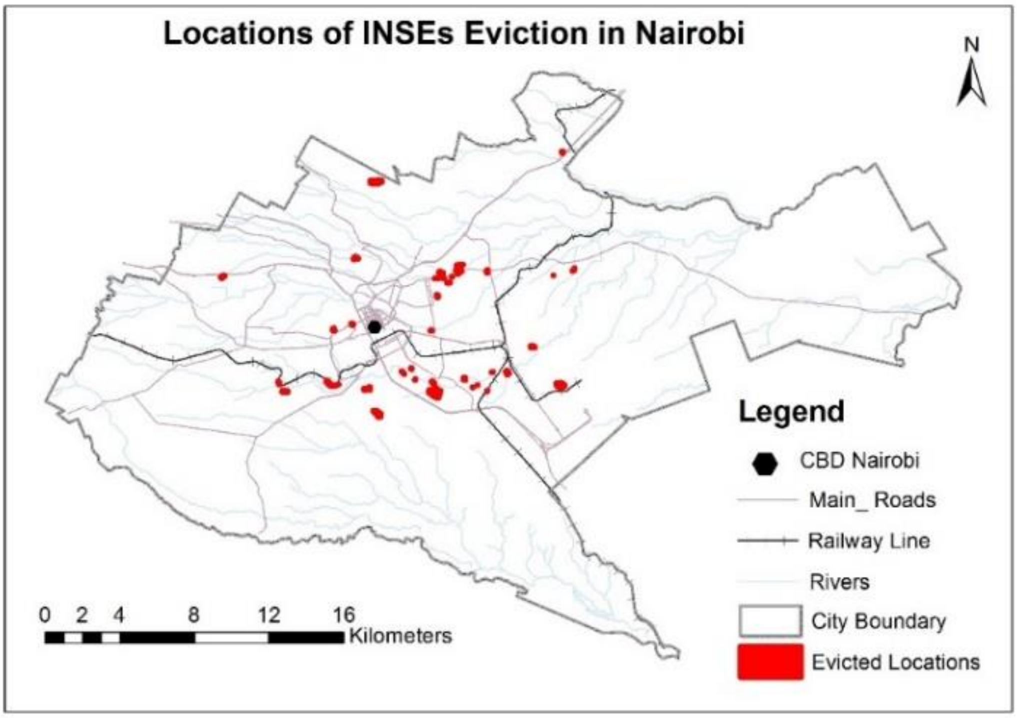


Figure 20: Evicted locations[4]

[4] Outline for eviction map has been made thick for visibility since some evicted locations are too small to be seen on a city-wide map

Additional dynamics
Eviction was analysed using available information from multiple sources, which led to the realization of additional dynamics. Literature and key informants' data were used to profile all INSEs of Nairobi where out of 153 INSEs, 31 were found to have been evicted at least once since their existence (listed in Table 26, Appendix F). Twenty-eight (28) of them occurred on public/government land (against 3 on private). Surprisingly, government led eviction cases were 21, others being led by non-state actors. This is predictably consistent with the observation by Amnesty International (2009) that while most INSEs are on government-owned public land, control of the land they occupy is with non-state actors. Eviction is therefore illegal in this respect, and even when it is government led, establishing its legality is often challenging as reasons for eviction could range from creating space for government infrastructure to land grabbing for private developers (Key informant No. 6). Further, it was noted that eviction has almost been on a continous trend since 1990 with classification of eviction periods into *before year 1990*, *between years 1990 and 2000* and *after year 2000* showing very minimal statistical variations of eviction incidences. In terms of development stage, it was found that most eviction happens during consolidation stage. A summary of these findings is presented in Figure 21.

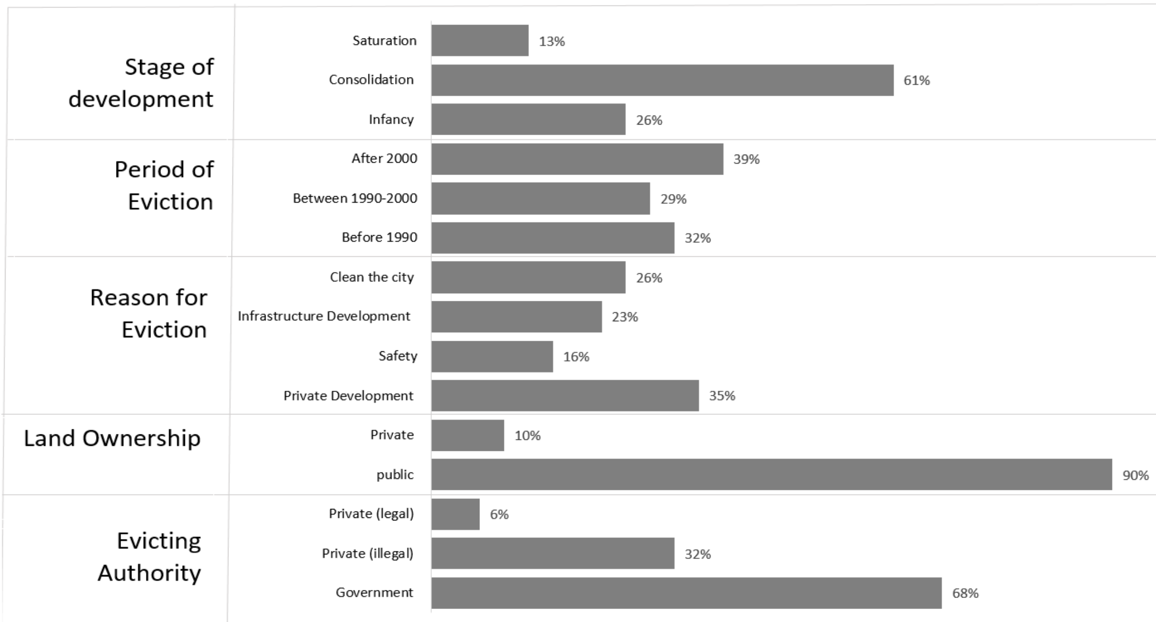


Figure 21: Summary findings on eviction

Sixty two percent (62%) of the evicted locations were restablished almost immediately. Some settlements have been continually evicted (e.g. Mitumba settlement which has been evicted 7 times), and many have experienced arson attacks, which experts argue is a way of frustrating INSE dwellers to vacate land (Key informant No. 8, 9 & 10). To underline the low success of eviction, Pamoja Trust (2009) states that where INSEs are not re-established following an eviction, they move to other locations (e.g. Village II Kwanduru moved to create Kosovo INSEs following and eviction).

Alongside eviction, threat[5] of eviction was assessed, with 64 settlement profiled under this category. Majority (60/64) of them were on public land. Thirty-six (36) of the threatened settlements are relatively old settlements, established before year 1980; those established between year 1980 and 2000 were 13 and those after year 2000 are 15. For some settlements (25%), eviction threat has existed since their establishment, but their eviction delayed due to NGOs' intervention in conjunction with anti-eviction

[5] Defined as having received any form of warning (verbal or written) to vacate land in regard to its tenure

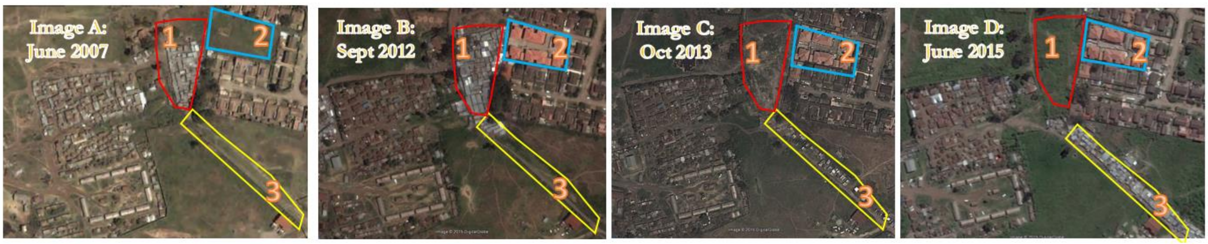
activism. Other settlements started receiving threats after their establishment (22% at consolidation and 53% at saturation). Key informants noted that a big number of such settlements are affected by spatial development and environmental plans made after their establishment.

Parties issuing eviction threats are those that claim tenure to the subject land, and may or may not be legitimate owners of the land. Of the 64 INSEs, 49 are threatened by government authorities and 15 by non-state actors, including influential politicians. Government authorities threatening to initiate eviction include Kenya Airport Authority, Kenya Railways Corporation, National Environmental Management Authority, Kenya Urban Roads Authority, and Kenya Airforce.

4.4. Patterns Linking Eviction to Expansion and Densification

The study revealed that INSEs eviction, growth and densification are sometimes interlinked processes. Eviction in one location may lead to expansion or densification in another. For Nairobi, this phenomenon could not be analysed at the citywide scale because threshold distances between evicted and growth locations that would give a conclusive link needs to be defined with the help of key informants, which would only be possible in another cycle of research. City Cotton settlement – unique in that its eviction and growth dynamics have been well (Amnesty Intenational, 2013; Betzema, 2013; InformalCity, 2015) – has been chosen to explain this phenomenon.

Figure 22 shows spatiotemporal changes of City Cotton starting at year 2007. It can be noted that at June 2007, site 2 and 3 were vacant. However, in September 2012, apartments are developed in the adjacent site (2), and immediately site 1 is evicted. The evicted residents settle at site 3 almost immediately, and this location later densifies as the June 2015 image shows. Such processes are likely to occur elsewhere.



A: INSEs occupies site 1; 2 and 3 are vacant

B: Formal housing is developed in site 2

C: Site 1 is evicted, part of it moving to site 3

D: INSEs at site 3 densifies

Figure 22: Development dynamics of City cotton INSEs

4.5. Vertical Growth – An Emerging Trend

During fieldwork, a tendency towards vertical INSEs' growth was noted (e.g. Figure 23). This concern was discussed with key informants who informed this is new trend (confirmed by shiny iron sheets) and increasingly gaining popularity because of the need to compensate for lack of expansion spaces. However, informants at *Pamoja Trust* estimated this growth currently at less than 1%, and unlikely to bias modelling results if overlooked.

Figure 23: Vertical growth example at Kangemi INSEs, Nairobi

4.6. Drivers of Change from Key Informants

4.6.1. Growth (Expansion and Densification) – Non-spatial Drivers

Aggregated responses from the key informants identified main external drivers of INSEs growth (including expansion and densification) as: *lack of livelihood means in rural areas* (rated at 27/30)[6], *low income from agriculture* (25/30), and *poor community and infrastructure services in rural areas* (18/30). This was alongside *liking for city lifestyle* with the same rating (Table 27 in Appendix G).

In addition, they identified *shortage of low cost or affordable housing*, *low incomes, wages and lack of employment* (28/30), and *slow rate of housing provision by housing agencies* as top three internal drivers of INSEs growth. Lesser influential drivers include *spatial policies*, *bad politics, inability of urban poor to access housing credit*, and *class segregation and inequality* (Table 27 in Appendix G).

4.6.2. Growth (Expansion and Densification) – Spatial Drivers

Rating of spatial drivers was done in categories of site-specific, proximity, and neighbourhood characteristics. Aggregated responses show that all drivers rated as *strong* or *very strong* are believed by key informants to have a positive effect to growth.

Only four drivers were identified under the site-specific characteristics with *population density* rating strongest. Others were *land tenure*, *land value*, and *slope*, all rated as strong drivers under expansion and densification. *Distance to industrial areas* is the strongest driver under proximity characteristics (30/30 for expansion and 28/30 for densification). The second strongest drivers was *distance to business centres* (24/30 for both expansion and densification). For densification, *distance to CBD* also has the same rating as distance to *business centres*. Ranked third for expansion were *distances to rivers* and *CBD* (21/30 for both). Other drivers also rated as strong but with lower scores include *distance to railway* and *distance to major roads*. Under neighbourhood characteristics, three strongest drivers for expansion were *proportion of surrounding commercial land uses* (26/30), *proportion of surrounding undeveloped land* (25/30), and *proportion of surrounding existing INSEs* (24/30). The same drivers were the strongest for densification, but rated differently (proportion of the surrounding commercial land (25/30); undeveloped land (25/30); and existing INSEs (24/30). Also strong drivers but not highly rated by informants were *proportion of surrounding planned residential areas* and *transport land uses* (Table 28).

[6] Refer to Section 3.3.3 on rating of drivers

4.6.3. Eviction – Non-spatial Drivers

Drivers of eviction were gathered from the same informants as growth. For non-spatial drivers, two drivers were rated as very strong: *illegal eviction by private developers* (27/30) and *lack of accountability in land governance* (25/30). Also under poor land governance, other drivers profiled with strong influence are *lack of transparency in land administration* (24/30), *disregard for rule of law* (24/30), and *lack of equity by government* (22/30). *Legal recovery of land by private developers* (22/30) is the only driver that explicitly links legality to eviction. Other non-spatial drivers of eviction with lower rating are *lack of anti-eviction legislation*, *city image-enhancement project* and *environmental health restoration policies* (Table 29).

4.6.4. Eviction – Spatial Drivers

Ranked top spatial drivers under site-specific characteristics is their *existence on infrastructure reserve* (28/30); this includes road, railway, electricity, and pipeline reserves. Another equally strong driver is *land tenure* under which *existence on private land* (28/30) is a stronger driver than *existence on public land* (20/30). Lesser drivers under this category include *size of settlement*, where small settlements are more likely to be evicted than big ones, and *density of settlements*, with lower density settlements being easier to evict. *Age of settlement* and INSEs *existence on hazardous locations* were rated as weak drivers.

Under proximity characteristics, *distance to prime investments* (27/30) was the only one rated a very strong driver. Others, *distance to roads* (22/30) and *distance to planned neighbourhoods* (19/30) were rated as strong drivers. *Proximity to environmentally sensitive areas* and *proximity to CBD* were categorized as weak drivers. In the category of neighbourhood characteristics, three drivers were identified: *proportion of the surrounding commercial land uses* (21/30), *proportion of the surrounding transport land uses* (also 21/30), and *proportion of the surrounding industrial land uses* (18/30). All the three are considered strong drivers (Table 30).

4.6.5. Summary of Drivers from Key Informants

In summary (Table 9), based on the opinions of the key informants, push factors of urbanization (from rural areas to urban) are very strong in the growth of INSEs. Central push factors are lack of livelihoods means in rural, reduced earnings from agriculture and poor services in rural areas. In the city, lack of housing and the inability of the housing sector to provide it, or at least financial support, leads to the development of INSEs. Spatially, distance to industrial areas and proportion of vacant land are prominent driving forces of INSEs growth. Regarding eviction, majorly poor governance is to blame while need to vacate INSEs for infrastructure development and expansion of prime developments also play a strong role.

Table 9: Summary of key drivers from key informants

	Growth (non-Spatial)		**Growth (Spatial)**		**Eviction**	
	External	**Internal**	**Expansion**	**Densification**	**Spatial**	**Non-Spatial**
1	Lack of livelihood means in rural areas	Shortage of low cost (affordable) housing	Distance to Industrial areas	Distance to Industrial areas	Illegal eviction by private developers	Their existence on infrastructure reserve
2	Low incomes from agriculture	Low incomes, wages & lack of employment	Proportion of surrounding commercial land uses	Population density	Lack of accountability	Land tenure - private land
3	Poor services in rural areas e.g. education	Slow rates of housing provision by housing agencies	Proportion of surrounding undeveloped land	Proportion of surrounding commercial land uses & Undeveloped land	Land of transparency in land administration	Distance to prime investments

4.7. Drivers of Change from Modelling

Modelling was limited to only drivers that can be spatially represented. Literature review and key informants informed modelling inputs. All spatial drivers gathered from both sources (ref. Table 1 for literature sources and Section 4.6 for key informants data) were included in the models except land tenure, land value, hazardous location and distance to prime investments. This was because of unavailability of reliable multi-temporal data.

4.7.1. Growth (Expansion and Densification)

Results for spatial drivers of growth were generated from 15 models (6 for expansion and 9 for densification) (ref. Section 3.2.1 for setting modelling environment & Section 3.5 for model variations and naming). Table 10 shows the variables included in the models and their nature.

Table 10: Variables in the expansion and densification models

Dependent	**Variable in the model**	**Variable**	**Nature of variable**	**No. of Models**
Dependent				
Expansion	Y_1	1- *Classic* INSEs; 0 – Other built-up locations	Binary	3 models (T_1, T_2, T_3)
	Y_2	1- *Atypical* INSEs; 0 – Other built-up locations	Binary	3 models (T_1, T_2, T_3)
Densification	Z_1	1-low-density; 0 – Other INSEs locations	Binary	3 models (T_1, T_2, T_3)
	Z_2	1-medim density; 0 – Other INSEs locations	Binary	3 models (T_1, T_2, T_3)
	Z_3	1-high-density; 0 – Other INSEs locations	Binary	3 models (T_1, T_2, T_3)
Independent variable				**Differences by Models**
Site specific characteristics	X_1	Slope	Continuous	Same for all models
	X_2	Population density	Continuous	Different for each model
Proximity characteristics	X_3	Distance to industrial areas	Continuous	Different for each model
	X_4	Distance to rivers	Continuous	Same for all models
	X_5	Distance to roads	Continuous	Same for all models
	X_6	Distance to railway	Continuous	Same for all models
	X_7	Distance to CBD	Continuous	Same for all models
	X_8	Distance to business centres	Continuous	Same for all models
Neighbourhood characteristics	X_9	Close interaction with undeveloped land	Continuous	Different for each model
	X_{10}	Close interaction with INSEs land uses	Continuous	Different for each model
	X_{11}	Close interaction with commercial land uses	Continuous	Different for each model
	X_{12}	Close interaction with planned residential land uses	Continuous	Different for each model
	X_{13}	Close interaction with transport land uses	Continuous	Same for all models

4.7.2. Limitation and uncertainties of the factors

Limited by data availability, the dependent variable for densification uses density classes, with modelling only focusing on the locations that shifted from one density class to another. As a result, small density variations at the built structure level are overlooked by this study. Additionally, this study does not have a basis of establishing the effect of missing factors to the models such as the master plan/ zoning guidelines, land tenure and land values.

4.7.3. Testing Samples for Modelling

Following the sampling method explained in Section 3.6.2, alternative sample points generated at a spacing of 3*3, 5*5, and 7*7 cells were created on the built-up layer for year 2015. Model-fit tests for each sampling scenarios based on SPSS regression outputs showed that the models' coefficients changed with change in sampling windows. Based on probability values (p-values), all models' predictive powers were significant at 95% confidence level. The best model was thus chosen based on *Nagelkerke R-square* (pseudo R^2), and PCP values (Table 11).

Table 11: Comparing performance of models on different sample sizes

Model	Window	Sample size	PCP	Variables in model	Nagelkerke R square	-2 log likelihood	Chi-square
All INSE at 2005	3x3	141,952	85.3148	10	.151	6261.422	134.976
	5x5	51,015	85.6235	9	.153	2225.182	42.726
	7x7	26,026	85.2978	8	.149	1092.277	22.40
All INSEs at 2010	3x3	141,952	84.4120	11	.239	7944.318	174.478
	5x5	51,015	84.6353	8	.249	2773.728	52.938
	7x7	26,026	84.6135	9	.248	1415.294	31.076
All INSEs at 2015	3x3	141,952	83.6892	11	.300	6956.378	237.088
	5x5	51,015	83.9023	10	.314	2392.734	79.894
	7x7	26,026	83.8934	8	.295	1255.254	38.990

Trend assessment of *chi-square* and *log-likelihood* values showed them increasing with reduction in sample window. While an increasing *chi-square* translates into increasing model fit (in favour of 3*3 sample points), increasing *log-likelihood* shows increasing unexplained outcome variance and reducing model's predictive strength (in favour of 7*7 sample points). For this conflict, the two were not used in defining the best model for use. This trend is explained by University of North Texas (2014) with the argument that *chi-square* related tests are prone to inflation as sample sizes increase. Thus, the model with sample points on 5*5-window spacing was picked because it provided better model fit based on PCP and *pseudo* R-square values.

