Agent-based modeling in geographical systems

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Content

How will rapid urbanization affect how cities develop sustainably in the future? What are the best interventions for reducing crime rates in an area? Can we balance human resource requirements with environmental preservation? These are not trivial questions. Any attempt to answer them requires an understanding of how the different processes and dynamics governing geographical systems fit together. Perhaps one of the most important aspects that we need to be able to understand and simulate is the role of individuals and the impact that their decisions have in space and time.

Our understanding of how geographical systems function is changing as a result of the appearance of new forms of “big data.” These include mobile phone and social media data that reveal individual movement and behavior—information that until recently was virtually impossible to obtain. These data are revealing a new level of complexity that connects different components of geographical systems, emphasizing the importance of individuals and their decisions. Understanding how these different components are linked is of critical importance if we are to gain new knowledge and understanding of the inner workings of geographical systems. For example, what types of connections exist, which of these are the most important, and how can we influence these relationships in a positive way? Consider, for example, the challenges of urban growth. Why and how do people make decisions about where to live? Is it for schools, jobs, or other reasons? How do such decisions vary among individuals? *See also:* **Big data (/content/big-data/YB150639)**; **Social media (/content/social-media/BR0630161)**

Until quite recently, the most common approaches to simulating and gaining new insights into these systems was through the use of established mathematical and statistical models such as system dynamics, microsimulation, cellular automata, spatial interaction, or diffusion models. In spatial interactions models, for example, large diverse groups of people are treated as one homogeneous (aggregate) group; that is, they are given the same behavior and movements. With the change in how we perceive these systems combined with technological developments, the emphasis has switched to simulating the system from the bottom up; that is, modeling individuals, their diversity, and how their decisions and relationships with others shape and form geographical systems in the form of emergent patterns. This has given rise to huge popularity in individual-based techniques such as agent-based modeling (ABM). *See also:* **Cellular automata (/content/cellular-automata/801050)**; **Mathematical geography (/content/mathematical-geography/409800)**; **Statistics (/content/statistics/652400)**

Differences among the various modeling styles are presented in the **table**. Here, the number of levels denotes whether the modeling technique is capable of simulating interactions between levels (for example, the individual and the society). This is important when studying the emergence of geographical systems. For example, how individuals buy and sell houses influences how property markets emerge; conversely, the state of the property market affects how, when, and where individuals buy a house. Communication among agents refers to the notion of whether it is possible for them to pass along information, such as rumors. Complexity refers to how sophisticated the agents are and whether they are homogeneous (possessing the same characteristics and rule sets) or heterogeneous (different characteristics and rule sets). The number of agents refers to how many agents are represented within the system under exploration. System dynamics models, unlike the other modeling techniques, do not model individuals but rather the system as a whole (for example, the city or the country). In such models, only one representative agent is captured, whereas individual-based approaches can represent anything from one agent to millions at varying levels of complexity. The **table** also highlights that ABM differs from many other styles of modeling in that it can capture multiple levels of interactions, including agent-to-agent communication. For a detailed discussion of the evolution of modeling techniques and their differences, readers are referred to N. Gilbert and K. G. Troitzsch (2005) and A. J. Heppenstall and coworkers (2012). We will briefly present an overview of what is a geographical system and how agent-based models are being applied to furthering our understanding of how these systems evolve and function. We will conclude with a discussion of the pros and cons of this approach and how the discipline might develop in the future.

Table - A comparison of modeling techniques used to study aspects of geographical systems

Modeling styles	Number of levels	Communication among agents	Complexity of agents	Number of agents
System dynamics	1	No	Low	1
Spatial interaction	1	No	Low	Many
Microsimulation	2	No	High	Many
Discrete event simulation	1	No	Low	Many
Cellular automata	2	Yes	Low	Many
Agent-based models	2+	Yes	High	Few–many

source: Adapted from Gilbert and Troitzsch, 2005.

