URBAN CELLULAR AUTOMATA AND AGENT BASED MODELS FOR THE SIMULATION OF URBAN DYNAMICS: A REVIEW OF PRACTICE AND APPLICATIONS

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AUTHOR'S DECLARATION

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ABSTRACT

Current scientific planning instruments and practices are inadequate to address the multidimensional problems and challenges faced by cities as complex dynamic systems. The aim of this research is to provide an international comparative analysis of Cellular Automata (CA) and Agent-based modelling (ABM) techniques and its potential application within spatial planning practices. The research provides explanations on the key considerations for spatial simulation model conceptualization, components, design and construction. Cellular Automata (CA) and Agent-based modelling (ABM) techniques abstract the real-world into a series of layers as a visual representation of complexity and spatial-temporal urban dynamics. The meta-analysis of published spatial simulation research results over the past decade (2009 – 2019) found that urban modelling approaches have grown consistently. Applications of urban simulation models appear to be regionally divergent with the major focus on the global North. Uptake of these urban models is lagging in areas with rapid urbanization and urban growth rates, which are predominantly located in the global South (including South Africa). The comparative analysis found that the development and design of urban models are also now incorporating aspects of strategic planning within their scenarios in order to measure and monitor the appropriateness and effectiveness of policy interventions, such as urban growth boundaries, zoning schemes, sustainable development outcomes and environmental protection zones. The research found that CA and ABM-based urban models improve the understanding of the local and historical contingent factors and how multidimensional and complex problems influence urban systems across time and space.

Keywords: spatial planning, complexity, model, dynamic, spatial simulation, urban model, complex systems, cities, cellular automata, agent-based model.

OPSOMMING

Huidige instrumente en praktyke vir wetenskaplike beplanning is onvoldoende om die multidimensionele probleme en uitdagings wat stede as komplekse dinamiese stelsels in die gesig staar, die hoof te bied. Die doel van hierdie navorsing is om 'n internasionale vergelykende analise van Cellular Automata (CA) en Agent-gebaseerde modellering (ABM) tegnieke te bied en die potensiële toepassing daarvan binne ruimtelike beplanningspraktyke. Die navorsing verskaf verduidelikings oor die sleuteloorwegings vir ruimtelike simulasiemodelkonseptualisering, komponente, ontwerp en konstruksie. Cellular Automata (CA) en Agent-gebaseerde modellering (ABM) tegnieke abstrakteer die werklikikeid in 'n reeks lae as 'n visuele voorstelling van kompleksiteit en ruimtelik-temporele stedelike dinamika. Die meta-analise van gepubliseerde navorsingsresultate vir ruimtelike simulasie oor die afgelope dekade (2009 - 2019) het bevind dat die benaderings vir stedelike modellering konsekwent gegroei het. Toepassings van stedelike simulasiemodelle blyk streeks uiteenlopend te wees, met die grootste fokus op die ontwikkelde wêrel. Die gebruik van hierdie stedelike modelle hou egter nie verband met gebiede wat 'n vinnige verstedeliking en stedelike groeikoers ondervind nie, soos byvoorbeeld die globale Suide (insluitend Suid-Afrika). Die vergelykende ontleding het bevind dat die ontwikkeling en ontwerp van stedelike modelle nou ook aspekte van strategiese beplanning binne hul vooruitbeplanning inkorporeer om die toepaslikheid en doeltreffendheid van beleidsintervensies, soos stedelike groeigrense, soneringskemas, volhoubare ontwikkelingsuitkomste en omgewingsbeskermingsones. Uit die navorsing is bevind dat CA- en ABM-gebaseerde stedelike modelle die begrip van die plaaslike en historiese faktore verbeter en hoe multidimensionele en ingewikkelde probleme stedelike stelsels oor tyd en ruimte beïnvloed.

Kernwoorde: ruimtelike beplanning, kompleksiteit, model, dinamiese, ruimtelike simulasie, stedelike model, komplekse stelsels, stede, sellulêre outomate, agent gebaseerde model

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Author

Chantel Hauptfleisch

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CHAPTER 1: INTRODUCTION

"*We live in an age of cities*" (Batty 2013: xvii).

1 INTRODUCTION AND RATIONALE

According to the United Nation's Report on World Urbanization Prospects for 2018, 55% of the global population resides in urban areas, and it is projected that by 2050, 68% of the population will be urban. Regional differences based on urbanisation levels are also evident with the most significant growth happening in large cities in the global South. These concentrations of large cities are experiencing an average annual growth rate of 1.8 percent, (UN: DESA 2019) which means that these cities will double their population in approximately 39 years. It is projected that the urban population growth rate between 2018 and 2050 will be concentrated (approximately 90 percent) within Asia and Africa which is also predominantly categorised as low-income and lower-middle-income countries (UN: DESA 2019).

"*The future of the world's population is urban*" (UN: DESA 2019:1) and phenomena of urbanisation and migration need to be integrated into strategic planning and should be adequately managed in order to achieve inclusive, safe, resilient and sustainable cities. Government policies for planning and managing sustainable urban growth should particularly be formulated and implemented in countries that will experience rapid urbanization (i.e. low-income and lower-middle-income within Africa and Asia) because when left unplanned or inadequately managed will lead to unprecedented pressures on cities and their ability to provide essential services (Crooks et al 2018). It will also result in increased inequalities, resource depletion, reduced quality of life and environmental degradation (UN: DESA 2019).

The role of spatial planners in this complex and dynamic urban landscape is to "*create bridges between 'what is' and 'what could be',* (or in normative terms) *'what should be' and 'what is desired'* (De Roo et al 2016:1). The 'what is' or 'object[1] of spatial planning' represents, for instance, the issues stated above namely uncontrolled and unplanned urbanisation, which

[1] Refers to the specific object which requires planning intervention and it is related in this instance to spatial planning practice (Alexander 2015).

requires specific planning interventions. This issue itself is not simple or straightforward and occurs within a highly complex dynamic landscape with inherent local and historical contingent factors (space complexity). Moreover, the issue is multidimensional, it occurs within different stages over time (dynamic and non-linear), and within contextually dynamic spatial planning practices[2] (De Roo et al 2016; Crooks et al 2018). Planners have noted over the last decade that there is an inadequacy of using existing scientific methods and practices rooted in logical positivism to address the problems and challenges that they must deal with daily (De Roo & Silva 2011; McAdams 2012; De Roo 2016).

Complexity science offers a perspective for understanding and dealing with aspects such as dynamics, flows, networks, uncertainty, open systems, and time, that can be found within reality and complex systems (Batty 2013; De Roo et al 2016). Complex systems such as cities are adaptive, emergent, dynamic and non-linear (De Roo & Silva 2011). The theory and application of complexity science can be considered as bridges and linkages between the theoretical ideas found within complexity sciences and urban theories and planning theory (De Roo et al 2016). Urban theories (theory in planning) refers to the object of planning, namely the city and how the 'desired' urban form and function of the city can be produced, while planning theory (theories in planning) refers to the processes, actions and interactions of how to plan in order to resolve problems and achieve outcomes (Alexander 2015).

The new 'science of cities' could provide insights into the complexity of the city and when combined with the normative discussion (De Roo 2011; De Waal 2018; Schintler & Chen 2018) of 'what should the sustainable, liveable and resilient city look like' can assist planners to become managers of change where negatives are avoided, and positive effects of change[3] are embraced over time and space (De Roo & Silva 2011).

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[2] Refers to the distinctive elements characterizing real-life practice of planning i.e. spatial planning and the planner's toolkit which provides them with their distinctive contribution in the co-construction of knowledge for collective decision-making and action (Alexander 2015).

[3] Change is an evolutionary process and includes time, evolution, transition and space (De Roo, 2011: 7).

An important element of the new 'science of cities', is the use of spatial simulation models as quantitative methods for measuring complex real-world systems and phenomena (e.g. urban expansion; growth etc.). Spatial simulation models represent distinct spatial elements and their relationships for a complete understanding of the system under consideration. Because cities cannot be analysed through controlled experiments, "*a computer is programmed to iteratively recalculate the modelled system state as it changes over time in accordance with the relationship represented by the mathematical and other relationships that describe the system*" (O'Sullivan & Perry 2013:9). It allows for a simplified view of the integrated phenomena and provides a platform for convenient exploration of the implications of a dynamic model without impacting on the real-world system (Batty 2005; O'Sullivan & Perry 2013).

It not only provides quantitative data but also qualitative interpretation which makes these techniques of interest in support of spatial planning practices (De Roo 2011; O'Sullivan & Perry 2013). The increased development of computer science coupled with the improvements in the availability of data, data quality and processing standards, have further increased the demand for these spatial simulation models (urban models).

1.1 RESEARCH PROBLEM

Complexity science offers a perspective for understanding and dealing with complex systems (Batty 2013; De Roo et al 2016). This science of cities can provide insights into the complexity of the city and when combined with the normative discussion (De Roo 2011; De Waal 2018; Schintler & Chen 2018) dealing with. 'what should the sustainable, liveable and resilient city look like' can assist spatial planners to become managers of change (De Roo & Silva, 2011) within the context of a rapidly urbanizing environment (UN: DESA 2019).

The science of cities uses *inter alia* spatial simulation models (urban models) for measuring the complex real-world systems and phenomena (e.g. urban expansion; growth etc.) and with the increased development of computer science coupled with the improvements in availability of data, data quality and processing standards have further increased the demand for these spatial simulation models (urban models). There is a lack of understanding in the fundamental and technical aspects of urban model design, construction and the application thereof within spatial planning practices.

The focus of this research is to understand the scientific theories, concepts and models around the application of the science of cities (complexity theory, spatial simulation modelling, spatial planning practices) in order to understand cities as complex and dynamic systems.

1.2 RESEARCH QUESTIONS

The following research questions will be addressed through this research study:

- What are the leading debates on complexity theory and how it is related to and describe the complexity of cities?
- Which quantitative spatial simulation models (urban models) are used to measure complex systems (cities) and what are the concepts, methods and techniques used by these models?
- In the body of knowledge/literature, has the amount of publications, distribution and nature of the applications within the field of spatial simulation models (urban models), which includes Cellular Automata (CA), Agent-based modelling (ABM) and hybrids (including both CA and ABM) grown internationally and within South Africa over the last ten (10) years (period 2009 – 2019)?
- In practice, how has the selected quantitative spatial simulation models (urban models) been developed and used internationally over the last five (5) years (period 2015 – 2019)?

1.3 RESEARCH AIMS AND OBJECTIVES

At a theoretical level, the research is interested in understanding the scientific theories, concepts and models around the application of the science of cities (complexity theory, spatial simulation modelling, spatial planning practices) in order to understand complex and dynamic systems. Many studies have attempted to define and demonstrate the relationship between complexity science and the applications of the science to cities (Batty 2013; De Roo & Silva 2011; O'Sullivan & Perry 2013; De Roo et al 2016; Silva et al 2014; Schintler & Chen 2018; Wilson 2017; McAdams 2012; Pumain 1998). However, little research has gone into providing a comparative analysis of the spatial simulation models (urban models) and its potential application within spatial planning practices.

The research hence aims to improve the knowledge base and explain the fundamental and technical aspects in urban model design and construction, including highlighting the relationship and operational application of spatial simulation modelling (urban models) within spatial planning practices.

In order to achieve this aim of the research, the following objectives have been set for the study:

- Conduct research and compile a comprehensive literature review and content analysis to explain complexity theory and demonstrate the connection between the theory; the way cities are conceptualised, spatial simulation models (urban models), and spatial planning practices.
- Conduct a conceptual analysis to identify and explain the key components (concepts, methods and techniques) of the quantitative spatial simulation models (urban models).
- Identify and provide an evaluation of spatial simulation publications which includes Cellular Automata (CA), Agent-based modelling (ABM) and hybrids (including both CA and ABM) that have been published internationally over the last ten (10) years.
- Identify the assessment criteria and provide a comparative evaluation of the selected quantitative spatial simulation models. The spatial simulation models (urban models) includes CA, ABM and hybrids (CA and ABM) that have been developed and practically implemented internationally over the last five (5) years.
- Analyse and interpret the results from the comparative assessment.
- Draw conclusions about the relationships between complexity theory; the way cities are conceptualised, spatial simulation models (urban models), and spatial planning practices.

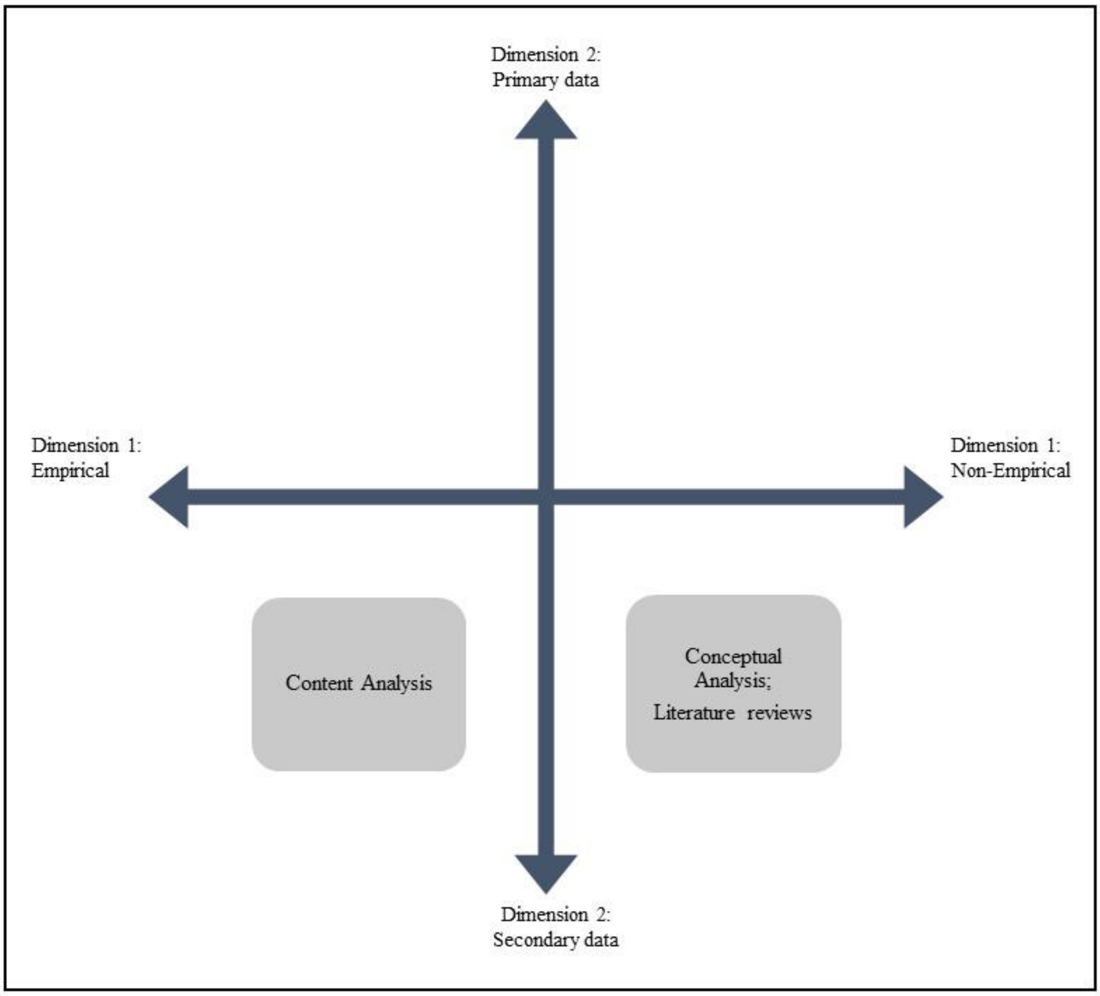
1.4 RESEARCH DESIGN

The research framework identified is a qualitative research approach focussing on content analysis, conceptual analysis and literature review. The typology of the research design is mapped out using the following four dimensions, namely:

- Empirical versus non-empirical studies;
- Primary versus secondary data;
- Numerical versus textual data; and –

- Degree of control (Mouton 2001).

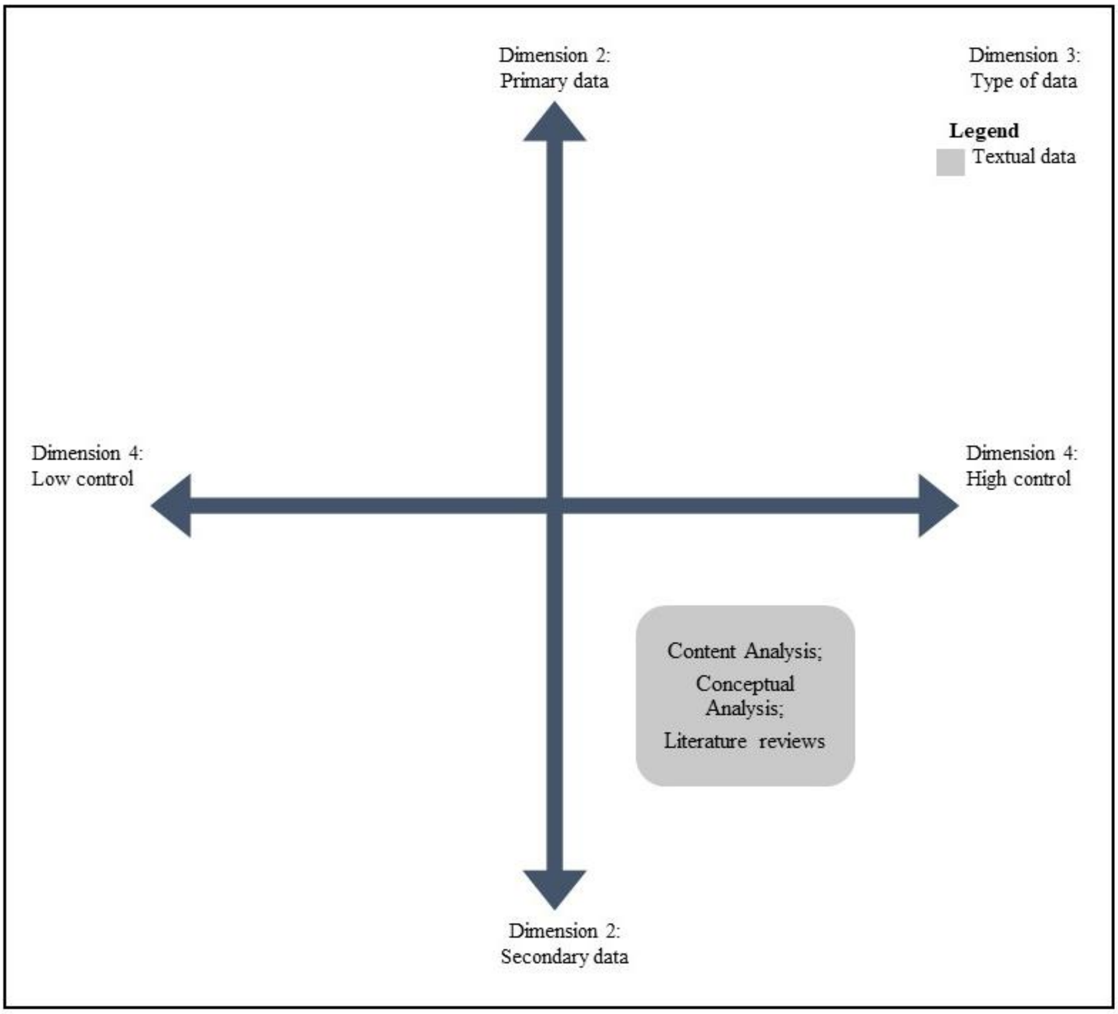
Figure 1 illustrates the design classification of the research framework by cross-tabulating the first two dimensions.



Source: adapted from Mouton 2001

Figure 1: Mapping designs (Level 1)

Figure 2 illustrates the design classification of the research framework by cross-tabulating the dimensions of primary/secondary data and the degree of control.



Source: adapted from Mouton 2001

Figure 2: Mapping designs (Level 2)

The research design is categorised as a textual analysis and assists with the achievement of the research aims and objectives.

The following components (refer to section 3.2 for detailed descriptions) have been highlighted as design elements for consideration in the comparative analysis of the selected spatial simulation models (urban models) (O'Sullivan & Perry 2013; Wray C et al 2013; Chang K 2014; Wray C et al 2015):

- Model name;
- Main purpose/description of the model;
- Key model components;
- Model classification;
- Data inputs;
- Indication of model calibration and validation;
- Model grain;
- Model extent;
- Type of agents and neighbourhoods; and –
- Time period.

Strengths of the identified research design include the ability to analyse large volumes of literature, and when the classification system is well-structured, it provides conceptual clarity, identifies theoretical linkages and reveals the conceptual differing viewpoints and applications (Mouton 2001).

Challenges and limitations to the approach include the lack of generalisability, methodological concerns on the selection of data sources, being vulnerable to interpretation biases and poor organisation and integration (Mouton 2001).

1.5 RESEARCH METHODOLOGY

1.5.1 Sources of data.

Data collection in the research strategy is predominantly focused on textual analysis, utilising secondary data sources accessed through the Stellenbosch University Library which includes books, articles, journals and e-databases, open source portals and other applicable internet sources.

1.5.2 Selection of cases.

The area selection will focus on spatially explicit simulation models (urban models) used to measure complexity in cities quantitatively. Based on the selection criteria, the urban models included are Cellular Automata (CA), Agent-based modelling (ABM), and hybrid models (these includes a combination of CA and ABM).

A meta-analysis will focus on a review of the number of academic publications on urban models, as well as the distribution and nature of applications throughout 2009 – 2019 (10 years), both internationally and within South Africa. From this main list, the detailed analysis (comparative evaluation) of the urban models will then focus on the period between 2015 – 2019, which follows on from the time period after the GCRO report and the subsequent publications (Wray C et al 2013; Wray C et al 2015). The detailed analysis will focus on the practical application of urban models within the five (5) year period and will include peer-reviewed and accessible academic publications.

CHAPTER 2: CITIES AND COMPLEXITY

"Roughly, by a complex system, I mean one made up of a large number of parts that interact in a nonsimple way. In such systems, the whole is more than the sum of the parts, not in an ultimate, metaphysical sense, but in the important pragmatic sense that, given the properties of the parts and the laws of interaction, it is not a trivial matter to infer the properties of the whole." (Herbert A. Simon, 1962 as referenced in Batty 2005:v, 65)

&

"*Cities happen to be problems in organized complexity, like the life sciences. They present situations in which half a dozen or several dozen quantities are all varying simultaneously and in subtly interconnected ways.... The variables are many but they are not helter skelter; they are interrelated into an organic whole". "Why have cities not long since been identified, understood, and treated as problems of organized complexity?...* (Jane Jacobs, 1961 as referenced in Batty 2005:1)

2 INTRODUCTION

Cities are examples of organised complexity where urban development (change) emerge from the bottom-up and the spatial order that we see are driven by patterns. General features of the structure and dynamics of these organised complex systems include path dependence, positive feedback, self-organisation and emergence. In studying organised complexity, the interaction effects are significant as individual interactions between components in one part of the system can unexpectedly change (non-linear dynamics & chaos) and can cause system-wide transitions (phase transitions/bifurcations). The complex and chaotic nature of the system makes predictability difficult, and these systems are deemed irreducible[4], which makes spatial simulation models (urban models) an important tool for understanding and exploring complex system behaviour (Batty 2005; Silva 2011a; Silva 2011b; Xie & Yang 2011; O'Sullivan & Perry 2013).

[4] The system behaviour cannot be easily reduced to "*aggregate rules of thumb or predict the precise outcome of a given starting configuration, even if the systems are completely deterministic*" (O'Sullivan & Perry 2013:22).

The role of spatial planners in this complex and dynamic urban landscape is to "*create bridges between 'what is' and 'what could be',* (or in normative terms) *'what should be' and 'what is desired'* (De Roo et al 2016:1). The 'what is' or 'object of spatial planning' represents, for instance, the issues of uncontrolled and unplanned urbanisation which requires specific planning interventions. This phenomenon itself is not simple or straightforward, it occurs within a highly complex dynamic landscape with inherent local and historical contingent factors; the phenomena is multidimensional; it occurs within different stages over time; and within contextually dynamic spatial planning practices (De Roo et al 2016; Crooks et al 2018). Planners have noted over the last decade that there is an inadequacy of using existing scientific methods and practices rooted in logical positivism to address the problems and challenges that they must deal with daily (De Roo & Silva 2011; McAdams 2012; De Roo 2016).

The new 'science of cities' could provide insights into the complexity of the city and when combined with the normative discussion (De Roo 2011; De Waal 2018; Schintler L.A & Chen Z 2018) of 'what should the sustainable, liveable and resilient city look like' can assist planners to become managers of change where negatives are avoided, and positive effects of change are embraced over time and space (De Roo & Silva, 2011).

The aim of the chapter is to acquaint the spatial planner (modeller/ user) with the language (i.e. meaning, metaphors[5], theories) of complexity science and how the science provides the bridge between complex systems, modelling techniques and practical applications within cities.

2.1 PROGRESS FROM METAPHOR, MEANING (THEORY) AND CITIES

According to Wilson (2014), Warren Weaver theorised during the 1940s and 1950s about complex systems and classified them broadly into simple and complex systems. These classifications were further defined, namely simple systems are describable by a small number

[5] Metaphors are symbols or linguistic representations which allows the simplification of very intricate and detailed discussions, mathematics and theories in order to facilitate their application and further understanding (McAdams 2012; Sui 2011).

of variables, while complex systems need many variables to describe them and they are divided into disorganised complexity and organised complexity.

Cities are defined as organised complexity comprising of numerous intricate and integrated components and subsystems, which through the interaction of agents (individuals, politicians, urban planners, developers or organisations with specific characteristics) create the behaviour of self-organisation (Batty 2005; Nel 2009; De Roo 2011; Bertolini 2011; McAdams 2012). Cities mainly grow from these local actions and are based on individual decisions about development, which includes planning decisions that are implemented locally (Batty 2005). Self-organisation is the process where agents interact collectively (McAdams 2012), and these local actions then create global patterns (Batty 2005). Self-organisation can also only emerge if individuals were free to interact and are capable of interacting and if their actions were facilitated by appropriate rules that command popular support (Nel 2009). In the context of cities, these patterns are formed from basic units of development for example neighbourhoods that grow and change, and which provides an essential social organisation for the delivery of basic services and infrastructure, social networks and economic opportunities (Batty 2005). Actions of agents also do not exhibit equal influence or result in the same spatial patterns, for example, politicians and developers based on their self-interest can influence land use development processes (McAdams 2012) to either produce urban sprawl or compact cities.

Another characteristic of complex systems is that they are non-linear and have an extreme sensitivity to initial conditions, also referred to as a chaotic system (Batty 2005; Nel 2009; Reggiani & Nijkamp 2009; McAdams 2012; O'Sullivan & Perry 2013). These non-linear and chaotic systems exhibit surprising shifts in their behaviour (phase transitions) in response to seemingly minor changes in their initial states (states of emergence) and can result in unplanned and unexpected patterns via positive feedback[6], self-organisation and path dependence[7] , for example, flocking of birds, weather patterns or the formation of galaxies and stars. These local

[6] Positive feedback itself tends to generate path-dependent behaviour and diffusion, giving rise to growing and declining structures. In economic systems growth takes place as returns to scale and can either be constant, increasing or decreasing. In cities it can simulate the distance effect on markets and locations and population growth (Batty 2005).

[7] Qualitative different trajectories that emerge from the application of initial conditions. Leading to lock-in mechanisms that leads to a growth path (Batty 2005:29).

interactions among the system components scale up to cause system-wide outcomes and effects (Batty 2005; Nel 2009; De Roo 2011; Silva 2011; O'Sullivan & Perry 2013). Cities are sensitive to initial conditions, which can be reflected in their morphology as well as the way they develop their economies (Batty 2005; Nel 2009). Some small initial factor, such as a particular industry or development, can determine the city's trajectory/growth path in a unique and non-replicable manner. Land use patterns, often spontaneously arising from local demand tend to persist, despite changing modes of production or transportation (Nel 2009). Non-linear systems lack the quality of predictability and spatial simulation is an essential tool for understanding and exploring their behaviour (O'Sullivan & Perry 2013).

Complex systems display many traits of chaotic systems (Batty 2005; Nel 2009; De Roo 2011; McAdams 2012). They comprise interrelated components, which change and develop over time while retaining coherence. The changes are dynamic and non-linear, and it can also mean that something is changing from order to disorder (catastrophe) or is in transition (phase transition) (Batty 2005; McAdams 2012). An example of a phase transition in cities is the difference between an industrial and post-industrial city, which are associated with technological shifts that lead to changes in the functional structure of the city (Batty 2005). Critically, these systems respond with modifications to changes in their environment. Such changes are evident in the global system and may be slow or sudden as the system moves from one emergent state to another. However, these changes to the components of the system may not necessarily translate into dramatic changes in the system. Many complex systems exist in a critical state, that is a state that occurs on the brink of a phase transition, where the state of the system is poised between two alternatives (equilibrium / steady-state or disequilibrium). A small perturbation can nudge the system into a new emergent state (Batty 2005; Nel 2009; De Roo 2011; Silva 2011) or dampen the system to return to its former state or similar trajectory (Nel 2009). Cities tend to exist in a critical state (far from equilibrium) where the components in the system change at different rates and where the impact differs across spatial scales and time periods (Batty 2005). Cities, therefore, maintain a perpetual balancing act between the benefits of the agglomeration and potential disasters such as epidemics of disease, terrorism and disruptions of the supplies on which the city rely. Cities remain resilient as they have survived changing technologies that influenced their economies, natural disasters, war and terrorist attacks. New technologies may change the local industries or the way the city connects, but it does not change the city as a whole (Nel 2009).

