Chapter 3
Multi-Agent Systems for Urban Planning

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ABSTRACT

Cities provide homes for over half of the world's population, and this proportion is expected to increase throughout the next century. The growth of cities raises many questions and challenges for urban planning including which cities and regions are most likely to grow, what the pattern of urban growth will be, and how the existing infrastructure will cope with such growth. One way to explore these types of questions is through the use of multi-agent systems (MAS) that are capable of modeling how individuals interact and how structures emerge through such interactions, in terms of both the social and physical environment of cities. Within this chapter, the authors focus on how MAS can lead to insights into urban problems and aid urban planning from the bottom up. They review MAS models that explore the growth of cities and regions, models that explore land-use patterns resulting from such growth along with the rise of slums. Furthermore, the authors demonstrate how MAS models can be used to model transportation and the changing demographics of cities. Through these examples the authors also demonstrate how this style of modeling can give insights into such issues that cannot be gleamed from other modeling methodologies. The chapter concludes with challenges and future research directions of MAS models with respect to capturing the dynamics of human behavior in urban planning.

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INTRODUCTION

In the year 2009, for the first time in history, more people lived in urban areas than in rural areas. By 2030, the global urban population is expected to contain 59% of the total world population (UN-Habitat, 2010). This expected growth will present many challenges, especially with respect to land-use planning, housing and transportation. For example, how will land-use change, where will people live, and how will the existing transport infrastructure cope with such increases? These are all important challenges with respect to urban planning. However, as each of these questions has their own associated problems (which we will discuss below), the combination of all of them represents an even greater challenge. This is compounded by the fact that the heterogeneous nature of cities makes it difficult to generalize localized dynamics up to the level of city-wide problems (Crooks, 2012), in the sense that the city is more than the sum of its parts. Our understanding of cities has increased throughout the twentieth century, incorporating ideas and theories from a diverse range of subjects including economics, geography, history, philosophy, mathematics and more recently computer science; however, it is now very clear that there are intrinsic difficulties in applying such understanding to policy analysis and decision-making (Wilson, 2000).

This relates to the notion that human behavior cannot be studied, understood, or predicted in the same way as the subjects of those sciences which explore the physical or chemical world (Wilson, 2000), in the sense that people do not behave as atoms or molecules. The effort to gain a greater understanding of urban problems such as sprawl, congestion, and segregation has recently lead researchers to focus on a bottom-up approach to urban systems, specifically researching the reasoning by which individual decisions are made. One such approach is Agent-Based Modeling (ABM) or Multi-Agent Systems (MAS), which allows one to simulate the individual actions of a diverse group of agents, measuring the resulting system behavior and outcomes over space and time. Some have classed this as a 'new wave' of urban modeling (Torrens, 2002) which can potentially address some of the weaknesses of previous generations of urban models. These improvements include incorporating dynamic feedback mechanisms, greater levels of detail, user interaction, flexibility, behavioral realism, and aggregation of different spaces (Torrens, 2000) when it comes to exploring cities and regions. That is not to say that previous generations of urban models were no good (as put forward by Lee, 1973) but more that these models were being developed when urban planners were just learning how to model cities and regions (Batty, 1994). With advances in computing and data availability, 'traditional' urban models have been extensively developed and applied to numerous applications around the world (see Wegener, 1994 for a review). Interested readers might want to read Batty (1976), which provides a detailed summary of the first generation of urban models.

'Traditional' urban models often focused on aggregate populations and dealt with residential or employment distributions within cities. However, issues such as inequalities between rich and poor, segregation along ethnic lines, or the redevelopment of urban areas are not well suited to traditional styles of urban modeling, and these issues raise questions about how best to handle such questions (Batty, 2005). We, along with others (e.g. Batty, 2005; Heppenstall et al., 2012a), argue that MAS models provide a good test bed for developing new models of cities. MAS and cities both operate on a cross-scale basis and are highly dynamic in both space and time. In cities interactions propagate through urban systems, from flows and relationships between individuals in space to regional scale geographies. But why do we need to develop models and what do we hope to achieve with them? Several authors have addressed this question for modeling in general (e.g. Lowry, 1965; Epstein, 2008). Modeling provides a particularly important medium for urban planning because of the countless economic, social, and environmental factors that affect the study and management of urban systems but are notoriously difficult to incorporate in urban planning (Torrens, 2000). Modeling also allows us to explore and test theories and practices about urban systems in a controlled computer environment, thus allowing scientists to understand urban phenomena through analysis and experimentation, a traditional goal of science (Batty, 2005). Urban modeling is equally important to planners, politicians, and the community to predict and invent urban futures (Batty, 1976). Policy measures regarding urban sustainability questions including growth management, congestion pricing, and pollution migration schemes can be explored via modeling to generate a range of scenarios for urban futures, allowing science to support decision-making.

The remainder of this chapter introduces the theory of MAS models, linking it to complexity theory before exploring several application areas where we believe MAS models have great potential. These application areas range across a broad scale of human activities, including modeling the growth of cities, regions, and specific urban areas; transportation throughout metropolitan areas; and the changing demographics of cities. One common theme across all these applications is their focus on urban problems from the bottom-up, in the sense that the aggregate structures (e.g. urban extent, congestion etc.) emerge from the complex interactions of many autonomous individuals. Finally, we will present future research directions and challenges with respect to using MAS for urban planning with a specific emphasis on human behavior. In each section, we provide a brief overview of various styles of models that have been used in the past before presenting MAS models.

BACKGROUND

Urban systems are constantly changing due to natural processes such as the growth or decline of populations and economies. Examining how they are affected by such change is a non-trivial task. These responses can be manifested in land-use change, the gentrification of neighborhoods, or residential segregation. Such processes are some of the core questions in understanding urban systems, especially how an individual's decisions impact other individuals. It is evident that cities are in constant flux: the processes seen within them are dynamic, and all of them take place at different spatial and temporal scales. Only through modeling can one gain insight into these processes and their interdependencies. Specifically, it has long been recognized that cities are problems of organized complexity (Jacobs, 1961). Cities present situations in which half a dozen quantities are all varying simultaneously and in subtly interconnected ways. Change is only noticeable when different patterns become discernable, but before change at the macro-level can be seen, it is taking place at many micro-levels (subsystems) simultaneously. All of these micro-level subsystems interact separately, together forming a complex Web of interactions (Holland, 1995). In essence, cities are more than a simple sum of their parts (Batty, 2005). To explore cities by studying the individual entities that make up such a system is to move away from traditional urban modeling and offers a potential new lens for understanding of cities. Previous urban theories examined the city as a whole, based on aggregate analysis; focusing on the individual at the micro-level offers a way to examine dynamics that take place within urban systems yet are difficult to observe in macro-trends (Batty, 1995).

