Chapter 46
Agent-Based Modeling and the City: A Gallery of Applications

Andrew Crooks, Alison Heppenstall, Nick Malleson, and Ed Manley

Abstract Agent-based modeling is a powerful simulation technique that allows one to build artificial worlds and populate these worlds with individual agents. Each agent or actor has unique behaviors and rules which govern their interactions with each other and their environment. It is through these interactions that more macro-phenomena emerge: for example, how individual pedestrians lead to the emergence of crowds. Over the past two decades, with the growth of computational power and data, agent-based models have evolved into one of the main paradigms for urban modeling and for understanding the various processes which shape our cities. Agent-based models have been developed to explore a vast range of urban phenomena from that of micro-movement of pedestrians over seconds to that of urban growth over decades and many other issues in between. In this chapter, we introduce readers to agent-based modeling from simple abstract applications to those representing space utilizing geographical data not only for the creation of the artificial worlds but also for the validation and calibration of such models through a series of example applications. We will then discuss how big data, data mining, and machine learning techniques are advancing the field of agent-based modeling and demonstrate how such data and techniques can be leveraged into these models, giving us a new way to explore cities.

46.1 Introduction

The start of the twenty-first century marked a milestone in human history: for the first time more than half of the world's population, approximately 3.9 billion people, lived in urban areas. This trend is expected to continue in the foreseeable future,

A. Crooks (✉)
Department of Geography, RENEW Institute, University at Buffalo, Buffalo, USA
e-mail: atcrooks@buffalo.edu

A. Heppenstall · N. Malleson · E. Manley
School of Geography, University of Leeds, Leeds, UK

The Alan Turing Institute, London, UK

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with 6.3 billion people living in cities by 2050 (United Nations 2014). Population growth will cause more urban land to be developed during the first 30 years of the twenty-first century than in all of human history (Angel et al. 2011). Less than five percent of the earth's surface is urbanized and with the urban population predicted to grow to 5 billion by 2030, the urban footprint will still be less than 10% (Seto et al. 2011). Combine this with the unprecedented urban expansion, especially in the form of megacities—cities with more than 10 million in population—which have grown from eight in the 1970s to 36 in 2016 and are expected to rise to 41 by 2030 as shown in Fig. 46.1, and society as a whole will be faced with unprecedented challenges and questions to be asked with respect to all aspects of city life. Will cities be sprawling or compact? How will cities adapt to climate change? How will new technologies such as autonomous cars, for example, affect our lives? These are challenging questions made more complicated by the fact that cities are excellent examples of complex systems, composed of people, places, flows, and activities (Batty 2013), all of which interact in a variety of different ways.

An exact definition of a complex system is difficult to pin down, as it has a different meaning to different people (Thrift 1999). A simple definition is one whereby a small number of rules or laws, applied at a local level and among many entities, are capable of generating complex global phenomena such as collective behaviors, extensive spatial patterns, and hierarchies, in such a way that the actions of their parts do not simply sum to the activity of the whole, due to self-organization, nonlinearities, feedbacks (both positive and negative), and path dependencies.[1] Cities are complex systems, composed of many parts, dynamic, and containing large numbers of discrete actors interacting within space and with other systems from nature and technology, and have a wide-ranging impact on the economy, public policy, national defense, social trends, public health, climate change, etc. As Wilson (2000) writes, understanding cities is "*…one of the major scientific challenges of our time*." Human behavior cannot be understood or predicted in the same way as in the physical sciences such as physics or chemistry. The actions and interactions of the inhabitants of a city, for example, cannot be easily described in a physical-science theory such as that of Newton's Laws of Motion. This notion is captured quite aptly by a quote by Nobel laureate Murray Gell-Mann: "*Think how hard physics would be if particles could think*." In the remainder of this chapter, we will introduce agent-based modeling (Sect. 46.2) as it offers a way to explore the processes that lead to the patterns we see in cities from the bottom up, but also allows us to incorporate ideas from complex systems (e.g. feedbacks, path dependency, emergence) along with providing a gallery of applications of geographically explicit agent-based models. Next, we discuss how we can incorporate various decision-making processes within such models, and also how we can integrate this style of modeling with data, with a specific emphasis on geographical and social information (Sect. 46.3). This section also discusses how

[1] Readers wishing to know more about cities and complexity are referred to the works of Allen (1997), Wilson (2000), and Batty (2007).