4.7.4. Multi-collinearity, Spatial Autocorrelation and Endogeneity Assessment

These tests were performed to check relationships of the factors in the model as well as factors that would potentially bias modelling results. The VIF and tolerance values from a linear regression model tested the H_0 which states there is no significant linear relationship between or among independent variables (r=0). This hypothesis was rejected because the test output results were not within threshold of significance (i.e. tolerance < 0.1 and VIF > 10) (Table 12).

Table 12: VIF and tolerance values for predictors

	2005		2010		2015	
Variable	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF
X_1	.878	1.139	.878	1.138	.878	1.139
X_2	.786	1.273	.664	1.507	.633	1.579
X_3	.162	6.188	.162	6.186	.161	6.205
X_4	.225	4.442	.224	4.457	.225	4.448
X_5	.244	4.106	.243	4.117	.244	4.093
X_6	.175	5.721	.172	5.799	.171	5.835
X_7	.217	4.603	.217	4.618	.216	4.634
X_8	.283	3.538	.277	3.616	.277	3.613
X_9	.924	1.082	.938	1.066	.941	1.063
X_{10}	.988	1.012	.935	1.070	.913	1.095
X_{11}	.988	1.012	.989	1.011	.988	1.012
X_{12}	.805	1.243	.805	1.242	.810	1.235
X_{13}	.973	1.028	.973	1.028	.973	1.028

As regards spatial autocorrelation, *Moran's I* test results for all model's were generated (e.g. for $M_{Ex}C_{CL}05$ results in Figure 39, Appendix I). At 95% confidence level, all expansion, densification and eviction models showed compliance to H_0: spatial randomness, with p-values > 0.05 and z-scores < -1.96 for dispersion and Z-score > 1.96 for clustering (Table 32, Appendix I).

Endogeneity was checked by sequentially inputting factors to the logistic model and checking their effect on coefficients of other factors; this way, the factor causing inflation of coefficients were identified.

Proportion of surrounding INSEs was eliminated in all densification models as it inflated the odds ratio, standard error, and raised *p-values*, leading to acceptance of H_0 for many factors. This was found to be caused by high correlation between this factor and the dependent variables.

4.8. Expansion Models' Outputs

Thirteen (13) variables were modelled (see their factor maps in Figure 24) in six models: $M_{Ex}C_{CL}05$, $M_{EX}C_{AT}05$, $M_{EX}C_{CL}10$, $M_{EX}C_{AT}10$, $M_{EX}C_{CL}15$, and $M_{EX}C_{AT}15$. A summary of the models' performance is in Table 13.

Table 13: Expansion models output summaries

	$M_{EX}C_{CL}05$	$M_{EX}C_{AT}05$	$M_{EX}C_{CL}10$	$M_{EX}C_{AT}10$	$M_{EX}C_{CL}15$	$M_{EX}C_{AT}15$
Year	2005	2005	2010	2010	2015	2015
INSE Type	1	2	1	2	1	2
Significant Variables (at α 0.05)	8	7	9	9	7	10
Step in Backward LR Procedure	6	7	5	5	7	4
P-value	0.000	0.000	0.000	0.000	0.000	0.000
PCP	94.9	95.1	94.5	92.7	94.4	91.5
Chi-square	21076.844	20905.227	21415.000	22289.311	21546.423	22405.690
Eliminated Variables & their corresponding p-values	X_1:0.487 X_2:0.653 X_8:0.850 X_{11}:0.775 X_{13}:0.950	X_1:0.730 X_3:0.443 X_{10}:0.360 X_2:0.250 X_{13}:0.267 X11:0.577	X_1:0.702 X_8:0.348 X_{11}:0.589 X_{13}:0.381	X_1:0.245 X_{10}:0.592 X_{11}:0.155 X_{12}:0.343	X_1:0.478 X_8:0.411 X_{11}:0.262 X_{12}:0.290 X_{13}:0.273 X_4:0.084	X_1:0.600 X_8:0.288 X_{10}:0.076
Reference for detailed output (for significant drivers) Appendix J	**Table 33**	**Table 34**	**Table 35**	**Table 36**	**Figure 38**	**Table 38**

All models were significant, with at least seven significant variables. The PCP are high, all being over 90, a quality indication of strong models. Appendix J tables shows variable coefficients, standard errors, Wald statistics, p-values and odds rations for each significant variable in the 6 models.

4.9. Results Summary for Expansion Models

A comparative assessment of the models' outputs show that INSEs driving forces have gradual changes over time (Table 14)

For *Classic* INSEs, *distance to industrial areas* is the strongest driver in year 2005 and 2010 but drops to second place in year 2015. This is the same to *distance to rivers* which is second in 2005, third in 2010 and insignificant in 2015. This shows *distance to industrial areas* and *distance to rivers* as strong drivers but with reducing influence; meanwhile, *distance to roads* (which is fourth in 2005, second in 2010, and first in 2015) is a strong driver and gaining influence. *Distance to railway* is a stable driver (being third in 2005, fourth in 2010, and third again in 2015). Other drivers that appears to gain prominence, though ranking averagely, include *distance to CBD*, *proportion of surrounding INSEs*, and *proportion of surrounding undeveloped land.* All the factors have a positive effect on expansion.

Atypical INSEs show lesser temporal dynamics with *distance to rivers*, *distance to roads*, and *distance to business centres* being the strongest drivers in all models and in that order. However, it is noted that their odds ratio is on the rise, a pointer to increasing strength of drivers. As *distance to CBD* and *distance to railway* rank averagely while showing temporal stability, *proportion of surrounding commercial land* and *proportion of surrounding undeveloped land* follow very closely in influence. *Proportion of surrounding transport land* uses is not a driver in year 2005 but appears in year 2010 and 2015 showing a negative effect to expansion. This factor is, however, the least of all significant drivers, and may there not create so much attention.

In summary, proximity characteristic dominates top drivers in all *Classic* and *Atypical* INSEs models with neighbourhood characteristics drivers appearing in the bottom half of the influence's list. Site-specific characteristics rank as either as weak not drivers at all.

Table 14: Summary of drivers for expansion models by their ranking

	Comparing Drivers for *Classic* INSEs						**Comparing Drivers for *Atypical* INSEs**					
	Model: MExCCL05		**Model: MExCCL10**		**Model: MExCCL15**		**Model: MExCAT05**		**Model: MExCAT10**		**Model: MExCAT15**	
	Factor [7]	**O.R**	**Factor**	**O.R**	**Factor**	**O.R**	**Factor**	**O.R**	**Factor**	**O.R**	**Factor**	**O.R**
1	Distance to Industrial areas	1.151	Distance to industrial areas	1.125	Distance to roads	1.125	Distance to rivers	1.567	Distance to rivers	1.73	Distance to rivers	1.796
2	Distance to rivers	1.122	Distance to roads	1.112	Distance to industrial	1.122	Distance to roads	1.129	Distance to roads	1.151	Distance to roads	1.156
3	Distance to railway	1.098	Distance to rivers	1.106	Distance to railway	1.065	Distance to business centres	1.08	Distance to industrial areas	1.07	Distance to industrial areas	1.092
4	Distance to roads	1.088	Distance to railway	1.071	Distance to CBD	1.041	Distance to CBD	1.041	Distance to railway	1.05	Distance to railway	1.044
5	Distance to CBD	1.04	Distance to CBD	1.046	Proportion of surrounding INSEs	1.008	Distance to railway	1.029	Distance to CBD	1.041	Distance to CBD	1.04
6	Proportion of surrounding undeveloped land	1.008	Proportion of surrounding INSEs	1.009	Proportion of surrounding undeveloped land	1.007	Proportion of surrounding commercial land	1.008	Distance to business centres	1.038	Proportion of surrounding commercial land	1.012
7	Proportion of surrounding INSEs	1.008	Proportion of surrounding undeveloped land	1.007	Population density	1	Proportion of surrounding undeveloped land	1.007	Proportion of surrounding undeveloped land	1.004	Proportion of surrounding undeveloped land	1.005
8	Proportion of surrounding planned residential land	1.002	Proportion of surrounding planned residential land	1.002					Population density	1	Proportion of surrounding planned residential land	1.003
9			Population density	1					Proportion of surrounding transport land uses (-ve effect)	0.981	Population density	1
10											Proportion of surrounding transport land uses (-ve effect)	0.983

[7] Factors whose effect on the dependent variable is not indicated have a positive effect

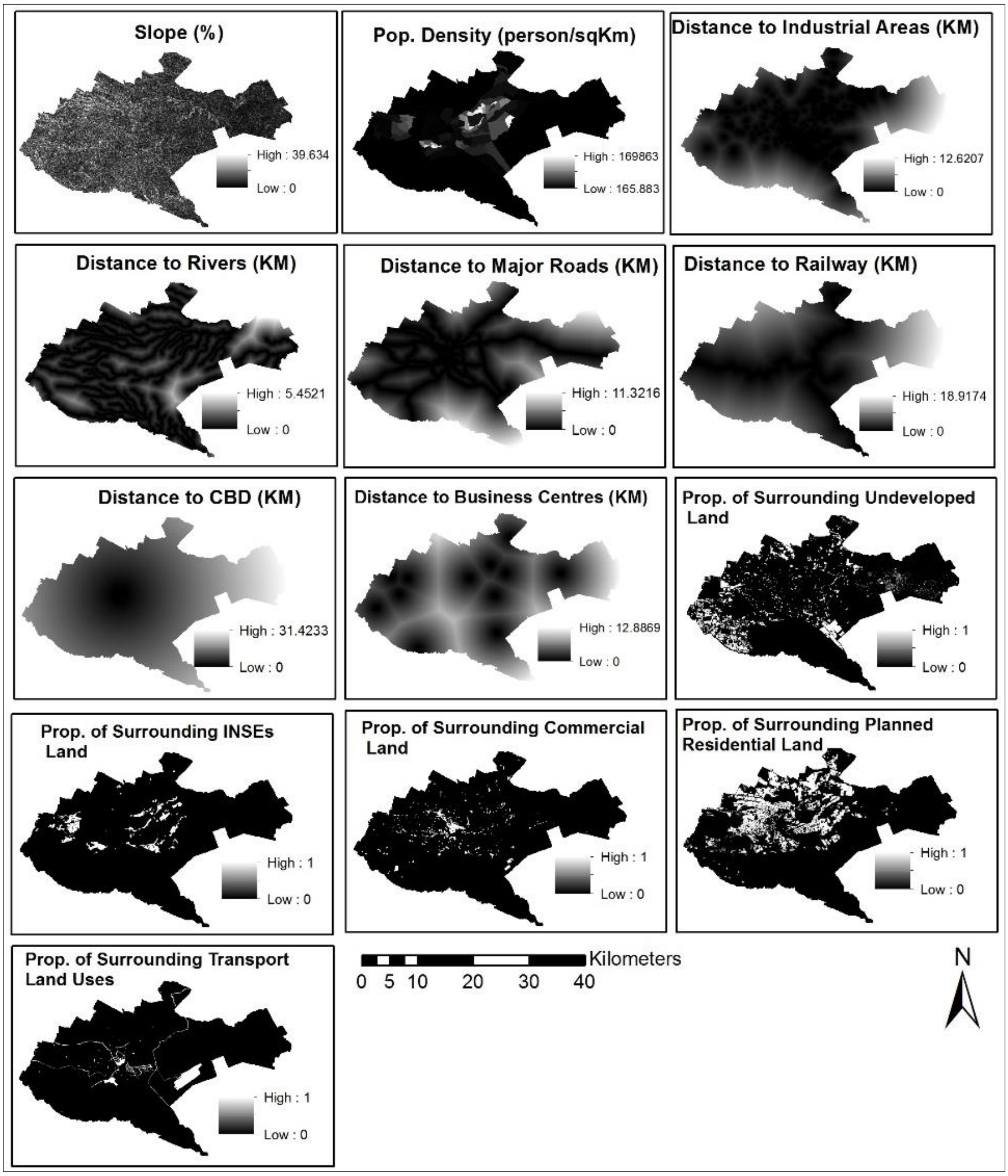


Figure 24: Factor maps for variable in 2005 expansion and densification models

4.10. Findings from Densification Models

Findings from the densification modelling are gathered from 9 separate models, namely: $M_{DE}C_{L}05$, $M_{DE}C_{M}05$, $M_{DE}C_{H}05$, $M_{DE}C_{L}10$, $M_{DE}C_{M}10$, $M_{DE}C_{H}10$, $M_{DE}C_{L}15$, $M_{DE}C_{M}15$, and $M_{DE}C_{H}15$. Out of the 13 independent variables incorporated into this model, *proportion of surrounding INSEs* was dropped for causing endogeneity, inflating the odds ratio and standard errors for all factors in the model. All densification models had a sample size of 7,295. A summary of the models performance is shown in Table 15.

Table 15: Densification models output summaries

Model:	**$M_{DE}C_L05$**	**$M_{DE}C_M05$**	**$M_{DE}C_H05$**	**$M_{DE}C_L10$**	**$M_{DE}C_M10$**	**$M_{DE}C_H10$**	**$M_{DE}C_L15$**	**$M_{DE}C_M15$**	**$M_{DE}C_H15$**
Year	2005	2005	2005	2010	2010	2010	2015	2015	2015
Density Category	Low	Medium	High	Low	Medium	High	Low	Medium	High
Significant Variables (at α 0.05)	6	9	8	7	6	6	5	8	9
Step in Backward LR Procedure	5	4	5	6	7	7	8	5	4
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PCP	89.3	74.2	71.4	88.1	79.5	68.8	79.8	76.6	75.4
Chi-square	3138.392	1547.639	798.117	3068.059	2072.300	2876.00	2275.280	1295.290	5758.500
Eliminated Variables & their corresponding p-values	X_3:0.798 X_2:0.235 X_{12}:0.748 X_{13}:0.125 X_4:0.970 X_{11}:0.983	X_1:0.696 X_3:0.287 X_{12}:0.700	X_1:0.885 X_{11}:0.730 X_{12}:0.240 X_{13}:0.579	X_3:0.234 X_2:0.116 X_{11}:0.488 X_1:0.453 X_{13}:0.64	X_1:0.221 X_{11}:0.360 X_{12}:780 X_3:0.86 X_5:0.630 X_{13}: 0.231	X_2:0.396 X_3:0.384 X_8:0.777 X_{11}:0.581 X_{12}:0.964 X_1:0.550 X_{13}:0.137	X_2:0.396 X_3:0.384 X_8:0.777 X_{11}:0.581 X_{12}:0.964 X_1:0.55 X_{13}:0.137	X_1:0.986 X_7:0.959 X_{11}:0.244 X_{13}:0.80	X_5:0.592 X_7:0.322 X_{11}:0.402
Reference for detailed output (for significant drivers) Appendix J	**Table 39**	**Table 40**	**Table 41**	**Table 42**	**Table 43**	**Table 44**	**Table 45**	**Table 46**	**Table 47**

All models were significant and had at least five significant variables at their final step in the backward LR procedure. Additionally, all had PCP values of above 60. These values are lesser than those in the expansion models, a likely reason being that the binary variable for expansion modelling is INSEs area against built-up area (whose ratio is 5%), while the binary variable for densification modelling is density classes against all INSEs area (whose average ratio is 33% for 3 density classes). Null models in LRM will thus give 95% and 66% as PCP for expansion and densification models respectively, and this difference will be maintained after inclusion of independent variables since both groups of models are based on similar independent variables.

4.11. Results Summary for Densification Models

The outputs show densification being sensitive to temporal dynamics. In fact, establishing a temporal trend for the drivers is difficult. See summary of drivers in Table 16.

From low-density models ($M_{DE}C_L05$, $M_{DE}C_L10$ & $M_{DE}C_L15$), *distance to business centres* is the strongest driver at 2005 and 2010 but not in 2015. *Distance to rivers* and *distance to roads* are within the top 3 drivers, but only at 2010 and 2015. An averagely ranking driver that is stable at position 4 is *proportion of surrounding undeveloped land*. Also worth noting is that *distance to CBD* and *distance to railway* have negative influence to the existence of low-density locations, and even though do not rank top, they are gaining influence over time.

Drivers from medium-density models ($M_{DE}C_M05$, $M_{DE}C_M10$ & $M_{DE}C_M15$) show more temporal stability than low-density models. Among the tops drivers, while *distance to rivers* and *distance to business* centres do not experience significant temporal shift in ranking, *proportion of surrounding undeveloped land* shows increasing influence by ranking 6th at 2005 and 3rd in 2010 and 2015. Other drivers are not stable except *distance to CBD* and *distance to the railway*, which are significant but weak drivers, both with a negative influence to densification.

For high-density models ($M_{DE}C_H05$, $M_{DE}C_H10$ & $M_{DE}C_H15$), only *distance to rivers* is consistently a top driver in all there models. Other top drivers, appearing at least twice in all the three models are *distance to* *railway* and *distance to roads*. Weak drivers do not show any apparent trend, which may be interpreted to mean that high-density locations experience small in impact but quick changes.

Proximity characteristics have the strongest drivers for all densification models. Only medium-density models show a strong influence of neighbourhood characteristics (proportion of surrounding undeveloped land). It is, however, noted that most of the weak drivers are neighbourhood characteristics. Site-specific characteristics appear as either weak drivers or not drivers at all.