Urban systems provides many examples of self-organization and emergence (Torrens, 2002); for example, local-scale interactive behavior (e.g. commuting) of many individual objects (e.g.

vehicles) gives rise to structured and ordered patterns, which emerge in aggregate forms like peak-hour traffic congestion (Nagel et al., 1997). In urban economics, large-scale economies of agglomeration and dispersion have long been understood to result from local-scale interactive dynamics (Krugman, 1996). Additionally, cities exhibit several signatures characteristic of complexity, including fractal dimensionality and self-similarity across scales (Batty & Longley, 1994), self-organization (Allen, 1997), and emergence (Portugali, 2000).

The growth of MAS coincides with how our views and thinking about urban systems have changed. Rather than adopting a reductionist view of systems, whereby the modeler makes the assumption that cities operate from the top-down so that results are filtered to the individual components of the system (see Torrens, 2003, for a review), people are now adopting a reassembly approach to study urban systems, in the sense of building the system from the bottom-up (O'Sullivan, 2004). This change follows the realization that planning and public policy do not always work in a top-down manner. The aggregate conditions one sees within urban systems develop from the bottom-up, from the interaction of a large number of elements at a local-scale thus policy and planning need to adapt to this realization and consider urban systems from the bottom-up (Pickles, 1995). Therefore there is currently a move towards individualistic, bottom-up explanations of urban form and behavior, which synthesizes nicely with what we know about complex systems.

While an exact definition of complexity is hard to pin down, as the term has different meanings to different people (Manson et al., 2012), the main characteristics of complex systems are self-organization, emergence, non-linearity, feedback, and path dependence. Together, these concepts provide a new way of thinking about cities and new tools for solving the problems faced by cities. Emergent phenomena are characterized by stable macroscopic patterns arising from the local interaction of individual entities (Epstein & Axtell, 1996). A small number of rules or laws, applied to many entities at a local level, are capable of generating complex global phenomena. Collective behaviors, extensive spatial patterns, hierarchies etc. are manifested in such a way that the actions of the parts do not simply sum to the activity of the whole. Thus, emergent phenomena can exhibit properties that are decoupled (i.e. logically independent) from the properties of the system's parts. For example, a traffic jam often forms in the opposing lane to a traffic accident as a consequence of 'rubber-necking'. Studying the behavior of collections of entities focuses attention on relationships between entities because before change is noticed at the aggregate level, it has already taken place at the micro-level (O'Sullivan, 2004). The characteristics of emergent phenomena make them difficult to understand and predict, particularly as emergent outcomes can be counterintuitive (Epstein, 1999). Furthermore, the importance of history/path dependence makes models based on such notions very sensitive to initial conditions and to small variations in interaction rules (Brown et al., 2005). Using such models for prediction can therefore be challenging (Crooks et al., 2008). Despite this, complexity theory has brought awareness of the subtle, diverse, and interconnected facets common to many phenomena, and continues to contribute many powerful concepts for MAS models. By combining complexity and MAS we obtain a new tool to 'think with' and therefore support decision-making. In a sense, MAS models can be used as decision support tools (e.g. Brail, 2008) to sketch out alternative futures.

There are several key features of MAS models that make them attractive for use in studying cities and as a tool for complexity science more generally. First is their ability to model multiple units autonomously (i.e. without the influence of centralized control), with those units situated within a model or simulation environment. Secondly, MAS models allow for the representation of a heterogeneous population; as a consequence, the notion of a mean individual is redundant, a common assumption of past urban models (Torrens, 2002). This notion of individual agents permits the representation of autonomous individuals, each behaving differently. For example, an agent representing a human could have attributes such as its age, sex, job, and so forth, all of which could impact on its decision of where to locate (Crooks, 2007). Groups of agents (e.g. households, crowds, etc.) can be created, but these are spawned from the behaviors of individuals from bottom-up, and are thus amalgamations of similar autonomous individuals. Heterogeneity also allows for the specification of agents with varying degrees of rationality (Axelrod, 2007). This offers advantages over methodologies that assume perfectly rational individuals, if they consider individuals at all. Thirdly, agents are active because they exert independent influence in a simulation. These autonomous units are capable of processing information and exchanging this information with other agents in order to make independent decisions. Relationships between agents are specified, linking agents to other agents and/or other entities within a system. Relationships may be specified in a variety of ways, from simply reactive (i.e. agents only perform actions when triggered to do so by some external stimulus) to goal-directed (i.e. seeking a particular goal). Agents can be designed to alter their state depending on their current state, permitting agents to adapt with a form of memory or learning (see Conte et al., 1998; Crooks & Heppenstall, 2012 for further reviews on the properties of agents and MAS modeling).

The ability of MAS models to describe the behavior and interactions of a system additionally allows for system dynamics to be directly incorporated into the model. This represents a movement away from the static nature of earlier styles of urban modeling, a feature which was one of their major failings (see Batty, 2008). While time in MAS models is still discrete in that it moves in ‘snapshots’, the time steps may be small enough to approximate real time dynamics. To an extent, this can be understood as a strength of MAS models as it is apparent that different urban processes occur in space and over different time scales (Liu & Andersson, 2004). For example, the location of residents and businesses is affected by long-term processes, such as economic cycles and transportation projects, as well as short-term events in the form of daily commuting or hourly social interactions. MAS models can incorporate these different time scales into a single simulation by using a variety of automata clocks designed to mimic the temporal attributes of the specific urban process under study (Benenson & Torrens, 2004), thus allowing the modeler to realistically simulate urban development (O’Sullivan, 2001). As one might expect, the choice of time in terms of both an event-scheduling approach and a temporal resolution can have important consequences for the behavior of the model (see Brown et al., 2005 for a more detailed discussion). In relation to urban dynamics, the ability to model different aspects of time is highly appealing. It is not just different temporal scales that can be incorporated within a MAS model: different spatial scales can be included as well. This flexibility is extremely important as it is the phenomena of interest that should determine the appropriate scale, not the modeling methodology. Examples of this range from the micro-movement of pedestrians within a building during an evacuation (e.g. Helbing, et al., 2000); to the movement of cars or people on a street network (e.g. Crooks & Wise, 2013); to the study of urban growth at a more macro-scale (e.g. Torrens, 2006). Additionally, as MAS allows for the representation of individual objects, it is possible to combine these objects to represent phenomena at different scales within the same model. This means MAS models can be useful tools for studying the effects of processes that operate at multiple scales and organizational levels (Brown, 2006). The utility of MAS models and ideas from complexity science have not been limited to urban planning, but have been recognized and applied across a broad range of fields. MAS models have also been developed in numerous disciplines including: economics (e.g. Tesfatsion & Judd, 2006), ecology (e.g. Grimm & Railsback, 2005), biology (e.g. Kreft et al., 1998), and geomorphology (e.g. Reaney, 2008), to name but a few. In the next section, we highlight how MAS can be used as a tool for exploring urban issues in specific application domains that are associated with urban growth and demographic change.