Geographical systems

What is a geographical system? Simply, one could remark that because everyone and everything has a spatial location, the world around us is one enormous complex geographical system. This, of course, is too broad and simple a definition to be useful. Instead, geographers have borrowed terms and concepts from other academic disciplines to articulate what they feel are the most essential ingredients that make up these systems. Most notable is the application of complexity theory. The patterns and processes that we see in geographical systems are governed by individual interactions that often lead to unexpected outcomes, with small shifts in behavior significantly altering how the system behaves. The classic example of this thinking applied within geography was by T. C. Schelling. Schelling's work showed how an individual's mild tastes and preferences to locate with similar types of people led to the emergence of segregation within a population. This notion that geographical systems are driven by individual decisions and behaviors, which are linked over varying spatial and temporal scales, has been crystallized in recent years by the proliferation of new forms of big data, resulting in unprecedented insight into the behavior of individuals. *See also:* **Complexity theory (/content/complexity-theory/802740)**

This marks a shift in how geographers are conceptualizing and attempting to simulate spatial systems. Capturing and replicating the complex relationships within geographical systems have always been significant challenges for researchers. As noted earlier, without data that could shed light on individual behavior and interactions, researchers had little option but to use statistical models that treat populations as one homogeneous group. Despite the recognition that these models aggregated out any interesting variation or "noise," they remain useful for replicating large-scale behavior and movement; for example, spatial interaction models are still used extensively in retail planning.

One of the central criticisms of these early models of geographical systems was their inability to capture and reflect the richness and diversity of populations. However, even if individual-level data were readily available 40 years ago, the necessary computational processing power and data storage required to run individual-level models were not. Nowadays, the upsurge in individual-based approaches (a change in thinking to emphasize the individual over the aggregate) has been driven by having all the important pieces of the puzzle in places as well as by increases in data storage and processing power and an abundance of individual-level data.

Agent-based modeling

At the very core of ABM is the individual. Through ABM, we can try to simulate and understand how an individual's behavior, relationships, and decisions affect the processes within a geographical system. This is achieved through using agents to represent individuals, such as people, buildings, or organizations, which have their own unique behaviors (rules) and relationships (**Fig. 1**). This type of bottom-up representation allows new knowledge and behaviors to emerge from interactions among the agents. Let us present two simple examples to highlight this.

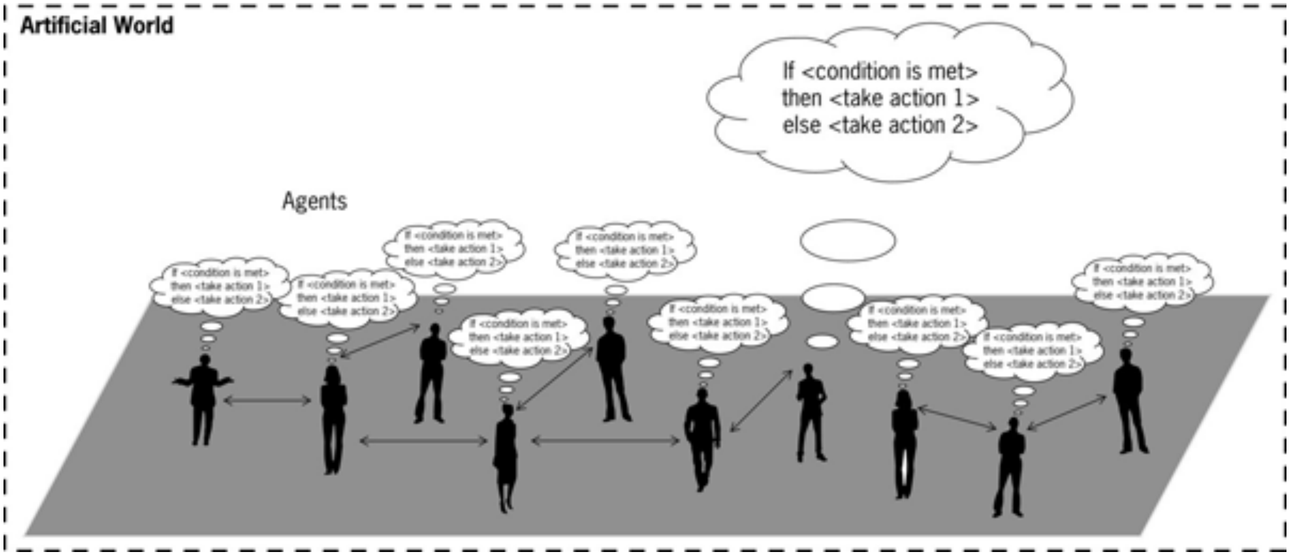

Fig. 1 Conceptualization of an agent-based model in which people are connected to each other and take actions when a specific condition is met.