Table 16: Summary of significant drivers from densification models

No.	**MDECL05**		**MDECL10**		**MDECL15**	
1	Distance to business centres	1.756	Distance to business centres	2.667	Distance to rivers	2.359
2	Distance to roads	1.112	Distance to rivers	1.957	Distance to roads	1.223
3	Slope	1.029	Distance to roads	1.511	Distance to railway	1.129
4	Proportion of surrounding undeveloped land	1.014	Proportion of surrounding undeveloped land	1.024	Proportion of surrounding undeveloped land	1.022
5	Distance to CBD (-ve effect)	0.839	Proportion of surrounding planned residential land	1.005	Distance to CBD (-ve effect)	0.781
6	Distance to railway (-ve effect)	0.656	Distance to CBD (-ve effect)	0.669		
7	Proportion of surrounding commercial land	0	Distance to railway (-ve effect)	0.398		
	MDECM05		**MDECM10**		**MDECM15**	
1	Distance to rivers	1.521	Distance to business centres	1.947	Distance to rivers	1.542
2	Distance to business centres	1.434	Distance to rivers	1.328	Distance to business centres	1.472
3	Distance to roads	1.091	Proportion of surrounding undeveloped land	1.006	Proportion of surrounding undeveloped land	1.018
4	Proportion of surrounding commercial land	1.031	Population density	1	Proportion of surrounding planned residential land	1.004
5	Proportion of surrounding transport land uses	1.008	Distance to CBD (-ve effect)	0.885	Population density	1
6	Proportion of surrounding undeveloped land	1.006	Distance to railway (-ve effect)	0.55	Distance to roads (-ve effect)	0.749
7	Population density	1			Distance to industrial areas (-ve effect)	0.611
8	Distance to CBD (-ve effect)	0.884			Distance to railway (-ve effect)	0.361
9	Distance to railway (-ve effect)	0.708				
	MDECH05		**MDECH10**		**MDECH15**	
1	Distance to railway	3.362	Distance to business centres	2.093	Distance to railway	1.978
2	Distance to roads	1.488	Distance to rivers	1.311	Distance to rivers	1.72
3	Distance to rivers	1.463	Distance to roads	1.115	Distance to industrial areas	1.351
4	Distance to industrial areas	1.147	Proportion of surrounding undeveloped land (-ve effect)	0.994	Slope	1.02
5	Proportion of surrounding undeveloped land	1.014	Distance to CBD (-ve effect)	0.856	Proportion of surrounding undeveloped land	1.02
6	Population density	1	Distance to railway (-ve effect)	0.526	Population density	1
7	Distance to CBD (-ve effect)	0.684			Proportion of surrounding planned residential land (-ve effect)	0.994
8	Distance to business centres (-ve effect)	0.253			Proportion of surrounding transport land uses (-ve effect)	0.991
9					Distance to business centres (-ve effect)	0.593

4.12. Eviction Modeling

Similar to growth modelling, probable drivers for this model were gathered from key informants and literature. However, three spatial factors gathered from literature and planning experts were not included in this model due to unavailability of spatiotemporal data. They include *land tenure* on private and public land (rated as very strong drivers by key informants); *proximity to prime investments* (also rated as a very strong driver); and *existence of settlements on hazardous locations* (rated as a weak driver). Additionally, *existence of INSEs on powerline' reserve*, which was mentioned by the planning experts within locations on infrastructure reserves was not included for the same reason. In total, 10 variables were included in the model (Table 17).

Table 17: Variables for eviction modelling

Variables	Label	Name	Nature
Dependent			
	D	Evicted location	Binary (1- Evicted locations; 0 – other INSEs locations)
Independent			
Site specific characteristics	E_1	Population density	Categorical (3- high-density; 2-medium-density; 1- low-density; 0- Non-INSEs locations)
	E_2	Existence on railway reserve	Binary (1-Railway reserve; 0 – other locations)
	E_3	Existence on road reserve	Binary (1-Road reserve; 0 – other locations)
Proximity characteristics	E_4	Distance to rivers	Continuous (Euclidean distance within city extents)
	E_5	Distance to protected areas (environmentally sensitive)	Continuous (Euclidean distance within city extents)
	E_6	Distance to protected areas (government)	Continuous (Euclidean distance within city extents)
	E_7	Distance to CBD	Continuous (Euclidean distance within city extents)
	E_8	Distance to business centres	Continuous (Euclidean distance within city extents)
Neighbourhood characteristics	E_9	Proportion of commercial land in the neighbourhood	Continuous (sum focal statistics neighbourhood of 90x90 metres)
	E_{10}	Proportion of INSEs in the neighbourhood	Continuous (sum focal statistics neighbourhood of 90x90 metres)

4.12.1. Limitations of variables

As noted in Section 4.4, some settlements are evicted and re-established immediately such that analysis of imagery years apart fails to capture their changes. Some evicted locations may therefore be left out in this study for that reason. Further, this model captures eviction for a huge time gap, and this presents a challenge to selection of dynamic independent variables such as *proportion of surrounding commercial land*. The study has chosen to use current land uses, which assumes that these land uses are not significantly differently from how they were at the time of eviction.

4.12.2. Multi-collinearity Diagnosis

Factors in this model did not show any tendency of multi-collinearity (VIF values were < 10 and tolerance values > 0.1) (Table 18).

Table 18 Multicollinearity results for eviction:

Variable	Name	Tolerance	VIF
E_1	Population density	.846	1.182
E_2	Existence on rail wayleave	.971	1.029
E_3	Existence on road reserve	.968	1.034
E_4	Distance to rivers	.704	1.421
E_5	Distance to environmentally sensitive areas	.693	1.442
E_6	Distance to government protected areas	.727	1.375
E_7	Distance to CBD	.789	1.267
E_8	Distance to business centres	.612	1.634
E_9	Proportion of commercial land in the neighbourhood	.875	1.142
E_{10}	Proportion of INSEs in the neighbourhood	.986	1.014

4.12.3. M_{EV}: INSEs Eviction Model

Factor maps of the included variables are in Figure 25.

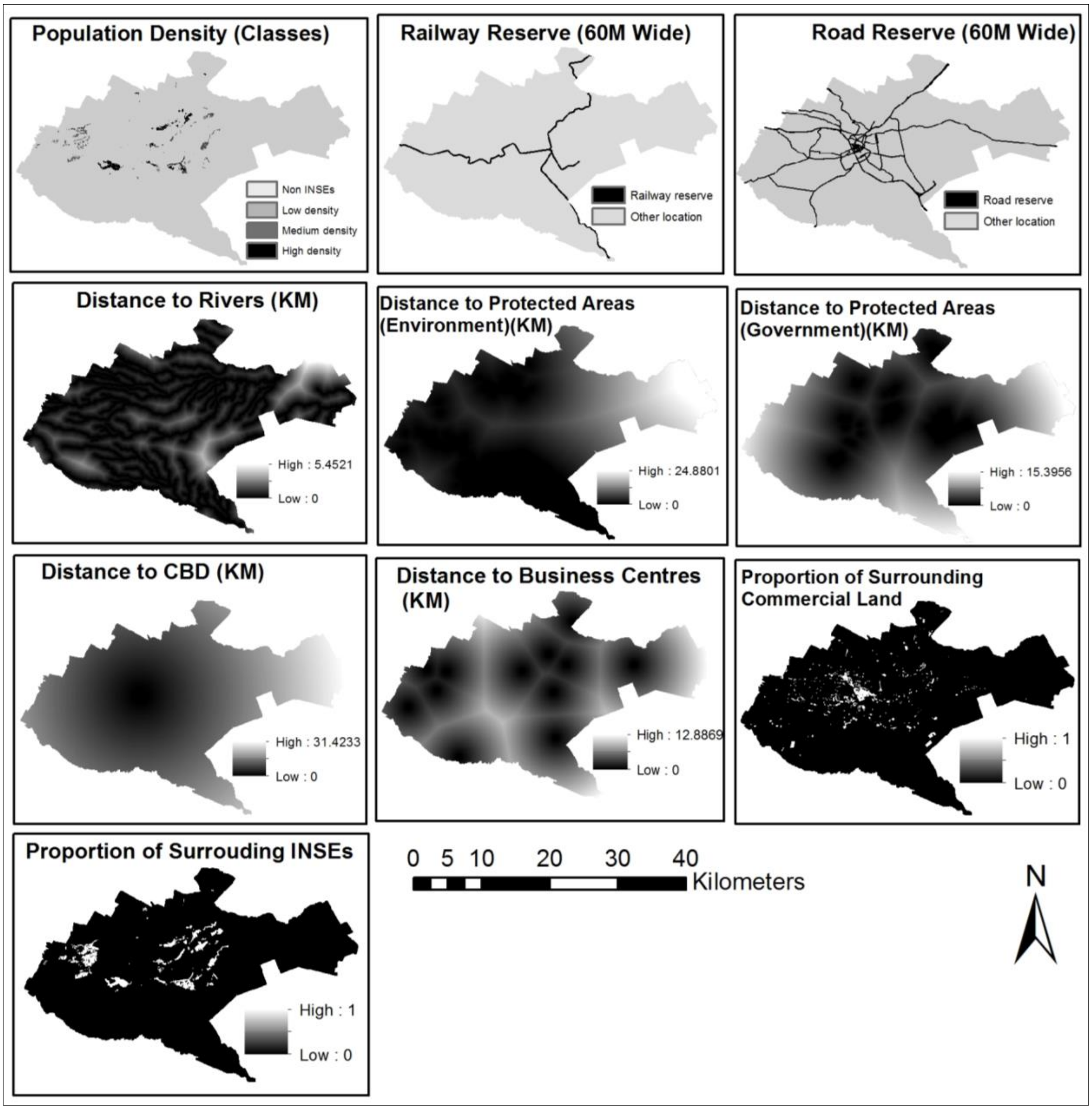


Figure 25: Factor maps for eviction model

This model had a sample size of 7,229 points. A significant set of variables was realized in the fifth backward step. This was after eliminating *proportion of surrounding INSEs* (p-values: 0.981), *population density* (p-values: 0.402), *railway reserve* (p-value: 0.639), and *road reserve* (p-values: 0.343). The model was significant with p-value of 0.000 (α 0.05), PCP of 87.6, chi-square of 2400.874. A spatial interdependency test on regression residuals gave a *Moran's I* of -0.168751; with z scores of -1.510378 and p values of 0.130947, an indication of lack of spatial interdependency. Significant variables are summarized in Table 19 (Appendix I).

Table 19: Significant drivers for eviction (M_{Ev})

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Distance to rivers	.875	.302	8.410	.004	2.399
Protected areas (environment)	.491	.071	48.398	.000	1.635
Protected areas (government)	.216	.045	23.147	.000	1.242
Distance to CBD	.000	.000	48.312	.000	1.000
Distance to centres	.000	.000	9.013	.003	1.000
Proportion of surrounding commercial land	.022	.010	4.470	.035	1.022
Constant	-4.922				

The model shows that the locations with the highest likelihood of eviction are close to rivers (O.R., 2.399), within protected areas (environment) (O.R., 1.635), and government protected areas – over security reasons (1.242). Other factors contributing to eviction are distances to CBD, distance to centres and surrounding commercial land.

4.13. Concluding Remarks

Results in this section have responded to study objective 2 through identification of INSEs locations, quantification of their change, and investigation of their drivers of change. Need to categorize INSEs in Nairobi by typology is a finding whose adoption has led to more detailed modelling results. Regarding change location, it is clear that locations expand, densify and get evicted at different rates, and these changes are subject to location characteristics, which can be investigated through spatial modelling. The study shows LRM as a strong model, being significant for all models in the study at a high confidence level (95%).

A close comparison of change drivers from literature, key informants and modelling are presented in Table 22 and Table 23. These summary tables show that non-spatial driver from literature and key informants, though could not be modelled, agree to a high degree. In a general sense, the spatial drivers from the three sources also agree, but their influences to growth and eviction processes vary minimally between key informants and modelling. The study adopts drivers from modelling outputs whenever there is a conflict of inconsistency between modelling results and other sources; meanwhile, a detailed assessment of these results and possible causes of their nature is done in **Chapter 6.**

5. PROBABILITY MAPPING AND THE IMPLICATION OF MODELLING FOR INSE MANAGEMENT

In this chapter, INSEs' growth and eviction drivers discussed in Chapter 4 are used to assess possible growth and eviction scenarios in future. An assessment of policies affecting INSEs in Nairobi is then done, leading to a discussion on the importance of such modelling processes to INSEs' management.

5.1. Probability Mapping for Growth and Eviction

This study notes that while logistic regression models have been used to predict general urban growth (e.g. Allen & Lu, 2003), their application in predicting INSEs growth, as applied by Abebe (2011), is only possible with shortcomings. Consistent with the observations of Ngau (2013) and Sietchiping (2005), key informants in this study noted that INSEs' policies have a huge impact on growth and eviction trends. The informants provided shortage of affordable housing, lack of employment, and poor spatial policies (Table 27) as the strongest non-spatial drivers of growth. Exclusion of these policy-related factors in INSEs growth prediction, as well as other important spatial factors dropped from the modelling for lack of reliable data such as land tenure and land value proxy measures (Table 28), present a huge limitation to making predictions in this study. For this reason, the study does not identify locations expected to experience INSEs change, but only assess the probability of locations to experience expansion, densification and eviction based on modelling outcomes.

5.2. INSEs Expansion Probability Mapping

Based on the factors of INSEs' expansions and their coefficients, the logistic regression function was used to produce probability maps for the 6 INSEs' expansion models. Probability maps for $M_{Ex}C_{CL}05$, $M_{Ex}C_{AT}05$, $M_{Ex}C_{CL}10$, and $M_{Ex}C_{AT}10$ models were used to test how reliably $M_{Ex}C_{CL}15$ and $M_{Ex}C_{AT}15$ could be used to show high-probability expansion locations. This was achieved first through generation of probability maps and classification of their probability values by quantiles (as applied by Dubovyk et al., 2011) for visualization. Subsequently, extracting probability values to each growth location cell enabled creation of box and whisker plots, showing distribution of probability values on actual growth locations.

The probability map for $M_{EX}C_{CL}05$ was overlaid on growth locations of *Classic* INSEs in P_1; map for $M_{EX}C_{AT}05$ overlaid on growth locations of *Atypical* INSEs in P_1; map for $M_{EX}C_{CL}10$ overlaid on growth locations of *Atypical* INSEs in P_2; and map for $M_{EX}C_{AT}10$ overlaid on growth locations of *Atypical* INSEs in P_2. Probability maps for these four models are in Figure 40 (Appendix K). The box and whisker plots are in Figure 26. Statistics for the box plot and the distribution of expansion locations on probability-maps' quantiles are show in Table 20.

The box plots show that probability values on actual growth locations have a small range, with only a few outliers especially for $M_{EX}C_{CL}05$ and $M_{EX}C_{AT}05$, which could be brought about by factors missing from the model. Also notable is that value ranges in the upper quantiles are smaller than in lower quantiles. On the probability maps, expansion locations are mostly in the *high probability* quantile, with at least 85% of all locations being in the *very-high probability* quantile, and at least 90% being within the combined *high* and *very-high probability* quantiles. While it may be concerning that models for 2005, 2010 and 2015 will show different probabilities for same locations, this study notes that factors of growth from year 2005, 2010 and 2015 models do not differ completely (Table 23). Precautionary, Allen and Lu (2003) urge use of LRM only for short term predictions as their reliability reduce over time.

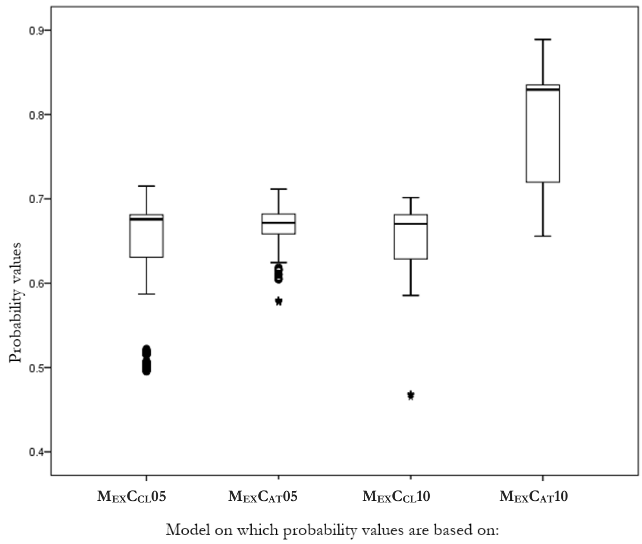


Table 20: Probability values of expanded locations

Model	MExCCL05	MExCAT05	MExCCL10	MExCAT10
Min	0.495	0.577	0.461	0.656
$\bar{x}$	0.665	0.666	0.595	0.779
Max	0.715	0.711	0.701	0.889
σ_X	0.050	0.022	0.045	0.045
% of pixels per class based on probability map quantiles (Appendix K)				
Model	**MExCCL05**	**MExCAT05**	**MExCCL10**	**MExCCL10**
Q5	85	91	88	78
Q4	8	9	7	15
Q3	7	0	5	7
Q2	0	0	0	0
Q1	0	0	0	0

Abbreviations and symbols:	Q5 – Very high probability
Min – Minimum probability value	Q4 – High probability
$\bar{x}$ - Mean of probability values	Q3 – Medium probability
Max – Maximum probability value	Q2 – Low probability
σ_X – Standard deviation	Q1 – very low probability

Figure 26: Overlay results of probability prediction maps and expansion locations

Similarly, probability maps for expansion models of year 2015 were generated. Masking locations of null probabilities for expansion (i.e. protected areas and built-up areas), a visualization is created to show all map locations and their probabilities of expansion for both *Classic* and *Atypical* INSEs (Figure 27)[8].

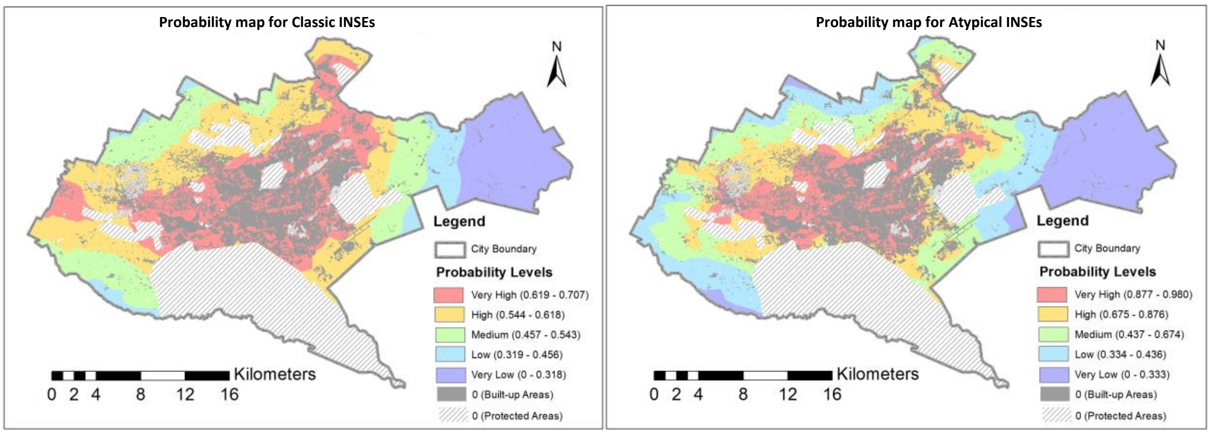


Figure 27: Probability of location to experience INSEs expansion

Further, probability maps in Figure 27 are used to show locations with very-high probabilities of expansion (based on quantiles classification) against the land use map for Nairobi. This is achieved through extraction of *very-high probability* classes for both types of INSEs and overlaying them with the current land use map for the city (Figure 28 and Figure 29).

For *Classic* INSEs, probable expansion locations are found mostly on small-in-size residential areas that are between built-up areas. They are also around industrial and commercial locations that are not built-up, and around the CBD, stretching to northeast of CBD, and minimally to the west of the CBD. This is also along the same strip where major transport networks are concentrated. They also appear to be considerably close to the existing *Classic* INSEs even though proximity to existing INSEs is not among the top three strongest drivers of expansion.

[8] Probability classes' values for the two typologies do not match since they have different probability ranges and frequencies, and not directly comparable

For *Atypical* INSEs, probable expansion locations are mostly on larger-plots of non-built-up agricultural and residential areas. They are also proportionally lesser near industrial areas than *Classic* (Figure 30).