APPLICATIONS OF MULTI-AGENT SYSTEMS FOR URBAN PLANNING

Urban and regional planners are often interested in knowing the potential evolution of urban system within a country, the geographical extent of an individual city, and the land-use patterns within cities. Similarly, urban planning focuses on specific sectors such as urban transportation and housing. Within this section, we discuss MAS models that have been developed to understand these various aspects of urban planning.

The Growth of Cities and Regions

As noted above, cities provide homes to over 50% of the worlds population; however, not all cities grow at the same rate. What causes some cities to grow more than others, and what can be learned from modeling the evolution of cities and regions? How could this modeling approach help with urban planning? We know that cities tend to evolve from small settlements: from hamlets, to villages and into larger forms (Batty, 2004). One of the remarkable emergent facts of this evolution is that together, settlement sizes often conform to a power law (Zipf, 1949), in the sense that the rank of the population in continents, countries, and counties are all scalable. While Zipf documented the distribution of city sizes, he had limited success in explaining the emergence of such a system. This has lead modelers to attempt to grow such systems from the bottom up. For example, Batty (2001) demonstrated how one could generate rank size city distributions based on positive feedback between cities, while Semboloni (2008) looked at the demand and supply of goods and services between cities to explain their rank size disruptions. At a national level, Gulden and Hammond (2012) produced a model that was able to generate the rank-size distributions of cities for France, Russia, and the USA from individual entities interacting from the bottom up. One thing that all these models suggest is the evolution of such hierarchies is highly path dependent; history dictates on how they evolve and how they restructure. While this is not a new notion (see Arthur, 1988), it does demonstrate how notions of complexity are being introduced into urban modeling.

Moreover, the interactions between cities and the ways in which they evolve are based on social and economic conditions, as well as the interactions between towns and cities. Understanding such interactions among cities is important because these interactions impact an individual city. This area of study goes back a long time: Central Place Theory (Christaller, 1933) aimed to explain the size and spacing of human settlements based on the notion that centralization is a natural principle of order and that human settlements follow it. The theory suggests that there are laws that determine the number, size, and distribution of towns based on the functions of markets. Firms are assumed to maximize profits when producing goods and services and selling them to a population. People are assumed to minimize transport costs in purchasing the goods and services they require. The geographical system is assumed to consist of a uniform distribution of population (both in terms of density and purchasing power) and a ubiquitous transport system in which transport is equally easy in all directions on a uniform flat plain. Space is thus treated in continuous terms as an isotropic landscape.

The basic economic assumption of the Central Place Theory is that for any good, there is a demand curve relating price and quantity purchased, and the quantity purchased is assumed to fall with distance (i.e. all goods have a range, beyond which no purchases are made). The other assumption is that there exist thresholds, or minimum areas that will support the provision of a given good or service. These two assumptions relate to a development of varyingly sized markets (or centers) throughout the region, based on the notion of the order of a good: low range and low threshold goods (e.g. food) correlate with low order settlements, and vice versa, thereby creating a hierarchy of settlements. Using these principles, Christaller (1933) proposed that there would be many low order centers and fewer higher order centers supplying higher range goods (e.g. specialty goods), all nested within a hierarchy of settlements. The model is consistent with a scaling or rank size law relating to the size of settlements. However, criticisms of Central Place Theory focus on it being static, as it does not incorporate the temporal aspect in the development of central places (i.e. path dependency). It also fails to offer any account for competition between settlements, thanks to the notion of non-overlapping market areas. Additionally, while the theory assumes that services are largely determined to serve an agricultural landscape, this is not the case for industrial or post-industrial areas, due to the different characteristics of their services.

However, the use of MAS models can address these limitations and it is perhaps fitting to start our discussion of the uses of MAS with respect to cities, exploring models that simulate the evolution of settlement patterns. For this we turn to the family of SIMPOP models (see Pumain, 2012 for a review). SIMPOP1 was the first MAS model published within the geographical literature (Bura et al., 1996; Sanders, et al., 1997) and attempted to identify the conditions that would lead to the emergence of a functionally differentiated system of towns and cities from an initial homogeneous rural settlement system over time. However, unlike other MAS models discussed in this chapter, the cities themselves are the individual entities within this model. This relates back to the way agents can be used to represent many different types of entities, as discussed above. More recently the SIMPOP models have been used to simulate European cities from the Middle Ages to the year 2000 (Pumain et al., 2009), as well as the evolution of settlement patterns in the USA (Bretagnolle & Pumain, 2010). The novelty of such models is that they simulate urban units competing for resources from the bottom up, which results in a hierarchy of cities similar to those observed by Zipf (1949) and Christaller (1933). With the study of urban systems expected to evolve further, this genre of models could prove useful. For example, once the SIMPOP models are validated they could be used in predicting urban hierarchies in Europe in 2050 (Sanders et al., 2005) or for other areas around the world. Because cities grow as a result of rural-urban migration as well as natural growth (e.g. births), we now turn to the urban growth of particular cities and the challenges associated with modeling this.

Urban Growth

While the above section dealt with modeling the evolution of cities and regions over time, such models do not emphasize the urban extent or its spatial footprint. Nonetheless, the questions of urban extent and spatial footprints of cities are important for urban sustainability. Several MAS models have been built to explore these questions as we will discuss in this section.