Emergence[8] is another fundamental characteristic of complex systems and refers to the novel way a system can behave that cannot be reduced to the behaviour of the component of the system (Batty 2005; Nel 2009; De Roo 2011). Emergence pertains to not only understanding the persisting patterns but the dynamics of how the parts behave in relation to one another. Complexity analysis plays an important role in the analysis of the phenomena that appears at these different scales and across different times. The representation of moments in time and space when a phenomenon is registered is referred to as a phase-transition. This allows for an understanding of when a phenomenon is triggered. The trigger points refer to actions or events that are used to initiate other actions/activities captured at a specific time and space which leads to positive feedbacks, for example, new transportation policies that are devised to change commuting patterns. These trigger points cause different phase-transitions or self-organisation of the system according to the variations registered in variables over time and represent a change in state. A fundamental change in a variable or phenomena refers to a bifurcation, for example, mass extinction, epidemics, diffusion of technology or changes from migrant to sedentary societies (Batty 2005; Silva 2011).

Hierarchies are also a feature of complex systems, arising spontaneously in the self-organising process (Nel 2009). As cities grow, their spatial units change between scales, for example, neighbourhood – district – city – a metropolis with the same kinds of functions manifesting themselves at higher scales and serving larger populations. Self-similarity is implied in the scaling of local units of development, and they appear as fractal patterns in urban morphology, which are self-similar across scaling (Batty 2005). Fractal forms appear everywhere, and their fractal dimensions (points, lines, polygons or pixels) also exhibit self-similarity at all scales (Batty 2005; Nel 2009; McAdams 2012). For example, a line can be divided into two and then those two lines can be divided into four and eight and so on (McAdams 2012). This implies that a view at one scale will be similar at any other scale for example clouds, drainage basins (Nel 2009). Self-similarity in cities is evident especially in multi-nodal cities with their central business district, regional centres and local centres.

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[8] Emergence is that process whereby unanticipated consequences arise from well-defined rules. An example is Schelling's segregation model that shows how decisions by individuals can lead to extreme spatial patterns of segregation of social groups. (Batty 2005:51)

Hierarchies are prevalent within cities and include functional hierarchies (for example economic services) and of systems that nestle within systems (such as transport) (Nel 2009). The transportation system, for instance, evolves at different intensities over time and space to, for example, a non-congested or congested state. This leads to different phase transitions, such as congestion in morning and afternoon traffic as a result of commuting to work. In addition to understanding the specific variable along with time and space, the evolution of the specific phenomena can also be understood through for example adding the timing of traffic lights, parking places and mode choices from individuals. This multidimensional representation of variables and phenomena plays an important role in complexity analysis as it provides an understanding of the different phase-transitions of each variable, phenomena at different scales and for different time periods (Silva 2011).

Complex systems are open systems, interacting with their environment and demanding a constant flow of energy and are thus far from equilibrium (equilibrium is equated to death) (Batty 2005; Nel 2009; Silva 2011). Cities demand constant inflow or resources to permit their functioning. These resources can range from basics such as water, food, energy, economic goods and information. The interactions tend to, however, to blur the boundaries between systems. As complex systems evolve, their history is important in understanding their present. Also, individual agents within the system may come and go, but their role and function may be replaced by a somewhat different kind of agent (such as autonomous buses replacing taxis). These descriptions emphasise the structure of interactions, non-linearity and openness to the environment. Feedback loops can amplify and move the system to another state, or the feedback loops can dissipate the effect of perturbations and ensures stability (Nel 2009; De Roo 2011).

Change is vital, and a minimum level of growth and change within a city is essential for survival. This has significant implications the way we manage our cities. A vision of a city within equilibrium, static and orderly, ignores the essential processes that create and maintain the city such as the flows and interactions between agents; its form, functions (land uses); densities; connectivity (transport modes) and aesthetics. The ‘control’ can move a city from vibrant dynamism to dull stability (Nel 2009).

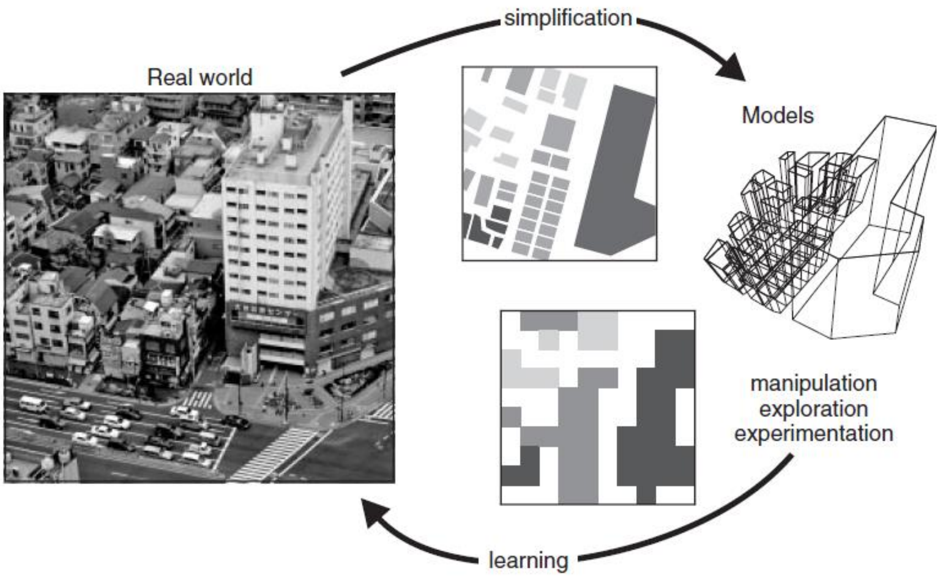
Complexity science and the modelling techniques (Cellular automata, agent-based modelling, dynamic modelling etc.) are becoming more relevant and are viewed as some of the best approaches to describe, represent, evaluate, simulate and explore scenario processes in order to obtain an understanding of urban dynamics, which can support spatial planning practices to become more subjective, impassioned and inclusive (De Roo 2011; Silva 2011; Couclelis 2009; McAdams 2012).

The aim of the next section of the chapter is to acquaint the spatial planner (modeller/user) with the structure and meaning (i.e. metaphors, theories etc.) that is already embedded in the conceptual foundations of urban models and to provide them with a means of understanding the science of cities through explaining the building blocks of these urban models (CA and ABM) and highlight where they can be useful in applications.

2.2 PROGRESS FROM METAPHOR, MEANING (THEORY) AND URBAN MODEL

Spatial simulation models (urban models) uses quantitative methods to measure and represents distinct spatial elements and their relationships for a complete understanding of the complex system under consideration. Because cities cannot be controlled and analysed through controlled experiments, "*a computer is programmed to iteratively recalculate the modelled system state as it changes over time in accordance with the relationships represented by the mathematical and other relationships that describe the system"* (O'Sullivan & Perry 2013:9). It allows for a simplified view of integrated phenomena and provides a platform for convenient exploration of the implications of a dynamic model without impacting on the real-world system (O'Sullivan & Perry 2013; Batty 2005).

The figure below provides a schematic illustration of the concept of models.



Source: O'Sullivan & Perry 2013:3

Figure 3: Schematic illustration of the concept of models

Spatial simulation models are primarily used as exploratory learning tools which assist us in clarifying our thinking of the complexities of the real world and to prompt further discussion and exploration. These urban models can be used as predictive tools in cases where reliable data is available, and when the model is an adequate representation of the system and its dynamics. The models are therefore flexible, adaptive and diverse in their methods of use. The models that are primarily used for analysing this complexity include Cellular Automata (CA) and Agent-based modelling (ABM) (Pumain 1998; Batty 2005; Silva 2011b; Torrens 2011; O'Sullivan & Perry 2013).

Conceptual metaphors are embedded in urban models, and it is important to reflect on how these metaphors influence the design and construction of urban models and how it also informs our understanding of reality (Sui 2011). "*A science without theory is an unsatisfactory approach",* and models are only as strong as the theories it is underpinned by and which they are trying to inform/prove (O'Sullivan & Perry 2013:14). An understanding of these conceptual metaphors and how it informs urban model development can assist spatial planners to understand the influence and constraints of each metaphor, including the intended and unintended consequences when the information from the modelling efforts are used in various practices.

Sui (2011:372-378) employed Pepper's world hypotheses to assist in identifying the role of metaphors in understanding reality. This hypothesis provided an inclusive conceptual framework, for understanding the diverse fundamentals within urban analysis and model development, particularly in the fields of social sciences and humanities.

Table 1: Pepper's world hypothesis

Pepper's world hypothesis	Dominant metaphors	Practice motto	Urban analysis & modelling tradition	Urban models / measurements
Formism[9]	Cities as fractals (forms)	"get to the top of things."	Spatial morphology	Fractals' spatial metrics
Mechanism[10]	Cities as machines	"get to the bottom of things."	Social physics[11]	ITLUP; UrbanSim
Organism[12]	Cities as organisms	"get to the whole of things."	Social biology	Cellular Automata (CA); Agent based model (ABM)

[9] Formism grounds itself in common sense experience based on similarity. Each form can be analysed and explained in terms of its own nature and appearance. (Sui 2011).

[10] Mechanism takes a common-sense experience with the machine as it root cause metaphor. A proposition is considered true only if there is an appropriate causal connection between the states of affairs (Sui 2011).

[11] Social physics is "the science of social phenomena subject to invariable natural laws" (Merriam Webster accessed 14 September 2019)

[12] Organism provides an integrated world view, but it aims to a obtain a synthetic understanding of the whole instead of an analysis of its parts. It implicitly assumes that every experience in the world follow a concealed process, all eventually reaching maturation in an organic whole (Sui 2011).

Pepper's world hypothesis	Dominant metaphors	Practice motto	Urban analysis & modelling tradition	Urban models / measurements
Contextualism[13]	Cities as arenas (events)	"get to each individual thing itself."	Spatial events	Field-based time geography; urban social analysis

Source: Adapted from Sui 2011

2.2.1 Cities as fractals.

Cities as fractals are the study of the physical dimensions of urban form (Reis et al 2014; Sui 2011, Batty 2005) to understand the causal forces underlying changes in urban patterns (Pacione 2009). The spatial morphology tradition focusses on the description, analysis and modelling of the existing and ideal urban form. Methods used by this tradition includes spatial metrics and modelling. Spatial metrics are quantitative measures used to assess the spatial characteristics of urban settlements and structures. The types of metrics include landscape -, geo-spatial -, accessibility metrics and spatial statistics (Reis et al 2014).

The spatial morphology tradition is the oldest and is linked to classical location theories. According to Sui (2011) and Batty (2005), the following theorists can be grouped into this tradition, such as Von Thunen's concentric rings (1826, 1966), Christaller's central place (1933, 1966), Rawstron's principles on industrial location (1958), Alonso's theory of residential location (1960), Weber's theory on location of industries (1909), - and from urban geography -, Burgess's concentric rings (1925), Hoyt's sectoral radiation (1939), Harris & Ullman's multiple-nuclei (1945). These classical and positivistic[14] models of urban land use were criticized during the 1960s for neglecting

[13] Contextualism draws inspiration from the common-sense experience of unique events. It seeks to unravel the texture and strands of processes operating within or associated with events (Sui 2011).

[14] Positivism is a philosophy of science characterized by adherence to the scientific method of investigation based on hypothesis testing, statistical inference and theory construction. This approach was central to spatial analysis in the 1950's, but has been superseded by approaches that incorporates

the underlying causal processes of spatial form which was mainly an outcome underlying social, institutional and economic forces (Pacione 2009). New theories such as White's 21st century city (1987), Berry (1963), Scott (1982), Garreau's edge city (1992), Borchert (1998), Prinsloo (2010), Henry & Dawley (2011) - and from new urbanism - Jacobs (1961), Alexander (1979), Friedman (1979), Lynch (1981), Harvey (1994), was then developed to respond to this criticism (Sui 2011; Batty 2005).

The spatial morphology tradition has grown, and approximately 160 different spatial metrics (Reis et al 2014) can be used, depending on the research question and urban processes under consideration. Batty and Longley (1994, 2005, 2014) have also done extensive work on studying the fractal city as viewing cities as systems within systems of cities and understanding the complex relationships between the parts and the whole (Sui 2011).

2.2.2 Cities as machines.

The metaphor of cities as machines incorporates the tradition of social physics and it aims to model social variables contained in large sets of geo-coded data through statistical measurements to reveal underlying relational patterns that can be explained by laws and theories within the field of physics. This form of analysis is an interdisciplinary method of inquiry and includes models such as integrated land use and transportation modelling. (Sui 2011; Barnes & Wilson 2014).

According to Sui (2011), Batty (2005 & 2014), Barnes and Wilson (2014), the social physics tradition is linked to the theories and spatial data analysis from Ravenstein's currents of migration (1885, 1889), Carey's migration studies (1895), Stewart's population potential (1947), Zipf's power law on city-size distribution (1949), Hansen's residential location model (1959), Lowry's model of the metropolis (1964), Wilson's law on spatial interaction (1970), Tobler's gravitational models (1970, 1976, 1981,

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social, economic and political structures in determining the nature of cities and urban life. (Pacione 2009:681)

1983), Bak's self-organizing criticality (1996), Allen's self-organizing systems (1997), Urry's small world / complex networks (2004).

Urban models that follow this tradition tend to be aggregated, static and non-temporal. These models have been overtaken by the next two traditions which are disaggregated, dynamic and includes temporal dimensions. The focus for studying cities has changed from the top-down[15] perspectives as reflected on through the spatial morphology and social physics traditions to the bottom-up[16] perspectives discussed below in the social biology and spatial event traditions (Sui 2011; Batty 2011; Crooks et al 2018).

2.2.3 Cities as organisms.

The social biology tradition conceptualises cities as organisms as it aims to understand the overall structure and dynamics of urban form. This approach explores the discrete parts of the system and how they interact with each over across space and at various scales (Sui 2011; Batty 2014; Crooks et al 2018). Metaphors are used to understand the complexity within the city, such as ecological metaphors for understanding resilience; the metabolism metaphor for exploring flows of nutrients, energy, storage and residue; and the metaphor of the neural network for understanding relations between places and people. (Sui 2011; Batty 2014).

This tradition is linked to the theories on sustainable development (Brundtland report 1987; Camagni, Capello & Nijkamp 1998, Tanguay et al 2009), urban ecology (Marzluff et al 2008), ecological footprints (Global Footprint network 2010), Brand's law on greener cities (2010) (Batty 2014), Clark's life course approach (2012), and the human ecosystem model (Grove et al 2015; Burch et al 2017 etc.).

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[15] It involves using repeated observations from patterns to make inferences about the processes responsible for those patterns. It is an inductive approach that builds on accumulated evidence in the form of multiple observations of similar and recurrent patterns (O'Sullivan & Perry 2013:50)

[16] Trying to understand the fine-scale processes to predict the broad-scale (macro / global) patterns that might emerge from them. This framework aims to provide a way to handle heterogeneity among individuals in their reciprocal interactions with complex environments and each other (O'Sullivan & Perry 2013:51).

Urban models that follow this tradition include cellular automata and agent-based modelling. These models simulate complex systems (cities as systems or systems of cities) which are dynamic, far from equilibrium, non-linear and temporal. It follows a bottom-up (disaggregate), micro, individual-based model approach where the models reflect the continual and dynamic change of individual and group processes of interaction and location (Batty 2005; Sui 2011; Xie & Yang 2011; Batty 2011; O'Sullivan & Perry 2013; Batty 2014; Crooks et al 2018).

2.2.4 Cities as arenas.

The tradition of conceptualising cities as spatial events aims to understand how individual events occur spontaneously within the city over time and space. The tradition links closely to the need for understanding cities in real-time. This tradition has great potential and momentum for growth, especially with the increase and development of technologies around infrastructure (remote sensors, cell phones, computers); software (GIS, data mining etc.); and the availability of dynamic internet platforms (Web 2.0 – social media, web services etc.) where agents can willingly share user-generated content (geotagged photographs, big data etc.) (Sui 2011). Examples include real-time disaster response and scenario planning on natural (or human-made) events such as fires, hurricanes, and so on. Theories and standardised urban analysis and measurements, especially on the use of big data, are currently being developed and debated.

2.3 PROGRESS FROM MEANING (THEORY) TO URBAN MODELS

The focus of modelling shifted from seeing cities as only physical systems (cities as fractals & machines) to seeing them as organisms during the 21st Century. This change has been facilitated with the increase and improved computational abilities and data, which has also become more accessible and cheaper. The new modelling paradigm (cities as organisms) is dominated by CA and AB models which is increasingly used to abstract the real-world into a series of layers (visual representation of complexity and dynamics) which allow modellers to place and connect agents to each other (spatial integration & self-organization mapping) through social networks (intelligent & adaptive micro behaviour) and proximity measures. It allows laws/rules to be applied to the agents resulting in the emergence of macro-scale phenomena (Batty 2005; Sui 2011; Silva 2011a; Silva 2011b; Xie & Yang 2011; O'Sullivan & Perry 2013; Batty 2014; Crooks et al 2018). An example of this dynamic behaviour across space (spatiotemporal dynamics) is the phenomena such as traffic congestion emerging from agents driving cars (Crooks et al 2018).

The remainder of this section will explain the building blocks of CA and ABM and highlight where they can be useful in applications.

2.3.1 Cellular Automata (CA).

CA is a standard type of spatially explicit simulation model, and it models spatial and temporal patterns that we observe in the physical world. These physical and spatial structures are the outcomes of processes[17] operating within the system at multiple scales and through time. CA consists of specific spatial components, and the building blocks include lattice of cells, cell states, neighbourhoods, transition rules (deterministic or stochastic) and a sequence of time steps (iterations) (Batty 2005; Sui 2011; Silva 2011a; O'Sullivan & Perry 2013;). Each of these building blocks is further discussed in the following sub-sections.

2.3.1.1 Cells

CA consists of a lattice of cells, such as a two-dimensional grid of square cells (also referred to as a matrix) that are the smallest in that grid/space. Each cell includes a set of states for each cell and a set of transition rules that determine how the cell changes from one-time step to the next based on its current state and those of its neighbours (Pumain 1998; Silva 2011a; O'Sullivan & Perry 2013).

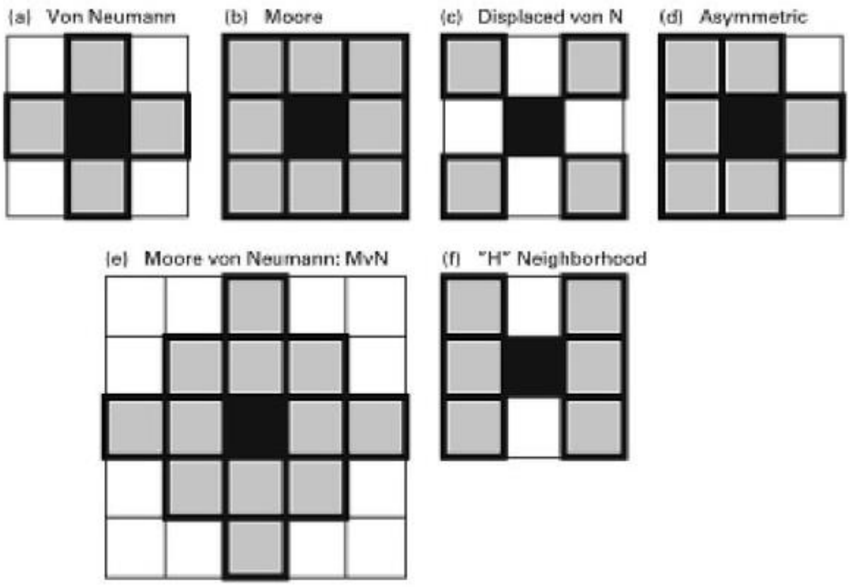
[17] Process is any mechanism that causes a system to change its state, and so potentially to produce characteristic patterns. Processes generate patterns and feedbacks are evident in both directions. Pattern and process are intertwined, and their definitions tend to be circular. An example is the neighbourhood life cycle of cities, where a newly built neighbourhood might be relatively prosperous, but over time the houses and occupants age and some neighbourhood go into relative decline which could lead to gentrification and later urban renewal etc. Disentangling pattern and process is difficult (O'Sullivan & Perry 2013:31, 32)

Cells are the basic units of spatial representation, which are assumed to be indivisible, namely the smallest unit of analysis which describes the system. Cells can be used to index any object or attribute, such as buildings, cadastre, land use, but they are fixed (immovable) and constitute the backdrop on which all urban change takes place. Each cell can take on only one state at a time, and the state of the cell depends on the states and configurations of other cells in the neighbourhood of that cell. The state of a cell can be restricted to integer values when the states are discrete (Batty 2005; O'Sullivan & Perry 2013). Examples of cell states can include urban – non-urban, developed – not developed, active – inactive.

2.3.1.2 Neighbours

The lattice of cells defines for each cell those other cells that are its neighbours. The neighbourhood around the cell is composed of geometrically contiguous cells. Neighbours are defined either as the four immediately adjacent orthogonal cells (called Von Neumann) or as the eight immediately adjacent cells (including the diagonals called the Moore neighbourhood). Other neighbourhoods relax the requirements of strict adjacency, although most contain cells that are no more than two nearest neighbours away from the core cell (e.g. Displaced von N; Asymmetric, circular MvN & H-neighbourhood) (O'Sullivan & Perry 2013; Batty 2005; Silva 2011a).

The figure below depicts the different configurations of local neighbourhoods.



Source: Batty 2005: 77

Figure 4: Local neighbourhood configurations

Within a 3 x 3 cellular space as depicted in Figure 4(b), there are a possible 511 combinations or forms that can be generated. The addition of transition rules can further increase the number of possibilities. Using the Moore neighbourhood (Figure 4b) as an example and with the inclusion of two transition rules (on-off cell states), the configuration possibilities are 2^9 or 512. With this scenario, the possible number of automata is $2^{(512)}$, which is an enormous amount of computational possibilities. The examples above is an illustration of the enormous variety of the kind of patterns and behaviours that might be computed using cellular automata.

2.3.1.3 Time steps / iterations

Time is represented by cells determining, and iteratively updating to their next state. The timing of state changes can occur either synchronously or asynchronously. Synchronously is defined when the cells determine their next state and are updated simultaneously, while asynchronously is defined when cells update their state one after the other, in random order. An asynchronous update can also define when cells may not be updated, while others are updated more than once or from a specific location. As a rule, either synchronous or asynchronous updating is preferred based on their appropriateness (O'Sullivan & Perry 2013).

2.3.1.4 Applications of CA

John Conway (1970) in the 'game of life' simplified the rules in the application of totalistic automata[18], while also still trying to obtain complex spatial patterns. The game of life is not a model of a specific system but a hypothetical and mathematical system with interest in the relationship between the intricacy of the rules that define a system's behaviour and the richness of the behaviour. The game of life is a two-dimensional grid (lattice) which can be infinite or as large as needed, and the configuration for the "Life" is a random distribution of developed and non-developed cells (Batty 2005; O'Sullivan & Perry 2013). It is also defined as follows:

- Cell neighbours are the eight (8) immediately adjacent orthogonal and diagonal grid cells (forming the Moore neighbourhood);
- Cell states are 'alive' or 'dead'; and –
- Two (2) transition rules, namely:
    - Birth (growth) – a dead cell is born if it has three (3) live neighbours to its Moore neighbourhood; otherwise it remains dead; and –
    - Survival – a live cell survives if it has two or three live neighbours (steady-state); otherwise, it dies. Fewer than two adjacent cells imply the cells die from isolation; more than three and it dies from overcrowding (O'Sullivan & Perry 2013; Batty 2005).

Further assumptions and conditions are also:

- The transition rules are uniform and apply across every cell, state and neighbourhood and every time step (iteration);
- Every change in the state must be local, which in turn implies no action at a distance;
- A start and endpoint of the simulation in space and time is specified and is termed initial and boundary conditions;
- Initial conditions apply to where and when the process begins within the lattice of cells, and it is termed the seed site;

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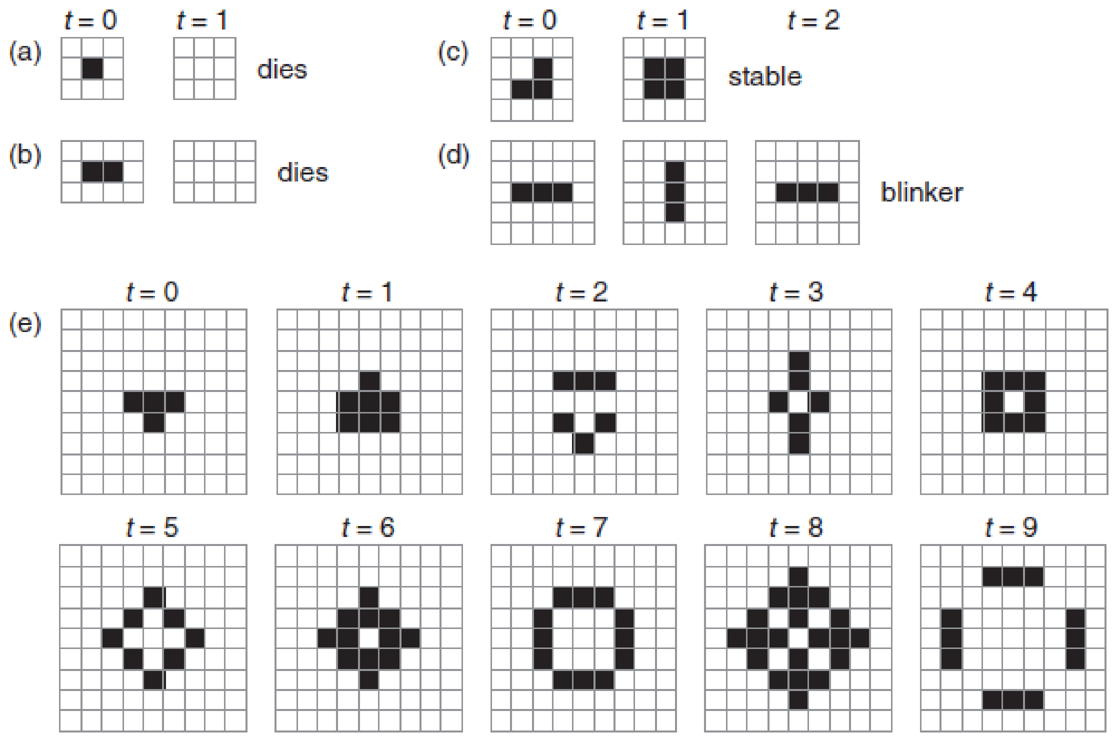
[18] Also referred to as the strict CA framework (Batty 2005; Silva 2011).

- Boundary conditions refer to the limit on the space and/or time over which the CA can operate; and -
- The framework emphasises the spatial viewpoint where the objects (contained in the cells) and their relations in space and time is organised instead of a temporal viewpoint (Batty 2005).

The figure below demonstrates the totalistic automata.