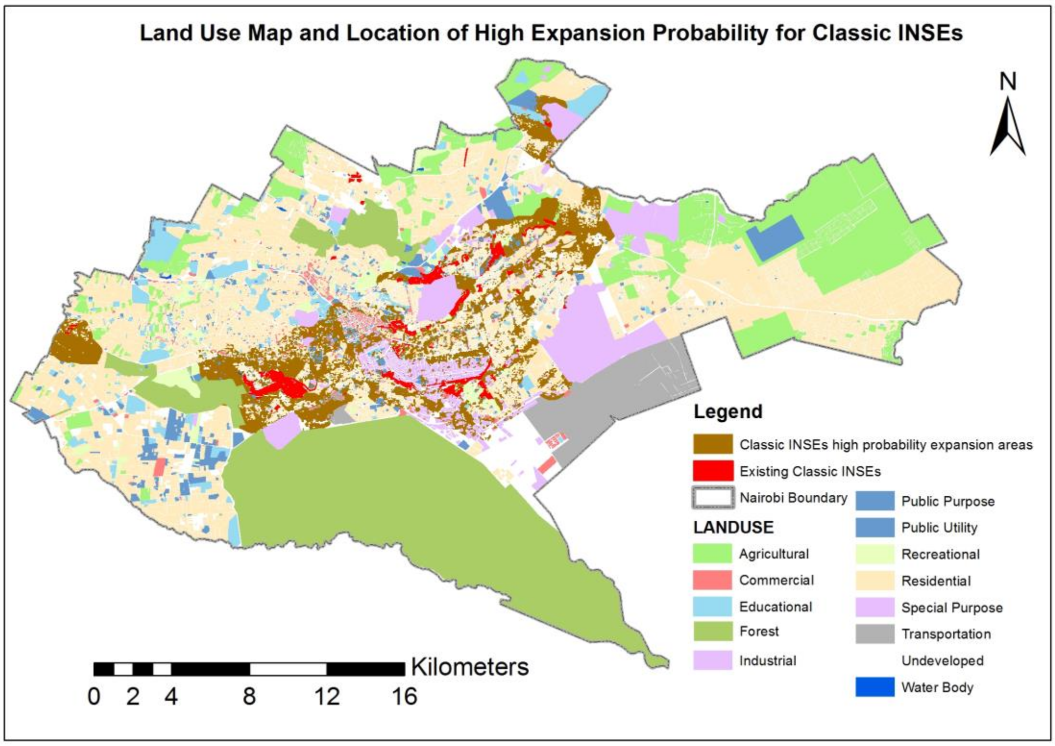


Figure 28: Classic INSEs high-probability expansion locations on Nairobi city map

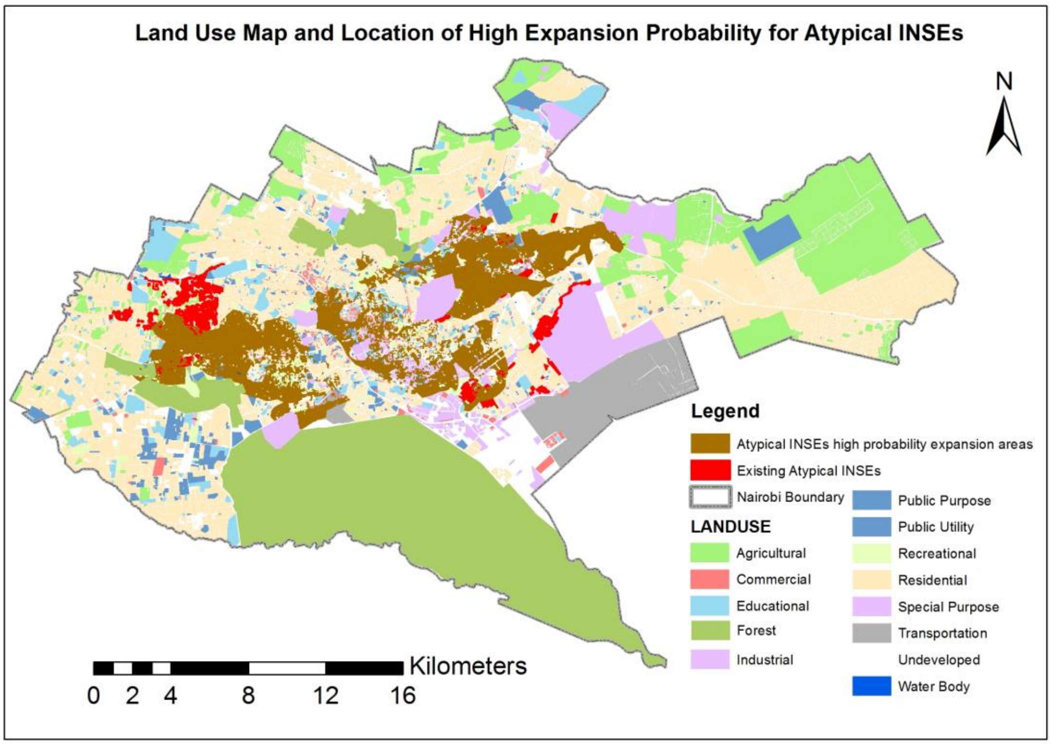


Figure 29: Atypical INSEs high-probability expansion locations on Nairobi city map

The fact that industrial areas and major roads are two of the strongest drivers of *Atypical INSEs* expansion explains their overlap with *Classic* INSEs high probability locations. In the *very high probability* quantiles, *Atypical* INSEs have higher values (0.877 - 0.980) than *Classic* INSEs (0.619 – 0.707), and this indicates that the overlap areas are more likely to develop *Atypical* than *Classic* INSEs.

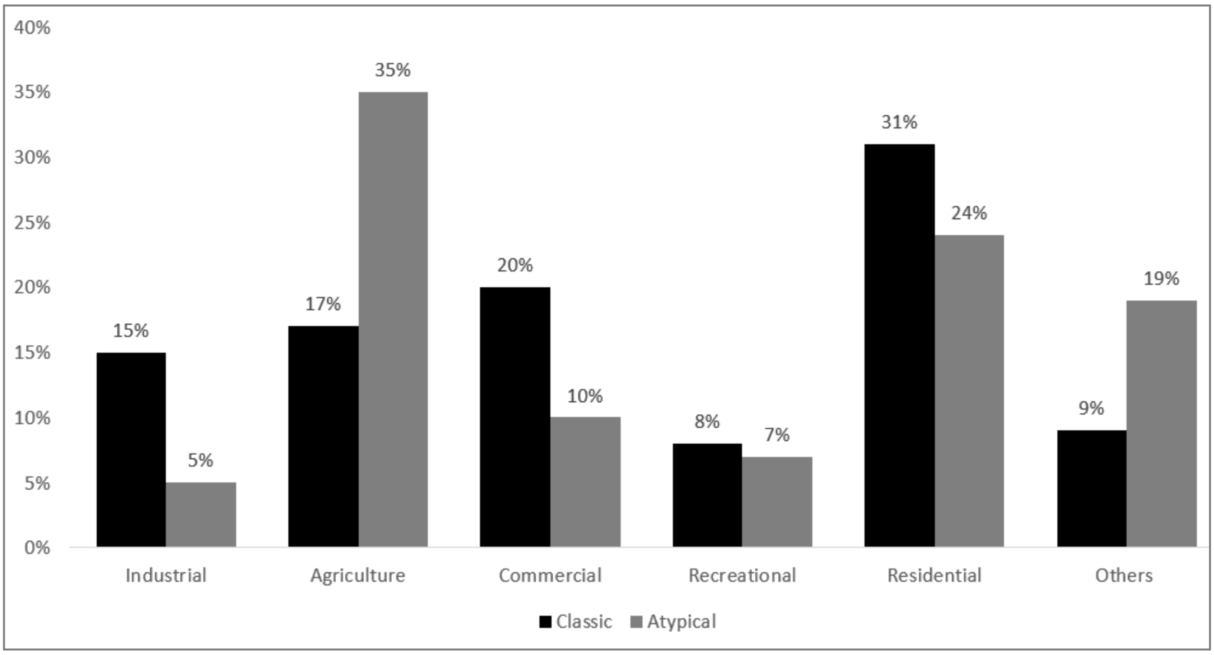


Figure 30: Non-built up land uses for probable expansion areas by typology (in %)

5.3. INSEs Densification Probability Mapping

Similar to the expansion-prediction operations in Section 5.2, predictive strength of the densification models was tested through: generation of probability maps based on year 2005 and 2010 models; classification of the maps into quantiles; and then overlay of the probability maps with actual densification locations. Different from expansion prediction, densification prediction was done within the extents of INSEs locations. This makes it unimportant to make predictions on low-density models since the results of such would show locations likely to have low densities in future, which can only be used explain low-density areas that retained their density, or reduced in density, which would otherwise be covered under eviction modelling.

Based on $M_{DE}C_M05$, $M_{DE}C_H05$, $M_{DE}C_M10$, and $M_{DE}C_H10$ models, densification probability maps were produced (Figure 41, Appendix K), reclassified (based on quantiles), and overlaid with actual densification locations. The overlay led to the assessment of $M_{DE}C_M05$ probability map against locations that changed from other density classes to medium-density in P_1; $M_{DE}C_H05$ probability map against locations that changed from other density classes to high-density in P_1; $M_{DE}C_M10$ probability map against locations that changed from other density classes to medium-density in P_2; and $M_{DE}C_H10$ probability map against locations that changed from other density classes to high-density in P_2. Overlay results are summarized in Figure 31 and statistics given in Table 21.

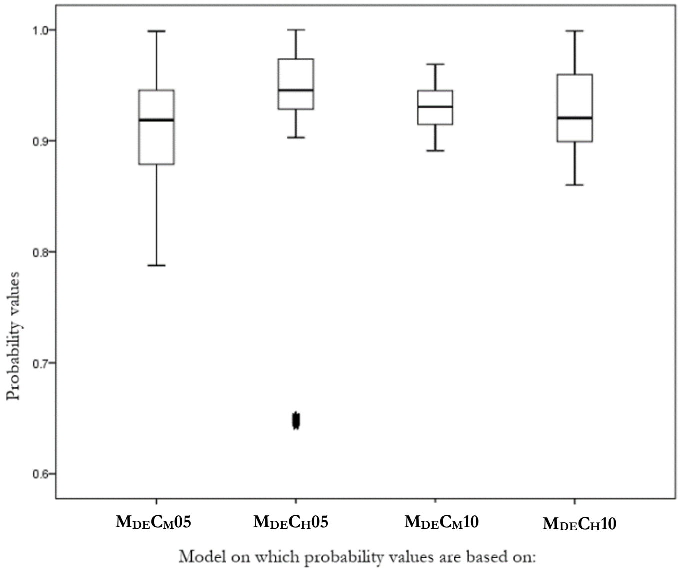


Table 21: Probability values of expansion locations

Model	$M_{DE}C_{M}05$	$M_{DE}C_{H}05$	$M_{DE}C_{M}10$	$M_{DE}C_{H}10$
Min	0.395	0.642	0.891	0.318
$\bar{x}$	0.794	0.956	0.930	0.768
Max	1.000	1.000	0.968	1.000
σ_X	0.165	0.040	0.019	0.216
% of pixels per class based on probability map quantiles (Appendix K)				
Model	**$M_{DE}C_{M}05$**	**$M_{DE}C_{H}05$**	**$M_{DE}C_{M}10$**	**$M_{DE}C_{H}10$**
Q5	81	89	90	85
Q4	13	6	10	15
Q3	6	5	0	0
Q2	0	0	0	0
Q1	0	0	0	0

Abbreviations and symbols:
Min – Minimum probability value
$\bar{x}$ - Mean of probability values
Max – Maximum probability value
σ_X – Standard deviation

Q5 – Very high probability
Q4 – High probability
Q3 – Medium probability
Q2 – Low probability
Q1 – very low probability

Figure 31: Overlay results of probability prediction maps and densification locations

The box and whisker plots show probability values being between 0.8 and 1 for all locations, except for a few outliers in $M_{DE}C_{H}05$. On the probability map, these outliers are found to be in the medium probability quantile, which may also be attributed to the factors not included in the model. Results also show over 80% of values in all models being within the *high-probability quantile* of the probability maps. For lack of other studies that have used this approach, or thereof set operational thresholds, the study takes this percentage as high, at least enough to reliably map future probabilities. This led to the generation of probability maps using $M_{DE}C_{M}15$ and $M_{DE}C_{H}15$ (Figure 32).

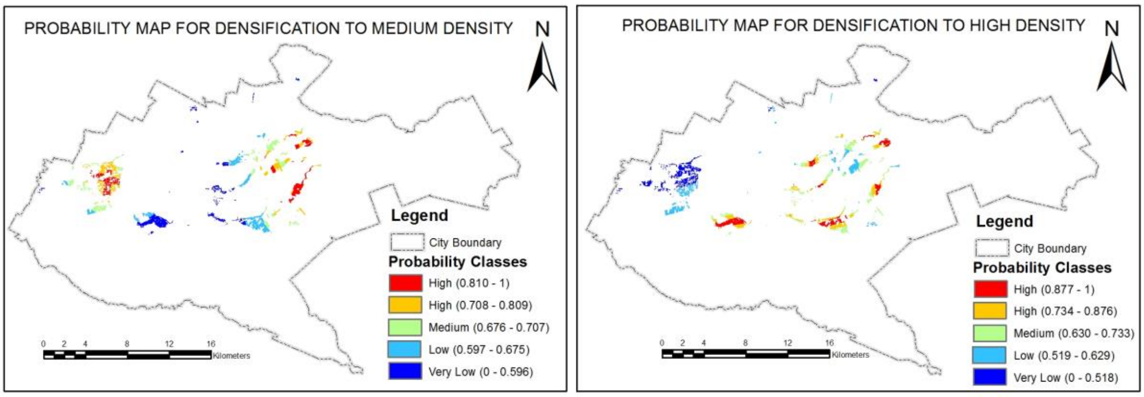


Figure 32: Probability maps for densification to medium and high densities

Areas with a *very-high probability* of densifying to medium and high densities were extracted from the reclassified probability maps and overlaid with INSEs' density classes at year 2015. This enabled assessment of current locations' densities against their likely density change. Locations of interest (those with low-density and high probability of changing to medium and high-density; and those with medium-density and with high probability of changing to high-density), were extracted and mapped as locations with high probability of densifying. These locations are shown in Figure 33.

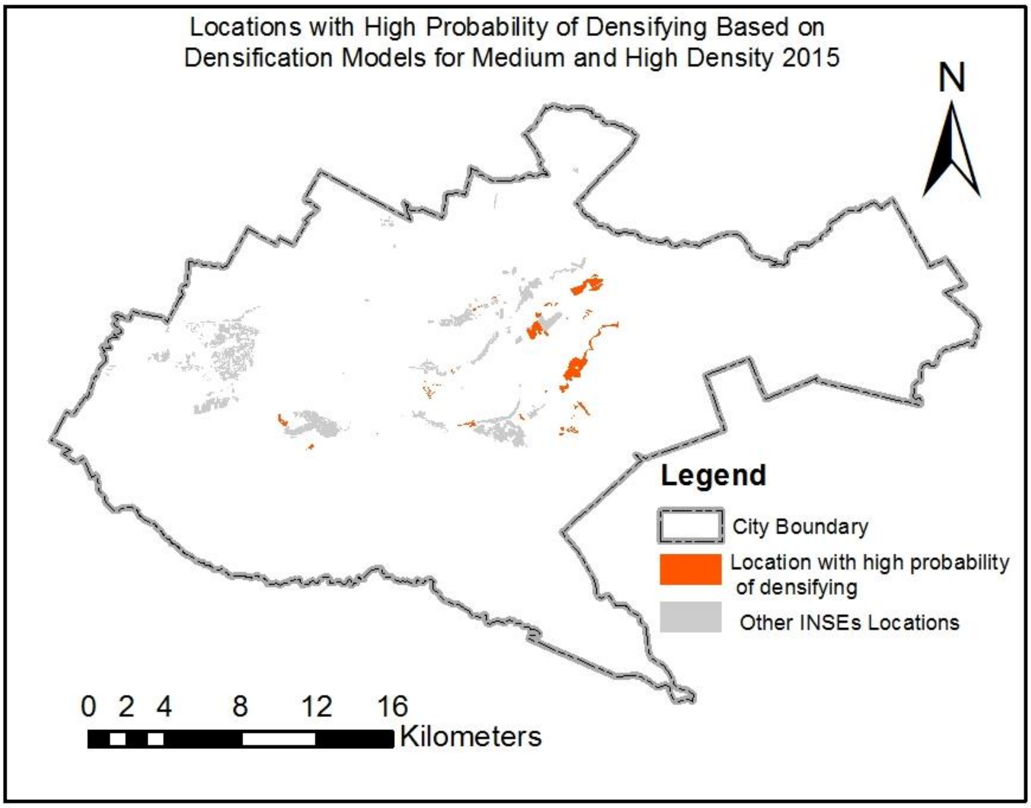


Figure 33: Location with high probability of densifying

These locations are in both types of INSEs. *Classic* INSEs locations are, or part of, Kianda (Kibera), South Lands Village, Vumilia village, Gitathuru and Kiamaiko settlements. *Atypical* settlements are Sokoni village, (Embakasi), Soweto (Kayole), Umoja, Kayole sabasaba, Kariobangi south (part), Dandora (part), Biafra, Bondeni (Dandora) and Huruma.

5.4. INSEs Eviction Probability Mapping

Unlike the growth modelling, eviction was not modelled along time steps, and could therefore not be validated by multi-temporal data. Probability mapping for eviction is also faced by the shortcoming that top drivers of eviction, as gathered from literature and key informants (Table 29), are non-spatial, with most of them being proxy indicators for poor land governance. Moreover, among the strongest ranked spatial drivers of eviction is proximity to prime investments and land tenure (Table 30), both of which have not been included in the eviction model for lack of reliable data. With more data, therefore, this probability mapping could be improved. Based on M_{EV}, a probability map for eviction locations was generated (Figure 34).

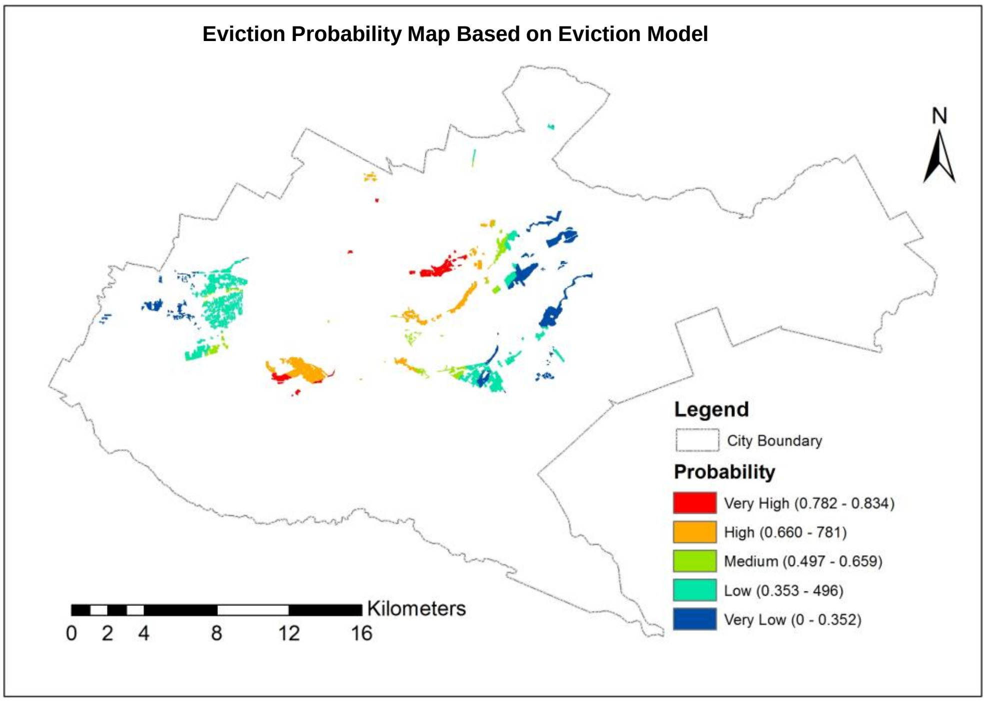


Figure 34: Eviction probability map

Incidentally, locations with high probability of eviction mostly have *Classic* INSEs. The reason for this, reflecting upon the drivers of eviction, could be their close proximity to rivers and protected areas compared to *Atypical* INSEs. These settlements include Raila (part of Kibera), which boarders Ngong road forest; Soweto west, also next to Ngong road forest; South land village and Kijiji, both sandwiched between planned residential development and also less than 1 KM from the National park; Deep Sea settlement, which borders Karura forest; Mathare slums (Kiamutisya, Kosovo, 3A, 3B, 4A, 4B, No 10, Mashimoni, Kwa Kariuki, Gitathuru, Madoya), all of which are in close proximity to Mathare river.