Cities have continued to grow over the last 200 years and show little sign of slowing down. Physically, they can grow in two different ways: expansion and compaction. The process of expansion leads to more space being occupied (e.g. sprawl); compaction leads to the same amount of space being occupied by more people, resulting in increased population density. Not only do cities grow physically, but they also come to require more water, building materials, food, goods, and services from the surrounding region, which results in population, economic activities and technology diffusion (as discussed above). The motivations for urban planners to want to model such processes should be obvious. If we can understand and model urban growth, we can not only raise awareness of the consequences of urban growth but also test out policy ideas (e.g. restricting growth on specific land-use types or promoting higher density development) to see how these policies might impact future land-use patterns.

Many 'traditional' urban growth models have focused on aggregate measures, for example by aggregating the population of an area or taking averages of income, tastes, and preferences when implementing the model. Often this is the case for spatial interaction models (e.g. Fotheringham, 1983; Wilson, 1971) and discrete choice models (e.g. de la Barra, 1989) where residents are assigned to areas based on some measure of attractiveness (e.g. distance to work, cost of land). This attractiveness can then be used for forecasting the demand for housing or employment (see Wilson, 2000). In general such models are deterministic and based on rules at the aggregate level; little attention is given to individual behavior, and the model includes limited heterogeneity or detail of the area (Torrens, 2000). Since many of the processes within a city operate at a finer resolution, this lack of detail may, in some cases, be regarded as a serious limitation of 'traditional' models for urban applications. This has led to a call for greater emphasis on disaggregated units rather than aggregate analysis when it comes to modeling cities (e.g. Harris, 1994; Lee, 1994; Wegener, 1994), and this has been facilitated with the development of sophisticated geographical information systems (GIS), remote sensing, and the availability of other detailed datasets (e.g. census data).

It was not until the 1990s that geographers started to explore urban systems at the individual level. This also coincided with the rise in digital data (especially remote sensing) and increased computer power that allowed urban modelers to explore these fine scale processes (Batty, 1997). Early efforts to model urban growth through the lens of complexity took the form of cellular automata (CA) models. Initially CA models exhibited several limitations, including homogenous behavioral rules insofar as the transition rates (e.g. the chance of any given parcel of land going from rural to urban land-use) were uniformly applied to all cells. CA had difficulties in accounting for regional or long distance interactions, or the incorporation of density (intensity) of activities. These limitations made it difficult to model flows like retail center competition, travel to work costs, and so forth (White, 1998).

In order to overcome the limitations of CA with respect to urban applications, several researchers have modified CA for urban planning purposes. For example, Wu (1998) developed a CA model to explore polycentric urban growth with respect to population density and Batty et al. (1999) assessed the role of density constraints in land development. Landis (1994) along with White and Engelen (1997) explored land-use transition linked to regional economics and demographics. Perhaps the most widely used CA model in context of urban modeling is that of Clarke et al. (1997) which explored the development of urban form. Numerous researchers have applied the model to cities around the world (see Clarke et al., 2006 for a review). However, these models focus only on urban growth via expansion, a process which results in urban sprawl and which has been made possible through the greater mobility of people (e.g. due to the car) and their preferences for more space and lower densities. A key aspect in developing a model is the process of verification and validation (Crooks et al., 2008), and with respect to CA models this is an active field of research. Several techniques have been developed for comparing model results to real world data (e.g. Visser & de Nijs, 2006; Pontius et al., 2008).

More recently researchers have started to combine MAS and CA models to explore urban growth, making them more 'agent-like' (Batty, 2005). This is in response to a variety of challenges, principal among them the difficulty of adequately modeling mobile entities within CA models (e.g. pedestrians, vehicles). Another major limitation is the inability to apply heterogeneous behaviors to all cells within CA models. Examples of this synthesis of MAS and CA include the work of Torrens (2006) who combined GIS data, a CA, and a MAS model to explore sprawl in Michigan. Along a similar line, Xie et al. (2007) explored urban growth in China and used agents to explore pressure on land from developers. Such models place more emphasis on the individual decision maker than on the transition potential of cells within CA models or the aggregate flow of people within 'traditional' urban models.

Because land-use change has temporal, spatial, and behavioral components, exploring urban growth through the combination of CA and MAS is a promising approach. By combing CA and MAS, urban modelers are able to capture all three of these elements (Torrens, 2002). This was not possible with previous generations of urban models (e.g. spatial interaction models) as they focused on equilibrium outcomes rather than the dynamics of the urban system (Batty, 2008). However, as noted above, cities are in constant flux and therefore it is important to capture such dynamics within models. It has also been argued that the combination of CA and MAS provide a more decentralized view, allowing for the exploration of urban systems from the bottom up (Torrens, 2002). Some call this class of models cell space models (Batty, 2005). Combining the two methodologies allows urban modelers to explore human behavior as well as how such behavior impacts urban growth patterns. For example, urban land markets are not captured in many CA models but are important determinants in land use change, given that land is one of the three basic factors of production in an economy and special because (unlike labor and capital) it is finite.

Land markets arise when land is traded (UN-ESCAP, 1998). Urban modelers are often interested in land markets because both residents and businesses face the fundamental question of where to locate, a choice that necessitates a trade-off between many factors and choices (e.g. dwelling type, space requirements, or location). Residential locational choice also varies with life cycle stage, social class, neighborhood preferences, income, ethnicity, gender, and so forth (McCarthy, 1982). Land price trends are an aggregate outcome of agent interaction in the land market. Classical urban theories such those of as Burgess (1927) and Hoyt (1939) often focus on the urban spatial structure but provide idealized insights into the relationship between urban land-use and its drivers, insights based on many simplifying assumptions. Similarly, Alonso (1964) explains rent-gradients using homogeneous agents subject to perfect competition and the rational choice paradigm; however, his model does not include any dynamics about how the system has evolved. He assumed that the locations of households were a trade-off between the size of house, the distance from the city center (transportation costs), and spending on other goods. In his model, households allocate a fixed budget to these three items with the aim of maximizing their utility: these trade-off results in a residential land-use pattern. Such models abstract key elements from the real world and use these elements to describe how the system might look under certain conditions, providing a theoretical economic base on which contemporary models can be built (Parker et al., 2002). For example, Crooks (2007) developed a MAS model to dynamically simulate the evolution of land-use patterns and rent-gradients in a mono-centric city. Such a model shows how dynamics can be added to static theories. We would argue that MAS models allow us to further explore the evolution of the system and account for other factors such as heterogeneous population, imperfect competition, and limited knowledge (Tesfatsion & Judd, 2006) which were not possible to accommodate in past modeling endeavors.