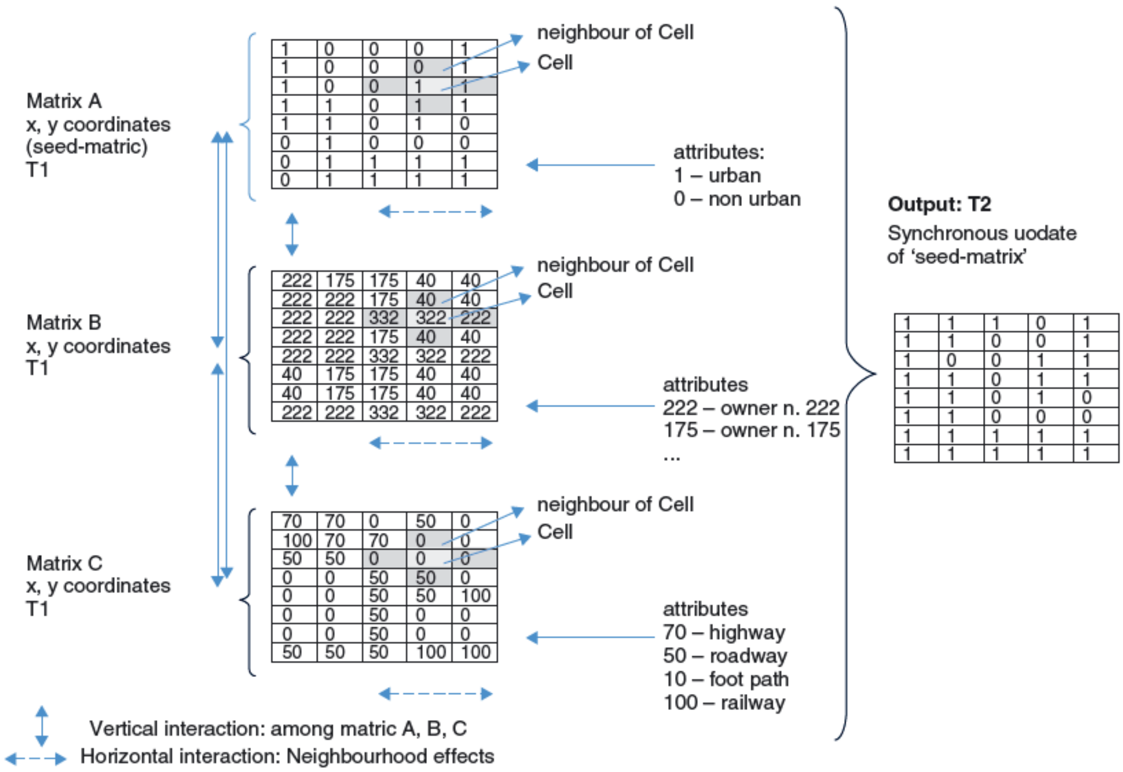
Source: O'Sullivan & Perry 2013:19

Figure 5: Conway's game of life simulation

In Figure (a) and (b) the cells die immediately while adding another live cell to produce the L-shaped pattern in (c) result in a four-cell block of live cells that is stable. In creating a linear pattern through adding another cell in Figure (d) creates a blinking pattern that switches each time step between a horizontal and vertical line. Adding one more cell to (d) to give the T-shaped pattern (e) produces a sequence of nine-time steps resulting in four (4) copies of the three-cell blinker pattern (d). Adding on a new live cell to the pattern (e) produces the 'R pentomino' which has been shown to persist indefinitely and extends indefinitely across space since the gliders will continue to move away from the origin. Conway's discovery in 1970 has led to an explosion of interest in CA because simple rules in even a deterministic system can yield an unexpectedly rich array of unpredicted dynamic behaviours. The "*application of CA can be found across numerous fields that have a spatial bias and involve the evolution of populations, from ecology to astrophysics"* (Batty 2005:76). The attraction of using CA lies in the ability to reduce systems to their most basic elements. (Batty 2005; O'Sullivan & Perry 2013).

The example described above is an illustration of non-linear dynamics, where the system exhibits surprising shifts in behaviour in response to minor changes in their initial states. Most real-world systems are non-linear and because of their structure requires a way to simplify them, while also retaining their dynamic nature. Cities as systems are also characterised as experiencing actions at a distance, for example, the higher-order transport network linking urban nodes along activity corridors which impacts on activities and accessibility. This action requires that the neighbourhood element should be redefined to allow a less strict adjacency rule. In addition to those mentioned above, the majority of cities do not have restrictive conditions on development (Batty 2005).

To accommodate the abovementioned complexities, cellular automata has evolved into random complex automata (also referred to probabilistic CA) and can include processes that are probabilistic and might impact local behaviour through changing the transition rules or the nature of the neighbourhood (Batty 2005; Silva 2011b; O'Sullivan & Perry 2013). One method includes altering the transition rules to make cells ineligible for activating a change in the state due to, for example, the implementation of government policies (i.e. urban edge delineation) or topological features (i.e. roads, mountains, rivers etc.). The transition rule can also consider the state of the developed cell-based on age and introduce an age limit parameter, which can empty cells of development exploring the gentrification and urban renewal process of cities (Batty 2005). When the same cells have different attributes in each of the layers as described above, the interaction (vertical and horizontal) is essential and the model uses matrixes that can perfectly overlay and are geo-referenced. Once the vertical and horizontal interactions have transpired based on the transition rules and time steps a new configuration matrix is developed where the cells can assume different values and different spatial configurations (Silva 2011a; O'Sullivan & Perry 2013). The Figure below indicates how this "*local self-organisation of cells allows for the identification of different regional patterns and allowing the development of new emergent behaviour where original conditions would not anticipate the formation of new/different patterns*" (Silva 2011a:325).



Source: Silva 2011a:326

Figure 6: The random complex cellular environment

2.3.2 Agent-based (AB) modelling.

CA modelling provides a spatially explicit simulation model, and it models spatial and temporal patterns that we observe. However, the locational decisions of agents also influence and modify the spatial structures that we observe. To enhance CA modelling, agent-based models (ABM) are incorporated which provides for the modelling of aspatial dynamics. ABM and CA modelling have become the most used approaches to work with complexity theory in a quantitative design (Batty 2005; Silva 2011a; Silva 2011b).

ABM focuses on the socio-economic conductions and aspatial structures (immaterial structures of behavioural and social systems, such as tastes and preferences) which produces action through public-individual choice and option. The goal of ABM is to explain the moment when an agent takes a decision and the moment when the agent moves from one place to another. Methods used are, for instance, decision trees and neuronal nets which are then extrapolated into the modelling environment as decision rules (Pumain 1998; Batty 2005; Silva 2011a; Silva 2011b; Crooks et al 2018).

The advantages of ABM are its ability to model individual decision-making entities and their interactions; it incorporates social processes on decision-making, and it provides dynamic socio-economic, environmental linkages. For instance, ABM can integrate the agent's physical space (natural environment) with the agent's intelligence (policy/decision-making rules) and combine the bottom-up actions (disaggregate, micro-based analysis) with global interactions and simulate processes such as the space-economy (Batty 2005; Silva 2011a; Xie & Yang 2011).

The ABM framework is flexible and can provide different types of models for studying different aspects of cities, such as;

- Abstract models, the intention is to discover new relationships or knowledge e.g. segregation model;
- Experimental models, exploring new ideas about the system of interest;
- Historical models, exploring the past trends and processes; and –
- Empirical models, the intention is to test different scenarios or to create future forecasts (Crooks et al 2018).

Refer to section 2.3.2.2. below for the explanation of the application of the segregation, experimental and empirical models mentioned above.

2.3.2.1 Agents.

ABM models are constituted of agents with the following characteristics;

- Individuals, agencies and institutions or movable physical but nonhuman objects (e.g. animals, particles systems in physics, robots, creatures from artificial life, software agents) can be classified as agents;
- Agents have mobility, and they can change their positions by moving from one cell to the next;
- Agents can be associated with a specific cell; however, they can be attributed in different ways and classified according to different activities for example property owners (like the CA modelling process);
- Agents usually act autonomously and are autonomous entities or objects that act independently of one another. Depending on various conditions displayed by other agents or the system, they may act in concert for example neighbourhood watch, community safety organisations and the police;
- The central feature of an agent is their ability to communicate with one another, as well as sense and respond to their environment;
- An autonomous agent is defined as "*a system situated within and part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so effect what is senses in the future*" (Batty 2005:210). More than one type of agent and environment can be simulated based on the decentralised behaviours within more than one kind of environment, for example, mobile robots, software agents, creatures from artificial life, humans, other animals or plants (Batty 2005:210-211).

The behaviour of agents can be classified according to properties summarized in Table 2 (refer to the table below).

Table 2: Properties of agents

Property	Meaning
Reactive	Responds in a timely fashion to changes in the environment or other agents.
Autonomous	Exercises control over its own actions.

Property	Meaning
Goal-orientated / proactive / purposeful / cognitive	Does not simply act in response to the environment but behave according to its own protocols or plans.
Temporally continuous	Is continuously running process.
Communicative / socially aware	Communicates with other agents.
Learning / adaptive	Changes its behaviour based on its previous experience.
Mobile	Able to transport itself from one cell to another.
Flexible	Actions are not scripted.
Character	Believe 'personality' and emotional state.

Source: Adapted from Batty 2005:212

The relations between agents and their environment can be characterised by;

- Agents influence their own behaviour for example personal preferences in what type of products they purchase;
- Environments influence their one state;
- Agents affect their landscapes for example resource extraction and depletion;
- Environments affect agents for movements within cities;
- Relations to all other agents and environments (i.e. action at a distance); and -
- Relations to external environments (i.e. action at a distance) (Batty 2005).

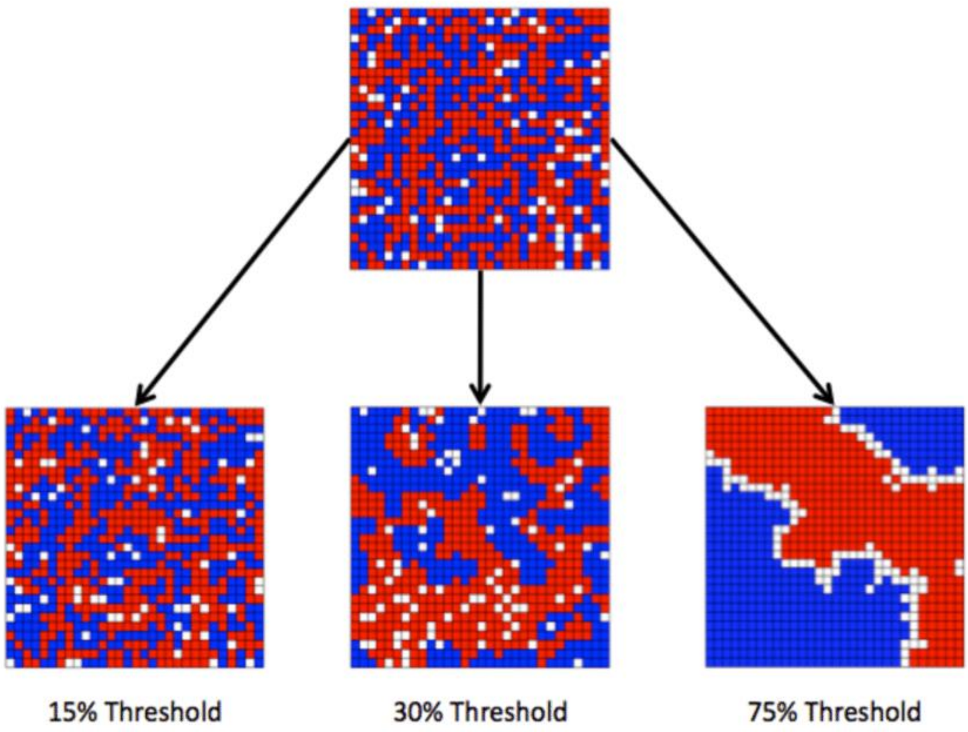
ABM is most appropriate when the focus is on agents reacting purposefully to their local environment, which is encoded into the spatial environment (cells or layers), and the action and interaction (spatial movement and location) between the agent and environment can be defined (Batty 2005; Silva 2001b; Xie & Yang 2011).

2.3.2.2 Application of ABM.

Schelling's simple segregation model (1971) was one of the earliest ABM (Crooks et al 2018; O'Sullivan & Perry 2013). The model aims to explore the disparity between the preferences on the agents (micro-behaviour) and their aggregate outcome (macro / global behaviour). The model is defined as follows:

- Two types of agents are randomly located on a two-dimensional grid;
- Each agent wants to live in a neighbourhood (Moore neighbourhood) wherein a certain percentage of neighbours are like themselves (likeness parameter);
- When an individual is dissatisfied with their current location, they can move to the nearest available location at which their requirements are satisfied (even empty areas); and -
- Rounds of the relocation of agents are repeated until all the agents are satisfied or until no more can be successfully relocated (O'Sullivan & Perry 2013; Crooks et al 2018).

In the example below, the parameter of likeness is set at 15%, 30% and 75%. The agents move over time to areas that they feel satisfied in and segregated neighbourhoods emerge at the aggregated level. As the individual preference increases for a similar neighbour, segregation increases and even with a relatively low likeness parameter (30%), agents still self-segregate (Batty 2005; O'Sullivan & Perry 2013; Crooks et al 2018).



Source: Batty 2005

Figure 7: Representation of Schelling's segregation model

In the urban modelling context, ABM needs to represent the agent's complex behaviour and interaction with other agents -such as households, businesses, planners, developers, or decision-makers within the system of interest. This requires the formulation of a multi-criteria evaluation framework, which can be employed to identify the decision-making tasks that drive urban land change or urban development policy. This decision-making framework will be abstracted and computerised in order to simulate how agents behave over the simulated landscape (Xie & Yang 2011). The functions developed also needs to take into account how the decisions by spatial agents change the spatial morphology of the landscape. For instance, when agents find and act on resources (location theory), the locations they originate from and the routes they take back to these origins (migration & mobility theories) are some of the elements of interest in the urban system. The models can also be extended to include actions or behaviours that occur when these resources are encountered, thus linking spatial logic to economic and social processes (Batty 2005). In this process, the spatial distribution/organisation of resources is considered; the agent's wealth accumulation or deterioration based on access and resource consumption, resource exploitation and conservation. When agents cannot access resources, this lack of access can lead to inactivity in space economy and 'death', and this is then remedied by income support (direct or indirect subsidies) providing them with an opportunity to gain wealth again. The model can be further extended to include population demographics (life span of agents); wealth distribution measures (i.e. Gini coefficient, poverty indexes etc.) and accessibility measures to economic opportunities and social facilities (Batty 2005).

2.4 MODEL UNCERTAINTY AND EVALUATION

A fundamental problem in modelling is uncertainty, and it is essential to note that in any modelling environment, uncertainty is unavoidable. The location, level and nature of uncertainty needs to be considered in model development and should be appropriately represented in models. In spatial simulation modelling, some of the aspects that impact on model uncertainty relate to the trade-offs that need to be made between analytical tractability (deterministic model[19]) and realism (stochastic model[20]). This is predominately influenced by the research question that is being asked to an urban model, as well as the data, processes and patterns that are being considered and analysed within the complex systems. This step evaluates the model's adequacy given its purpose (O'Sullivan & Perry 2013).

Model evaluation is also an essential part of model development and is defined as "*the process of determining model usefulness and estimating the range or likelihood of various interesting outcomes*" (O'Sullivan & Perry 2013:198). Calibration and verification are methods used to evaluate the model's 'fit for purpose'.

2.4.1 Design and construction of models.

Different patterns are perceived at different scales[21] and the inferences made will have to change as the scale changes. Patterns contain information on what we observe in nature, and within the context of spatial simulation models (urban models), they are the defining characteristics of a system and the underlying processes and structures. Spatial patterns can be defined as a pattern in which features recur recognizable and regularly, and often identically or symmetrically (O'Sullivan & Perry 2013). Spatial processes are inferred from patterns, and they can be viewed differently at various scales and time frames.

Deciding on the scale is one of the critical steps in model development as the decision of the scale will determine the appropriate representation of the spatial processes under consideration as well as the inferences that can be made from the model (O'Sullivan & Perry 2013).

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[19] A deterministic model does not represent uncertainty and so for a given set of boundary conditions and input parameters will always produce the same outcomes. The model buys analytical tractability, but at the cost of realism (O'Sullivan & Perry 2013:194).

[20] A stochastic model includes some random component, such as variation in parameter growth rates from year to year in a population model. The model is intractable and increases realism (O'Sullivan & Perry 2013:195)

[21] Scale denotes the resolution within the range or extent of a measured quantity

2.4.1.1 *Scale and scaling*

In spatial simulation models, the scale can be categorised into grain and extent. Spatially, grain refers to the resolution of data, such as the pixel size in remotely sensed imagery. Temporally, grain refers to the frequency of data, such as how often measurements are taken (O'Sullivan & Perry 2013).

Spatially, extent refers to the total area that the dataset spans and temporal extent are defined by the duration over which the data were collected (O'Sullivan & Perry 2013).

Spatial and temporal extent places restrictions on models, or data, and affect the ability to make inferences (generalisations) from them. The scaling problem within urban models relates to the nature of the systems under investigation, which is both fine-grained and of considerable extent. For example, when we consider climate change, we need to be able to integrate across different spatial scales (local to global) and temporal scales (millisecond to multi-millennial). This is practically challenging, and the scaling problem forces the considerations within model conceptualization, development and analysis about decisions on model representation (trade-offs between grain and extent – What processes shall I include?) and the interpretation of model outcomes (What patterns am I seeing, and what do they tell me?) (O'Sullivan & Perry 2013).

With increased access to computing power, software tools, detailed remote sensing, and big data, the possibility exists to develop fine-grain simulation models that cover large extents. The challenge with this is that such models lose their usefulness in simplifying the phenomena and they become difficult to interpret (O'Sullivan & Perry 2013).

2.4.1.2 *Scale-dependence: patterns and processes*

A disconnect exists between the scale of the processes of interest and the scale of the available observational data. In these cases, the model needs to be designed in a manner that allows the user to extrapolate or interpolate data from one scale to another to describe or make inferences. Also, the patterns that are perceived within a system can change when the space-time scale is changed, and this phenomenon is termed scale-dependence. Scale-dependence in patterns, do not necessarily translate into scale-dependence in processes. Processes can occur rapidly, but their effects on patterns are slow to emerge, i.e. lagging effects. The decision on the appropriate scale is influenced by the research question (O'Sullivan & Perry 2013).

Some processes do not change with changes in space-time scales, and these patterns are termed scale-invariant, self-similar, self-affine or fractal. Many real-world objects, such as coastlines, mountain ranges, drainage systems and cities, can be shown to have fractal properties (O'Sullivan & Perry 2013).

2.4.2 Calibrating and validating models.

Calibration and validation exercises are essential in urban models mainly when they are used in spatial planning practices as planning support systems. Calibration involves adjusting model parameters for simulations (referring to the act of running a model on data or applying it to a given scenario) to perform within a level of fitness of sufficiency concerning its intended purpose (Torrens 2011; Xie & Yang 2011).

Validation involves assessing the success of a model or simulation run in achieving its (specific) intended goals. The method involves comparing the performance of the model to some properties of the real system being simulated. Comparisons usually are made to register a model as generally applicable to a specific system, place and time, or the model fits a particular purpose, for example, decision support or normative modelling (Torrens 2011; Xie & Yang 2011).

Another factor that influences the calibration and validation of models is the paradigm shift in urban models, away from thinking of them as diagnostic or prescriptive tools, towards conceptualising them as laboratories for experimenting or 'tools to think with'. The nature of the spatial dynamics being explored within these urban models are self-organising, stochastic, catastrophic and chaotic, and different models can produce the same outcomes using different parameters or rules. This non-uniqueness or under-determination makes calibration and validation of urban models difficult. (Xie & Yang 2011; Silva 2011a; Torrens 2011; O'Sullivan & Perry 2013;).

Calibration and validation also require adequate data based on the different dynamics modelling (i.e. CA – spatial or ABM – aspatial; and temporal), which in turn influences the choices of calibration - and validation mechanisms that can be employed and the subsequent outcomes. In addition, the data can result in the result in a model to be 'fit' for use in a specific location, and it, therefore, cannot be used for inferences in a different location or as generalisations within the system of interest (Torrens 2011; Xie & Yang 2011).

Urban models are also only as strong as the theories that underpin them, and in many instances, the theory has been found lacking, particularly at microscale / local behaviour and concerning phenomena that operate across scales, for example, demographic transitions, urbanisation and migration (Torrens 2011; O'Sullivan & Perry 2013).

The crucial factor in model evaluation, is to keep the purpose of the model firmly in mind and can be as simple as to ask, *"Did I learn anything useful from building this model? And if so, what?"* (O'Sullivan & Perry 2013:228).

2.5 CONCLUDING REMARKS

Within a complex and dynamic landscape (reality), a spatial planner's role is to "*create bridges between 'what is' and 'what could be',* (or in normative terms) *'what should be' and 'what is desired'* (De Roo et al 2016:1). This requires an understanding of the city as a complex dynamic system and how planning interventions should be contextually formulated and implemented to address the multidimensional urban phenomena such as uncontrolled and unplanned urbanisation challenges. Spatial planners need to become managers of change where negatives are avoided, and positive effects of change are embraced over time and space. However, the current scientific planning instruments and practices are noted as being inadequate to address these multidimensional problems and challenges being faced within cities.

The new 'science of cities' has been identified as a method which can provide insights into the complexity of the city. The purpose of the chapter is to bring together the concepts of complexity theory and complexity science in an attempt to assist spatial planners with an understanding of how cities as organisms are theoretically conceptualised. Cities are examples of organised complexity where urban development (change) emerge from the bottom-up and the spatial order that we see are driven by patterns. The main components from complexity science that relates to the general features of the structure and dynamics of cities as organised complex systems include path dependence, positive feedback, self-organisation, emergence, non-linear dynamics, and phase-transitions. The components of a complex system make predictability difficult, and this makes spatial simulation models (urban models) an important tool for understanding and exploring complex system behaviour.

The spatial simulation models (urban models) used by complexity science are CA and AB models which abstract the real-world into a series of layers as a visual representation of the complexity and spatial-temporal urban dynamics. Spatial simulation (urban models) allow for the complex reality to be shown in a simplified form, in order that spatial strategies and their impacts can be explored in advance. The chapter provides explanations on the key considerations for spatial simulation model (urban model) conceptualisation, the components, design and construction. These modelling techniques play a fundamental role in understanding the functionality, practicality, accuracy and 'fit for purpose' use of these urban models within cities. In general, the primary role of urban models (CA & ABM) is as heuristic tools for learning about the real world and enables scenario planning which can support spatial planning practices.

"models, of course, are never true, but fortunately it is only necessary that they be useful."

(George Box, 1979 as referenced in O'Sullivan & Perry 2013:2)

CHAPTER 3: URBAN CA AND ABM MODELS FOR THE SIMULATION OF URBAN DYNAMICS: A REVIEW AND ANALYSIS

"Just as settlements are diverse and complex, so there are many ways to describe and understand them." (K. Kropf, 2009 as referenced in Reis et al 2014:279)

3 INTRODUCTION

Spatial simulation models (urban models) are primarily used as exploratory learning tools which can assist spatial planners in clarifying their thinking of the complexities of the real world and to prompt further discussion and exploration. These urban models can be used as predictive tools in cases where reliable data is available, and when the model is an adequate representation of the system and its dynamics. The urban models are therefore flexible, adaptive and diverse in their methods of use. As discussed in Chapter 2, urban models that are primarily used for modelling complex dynamic systems, such as urban systems include Cellular Automata (CA) and Agent-based modelling (ABM). These models are used as planning tools to understand how cities develop, including their driving force of land-use change and the configuration of its spatial pattern (Reis et al 2014). Urban land dynamics experience different driving forces at varying speeds, intensity or trajectory, which has been a dominant research agenda for spatial planners (Wu & Silva 2010).

In recent years these models for urban growth simulation have proliferated because of their conceptual simplicity, flexibility and their ability to incorporate spatial and temporal dimensions of urban processes. The applications have also improved with the advances in computer techniques, such as the integration with geographic information systems (GIS), artificial intelligence (AI) and advanced spatial analytics (Santé et al 2010; Wu & Silva 2010). Even though the ability to use these models have become easier, one of the main problems in applying these models to spatial planning practices, is the choice or design of the most suitable urban model for a particular situation or application (Santé et al 2010) which then informs policy decisions and/or support decision-makers (Reis et al 2014).

The chapter provides a meta-analysis of urban models applied internationally in urban contexts over the last decade. Academic publications over the past ten years (2009 – 2019) were surveyed in the Web of Science platform in order to provide an overview of the models being adopted in research and practice. From this main list, a detailed analysis (comparative evaluations) is conducted on the key urban models over the last five years (2015 – 2019). The detailed analysis period follows on from the time period after the GCRO report and the subsequent publications (Wray C et al 2013; Wray C et al 2015). The detailed analysis will focus on the practical application of urban models within the five (5) year period and will include peer-reviewed and accessible academic publications.

The overall purpose of this analysis is to identify the components of the urban models; evaluate spatial and temporal scale; delimit their physical boundaries of the system under review; articulate the connection among the components (four complexes of urban systems i.e. biotic, physical, social and built), and identify the capabilities and limitations (Santé et al 2010; Pickett & Cadenasso 2002).

3.1 META-ANALYSIS

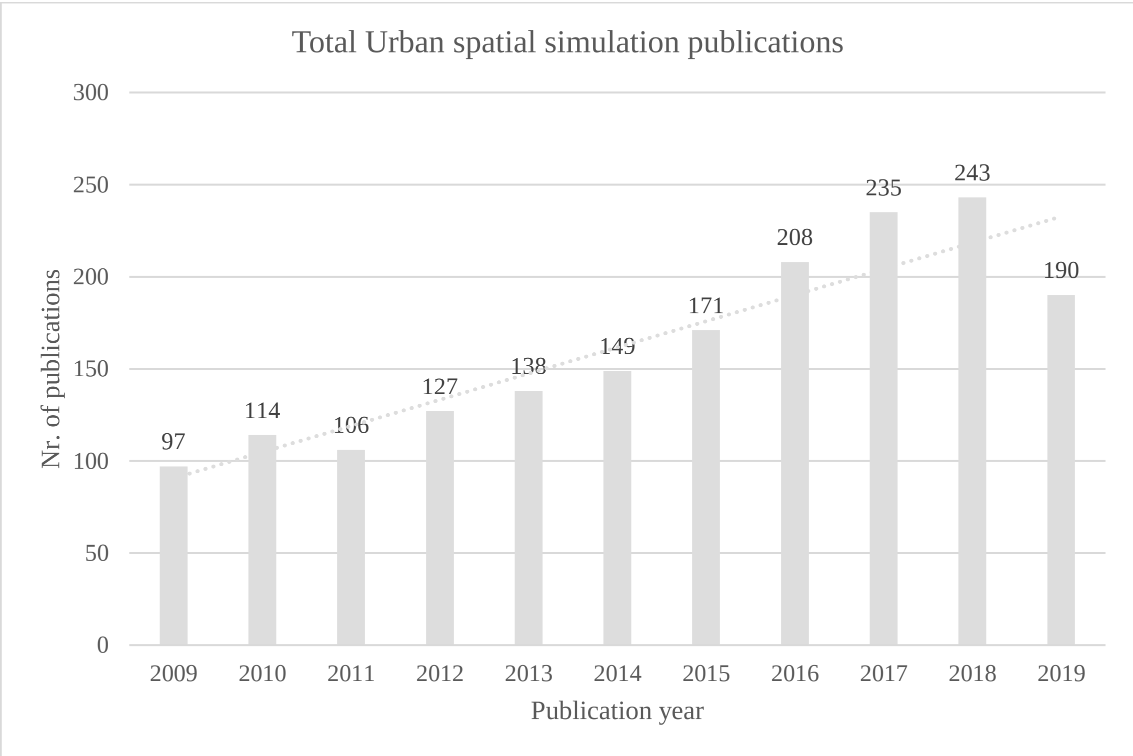
In order to cover as many urban models as possible, a comprehensive review of the literature was carried out of the subject area or methodology over the past ten years (2009 – 2019). The keywords used in the Web of Science platform included "spatial simulation" and "urban". The results were then assembled into four groups, based on the specific methodological approach in which the urban models analysed in this research (CA and ABM) were developed. The four groups are:

1. Urban spatial simulation models;
2. Urban spatial simulation models using a CA approach;
3. Urban spatial simulation models using an ABM approach; and -
4. Urban spatial simulation models using a hybrid (CA-AB) approach.

The intention of these groups does not intend to constitute a comprehensive classification or typology of urban models. The main aim is to facilitate the analysis and provide a broad methodological approach to compare the different models applied in practice over the time period of the meta-analysis.

The results indicate a consistent increase in the number of publications dealing with urban spatial simulation (urban models). A total of 1778 records were returned over the ten-year period (2009 – 2019) (Refer to Appendix A.4). In 2009 the number of records totalled 97 records (5,5% of total) and 243 in 2018 (13,7% of total) (refer to Figure 8).

The rate of change over the time period (excluding 2019), is 66,4%. The average annual growth rate over the period of 6,95 %.