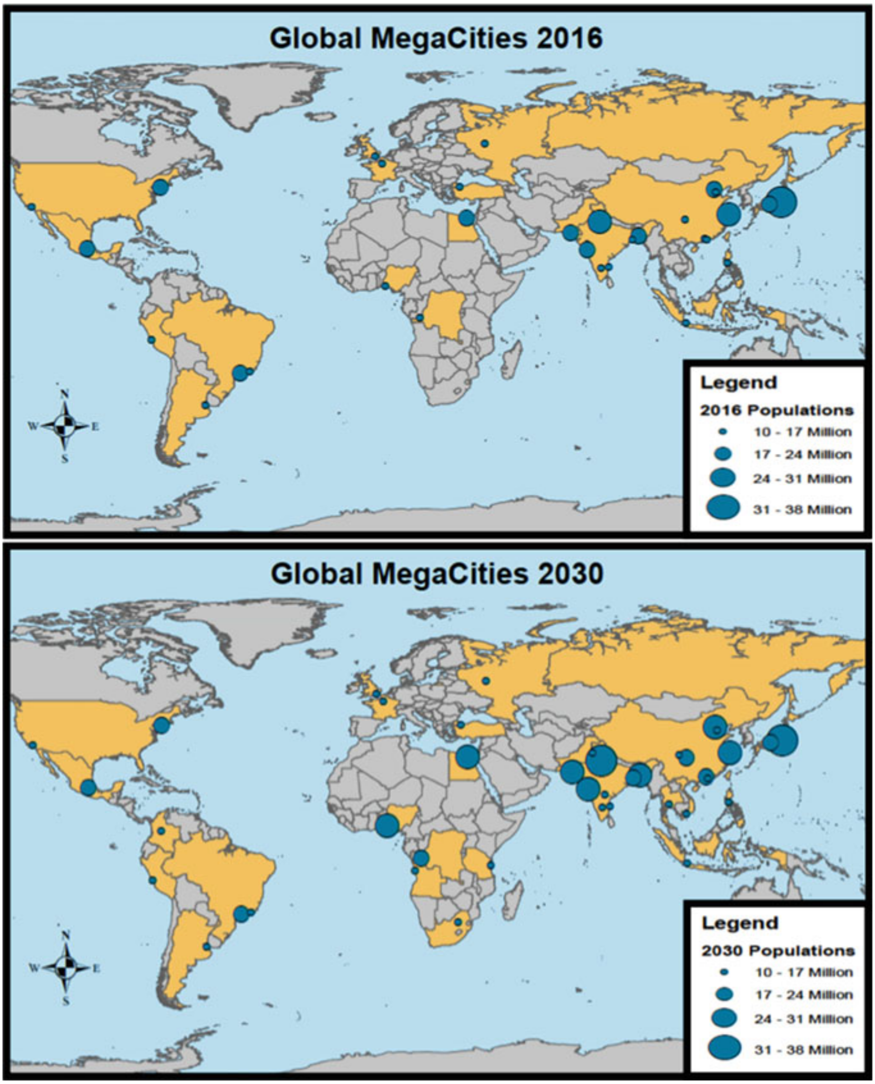

Fig. 46.1 Global megacities in 2016 and estimated megacities by 2030 (data source: United Nations 2016)

agent-based modelers are utilizing machine learning within their models. Finally, in Sect. 46.4, we will provide a summary and discuss new opportunities with respect to agent-based modeling and the city.

46.2 What is Agent-Based Modeling?

Over the past two decades, with the growth of computational power and data (which we will discuss in more detail in Sect. 46.3), agent-based models have evolved into one of the main modeling paradigms for urban systems and understanding the problems that today's cities face (see: Benenson and Torrens 2004; Batty 2005; Crooks et al. 2019). In this section, we first give a general yet brief overview of agent-based modeling before discussing the various reasons to model (Sect. 46.2.1). We then discuss steps in building such models (Sect. 46.2.2) before turning our attention to geographically explicit agent-based modeling examples (Sect. 46.2.3) which demonstrate the types of problems such a style of modeling can explore.

Agent-based modeling, as with other modeling techniques (e.g. spatial interaction models, microsimulation) is a way to take the complexities of the real world and, through abstraction, reductionism, and simplification, to focus on the important task at hand (Gilbert and Troitzsch 2005). The main difference between agent-based modeling and other styles of modeling is that the focus is on interactions of individual entities and their behaviors, and how more aggregate patterns emerge through such interactions (e.g. how individual cars can lead to the emergence of traffic jams). Broadly defined, an agent-based model can be considered as an artificial world inhabited by autonomous and heterogeneous agents, each with their set of goals and preferences. It is through interactions with other agents that the agent makes decisions and decides what actions are to be carried out based on specific goals. These interactions lead to more aggregate patterns emerging as shown in Fig. 46.2.

For example, if one were to build an agent-based model of a housing market, individual agents could be considered as households. Each household has to decide where to live and as with real households, each can have its own preferences for hosing style and neighborhood type, and each has its own income constraints. The interactions with other households in the form of buying and selling a house lead to the emergence of property markets (e.g. Geanakoplos et al. 2012). Or considering traffic congestion during the morning rush hour, individual agents could be considered as drivers of cars: each agent has to decide what time to leave home to go to work, and by driving on the road its interactions with other agents (i.e. cars) is what leads to traffic jams forming (e.g. Manley et al. 2014).

46.2.1 Examples of Why to Model

As with other modeling styles, within agent-based modeling, there are multiple reasons for why one should model, from understanding a certain phenomenon to predicting and forecasting (see Epstein 2008 for a discussion on the various reasons to model) and therefore agent-based models range from abstract thought experiments to more empirically applied applications. For example, Schelling's (1971) model of segregation is not only a classic example of an abstract model, but it also

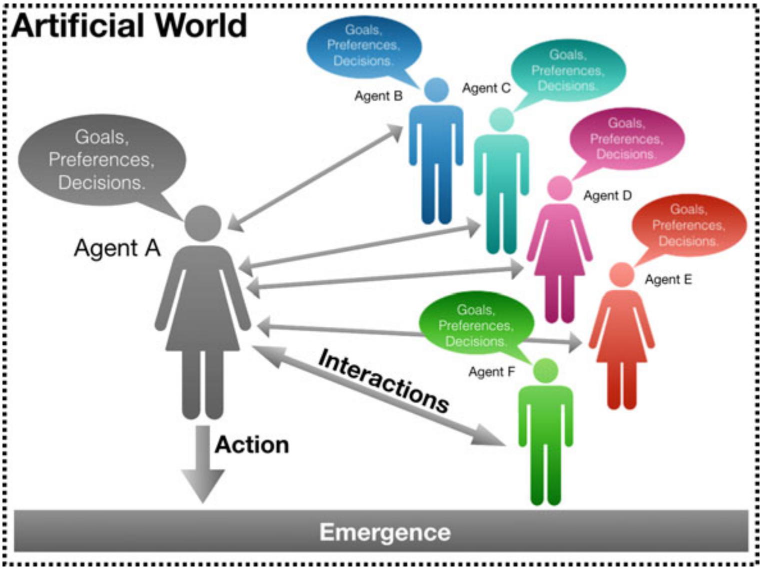

Fig. 46.2 Schematic of an agent-based model, showing how interactions between agents lead to emergent phenomena within an artificial world

demonstrates how emergent phenomena (in this case segregation) can occur through individual preferences. Moreover, it demonstrates how macro-level segregation does not necessarily reflect micro-level preferences. For example, in Fig. 46.3, we show two types of agents, those who prefer football versus those who prefer baseball. In this simple example, based on notions from Schelling's (1971) model, agents (i.e. individuals) want to be in locations (a cell on a 11 by 11 grid which acts as our artificial world) where a certain percentage of their neighbors are similar to themselves (in this example 30%).

Over time (T), agents move if their preference for their neighborhood composition is not met. As one can see, from an initial randomly distributed population, segregated neighborhoods emerge due to agents interacting with other agents and taking actions (in this case moving) and to the resulting feedbacks and past locational choices of others. Also, the model demonstrates how the actions of one agent might affect others. For example, an agent may be satisfied in a certain location but another agent moving into the neighborhood might cause this agent to become dissatisfied and therefore cause it to move. By altering the agent's preferences for certain neighborhood compositions (e.g. from 30 to 70% of similar neighbors), we can also see how individual preferences and interactions at the micro-level lead to more macro-level phenomena emerging as we show in Fig. 46.4; specifically in this example, we see how more segregated communities emerge as preferences are increased.