There are only a handful of models that explore land markets. These include the work of Sasaki and Box (2003) who demonstrated how a collection of autonomous individuals operating in cellular space can contribute to the formation of an optimal land-use pattern as described by von Thünen (1826). Hammam et al. (2004) extended the Sasaki and Box (2003) model to include irregular cells for farm parcels. In their model, the cells have the ability to change shape, growing or shrinking depending on competition for land and profits derived from growing a particular crop. However, today most land-use change is seen at the urban-rural fringe (Parker et al., 2012), resulting not from individual farmers competing for land but from developers buying farmland and so forth. This trend has lead researchers to explore models of competing land-uses. For example, Parker and Meretsky (2004) used the von Thünen model as a basis of a MAS model to explore conflicts between urban and agricultural land-uses which affect the value of particular land at the urban-rural fringe. More recently, Filatova et al. (2009), Magliocca (2012) and Wise and Crooks (2012) have explored how heterogeneous agents representing farmers, developers, and buyers could influence the spatial pattern of residential development through interactions in the land market. The results from such models are in accord with the classical urban theory (e.g. Alonso, 1964), in the sense that as the distance from the central business district increases, land prices and housing density decrease, a pattern which is also empirically observed in many US cities. By building on such models, one can explore how various planning scenarios like lot-size zoning and municipal land acquisition strategies could reduce the impact of urban sprawl (Robinson & Brown, 2009).

It is not just what is happening at the urban-rural interface that is important, but also how do people decide where to locate within a city. By focusing on how people choose to buy a house at a specific location within an urban area, MAS modelers are also able to explore how housing markets evolve from the bottom up. For example, Gilbert *et al*. (2009) modeled how house prices evolved from the interactions of buyers, sellers, and estate agents (realtors) within an artificial world. Moreover, such models can also incorporate macro-level factors such as economic conditions relating to interest rates, employment, availability of housing stock, government taxation, and legislation with respect to buying and selling a house. MAS models provide us with a means to explore not only how a city might grow but also why people make decisions on where to live. A greater understanding of both the potential growth trajectories and the possible restructurings of cities could potentially help planners better anticipate what the future might hold.

The Challenge of Slums

Coinciding with urban growth is the rise of slums, especially in developing countries (Patel, et al., 2014). Over 900 million people live in either slums or squatter settlements, a number that is projected to increase to approximately 2 billion by 2030 (UN-Habitat, 2003). Most of this growth is expected to occur in the developing world, especially in Asia and Africa (UN-Habitat, 2010). It is predicted that many large cities in developing countries will nearly double their population by 2020, but the development of formal housing will not be able to keep pace with this rapid urbanization (UN-Habitat, 2003). Just as MAS has proved useful in exploring urban growth, we believe that it will be a useful tool to study questions about how slums come into existence, how they expand, and which processes may make some slums disappear. We believe this is especially true because MAS modeling is inherently dynamic and focused on the individual behaviors that manifest in the formation of slums. However, there has been little work with respect to slum modeling from the specifically MAS perspective.

As with other urban challenges, there have been previous efforts to model slums. Slum formation has been a subject of interest for several disciplines: urban geography, economics, sociology, politics, environmental science, and demography, to name but a few. There have been several attempts to explain the forces behind slum formation. The Burgess (1927) model, the pioneer of the 'Chicago School', was perhaps the first model in urban geography to identify where 'working men's housing' and 'zones in transition' were located, highlighting ghettos and slums in inner city locations. Over time the 'Chicago School' became more rigorous with the advances in neo-classical economics. In particular, the works of Alonso (1964), Muth (1969) and Mills (1972) which demonstrated how a 'rent-gradient' of declining prices and rents away from the center could be calculated to predict the locations of various groups of people within a city.

There have been several attempts to explain slum formation using urban census data with models largely known as factorial ecology (see Janson, 1980 for a review). Amongst them is Shevky and Bell's (1955) model of social area analysis, which showed that households were spatially separated from each other based on five key factors: i) socio-economic status, ii) familism, iii) ethnicity, iv) accessibility/space trade-off and v) socio-economic disadvantage. While such work allows one to define different areas in a city, the approach has often been criticized for lacking a link between theories of social change and the realities of areal differentiation within cities (Johnston, 1971). For example, these works tell us little about the behavior and reasoning of why people decide to move to a specific type of area.

The majority of previous models that explored slum formation and city growth approached the problem as a static phenomenon (e.g. Alonso, 1964), an assumption which has been challenged with the growing realization that urbanization and slum formation are largely dynamic processes. Dynamic models such as MAS that accommodate this flux and complexity are thus called for (Batty, 2005). A simulation approach also provides us an opportunity to explore the possibility of subsystems (e.g. slums) being complex themselves but also being a part of an overall complex system (e.g. the city).

While there is a growing amount of work focusing on MAS models and urbanization (as discussed above), the use of MAS for exploring slum formation is still in its infancy. Only a handful of attempts have been made to explain slum formations using MAS, principal amongst them Sietchiping (2004); Barros (2005); Vincent (2009); and Augustijn-Beckers et al. (2011). Sietchiping's (2004) CA model is one of the earliest simulation-based attempts to predict informal settlements as a type of land-use, adapting the CA-based urban growth model originally developed by Clarke *et al*. (1997) to incorporate informal settlements. However, such a model does not capture individual behavior and focuses more on mathematical cell transitions from previous states of the system. One of the first MAS models to incorporates household behavior with a particular focus on slums is that of Barros (2005). The model explored how decentralized decision-making can be incorporated into slum modeling. Augustijn-Beckers et al. (2011) advanced MAS modeling in the slum literature by creating a model based on empirically founded behavioral rules to predict the geometry of slum layouts. Further, Vincent (2009) demonstrated that socio-economic characteristics of a city's inhabitants play a significant role in shaping the growth patterns of informal settlements.

Building on these models, Patel et al. (2012) identified four main points. The first is that explicit modeling of the spatial environment is important, as slums emerge in distinct areas. Secondly, slums are a result of human-environment interactions. Thirdly, individual households make locational choices. Lastly, local government plays an important role, as it has the power to take city-wide actions such as slum eviction or slum up-gradation, to alter slum conditions or to eradicate them. While previous models incorporate one or some of these aspects, none of them incorporate all of them into a single modeling framework. Patel et al. (2012) attempt to model a city system where several slums form, grow, and disappear as a result of human-environment interactions at multiple spatial scales. For example, the household level behavior is confronted with the city level political forces in a multi-scale environment. This point of view calls for creating a human-environment interaction model where the human behavior is modeled in a multi-scalar spatial environment. Hence, the model attempts to incorporate the complexity of urban morphology with the social complexity of human behavior in a stylized manner. Although multi-scale modeling of urban systems is not a completely new idea with respect to MAS (e.g. O' Sullivan, 2009), the Patel et al. (2012) model is the first attempt to build a multi-scale model of slum formation. However, there is still much to be done with respect to modeling and improving our understanding of slums.