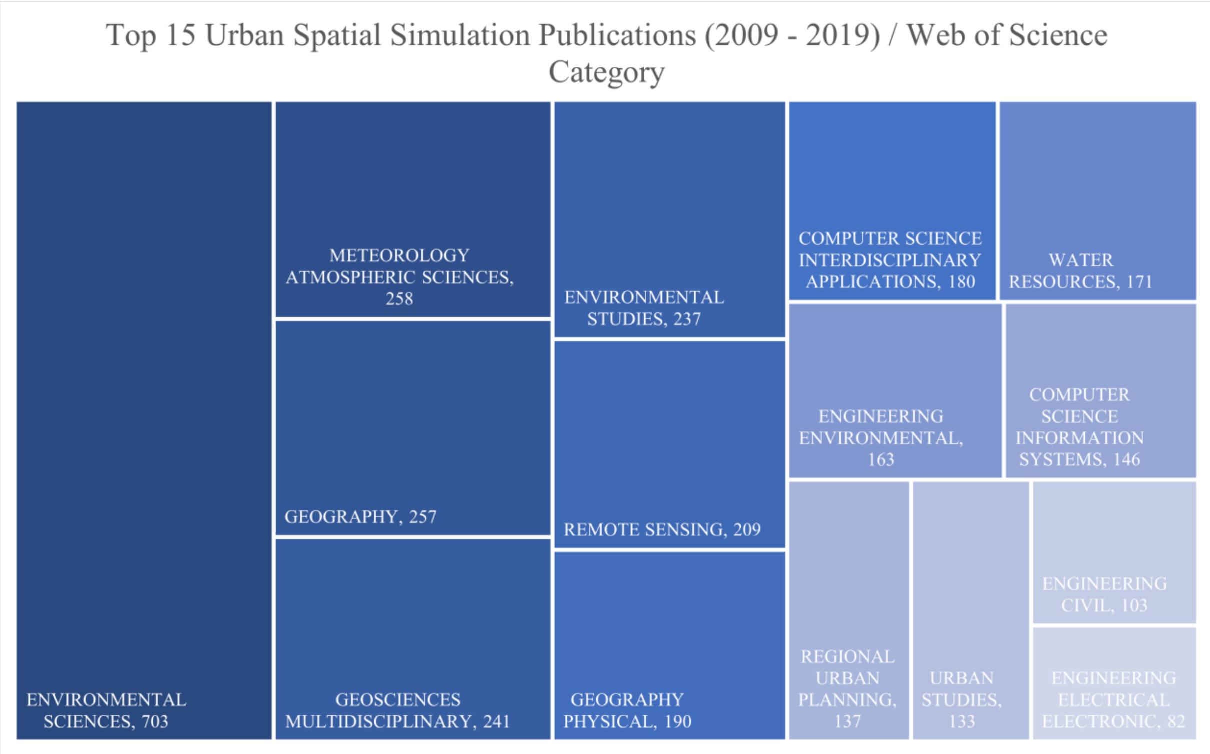


Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 8: Total urban simulation publications

The urban spatial simulation publications over the period were predominantly published in the Web of Science categories of Environmental Sciences, Meteorology atmospheric sciences, Geography, Geosciences multidisciplinary, Environmental studies, Remote sensing, Geography physical, Computer science interdisciplinary application, Water resources, Engineering environmental, Computer science information systems, Regional urban planning and urban studies. In the regional and urban studies publications, a total number of 270 records were cited (Refer to Appendix A.5).

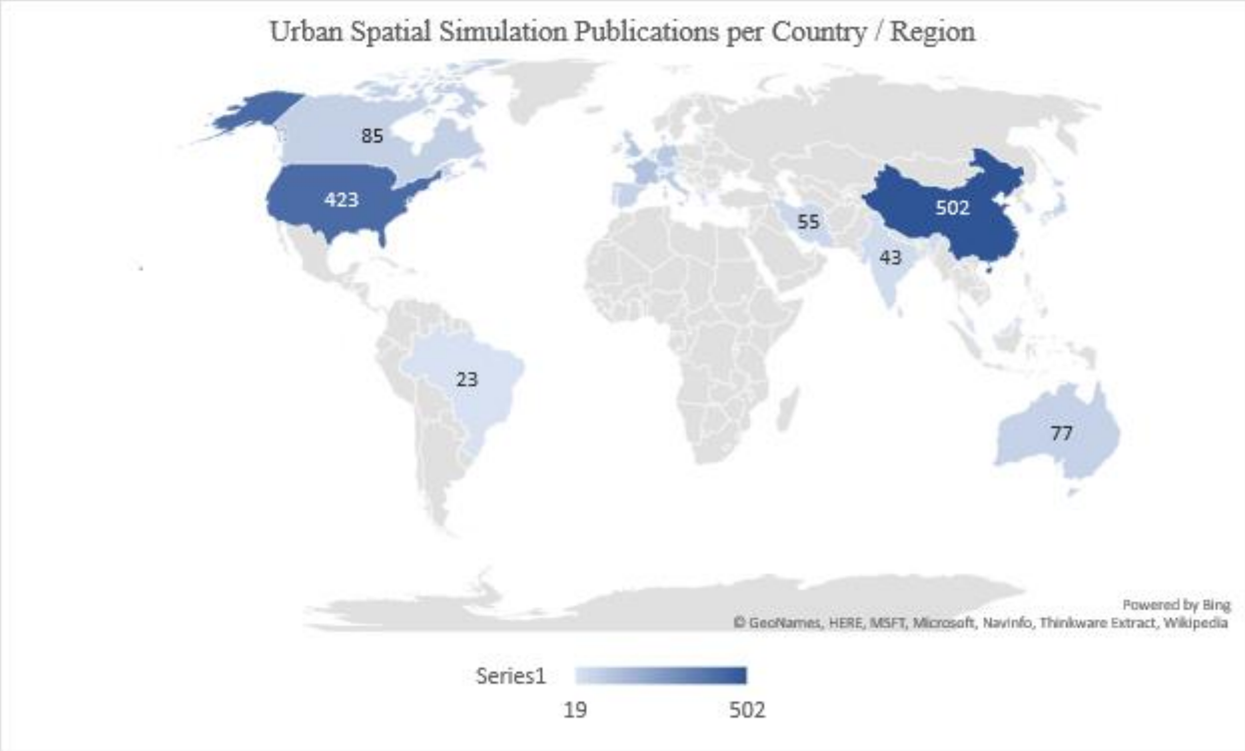
The publication categories are predominantly focused on the research themes of environmental sciences and geography, which includes research types of long-term monitoring, experimentation, comparative analysis and models / methodological approaches. The varying coverage of the publications also demonstrates the multi-disciplinary nature of the models and their application (Refer to Figure 10).



Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 9: Treemap of urban spatial simulation publications

In addition to the varying publication categories, the publications predominantly focused on applications in China (28,2%), United States of America (23,8), France (7,3%), England (6,6%), Germany (5,9), Italy (5,2%), Canada (4,8%), Australia (4,3%), Spain (4,2%), Netherlands (4,1%) and Japan (3,9%) (Refer to Figure 11 and Appendix A.6).



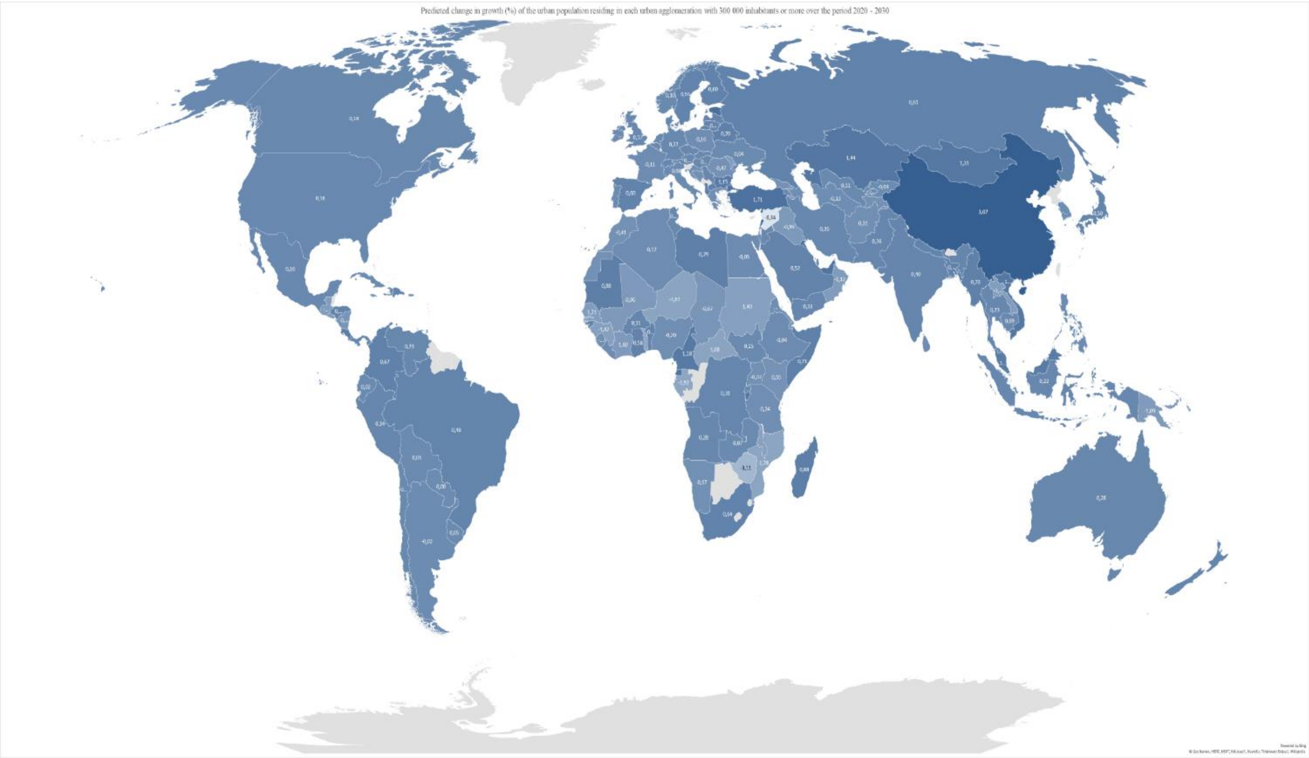
Source: Author adapted from Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 10: Spatial distribution of urban simulation publications

Comparing the urban simulation publications with the urban agglomerations (300 000 or more inhabitants) that are predicted to change over the period of 2020 – 2030, a visual comparison can be distinguished between the areas with a high growth percentage and the research into urban models (refer to Figure 12).

Table B.1 in Appendix B sets out the top 30 countries with the highest aggregate national predicted change in urban agglomerations over the period of 2020 – 2030. China is predicted to have the most substantial increase in the percentage urban population over this period, with the urban population at 70,1% in 2030 (UNDESA 2019). This necessitates an understanding of the driving forces behind this growth, as well as a measure of prediction, not only at a local level but also considering the national and regional implications. This explains the dominance of applications in China with a total of 502 records over the past ten (10) years to understand and predict the growth of the urban system. Based on the published research output China is thus dominating the active research of long-term monitoring, experimentation, comparative analysis and modelling techniques.

Although South Africa is listed under the top 30 countries which are predicted to experience significant change in the next 11 years, only a single urban spatial simulation publication found was found on urban modelling practices/initiatives and the opportunities and challenges within the South African context (Wray C et al 2013; Wray C et al 2015).



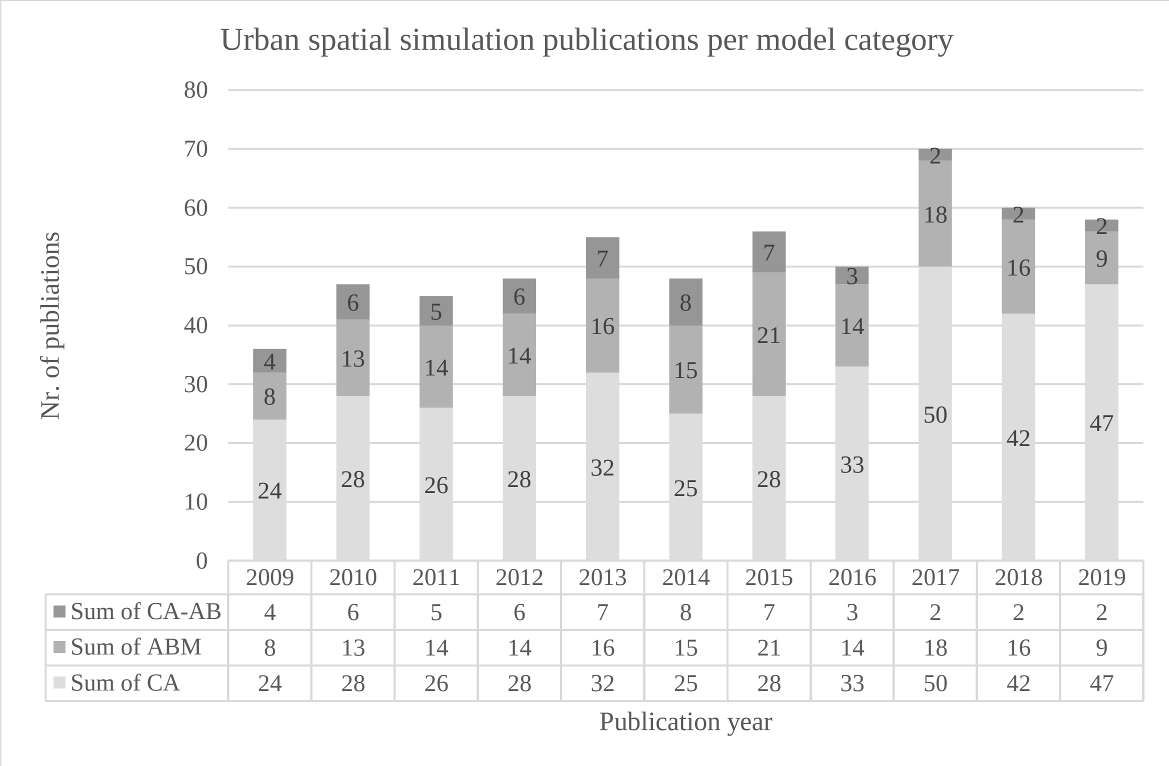
Source: Author adapted from UNDESA population prospects database 2019 [online]. [Accessed 4 October 2019].

Figure 11: Spatial distribution of percentage urban population

3.2 DETAILED ANALYSIS OF URBAN SIMULATION INITIATIVES

In the review of the urban spatial simulation model publication per model category, it was found that there was a consistent increase of publications within the CA and ABM categories.

A total of 573 records were returned over the ten-year period (2009 – 2019) consisting of CA urban models (63,4%), urban ABM (27,6%) and urban CA-AB (9,1%) records (refer to Figure 13).



	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Sum of CA-AB	4	6	5	6	7	8	7	3	2	2	2
Sum of ABM	8	13	14	14	16	15	21	14	18	16	9
Sum of CA	24	28	26	28	32	25	28	33	50	42	47

Source: Author adopted from Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 12: Urban simulation publications per model category

Most publications regarding urban simulation appeared over the five years between 2015 - 2019. This time period is, therefore considered in further detail in order to identify and analyse the key urban models that have been applied.

The various individual applications were considered by applying the following assessment criteria:

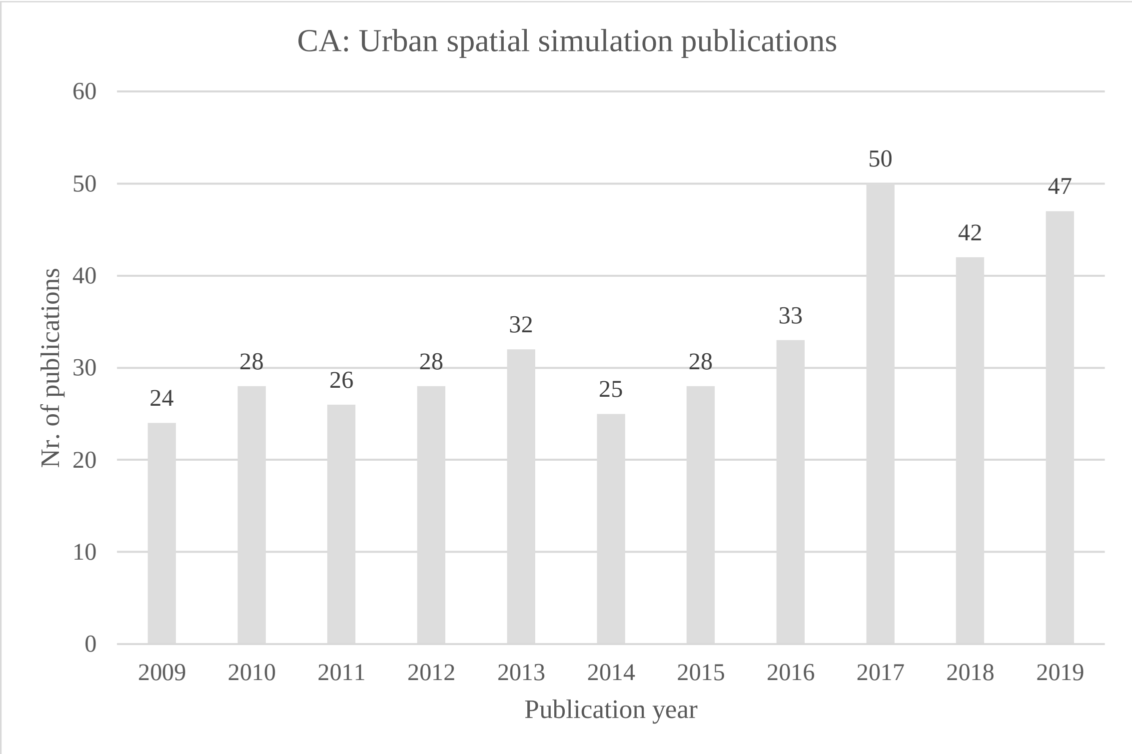
1. Objective. The various categories of urban simulation models are classified according to four categories of objectives:
   a. descriptive models, which analyse the factors and dynamics that provide insights into the past (What has happened?);
   b. predictive models, which uses statistical models and forecasting techniques to understand the future (What could happen?);
   c. prescriptive models, which aims at obtaining optimisation and simulation algorithms to advise on possible outcomes (What should we do?);

d. conceptual models, which looks at theories, models, concepts and different methodological approaches through experimentation to test specific hypotheses.

2. Main purpose and issues. The model applications can be grouped into four main components of urban systems, i.e. biotic, physical, social and built.
3. Model components. Modelling techniques and application software are identified to evaluate if the models are integrated with other models and how they are applied within the computer environment.
4. Data inputs. The data inputs needed between the various categories of urban models differ according to their needs and the scale at which the components of the system are investigated, and the requirements are compared between the different categories and practical application of the models.
5. Calibration. Calibration aims to obtain the values of the model parameters that allow for the most accurate reproduction of the real world. This measure provides an understanding in terms of the level of fitness of the model, based on its intended purpose.
6. Validation. The aim of validation is the evaluation of the overall accuracy of the model with the real system being simulated. This measure provides a measure of confidence based on the accuracy of the urban model and its ability to predict the future.
7. Model grain. According to their objective, the various categories of urban simulation models can be classified into four categories: global, national, regional, local (cities) and micro (suburbs). The classification allows the analysis of the hierarchy of the urban models and a comparative analysis between the same levels.
8. Model extent identifies the specific urban system under investigation and allows a comparative analysis between the same urban systems under investigation.
9. Type of agent. The ABM and CA-AB models identify the different individual decision-making entities and their interactions within the system.
10. Cell states. Depending on the components and the purpose of the urban model, the cell states can vary between the different CA and CA-AB models. The cell states can be as simple as a simulation from urban to non-urban, or it might have multiple transitions to multiple land-uses.
11. Neighbourhood. The neighbourhood size and type significantly affect the model outcomes within the different CA and CA-AB models.
12. Time period. The time period specifies the period used in validating and calibrating the different categories of models, including the projection of model outcomes over time which highlights its temporal dynamics.

3.2.1 Cellular automata (CA).

As indicated in Figure 13, the number of CA urban simulation publication showed a steady increase, especially since 2014 (refer to Appendix A.7).

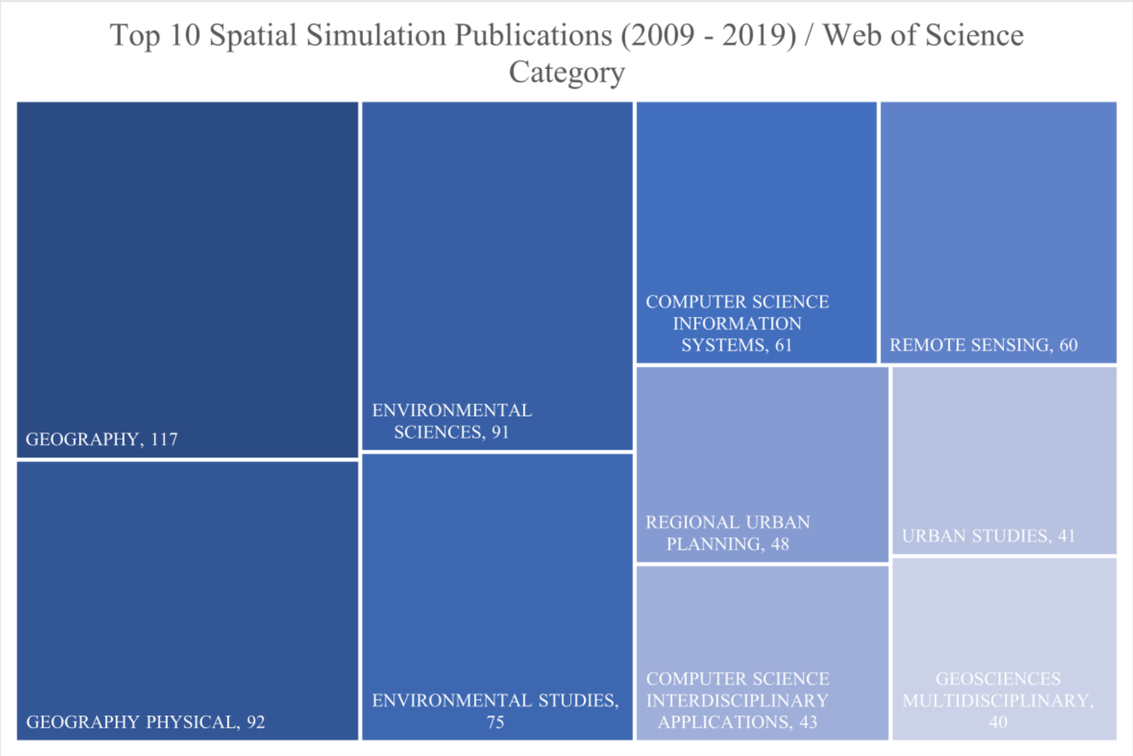


Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 13: CA: Urban spatial simulation publications

The CA category of urban spatial simulation publications over the period was predominantly published in the Web of Science categories of Geography, Geography physical, Environmental sciences and Environmental studies. In the regional and urban studies publications, a total number of 89 records were cited (Refer to Appendix A.8).

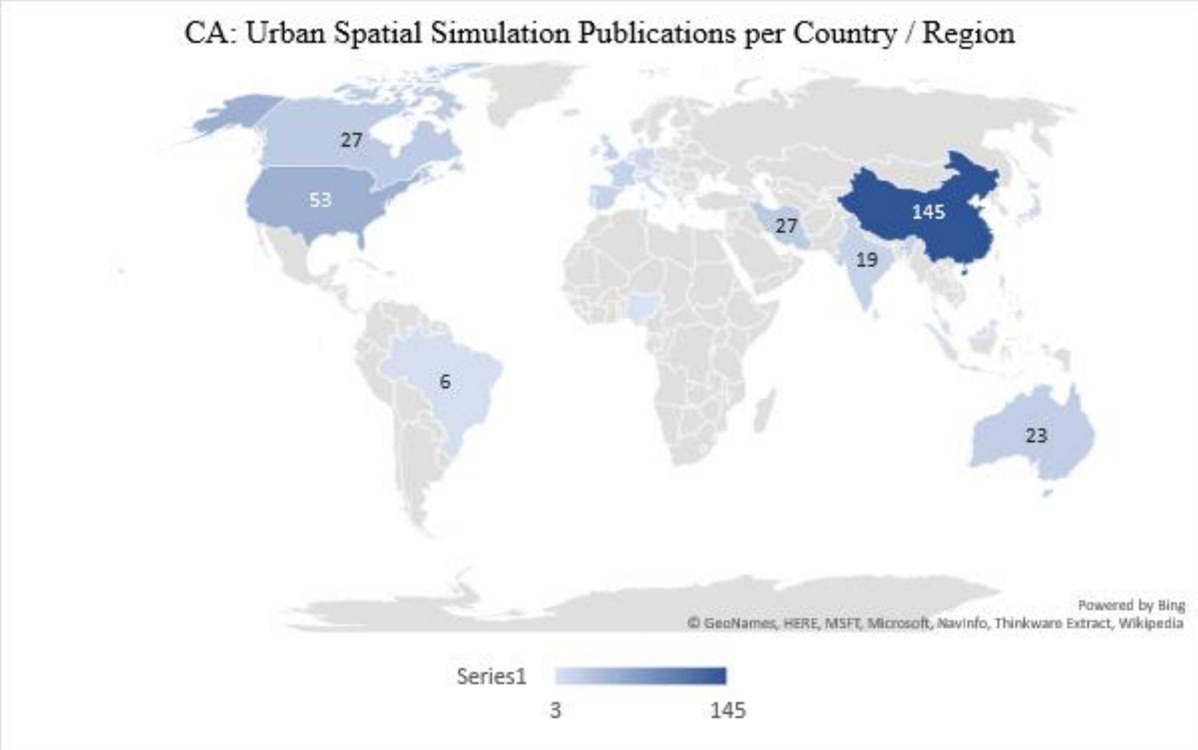
The publication categories are predominantly focused on the research themes of environmental sciences, computer sciences and geography, which includes research types of long-term monitoring, experimentation, comparative analysis and models / methodological approaches. The varying coverage of the publications also demonstrates the multi-disciplinary nature of the models and their application (Refer to Figure 14).



Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 14: CA: Treemap of urban spatial simulation publications

The majority of the publication CA urban simulation studies have applications in China (39,9%), United States of America (14,67%), Canada (7,4%), Iran (7,4%) and Australia (Refer to Figure 15 and Appendix A.9).



Source: Author adapted from Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 15: CA: Spatial distribution of urban spatial simulation publications

According to the main purpose, issues, parameters and data inputs, the urban CA models and their components/relationships can be grouped into the four components of an urban system i.e. biotic, physical, social and built. The biotic refers to the natural ecosystem and ecosystem services (organism interactions), physical states the space, scale and time structure of the system (biophysical structure), social refers to cultural resources, social-economic and institutional processes (people-people interactions), while built refers to the built structures such as roads, buildings, infrastructure etc. The visual representation of the components and their subsequent interactions are displayed in an x-y graph and illustrate the connections being simulated between the components of the urban systems.

As indicated in Figure 16, most urban CA models simulate the following two interactions namely:

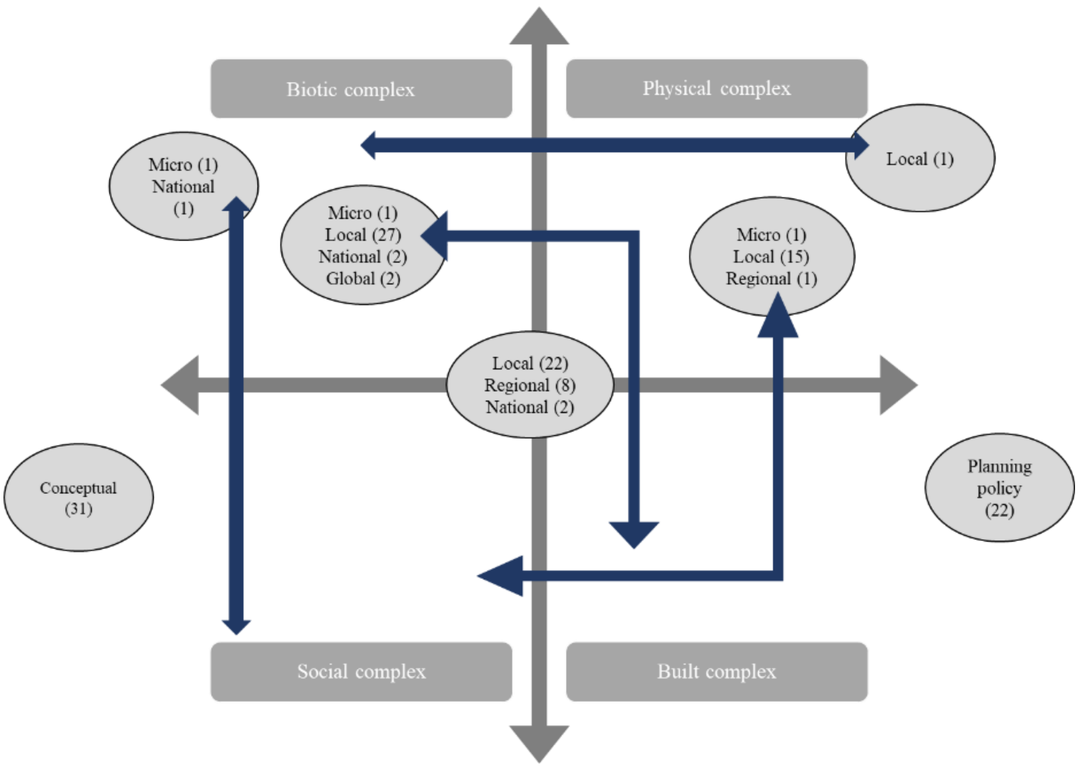
- Organisms-built environment-land resources/potential across the micro (1), local (27), national (2) and global (2) scales; and –

- People-organisms-built environment-land resources / potential across local (22), regional (8) and national (2) scales.