In the first example, imagine how a disease spreads through a population. In an ABM, each person could be represented as an agent and only those who come into contact with an infected individual will contract the disease. By capturing such interactions at the individual level, one can explore how a disease emerges at the macro level; that is, among the population. *See also:* **Disease (/content/disease/200100)**; **Population ecology (/content/population-ecology/538150)**

For a second example, take the phenomenon of a traffic jam. If we model such an issue from an ABM perspective, each car can be constructed as an agent. Each car agent can be assigned a few simple rules, such as (1) if there is a car ahead of you, you need to slow down, and (2) if there is no car ahead of you, you can speed up. If we apply these rules to numerous agents, we can simulate the formation of a traffic jam without any accidents.

More important, we can carry out such experiments within the safe environment of a computer (that is, in silico). This allows researchers to explore ideas and hypotheses that might be too costly or unethical to implement in reality. For example, one cannot set a new building on fire and observe how people evacuate, but we can simulate this scenario in an agent-based model. Moreover, by carrying out such an exercise before the building is built, we might be able to identify potential bottlenecks and improve the safety of the final building.

This flexibility in how an agent-based model can be constructed provides a very powerful framework within which different types of models can be constructed. For example, researchers can test various scenarios or future projections by using abstract models to discover new relationships or knowledge, experimental models to try out new ideas about a system, and historical models to explain past trends and processes.

Several examples in the literature illustrate how these different models have been applied successfully within ABM. An excellent example of an empirical model is seen in the work of N. Malleson and coworkers. Here, agents were used to simulate the processes that influenced occurrence of burglary. In this example, agents were represented as burglars and embedded with behavioral information derived from a mixture of quantitative data (time/location of crime) and qualitative information (what motivated the burglar). Houses, and their relative vulnerability to burglaries, were also represented as agents within the physical environment. By representing individual dynamics and spatial relationships more realistically, researchers and policy practitioners are better able to understand the outcomes of implementing new crime-prevention initiatives. *See also:* **Criminalistics (/content/criminalistics/757510)**

A. T. Crooks and A. B. Hailegiorgis modeled the spread of cholera by combining an agent-based model with a commonly used epidemiological model, called the susceptible-exposed-infected-recovery (SEIR) model. This allowed the authors to represent interactions between humans and their environment explicitly. This experimental model sought to gain a greater understanding of the dynamics of cholera transmission by incorporating a fine level of detail about individuals' daily routine into their behavior, by emphasizing the connections between individuals as well as individuals and the environment. *See also:* **Cholera (/content/cholera/132800)**

Figure 2 shows how ABM has been used to explore a variety of issues at various spatial and temporal scales, ranging from the micro movement of pedestrians over seconds and hours to that of macro-scale phenomena of urban growth and migration over years and decades.