Transportation

Traffic congestion is the norm for many cities around the world such as Los Angeles and San Francisco in the United States; Istanbul, Turkey; London in the United Kingdom; Warsaw, Poland; Rome, Italy; and Beijing, China, to name but a few. The cost of congestion is not only the time citizens spend in traffic jams, but also pollution (e.g. SO_2 CO_2) and traffic accidents. As more and more people are living in cities, an efficient transportation system is essential for urban futures (Banister et al., 1997). As finer resolution data including remotely sensed images have helped the development of urban growth models, advances in GIS provide a mechanism for storing, manipulating, and visualizing spatial data to create artificial worlds in which agents interact.

Most urban simulation models rely on transport accessibility as the primary determinant of growth or decline of an area (Batty, 1976). However, it is not just a determinate with respect to urban growth: transportation plays a key role with respect to how easy it is to move around the city. The cost of transportation plays a large role in determining where individuals decide to locate themselves. In the more traditional styles of urban models such as spatial interaction models, access to transportation was one of the key determinants used for assessing the attractiveness of an area. Due to the importance of transportation and its effect on city life, several MAS models have been developed to explore how traffic patterns arise from the bottom up. MAS is inherently suited to model transportation applications, particularly because route choice is an individual decision (e.g. commuting to and from work) and traffic congestion is a direct result of these kinds of individual behaviors. Agents in such models are typically individual travelers, which can make independent decisions about their actions (Raney et al., 2003). What emerges from the micro-movements of individuals are macro-patterns, such as traffic congestion (e.g. Beuck et al., 2008) and densely packed subways (e.g. Samuelson et al., 2008). This approach replaces the static and reductionist approaches of past transportation models, and in the same way it can replace 'traditional' urban models which treat systems as simple top-down aggregations of the systems parts (Helbing, 2001; Torrens, 2004). In the sense that 'traditional' models provided an aggregate representation of traffic, typically expressed in terms of total flows per hour (e.g. Fox, 2005). Within these models, all vehicles of a particular group obey the same rules of behavior. As with urban growth models, spatial interaction models have been the cornerstone of transportation models (see Waters, 2005); however, as noted above these types of models focus on aggregates of population movement (i.e. aggregate flows) and not the individual. Moreover, 'traditional' models focused on route choice based on the shortest path in terms of in terms of time, distance, and cost (e.g. Lee & Tomlin, 1997) for determining location-allocation for trip assignment (e.g. Nyerges, 1995) which does not have to be the case within MAS models.

As with urban growth, CA models were the first to show the utility of modeling traffic at the individual level. These models ranged from cars moving along in single line of traffic (e.g. Nagel & Schreckenberg, 1992) to model simple two-lane traffic (e.g. Rickert et al., 1996) to emulating the size-frequency distributions for traffic jams (e.g. Nagel & Rasmussen, 1994). Such model have been greatly extended not only through the availability of rich spatial datasets but also by using concepts from microsimulation to build 'realistic' synthetic populations (Cameron & Duncan, 1996; Beuck et al., 2008) which now allow us to explore route choice behavior at the individual level. In such models, congestion emerges as a result of interaction between the individuals from these realistic synthetic populations. For example, the TRansportation ANalysis SIMulation System (TRANSIMS) creates a synthetic population which is used to simulate people's daily activities (such as going to work) at an individual level (Nagel et al., 1999). Such models can be used to estimate pollution and can be used as a planning support system (e.g. Brail & Klosterman, 2001). Just as MAS models of urban growth can be used to explore alternate futures, transportation models can give insight into future traffic conditions.

MAS models have been used to explore many traffic related issues, as the methodology can be used to simulate thousands of individual cars and test the impact of various aspects of the system being modeled. Researchers have studied what the mechanisms of stop and go traffic are (Helbing, 2001); the impact of new radial highways on congestion (e.g. Makarov et al., 2008), the potential for accidents between cars and people (e.g. Banos et al., 2005); the impact of tolls for entering an area (Takama & Preston, 2008); how severe weather can impact the flow of traffic (Zhao & Sadek, 2012); evacuation routing (Thorp et al., 2006); the effects of restricted parking (Benenson et al., 2008); the impact of a closure of a section of a road (Manley et al., 2011); or how one can improve the flow of traffic during the journey-to-work by combining traffic light controls and speed limits (Nagel, 2003). Once the dynamics of traffic are understood, one can then potentially link such models to other types of models such as urban growth models to explore what future urban development patterns might look like (e.g. Miller et al., 2004; Troy et al., 2012) and how these patterns will, in turn, affect commuting. Traffic models can also be linked to epidemic models since the transportation systems also play a role in the spread of diseases (e.g. Barrett et al., 2005). Thus, if we know how people move about an urban area, we can potentially model the spread of diseases as well.

Changing Demographics and Urban Restructuring

Apart from dealing with population growth and the resulting expansion of urban areas in the coming decades, cities will also face the challenge of substantial aging within their populations as a result of rising life expectancies (United Nations, 2003). This will be especially acute in the developed world. There are few MAS models that explore these issues, and such analysis tends to focus on microsimulation techniques (see Birkin & Wu, 2012 for a review) developed for exploring issues such as future pensioners incomes and their effect on the economy (Curry, 1996) or how aging populations will affect the cost of health care services (Smith, 2012). But just as the boundary between CA and MAS has become blurred, so is the boundary between microsimulation models and MAS (e.g. Boman & Holm, 2004). More and more, researchers are either adding behavior and interaction rules to microsimulation models or using microsimulation techniques to create synthetic populations for use with MAS. In both cases, researchers are now combining the two techniques in order to take advantage of their unique offerings, specifically the ability to create realistic synthetic populations and to capture individual characteristics of the population including individual movement, interactions between people, and heterogeneous behaviors. For example, Wu and Birkin (2012) combine a microsimulation model with a MAS model to explore UK population projections, specifically focusing on the mortality rates and demographic characteristics of specific regions in the coming decades.