The other interactions that are simulated are characterised and ranked as follows:

- people-built environment-land resources / potential across micro (1), local (15) and regional (1) scales;
- people-organisms across micro (1) and national (1) scales; and –
- organisms-land resources/potential across a local scale.

In addition to those mentioned above, several conceptual models (31) and models trying to support and/or inform planning policy (22) is also highlighted.



Source: Author

Figure 16: CA: Components of urban simulation publications

Based on the assessment criteria, the following are noted:

- The majority of the urban CA models reviewed had a combination of descriptive and predictive objectives as part of the model design. The factors and dynamics explored in the past provide the foundation of using forecasting techniques to understand the future. In addition to the aforementioned, a large number of urban CA models started to incorporate prescriptive objectives as a way of understanding the possible constraints within the system (e.g. urban growth boundaries, zoning, environmental protection zones), as well as trying to measure and predicting the outcomes of implementing these policy interventions through scenario planning.
- Data inputs varied across the various categories of urban models according to their needs and the scale at which the components of the system were investigated. Although, all the models required satellite images in order to apply remote sensing techniques for land use/land cover classification. Basic geographic information such as road networks, administrative boundaries, topographical was also required within all the urban models.
- Calibration and validation formed part of the design and construction of the majority of the urban models and was viewed as an essential factor in terms of measuring the level of fitness of the model based on its intended purpose and its accurate reproduction of the real world and its ability to predict the future.
- The model grain of the urban models ranged from micro (30m resolution), local (10m, 30m, 100m & 1 000m resolutions), regional (30m & 100m resolutions), national (500m & 1 000m resolutions) and global (300m, 1 000m & 10km resolutions). It appears that there are no limitations as to the model grain that can be modelled across the various scales. Even though the objectives of the various categories of urban simulation models are different in terms of their applications, most of the phenomena / urban dynamics that were simulated related to urban expansion due to urbanisation and its associated impacts. It appears from the comparison that there is no standardisation in terms of the most appropriate view on urban growth and dynamics.
- The time period specifies the period used in validating and calibrating within the urban models which generally coincided with data points such as updates

in census data, household and travel surveys. The time period between these data points generally ranged between five (5) and ten (10) years. The projection time periods in many of the models did not follow a continues / yearly update but followed a time interval update of five (5), ten (10) and 15 years. The most significant time interval used in prediction was 35 years.

The detailed analysis of the selected urban CA models (excluding conceptual models) are contained in the assessment matrix below (Refer to Table 3).

Table 3: Characteristics of urban CA

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
Quesada-Ruiz *et al* 2019	Not explicit	D; P	Simulation of the housing bubble's impact on illegal landfill proliferation and the forecasting of the proliferation of illegal landfill.	Illegal landfills & impact on the environment and causes of public health risks.	CA + CA-Markov + Multiobjective land allocation model	CA	Orthophotos; Land use data; Socioeconomic data; Topographic data; Road network;	Yes	Yes	Local	Las Palmas Gran Canaria, Spaim	Not explicit	5 x 5	2000 – 2006; 2006 – 2012; Projection - 2018
Huang *et al* 2019	Not explicit	D; P; PC	Simulation of urban expansion based on the ecological priority principle.	Ecological & environmental issues due to urban expansion.	CA (ArcGIS)	CA	Land use survey; Landsat imagery; climate observations; Urban-rural master planning map; Soil fertility data; Administrative boundaries	Not explicit	Not explicit	Local (30 x 30m)	Zhangjiakou, Zhangbei County, China	Not explicit	3 x 3	2013 - 2030
Tong & Feng 2019	PCGA-CA	D; P; PC	Simulation of the current and future urban patterns under the spatial constraints of urban planning regulations.	Illegal urban development due to ineffective implementation of planning regulations.	CA (UrbanCA + ArcGIS) + Genetic Algorithm (GA)	CA	Satellite images; Terrain datasets; Socio-economic data; Facility data; Urban planning map;	Yes	Yes	Local	Ningbo City, China	Non-urbanized; Urbanized	5 x 5	2000 - 2015; Projections 2030 & 2045

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
							Population density.							
Wang et al 2019	Not explicit	D; P	Coupling of top-down and bottom-up CA models and the simulation of urban development dynamics under three scenarios (compact, stability, sprawl).	Rapid urbanisation	CA (ArcGIS) + Artificial neural network (ANN) + Markov chain model	CA	Historical urban land use; topographical data; road network data	Yes	Yes	Local (30 x 30m)	Wuhan, China	Urban (commercial, residential, industrial, transportation, other impervious surfaces); non-urban (forest, grassland, vegetation, other unused lands); water bodies (rivers, lakes, ponds)	5 x 5 Moore	2007 - 2016; Projection – 2026
Feng & Tong *et al* 2019	UrbanCA	D; P; PC	Simulation of dynamic urban growth and to project future urban scenarios and assess their natural and socio-economic impacts.	Urban encroachment on agricultural and ecologically valuable land.	CA (UrbanCA + ArcGIS)	CA	Not explicit	Yes	Yes	Local	Shanghai, China	Urban; non-urban	Moore; Circular; Von-Neumann	2005 – 2015; Projection - 2025
Guan *et al* 2019	Not explicit	D; P	Simulation of spatial patterns of land use and land cover change within the region to inform the formulation of structural optimisation and land policies.	Significant infrastructure investment impacting on land use structure and ecological environments.	Logistic-CA-Markov; WLC-CA-Markov (ArcGIS)	CA	Land use data; remote sensing data; ecological data; topographic data; population data; economic data; hydrological	Yes	Yes	Local	Zhongxian County, Chongqing, China	6 conversion probabilities (grassland; farmland; construction land; forest land; waters; unused land)	Not explicit	1990; 2000; 2005; 2010; Projection – 2015, 2020, 2025 & 2030

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
							data; road network; boundaries data							
Tripathy & Kumar 2019	Not explicit	D; P	Spatio-temporal land use/land cover monitoring and urban growth modelling to predict urban growth	Rapid urbanisation leading to environmental degradation & socio-economic disparities.	CA (ArcGIS)	CA	Satellite imager; Census data; topographical data; land use/land cover maps; road networks.	Yes	Yes	Local (30 x 30m)	Delhi, India	Built up land; Vegetation cover: Water body; Others	3 x 3	1989; 1994; 2004; 2009 & 2014; Projection – 2019 & 2024
He *et al* 2019	UEMCPI	D; P	Modelling integrated urban spatial expansion, including the population interaction to simulate the collaborative development process of an urban area.	Rapid urbanization & migration	CA (ArcGIS; SPSS) + UEMPI	CA	Land cover; land use; socio-economic; population (Census data); migration; administrative boundaries, rivers, road networks.	Yes	Yes	Local	Ezhou, China	Urban land; Cultivated land; Forest: Water; Others	5 x 5	2004; 2013; Projection - 2022
Ou *et al* 2019	Not explicit	D; P	Simulation of landscape pattern optimisation allocation to achieve ecological security.	Ineffective regulation for urban expansion; ecological environmental problems.	CA + LPOA	CA	GIS data, remote sensing images, socioeconomic statistics, environmental data.	Yes	Yes	Local	Longquanyi District, Chengdu City, Sichuan Province, China	Farmland; Orchard; Forest; Urban-rural residential and industrial mining; Waters	Not explicit	2014; Projection 2021; 2028.
Mousivand & Arsanjani 2019	Not explicit	D; P	Simulating the global land cover changes.	Unsustainable urban growth	CA	CA	Remote sensing data	Not explicit	Not explicit	Global (300m)	Global	Agriculture; Forest; Grassland; Wetland; Settlement; Sparse vegetation; Bare	Not explicit	1992 – 2015; Projection

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
												area; Water; Permanent snow and ice.		2030 & 2050
Feng & Tong 2019	Not explicit	D	Simulation of the spatial heterogeneity of land use within a rapidly growing urban area.	Not explicit	CA + GA	CA	Satellite imagery; boundary; transportation networks; demographics; population; socioeconomic.	Yes	Yes	Local (30m)	Shaoxing City, China	Urban; nonurban; excluded	5 x 5 (Moore)	1995 - 2015
Musa et al 2019	Not explicit	D; P; PC	Geospatial modelling of urban growth for sustainable development (UN SDGs 11 & 15)	Land degradation & fragmentation, biodiversity loss, water crisis & environmental pollution.	CA-Markov	CA	Satellite imagery; topographical maps; population; economic; ground truth points.	Yes	Yes	Regional (30m)	Abia, Akwa-Ibom, Bayelsa, Cross-River, Delta, Edo, Imo, Ondo & Rivers (Niger Delta region), Nigeria	Built-up (residential, commercial, industrial buildings, roads, infrastructures), waterbody (open waters, ponds, reservoirs, rivers, lakes), bare surface (intrusions, mining, vacant land)	Not explicit	1985 – 2015; Projection 2030
Hou et al 2019	Not explicit	D; P	Scenario-based modelling for urban sustainability focusing on spatial-temporal changes in cropland under rapid urbanisation.	Rapid urbanisation; agricultural production & biodiversity loss	CA-Markov	CA	Satellite imagery; transportation networks; water bodies; reservation areas; land uses.	Yes	Yes	Local (100m)	Hangzhou, Zhejiang Province, China	Built-up; cropland; bareland; forest; grassland; water.	8 cell rule	1990 - 2035

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
Yang et al 2019	Not explicit	D; P	Simulation of landscape spatial layout evolution in rural-urban fringe areas to provide insights into regional land use planning, urban development and ecological environment management.	Rapid urbanization; agricultural production & biodiversity loss	CA + Markov + MLP-ANN	CA	Satellite imagery; topographical maps; socioeconomic; transportation networks; land uses; zoning regulations.	Yes	Yes	Local (30m)	Ganjingzi District, China	Farmland, garden land; forest land; construction land; water; other lands.	Not explicit	2000 – 2015; Projection - 2020
Rimal et al 2019	Not explicit	D; P	Simulating the spatiotemporal dynamics of urbanisation and predicting future growth for sustainable urban planning and policymaking.	Rapid peri-urban expansion; decline in cultivated land; food security.	CA-Markov	CA	Satellite imagery; topographical maps; population; transportation networks; land uses; administrative boundaries.	Yes	Yes	Local (30m)	Biratnagar, Itahari & Dharan, Tarai, Nepal	Urban, cultivated land, vegetation, sand, water.	Not explicit	1996 – 2006; 2006 – 2016; Projections – 2026; 2036
Zhang et al 2019	Not explicit	D	Simulation of intra-urban land-use changes to identify the contribution of different driving factors in urban growth and to aid in the formulation of planning strategies.	Urban sprawl	CA + Random forest (RF)	CA	Points of interest; land use, administrative data (boundaries); transportation data; population data	Yes	Yes	Local (10m)	Huicheng, China	Non-urban; water body; Urban (commercial, industrial, residential, administration & public services)	7 x 7	2000 – 2015.

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
Wang et al 2019	Not explicit	D	Simulation of spatial and temporal processes in land cover changes.	Land degradation & fragmentation, biodiversity loss, water crisis & environmental pollution.	CA + temporal-dimension-extension (TDE)	CA	Satellite imagery; Land cover; Land use; Basic geographic information data.	Yes	Yes	Micro (30m)	Shendong, China	Urban; non-urban; other	3 x 3; 5 x 5; 7 x 7 & 9 x 9 (Moore)	2005 - 2015
Yu et al 2019	Not explicit	D; P	Modelling of the spatial distribution of green GDP (ecosystem service value & GDP) and the impact of land-use change and socio-economic development on this value.	Ecosystem degradation; biodiversity loss, water crisis & environmental pollution.	CA-Markov	CA	Land use; economic data; agricultural production data; administrative boundaries	Yes	Yes	National (1 000m)	China	Cultivated land; forest land; grassland; waterbody; construction land; unused land	Not explicit	1995 – 2015; Projection 2020 - 2050
Nguyen et al 2019	Not explicit	D; P	Simulation of land use/land cover changes in Hanoi City, to improve urban planning efficiency, local governance, socioeconomic development and environmental protection.	Rapid urbanisation, inefficient urban spatial planning; socioeconomic growth pressure.	CA-Markov	CA	Satellite imagery; Land cover; Land use; Basic geographic information data; ground truth points.	Yes	Yes	Local	Hanoi City, Vietnam	Built up; non built-up; water bodies.	5 x 5	1990 – 2015; Projection - 2030
Jamali & Kalkhajeh 2019	Not explicit	D; P	Simulation and prediction of urban growth through	Rapid urbanization; land	CA + ANN	CA	Satellite imagery; Land cover; Land use; Basic	Yes	Yes	Local	Tehran, Iran	Urban; green space; agriculture; mountain; open land; clay plain.	Not explicit	2000 - 2016

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			land use/land cover changes.	fragmentation; deforestation.			geographic information data.							
Xia et al 2019	Not explicit	D	Simulating urban landscape dynamics in metropolitan areas based on intercity urban flows across a regional scale.	Rapid urbanization	Logistic-CA	CA	Geospatial big data; population data; socioeconomic data; land use; land cover; ecological; basic geographic data.	Yes	Yes	Regional	Wuhan, Changsha, Nanchang, China	Urban; non-urban; water	3 x 3 (Moore)	2005 - 2015
Li et al 2019	GIA-CCA	D; P	Spatial-temporal simulation of green infrastructure preservation through the establishment of an urban growth boundary (UGB).	Rapid urbanisation; land fragmentation; degradation of ecosystem services.	CA + green infrastructure assessment (GIA)	CA	Satellite imagery; Land cover; Land use; Basic geographic information data; urban construction constraint; ecological constraint.	Yes	Yes	Local	Hangzhou, China	Farmland; forestry; construction land; water & unused land.	3 x 3 (Moore)	2000; 2005; 2010; 2015; Projection – 2020.
Gounaridis et al 2019	Not explicit	D; P	Simulation of potential future land use/land cover dynamics under different economic performance and planning option scenarios.	Unregulated urban growth; increasing housing demand; limited land use planning controls.	CA + RF	CA	Satellite imagery; Land cover; Land use; Basic geographic information data; social infrastructure;	Yes	Yes	Regional (30m)	Athens, Attica region, Greece	Continuous urban fabric; discontinuous dense urban fabric; discontinuous medium density; discontinuous low density; industrial,	Not explicit	1991; 1999; 2003; 2010; 2016; Projection - 2040.

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
							administrative boundaries; land use management policies.					commercial & transport units; arable land & permanent crops; forests, scrubs & other natural areas; other.		
Yin et al *2018*	Not explicit	D; P	Simulation of the potential impacts of zoning as a growth management policy on urban growth.	Rapid urbanisation; land fragmentation; degradation of ecosystem services & quality of life.	CA-SLEUTH	CA	Satellite imagery; topographic maps; urban planning documents; basic geographic information.	Yes	Yes	Local	Jinan, China	No zoning; zoning based on land-use; zoning based on urbanisation suitability; zoning based on administrative division; zoning based on development planning subdivision.	Not explicit	1996 - 2020
Xu et al 2018	SLUCS	D; P	Land-use change simulation model reflecting the scale differences of land-use change and includes the zoning constraints that impact on urban growth.	Rapid urbanisation; land fragmentation; degradation of ecosystem services & quality of life.	CA + elevation-based stratification strategy.	CA	Satellite imagery; socioeconomic data; population data; economic data; land use; zoning policies; basic geographic information.	Yes	Yes	Local (1 000m)	Guizhou, China	Paddy field; dry land; forest; grassland; water; built-up land; bare land.	Not explicit	1981 – 2000; Projections - 2015 - 2030
Feng et al 2019	Not explicit	D	Simulation of the impact of changing the observation	Not explicit	CA – particle swarm		Satellite imagery; socioeconomic	Yes	Yes	Local (120m)	Shanghai, China	Urban; non-urban; water	5 x 5	1995 - 2015

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			scale (regional, meso & city) on the model of urban growth.		optimisation based (PSO)		data; population data; economic data; land use; basic geographic information.							
Zhang et al 2018	Not explicit	D; P	Modelling of the spatial relationships between the aerosol optical depth (aerosol loading/air quality) and urban land-use change.	Increase air pollutants are leading to decreased air quality in urban areas.	CA-Markov	CA	Satellite imagery; air quality data; precipitation; land use; economic; population; basic geographic information.	Yes	Yes	Local (1 000m)	Wuhan, China	Built-up; unused; forest; water body; agricultural; grassland.	5 x 5	2010; Projection 2030
Feng & Qi 2018	Not explicit	D	Urban growth simulation model considering the land use/land cover changes over the entire nation.	Rapid urbanisation & population growth; informal settlement; insufficient urban service; degradation of agricultural and natural land.	CA + analytical hierarchical process (AHP)	CA	Satellite imagery; Nighttime imagery; socioeconomic data; land use; economic; population; basic geographic information.	Yes	Yes	National	650 cities, China	Urban; non-urban	5 x 5	2000; Projections – 2015; 2020; 2025; 2030
Mei et al 2018		D; P	Simulation of land use and its drivers, including the prediction of land-		CA + CLUE-S	CA	Satellite imagery; socioeconomic data; land use;	Yes	Yes	Local (150m)	Zengcheng District, Guangzhou, China	Arable land; woodland; traffic land; residential/industrial	5 x 5	2001; 2005, 2009;

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			use change probabilities under different scenarios (natural growth, ecological protection, economic development).				basic geographic information.					land; water area; unused land.		Projection - 2020
Xu et al 2018	Not explicit	D; P	Simulation of the impact of future urban development on the surrounding environment using land ecological suitability.	Rapid urban expansion & sprawl; loss of high ecological value resources.	CA-RF	CA	Satellite imagery; population data; land use; basic geographic information.	Yes	Yes	Local	Changzhou City, China	Arable land; woodland; grassland; waterbody; artificial surface; unutilized land.	Not explicit	2007 – 2014; Projection 2020
Yu et al 2018	Not explicit	D; P	Multi-scale (macro, meso & micro) simulation model to simulate the agglomeration development process of the area and includes the prediction of the demand for new urban land at an aggregated urban scale.	Rapid urbanisation.	CA	CA	Satellite imagery; population data; economic data; land use; basic geographic information.	Yes	Yes	Local (150m)	Wuhan, China	Arable land; grassland; forest land; urban land; water & unused land.	3 x 3 (Moore)	1995; 2005; 2015; Projection – 2020.
Zhang et al 2018	Not explicit	D; P	Simulation of land use and land cover change	CA	CA-CLUE-S	CA	Satellite imagery; socioeconomic; population data; economic	Yes	Yes	Local (30m)	Tekes County, Xinjiang, China	Forest; grassland; cropland; urban; barren land; water.	Not explicit	1998; 2006; 2011; Projection - 2020

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
							data; land use; natural resource; hydrological data; basic geographic information.							
Jia et al 2018	Not explicit	D; P	Simulation of spatial and temporal changes in land use, taking into consideration the ecological redline areas.	Negative ecological impacts during urban expansion.	CA – CLUE-S	CA	Satellite imagery; socioeconomic; population data; basic geographic information.	Yes	Yes	Local (90m)	Beijing, China	Croplands; forest lands; grasslands; water bodies; construction lands.	Not explicit	2010 - 2020
Feng & Tong 2018	DE-CA	D; P	Simulation model that integrates differential evolution (DE) into CA to generate the optimal sets of CA parameters for prediction of future scenarios to address urban growth, environmental protection & urban planning.	Optimisation of the CA model to represent land-use dynamics adequately.	DE-CA	CA	Satellite imagery; land use; socioeconomic; population data; basic geographic information; administrative boundaries.	Yes	Yes	Local	Kunming City, China	Urban; non-urban; other	3 x 3; 5 x 5; 7 x 7.	2006; 2016 - 2026
Fan et al 2018	UECDM	D; P	A simulation model that links urban planning and the dynamics of regional ecosystem	Rapid urbanization	CA + urban-ecological coordinated development model	CA	Satellite imagery; land use; socioeconomic; population	Yes	Yes	Regional	Fuzhou City, Fuqing City, Changle City, Pingtan County,	Original construction land; new construction land; forest land;	Not explicit	1990 – 2015; Projection 2020

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			services value (ESV) to model urban expansion impact on ESV.				data; basic geographic information; administrative boundaries.				Luoyuan County, Minhou County, China	arable land; a water area		
Liu et al 2018	Not explicit	D; P	National simulation model considering the gradient of development differences among cells and to detect past and future urbanisation states and temporal evolution trends, including national planning policy implementation.	Ecological & environmental deterioration due to urban expansion.	Gradient CA	CA	Satellite imagery; Nighttime imagery; socioeconomic data; land use; economic; population; vegetation index; basic geographic information.	Yes	Yes	National (500m)	China	Built-up; no built-up	Not explicit	2000; 2005; 2010; Projection - 2050
Liang et al 2018	Not explicit	D; P	Urban simulation model focused on future land use simulation and the integration of different planning drivers (traffic planning, development zones) into the model.	Rapid urbanisation	CA – Future land-use simulation (FLUS)	CA	Satellite imagery; socioeconomic data; land use; economic; population; master planning; ecological data; basic geographic information.	Yes	Yes	Regional (100m)	Guangzhou, Shenzhen, Foshan, Dongguan (Pearl River delta), China	Non-urban; urban; water area.	3 x 3 (Moore)	2000 – 2013; Projection 2052
Feng et al 2018	Not explicit	D; P	Simulation of dynamic	Rapid land-use change	CA - GWR	CA	Satellite imagery;	Yes	Yes	Local	Suzhou City, China	Urban; non-urban; excluded areas.	5 x 5	2000 - 2015

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			relationships between land-use change and its driving forces.				socioeconomic data; land use; economic; population; ecological & agricultural protection zones; basic geographic information.							
Kuo & Tsou 2018	Not explicit	D; P	Simulation of urban expansion and its impact on habitat diversity.	Ecological & environmental deterioration due to urban expansion.	CA - SLEUTH	CA	Satellite imagery; land use; surface temperature; surface runoff; habitat diversity; basic geographic information.	Yes	Yes	Local	Tainan, Taiwan	Urban; agriculture; water; forest; other	Not explicit	1993 – 2008; 2008 - 2030
Zheng et al 2017	Not explicit	D	Modelling of a new urban growth boundary (UGB) delimitation method, combined with land suitability evaluation and CA to use in urban management.	Uncontrolled urban expansion.	CA	CA	Satellite imagery; socioeconomic data; land use; economic; population; ecological safety data; planning maps; basic geographic information	Yes	Yes	Regional (30m)	Ningbo, China	Suitable region; Basic suitable region; Unsuitable region.	Not explicit	2002; 2009; 2015
Zhou et al 2017	Not explicit	D; P	Simulation of land-use change and	Rapid urbanisation	CA – heuristic bat algorithm	CA	Satellite imagery; land	Yes	Yes	Local	Jiaxing City, China	Non-urban; urban	7 x 7 (Moore)	2000 – 2015;

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			urban expansion to assist policymakers in strategising and facilitating sustainable urbanisation development.		(BA) + deep belief network (DBN)		use; zoning suitability; basic geographic information							Projection 2024
Li et al 2017	Not explicit	D; P	Global land use and land cover change model, including the simulation of the relationship between LUCC and human-environment interactions at local and global scales.	Rapid urban expansion, altering processes and functions of natural ecosystems.	CA - FLUS	CA	Satellite imagery; land use; soil data; hydrological data; basic geographic information	Yes	Yes	Global (1km; 10km)	Global	Forest; grassland; farmland; urban; barren.	Not explicit	2010 - 2100
Pérez-Molina et al 2017	Not explicit	D; P	Simulation of urban growth and the resultant intensification of local flooding problems.	Increased flooding due to urban expansion.	CA + openLISEM (integrated flood modeling tool)	CA	Satellite imagery; land use; soil data; hydrological data; basic geographic information	Yes	Yes	Local	Kampala, Uganda	Not explicit	3 x 3	2004 – 2010; Projection 2020
Feng & Tong 2017	Not explicit	D	Simulation of dynamic urban growth and prediction thereof based on future scenarios under various spatial	Rapid urbanisation	CA + generalised additive model (GAM)	CA	Satellite imagery; administrative data; protected areas; land use; basic geographic information	Yes	Yes	Local	Shanghai, China	Urban; non-urban; water	7 x 7	2000 - 2015

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			constraints and conditions.											
Long & Wu 2017	Not explicit	D	Development of a mega-vector-block CA to simulate urban expansion at the block level on a national scale.	Not explicit	CA + mage-vector-blocks (MVB)	CA	Satellite imagery; administrative data; land uses; points of interest; basic geographic information	Yes	Yes	National (90m)	654 cities, China	Expanded (no development); Non-expanded (rural to urban development)	Not explicit	2012 - 2017
Shafizadeh-Moghadam et al 2017	Not explicit	D; P	Land cover change modelling and the inter-relations among the driving forces influencing urban growth processes.	Rapid urban growth	CA + ANN	CA	Satellite imagery; OpenStreetMap data; basic geographic information	Yes	Yes	Local (30m)	Mumbai, India	Urban extent; urban growth; water bodies; wetlands; forest & green spaces; cropland & open land.	7 x 7	2001 – 2010; Projection - 2020
Rahman et al 2017	Not explicit	D; P	Simulation of land use and land cover changes and the impact on land surface temperature.	Increase of urban heat islands due to rapid urban developments	CA-Markov	CA	Satellite imagery; administrative data; land uses; basic geographic information; ground truth points.	Yes	Yes	Local (30m)	Dammam, Saudi Arabia	Built-up; bare soil' vegetation; water body.	Not explicit	1990; 2002; 2014; Projection 2026
Zare et al 2017	Not explicit	D; P	Simulation of current and future land-use changes and the impact on soil characteristics based on land use	Vegetation cover reduction	CA-Markov	CA	Satellite imagery; administrative data; land uses; basic geographic information;	Yes	Yes	Regional	Shirgah, Zirab, Darzikola, Kaleh, Rig Cheshmeh, Sangdeh,	Forest; rangeland; settlement; agriculture	Not explicit	1961 – 1990; 1991 – 2000; 2011-2030

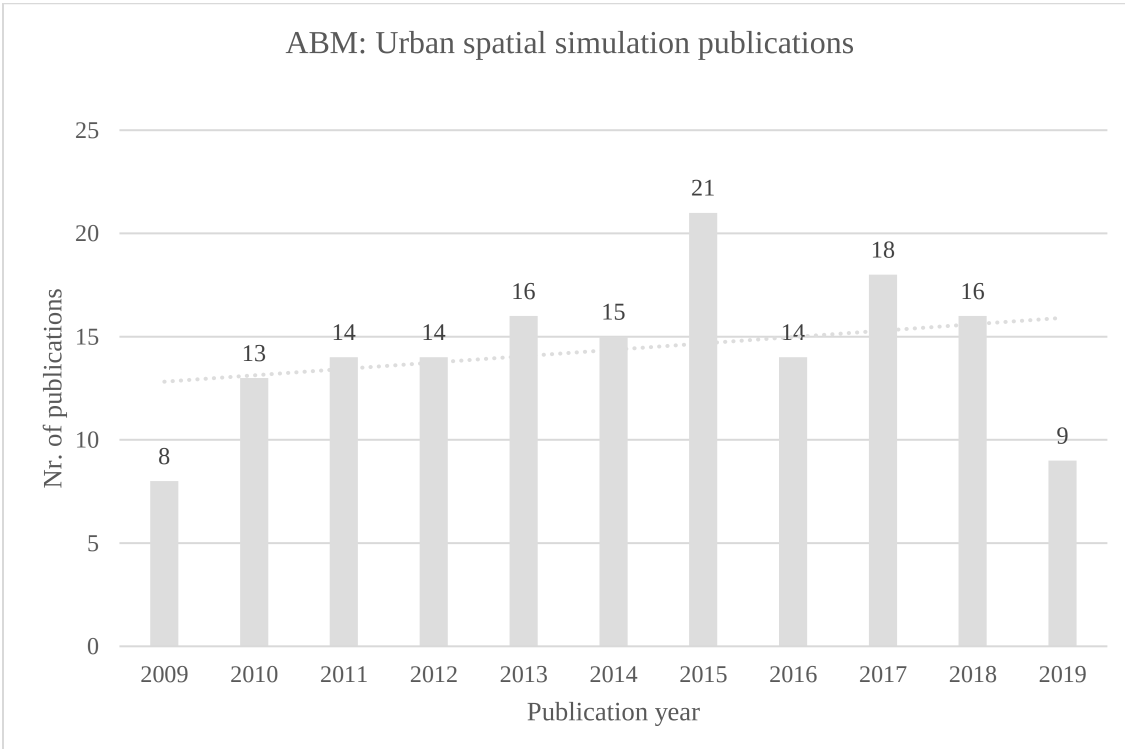
Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			and climate scenarios.				soil data; hydrological data; population.				Talar Cities, Iran			
She et al 2017	CA-MAS-SEF	D; P	Monitor land-use change and cover change in coastal areas, assess coastal wetland change & predict land use requirements	Reclamation of land to address land shortages Environmental degradation, e.g. soil and water pollution, nutrient over-enrichment & reduction in biodiversity; Landscape fragmentation	CA + MAS + Digital Shoreline analysis system (DSAS)	CA	Satellite images; land use data; river data; basic geographic information.	Yes	Yes	Local (30m)	Dongtai County, China	Landowners Entrepreneurs	Not explicit	1985 – 2014 (6-year intervals); Projections in 2020 & 2030
Kazemzadeh-Zow et al 2017	Not explicit	D; P	Spatial zoning approach simulating the long-term urban expansion and distinguishing between local-scale urban dynamics and their different socioeconomic characteristics.	Not explicit	CA-Markov + multi-layer perceptron (MLP) neural network.	CA	Satellite imagery; administrative data; land uses; basic geographic information.	Yes	Yes	Local (30m)	Mashhad, Iran	Urban; vegetation; urban green space; barren land; mountainous & rocky land; water surfaces; sedimentary surfaces.	Not explicit	2013 - 2025
He et al 2017	BPANN-CBRSortCA	D; P	Simulation of future urban building heights (vertical) and their	Rapid urbanisation	BPANN-CBRSortCA	CA	Satellite imagery; socioeconomic data; land use;	Yes	Yes	Local	Wuhan, China	Low building; multi-story building; middle-	Not explicit	2005; 2015 - 2025

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			spatial distribution (horizontal).				economic; population; planning maps; basic geographic information					high building; high building; water.		
Feng & Liu 2016	Not explicit	D; P	Simulation of future scenarios for urban expansion, including the impact on ecological and environmental conditions as spatial constraints.	Rapid urbanisation; increased risk of ecological damage and storm surge related to global climate change and sea-level rise.	CA + self-adaptive genetic algorithm (SAGA)	CA	Satellite imagery; administrative data; protected areas; land use; basic geographic information	Yes	Yes	Local	Lingang, Shanghai, China	Urban; non-urban; water	Not explicit	2005; 2015; Projection - 2030
Jiang et al 2016	Not explicit	D; P	Simulation of the future urban change of the urban agglomeration and its impacts on ecological services.	Degradation of ecological landscapes and ecosystem structures due to urbanisation.	CA + CLUE-s	CA	Satellite imagery; administrative data; protected areas; land use; socioeconomic; basic geographic information	Yes	Yes	Regional	Changsha-Zhuzhou-Xiangtan, China	Built-up ecosystem; green land ecosystem; cultivated ecosystem; wetland ecosystem; other.	Not explicit	2000; 2005; 2009; Projections - 2014; 2019; 2024
Osman et al 2016	Not explicit	D; P	Simulation of current and future urban change and their effects on arable lands, including the application of	Rapid urban growth	CA + SLEUTH	CA	Satellite imagery; administrative data; protected areas; land use; socioeconomic; basic	Yes	Yes	Local	Cairo, Egypt	Urban; water; agricultural land; urban sprawl; hillshade relief.	Not explicit	1984; 2000; 2013; Projections 2015 - 2035

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Time period
			different urban policy scenarios.				geographic information							
Liu et al 2016	SMDUGP	D; P	Simulation of urban land expansion.	Rapid urbanisation	CA + simulation of different urban growth pattern (SMDUGP)	CA	Satellite imagery; administrative data; land use; basic geographic information	Yes	Yes	Local	Huangpi, Wuhan, China	Outlying; adjacent; urban land; non-urban land.	3 x 3	2004 - 2024

3.2.2 Agent-based modelling (ABM).

The review of ABM urban spatial simulation models revealed a consistent publication stream since 2010 (refer to Figure. 14 and Appendix A.10).