What is interesting about this phenomenon is that often when we see segregated neighborhoods, the process and actions that led to this pattern have already occurred. However, through agent-based modeling, we can explore what processes or actions

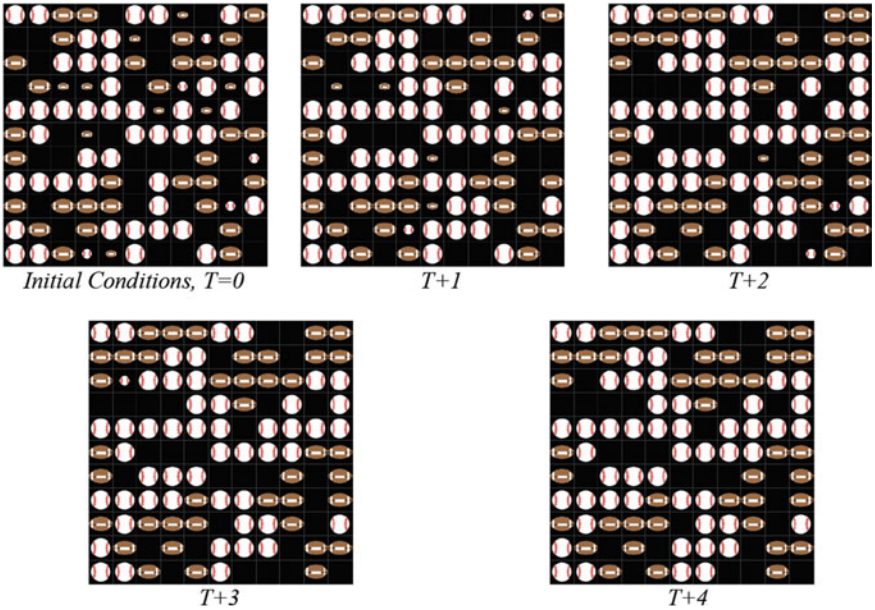

Fig. 46.3 Example of segregation emerging over time as agents move to locations where their preferences are met (note smaller balls are dissatisfied agents)

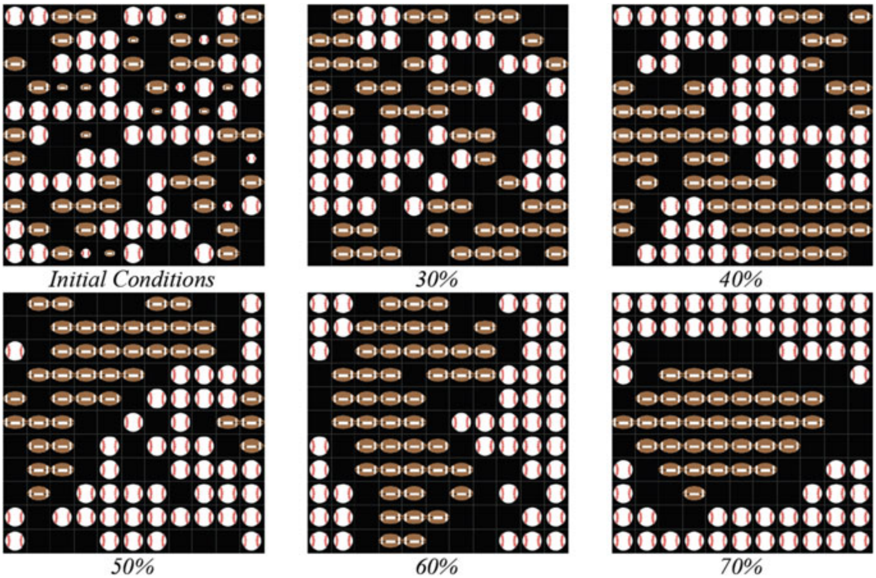

Fig. 46.4 Examples of how different preferences lead to different patterns of segregation

might have led to such patterns emerging in the first place, and thus devise potential interventions before it is too late. However, as noted above, agent-based models can also be empirically grounded. Take for example the work of Benenson et al. (2002), which explored how people's preferences for certain neighborhoods and building types lead to distinct residential patterns emerging in Tel Aviv, Israel. While both have their own purpose, Schelling's (1971) to explore basic behavior and that of Benenson et al. (2002) to explain residential choice based on empirical data and test various scenarios, both show that individual preferences for certain types of neighborhoods lead to distinct residential patterns emerging, which would be difficult to explain from just looking at aggregate data alone. It should however be noted that agent-based modeling is not just an academic exercise, but has been used by companies and organizations for a variety of decision-making purposes. These range from the potential impact of decimalization of the NASDAQ Stock Market (Darley and Outkin 2007), to that of understanding store design, consumer markets, or hiring strategies for companies (see Bonabeau 2003). Readers of this chapter might also be surprised to know that they have probably seen agent-based models while at the cinema or watching TV as they are often used for massive crowd scenes in movies, replacing the need for a large cast of extras (see Massive 2019). Companies, especially engineering ones, are also utilizing agent-based models to study pedestrian (e.g. products such as Legion 2019 and STEPS 2019) or traffic dynamics (e.g. PTV Visum 2019 and Paramics 2019) in order to assess new designs for buildings or traffic measures before they are built or implemented.

46.2.2 Steps in Building an Agent-Based Model

When it comes to building an agent-based model, the process can be broadly viewed as having three steps. First, before we can get to the model itself, we need to identify the research question we are trying to solve with the model (e.g. reasons for traffic patterns), define the target of the model, know specifically what we are we trying to solve (e.g. traffic dynamics), and consider if there are any observations of the target we wish to include to provide parameters and initial conditions for the model (e.g. origin–destination data). We then need to make assumptions and design the model. Once the model has been designed and implemented (often in computer code), the second step is to run (execute) the model, which creates an artificial world. This is then populated with agents (e.g. cars) that are assigned attributes and rules (depending on the application or phenomena of interest). We then run the model until a certain condition is met or a specific time epoch is reached, and report and observe the results which are shown in Fig. 46.5a (while Fig. 46.5b shows a simple worked example of the segregation model discussed in Sect. 46.2.1). While this figure and the description given above are highly generalized and simple, in essence, one could make the argument that agent-based models are just rule-based systems, in the sense that they could be considered as just a series of *if-then-else* statements. For example, *if* the fire alarm goes off, *then* exit the building, *else* stay in