While eviction threat is so widespread in the settlements of Nairobi (with 64 settlements currently in active threat) for its objective comparison with modelling outputs, it can be noted that of the aforementioned settlements, only South Land and Kijiji do not have documented threat of eviction at any time (Pamoja Trust, 2009). Mathare slums, which have the highest eviction probabilities, have extended to the river channels (Figure 35). Reflecting on the dynamics of INSEs eviction (Section 4.3.3), however, the reliability of the eviction probability mapping needs to be defined by the factors included as well as missing from the model. In an example, while spatial analysis shows large and established settlements such as Mathare at a high risk of eviction, Mmust (2015) explains that established settlements have residents' organization, are well linked to human rights grounds and have higher levels of awareness, and this significantly reduced their risk of eviction. For these settlements, even when eviction is intended for development, e.g. eviction to protect riparian reserves (see Figure 35), a negotiated approach involving community mapping, impact assessment, scenario development and consensus building must be adopted (Karisa, 2010).

Source: Mwau (2011)

Source: Amnesty International (2012)

Figure 35: INSEs along Mathare River & residents along railway on resisting eviction, Kibera

5.5. Policies Impacting Growth and Evicting of INSEs

There is no policy document in Kenya that is singularly dedicated to informal settlements. Growth and eviction of INSEs in Nairobi is therefore impacted by lack a policy or general land use and development control policies as discussed below:

5.5.1. Land-use Planning Policies

INSEs are often not part of spatial development plans; therefore, they are more directly impacted by development control policies (discussed in Section 5.5.2) than land use planning policies. The NCC holds the central role of spatial planning for Nairobi as stipulated in the Urban Areas and Cities Act (GoK, 2011b). The act requires the city to prepare an integrated city or urban development plan, ensuring provision for (1) proper assessment of current social cultural, economic, of environmental situation of the city, (2) community needs and their alignment to the constitution, (3) promotion of interests and rights of minority and marginalized groups, (4) projects to achieve intended goals, (5) development control, and (6) performance management tools to measure impact among others.

The Integrated Nairobi Master Plan (JICA, 2014) is the spatial planning policy document currently guiding spatial development in Nairobi. The document provides a land use policy based on the principles set in the *Kenya Vision 2030* national planning guidelines (The Ministry of Planning and Devolution, 2007). This plan recognizes the undesirable growth of INSEs but does not provide a detailed intervention for them. It has provided interventions for INSEs locations as: urban re-development from low to medium-to-high densities (by way of high-rise development); establishment of housing schemes for low income groups; and readjustment of land /replotting. Further, the plan guides that land possessed by large land occupants (including KRC, NCC, KPLC, schools, police station and land buying companies) be utilized for housing and other urban development.

5.5.2. Development control Policies

All spatial developments in Nairobi are required to comply with the county government's development guidelines. Any development not compliant to the zoning ordinance (City Council of Nairobi, 2004) should be removed by the NCC, with the owner(s) bearing the cost of removal. In the ordinance, and also in the amendments proposed by Mwaura (2006), minimum plot sizes allowed in each zone, the nature of buildings, and their maximum plot coverages and ratios are provided. Also empowering the NCC to control illegal development is the Physical Planning Act (GoK, 2012b) which stipulates that each local authority must prohibit development of land and building for orderly development; control sub-division of land; receive and approve (compliant) development applications; formulate by-laws to regulate zoning; and maintain land planned for open spaces, parks, forest and greenbelts.

Other than the NCC, land owners can stop INSEs from occupying their private land under the Land Act (GoK, 2012a). Furthermore, government owned establishments that own land are empowered by laws establishing them to protect land under their possession, including demolishing such structures and selling their building materials to pay for the cost of demolitions. Examples of such legislations include: Traffic Act (GoK, 2013), which authorizes removal of any encroachment on road reserves; the Wayleaves Act (GoK, 2010) which provides for removal and penalization of any person who erects any structures over sewer, drains and pipelines; and the Environment Management and Coordination Act (GoK, 1999), which empower the National Environment Management Authority (NEMA) to demolish any structure constructed on a location where it disturbs a river, lake or wetland, and the Protected Areas Act (GoK, 2011a) which defines all areas protected for the purposes of national security and prohibits any unauthorized access.

5.5.3. INSEs Intervention Projects in Nairobi

Major development projects, including housing infrastructure projects, environmental management projects in Nairobi mention INSEs. However, intervention projects that singularly focus on INSEs are *Kenya Slum Upgrading Project* (KENSUP) (UN-HABITAT, 2015b) and *Kenya Informal Settlements Improvement Program* (KISIP) (GoK, 2014). KENSUP was started in year 2003 by the UN-Habitat, Government of Kenya, and City Alliance, its goal being to mobilize financial and other resources for slum upgrading and low cost housing within the framework of MDGs. KISIP, on the other hand, is funded by The World Bank, AFD and SIDA, and implemented by Ministry of Lands, Ministry of Housing and the local authorities. The project was set to run between year 2011 and 2016 with the objective of building the capacities of housing institutions, enhancing security of tenure, enhancing infrastructure and service delivery, and planning urban growth.

Other projects include NGO initiatives. There are many NGO initiatives for INSEs in Nairobi, with most focusing on thematic areas e.g. sanitation, youth empowerment and small-scale upgrading. Pamoja Trust (2015) is perhaps the biggest NGO actor. It carries out projects of tenure regularization, community empowerment, slum mapping and upgrading and relocation planning across the INSEs in Nairobi. Others include *Slum Dwellers International Kenya*, also working in numerous projects, and *Amnesty International* and *Informal City*, both campaigning against forceful eviction.

As regards spatial intervention, INSEs' intervention plans have been continuously developed by NGOs, planning authorities and learning institutions in Nairobi, but all are common in that they lack a history of implementation. Examples of elaborate spatial plans not implemented include the Mathare Zonal Plan, developed by Muungano Support Trust et al. (2012); Mukuru kwa Njenga Slum Upgrading Plan developed by Centre for Urban Research and Innovations and University of Nairobi (2012); and also Public Toilet Allocation Plan in Kibera settlement developed by Holderness, Walker, Alderson and Evans (2013) using spatial multi-criteria assessment.

5.5.4. Appraising INSEs Intervention policies and projects

The lack of a policy for INSEs in Nairobi means employing other policies touching on INSEs to make decisions on INSEs. Ministry of Lands (2009) notes that these policies lack harmony particularly among planning and enforcement statutes. Further, land use planning policies do not mention INSEs, and even where they do, only an appreciation of their existence is given (e.g. JICA, 2014), without any attempt to provide an intervention for them. Not surprisingly, a strong framework for development control exists, but this only translates into restricting development or initiating eviction, which this study has marked as largely ineffective. Restricting development will be effective only when the city can provide housing at the rates of urbanization. Unfortunately, the need for affordable housing is Nairobi is far higher than supply, which Mwaniki, Wamuchiru, Mwau, and Opiyo (2015) attribute to low capacity of state and the city authority. JICA (2014) confirms this by stating that half of Nairobi's population increase in the last decade settled in INSEs.

As regards intervention projects such as KISIP and KENSUP, some success has been reported e.g. upgrading Soweto-East settlement in Kibera to high-rise development. However, Bafo (2012) argues that these projects are being implemented without a clear policy guideline, making it impossible to evaluate their performance. Furthermore, their scales are too small to match the needs of a growing city like Nairobi. The World Bank (2011) notes that because of limited resources, KISIP prioritizes settlements without land tenure disputes; in location which are not hazardous; with large and dense settlements; in close proximity to trunk infrastructure; and with communities showing readiness to participate in projects. Many settlements in Nairobi are unlikely to meet these requirements.

Focusing on spatial planning, considerable efforts are being made to prepare plans, especially at small scale (settlement by settlement), for example, Mathare Zonal Plan. These plans have nevertheless not been implemented which is attributed to lack of implementation capacity by city authorities (Mwaniki et al., 2015). Moreover, these plans are not informed by spatiotemporal dynamics of INSEs, which would otherwise provide a link between settlements, their pasts and possible futures. World Bank (2011) argues that INSEs need to be integrated to the city, a reason for which their studies must be done first at city-wide scale. The existing plans for Nairobi are found narrow and insufficient in this sense.

5.5.5. From Static to Dynamic Spatial Planning

The World Bank (2011), based on lessons from its experience with INSEs project in sub-Saharan Africa, came a conclusion that INSEs' interventions need to be tailored to local contexts. This means recognizing unique characteristics of INSEs and using that as a basis for decision-making. Static mapping, as has been applied in existing plans for Nairobi's INSEs, is neither able to monitor temporal change nor incorporate INSEs' change dynamics into decision-making. The need for dynamic mapping (realized though simulation and modelling) is emphasized by Sietchiping (2005) who informs that it results into clear decision-making and better informed policies. Additionally, Abbott and Douglas (2003) argue that a shift from ineffective INSEs intervention policies to pro-active ones needs new knowledge on spatial growth dynamics, which starts with establishing factors of INSEs' change and their contribution to the change. In the case of Nairobi, spatial modelling will help to visualize INSEs at the citywide scale, show spatial change trends, and even provide a basis for assessing spatial implications of spatial change based on different scenarios (specific application of LRM modelling to Nairobi is discussed in section 6.4).

5.5.6. Concluding Remarks

This chapter shows that spatial modelling can be used to understand INSEs change, providing knowledge for use in anticipating future INSEs change. In Nairobi, there are identifiable INSEs policy deficiencies, the first being lack of an INSEs' policy. It is from its absence that other policy challenges emerge, for example, conflicting statutes. Additionally, preparation of city spatial plans has disregarded INSEs, and even so, the gap between plan making and implementation is wide. While INSEs' plans have been prepared continually for Nairobi, these plans are static and uninformed by spatiotemporal dynamics, otherwise possible with dynamic modelling and simulations. These plans are also small scale, mostly settlement based, and this translated into limited knowledge on the dynamics of aggregated INSEs'. It is also true that no spatial plan has attempted to categorize INSEs into typologies. Because of these deficiencies, anticipating future of INSEs based on their development trends is not possible.

6. REFLECTION ON RESULTS AND METHODOLOGICAL APPROACH

This section synthesizes the results of the study and reflects on their reliability as research outputs. Additionally, it looks at similar studies, their methodological approaches and draws a parallel between them and this study.

6.1. Dynamics of Informal Settlements

The study has shown that INSEs in Nairobi are diverse in character but can be categorized into two categories: *Classic* and *Atypical*. Incidentally, this observation complements the view by Majale (1993) and UN-HABITAT (2003b) that INSEs worldwide have diverse characters and their names will unsurprisingly differ from location to location. While majority of studies tackle INSEs under one general category (e.g. Magalhaes & Rojas, 2007; Sirueri, 2015; UN-HABITAT, 2005), few studies have found the need to appreciate typological variations in INSEs (e.g. Fekade, 2000; Geddes, 1915; Soliman, 2004).

In terms of INSEs growth, *Atypical* settlements are expanding 4 times faster than *Classic* settlements (Section 4.3.1), which creates the need to know the differences in their drivers of growth (explained in Section 6.2). Combining both typologies of settlements, the ratio of INSEs' to built-up area has increased from 3.1 to 4.3% between 2005 and 2015, an indication that INSEs are gaining more prominence in the city's built-up area. Additionally, Nairobi's INSEs are densifying, with this study showing 32% of INSEs area shifting from one density class to a higher class between 2005 and 2010, and 18.2% between 2010 and 2015. Yet, there is a developing trend of vertical growth that needs to be investigated in a future research, a pointer that densification rates could be higher. An observation is made that INSEs growth rates for Nairobi are competing with urban growth rates for the city (estimated at 3.9% (JICA, 2014)). JICA (2014) argues that in the last decade, which also corresponds to the period for this study, half of Nairobi's population growth settled in INSEs, and this trend is expected to continue.

About eviction, 2.5% of the INSEs area (46.3 Ha) has experienced eviction. Statistically, the figure is not huge, but the impact of this eviction on livelihoods is huge (see Amnesty International, 2009; Pamoja Trust, 2009). A baseline survey has established that spatial dynamics are only a part of eviction, with settlements' history, land ownership history, political regimes being a few of the causes of its complexities. From various sources (e.g. Amnesty International, 2009; Betzema, 2013; Pamoja Trust, 2009), the study has established that eviction has been on a continuous trend since the 1980s, with 32% of all recorded eviction cases happening before year 1990, 29% between 1990 and 2000, and 39% after 2000. This is in spite of the observation by Ngau (2013) that establishment of anti-eviction organizations and increased human-rights activism provided protection for INSEs' dwellers against eviction starting early year 2000. While evictions that are explicitly illegal account for only 32% of all eviction cases (led by non-state actors), key informants argue that state-led evictions (68%) have questionable legal groundings, and are, in fact, often led by non-state actors disguised as the state.

From a broader perspective, Nairobi INSEs growth trends are not very different from global trends. In Dar es Salaam INSEs expanded by 57% between 1982 to 1992 (Abebe, 2011); Istanbul by 110% between 1990 and 2005 (Dubovyk et al., 2011); and Hyderabad by 70% from 2003 to 2010 (Kit & Ludeke, 2013). By annual growth rates, the three aforementioned cities expanded faster than Nairobi, but only by a small margin. On the other hand, eviction of INSEs is common in the urban areas of the developing world (GUO, 2003), and even where there is established laws against eviction (e.g. the PIE act by Republic of South Africa, 1998), contravention of law is often reported (Huchzermeyer, 2004).

6.2. Modelling Data and Approach

Data

The modelling approach used in the study is LRM. Data on factors of growth were largely gathered from ITC archives, and validity checks proved them accurate for modelling. Dependent variables data were generated from Google Earth imagery. The advantage of using Google-Earth is that it provides free-of-cost historical imagery, which enables temporal assessment of land cover (Q. Hu et al., 2013). The study extracted planning data though on-screen digitizing, which was done by the author. These data were satisfactory for modelling; within two classes, correct classification was 97% which is higher than for Baud et al. (2010) who achieved an accuracy of 90% but based on 4 classes. However, this approach is laborious, demands local knowledge by users (I. Baud, Sridharan, & Pfeffer, 2008), and is prone to errors if done by different interpreters (Sliuzas, 2004). In other studies, the commonly used approach for extracting modelling data is image classification, which relies on spectral properties of land cover (Cheng, 2003). This approach could not be applied to this study since – besides distinguishing INSEs from other built-up areas by spectral properties being challenging (Hofmann et al., 2015) – the study has two typologies of INSEs whose roof surfaces has a huge spectral characteristics overlaps. There is, however, need for automated methods of data extractions, especially where huge volumes of data are required. In the study of densification, small density changes were not analysed because of the laborious work of generating building footprints; yet, based on a select settlements, Sartori et al. (2002) could quantifying small density changes as less as 5% in Kibera based on image classification, but on an image with extents limited to INSEs' locations. New developments in extraction of INSEs from imagery through advanced remote sensing algorithms e.g. lacunarity-based slum detection (Kit & Ludeke, 2013) and comprehensive object-oriented image analysis (OOIA) (Kohli, 2015) could potentially be used in a future study.

Missing data from the modelling (LRM) included the zoning plan/master plan and land tenure for expansion models; INSEs building footprints for densification models; and locations of prime investments for the eviction model. Data (e.g. for location of prime investments and building footprints) could be generated with the help of local experts and city authorities, but this was not possible in the study due to time limitations. Dubovyk et al. (2011) and Huang et al. (2009) acknowledge that data shortage in land use change modelling is a common problem, and can potentially cause overestimation of causative effect of model variables. A repeat modelling exercise with all relevant data can be used to establish the significance of the missing data.

Methods

The study used LRM to establish the drivers of change and the levels of their influence. PCP was used to tests the performance of the models, where value ranges were 83 to 85% for expansion models, 68 to 89% for densification models and 87.6% for the eviction model. Other studies that have used LRM to model have realized different PCPs (e.g. 75 – 87% by Dubovyk et al. (2011), 75 – 96% by Abebe (2011) and 75 – 83% by Cheng & Masser (2003)). While PCP will depend on the model' settings and the variables in it, Huang et al. (2009) used LRM to realize PCPs of between 60 and 76%, which they argue are satisfactory. LRM is usable in establishing the drivers of INSEs in Nairobi, and this corresponds to the observation in literature that the LRM is easy to interpret (Field, 2009), has strong explanatory power, and is spatially explicit (Dendoncker et al., 2007).

A limitation to LRM in the study is its inability to incorporate non-spatial factors of change e.g. land governance proxy indicators e.g. *regard for rule of law* and *accountability*. In their study, Dubovyk et al. (2011) made a similar observation, noting that LRM does not have the ability to incorporate some important drivers of INSEs change such as people's preference and political influences. Other researchers have emphasized other issues that this study could not reveal, but important to note while employing LRM.

Allen and Lu (2003) and Dubovyk et al. (2011), who modelled growth using raster cells of 30*30 metres (as opposed to 10*10 metres in this study), argue that the scale of the study area and spatial units of analysis are aspects to which LRM is sensitive to. Whereas Dubovyk et al. (2011) found that experimenting with different spatial scales yield varying results, Allen and Lu (2003) argue that the success of LRM in prediction can range from 30 to 90% and will get more unreliable as prediction time is lengthened.

As a way to improving the LRM, particularly its inability to incorporate spatial-temporal dynamics, use of hybrid models has been recommended by Allen and Lu (2003). This has been done by Arsanjani et al. (2012) who combined LRM, Markov Chain and CA approaches. They found that deficiencies of LRM such as inclusion of SLEUTH factors could be overcome by this approach, but found the model's strongest limitation as its inability to factor individual behaviour and personal preference, to which they recommend use of ABM. Roy et al. (2014) discuss *slum*-modelling approaches that could overcome the weaknesses experienced with LRM. They argue that INSEs change can be studied by assessing household behaviour and decision-making based on an ABM. This model, though weak in geographic analysis, is strong in combining urban dynamics and social processes while incorporating human decision making (Tian & Qiao, 2014). Schwarz, Flacke and Sliuzas (2016) have used this approach in a hypothetical model where they incorporated land tenure, household income and preferences regarding location in investigating options of urban upgrading on infrastructure and income segregation. A model combining potentials of ABM and LRM will potentially reveal more INSEs dynamic and yield better results.