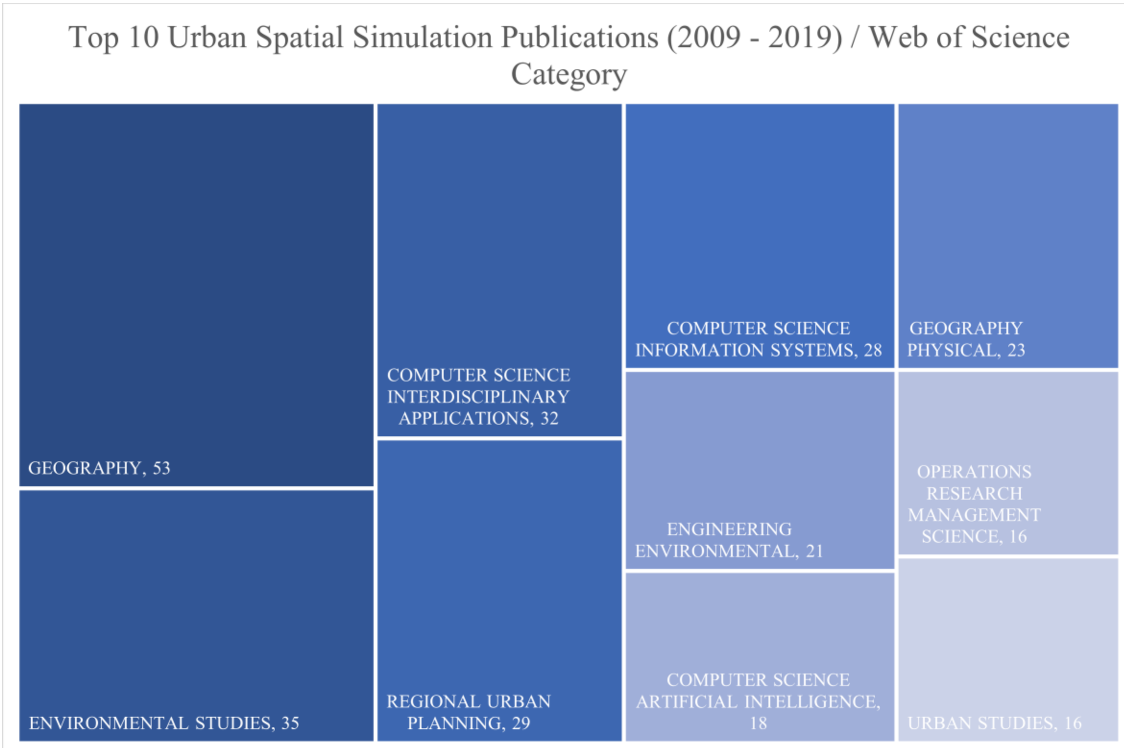


Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 17: ABM: Urban spatial simulation publications

The ABM category of urban spatial simulation publications over the period was predominantly published in the Web of Science categories of Geography, Environmental Studies, Computer science interdisciplinary application and Regional urban planning. In the regional and urban planning and urban studies categories, a total number of 45 publications were cited over the 2009 - 2019 time period (Refer to Appendix A.11).

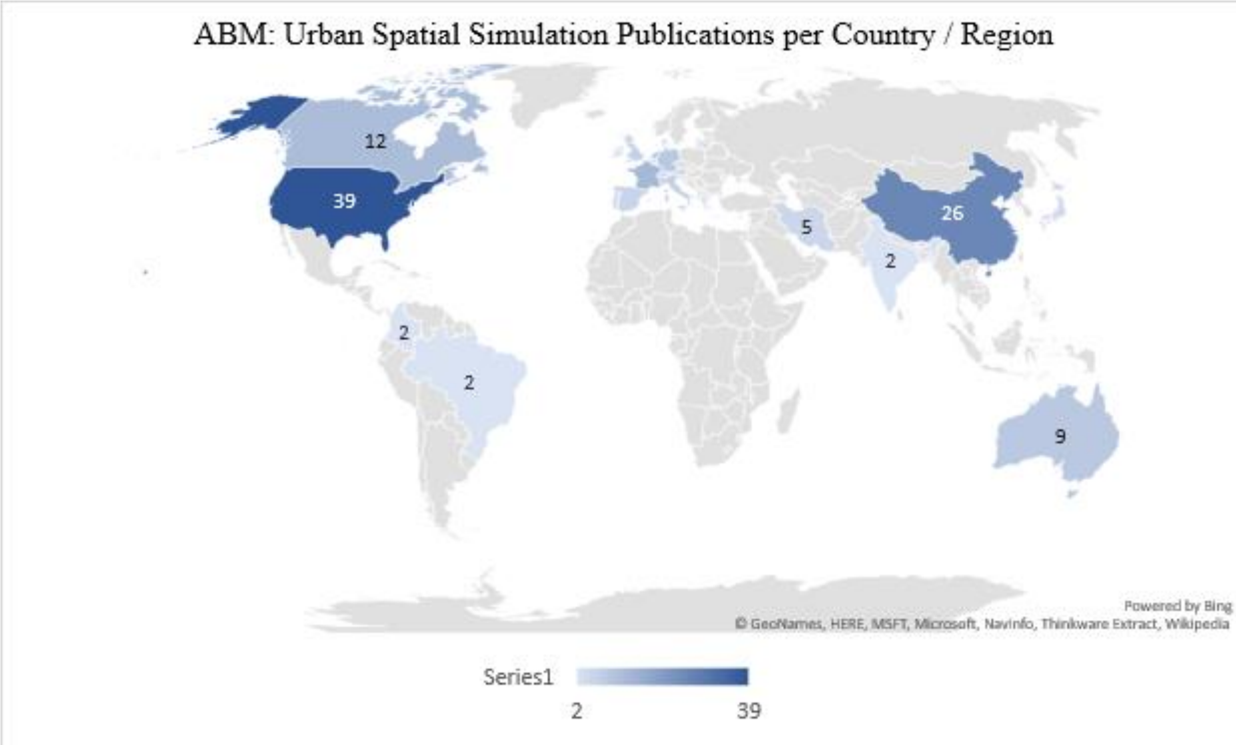
The publication categories are predominantly focused on the research themes of environmental sciences, computer sciences and geography, which includes research types of long-term monitoring, experimentation, comparative analysis and models / methodological approaches. The varying coverage of the publications also demonstrates the multi-disciplinary nature of the models and their application (Refer to Figure 18).



Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 18: ABM: Treemap of urban spatial simulation publications

Publications dealing with ABM urban spatial simulation have their applications in the United States of America (24,7%), China (16,5%), France (8,2%), Canada (7,6%), and the Netherlands (7%) (Refer to Figure 19 and Appendix A.12).

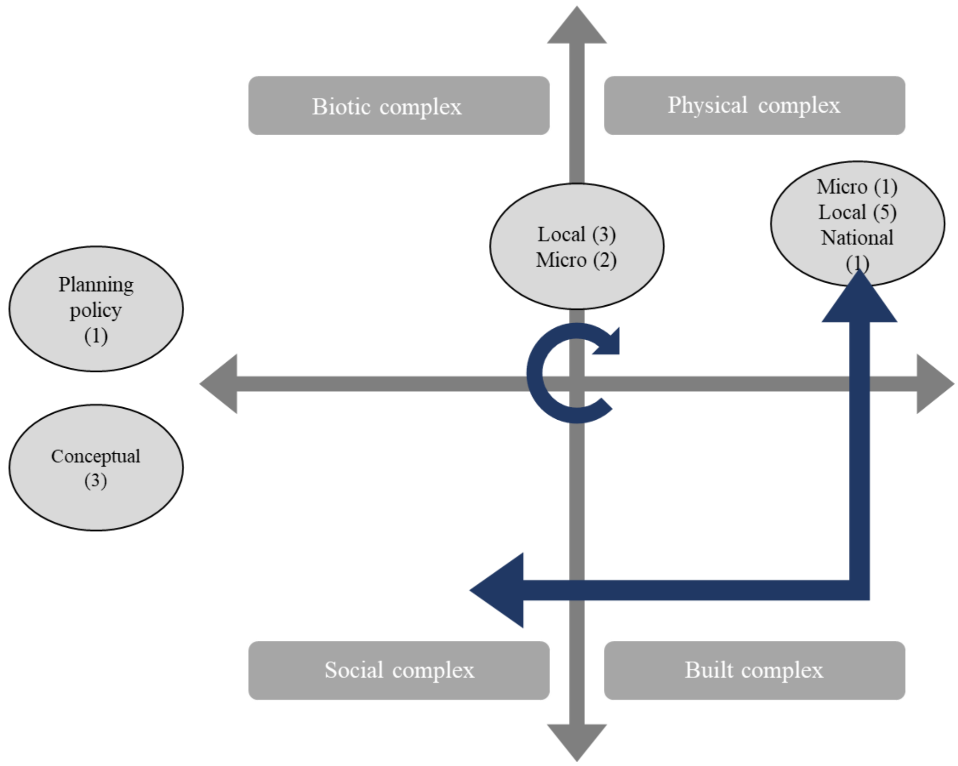


Source: Author adopted from Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 19: ABM: Spatial distribution of urban spatial simulation publications

According to the primary purpose, issues, parameters and data inputs, the urban ABM models and their components/relationships can be grouped into the four components of an urban system i.e. biotic, physical, social and built. In addition to the categories mentioned above, several conceptual models (3) and models trying to support and/or inform planning policy (1) is highlighted.

Most urban ABM models simulate the interactions between people-built environment-land resources/potential across the micro (1), local (5) and national (1) scales. A total of three local and two micro-level urban ABM models simulates the interactions between people-organisms-built environment-land resources/potential.



Source: Author

Figure 20: ABM: Components of urban simulation publications

Based on the assessment criteria, the following are noted:

- The majority of the urban ABM models reviewed had a combination of descriptive and predictive objectives as part of the model design. The factors and dynamics explored in the past provide the foundation of using forecasting techniques to understand the future. In addition to the aforementioned, several urban ABM models started to incorporate prescriptive objectives as a way of understanding the possible constraints within the system (e.g. political decision making, priorities, governance criteria and budget), as well as trying to measure and predicting the outcomes of implementing these decision-making models.
- Data inputs varied across the various categories of urban models according to their needs and the scale at which the components of the system were investigated. Although, all the models required demographic, socio-economic and basic

geographic information such as road networks, administrative boundaries, land uses and topography.

- Calibration and validation formed part of the design and construction of the majority of the urban models and was viewed as an important factor in terms of measuring the level of fitness of the model based on its intended purpose and its accurate reproduction of the real world and its ability to predict the future.
- Most of the urban ABM models did not explicitly mention a time period. The time periods noted ranged between days, weeks, a year or time periods ranging between five (5) and ten (10) years. The models that incorporated predictive objectives, set projection time interval update of five (5), ten (10) and 15 years. The biggest time interval used in prediction was 35 years.

The detailed analysis of the selected urban ABM models (excluding conceptual models) is contained in the assessment matrix below.

Table 4: Characteristics of urban ABM

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
Wu *et al* 2019	Not explicit	D; P; PC	Urban space optimisation through understanding commuting behaviours in a local urban residential area and simulation of behaviours of residents through ABM and inducing backwards the causes of congestion.	Traffic congestion	MAS (Repast S; RepastCity); Geospatial simulation (ArcGIS)	ABM + origin-destination matrix	Big data – mobile phone data; Spatial data – aerial photographs; urban road network	Not explicit	Yes	Micro	Baishazhou area, Wuhan, China	Mobile agent – resident Static agent – urban roads	Not explicit
Baeza et al 2019	Not explicit	D; P	Simulation of complex socio-political decision models (socio-political / social-institutional module) to analyse urban vulnerability under different scenarios (governance – criteria, priorities, actions & budget) of climate change and to explore the hydrological vulnerability/risk of the case study area.	Influence by agents (social pressure) on socio-political infrastructure investment decisions and the patterns of urban vulnerability & climate-related hazards (flooding, water scarcity).	ABM; Geospatial simulation (ArcGIS)	ABM + multi-criteria decision analysis	Not explicit	Yes	Not explicit	Local	Mexico City, Mexico	Local agent (resident); Institutional agent (water body);	Not explicit
Wahyudi *et al* 2019	Not explicit	D; P	Simulation of private land developers' role in stages of the land	Lack of knowledge in how the spatial	ABM (NetLogo); Geospatial	ABM + microeconomic theory	Economic data; Satellite images;	Yes	Yes	Local 300m	Jakarta, Indonesia	Large, medium and	1994 - 2012

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			development process (supply-side) and how their spatial decision behaviours affect the spatial form of the urban footprint and urban land market.	decision of individual developers collectively influences urban growth.	simulation (ArcGIS)		Spatial data (land use, roads, economic value)					small developer	
Hackl & Dubernet 2019	Not explicit	D	Modelling and quantifying human mobility for studying the large-scale transmission of infectious diseases (seasonal influenza) and improving epidemic control.	The rapid geographical spread of emergent infectious diseases through a complex web of mobility	ABM (MATSim)	ABM + Compartmental model – Susceptible – Infected – Recovered (SIR)	Socio-demographic data; health data; road network	Yes	Yes	Local	Zurich, Switzerland	Synthetic individual (1:100)	Week 50/2016-Week 8/2017
Morelle *et al* 2019	SiReMo	D; P	Simulating the close-to-home recreation activities of multiple individuals by foot, in order to assess the movement flows & gaps along with the mobility network	Lack of access to recreation areas & poorly located and quality recreation areas	ABM (NetLogo); Geospatial simulation (QGIS)	ABM + origin-destination matrix	Land use data; road networks	Yes	Yes	Local 70m x 70m cell	Will, Switzerland	Synthetic individual (200 agents)	Not explicit
Lu *et al* 2018	Not explicit	D; P	Simulation of commuters' travel patterns by autonomous taxis on road networks, including the travel costs and environmental	Traffic congestion; Air pollution	ABM (GAMA); Geospatial simulation (GIS)	ABM + origin-destination matrix	Spatial data (road network; land use) Commute data; Population data	Yes	Yes	Local	Ann Arbor, Michigan	Commuter; aTaxi agents	Not explicit

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			implications of substitution of personal vehicle travel with aTaxi travel.										
Jin *et al* 2018	Not explicit	D; PC	Modelling of socioeconomic means and social support of older adults and their transportation mode of choices in accessing oral healthcare screening events/services.	High burden of access to healthcare by older adults; Inequities in healthcare for poor & disabled populations.	ABM (AnyLogic); Geospatial simulation	ABM + transportation model	Administrative data; Population data; Spatial data (facilities; road network); Commute data	Yes	Not explicit	Local	Manhattan, New York, USA	Synthetic agent (500 agents)	Not explicit
Alghais & Pullar 2018	Not explicit	D; P; PC	Modelling of disaggregate future changes in land use patterns given forecast population estimates and planning policies.	Rapid urbanisation; Housing shortages; Traffic congestion	ABM (ArcGIS Agent Analyst extension); Geospatial simulation (ArcGIS)	ABM	Satellite images; Administrative data (housing applicants; master plans); Population data; Spatial data (road network; boundaries; land use); Commute & accident data	Yes	Yes	Local	Kuwait City, Kuwait	Citizens; non-citizens; Decision-makers	1995 – 2015; Projection 2050
Yu *et al* 2018	Not explicit	D; P; PC	Modelling spatial allocation of emergency shelters during unexpected disaster events and optimising shelter to	Disaster events; time-consuming evacuation processes; Road congestion.	MAS; Geospatial simulation (ArcGIS)	ABM	Aerial images; Spatial data (population; road network; emergency shelter; land use)	Yes	Yes	Micro	Jing'an District, Shanghai, China	Government; Shelter; Resident	Not explicit

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			improve evacuation of residents.										
Cantergiani & Delgado 2018	AMEBA	D;	Simulation of the urban development process at the sub-regional scale considering urban planners, developers and the population's decision-making process in different future urban growth scenarios.	Urban growth	ABM (NetLogo); Geospatial simulation (GIS)	ABM	Satellite imagery; Spatial data (population, boundaries, zoning, housing distribution, natural protected zones, environmental layers; land use; facilities; cadastral data; road network)	Yes	Yes	Micro (50 x 50m)	*"Corredor del Henares"*, Madrid, Spain	Urban planners; Developers; Population	Not explicit
Lu & Hsu 2017	ALENT	D	Dynamic urban transportation simulation model for lifecycle environmental performance evaluation of transport modes under different market scenarios.	Not explicit	ABM (NetLogo); Geospatial simulation (GIS)	ABM + lifecycle analysis	Spatial data (road & rail network); Commute data; Census data	Yes	Yes	Local	Hong Kong	Modes; Passengers	Not explicit
Zhou *et al* 2017	WECC	D; PC	Simulation of the economic and water environment information for industrial structure upgrading (equipment & machinery industry) and spatial optimisation based	Rapid industrialization; Water pollution	MAS (RNetLogo); Geospatial simulation (GIS)	ABM +	Social – Population data; Industrial data; Pollution data; Water environment data; Satellite imagery (land use; drainage; ecological constraint maps)	Yes	Yes	Local	Changzhou, Jiangsu, China	Population (urban & rural); Industrial, Tertiary & Agricultural enterprises Sewage treatment	Not explicit

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			on water environment carrying the capacity to promote socio-ecological sustainability.									plants & outlets; Pollutant flow & pollutants; River; Monitored sections Landscape	
Démare et al 2017	Not explicit	D; P	Simulation of the logistic system to describe the movement of goods over the territory through a supplying network.	Inefficient management of the flow of goods & infrastructure network constraints	MAS (GAMA); Geospatial simulation (GIS)	ABM	Goods production & consumption data; Network data (road, rail & river infrastructure; logistics flow; traffic); Building permit data	Not explicit	Not explicit	Regional (50 x 50)	Paris, Orléans, Rouen, Le Havre, Caen,	Goods provider; Land transporter (road, river, rail); Warehouses; Logistics service provider; Terminal operator; Shipowner; Final co-signees	80 days
Ghavami & Taleai 2017a; Ghavami et al 2017b; Ghavami et al 2016	CaféSCP	D; PC	Simulation of the spatial group decision-making process as well as the relationship that exist among the influencing entities/stakeholders in the approval of the	Lack of understanding of the influence of different factors/actors on the outcome and performance of the decision-making process	MAS (GAMA); Geospatial simulation (GIS)	ABM	Not explicit	Yes	Yes	Local (40 x 40m)	Zanjan, Iran	Land use agents (residential, business, educational, green, medical);	Not explicit

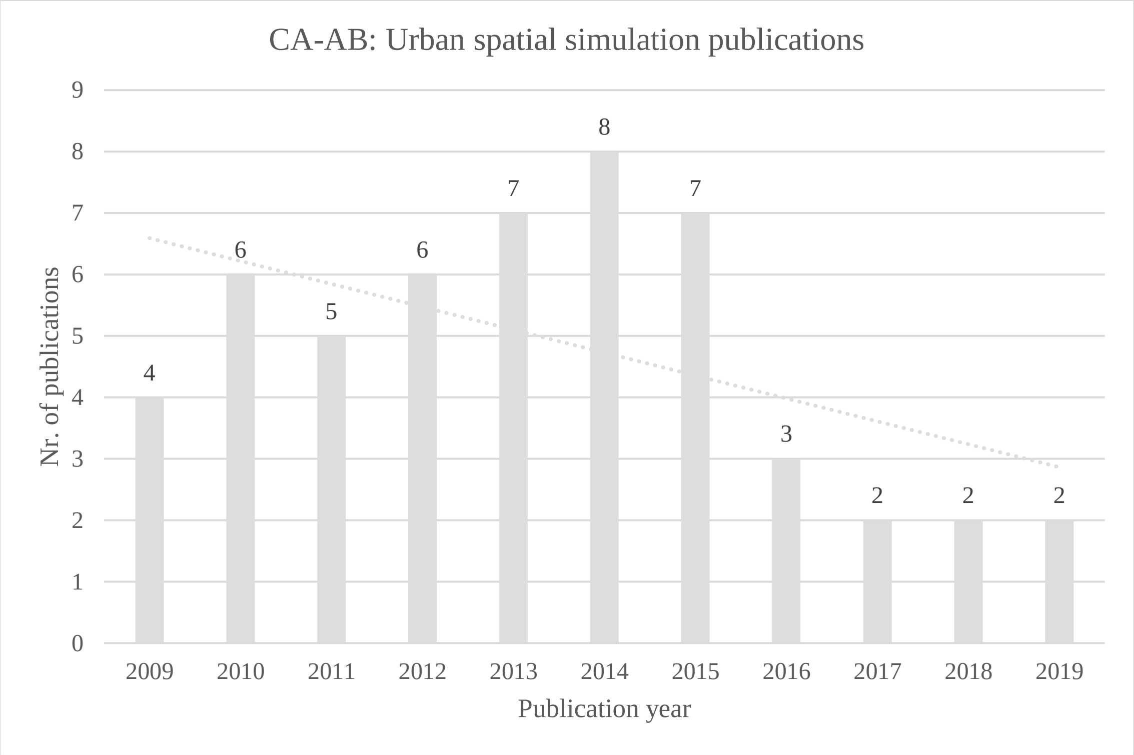
Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			urban land use master plan.	& implementation.								Decision maker; Facilitator;	
Malik & Abdalla 2017	Not explicit	D	Simulation of urban dynamics and to model the settlement pattern of students of the University of Waterloo Campus.	Urban sprawl	ABM (NetLogo); Geospatial simulation (ArcGIS)	ABM	Political boundaries; Road network; Residential zones; Grocery stores; Light rail transit stops	Not explicit	Not explicit	Local	Waterloo, Canada	Students	Not explicit
Liu & Lim 2016	Not explicit	D; P	Simulation of evacuation planning (shelter assignment & routing strategy) from both the spatial and temporal perspectives during a flood event scenario.	Ineffective evacuation planning during natural disasters.	ABM (Agent Analyst ArcGIS); Geospatial simulation (ArcGIS)	ABM + urban network analysis	Flood lines; Road networks; shelters; census boundaries; census data; hydrology; slope; historical flood events	Not explicit	Not explicit	Local (5 x 5m)	Brisbane, Australia	Households	Not explicit
Liu et al 2016	CID-USST_GIS	D; P; PC	Simulation of policy scenarios to reflect on the dynamics of spatial distributions of creative firms and creative workers across time within a city/district.	Lack of local land-use policies for the optimisation of land use in support of creative industries.	ABM (NetLogo); Geospatial simulation (GIS)	ABM	Administrative boundaries; City centres; Infrastructure networks (rail, air, road, water, stations); Facilities (cultural, leisure; education); Hydrological data; Services (internet) Land uses	Yes	Not explicit	Micro	Jiading District, Shanghai, China	Creative firms; Creative workers; Urban government	2013, 2018, 2023 (5 year plan period intervals)
Li et al 2016	Not explicit	D	Analysis of historical and future land-use changes and	Food security	ABM (Analyst Agent ArcGIS); Geospatial	ABM	Satellite imagery; Land use	Yes	Yes	National	Uganda	Agricultural; Non-agricultural	1993; 2001; 2013

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			simulation of scenarios of potential agricultural land-use changes and the decision-making process of farmers.		simulation (ArcGIS)							developers; Land parcels	
Vermeiren et al 2016	ASSURE	D	Simulation of urban growth and intra-urban social segregation, including alternative policy strategies (quality of life, accessibility, affordability) and expected social dynamics over space and time.	Urban sprawl; Inequality; Spatial segregation & accessibility problems.	ABM (Analyst Agent ArcGIS); Geospatial simulation (ArcGIS)	ABM	Not explicit	Yes	Not explicit	Local	Kampala, Uganda	Households (Agent group)	2010 – 2013; Projection 2014 - 2030
Lichter et al 2015	Not explicit	D	Simulation of long-term consequences of disasters (earthquake & missile attack) and the outcomes in disaster management.	Climate change	ABM (RePast); Geospatial simulation (GIS)	ABM	Census data; GPS survey; National tax authority data (property value); Capital stock estimates.	Not explicit	Yes	Micro	CBD, Jerusalem, Israel	Households; workers; land developers; firms; city authorities; intervention agencies.	Not explicit
Xu et al 2015	Not explicit	D; P	Simulation of the spatiotemporal process model for land use/land cover changes (LUCC) that simulated dynamic	Rapid socio-economic development & urbanisation; Loss of agricultural production;	ABM (RePast); Geospatial simulation (GIS)	ABM	Satellite imagery; Road network; Hydrological data; Census data; Economic data; Land use data	Yes	Yes	Regional	Dali City, Erhai Lake Basin, China	Farmer; Habitat; Government	2010 - 2020

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Type of agent	Time period
			land-use changes in the case study area.	Pollution,									

3.2.3 Cellular automata and agent-based modelling (CA-AB).

As can be expected, the total number of publications over the analysis period that dealt with CA-AB simulation publications are much lower than in the two individual categories. Over this period, the number of CA-AB urban spatial simulation publications represented between 3,8% and 15,4% of the total publications (refer to Figure 21 and Appendix A.13).