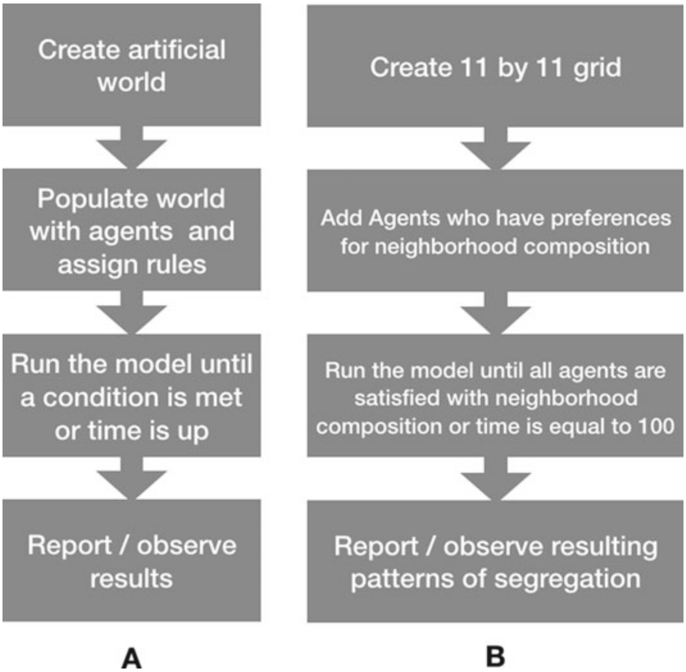

Fig. 46.5 Highly generalized flow of an agent-based model **a** and the corresponding flow of the basic segregation model **b**

the building. However, the richness of agent-based modeling is that while the agents themselves might be highly specified and their rules of interactions are well-known, and it is not until the model is run that we can know the outcome, due to the variety of possible interactions of autonomous heterogeneous decision-making agents. In essence, like complex systems themselves, agent-based models are more than the sum of their parts. Once the model is run, the third step is to evaluate the model (e.g. verification, calibration, validation, sensitivity analysis). For further guidelines on designing, implementing, and evaluating agent-based models, readers are referred to Gilbert and Troitzsch (2005) and Crooks et al. (2019).

46.2.3 Application Areas for Geographically Explicit Agent-Based Models

Geographically explicit agent-based models (i.e., those utilizing geographical information which we will go into more detail about in Sect. 46.3) have been developed to explore a range of problems which society faces over a variety of spatial and temporal scales from the micro-movement of pedestrians over seconds (e.g. Torrens 2012) to that of the macro-evolution of city systems over centuries (Pumain and Sanders 2013). The flexibility that the agent-based modeling approach provides has allowed such models to be used in a diverse set of applications. These range from archeology (Axtell et al. 2002), agriculture (Hailegiorgis et al. 2018), basketball (Oldham and Crooks 2019), crime (Malleson et al. 2013), diseases (Perez and Dragicevic 2009), disasters (Jumadi et al. 2018), invasive species (Anderson and Dragićević 2018), to urban growth (Xie and Yang 2011), housing markets (Geanakoplos et al. 2012), gentrification (Jackson et al. 2008), slum formation (Patel et al. 2018), and traffic (Manley and Cheng 2018). So, while agent-based modelers have been utilizing geographical data in their models, what has changed is the growth of data and ways of integrating such data within models (which will be discussed more in Sect. 46.3.2).

Open-source agent-based modeling toolkits such as GAMA (Taillandier et al. 2019), MASON (Luke et al. 2018), Repast (North et al. 2013), and NetLogo (Wilensky 1999) have evolved substantially over the past 20 years and many have built-in functionality to directly integrate data into models (e.g. raster and vector data structures), thus lowering the bar for creating geographically explicit models (for a review of these platforms and their applications readers are referred to Crooks et al. 2019). For example, in Fig. 46.6, we show a selection of models created utilizing the MASON toolkit and its GeoMason extension for GIS integration that span both spatial and temporal scales. These include such things as the micro-movement of pedestrians over seconds to that of the macro-movement of migrants over years, and many things in between such as modeling traffic, responses to disasters, disease outbreaks, and urban growth (for access to these models see MASON 2019, and for equivalent geographically explicit models in NetLogo see https://www.abmgis.org/).

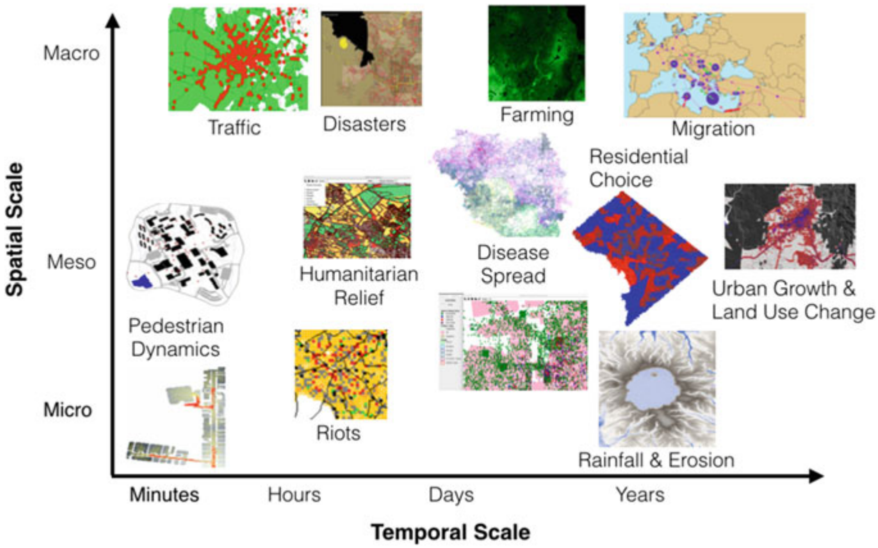

Fig. 46.6 Selection of GeoMason models across various spatial and temporal scales

In addition to these general-purpose open-source toolkits which allow for a range of urban phenomena to be simulated, where one could argue that the only constraint is that of the modeler's imagination, there are others that are dedicated to specific domains such as the open-source transportation simulations (e.g. MATSim of Horni, Nagel, Axhausen 2016, POLARIS of Auld et al. 2016, or TRANSIMS 2019), which are being used to study a wide range of transportation issues (e.g. daily trips, route planning, evaluation of intelligent transportation systems) in multiple cities around the world.