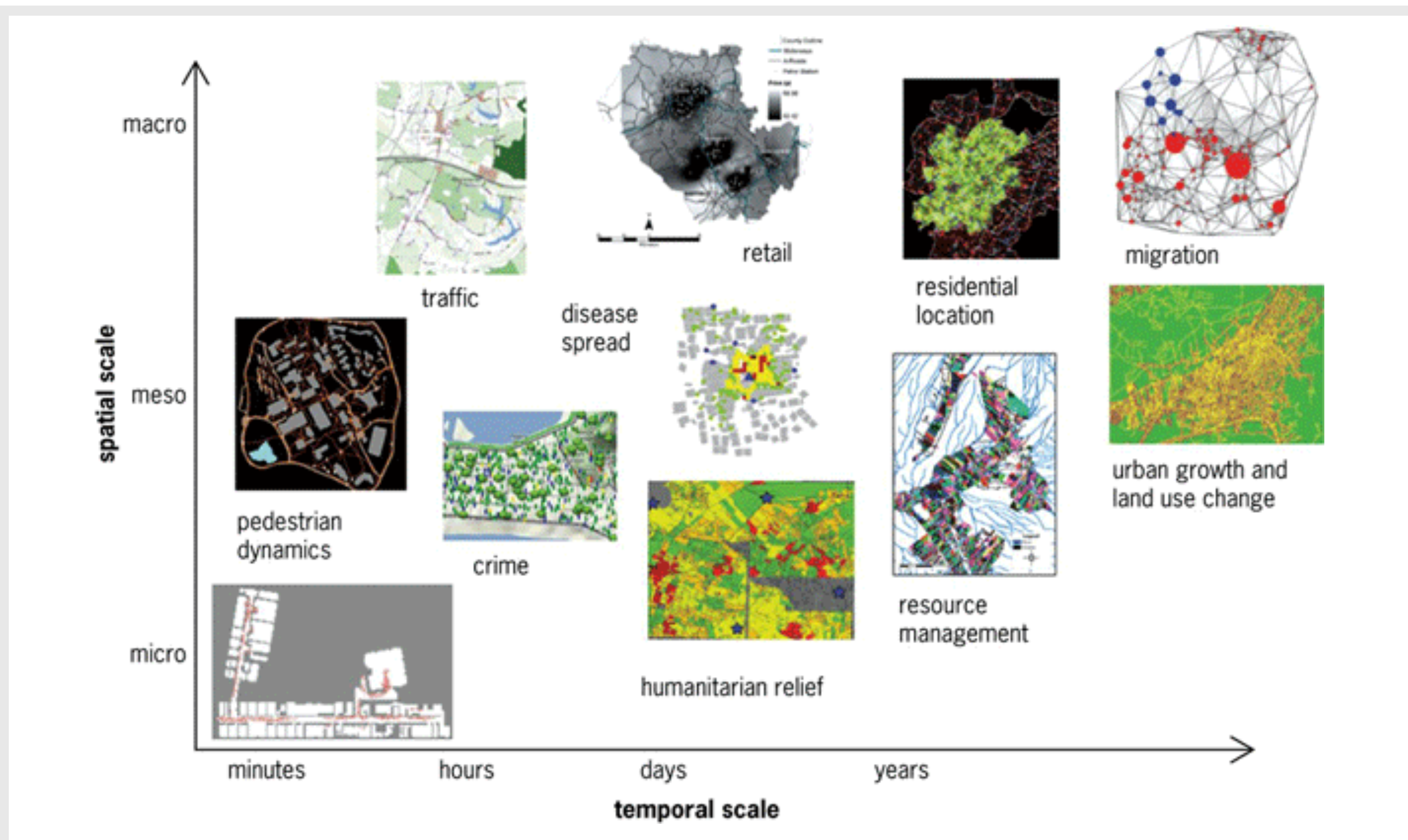

Fig. 2 A sample of application domains for agent-based models for geographical systems.

Limitations of ABM

Although there is growing use of agent-based models for a variety of applications, several key challenges still need to be overcome. These range across the spectrum from theory to practice as well as from hypothesis to application. However, the greatest challenge to ABM is akin to that of many other modeling methodologies, in that the realism that ABM can bring to a simulation is highly dependent on the quality of the data that it uses. Agents in particular require accurate individual-level behavioral data if they are to produce simulation results that can be used for policy. Without rigorous calibration (fine tuning of the model) and validation (testing the model on unknown data) of an agent-based model, any outputs are essentially meaningless. A typical agent-based model can comprise hundreds to thousands of heterogeneous agents, each operating under its own individual rule sets. Calibrating and validating these models therefore requires a huge amount of individual-level data.