It is not just changes in aggregated demographics that are important but also changes in specific urban areas ranging from land-use change to urban decline and regeneration. For example, once an area has been developed, it can continue to change in form and function; however, many of the urban growth models presented above focus only on growth, ignoring change within cities (Schwarz et al., 2010). White and Engelen (1993) were the first to investigate change within cities with CA models, developing a land-use model with four different states denoting a specific land-uses: vacant, housing, industrial, and commercial. A given piece of land's transition potential between different states was dependent upon the land-use states of its surrounding cells. However, a limitation with this model was that cells could never become vacant, in the sense that the land's transition was a one way process from vacant to commercial, industrial or housing. To overcome this, the Dynamic Urban Evolutionary Modeling (DUEM) model of Batty et al. (1999) introduced the concept of a 'life cycle' (e.g. new, mature, and declining) to cells. By modeling several different types of land uses (e.g. housing, manufacturing, commerce, and services), assuming that the transition from one land use to another is dependent upon a piece of land's current stage in its life cycle, and factoring surrounding land uses into the transition probability, vacant land reappears within the city. This style of model sets the scene for MAS models that explore the regeneration or gentrification of an area. Regeneration touches upon urban land markets, but in these types of models the focus is on new building efforts within the existing urban core rather than new buildings at the urban-rural fringes. For example, Jordan et al. (2012) explored how regeneration within a deprived area of Leeds, UK, might alter the socio-economic structure of the neighborhood.

In contrast with regeneration is the process of gentrification, a term which refers to "the transformation of a working-class or vacant area of the central city into middle-class residential and/or commercial use" (Lees, et al., 2008). Initially the process of gentrification was explained by Smith's (1979) Rent-Gap Hypothesis whereby a rent-gap develops between the potential ground rent (potential income) and the capitalized ground rent (actual income); if such a gap exists, developers will buy properties from lower-income groups, improve them, and sell them back to higher-income groups. Such gaps evolve as affluent households move to the suburbs in search of better opportunities and modern housing. This in turn leads to higher rates of tenancy within the inner city. It is suggested that landlords of these inner city properties under-maintain them, which leads to a rapid depreciation of building prices in some neighborhoods. This further reduces the value of the stock and prompts further out-migration of more affluent households, thus accelerating a neighborhood's decline further (and further reducing the capitalized ground rent). Not only is this a nice example of a positive feedback in action, but this decline in building values in inner city areas is seen as an opportunity for reinvestment by developers who believe people will want to live in areas close to the city center provided they are improved.

O'Sullivan (2002) was one of the first to apply complexity science to this problem in his irregular CA model, and since then several authors have developed 'agentized' versions of Smith's (1979) Rent-Gap Hypothesis (e.g. Diappi & Bolchi, 2008). These examples also demonstrate how the ideas, concepts, and techniques pertaining to 'classical' urban theory and modeling can be combined using MAS to add dynamics to such models (North & Macal, 2007). However, these models only focus on the supply side of housing in the sense they fail to explain why reinvestment becomes profitable – they explain production but not consumption. Why do people want to move to these areas? For MAS models exploring residential choice (i.e. the consumption) with respect to gentrification, we have to turn to models proposed by Jackson et al., (2008) or Torrens and Nara (2007). These models focus on residential choice and in particular on the question of why people move to inner city areas: accessibility and proximity to shops and services. If one can understand the supply and demand for land within urban areas, one can then potentially model how an area might change and evolve over time or how one might encourage people to move to a specific area. MAS models provide good tools for such questions since gentrification results from many individuals interacting at different spatial scales. It is difficult to predict when and where such processes will occur using 'traditional' models, as by the time gentrification becomes noticeable the process would be already underway.

Discussion and Summary

This chapter has presented several MAS models that have been developed to address a wide range of urban planning problems at a variety of spatial and temporal scales. The examples here have ranged from the growth of cities and regions over decades, to regeneration and gentrification over years, to daily commuting patterns. MAS models offer an alternative approach to modeling urban problems, one that moves away from the reductionist (or top-down) approach for studying such systems which characterizes previous generations of urban models. Instead of dissecting models into logically justified components, MAS models focus on understanding the interactions among simple basic units that correspond to existing entities such as people. This generative (or bottom-up) approach allows us to explore how a small number of rules or laws, applied at a local level and among many entities, are capable of generating complex global phenomena at different temporal resolutions. These collective behaviors, extensive spatial patterns, and hierarchies are manifested in such a way that the actions of the parts do not simply sum to the activity of the whole. They provide us with a new way of thinking about cites, taking ideas and insights from complexity science.

However, there are several challenges with respect to using MAS models for urban planning, ranging across the spectrum of theory to practice, hypothesis, to application (see Crooks *et al.*, 2008). Validation schemes are a classic example of this. One reason validation poses such a challenge is the degree to which the true micro-geography of urban systems is still largely unknown in many situations. Nevertheless, this style of modeling provides a tool for testing the impact of changes in land-use type or the transportation network in dense metropolitan areas via a simulation approach. This approach is less focused on predicting the future accurately, but rather on understanding and exploring the system. It focuses on the system's behavior and forecasting of possible outcomes based on informed speculation incorporating individuals and dynamics. To this extent MAS models may potentially assist policy makers in the same way as planning support systems do today (see Brail & Klosterman, 2001), in the sense of designing possible futures. The MAS modeling approach is consistent with the notion that cities, and the societies they are part of, are intrinsically complex and inherently unpredictable (Batty, 2008).

While past generations of large-scale urban models were economically driven and focused on urban growth and transport infrastructure investments, the MAS style of modeling also focuses on other issues which affect cities. MAS models have been used to study inequalities between the rich and poor, segregation along ethnic lines, redevelopment and so on. Such a move offers a greater understanding of urban areas, to model future scenarios for cities, and to prepare for challenges such as land-use, population, housing, and employment change. However, this sharpening of focus in and of itself raises another challenge. While previous generations of urban models focused on the evolution of the city as a whole, many MAS models only focus on one specific aspect or problem and do not look at the city as a system of interlinked models. One could argue that an integrated approach to modeling is needed, as seen in with the integration of CA models with spatial interaction models by Engelen *et al*. (2003) who explored the effect of population and economic growth at the national and regional scale and the resulting land-use patterns at the local scale.