46.3 Integrating Data and Decision-Making into Agent-Based Models

Apart from the individual entities within agent-based models interacting with each other, these entities are also interacting and are affected by the artificial world (or environment) which they inhabit; similar to how the world around us affects our lives. For example, take land-use change. Developers may buy agricultural land, convert the land to residential use, and then sell it to residents who then move into it (e.g. Magliocca et al. 2011). Agents can also perceive their environment and respond to it (e.g. changing climatic conditions may alter farming practices as discussed in Hailegiorgis, Crooks, Cioff-Revilla 2018). Initially, many agent-based models represented space rather abstractly as we showed with the Schelling (1971) model in Sect. 46.2.1. However, perhaps with the demonstration of the Sugarscape model by Epstein and Axtell (1996), which showed how the environment can affect agents' wealth and survival, modelers started to realize that the artificial world that the agents inhabited could be stylized on geographical data. From earlier works such as those by Gimblett (2002) or Benenson and Torrens (2004) to current day work (e.g. Crooks et al. 2019), researchers have utilized data not only to represent the physical aspects of the artificial world (e.g. land cover, road networks) but also to help inform the social aspects (e.g. census data to help with knowing how many agents live in an area). Such data take the abstract representations of space and make it more grounded in real-world locations as we show in Fig. 46.7.

Different data layers in the form of rasters (e.g. land-use and land-cover, elevation) and vector formats (e.g. census areas, road networks) can act as the environment for the artificial world in which our agents interact. For example, vector data about roads can be used for a traffic simulation in the sense of allowing agents to navigate from one location to another. Or census data can be used to create a specified number of agents for a given location with associated socio-economic characteristics (e.g. Burger et al. 2017). Raster data such as those from the national land-cover dataset (Wickham et al. 2014) can be used for initialization of an urban growth simulation as they provide details on urban and non-urban land extents which affect where cities can and cannot grow (see Crooks et al. 2019 for further details and examples of how one can use such data in models). Such social and physical data layers in

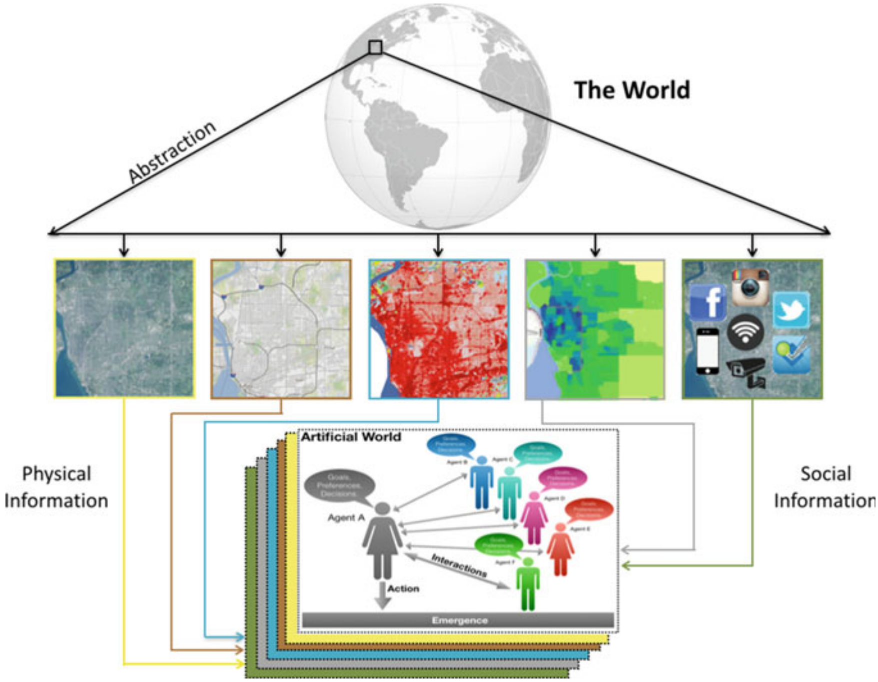

Fig. 46.7 Using geographic information as a foundation for artificial worlds

Fig. 46.7 replace the abstract artificial world presented in Fig. 46.2 and ground the model to actual real-world locations, which can have an impact on individual agents' interactions. Compare, for example, the abstract room in Fig. 46.8a which is used to test basic pedestrian movement to that of Fig. 46.8b which is based on actual

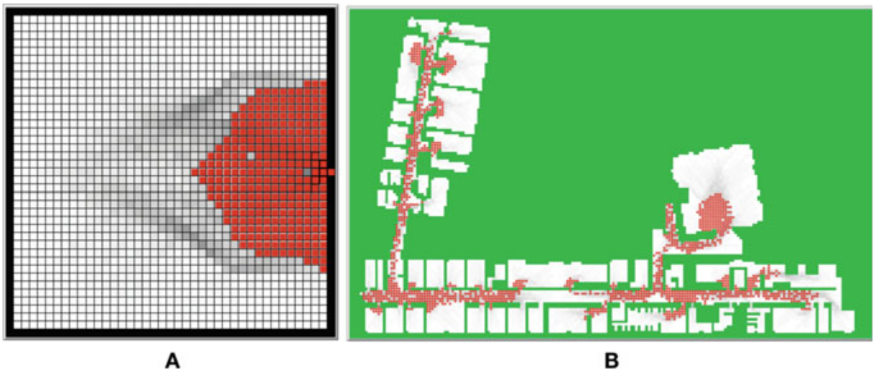

Fig. 46.8 Moving from an abstract room **a** to one where the artificial world is based on a real-world building floor plan **b**

CAD data of a real-world building. Here, actual walls, corridors, and exits constrain the agent's movement. While we already have discussed in Sect. 46.2.3 application areas, where researchers have created geographically explicit agent-based models to explore a wide range of phenomena, in the remainder of this section, we first discuss how one can incorporate decision-making into agent-based models (Sect. 46.3.1), before turning our attention to how new forms of data are being used in such models, to help inform decision-making (Sect. 46.3.2) and how with such data researchers are utilizing machine learning methods for various phases (steps) within the agent-based modeling (Sect. 46.3.3).

46.3.1 Incorporating Decision-Making into Agent-Based Models

As noted in Sect. 46.2.2, agent-based models are essentially rule-based systems in the sense that an agent's actions are programmed directly into them. Therefore, it is important to consider how we go about choosing these rules. However, as discussed in Sect. 46.1, modeling human behavior is not as simple as it sounds. This is because humans do not just make random decisions, but base their actions upon their knowledge and their abilities. In addition, it might be nice to think that human behavior is rational, but this is not always the case. Decisions can be based on emotions, such as self-interest, happiness, anger, or fear (see Izard 2007). In addition, emotions can influence one's decision-making by altering perceptions about the environment and future evaluations (Loewenstein and Lerner 2003). The question therefore is: how do we model human behavior? This is where agent-based models excel over other modeling approaches (as discussed in Sect. 46.2). Agent-based modeling allows us to focus on individuals or groups of individuals and give them diverse knowledge and abilities, which is not possible in other modeling methodologies. As such, agent-based models act 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.