Retrospectively, the need to link INSEs change processes (expansion, densification and eviction in this case) in modelling is recognised. The study noted patterns that could not be investigated because of being outside the research scope, but needs consideration in a future research. They include incorporating vertical growth into INSEs modelling, and investigating development of a model that can link eviction, expansion and densification processes. With Dubovyk et al. (2011) noting that current modelling techniques for INSEs modelling are too computational and un-friendly for application by planning authorities, such a model must be aimed to be simple.

6.3. Driver of Change

6.3.1. Overview

The study has revealed the spatial and non-spatial drivers of INSEs expansion, eviction and densification in Nairobi. Only spatial drivers were modelled (see summary tables Table 22 and Table 23), and, in general, there is agreement between non-spatial drivers of change from literature and key informants.

For spatial drivers, agreement exist as far as defining significance of the drivers, differences being in the levels of their influences. Limited variations were noted to exist along modelling temporal scales (i.e. from T_1 to T_3), which is attributed to spatiotemporal dynamics of INSEs. The differences observed between the rankings of drivers by key informants and modelling, however limited, are speculated to be caused either the missing data or subjectivity of key informants, and the validity of this observation can only be established in another cycle of modelling when missing data is available for inclusion into the model. Meanwhile, the study takes the drivers from modelling as the true drivers of change as they are generated through statistical processes. Further, the drivers for the latest modelling time step (year 2015) are assumed to be the current drivers of change by which decision on management of INSEs can be made.

By typology, drivers of change for INSEs in Nairobi do not differ significantly. Along modelling time steps, only *distance to railway* (for *Classic* INSEs) and *distance to business centres* (for *Atypical* INSEs) appear in the top three drivers and are missing in the models of the other typology. At present, the strongest driver for *Classic* INSEs growth is *proximity to major roads* while for *Atypical* INSEs is *proximity to rivers*. The only drivers showing temporal stability are *proximity to industrial areas for Classic INSEs;* and *proximity to rivers* and *proximity to roads* for *Atypical* INSEs. Informant No. 9, contacted to discuss these findings, informed that *Classic* INSEs dwellers work more in industrial areas than *Atypical* INSEs dwellers, who are more attracted to the booming businesses sector in the suburbs/business centres.

For density, drivers differ by density classes and over time. For low-density, no driver in the top three has been stable through the modelling time steps, but *distance to business centres* and *distance to rivers* are stable for medium-density while *distance to river* is stable in the high-density. At present the strongest driver for low and medium densities is *distance to river*, which is the second in the high-density class, which has *distance to railway* as the top driver. Informant No. 9 argues that densification is detected close to riparian reserve because these locations often have expansion spaces, and therefore, INSEs expand rapidly without densifying until they reach an expansion constraint after which they start densifying.

Distance to rivers and *distance to roads* are the most prominent of drivers in all growth models. The affinity to settle near rivers being caused by availability of vacant space.

6.3.2. Comparative Assessment

Having appreciated the fact that INSEs are so diverse to be generalized even within one city, a comparison of drivers of INSEs change for Nairobi with other cities with INSEs may be done, but with less expectations. However, for clues on global behaviour on INSEs, a brief review is hereby done:

Expansion: Different INSEs modelling studies show different drivers of growth. In Dar es Salaam Abebe (2011) found *distances to roads, proportion of surrounding INSEs* and *other urban land uses* as the major drivers of INSEs expansion. *Proximity to roads*, which appears within the top 3 drivers of both typologies of INSEs is the only common drivers. In Sancaktepe (Istanbul), top three drivers of expansion are *population density*, *slope* and *undeveloped land* (Dubovyk et al., 2011) which are completely different with those of Nairobi. However, both key informants for Nairobi and Sancaktepe cite *proportion of undeveloped land* and *proximity to existing INSEs* as strong drivers. Incidentally, these are among the two strongest drivers of expansion in Pune as found by Shekhar (2012). From this assessment, it can be concluded that while factors such as *proximity to roads*, *proportion of surrounding INSEs* and *proportion of surrounding undeveloped land* appear common drivers for INSEs expansion, each city has its own dynamics and demands an independent investigation.

Densification: Densification has been modelled in studies lesser than expansion. The approach taken in this study is similar to that taken by Abebe (2011) in terms of basing density analysis on low, medium, and high classes. This study however uses binary logistic regression while Abebe (2011) uses multi-nominal logistic regression. These two approaches use the same logic, with multinomial logistic regression being an extension of ordered logit models (Field, 2009). While the strongest drivers of densification in Dar es Salaam for low, medium and high densities locations are *population density*, *distance to existing INSEs* and *distance roads* respectively, the strongest drivers for Nairobi are *distance to rivers* (for both low and medium) and *distance to railway* (for high-density). As has been found with growth, a parallel between the two cities is not possible to draw, at least from these findings. This is attributed to location dynamics for each city. A plausible explanation why *distance to CBD* is among the strongest drivers in Dar es Saalam while *distance to business centres* is among the strongest drivers for Nairobi, for example, may be that Dar es Salam is more monocentric (Kiunsi, 2013) than Nairobi, which has several prominent business centres.

Eviction: This study has not found other studies that have modelled eviction, and its undertaking was therefore both exploratory and insightful. The eviction model was based on the same logic as the growth models. What is different in this model is that while growth models are subject to forces of urbanization, otherwise hard to contain (United Nations, 2012), eviction is largely subject to government policies which can change as fast as governments get replaced (Ngau, 2013). For this reason, the effect of policies would need to be appropriately catered for in any eviction model. This also implies only short-term prediction can provide assurance for valid results. The results, though could not be validated statistically, enabled probability mapping and identification of locations at high risk of eviction. These modelling outputs showed strongest drivers as *proximity to rivers*, *proximity to protected government areas* and *proximity to protected environmentally sensitive areas*. This is opposed to *infrastructure development and restoration projects*, *proximity to prime lands* and *spatial development plans from* key informants. The last two were not included in the model for lack of reliable data. Further, as limitation to the study, some settlements which got evicted and re-established between successive Google earth historical imageries were note captured. A method that would capture such locations is participatory slum mapping (Tsion Lema, Sliuzas, & Kuffer, 2006).

6.4. Modelling and Management of INSEs

Prediction of expansion, densification and eviction locations is possible, but all relevant factors needs to be included in the modelling. An investigation of INSEs' modelling approaches has shown that incorporating other approaches such as ABM can lead to this achievement. In this study, the probability mapping approach employed was able to show probable locations of change based on the available data. While the impact of the missing data is unknown, the study has shown that change of INSEs in Nairobi can be monitored and predicted.

Major findings under probability mapping is that probable areas for *Classic* INSEs differ from those of *Atypical*. Where *Classic* INSEs' high probability locations exist between built-up locations and locations where major transports networks converge while *Atypical* INSEs have a big overlaps with *Classic* but will likely favour locations with bigger plots which had been on agricultural use. The probability value ranges (Figure 27) show that *Atypical* INSE have higher values in the *very high probability* quantile; this is interpreted to mean that where a location is favoured by both typologies for expansion, *Atypical* INSEs will more likely occupy it. Accordingly, probable densification locations are located to the east of the CBD in the area between the CBD and major industries. This locality has a concentration of transport networks, and INSEs with vacant spaces (mostly at the consolidation stage). Eviction probability mapping showed that eviction is likely to happen on settlements near national parks, forests, national reserves and rivers, which is consistent with the findings on the drivers for eviction.

This knowledge is indeed vital for policymaking. An appraisal of INSEs policymaking in Nairobi has show that there is need to create an environment that will make such knowledge useful. This is through development of an INSEs' policy that: defines INSEs (including their legitimacy), recognize INSEs in spatial plans, links plan making and implementation, and embeds single-settlement-based planning into the integrated citywide plan for INSEs.

As to the exact application of INSEs' monitoring and simulation, Hofmann et al. (2015) argue that continuous monitoring of INSEs change will lead to the development of systematic knowledge vital in understanding INSEs' genesis. This knowledge will then lead to the establishment of factors influencing INSEs change and be the basis for replacing rigid and outdated policies often been used to provide interventions for INSEs (Roy et al., 2014; Sietchiping, 2005). In Nairobi, knowing locations favoured by INSEs because of opportunity, for example, industrial areas and business centres for employment or business can help in location suitability assessments for low-income housing. Furthermore, prior identification of locations favoured by INSEs because of space availability but are not favourable for occupation e.g. along road, river and rail reserve will be the basis for development control strategies where those locations can either be protected by fencing, for example, or, at the very least, planned and supported with basic services while alternatives are being sought. In such cases, future relocation can be easy and organized.

Table 22: All drivers of INSEs change (A)

EXPANSION (NON-SPATIAL)		DENSIFICATION (NON-SPATIAL)		EVICTION (NON –SPATIAL)		EVICTION (SPATIAL)		
From Literature (not in any order)	**From Informants**	**From literature**	**From Informants**	**From literature**	**From Informants**	**From Literature**	**From Informants**	**From Modelling (Top 3)**
1. Rapid urbanization 2. Housing supply incommensurate to urban growth 3. Low incomes from agriculture 4. Escape from rural poverty 5. Vulnerability and economic downturns 6. Better job prospects in urban areas 7. Better services in urban areas	1. Shortage of affordable housing 2. Low incomes & lack of employment 3. Lack of livelihood in rural areas 4. Low income from agriculture 5. Slow rates of housing provision by housing agencies 6. Spatial policies – poor planning and development control	(same as expansion)	(same as expansion)	1. Poor land governance (lack of transparency; equity, accountability, pro-poor legislation; rule of law and participation) 2. Projects of city image restoration 3. Public safety	1. Illegal eviction by private developers 2. Lack of accountability 3. Lack of transparency in land administration 4. Disregard for rule of law Lack of equity by government 5. Lack of equity by government	1.Infrastructure development and restoration 2. Proximity to prime lands in the city 3. Spatial development plans	1.. Existence on infrastructure reserve 2. Existence on private land 3. Proximity to prime investment 4. Proximity to major roads 5. Proportion of surrounding commercial land uses	1.. Proximity to rivers 2. Proximity to protected areas (environment) 3. Proximity to protected areas (government)

Table 23: All drivers of INSEs change (B)

EXPANSION (SPATIAL)				DENSIFICATION (SPATIAL)				
From Literature (no order/rank)	**From Key informants**	**From Modelling (Top 3 for each)**		**From Literature**	**From Informants**	**From Modelling (Top 3 for each)**		
	Top 5 (In this order)	**Classic 2005**	**Atypical, 2005**			**Low 2005**	**Medium 2005**	**High 2005**
1.. Spatial planning policies 2. Slope/topography 3. Population density 4. Proximity to transport networks 5. Proximity to rivers and water bodies 6. Proximity to business centres, markets and the CBD 7. Close interaction with existing INSEs 8. Close interaction with empty/undeveloped land 9. Close interaction with commercial land uses and other urban land uses 10. Close interaction with planned residential land uses	1. Proximity to industrial areas 2. Proportion of surrounding commercial land uses 3. Proportion of surrounding undeveloped land 4. Population density 5. Proximity to business centres	1. Proximity to industrial areas. 2. Proximity to rivers 3. Proximity to railway	1. Proximity to rivers 2. Proximity to main roads 3. Proximity to business centres	(same as expansion)	1. Proximity to industrial areas 2. Population density 3. Proportion of surrounding commercial land use 4. Proportion o surrounding undeveloped land 5. Proximity to business centres	1. Proximity to business centres 2. Proximity to roads 3. Slope	1. Proximity to rivers 2. Proximity to business centres 3. Proximity to roads	1. Proximity to railway 2. Proximity to major roads 3. Proximity to rivers
		Classic, 2010	**Atypical, 2010**			**Low 2010**	**Medium 2010**	**High 2010**
		Proximity to industrial areas. 2. Proximity to main roads 3. Proximity to rivers	1. Proximity to rivers 2. Proximity to main roads 3. Proximity to industrial areas.			1. Proximity to business centres 2. Proximity to rivers 3. Proximity to roads	1. Proximity to business centres 2. Proximity to rivers 3. Proportion of surrounding undeveloped	1. Proximity to business centres 2. Proximity to rivers 3. Proximity to roads
		Classic, 2015	**Atypical, 2015**			**Low 2015**	**Medium 2015**	**High 2015**
		1. Proximity to main roads 2. Proximity to industrial areas. 3. Proximity to railway	1. Proximity to rivers 2. Proximity to main roads 3. Proximity to industrial areas.			1. Proximity to rivers 2. Proximity to roads 3. Proximity to railway	1.Proximity to rivers 2. Proximity to business centres 3. Proportion of surrounding undeveloped land	1. Distance to railway 2. Distance to rivers 3. Proximity to industrial areas

7. CONCLUSION AND RECOMMENDATIONS

The study was set out to improve the knowledge of growth and eviction of INSEs for local planning in Nairobi with the first objective being to identify INSEs locations and quantify their change in terms of expansion, densification and eviction between years 2005 to 2015 through 2010. A total of 153 settlements were identified. These settlements were found not homogenous, which led to their categorization into *Classic* and *Atypical* INSEs, their defining elements being housing quality, access to services and levels of spatial planning. In general, *Classic* settlements show more characteristics of impoverishment than *Atypical*. The settlements are widely spread on the city landscape, but the southern and far eastern parts are notably free of INSEs, and this is linked to the presence of a protected national park and location being away from city's main activity axis respectively.

The quantification results showed that INSEs are expanding at a rate of 4.1%, with *Atypical* INSEs expanding five times faster than *Classic* INSEs (1.2% against 7.1% p.a). For densification, low-density locations are losing areas to medium and high-density, with total area of high-density locations rising continuously. In general, 26% of the total INSEs' areas at year 2015 (found in 32 out of the 153 settlements in Nairobi) experienced a shift in density class between year 2005 and 2015. Moreover, eviction has been happening continuously since 1970. Despite the total evicted area being 2.5% of total INSEs' area (affecting 31 out of 153 settlements), the impact of eviction on livelihoods are described by NGOs and human rights groups as enormous. By historical trends analysis, *Classic* settlements are 10 times more likely to be evicted than *Atypical* settlements. In addition fieldwork showed emerging trends of vertical growth that needs to be investigated while assessment of Google Earth historical imagery showed possible links between eviction, expansion and densification, also worth investigating.

Objective two was set to establish the spatial and non-spatial drivers of INSEs expansion, densification and eviction. This was achieved through accumulating knowledge from literature, key informants and modelling. This approach is desirable because comparison of results from literature (global views) and local contexts is possible. Differences in results were noted between key informants and modelling results where the study adopted the modelling results as they are based on statistical processes, but advises a repeat of the modelling processes while including missing data and related the results again. Non-spatial drivers were not modelled and from literature and key informants, it emerged that *lack of livelihoods means*, *opportunities*, and *quality public services* are the main external causes of growth of INSEs. Slow rates of housing provision by city authorities coupled by low incomes by city dwellers are the main internal causes of development of INSEs. For eviction, non-spatial forces are majorly proxy indicators for poor land governance, including *lack of equity*, *accountability* and *adherence to rule of law*.

In modelling, the approach used was LRM. The model achieved PCPs of 68 to 89% for all models which literature show as satisfactory. The model was easy to apply and found statistically strong in explain spatial change. However, its inability to accommodate temporal dynamics and factors such as political influences, which play a huge role in INSEs change, led to the proposition that it could be combined with other models while modelling INSEs. Results under this objective show that *Classic* INSEs are likely to develop near main roads, industrial areas and railway, while *Atypical* INSEs are likely to develop near rivers, main roads and industrial areas. These drivers are dynamic that there is at least a change of one driver in the tops 3 from one modelling time step to another, and this is an indication that long-term predictions should be done with caution. Regarding densification, the strongest drivers are also proximity characteristics with top driver for low, medium and high-density classes being distance to railway, distance to business centres and distance to railway (again) respectively. Observation is made that these factors change with time, also leading to a caution against long-term predictions. According to the model, eviction is more likely happen in areas close to rivers, and protected areas. These findings are confirmed by the assessment of evicted locations. They are, however, deficient in that eviction was found to be largely subject to political influences, and land governance proxy indicators, factors which the LRM is unable to incorporate. Yet again, need for an approach that can incorporate household dynamics and political influences to the modelling processes is underlined.

Objective three focused at providing INSEs' management direction after using the outputs from objective two to map possible INSEs' futures for Nairobi. Mapping INSEs' futures was found possible but caution needs to be taken as difficult-to-predict forces such as political or spatial planning regime change could abruptly change the trend of INSEs' development. High probability locations for INSEs expansion and densification are spread out, but are generally *between built-up locations* and *between CBD and major industries* respectively. This knowledge can be applied in Nairobi to inform locations of lows housing development and pro-active protection and provision of spatial planning support before occupation. However, development of an INSEs' policy framework in Nairobi is required, most importantly to recognize INSEs in spatial plan making. This will enable the city to benefit from the advancing spatial modelling technologies better.

7.1. Recommendations and Areas for Further Studies

This study recommends policy adjustments be made to enable full utilization of spatial planning technologies for INSEs' intervention in Nairobi. The policy should provide a definition for INSEs and their legitimacy, recognize them in citywide spatial plans, and provide a framework for implementation of INSEs interventions. This policy should also outline eviction guidelines (e.g as initiated by ESRC, 2012). Further, a system of monitoring INSEs at a citywide scale and across time should be developed.

Further research direction

- A repeat of the LRM process while incorporating the missing data. This will show the impact of the variables missing from the study.
- Integration of LRM with other modelling approaches with more temporal dynamics, particularly ABM
- An investigation into the spatiotemporal links between INSEs expansion, densification and eviction and their possible integration into one model.
- A study of on vertical growth trends in Nairobi and its possible inclusion into INSE growth modelling.

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APPENDICES

Appendix A: Key-informants questionnaire and key informants list

UNIVERSITY OF TWENTE – ITC

INTERVIEW QUESTIONS/QUESTIONNAIRE

MSc. Research Project 2015/16

Growth and Eviction of Informal Settlements in Nairobi

This interview/questionnaire sheet is to collect data for the research of Mr. Daniel Njoroge for a study on the aforementioned topic of study. His main objective of study is to improve understanding of growth and eviction of informal settlements for planning policy in Nairobi.