The need for integrated models also relates to the connections between the many different elements of the city and surrounding regions. Cities and regions will face challenges in the next decades such as aging, urbanization and migration, energy depletion, climate change, poverty, health and disease, and security and conflict, and to face these challenges, an integrated approach to modeling is needed. However, while each MAS model adds to our understanding of cities and regions, they do so in a piecemeal fashion. As Heppenstall et al. (2012b) write, the grand challenge is to develop our models so that they cannot only address pieces but also be combined to explore the whole.

However, linking models and understanding the internal workings of different MAS models is a challenge, as they are often programmed in different languages, using different toolkits (see Crooks & Castle, 2012), or lack documentation of full model specifications. The review presented here has demonstrated how several MAS models have been developed to explore the same phenomena, but there is a need for comparisons of such models. Attempts at devising ontologies and protocols for model comparison are being made. For example, the ODD (Overview, Design Concepts, Details) protocol proposed by Grimm et al. (2006) or the Mr. Potato Head framework of Parker et al. (2008). These protocols could be one solution along with sharing and documenting model source code. In the sense, such ontologies allow one to see the common workings among many models and explore the various behaviors embedded within such models.

Representing realistic human behavior within models is another challenge, and modelers need to be explicit about this. Often too little attention is given to human behavior within MAS models. Humans do not make random decisions, but rather base their actions upon their knowledge and their abilities. Moreover, it might be nice to think that human behavior is purely rational, but this is not always the case: decisions can also be based on emotions (e.g. interest, happiness, anger, and fear; see Izard, 2007). Moreover, emotions can influence ones decision-making by altering one's perceptions about the environment and future evaluations (Loewenstein & Lerner, 2003). The question therefore is how does one model human behavior, and what rationale do we have for incorporating specific behavior within or models? Often modelers are not specific about this. Arguably the primary utility of MAS is as a testing ground for a variety of theoretical assumptions and concepts about human behavior (Stanilov, 2012) within the safe environment of a computer simulation. For example, we know humans process sensory information about the environment, their own current state, and their remembered history to decide what actions to take (Kennedy, 2012), all of which can be incorporated within MAS models. Through the ability to model heterogeneity within MAS models, we can capture some of the uniqueness that makes us human, in the sense that all humans have diverse personality traits (e.g. motivation, emotion, risk avoidance) and complex psychology (Bonabeau, 2002). We also know that human behavior is influenced by others (Friedkin & Johnsen, 1999), for example via their social networks, which can introduce positive and negative feedbacks into the system. When people form groups, the resulting dynamics emergent within such groups can be greater than the sum of the group (Hong & Page, 2004). These properties again can be captured through the agent's heterogeneity and active status. However, what drives humans? What motivates us to take certain actions? By endowing our simulated individual with a agency and allowing them to make decision and interact, we can test ideas and theories (e.g. Maslow's (1943) 'Hierarchy of Needs') about what motivates people and why do they do certain things.

Decision-making within MAS models often take one of three approaches (Kennedy, 2012). The first is the mathematical approach (e.g. Gode & Sunder, 1993), and the second uses some sort of cognitive framework (e.g. Malleson, 2012). Both of these approaches can be considered as rule based systems and are often applied to tens to millions of agents. The third approach, that of cognitive architectures, (e.g. Laird, 2012) focuses on abstract or theoretical cognition of one agent at a time, placing a strong emphasis on artificial intelligence relative to the other two approaches. Cognitive architectures are not really applicable for large-scale MAS models for urban planning due to their high processing and data requirements. Deciding how to incorporate decision-making into MAS is not the only question when building a simulation – more generally, how does one observe/capture human behavior for the specific system being studied? Robinson et al. (2007) provides a discussion of empirical methods for building MAS models including sample surveys, participant observation, field and laboratory experiments, companion modeling, and GIS and remotely sensed data. However, all of these efforts require a large investment in terms of time and money. That said, combining different methods for gathering data about human behavior helps informing the behaviors of the agents and in a sense can make our MAS models more realistic. An increased emphasis on such efforts would move MAS models away from 'toy models' and toward making them with defensible representations of micro-processes relevant to policy makers (Robinson et al., 2007).

In conclusion, this chapter has provided an overview of MAS models and compared and contrasted them to previous generations of urban models. By understanding how different elements of the city interact, we now have the ability to better understand what might happen in the future. As mentioned above, by combing MAS models with GIS we are capable of exploring the spatio-temporal dynamics of the formation and expansion of urban slums. Thus we can investigate several challenges faced by society with respect to dealing with slums. For example, with the help of such a fully developed model, we can test policy interventions that could improve housing conditions for urban poor within a simulation environment. Researchers could pose questions such as "what-if lower income group households are provided with easy access to incremental housing finance?" and forecast a range of possible futures. However, MAS models are not without their challenges, perhaps most notably how to incorporate realistic human decision making into such models and where to acquire adequate and accurate data. Moreover, modelers need to make efforts to share and clearly document their MAS models so researchers can compare and contrast models that explore the same phenomena. If we can do this, we can build a greater body of knowledge of how cities function from the bottom up.

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KEY TERMS AND DEFINITIONS

Complexity: Complexity arises when a small number of rules or laws, applied at a local level and among many entities, are capable of generating complex global phenomena: collective behaviors, extensive spatial patterns, hierarchies etc. are manifested in such a way that the actions of the parts do not simply sum to the activity of the whole.

Geographical Information Systems: A computer-based system for the storage, manipulation and analysis of geographically referenced data (e.g. ArcGIS, QGIS).Human Behavior: How human base their actions upon their knowledge and their abilities.

Multi-Agent Systems: A computer simulation comprising of multiple types of heterogeneous agents which are autonomous decision making entities (e.g. cars). Agents are given specific rules for interaction with other agents and / or other entities within a system. Through such rules and interactions more aggregate patterns emerge (e.g. traffic jams).

Population Growth: The positive growth of a population over time. With respect to demography, a more specific term is population growth rate. This is an important concept with respect to cities and regions in the sense that as the world becomes more populated, more and more people are expected to live in cities.

Urban Modeling: A model is an abstraction of reality, developed to help us better understand an aspect of the real world. Urban modeling relates to creating models that attempt to help our understanding or to predict the form or function of cities and regions.

Urban Planning: A technical and political process concerned with managing / planning land-use transportation networks etc. to ensure that settlements are developed in an orderly way.

Urban Sustainability: A term referring to a way of managing growth (e.g. population, and / or economic) while ensuring to maintain or improve the quality of live for its residents. In essence a sustainable city should meet the needs of the current residents without sacrificing future generations.