Broadly speaking, there are three main approaches to capturing such decision-making processes within agent-based models (Kennedy 2012). The first is a mathematical approach such as the use of ad hoc direct and custom coding of behaviors within the simulation, such as using random number generators to select a predefined possible choice (e.g. to buy or sell; Gode and Sunder 1993). But, people are not random, which has led researchers to develop other methods such as directly incorporating threshold-based rules; that is, when an environment parameter passes a certain threshold a specific agent behavior will result (e.g. move to a new location when the neighborhood composition reaches a certain percentage) as in the Schelling (1971) example introduced in Sect. 46.2.1. One could argue that these modeling approaches are appropriate when behavior can be well-specified. The second approach to modeling human behavior within agent-based models uses conceptual cognitive frameworks. Within such models, instead of using thresholds, more abstract concepts such as beliefs, desires, and intentions (BDI; Rao and Georgeff 1991) or physical, emotional, cognitive, and social factors (PECS; Schmidt 2002) are given to individual agents. Both the BDI and PECS frameworks have been successively applied to modeling human behavior in a number of applications, such as what drives people to crime (see Brantingham et al. 2005 and Malleson et al. 2010, respectively).

These conceptual cognitive frameworks and mathematical approaches for representing behavior, like agent-based models more generally, can both 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. Soar (Laird 2012) and ACT-R (Anderson and Lebiere 1998)) focuses on abstract or theoretical cognition of one agent at a time with a strong emphasis on artificial intelligence. This approach is rarely used to model more than a small number of agents, which makes their utility for modeling challenges faced by cities rather limited. However, while there are multiple ways of representing decision-making within agent-based models, why a modeler chooses one over the other is rarely discussed (Schlüter et al. 2017) or why a certain theory was chosen (if at all) to build upon (Groeneveld et al. 2017). Readers wishing to know more about decision-making within agent-based models are referred to Balke and Gilbert (2014) and to learn how such models can be used in a policy context see Calder et al. (2018).

46.3.2 The Growth of Data and Its Utilization Within Agent-Based Models

Coinciding with the ease of incorporating data into agent-based models (as discussed in Sects. 46.2.3) is the growth and availability of digital data (i.e. big data) for urban areas, many of which have an explicit or implicit geographic component (Stefanidis et al. 2013). Such data range from more traditional types such as census data, or remotely sensed imagery or in situ sensing devices (e.g. weather stations and air-pollution monitoring systems) to data from mobile sensors such as smartphones, GPS devices attached to taxis, or social media. This rise in data in a variety of shapes and forms coupled with increased computational resources has led to the rise of urban analytics. There are several definitions for urban analytics: for example, Singleton et al. (2017) defines it as a "*multidisciplinary area of research concerned with using new and emerging forms of data, alongside computational and statistical techniques to study cities*," while Batty (2019) places urban analytics in the wider scope of analytics more generally, stating the "*term analytics implies a set of methods that can be used to explore, understand and predict properties and features of any system, in our case of cities*." What is common between the definitions is utilizing data and computational techniques to explore cities. If we first turn to data, we are not only referring to traditional datasets such as census and infrastructure (e.g. roads) traditionally collected and distributed by governmental organizations and industry but also to volunteered geographic information (e.g. OpenStreetMap) and social media, Internet of things (IoT), and cell phones, which are giving us new ways to explore the urban environment (Batty et al. 2012; Crooks et al. 2015b).

By bringing and analyzing these data together, we can begin to understand the wider patterns of cities. For example, smart-city data are founded at the individual level and through the analysis of travel cards can tell us how many people commute into a city every day (e.g. Zhong et al. 2015) and hint at the purpose of trips when combined with land-use information and social-media check-ins (Yang et al. 2019b). Dockless-bike data can provide information on urban flows and impacts of new infrastructure (e.g. Yang et al. 2019a) Similarly, cell-phone data can show origin–destination pairs for urban mobility (e.g. Louail et al. 2015) or patterns of movement and interactions (e.g. Malleson et al. 2018; Manley and Dennett 2019). What such data cannot tell us explicitly is the purpose of one's trip or their experience of the city while one is there. Bringing in data about the individual (social data) from multiple sources (e.g. Twitter, Facebook) might help complete the picture but still gives us only patterns and not necessarily the processes and the underlying motivations that led to the patterns emerging.

Identifying how and when these patterns will emerge is extremely difficult. Take for example congestion: it arises as a result of individual mobility decisions based on factors such as life stage, accessibility to workplace, shops, or other facilities which are constantly changing. Congestion can build locally at pinch points, placing sections of the city's transportation networks under severe strain. There is some irony that while we inhabit a data-rich world, without modeling it is extremely challenging to understand how the combination of physical environment and social dynamics contributes to how our cities function and grow. Data alone will not solve all the problems cities face, especially when using data from the past to look at the future. For example, with respect to financial or housing markets, we might have data on the stock market from 2010 to 2019 but this does not capture the 2007–2008 financial crisis. What happens if there is a structural change or some sort of evolution of the system or something happens outside of these bounds? Data capture only what they see, not necessarily extreme market events. Or to quote Heraclitus: "*No man ever steps in the same river twice, for it's not the same river and he's not the same man.*" This is one of the motivations for modeling, specifically agent-based models. We can explore such issues and pose *what-if* scenarios based on individuals making their own decisions. For example, what would be the implications of imposing congestion charging, in terms of improvements to both congestion and people's activities (e.g. Zheng et al. 2012)?

If we refer back to Fig. 46.7, we can utilize such data to inform our models, act as inputs to a model, or validate model outcomes. For example, there are numerous applications that are utilizing OpenStreetMap data to act as the foundation of their artificial worlds. These range from assessing route choice for humanitarian support after an earthquake (Crooks and Wise 2013), or utilizing building and infrastructure information during disease outbreaks (Crooks and Hailegiorgis 2014) to vehicle routing over a network (Horni et al. 2016) or as a basis for evacuation-route choice

(Goetz and Zipf 2012). If we turn our attention to pedestrian movement, which is of paramount importance if we wish to design more walkable cities, new sensor technology such as GPS has been used to test walking behaviors (Torrens et al. 2012), while others have utilized CCTV to calibrate how people move through small areas (Crooks et al. 2015a) or calibrate crowd densities (Batty et al. 2003). Crols and Malleson (2019), on the other hand, used footfall data collected via sensors to validate their pedestrian model of daily mobility in the town center of Otley, West Yorkshire in order to better understand how the town center is being used by its inhabitants. Similarly, Grübel et al. (2019) used footfall data to validate their model of pedestrian flows through Westminster in London.