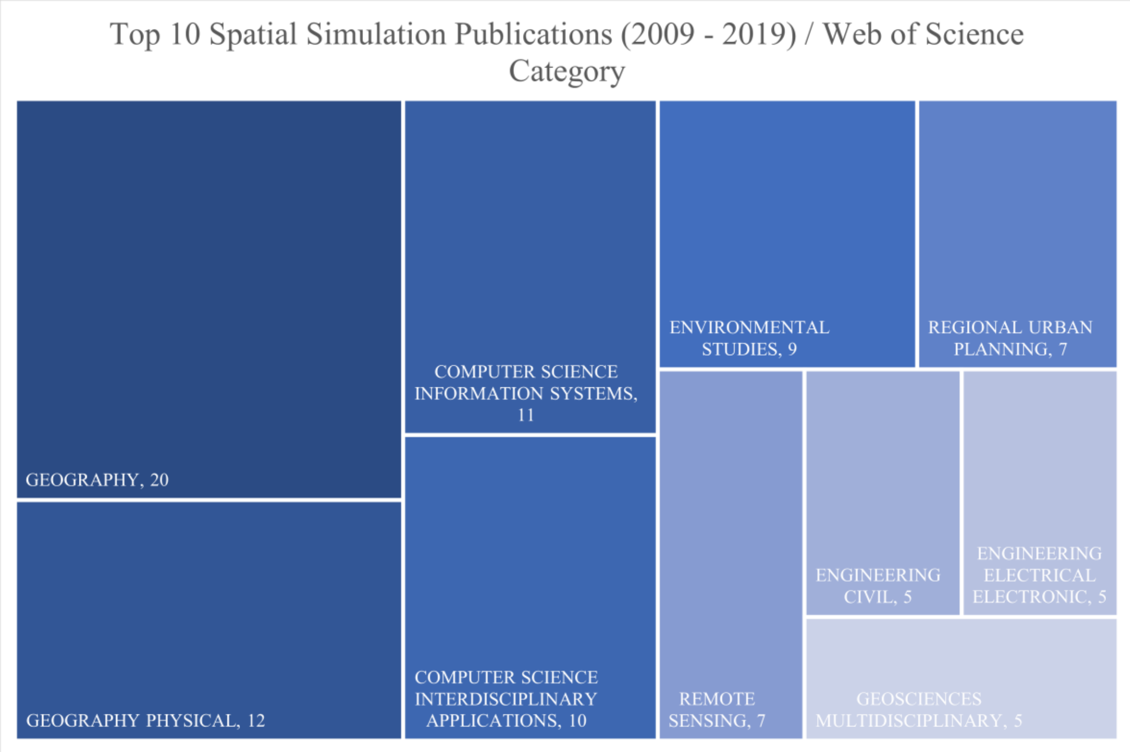


Source: Web of Knowledge database 2019 [online]
[Accessed 4 October 2019].

Figure 21: CA-AB: Urban spatial simulation publications

The CA-AB category of urban spatial simulation publications over the period were predominantly published in the Web of Science categories of Geography, Geography physical and Computer science information systems. Regional urban planning and urban studies cited a total of 13 over the selected time period (Refer to Appendix A.14).

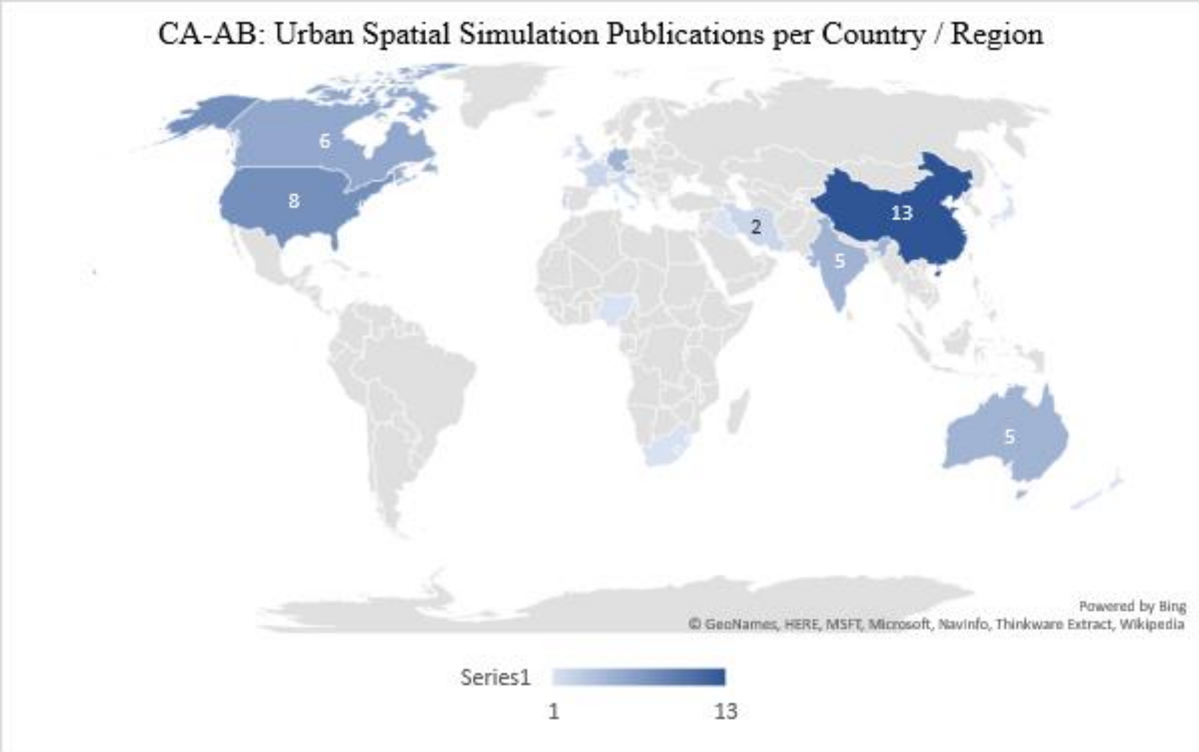
The publication categories are predominantly focused on the research themes of environmental sciences, computer sciences and geography, which includes research types of long-term monitoring, experimentation, comparative analysis and models / methodological approaches. The varying coverage of the publications also demonstrates the multi-disciplinary nature of this category of models and their application (Refer to Figure 22).



Source: Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 22: CA-AB: Treemap of urban spatial simulation

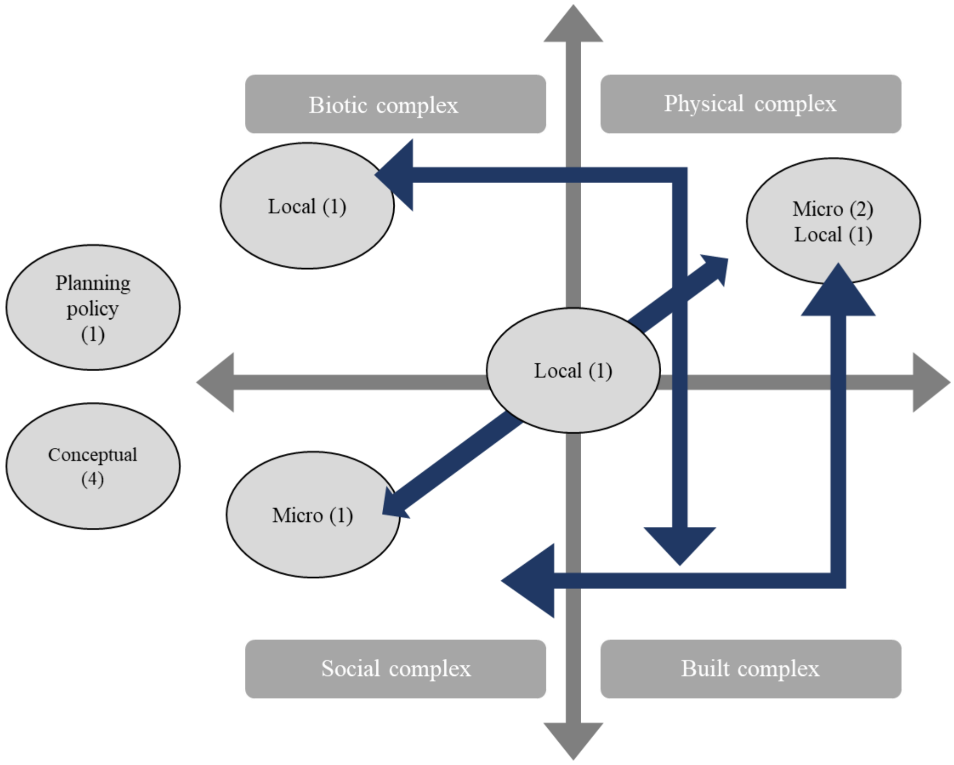
Similar to the other categories the application areas of these studies are predominantly focused on China (25%), United States of America (15,4%) and Canada (11,5%) (Refer to Figure 23 and Appendix A.15).



Source: Author adopted from Web of Knowledge database 2019 [online] [Accessed 4 October 2019].

Figure 23: CA-AB: Spatial distribution of urban simulation publications

As indicated in Figure 24, most of the urban CA-AB models simulate the interactions between people-built environment-land resources/potential across the micro (2) and local (1) scales. One local scaled CA-AB model simulates the interactions between people-organisms-built environment-land resources/potential and one each for people-land potential /resources and people-organisms-built environment, respectively. In addition to the aforementioned, several conceptual models (4) and models trying to support and/or inform planning policy (1) is highlighted.



Source: Author

Figure 24: CA-AB: Components of urban simulation publications

Based on the assessment criteria, the following are noted:

- Most of the urban CA-AB models reviewed had a combination of descriptive and predictive objectives as part of the model design. The factors and dynamics explored in the past provide the foundation of using forecasting techniques to understand the future. None of the models reviewed incorporated prescriptive objectives as a way of understanding the possible constraints within the system (e.g. urban growth boundaries, zoning, environmental protection zones), as well as trying to measure and predicting the outcomes of implementing these policy interventions through scenario planning.
- Data inputs varied across the various categories of urban models according to their needs and the scale at which the components of the system were investigated. Although, all the models required satellite images in order to apply remote sensing techniques for land use/land cover classification. Basic geographic information such as road networks, administrative boundaries, topographical and population data was also required.

- Calibration and validation formed part of the design and construction of the majority of the urban models and was viewed as an essential factor in terms of measuring the level of fitness of the model based on its intended purpose and its accurate reproduction of the real world and its ability to predict the future.
- The model grain of the urban models ranged from micro (10m & 50m resolution) and local (30m & 100m resolutions). The reviewed models did not incorporate model grains of regional, national and global, and most of the modelling was done across various scales.
- Cell states in the urban CA-AB mostly focused on two-state cells, for example, feel good / not feel good; suitable for vertical development / not suitable; built-up / non-built-up and approval probability / no approval. The characteristics of the agents across the models were different which hampered a comparative analysis.
- The time period specifies the period used in validating and calibrating within the urban models which generally coincided with data points such as updates in census data, household and travel surveys. The time period between these data points generally ranged between five (5) and ten (10) years. The projection time periods in most of the models did not follow a continues / yearly update but followed a time interval update of five (5), ten (10) and 15 years.

The detailed analysis of the selected urban CA-AB models (excluding conceptual models) is contained in the assessment matrix below.

Table 5: Characteristics of urban CA-AB

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Type of agent	Time period
Mueller et al 2018	SimUSys	D	Integrate geospatial methods for measuring spatial attractiveness and combines gamification, system dynamics and ABM for creating a spatial simulation for smaller urban systems.	Impact on location choices and spatial attractiveness (noise pollution, traffic intensity) during, e.g. events.	CA (ArcGIS) + ABM + gamification approach	Hybrid + conceptual for smaller size (<25 000 citizens) municipalities.	Environment and services (land use, protected areas etc.) Networks (streets, pipelines etc.) Points of interest (parks, shops etc.) Planning entities (administrative districts, zoning, addresses); Volunteered Geographic data	Yes	Yes	Local CA – (100 x 100m); (5 x 5m network distance grid)	CBD, Herdecke, Germany	Feel good; Not feel good	Not explicit	Landowner	Not explicit
Liu et al 2016	SGCABM	D; P	Simulate urban growth at the urban fringe of the city and considers the microeconomic behaviour of farmers and government, the	Urban sprawl; Rapid urbanization; Land expropriation (legal / forcibly / illegally) &	Static game model + CA + ABM	Hybrid	Satellite images; Land use data; Public infrastructure points; socio-	Yes	Yes	Micro (50 x 50m)	Jiangxia, Wuhan, China	Land-use conversion in line with land-use planning; land use conversion not in line with land	3 x 3	Residents, farmers; government	2003 – 2013 Projection to 2023

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Type of agent	Time period
			selection of housing by agents and it explores drivers of urbanisation using a game theory-based economic model.	acquisition (force / willingly) conflicts.			economic data					use planning; Urban; Non-urban			
Koziatek et al	Not explicit	D	A geospatial modelling approach to represent the urban densification process in 3D by generating urban development in the form of mid- and high-rise buildings.	Environmental impact of urban sprawl, sustainability	CA (ArcGIS) + Computer Graphic architecture	Hybrid	Satellite imagery; LiDAR; cadastral data; buildings; land uses & designation; population data	Yes	Not explicit	Micro (10m spatial resolution)	Town centre, Surrey, Vancouver, Canada	Suitable for vertical development; unsuitable for vertical development	Not explicit	Not applicable	Not explicit
Pandey & Joshi 2015	CA-MAS	D; P	Modelling urbanisation dynamics for the urban and rural population within the regional landscape and how it shapes the urban morphology.	Environmental degradation due to uncontrolled urbanization and urban growth.	CA (ArcGIS) + MAS (Netlogo)	Hybrid	Satellite imagery; Settlement point dataset; Population data	Yes	Yes	Local (30m spatial resolution)	Chandigarh, India	Built-up; non-built-up	Moore & Von-Neumann	Urban; Rural	1999 – 2009 Projection to 2019

Author	Model name	Objective	Main purpose/description of the model	Issues	Key model components	Model classification	Data inputs	Calibration	Validation	Model grain	Model extent	Cell states	Neighbourhood	Type of agent	Time period
Zhang *et al* 2015	GIS-MAS	D; P	Simulate and analyse 3 target scenarios, including maintenance of current trends, priorities for economic development, and priorities for environmental protection to obtain a better understanding of land-use preferences and the driving mechanism of urban growth.	Rapid urbanization Environmental degradation Urban management	GIS + MAS	Hybrid	Geographic data – transportation, land price, public facilities, land use, urban master planning. Socio-economic data - population, GDP, economic sector data.	Yes	Yes	Not explicit	Lianyungang City, China	Approval probability; no approval probability	3 x 3	Residents, farmers, industrial enterprises, environmentalists, government	2008 (base year) Projections – 2020 & 2030

3.3 APPLICATION OF URBAN SPATIAL SIMULATION MODELS

3.3.1 Demography

A fundamental aspect of urban models is the creation of a micro-dataset containing the spatial distribution of demographic features. This dataset assists in the demographic modelling and population projection in the urban models (O'Donoghue et al 2014).

Many of the urban models under review, used population and socio-economic data to dynamically simulate demographic processes for use in the spatial distribution and to inform population projections. The model developed by Alghais & Pullar (2018), for example, used the demographic analysis to inform their forecast for population estimates in Kuwait City, Kuwait.

The socio-economic analysis underpins the dynamic simulation processes of transport (Jin et al 2018; Lu et al 2018; Lu & Hsu 2017; Xia et al 2019; Liang et al 2018), social mobility (Hackl & Dubernet 2018; Pandey & Joshi 2015); planning policy formulation (Alghais & Pullar 2018; Tong & Feng 2019; Guan et al 2019; Liu et al 2018; Zheng et al 2017; Osman et al 2016); and land market and housing (Liu et al 2016; Quesada-Ruiz et al 2019; Yu et al 2018; He et al 2017);

3.3.2 Welfare, poverty and inequality

The ASSURE urban model developed by Vermeinen et al (2016) simulates urban growth and how this can drive intra-urban social segregation and further impact on the quality of life, accessibility and affordability within Kampala, Uganda.

Other applications where socio-economic and income analysis data was used include the dynamic simulation processes of disparities/inequality (Tripathy & Kumar 2019; Feng & Qi 2018)), food security (Li et al 2016; Rimal et al 2019), access to and social program interventions for example access to healthcare programs (Jin et al 2018) and land through expropriation programs (Liu et al 2016).

3.3.3 Health

Health care service provision is an important policy area, which involves significant expenditure and requirements of access to services and facilities (O'Donoghue et al 2014). Urban models that contain facility data in their spatial location with health attributes and the spatial distribution of health services can be useful in planning and analysing health services and the spread of infectious diseases. Hackl & Dubernet (2019), utilised an urban model to examine the spread of seasonal influenza across Zurich, Switzerland, while Jin et al (2018) modelled the individual level demands of older adults in accessing oral healthcare services.

3.3.4 Regional development

Yu et al (2019) developed an urban model, simulating the distribution of the green gross domestic product (GDP of ecosystem service value) and the impact of land-use change and the socio-economic benefits derived from this development across China. A further example is the CID-USST-GIS model developed by Liu et al (2016) that simulated the spatial location and the impact of land-use policies in the development and distribution of creative industries and creative workers.

Both the abovementioned examples of urban models aim to understand the changes in the economy, the driving forces impacting on the spatial distribution of these new economies and it tries to analyse and assess the impact of planning policies in order to inform them and to improve the support to these new industries.

3.3.5 Transport planning

Several urban models in the ABM list such as Wu et al (2019), Lu et al (2018), Jin et al (2018), Lu & Hsu (2017) and Demare et al (2017) explored this theme. Within this theme the following areas are generally considered:

- Travel over transport networks, the mode of transport, car ownership, congestion and transport control measures.
- Transportation issues such as congestion and their relevance for extensive land use and transportation requirements.
- Impact of road management planning and civil engineering issues.
- Prediction and impact on the changes in travel behaviour (travel plans, modal and route choice) following from changes in the travel environment and population dynamics.
- Economic analysis of transport and its potential impacts of instruments such as congestion charging or road pricing systems.
- Environmental issues related to travel, commuting and transporting goods (O'Donoghue et al 2014).

3.3.6 Agriculture, marine and environment

The interaction between people and the environment is strongly influenced by spatial location, and the use of urban models can assist in the modelling of socio-economic-environmental interactions and policy.

Examples of urban simulation models within this category reviewed as part of this study include Baeza et al (2019), Morelle et al (2019) (SiReMo), Zhou et al (2017), Li et al (2016), Ou et al (2019), Hou et al (2019), Zhang et al (2018), Fan et al (2018), Kuo & Tsou et al (2018), Rahman et al (2017), Zare et al (2017), She et al (2017), Feng & Liu (2016), Jiang et al (2016) and Osman et al (2016).

3.3.7 Disaster planning and management

One of the advantages of urban simulation models is their capacity for use as an experimental platform for examining the impact of disaster events and the economic cost of an incident and how to improve the planning and management of these events.

A number of the models reviewed have been developed to simulate the allocation of emergency shelters (Yu et al 2019), evacuation planning (Liu & Lim 2016; Perez-Molina et al 2017) and the long term consequences of these disasters and their outcomes on disaster management (Lichter et al 2015).

3.3.8 Land use and spatial planning

Urban models are increasingly recognised as an essential tool for scenario planning and measuring outcomes and geographical impact of government policies, public and private investment (O'Donoghue et al 2014). Within this context, some of the urban simulation models reviewed dealt with migration and urbanization (Alghais & Pullar 2018), access to facilities, infrastructure, and transport planning (Lu et al 2018; Lu & Hsu 2017; Guan et al 2019; Liang et al 2018), land use (Xu et al 2015; Xu et al 2015; Quesada-Ruiz et al 2019; Mousivand & Arsanjani 2019; Feng & Tong 2019; Wang et al 2019); buildings (Koziatek et al 2016; Long & Wu 2017; He et al 2017), land markets and environmental protection (Huang et al 2019; Yang et al 2019; Li et al 2019; Xu et al 2018; Jia et al 2018; She et al 2017).

Most of the urban models reviewed linked planning policy and attempted to use it as a constraint in the simulation of urban change (Tong & Feng 2019; Feng & Tong 2017); forecasting of the impacts and outcomes on individual spatial decisions (Cantergiani & Delgado 2018; Ghavami & Taleai 2017a; Ghavami et al 2017b; Ghavami et al 2016; He et al 2019); estimating the intended and unintended consequences of planning decisions related to land use (urban edges, zonings); and the impacts of different scenarios and the resulting urban changes (Wang et al 2019; Tripathy & Kumar 2019; Nguyen et al 2019;

Yin et al 2018; Xu et al 2018; Mei et al 2018; Zheng et al 2017) in order to achieve sustainable development (Musa et al 2019; Rimal et al 2019; Zhou et al 2017).

3.4 STRENGTHS AND WEAKNESSES OF URBAN MODELS

The application of urban CA tends to replicate urban morphology best and its limitations are the limited incorporation of the connections and driving forces behind the different elements of the system under consideration (Wahyudi & Liu 2015; Batty 2014). The limitation stems from the neighbourhood building block/element and its application in practice. It is often difficult to associate cells and cell states with those of real systems. For example, buildings are considered as basic elements of cities, and within each building, there are many distinct activities. This implies that buildings cannot be cells as the fundamental principle in deciding cell size is the consideration that it must be the smallest unit of measurement for the specific component in the system. In the example provided the activities will have to be further disaggregated to be associated with a single cell (Batty 2014). Another factor is the changing of cell states through the transition rules within the neighbourhood concept, which is viewed endogenous to the system. However, distant objects (commercial properties, facilities, noxious industries etc.) through push and pull factors, or decay functions also influence the changes in the state of the cell. The transition rules can be relaxed on an ad hoc basis, but these methods have a weak theoretical basis, and new methods need to be explored and adopted (Wahyudi & Liu 2015).

In addition to the abovementioned, another factor that influences the system is not only the physical and socio-economic factors of the system but the actors within the system such as developers, farmers, landowners and other actors. The relationship of these actors with each other and the physical component of the system also changes the urban processes, and CA lacks the capability in representing the actors and behaviours in the urban system.

To address the abovementioned limitation, the application of ABM and integration of ABM in CA has been introduced. The application of ABM in urban simulation modelling has some limitations, such as the decision criteria of the agents that are extrapolated from data and the fact that it only models behaviours of the grouping of agents with similar considerations and how they would influence the structure of the system. They are therefore not an entirely accurate reflection of the real world, and specific attributes/behaviours might be hidden from view. An example of the can be the learning and then the adaptation in terms of their behaviour from this learning experience (Wahyudi & Liu 2015).

All models have advantages and disadvantages, and in addition to the system design, some of the following factors can also influence the choice of a model and its outcomes. The selection of the factors focuses on relatively high-level fundamental choices rather than particular modelling choices, namely:

1. Data requirements;

   The ability to create robust micro-level data through data techniques in urban simulation offers a powerful alternative to the expensive and time-consuming assembling of official micro-datasets, such as published census records or individual / household survey data (O'Donoghue et al 2014).

   The ideal base dataset for urban models is one collected specifically for modelling purposes with the appropriate scope and level of spatial disaggregation. Many models require the linkage of datasets of different types using statistical techniques.

   These sets of official and application-specific data are still crucial in model development and design as they are used predominantly in the calibration and validation of urban models. The importance of Statistical Offices and good quality statistical products are paramount in model development and impacts significantly on measuring model outcomes.

2. Software availability;

   Most of the models reviewed use GIS and other software models where programming languages are required to implement and integrate the different models. Modellers, therefore, need programming knowledge to implement and interpret the outcomes of models. This impedes non-expert users in applying and utilising models in spatial planning applications (Sante et al 2010).

3. Accuracy of the results.

   The key to having confidence in an urban model is adequate validation and evaluation of the matching or data generation process. When validation is understood it translates into an understanding of the relationships and interconnections between the different variables in the system. Even though the accuracy of models can be found to be good, the results are not directly comparable to other areas or models as they are largely dependent on the specific system under consideration.

3.5 CONCLUDING REMARKS

Spatial simulation (urban models) allow for the complex reality to be shown in a simplified form, in order that spatial strategies and their impacts can be explored in advance. It is mainly used as an exploratory learning tool which can assist spatial planners in clarifying their thinking of the complexities of the real world and to prompt further discussion and exploration. These urban models can be used as predictive tools in cases where reliable data is available, and when the model is an adequate representation of the system and its dynamics. The urban models are therefore flexible, adaptive and diverse in their methods of use and they can become valuable decision support tools for monitoring and guiding spatial planning and development.

In reviewing the urban models, it was found that the development and design of urban models are also now incorporating aspects of strategic planning within their scenarios in order to measure and monitor the appropriateness and effectiveness of policy interventions, such as urban growth boundaries, zoning schemes, sustainable development outcomes and environmental protection zones. With the incorporation of these prescriptive elements creates the bridges between the reality ('what is' and 'what could be') and normative terms ('what should be' and 'what is desired') (De Roo 2011; De Roo et al 2016; De Waal 2018; Schintler & Chen 2018), which can aid spatial planners in their daily operations. The urban models can improve the understanding of the local and historical contingent factors, how multidimensional and complex problems (e.g. demography; welfare, poverty & inequality; health; education; housing; regional development; transport planning; agriculture, marine & environment; disaster planning & management; and land use and spatial planning) impact and drive the complex urban systems and then accordingly use the laboratory environment provided by urban models to explore and experiment with different scenarios without impacting on the real-world systems.

In reviewing the urban models, most of the issues identified relate to rapid urbanisation, migration and unplanned and uncontrolled urban expansion. The urban models acknowledge that with this increased urbanisation that cities will face unprecedented pressures to provide basic services and aspects around increased inequalities, resource depletion reduced the quality of life and environmental degradation. The aforementioned aspects correspond to the United Nation's Report on World Urbanization Prospects for 2018 (UN: DESA 2019), however, the spatial extent of these urban models are predominantly distributed in the global North (USA, UK, Canada, France, Germany, Italy, Spain, Netherlands), Australia and in Asia (China, Japan and India) with Africa lacking an in any development and practical application of urban models.

In recent years these models for urban growth simulation have proliferated because of their conceptual simplicity, flexibility and their ability to incorporate spatial and temporal dimensions of urban processes. "*Just as settlements are diverse and complex, so there are many ways to describe and understand them.*" (K. Kropf, 2009 as referenced in Reis et al 2014:279), which was found to be an accurate assessment of the types of applications of the different urban models that were reviewed.

The applications have also improved with the advances in computer techniques, such as the integration with geographic information systems (GIS), artificial intelligence (AI) and advanced spatial analytics. The increased development of computer science coupled with the improvements in the availability of data, data quality and processing standards, have further increased the demand for these urban models. The meta-analysis of urban models applied internationally in urban contexts over the past decade (2009 – 2019) have shown that the total rate of academic publications in urban models (CA, ABM & CA-AB) has grown consistently. Both CA and ABM experienced growth over the period; however, the urban modelling category of CA-AB has shown a significant decline. Throughout the literature, the hybrid approach has been viewed as the modelling approach that can fully simulate the complex urban system and its urban dynamics. Even though the ability to use these models have become easier, some of the main problems could relate to the access and availability of appropriate data; data and model accuracy; software requirements; resource constraints (time, human resources, hardware) and modelling skills.

CHAPTER 4

4 CONCLUSION AND RECOMMENDATIONS

4.1 SUMMARY OF KEY FINDINGS AND REFLECTION ON RESEARCH OBJECTIVES

Within a complex and dynamic landscape (reality), a spatial planner's role is to "*create bridges between 'what is' and 'what could be',* (or in normative terms) *'what should be' and 'what is desired'* (De Roo et al 2016:1). This requires an understanding of the city as a complex dynamic system and how planning interventions should be contextually formulated and implemented to address the multidimensional urban phenomena such as uncontrolled and unplanned urbanisation challenges. Spatial planners need to become managers of change where negatives are avoided, and positive effects of change are embraced over time and space. The current scientific planning instruments and practices are, however, inadequate to address these multidimensional problems and challenges being faced within cities.

Within this context, one of the objectives of this research was to compile a comprehensive literature review and content analysis to explore the new 'science of cities' as a method that can provide insights into the complexity of the city. It was found that the concepts of complexity theory can be used to conceptualise cities as organised complex systems and the main components (metaphors) provided a means of understanding and exploring complex system behaviour. Complexity theory and complexity science can assist spatial planners with an understanding of how cities are theoretically conceptualised.

The components of a complex system make predictability difficult, and this makes spatial simulation models (urban models) an important tool for understanding and exploring complex system behaviour. Complexity science uses Cellular Automata (CA) and Agent-based modelling (ABM) techniques to abstracts the real-world into a series of layers as a visual representation of the complexity and spatial-temporal urban dynamics. A conceptual analysis was conducted to identify and explain the key components (concepts, methods and techniques), design and construction of the spatial simulation models (urban models). The research provides explanations on the critical considerations for spatial simulation model (urban model) conceptualisation, components, design and construction. It was established that the modelling techniques play a fundamental role in understanding the functionality, practicality, accuracy and 'fit for purpose' use of these urban models within cities. In general, the primary role of urban models (CA & ABM) is as heuristic tools for learning about the real world and enables scenario planning which can support spatial planning practices.