Name: *Date:*

Sector	Education	Government	Local Authority	Private Sector	NGO
Tick	☐	☐	☐	☐	☐

Position: ……………………………………………………………………………………………………

Experience in Urban Planning: (in years) ……………………………………………………

1. ***In your opinion, which of the following are non-spatial causes of growth of informal settlements (INSEs) in Nairobi?***

	Yes (Yes, it is a driver of informal settlements growth)			No (Not a driver)
	Very strong Driver (3)	Strong Driver (2)	Weak Driver (1)	No (0)
External – Migration caused by:				
Lack of livelihood means in rural areas				
Low income from agriculture				
Poor services in rural areas e.g education				
Rural conflicts, violence and clashes				
Attraction/liking for city lifestyle				
Others (specify)				
Internal:				
Slow rates of housing provision by housing agencies				
Difficulties by urban poor to access land & housing credit/loans				
Shortage of low cost housing				
Low incomes/wages				
Availability of land for encroachment				
Class segregation & inequalities				
Politics – ruling class failing to intervene for political interests				
Spatial policies – poor urban planning & development control				
Social-cultural factors (comfort living in INSEs)				
Others (specify) …				

2. ***In your opinion, which of the following spatial factors drive EXPANSION of informal settlements in Nairobi?***

Characteristics			Yes (It is a driver of Growth)			No (Not a driver)
			Very Strong Driver	Strong Driver	Weak Driver	Not a driver
Location Characteristics						
Slope						
Population Density						
Land tenure						
Land value						
Zoning plan/Master plan						
Others (specify) …						
Proximity Characteristics						
	Effect on Expansion		Very strong driver	Strong driver	Weak driver	Not a driver
	Positive	*Negative*				
Distance to Industrial areas						
Distance to rivers						
Distance to major roads						
Distance to railway						
Distance to CBD						
Distance to business centres						
Others (specify) …						
***Neighbourhood characteristics:** Proportion of surrounding :*						
Undeveloped land						
Existing Informal Settlements						
Commercial land uses						
Planned residential settlements						
Transport land uses						

4. *Which spatial factors drive DENSIFICATION of informal settlements?*

Characteristics			Yes (It is a driver of Growth)			No (Not driver)
			Very Strong Driver	Strong Driver	Weak Driver	
Location Characteristics						
Slope						
Population Density						
Land tenure						
Zoning plan/Master plan						
Others (specify) …						
Proximity Characteristics	Effect on Densification		Very Strong Driver	Strong Driver	Weak Driver	No (Not driver)
	Positive	Negative				
Distance to Industrial areas						
Distance to rivers						
Distance to major roads						
Distance to railway						
Distance to CBD						
Distance to business centres						
Others (specify) …						
Neighbourhood characteristics: Proportion of surrounding						
Undeveloped land						
Existing Informal settlements						
Commercial land uses						
Planned Residential settlements						
Transport land uses						

5. *Are you aware of any evictions of informal settlements that have taken place in Nairobi?*

   Yes ☐ No. ☐. If yes, of which settlements?

6. *In your opinion, which of the following factors drive EVICTION of informal settlements in Nairobi?*

Non-spatial		Yes (Drives Growth)			No (Not a driver)
Driver		Very strong Driver	Strong Driver	Weak Driver	
Poor Land Governance	*Lack of transparency in land administration*				
	Lack of accountability				
	Lack of anti-eviction legislation				
	Lack of equity by government				
	Disregard for rule of law				
Private developers	Legal recovery of land by private developers				
	Illegal eviction by private developers on prime lands				
Others (specify)					

7. *In your opinion, which spatial factors drive EVICTION of informal settlements in Nairobi?*

			Yes (Drives Growth)			No (Not a driver)
Spatial Drivers			Very strong Driver	Strong Driver	Weak Driver	
Location characteristics	Their existence on infrastructure reserves e.g riparian, power, rail					
	Existence on geographically hazardous areas					
	Land tenure – *Private land*					
	Land tenure – *Government land*					
	Age of settlement					
	Size of settlement					
	Density of settlement					
	Others (specify)…					
Proximity characteristics	Proximity to CBD					
	Proximity to business centres					
	Proximity to major roads					
	Proximity to railway					
	Proximity to environmentally sensitive areas	Protected areas				
		Rivers				
	Proximity to government protected areas					
	Others					

Neighbourhood characteristics	Close interaction with other land uses:				
	Commercial land uses				
	Existing INSEs				
	Others(specify)				

Thank you very much.

Table 24: Questionnaire respondents list

Key Informants No.	Position	Experience in Physical Planning	Mode of Response
1	Senior Lecturer – University of Nairobi	15	Questionnaire
2	Lecturer – University of Nairobi	10	Interview
3	Physical Planner – Ministry of Lands	7	Questionnaire
4	Physical Planner – County Government	8	Interview
5	Director – Informal city	14	Questionnaire
6	Technical adviser – Pamoja Trust	3	Interview
7	Researcher – Global Observatory for Research and Action	7	Interview
8	Development control Officer – Nairobi Country Government	10	Interview
9	Consulting Urban Planner and Research – UN Habitat	7	Questionnaire
10	Program officer – Pamoja Trust	6	Questionnaire

Appendix B: Field visit data form

	A	B	C	D	E	F	G	H	I	J	K	L	M
1			Ground Truthing Points										
2	Random Points from ArcMap		type of settlement from imagery	Land tenure	Estimate of roof coverage on land.	Sewer-connection	Water connection	Electricity	Buildings	Street layout	Type of Settlment on ground	Image-ground match	Image-Ground mismatch
3	Points	Name of Settlement	1) INSE Type_1 ; 2) INSE Type_2	1-private; 2-government; 3-unknown	1- <70%; 2- > 70%	1-yes; 2-septic tanks; 3-pit latrines; 4) No system (flying toilets)	1-Household; 2-Communcal; 3-None	1-yes; 2-No	1-shanty/shack housing ; 2-Semi-permanent building 3-Permanent housing	1- No evidence of planning; 2-basic layout plan; 3-Evident plan	1) INSE Type_1 ; 2) INSE Type_2	1 -- true; 2-false	1 -- true; 2-false
57	54	Mukuru	1	1	2	4	2	1	1	1	1	1	2
58	55	Mukuru	2	1	1	2	2	1	2	2	2	1	2
59	56	Mukuru	1	1	2	4	2	1	1	1	1	1	2
60	57	Mukuru	1	1	2	4	2	1	1	1	1	1	2
61	58	Mukuru	1	1	2	4	2	1	1	1	1	1	2
62	59	Mukuru	2	1	1	2	2	1	2	2	2	1	2
63	60	Mukuru	1	1	2	4	2	1	1	1	1	1	2
64	61	Mukuru	1	1	2	4	2	1	1	1	1	1	2
65	62	Mukuru	1	1	2	4	2	1	1	1	1	1	2
66	63	Majengo	1	1	2	4	2	1	1	1	1	1	2
67	64	Majengo	1	1	2	4	2	1	1	1	1	1	2
68	65	Majengo	1	1	2	4	2	1	1	1	1	1	2
69	66	Majengo	1	1	2	4	2	1	1	1	1	1	2
70	67	Kiambiu-Kamande	1	1	2	4	2	1	1	1	1	1	2
71	68	Kiambiu-Kamande	1	1	2	4	2	1	1	1	1	1	2

Figure 36: Field data validation form

Appendix C: DEM for Nairobi

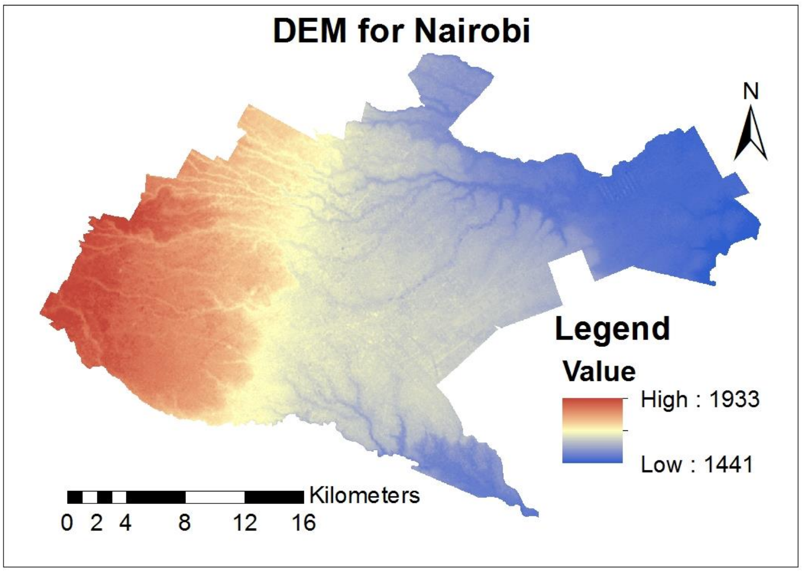

Figure 37: DEM for Nairobi

Appendix D: Locations of INSEs by typology at 2005 and 2010

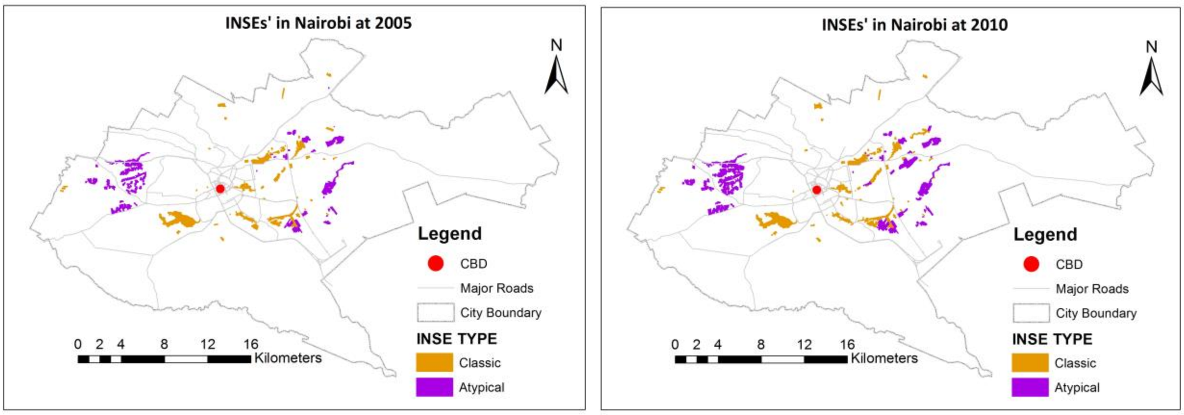

Figure 38: Spatial locations of INSEs at years 2005 and 2010

Appendix E: Densified Settlements

Table 25: List of settlements (locations) where density changes was detected

	Name of Settlement	INSE Type	Change code	2005	2010	2015	Density change	Densification Classification for use in Modelling
1	Dandora	2	012	None	Low	Medium	Densified in P_1 & P_2	Densified to Medium-density in P_2
2	Githogoro	1	012	None	Low	Medium	Densified in P_1 & P_2	Densified to Medium-density in P_2
3	Kamande (part)	1	012	None	Low	Medium	Densified in P_1 & P_2	Densified to Medium-density in P_2
4	Umoja (part)	2	012	None	Low	Medium	Densified in P_1 & P_2	Densified to Medium-density in P_2
5	Umoja (part)	2	112	Low	Low	Medium	Densified in P_2	Densified to Medium-density in P_2
6	Agare	1	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
7	Biafra	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
8	Bondeni	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
9	Central	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
10	Embakasi	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
11	KPCU	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
12	Riruta	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
13	Santon	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
14	Vumilia	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
15	Waithaka	2	122	Low	Medium	Medium	Densified in P_1	Densified to Medium-density in P_1
16	Eastleigh South	2	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
17	Gitabi Marigu	1	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
18	Imara_village	2	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
19	Kamande (part)	1	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
20	Kariobangi South	1	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
21	Kibarage Vilage	1	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
22	Kinyago	1	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
23	Mukura Sinai	2	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
24	Soweto_Kayole	2	123	Low	Medium	High	Densified in both p_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
25	Tassia	2	123	Low	Medium	High	Densified in both P_1 & P_2	Densified to Medium-density in P_1 & High-density in P_2
26	Kawangware	2	223	Medium	Medium	High	Densified in P_2	Densified to High-density in P_2
27	Dagoretti	2	223	Medium	Medium	High	Densified in P_2	Densified to High-density in P_2
28	Deep Sea	1	233	Medium	High	High	Densified in P_2	Densified to High-density in P_1
29	Kaptagat	2	233	Medium	High	High	Densified in P_2	Densified to High-density in P_1
30	Kibera_Raila	1	233	Medium	High	High	Densified in P_2	Densified to High-density in P_1
31	Motherland Village	1	233	Medium	High	High	Densified in P_2	Densified to High-density in P_1
32	Mukura Kwa Njenga	2	233	Medium	High	High	Densified in P_2	Densified to High-density in P_1

Appendix F: Evicted Settlements and their Attributes

Table 26: Evicted settlements and attributes

	Name	Locality	owners	Land ownership	Scale	Success	Year of establishment	Year of Eviction	Stage	Evicting Authority	Reason for Eviction
1	Sinai	Mukuru	KPC	PU	full	NR	1980	2001	Con	GA	Evacuated from fire
2	Githogoro	Ruaka-by pass	KCG	PU	part	NR	1991	2010	Con	GA	Infrastructure development
3	Raila	Kibera	NCG	PU	Part	NR	1960	2004	Con	GA	Infrastructure development
4	Mathare 4A	Mathare	NCG	PU	part	NR	1960	2000	Con	GA	Construction of a primary school
5	Maasai	Highridge	KPLC	PU	full	Re	1968	1995	Con	GA	Kenya Power Company
6	Mworoto-country bus	Country bus	KCG	PU	full	NR	1960	1990	Con	GA	NCG strategy to clear INSEs
7	Pipeline	Pipeline	NWSC	PU	full	Re	1970	1984	Con	GA	water pipeline
8	Kitui village in Eastleigh	Mathare	--	PU		Re	1970	1980	Con	GA	Government strategy to clear INSEs
9	Kandutu	Dagoretti	NCG	PU	full	Re	1969	1980	Con	GA	NCC strategy to clear INSEs
10	Kiamaiko	Huruma	NCG	PU	part	NR	1960	1978	Con	GA	Construction of a market
11	Njiku	Mutuini	NCG	PU	full	Re	1965	1978	Con	GA	Clearing slums from city
12	Kwale - Dumpsite	Kasarani	Government	PU	full	NR	1970	1980	Inf	GA	Evacuated from dumpsite
13	Kareru	Kangemi	NCG	PU	full	Re	1975	1978	Inf	GA	Clearing slums from city
14	Dogoretti Centre village	Dagoretti Market/Kikuyu	NCC	PU	full	Re	1960	1975	Inf	GA	Strategy to clear INSEs
15	Soko ya Mawe	Kariobangi	Government	PU	full	NR	1970	1975	Inf	GA	Strategy to clear INSEs
16	Kanguku village	Dagoretti	NCC	PU	Part	Re	1960	1970	Inf	GA	Plots were privatized
17	Kiarie	Pipeline	KPC	PU	full	NR	1960	1970	Inf	GA	Relocated for safety
18	Mathare 3C	Mathare		PU	part	Re	1960	2000	Sat	GA	Infrastructure development
19	Mlango kubwa	Mathare	NCG	PU	part	Re	1970	2000	Sat	GA	For private development
20	Korogocho	Korogocho	NCG	PU	Part	NR	1960	1993	Sat	GA	Infrastructure development
21	City cotton - Biafra	Pumwani	Kenya Airforce	PU	full	Re	1970	1980	Sat	GA	Kenya Airforce
22	Deep sea	Highridge	KCG	PU	full	Re	1979	2009	Con	PDI	Private investments
23	Mukuru kwa Reuben	Mukuru	KCG	PU	part	Re	1970	1999	Con	PDI	Private investments
24	Mukuru kwa Njenga	Mukuru	KCG	PU	part	Re	1970	1999	Con	PDI	Private investments
25	City cotton	Wilson	KAA	PU	full	Re	1958	1990	Con	PDI	Private investments
26	Kyangombe	Embakasi	KAA	PU	full	NR	2005	2011	Inf	PDI	Private investments
27	Mitumba	Wilson	KAA	PU	full	NR	1992	1994	Inf	PDI	Private investments
28	Mariguini	South B/Industrial area	NHC	PU	Part	Re	1983	1995	Con	PDI	Private investments
29	Maasai	Highridge	Private	PR	full	Re	1968	1995	Con	PDI	Private investments
30	Mohra Moldada	Donholm	Private	PR	full	Re	1935	2005	Con	PDL	Private investments
31	Village II (Kwa Nduru)	Muthaiga	Private	PR	full	NR	1990	2000	Con	PDL	Private investments

-Ownership: (refer to the list of acronyms)
-Stage of development at the time of eviction: In - Infancy; Con – Consolidation; Sat – Saturation
-Success in eviction: Re – Re-stablished; NR - Not re-established
-Tenure: PU - Public; PR - Private
-Scale: Pa - part; Fu – Full
-Evicting authority: G - Government authorities; PDI -- Private developer (illegal eviction); PDL – Private developer (legal eviction

Appendix G: Drivers of Growth and Eviction from Key Informants

Table 27: Non-spatial drivers of growth (expansion and densification)

	External		Rating	Internal		Rating
1	Lack of livelihood means in rural areas	Very strong	27/30	Shortage of low cost (affordable) housing	Very strong	29/30
2	Low incomes from agriculture	Very strong	25/30	Low incomes, wages & lack of employment	Very strong	28/30
3	Poor services in rural areas e.g. education	Strong	18/30	Slow rates of housing provision by housing agencies	Very strong	25/30
4	Liking for city lifestyle	Strong	18/30	Spatial Policies - poor urban planning & development control	Strong	22/30
5				Politics-ruling class failing to intervene for political interests	Strong	21/30
6				Difficulties by urban poor to access housing credit	Strong	20/30
7				Class segregation/inequalities	Strong	20/30

Table 28: Spatial drivers of growth

Drivers	Expansion	Rating	Densification	
Site specific characteristics				
Population density	Strong	24/30	v. strong	27/30
Land tenure	Strong	20/30	Strong	21/30
Land value	Strong	20/30	Strong	21/30
slope	Strong	15/30	Strong	18/30
Proximity Characteristics				
Distance to Industrial areas	v. strong	30/30	v. strong	28/30
Distance to business centres	Strong	24/30	Strong	24/30
Distance to rivers	Strong	21/30	Strong	22/30
Distance to CBD	Strong	21/30	Strong	24/30
Distance to railway	Strong	19/30	Strong	19/30
Distance to major roads	Strong	17/30	Strong	20/30
Neighbourhood characteristics				
Proportion of surrounding:				
Commercial land uses	v. strong	26/30	v. strong	25/30
Undeveloped land	v. strong	25/30	v. strong	25/30
Existing INSEs	Strong	24/30	Strong	24/30
Residential land uses	Strong	22/30	Strong	23/30
Transport land uses	Strong	21/30	Strong	21/30

Table 29: Non-spatial drivers of eviction

No.	Non-spatial Drivers of Eviction	Rating	Score
1	Illegal eviction by private developers	v. strong	27/30
2	Lack of accountability	v. strong	25/30
3	Land of transparency in land administration	Strong	24/30
4	Disregard for rule of law	Strong	24/30
5	Lack of equity by government	Strong	22/30
6	Legal recovery of land by private developers	Strong	22/30
7	Lack of anti-eviction legislation	Strong	20/30
8	City image enhancing projects	Strong	17/30
9	Environmental health restoration policies	Weak	10/30

Table 30: Spatial driver of eviction

	Site Specific		Proximity	(v-very)	Neighbourhood characteristics	
1	Their existence on infrastructure reserve	Very strong (28/30)	Distance to prime investments	v. strong (27/30)	*Proportion of surrounding:*	
2	Land tenure - private land	Very strong (28/30)	Proximity to major roads	Strong (22/30)	Commercial land uses	Strong (21/30)
3	Land tenure - government land	Strong (20/30)	Proximity to business centres	Strong (21/30)	Existing INSEs	Weak (14/30
	Size of settlement		Proximity to railway	Strong (21/30)		
4	Density of settlement	Strong (17/30)	Proximity to environmentally sensitive areas (rivers)	Weak (14/30)		
5	Their existence on hazardous location	Strong (17/30)	Proximity to environmentally sensitive areas (protected areas)	Weak (14/30)		
6	Age of settlement	Weak (14/30)	Proximity to CBD	Weak (14/30)		
7		weak (13/30)	Proximity to government protected areas	Weak (14/30)		