New sources of data are also shedding light into how people navigate around the city; for example, Manley et al. (2015) found in analyzing GPS data from London minicabs that the shortest path models often used in transportation studies poorly predicted the actual behavior of minicab drivers; but through an agent-based model they showed how drivers used specific urban features (i.e., "anchor points") with respect to navigating around the city. Moving beyond just geographic data, others are using natural language processing (NLP) to mine textual data to inform agent decision-making (Runck et al. 2019). In another example, Wise (2014) developed an agent-based model to explore a wildfire event and subsequent evacuation in Colorado Springs over the space of a week in 2012. Specifically, Wise mined social media, in this case, Twitter, to derive the moods of people in the area and fed this into an evacuation model. For example, if one of the agents (i.e. a Colorado Springs resident) knew that the fire was nearby, and this information was passed along his or her social network to other agents who then decided whether to evacuate or not. This decision to evacuate or not also led to congestion, which was validated based on data that were harvested from the crowd and news outlets. What the above examples show is that new sources of data can be utilized in many aspects of agent-based modeling, especially those related to urban applications over a variety of spatial and temporal scales.

46.3.3 The Potential of Machine Learning and Agent-Based Modeling

While there has been a tremendous growth over the past decade in machine learning, a subfield of artificial intelligence, which is partly due to increases in computational power and the availability of data and is leading to new areas of research within urban analytics, and terms such as geographic data science are appearing (see Singleton and Arribas-Bel 2019). By using machine learning techniques (such as genetic algorithms, artificial neural networks, Bayesian classifiers, decision trees, or reinforcement learning) and data mining (i.e. finding patterns in the data), researchers have been exploring many aspects of city life such as the identification of slums via decision trees (Mahabir et al. 2018) and using natural language processing to find meanings of place (Jenkins et al. 2016).

However, while machine learning and data mining have seen a large growth in urban analytics, there has only been limited uptake of these methods in agent-based models, even though as Rand (2006) notes they are similar in the sense that both can be considered as rule-based systems (as we discussed in Sect. 46.2.2), and as both need to be initialized with a specific set of parameters. Both need to be run, and while in agent-based models, we observe the dynamics, in machine learning, we observe the outputs of the machine learning process (such as numbers, rules, or categories), and conclude when the stopping conditions are met (Rand 2006).[2] For example, in an agent-based model, this might be when all agents are happy, while in machine learning, it could be when the algorithm completes its processing (e.g. the value of the objective function cannot be further improved).

As noted in Sect. 46.2.2, agent-based modeling has broadly three major steps: the design of the model, the execution of the model, and evaluation of the model. Machine learning techniques have been applied to all three of these phases (see Abdulkareem et al. 2019). For example, in the first phase, the designing of the model, machine learning has been used to derive parameter values for agent-based models such as in cases of human mobility and obesity (e.g. Kavak 2007; Padilla et al. 2016). Machine learning has also been used during the running of the model, often for agents to learn from past experiences and make more informed decisions via reinforcement learning or genetic algorithms or random forests (e.g. Ramchandani et al. 2017; Rand 2006; Wolpert et al. 1999). Zhang et al. (2018) used neural networks for traffic prediction under various traffic configurations. In another example, Abdulkareem et al. (2019) used Bayesian networks and survey data to explore the spread of cholera in Kumasi, Ghana. Specifically, they used Bayesian networks with respect to improving risk perception and decision-making about where to get water during a cholera outbreak. Others have used reinforcement learning with respect to retirement planning (Ramchandani et al. 2017) or Bayesian networks to infer agents' locational choice and how this affects land-use change (Kocabas and Dragicevic 2013). Bone and Dragicevic (2010) used reinforcement learning to achieve optimal forest harvesting strategies. With respect to using machine learning algorithms to analyze model outputs (i.e. Step 3), Heppenstall et al. (2007) used a genetic algorithm to validate model outcomes of an agent-based model which simulates the retail gasoline market.

The examples above are just a few agent-based models utilizing machine learning and are intended to show the reader that researchers are exploring the use of such techniques in various aspects of the agent-based modeling process. However, unlike in the data science community, the use of machine learning is rather limited. Perhaps, this is because in the data science community packages exist (such as those implemented in Python or R) for machine leaning, but this is not the case for agent-based modeling. While agent-based toolkits exist, modelers still need to design and implement their

[2]For a greater discussion on the similarities between agent-based modeling and machine learning, readers are referred to Rand (2006).

own models, which in itself is a time-consuming task. Also, agent-based models focus on individual behavior, and to fully utilize machine learning one needs training data which are often not available (due to ethical implications, privacy concerns, etc.) at the level of detail for agent-based models (e.g. Runck et al. 2019; Weinberger 2011). We do not have space to delve deeper into why there has only been limited uptake of machine learning within agent-based models, but we envisage that with the growth of data, more agent-based modelers will utilize machine learning, especially as there are increasing calls to incorporate empirical data into models (e.g. Janssen and Ostrom 2006; Robinson et al. 2007) along with efforts to validate such models. For example, there might be abundant fine-resolution trajectory data about people's movement in cities which can be used to validate movement models and thus test ideas and theories of what motivates such patterns to emerge.

46.4 Summary and Outlook

As the world is increasingly becoming more densely urbanized, it is becoming more important to understand each city as a complex system whose whole is more than the sum of its parts. Without such understanding, it will be difficult to grapple with future societal challenges such as climate change. Cities are composed of many individuals whose interactions and behaviors lead to many issues emerging (Sect. 46.1). In this chapter, we have introduced agent-based modeling (Sect. 46.2) which allows one to model social systems from the bottom up. The focus of such models is the creation of artificial worlds in which individuals are given unique behaviors and rules and interact with each other and their environment. It is through such interactions that more macro-patterns emerge: for example, how individuals form crowds, or people going to and from work result in traffic jams, or people buying and selling homes lead to property markets emerging. By integrating geographic information into such models, we can turn abstract artificial worlds to those that mimic real-world locations (Sect. 46.3).