The application of spatial simulation models has in recent years increased because of their conceptual simplicity, flexibility and their ability to incorporate spatial and temporal dimensions of urban processes. The applications have also improved with the advances in computer techniques, such as the integration with geographic information systems (GIS), artificial intelligence (AI) and advanced spatial analytics. The increased development of computer science coupled with the improvements in the availability of data, data quality and processing standards, have further increased the demand for these urban models. The meta-analysis of the spatial simulation publications over the past decade (2009 – 2019) found that urban modelling approaches have grown consistently. Applications of urban simulation models appear to be regionally divergent with the primary focus on the global North (USA, UK, Canada, France, Germany, Italy, Spain, Netherlands), Asia (China, Japan) and Australia. Uptake of these urban models is lagging in areas with rapid urbanisation and urban growth rates, which are predominantly located in the global South, such as South Africa.

To move beyond the conceptual frameworks as discussed above, the research focused on identifying and evaluating spatial simulation applications in peer-reviewed scientific literature which includes Cellular Automata (CA), Agent-based modelling (ABM) and hybrids (including both CA and ABM) that have been published internationally and within South Africa over the last five (5) years. The comparative analysis found that the development and design of urban models are also now incorporating aspects of strategic planning within their scenarios in order to measure and monitor the appropriateness and effectiveness of policy interventions, such as urban growth boundaries, zoning schemes, sustainable development outcomes and environmental protection zones. The review found that urban models improve the understanding of the local and historical contingent factors, how multidimensional and complex problems (e.g. demography; welfare, poverty & inequality; health; education; housing; regional development; transport planning; agriculture, marine & environment; disaster planning & management; and land use and spatial planning) impact and drive the complex urban systems across time and space. Urban simulation models provide the laboratory environment to explore and experiment with different scenarios without impacting on the real-world systems, and with the incorporation of these prescriptive elements creates the bridges between the reality ('what is' and 'what could be') and normative terms ('what should be' and 'what is desired'), which can aid spatial planners in their daily operations.

4.2 LIMITATIONS OF RESEARCH

Challenges and limitations to the approach include the lack of / or restricted access to literature especially in the detailed comparative analysis of urban simulation models. The restricted access limited the data collection process. In addition to the accessibility issues, the amount of time afforded for the review, evaluation and comparison of the entire publication information set over the ten (10) year period was limited and the detailed analysis period had to be shortened to five years, which follows on from the analysis period (2014) of the GCRO report. The type of meta-analysis conducted in this research is also potentially vulnerable to interpretation biases.

4.3 RESEARCH CONTRIBUTION AND FURTHER RESEARCH

At a theoretical level, the research is interested in understanding the scientific theories, concepts and models around the application of the science of cities (complexity theory, spatial simulation modelling, spatial planning practices) in order to understand complex and dynamic systems. This research attempted to define and demonstrate the relationship between complexity science and the applications of the science to cities and urban simulations from a spatial planning perspective. Through the literature review, it was also found that little research has gone into providing a comparative analysis of the spatial simulation models (urban models) and its potential applications. The research aimed to improve the knowledge base and expand on the concepts, relationship and operational application of spatial simulation modelling (urban models) within different places and across different times in order to provide conceptual clarity and revealing the different methodologies and applications for analysing complex city systems.

Some areas of further research to consider includes an in-depth understanding of what impacts the use and application of these spatial simulation models (urban models) and demonstrating how these models solve practical planning issues, especially in the South African context.

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APPENDIX A

Table A.1. Spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals as selection criteria.

Year	Publications	% of Total
2009	1388	7.315
2010	1302	6.862
2011	1392	7.336
2012	1424	7.505
2013	1529	8.058
2014	1810	9.539
2015	2011	10.599
2016	2062	10.868
2017	2197	11.579
2018	2262	11.922
2019	1597	8.417
TOTAL	**18974**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.2. Spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Web of Science category.

Web of Science categories	Publications	% of Total
Environmental sciences	4945	26.062
Geosciences multidisciplinary	4763	25.103
Computer science interdisciplinary applications	3297	17.376
Engineering electrical electronic	3015	15.890
Water resources	2539	13.381
Computer science information systems	2443	12.876
Computer science theory methods	2069	10.904
Remote sensing	1887	9.945
Meteorology atmospheric sciences	1665	8.775
Telecommunications	1563	8.238
Computer science artificial intelligence	1450	7.642
Geography physical	1174	6.187
Engineering civil	1038	5.471
Imaging science photographic technology	986	5.197
Engineering environmental	858	4.522
Ecology	638	3.362
Mathematics interdisciplinary applications	618	3.257
Environmental studies	615	3.241
Computer science hardware architecture	596	3.141
Physics mathematical	587	3.094
Geography	581	3.062
Statistics probability	558	2.941
Computer science software engineering	477	2.514
Limnology	449	2.366
Operations research management science	356	1.876
TOTAL	**18974**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.3. Spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Country / Region.

Country / Region	Publications	% of Total
USA	5419	28.560
Peoples Republic of China	4723	24.892
Germany	1644	8.664
France	1300	6.851
England	1259	6.635
Canada	1070	5.639
Italy	957	5.044
Australia	935	4.928
Japan	763	4.021
Spain	703	3.705
Netherlands	646	3.405
India	627	3.305
Switzerland	559	2.946
South Korea	494	2.604
Taiwan	341	1.797
Iran	338	1.781
Brazil	314	1.655
Belgium	307	1.618
Sweden	296	1.560
Austria	276	1.455
Norway	250	1.318
Scotland	235	1.239
Greece	220	1.159
Denmark	212	1.117
Portugal	212	1.117
TOTAL	**18974**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.4. Urban spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals.

Year	Publications	% of Total
2009	97	5.456
2010	114	6.412
2011	106	5.962
2012	127	7.143
2013	138	7.762
2014	149	8.380
2015	171	9.618
2016	208	11.699
2017	235	13.217
2018	243	13.667
2019	190	10.686
TOTAL	**1778**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.5. Urban spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Web of Science category.

Web of Science categories	Publications	% of Total
Environmental sciences	703	39.539
Meteorology atmospheric sciences	258	14.511
Geography	257	14.454
Geosciences multidisciplinary	241	13.555
Environmental studies	237	13.330
Remote sensing	209	11.755
Geography physical	190	10.686
Computer science interdisciplinary applications	180	10.124
Water resources	171	9.618
Engineering environmental	163	9.168
Computer science information systems	146	8.211
Regional urban planning	137	7.705
Urban studies	133	7.480
Engineering civil	103	5.793
Engineering electrical electronic	82	4.612
Operations research management science	78	4.387
Computer science theory methods	74	4.162
Transportation	73	4.106
Imaging science photographic technology	68	3.825
Green sustainable science technology	64	3.600
Computer science artificial intelligence	61	3.431
Ecology	61	3.431
Transportation science technology	59	3.318
Information science library science	48	2.700
Economics	47	2.643
TOTAL	**1778**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.6. Urban spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Country / Region.

Country / Region	Publications	% of Total
Peoples Republic of China	502	28.234
USA	423	23.791
France	130	7.312
England	117	6.580
Germany	105	5.906
Italy	92	5.174
Canada	85	4.781
Australia	77	4.331
Spain	74	4.162
Netherlands	72	4.049
Japan	70	3.937
Iran	55	3.093
India	43	2.418
South Korea	42	2.362
Portugal	40	2.250
Belgium	37	2.081
Switzerland	34	1.912
Greece	32	1.800
Taiwan	31	1.744
Denmark	28	1.575
Austria	24	1.350
Israel	24	1.350
Brazil	23	1.294
Singapore	22	1.237
Malaysia	19	1.069
TOTAL	**1778**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.7. Urban cellular automata (CA) spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals.

Year	Publications	% of Total
2009	24	6.612
2010	28	7.713
2011	26	7.163
2012	28	7.713
2013	32	8.815
2014	25	6.887
2015	28	7.713
2016	33	9.091
2017	50	13.774
2018	42	11.570
2019	47	12.948
TOTAL	**363**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.8. Urban CA spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Web of Science category.

Web of Science categories	Publications	% of Total
Geography	117	32.231
Geography physical	92	25.344
Environmental sciences	91	25.069
Environmental studies	75	20.661
Computer science information systems	61	16.804
Remote sensing	60	16.529
Regional urban planning	48	13.223
Computer science interdisciplinary applications	43	11.846
Urban studies	41	11.295
Geosciences multidisciplinary	40	11.019
Information science library science	34	9.366
Engineering environmental	32	8.815
Ecology	21	5.785
Green sustainable science technology	21	5.785
Operations research management science	21	5.785
Engineering electrical electronic	19	5.234
Computer science theory methods	18	4.959
Imaging science photographic technology	17	4.683
Engineering civil	15	4.132
Computer science artificial intelligence	13	3.581
Water resources	11	3.030
Computer science software engineering	6	1.653
Telecommunications	5	1.377
Transportation	5	1.377
Transportation science technology	5	1.377
TOTAL	**363**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.9. Urban CA spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Country / Region.

Country / Region	Publications	% of Total
Peoples Republic of China	145	39.945
USA	53	14.601
Canada	27	7.438
Iran	27	7.438
Australia	23	6.336
England	22	6.061
France	19	5.234
India	19	5.234
Spain	18	4.959
Netherlands	16	4.408
Germany	13	3.581
Japan	12	3.306
Belgium	10	2.755
Italy	9	2.479
Luxembourg	8	2.204
Portugal	8	2.204
Brazil	6	1.653
Denmark	6	1.653
Malaysia	6	1.653
Taiwan	5	1.377
Austria	4	1.102
Ireland	4	1.102
Israel	4	1.102
Nigeria	3	0.826
Scotland	3	0.826
TOTAL	**363**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.10. Urban agent-based (ABM) spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals.

Year	Publications	% of Total
2009	42	5.063
2010	59	8.228
2011	43	8.861
2012	52	8.861
2013	59	10.127
2014	71	9.494
2015	81	13.291
2016	101	8.861
2017	140	11.392
2018	138	10.127
2019	118	5.696
TOTAL	**158**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.11. Urban ABM spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Web of Science category.

Web of Science categories	Publications	% of Total
Geography	53	33.544
Environmental studies	35	22.152
Computer science interdisciplinary applications	32	20.253
Regional urban planning	29	18.354
Computer science information systems	28	17.722
Geography physical	23	14.557
Engineering environmental	21	13.291
Computer science artificial intelligence	18	11.392
Operations research management science	16	10.127
Urban studies	16	10.127
Computer science theory methods	13	8.228
Environmental sciences	13	8.228
Transportation	13	8.228
Remote sensing	12	7.595
Engineering civil	11	6.962
Information science library science	10	6.329
Transportation science technology	10	6.329
Engineering electrical electronic	9	5.696
Computer science software engineering	8	5.063
Geosciences multidisciplinary	7	4.430
Ecology	6	3.797
Economics	6	3.797
Water resources	5	3.165
Green sustainable science technology	4	2.532
Architecture	3	1.899
TOTAL	**158**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.12. Urban ABM spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Country / Region.

Country / Region	Publications	% of Total
USA	39	24.684
Peoples Republic of China	26	16.456
France	13	8.228
Canada	12	7.595
Netherlands	11	6.962
Australia	9	5.696
Germany	9	5.696
Israel	8	5.063
England	7	4.430
Italy	7	4.430
Spain	6	3.797
Iran	5	3.165
Switzerland	5	3.165
Austria	4	2.532
Japan	4	2.532
Scotland	4	2.532
Belgium	3	1.899
Portugal	3	1.899
Brazil	2	1.266
Colombia	2	1.266
Denmark	2	1.266
Greece	2	1.266
India	2	1.266
Ireland	2	1.266
Latvia	2	1.266
TOTAL	**158**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.13. Urban AB & CA spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals.

Year	Publications	% of Total
2009	4	7.692
2010	6	11.538
2011	5	9.615
2012	6	11.538
2013	7	13.462
2014	8	15.385
2015	7	13.462
2016	3	5.769
2017	2	3.846
2018	2	3.846
2019	2	3.846
TOTAL	**52**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.14. Urban AB & CA spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Web of Science category.

Web of Science categories	Publications	% of Total
Geography	20	38.462
Geography physical	12	23.077
Computer science information systems	11	21.154
Computer science interdisciplinary applications	10	19.231
Environmental studies	9	17.308
Regional urban planning	7	13.462
Remote sensing	7	13.462
Engineering civil	5	9.615
Engineering electrical electronic	5	9.615
Geosciences multidisciplinary	5	9.615
Information science library science	5	9.615
Urban studies	5	9.615
Computer science artificial intelligence	4	7.692
Engineering environmental	4	7.692
Environmental sciences	4	7.692
Ecology	3	5.769
Green sustainable science technology	3	5.769
Computer science software engineering	2	3.846
Computer science theory methods	2	3.846
Imaging science photographic technology	2	3.846
Operations research management science	2	3.846
Transportation	2	3.846
Development studies	1	1.923
History of social sciences	1	1.923
Instruments instrumentation	1	1.923
TOTAL	**52**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

Table A.15. Urban AB & CA spatial simulation publications per year over the period 2009-2019 using selected environmental, GIScience and planning journals per Country / Region.

Country / Region	Publications	% of Total
Peoples Republic of China	13	25.000
USA	8	15.385
Canada	6	11.538
Australia	5	9.615
Germany	5	9.615
India	5	9.615
Austria	3	5.769
Belgium	2	3.846
England	2	3.846
France	2	3.846
Iran	2	3.846
Israel	2	3.846
Italy	2	3.846
Portugal	2	3.846
Scotland	2	3.846
Iraq	1	1.923
Ireland	1	1.923
Japan	1	1.923
Luxembourg	1	1.923
Netherlands	1	1.923
New Zealand	1	1.923
Nigeria	1	1.923
Singapore	1	1.923
South Africa	1	1.923
TOTAL	**52**	**100**

Source: Web of Knowledge database 2019 [online]. Available from http://apps.webofknowledge.com.ez.sun.ac.za/ [Accessed 4 October 2019].

APPENDIX B

Table B.1. Percentage of the urban population residing in each urban agglomeration with 300,000 inhabitants or more in 2018, by Country, 2020-2035.

Country	2020	2025	2030	Difference	Rate of change
China	67,03	69,17	70,09	3,07	4,57
Bahrain	41,76	44,27	44,73	2,97	7,12
Lebanon	45,29	47,28	47,51	2,22	4,91
Kuwait	72,38	73,98	74,31	1,93	2,66
Estonia	49,45	50,90	51,33	1,87	3,79
Turkey	66,71	68,13	68,42	1,71	2,57
Equatorial Guinea	40,40	41,61	41,92	1,52	3,77
United Arab Emirates	82,52	83,78	84,02	1,50	1,82
Kazakhstan	59,17	60,39	60,60	1,44	2,43
Burundi	61,90	62,89	63,31	1,41	2,28
Mongolia	71,90	73,00	73,21	1,31	1,82
Vietnam	55,05	56,02	56,33	1,28	2,33
Cameroon	66,54	67,51	67,71	1,18	1,77
Bulgaria	37,36	38,00	38,52	1,15	3,09
Malaysia	52,92	53,70	54,01	1,09	2,06
Costa Rica	51,69	52,32	52,61	0,93	1,80
Madagascar	38,98	39,62	39,86	0,88	2,27
Mauritania	49,67	50,30	50,55	0,88	1,76
Libya	53,40	53,98	54,18	0,79	1,47
Myanmar	43,14	43,77	43,87	0,73	1,69
Albania	27,02	27,49	27,74	0,72	2,65
Somalia	66,04	66,57	66,75	0,71	1,08
Belarus	54,75	55,32	55,46	0,70	1,28
Bangladesh	49,27	49,70	49,96	0,68	1,39
Colombia	69,98	70,50	70,65	0,67	0,96
TFYR Macedonia	48,75	49,31	49,41	0,66	1,35

Country	2020	2025	2030	Difference	Rate of change
South Africa	68,24	68,72	68,88	0,64	0,93
Honduras	41,38	41,81	42,01	0,63	1,52

Source: Adapted from UNDESA population prospects database 2019 [online]. Available from https://population.un.org/wpp/DataQuery/ [Accessed 4 October 2019].

Table B.2. Percentage of the urban population residing in each urban agglomeration with 300,000 inhabitants or more in 2018, by Country, 2020-2035.

Countries	**Bing map reference**	**2020**	**2025**	**2030**	**Difference**	**Rate of change**
China	China	67,03	69,17	70,09	3,07	4,57
Bahrain	Bahrain	41,76	44,27	44,73	2,97	7,12
Lebanon	Lebanon	45,29	47,28	47,51	2,22	4,91
Kuwait	Kuwait	72,38	73,98	74,31	1,93	2,66
Estonia	Estonia	49,45	50,90	51,33	1,87	3,79
Turkey	Republic of Turkey	66,71	68,13	68,42	1,71	2,57
Equatorial Guinea	Equatorial Guinea	40,40	41,61	41,92	1,52	3,77
United Arab Emirates	United Arab Emirates	82,52	83,78	84,02	1,50	1,82
Kazakhstan	Kazakhstan	59,17	60,39	60,60	1,44	2,43
Burundi	Burundi	61,90	62,89	63,31	1,41	2,28
Mongolia	Mongolia	71,90	73,00	73,21	1,31	1,82
Viet Nam	Viet Nam	55,05	56,02	56,33	1,28	2,33
Cameroon	Cameroon	66,54	67,51	67,71	1,18	1,77
Bulgaria	Bulgaria	37,36	38,00	38,52	1,15	3,09
Malaysia	Malaysia	52,92	53,70	54,01	1,09	2,06
Costa Rica	Costa Rica	51,69	52,32	52,61	0,93	1,80
Madagascar	Madagascar	38,98	39,62	39,86	0,88	2,27
Mauritania	Mauritania	49,67	50,30	50,55	0,88	1,76
Libya	Libya	53,40	53,98	54,18	0,79	1,47
Myanmar	Myanmar	43,14	43,77	43,87	0,73	1,69
Albania	Albania	27,02	27,49	27,74	0,72	2,65
Somalia	Somalia	66,04	66,57	66,75	0,71	1,08
Belarus	Belarus	54,75	55,32	55,46	0,70	1,28

Countries	**Bing map reference**	**2020**	**2025**	**2030**	**Difference**	**Rate of change**
Bangladesh	Bangladesh	49,27	49,70	49,96	0,68	1,39
Colombia	Colombia	69,98	70,50	70,65	0,67	0,96
TFYR Macedonia	TFYR Macedonia	48,75	49,31	49,41	0,66	1,35
South Africa	South Africa	68,24	68,72	68,88	0,64	0,93
Honduras	Honduras	41,38	41,81	42,01	0,63	1,52
Russian Federation	Russian Federation	54,72	55,23	55,33	0,61	1,12
Spain	Spain	48,23	48,73	48,83	0,60	1,24
Finland	Finland	34,50	35,00	35,10	0,60	1,73
Ghana	Ghana	42,26	42,69	42,85	0,58	1,38
Guinea-Bissau	Guinea-Bissau	67,82	68,28	68,40	0,57	0,84
Benin	Benin	41,74	42,19	42,28	0,55	1,31
Sweden	Sweden	28,81	29,24	29,36	0,55	1,90
Nepal	Nepal	29,62	30,06	30,15	0,53	1,79
Saudi Arabia	Saudi Arabia	77,94	78,35	78,46	0,52	0,67
Dominican Republic	Dominican Republic	43,43	43,77	43,95	0,52	1,20
Japan	Japan	79,93	80,17	80,42	0,50	0,62
Latvia	Latvia	48,77	49,25	49,26	0,49	1,01
Brazil	Brazil	58,19	58,54	58,68	0,49	0,84
New Zealand	New Zealand	57,74	58,09	58,17	0,43	0,75
Democratic Republic of the Congo	Democratic Republic of the Congo	70,59	70,75	71,00	0,41	0,59
Lithuania	Lithuania	27,76	28,07	28,17	0,40	1,46
India	India	58,31	58,62	58,71	0,40	0,69
Denmark	Denmark	26,36	26,69	26,76	0,40	1,51

Countries	Bing map reference	2020	2025	2030	Difference	Rate of change
Pakistan	Pakistan	67,90	68,19	68,25	0,36	0,52
Peru	Peru	60,02	60,27	60,36	0,34	0,57
Yemen	Yemen	60,82	60,97	61,15	0,33	0,54
Switzerland	Switzerland	53,67	53,93	53,98	0,32	0,59
Panama	Panama	63,39	63,62	63,71	0,31	0,49
Burkina Faso	Burkina Faso	58,65	58,72	58,96	0,31	0,53
Congo	Congo	93,39	93,65	93,70	0,31	0,33
Venezuela (Bolivarian Republic of)	Venezuela (Bolivarian Republic of)	52,22	52,42	52,50	0,29	0,55
Australia	Australia	83,42	83,64	83,70	0,28	0,34
Angola	Angola	61,36	61,38	61,64	0,28	0,45
Serbia	Serbia	28,45	28,70	28,72	0,27	0,94
Rwanda	Rwanda	49,63	50,00	49,88	0,26	0,52
Iran (Islamic Republic of)	Iran (Islamic Republic of)	50,99	51,12	51,25	0,26	0,51
Belgium	Belgium	41,07	41,27	41,31	0,24	0,59
Thailand	Thailand	76,30	76,48	76,53	0,23	0,30
Indonesia	Indonesia	31,79	31,87	32,01	0,22	0,71
Germany	Germany	26,40	26,60	26,62	0,22	0,83
Jordan	Jordan	50,05	50,32	50,26	0,22	0,43
China, Taiwan Province of China	Taiwan	73,89	74,04	74,10	0,21	0,29
Czechia	Czechia	21,39	21,53	21,58	0,19	0,90
Austria	Austria	37,41	37,57	37,60	0,19	0,51
Hungary	Hungary	25,54	25,69	25,73	0,19	0,73
Canada	Canada	75,50	75,65	75,68	0,19	0,25

Countries	Bing map reference	2020	2025	2030	Difference	Rate of change
Netherlands	Netherlands	23,73	23,83	23,91	0,18	0,77
Tunisia	Tunisia	36,17	36,26	36,35	0,18	0,50
Slovakia	Slovakia	14,84	15,01	15,02	0,18	1,19
United Kingdom	United Kingdom	53,38	53,49	53,54	0,17	0,31
United States of America	United States of America	76,02	76,15	76,19	0,16	0,22
Mexico	Mexico	70,04	70,08	70,21	0,16	0,23
South Sudan	South Sudan	14,67	14,80	14,82	0,15	1,02
Qatar	Qatar	64,90	64,97	65,04	0,14	0,21
Chile	Chile	61,07	61,15	61,19	0,13	0,21
Haiti	Haiti	42,73	42,67	42,83	0,11	0,25
Uzbekistan	Uzbekistan	26,29	26,40	26,40	0,11	0,41
Norway	Norway	23,03	23,10	23,13	0,10	0,43
Cambodia	Cambodia	51,30	51,38	51,39	0,09	0,18
Italy	Italy	62,01	62,07	62,08	0,08	0,13
Zambia	Zambia	48,01	48,00	48,09	0,07	0,15
Armenia	Armenia	58,39	58,46	58,45	0,06	0,11
Bolivia (Plurinational State of)	Bolivia (Plurinational State of)	64,14	64,15	64,20	0,05	0,08
State of Palestine	State of Palestine	17,48	17,49	17,53	0,05	0,30
Uruguay	Uruguay	52,50	52,52	52,56	0,05	0,10
Israel	State of Israel	85,51	85,55	85,56	0,05	0,06
Ukraine	Ukraine	40,03	40,13	40,07	0,04	0,10
Ecuador	Ecuador	50,72	50,72	50,74	0,02	0,04
Portugal	Portugal	63,02	62,98	63,02	0,00	0,01
Paraguay	Paraguay	83,26	83,26	83,26	0,00	0,00

Countries	Bing map reference	2020	2025	2030	Difference	Rate of change
China, Hong Kong SAR	China, Hong Kong SAR	100,00	100,00	100,00	0,00	0,00
China, Macao SAR	China, Macao SAR	100,00	100,00	100,00	0,00	0,00
Singapore	Singapore	100,00	100,00	100,00	0,00	0,00
Argentina	Argentina	63,22	63,13	63,20	-0,02	-0,03
Cuba	Cuba	32,55	32,52	32,53	-0,02	-0,06
Kyrgyzstan	Kyrgyzstan	44,71	44,73	44,68	-0,03	-0,06
Ireland	Ireland	39,47	39,43	39,43	-0,04	-0,10
Ethiopia	Ethiopia	26,43	26,30	26,39	-0,04	-0,16
Philippines	Philippines	59,29	59,25	59,25	-0,05	-0,08
Egypt	Egypt	71,30	71,37	71,25	-0,05	-0,08
Puerto Rico	Puerto Rico	80,45	80,43	80,35	-0,10	-0,12
Liberia	Liberia	57,07	56,97	56,96	-0,11	-0,19
France	France	45,64	45,53	45,53	-0,11	-0,24
Algeria	Algeria	18,96	18,77	18,84	-0,12	-0,63
Eritrea	Eritrea	42,88	42,69	42,74	-0,13	-0,31
Turkmenistan	Turkmenistan	26,72	26,58	26,59	-0,13	-0,49
Republic of Korea	South Korea	82,81	82,68	82,66	-0,15	-0,18
Croatia	Croatia	28,91	28,82	28,75	-0,16	-0,55
Poland	Poland	26,12	26,14	25,96	-0,16	-0,62
Sri Lanka	Sri Lanka	15,53	15,44	15,35	-0,17	-1,10
Greece	Greece	44,81	44,63	44,61	-0,20	-0,44
Nigeria	Nigeria	53,76	53,38	53,56	-0,20	-0,38
United Republic of Tanzania	United Republic of Tanzania	46,79	46,52	46,55	-0,24	-0,51
Azerbaijan	Azerbaijan	53,31	53,01	53,06	-0,25	-0,47

Countries	**Bing map reference**	**2020**	**2025**	**2030**	**Difference**	**Rate of change**
Sierra Leone	Sierra Leone	34,80	34,54	34,52	-0,28	-0,80
Afghanistan	Afghanistan	59,14	58,85	58,83	-0,31	-0,52
Bosnia and Herzegovina	Bosnia and Herzegovina	20,01	19,70	19,65	-0,36	-1,79
Dem. People's Republic of Korea	North Korea	30,74	30,42	30,38	-0,36	-1,17
Namibia	Namibia	30,73	30,37	30,37	-0,37	-1,19
Uganda	Uganda	28,01	27,64	27,65	-0,37	-1,30
Morocco	Morocco	52,32	51,80	51,91	-0,41	-0,79
Tajikistan	Tajikistan	35,14	34,81	34,69	-0,45	-1,28
Georgia	Georgia	46,50	46,08	46,04	-0,46	-1,00
Romania	Romania	26,03	25,79	25,56	-0,47	-1,81
Kenya	Kenya	50,43	49,88	49,89	-0,55	-1,08
Chad	Chad	37,14	36,65	36,47	-0,67	-1,80
Nicaragua	Nicaragua	28,09	27,53	27,42	-0,67	-2,39
Trinidad and Tobago	Trinidad and Tobago	74,23	73,70	73,52	-0,71	-0,95
Jamaica	Jamaica	36,02	35,38	35,31	-0,72	-1,99
Djibouti	Djibouti	73,82	73,06	72,95	-0,87	-1,18
Mali	Mali	33,73	32,78	32,77	-0,96	-2,83
Iraq	Iraq	62,71	61,79	61,72	-0,99	-1,57
Côte d'Ivoire	Côte d'Ivoire	42,67	41,77	41,66	-1,02	-2,38
El Salvador	El Salvador	23,24	22,27	22,16	-1,08	-4,63
Papua New Guinea	Papua New Guinea	32,74	31,96	31,65	-1,09	-3,32
Oman	Oman	44,34	43,37	43,21	-1,12	-2,54
Guatemala	Guatemala	31,61	30,56	30,42	-1,19	-3,76

Countries	Bing map reference	2020	2025	2030	Difference	Rate of change
Republic of Moldova	Republic of Moldova	28,99	28,01	27,79	-1,20	-4,15
Senegal	Senegal	46,70	45,59	45,49	-1,21	-2,59
Lao People's Democratic Republic	Lao People's Democratic Republic	26,25	25,04	24,95	-1,30	-4,94
Sudan	Sudan	57,41	56,30	56,01	-1,40	-2,43
Guinea	Guinea	38,23	37,02	36,81	-1,42	-3,71
Malawi	Malawi	58,11	56,89	56,51	-1,60	-2,75
Niger	Niger	44,50	43,28	42,82	-1,67	-3,76
Central African Republic	Central African Republic	42,82	41,45	41,14	-1,68	-3,93
Mozambique	Mozambique	45,46	43,85	43,67	-1,78	-3,92
Gabon	Gabon	43,04	41,42	41,12	-1,92	-4,47
Togo	Togo	50,94	49,09	48,88	-2,06	-4,04
Gambia	Gambia	31,40	29,48	29,30	-2,10	-6,69
Zimbabwe	Zimbabwe	44,81	42,33	41,70	-3,11	-6,94
Syrian Arab Republic	Syrian Arab Republic	84,60	77,11	78,27	-6,34	-7,49

Source: UNDESA population prospects database 2019 [online]. Available from https://population.un.org/wpp/DataQuery/ [Accessed 4 October 2019].