Appendix H: All models – list and names

Table 31: INSEs change models and their simplified names

Models for Expansion			
Type of Model	**Type of Settlement**	**Year**	**Model's Name**
Expansion	*Classic* INSEs	2005	$M_{EX}C_{CL}05$
Expansion	*Atypical* INSEs	2005	$M_{EX}C_{AT}05$
Expansion	*Classic* INSEs	2010	$M_{EX}C_{CL}10$
Expansion	*Atypical* INSEs	2010	$M_{EX}C_{AT}10$
Expansion	*Classic* INSEs	2015	$M_{EX}C_{CL}15$
Expansion	*Atypical* INSEs	2015	$M_{EX}C_{AT}15$

Modelling Eviction			
Eviction			M_{Ev}

Models for Densification			
Type of Model	**Type of Settlement**	**Year**	**Model's Name**
Densification	Low	2005	$M_{DE}C_{L}05$
Densification	Medium	2005	$M_{DE}C_{M}05$
Densification	High	2005	$M_{DE}C_{H}05$
Densification	Low	2010	$M_{DE}C_{L}10$
Densification	Medium	2010	$M_{DE}C_{M}10$
Densification	High	2010	$M_{DE}C_{H}10$
Densification	Low	2015	$M_{DE}C_{L}15$
Densification	Medium	2015	$M_{DE}C_{M}15$
Densification	High	2015	$M_{DE}C_{H}15$

Appendix I: Spatial Autocorrelation Test Results

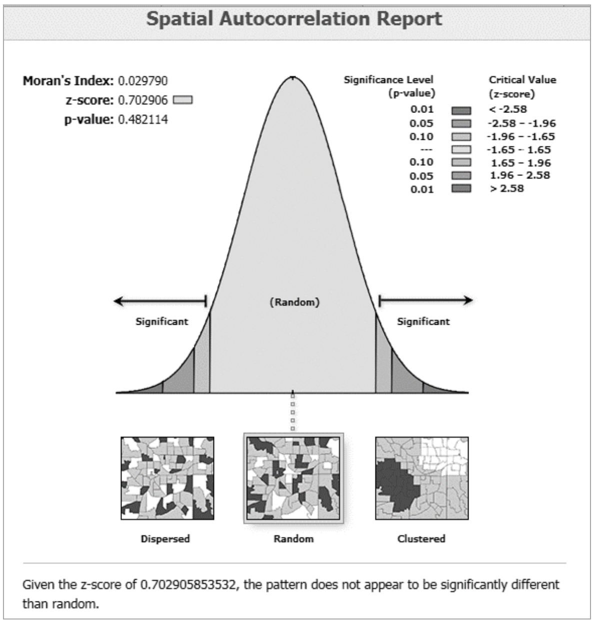

Figure 39: Moran's I report $M_{EX}C_{CL}05$

Table 32: Logistic regression residuals' Moran's I

Model Name	Time	Category	Moran's I	Z-Scores	P-values
	Expansion Models				
$M_{EX}C_{CL}05$	2005	*Classic*	0.029790	0.702906	0.482114
$M_{EX}C_{AT}05$		*Atypical*	0.062070	1.228346	0.219317
$M_{EX}C_{CL}10$	2010	*Classic*	0.030533	0.717765	0.472902
$M_{EX}C_{AT}10$		*Atypical*	0.072195	1.359468	0.173998
$M_{EX}C_{CL}15$	2015	*Classic*	0.029808	0.703226	0.481915
$M_{EX}C_{AT}15$		*Atypical*	0.039181	0.921423	0.356830
	Densification Models				
$M_{DE}C_{L}05$	2005	Low	-0.011235	0.168680	0.866048
$M_{DE}C_{M}05$		Medium	-0.023181	0.040104	0.968011
$M_{DE}C_{H}05$		High	-0.019778	0.076911	0.938695
$M_{DE}C_{L}10$	2010	Low	0.148030	1.828240	0.067514
$M_{DE}C_{M}10$		Medium	0.022974	0.521584	0.601960
$M_{DE}C_{H}10$		High	0.067577	0.987928	0.323188
$M_{DE}C_{L}15$	2015	Low	0.112365	1.504834	0.132367
$M_{DE}C_{M}15$		Medium	0.015700	0.467715	0.639988
$M_{DE}C_{H}15$		High	-0.020335	0.072070	0.94246
M_{EV}	Eviction Model		-0.168751	-1.510378	0.130947

Appendix J: Significant drivers of change from modelling – detailed statistics

Table 33: Significant drivers of expansion for $M_{EX}C_{CL}05$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Distance to Industrial areas	.140	.022	39.567	.000	1.151
Distance to rivers	.115	.042	7.658	.006	1.122
Distance to roads	.084	.023	13.424	.000	1.088
Distance to railway	.094	.010	93.277	.000	1.098
Distance to CBD	.040	.006	38.229	.000	1.040
Proportion of surrounding undeveloped land	.008	.002	24.883	.000	1.008
Proportion of surrounding INSEs	.008	.004	4.444	.035	1.008
Proportion of surrounding planned residential land	.002	.001	7.884	.005	1.002
Constant	-6.957				

Table 34: Significant drivers of expansion for $M_{EX}C_{AT}05$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Distance to rivers	.449	.042	111.937	.000	1.567
Distance to roads	.121	.023	27.739	.000	1.129
Distance to railway	.029	.011	6.637	.010	1.029
Distance to CBD	.040	.006	43.694	.000	1.041
Distance to business centres	.077	.018	18.156	.000	1.080
Proportion of surrounding undeveloped land	.007	.001	50.920	.000	1.007
Proportion of surrounding commercial land	.008	.004	4.436	.035	1.008
Constant	-5.484				

Table 35: Significant drivers of expansion for $M_{EX}C_{CL}10$

Factor	Coefficient	S.E.	Wald	P-Value	O.R.
Population density	.000	.000	6.714	.010	1.000
Distance to industrial areas	.117	.022	29.717	.000	1.125
Distance to rivers	.100	.040	6.165	.013	1.106
Distance to roads	.106	.022	22.851	.000	1.112
Distance to rail	.069	.010	46.581	.000	1.071
Distance to CBD	.045	.006	51.490	.000	1.046
Proportion of surrounding undeveloped land	.007	.002	21.113	.000	1.007
Proportion of surrounding INSEs	.009	.003	7.964	.005	1.009
Proportion of surrounding planned residential land	.002	.001	7.115	.008	1.002
Constant	-6.544				

Table 36: Significant drivers of expansion for $M_{EX}C_{AT}10$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	24.316	.000	1.000
Distance to industrial areas	.067	.022	9.490	.002	1.070
Distance to rivers	.548	.036	237.827	.000	1.730
Distance to roads	.141	.019	52.955	.000	1.151
Distance to railway	.048	.011	18.300	.000	1.050
Distance to CBD	.040	.006	46.668	.000	1.041
Distance to business centres	.037	.015	5.851	.016	1.038
Proportion of surrounding undeveloped land	.004	.001	20.764	.000	1.004
Proportion of surrounding transport land uses	-.019	.008	5.108	.024	.981
Constant	-5.761				

Table 37: Significant drivers of expansion for $M_{EX}C_{CL}15$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	10.988	.001	1.000
Distance to industrial	.115	.021	29.404	.000	1.122
Distance to roads	.118	.022	29.500	.000	1.125
Distance to railway	.063	.010	39.803	.000	1.065
Distance to CBD	.040	.006	46.850	.000	1.041
Proportion of surrounding undeveloped land	.007	.001	20.670	.000	1.007
Proportion of surrounding INSEs	.008	.004	5.232	.022	1.008
Constant	-6.242				

Table 38: Significant drivers of expansion for $M_{EX}C_{AT}15$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	18.687	.000	1.000
Distance to industrial areas	.088	.020	18.760	.000	1.092
Distance to rivers	.585	.033	306.941	.000	1.796
Distance to roads	.145	.018	63.114	.000	1.156
Distance to railway	.043	.009	21.520	.000	1.044
Distance to CBD	.039	.006	50.649	.000	1.040
Proportion of surrounding undeveloped land	.005	.001	32.147	.000	1.005
Proportion of surrounding commercial land	.012	.003	20.831	.000	1.012
Proportion of surrounding planned residential land	.003	.002	4.725	.030	1.003
Proportion of surrounding transport land uses	-.017	.008	5.099	.024	.983
Constant	-5.822				

Table 39: Significant drivers of densification for $M_{DE}C_{L}05$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Slope	.028	.014	3.981	.046	1.029
Distance to roads	.106	.042	6.324	.012	1.112
Distance to railway	-.422	.085	24.549	.000	.656
Distance to CBD	-.176	.052	11.569	.001	.839
Distance to business centres	.563	.094	36.184	.000	1.756
Proportion of surrounding undeveloped land	.014	.004	10.468	.001	1.014
Constant	-3.550				

Table 40: Significant drivers of densification for $M_{DE}C_{M}05$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	4.795	.029	1.000
Distance to rivers	.420	.101	17.327	.000	1.521
Distance to roads	.087	.032	7.173	.007	1.091
Distance to railway	-.345	.065	28.532	.000	.708
Distance to CBD	-.124	.039	9.833	.002	.884
Distance to business centres	.361	.068	28.418	.000	1.434
Proportion of surrounding undeveloped land	.006	.002	6.874	.009	1.006
Proportion of surrounding commercial land	.030	.011	7.835	.005	1.031
Proportion of surrounding transport land uses	.008	.003	6.730	.009	1.008
Constant	-2.917				

Table 41: Significant drivers of densification for $M_{DE}C_{H}05$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	25.802	.000	1.000
Distance to industrial areas	.137	.051	7.206	.007	1.147
Distance to rivers	.380	.103	13.598	.000	1.463
Distance to roads	.398	.042	88.238	.000	1.488
Distance to railway	1.213	.070	299.681	.000	3.362
Distance to CBD	-.380	.041	84.877	.000	.684
Distance to business centres	-1.374	.085	261.773	.000	.253
Proportion of surrounding undeveloped land	.014	.002	45.442	.000	1.014
Constant	5.152	1.030	25.014	.000	172.844

Table 42: Significant drivers of densification for $M_{DE}C_{L}10$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Distance to rivers	.671	.140	22.959	.000	1.957
Distance to roads	.413	.047	76.606	.000	1.511
Distance to railway	-.922	.094	96.929	.000	.398
Distance to CBD	-.401	.058	48.266	.000	.669
Distance to business centres	.981	.095	106.015	.000	2.667
Proportion of surrounding undeveloped land	.024	.005	26.998	.000	1.024
Proportion of surrounding planned residential land	.005	.002	9.398	.002	1.005
Constant	-5.224				

Table 43: Significant drivers of densification for $M_{DE}C_{M}10$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	10.796	.001	1.000
Distance to rivers	.284	.090	9.861	.002	1.328
Distance to railway	-.599	.062	93.785	.000	.550
Distance to CBD	-.122	.039	9.978	.002	.885
Distance to business centres	.666	.077	73.972	.000	1.947
Proportion of surrounding undeveloped land	.006	.002	10.215	.001	1.006
Constant	-.820				

Table 44: Significant drivers of densification for $M_{DE}C_{H}10$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Distance to rivers	.271	.091	8.952	.003	1.311
Distance to roads	.109	.028	14.944	.000	1.115
Distance to railway	-.642	.056	132.866	.000	.526
Distance to CBD	-.155	.033	21.690	.000	.856
Distance to business centres	.739	.060	153.468	.000	2.093
Proportion of surrounding undeveloped land	-.006	.002	10.503	.001	.994
Constant	-.854				

Table 45: Significant drivers of densification for $M_{DE}C_{L}15$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Distance to rivers	.858	.336	6.531	.011	2.359
Distance to roads	.201	.076	7.018	.008	1.223
Distance to railway	.121	.054	5.056	.025	1.129
Distance to CBD	-.247	.068	13.232	.000	.781
Proportion of surrounding undeveloped land	.022	.010	4.915	.027	1.022
Constant	-7.271	2.360	9.493	.002	.001

Table 46: Significant drivers of densification for $M_{DE}C_{M}15$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Population density	.000	.000	6.488	.011	1.000
Distance to industrial areas	-.492	.051	95.069	.000	.611
Distance to rivers	.433	.095	20.811	.000	1.542
Distance to roads	-.290	.047	38.338	.000	.749
Distance to railway	-1.020	.046	491.490	.000	.361
Distance to business centres	.387	.050	60.072	.000	1.472
Proportion of surrounding undeveloped land	.018	.002	59.083	.000	1.018
Proportion of surrounding planned residential land	.004	.001	15.194	.000	1.004
Constant	2.710				

Table 47: Significant drivers of densification for $M_{DE}C_{H}15$

Factor	Coefficient	S.E.	Wald	P-Value	O.R
Slope	.020	.009	4.480	.034	1.020
Population density	.000	.000	10.622	.001	1.000
Distance to industrial areas	.301	.036	71.433	.000	1.351
Distance to rivers	.543	.091	35.317	.000	1.720
Distance to railway	.682	.032	448.553	.000	1.978
Distance to business centres	-.523	.035	223.099	.000	.593
Proportion of surrounding undeveloped land	.019	.002	69.286	.000	1.020
Proportion of surrounding planned residential land	-.006	.001	31.556	.000	.994
Proportion of surrounding transport land uses	-.009	.003	7.111	.008	.991
Constant	-2.312				

Appendix K: Growth probability maps for 2005 and 2010 models

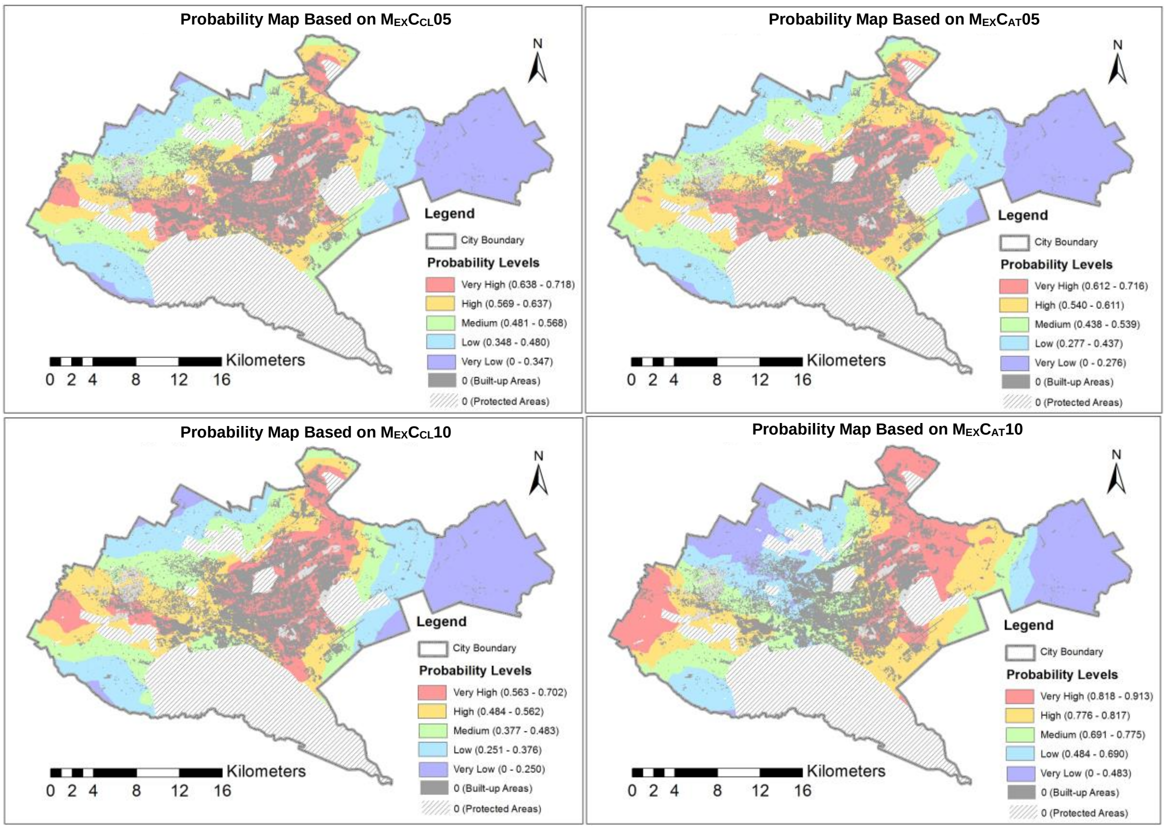

Figure 40: Probability maps based on expansion models for 2005 and 2010

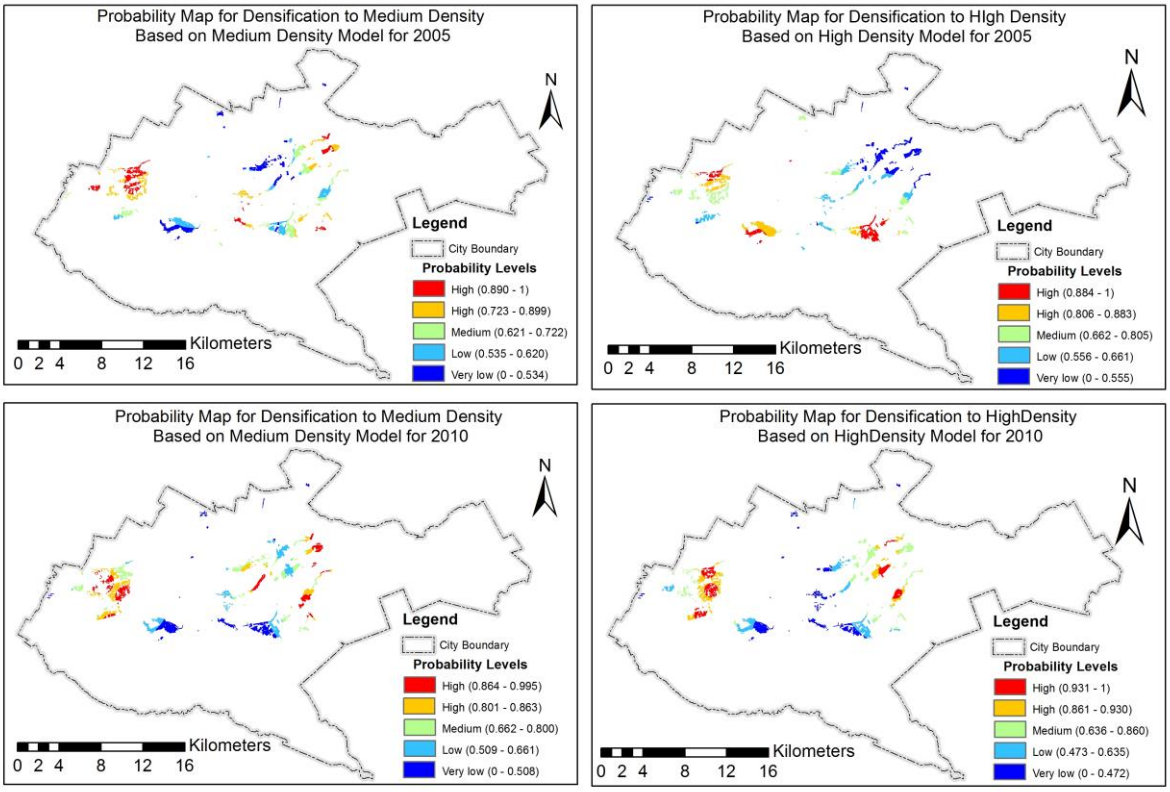

Figure 41: Probability maps based on medium and high-density models for 2005 and 2010