We also discussed how agent-based modeling has seen a large uptake over the past 20 years, spurred by the growth and availability of data (Sect. 46.3.2), which is providing many application domains for study. Such data when mined not only provide new ways to explore how people perceive and use the space around them, but also through machine learning methods can be integrated into the various aspects of agent-based modeling, from model parameterization to validation and calibration (Sect. 46.3.3). However, this is still an area which is evolving and there is still a significant amount of research to be done. New sources of data can potentially be mined to provide information pertaining to who, what, when, where, and why people do what they do. However, as Robert Axtell notes "*…there is a large research program to be done over the next 20 years, or even 100 years, for building good high-fidelity models of human behavior and interactions*" (cited by Weinberger 2011). Potentially, machine learning methods could help with, this especially with respect to improving decision-making within agent-based models.

Moreover, readers might have noted that a gallery of applications was discussed in this chapter, but there were very few attempts to integrate or couple various urban processes together, which was often the case with more traditional styles of land-use transportation interaction (LUTI) models (see Wise et al. 2017 for such a discussion). Perhaps, this is because agent-based models are being applied on a variety of spatial and temporal scales depending on the question at hand. For example, rush-hour traffic or various longer-term processes such as urban growth make it difficult to resolve temporal clocks or computational issues when scaling models to larger areas or greater numbers of agents, etc. However, the argument could be made that we are still in the initial stages of understanding cities from the bottom up, and the focus until now has been on specific problems but not on the city as a whole system. There is some justification for this based upon Simon's (1996) concept of the near-decomposability of systems, in which parts of a system interact among themselves in clusters or subgraphs, with interactions among subsystems being relatively weaker or fewer but not negligible, and therefore in the short term, one can study such systems (or problems) in isolation.

Looking ahead, as we noted above, today we are in a data-rich world and we discussed how one can utilize such data for model initialization, the parameterization of agents' attributes, or for the validation of model outcomes. However, as agent-based models are often used to simulate the behavior of complex systems, these systems often diverge rapidly from initial starting conditions. One way to prevent a simulation from diverging from reality would be to occasionally incorporate more up-to-date data and adjust the model accordingly. Data, especially streaming data produced through near-real-time observational datasets (e.g. social media or vehicle routing counters) could be utilized in such a case as shown in Fig. 46.9.

This process is known as dynamic data assimilation. There is a range of techniques that come under the banner of data assimilation that are designed for exactly this purpose. However, they have largely evolved from fields such as meteorology (i.e. to incorporate up-to-date environmental data into weather forecasts) and only recently have they started to be applied to agent-based modeling (e.g. Malleson et al. 2017; Rai and Hu 2013; Ward et al. 2016). The marriage of data assimilation methods and agent-based models could be transformative for the ways that some systems, for example, smart cities, are modeled. In addition to this, with new sources of big data and methods from machine learning and the growth of computational resources, we are perhaps nearing a point where we can explore and model cities from the bottom up at resolutions and scales that have not yet been possible.

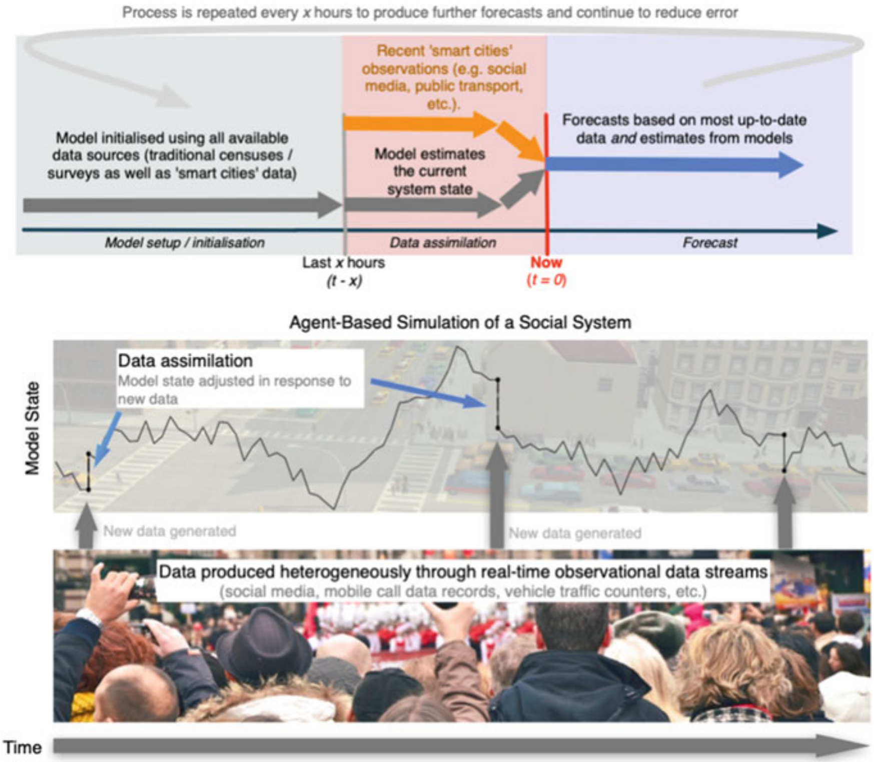

Fig. 46.9 Dynamic data assimilation and agent-based modeling

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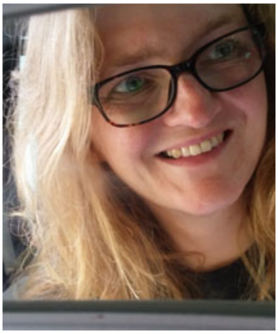
Andrew Crooks is a Professor of Geography within the Department of Geography and a faculty member in the RENEW Institute at the University at Buffalo. His research interests relate to exploring and understanding the natural and socio-economic environments, specifically urban areas, using GIS, spatial analysis, social network analysis, and agent-based modeling methodologies.



Alison Heppenstall is Professor of Geocomputation at the University of Leeds (UK) and a Fellow at the Alan Turing Institute. She is currently developing approaches within urban analytics, including detecting spatio-temporal patterns in data, quantifying uncertainty in agent-based models, and building more robust models via probabilistic programming and reinforcement learning.

Nick Malleson is a Professor of Spatial Science at the University of Leeds (UK). His research focuses on the development of agent-based models aimed at understanding and explaining social phenomena. He is also interested in how "Big Data" and smart cities initiatives can be used to understand the daily dynamics of cities.

Ed Manley is Professor of Urban Analytics in the School of Geography, University of Leeds, and Turing Fellow at the Alan Turing Institute for Data Science and Artificial Intelligence. He is Associate Editor of the Applied Spatial Analysis and Policy journal and chairs the GIScience Research Group at the Royal Geographical Society.