Big data can potentially provide the level of detail required. The term big data refers to both traditional large data sets (for example, national censuses) as well as new digital information generated from social media. Social media platforms, such as Twitter, capture data about individual behavior and movements that have previously been absent from modeling efforts. Despite the obvious potential of big data, there are considerable issues to overcome, such as bias, noise, generalization, and in some cases, the ethics of whether researchers should be using these data.

Another important question that arises with using ABMs concerns how these models can be used to support real-world decision making. As discussed earlier, using ABM allows the dynamics of the system to be captured in a level of detail that is beyond the scope of more traditional styles of models. Through ABM we can represent the interactions of heterogeneous individual agents both with other agents and with their environment. This approach allows phenomena to emerge from the bottom up. However, within complex systems, predicting how a system will evolve in the future is fraught with uncertainty. One of the advantages of ABM is that it is able to handle this uncertainty. This makes ABM a valuable tool for exploratory modeling that can be used to inform policy analysis. Using ABM to influence decisions and understand alternatives has already been used in a number of settings such as theme parks, air transit, pedestrian and traffic simulations, and the spread of diseases or wildfires, as well as for financial markets and improved revenue generation. *See also:* **Simulations of pedestrian behavior applied to traffic management (/content/simulations-of-pedestrian-behavior-applied-to-traffic-management/BR1110152)**

Outlook

The future for ABM is very promising. Increased computational power and data storage, combined with the increasing proliferation of individual-level data, are making ABM a powerful tool for understanding and simulating the different processes and components in geographical systems. Although there is still work to be done in the area of calibration and validation of these models (for example, what metrics we should use at which geographical scale), there is no sign of the popularity of ABM abating.

We anticipate that ABM will be applied in the future to larger geographical areas and represent potentially millions of heterogeneous individuals. Although ABM is a popular modeling choice across the social sciences, including geography, comparatively little work has been done in simulating environment–human interactions. For instance, there is a lack of applications linking climate-change models to agent-based models of, say, urban growth. Linking these systems together represents a rich vein of future work. The future of this area will be characterized by big data powering complex agent-based models for large-scale simulations. *See also:* **Climate modeling (/content/climate-modeling/140350)**

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Bibliography

R. Axtell et al., Population growth and collapse in a multiagent model of the Kayenta Anasazi in Long House Valley, *Proc. Natl. Acad. Sci. USA*, 99(3):7275–7279, 2002 DOI: 10.1073/pnas.092080799 (http://dx.doi.org/10.1073/pnas.092080799)

S. Bankes, Exploratory modeling for policy analysis, *Oper. Res.*, 41(3):435–449, 1993 DOI: 10.1287/opre.41.3.435 (http://dx.doi.org/10.1287/opre.41.3.435)

O. Barreteau, F. Bousquet, and J. M. Attonaty, Role-playing games for opening the black box of multi-agent systems: Method and lessons of its application to Senegal River Valley irrigated systems, *J. Artif. Soc. Social Simul.*, 4(2):5, 2001, http://jasss.soc.surrey.ac.uk/4/2/5.html (http://jasss.soc.surrey.ac.uk/4/2/5.html)

M. Batty, *Urban Modeling: Algorithms, Calibrations, Predictions*, Cambridge University Press, 1976

M. Birkin, Retail and service location planning, in D. J. Maguire, M. Batty, and M. F. Goodchild (eds.), *GIS, Spatial Analysis and Modeling*, ESRI Press, pp. 221–244, 2005

E. Bonabeau, Agent-based modeling: Methods and techniques for simulating human systems, *Proc. Natl. Acad. Sci. USA*, 99(3):7280–7287, 2002 DOI: 10.1073/pnas.082080899 (http://dx.doi.org/10.1073/pnas.082080899)

A. T. Crooks and C. Castle, The integration of agent-based modeling and geographical information for geospatial simulation, in A. Heppenstall et al. (eds.), *Agent-Based Models of Geographical Systems*, Springer, pp. 219–252, 2012

A. T. Crooks, C. J. E. Castle, and M. Batty, Key challenges in agent-based modeling for geo-spatial simulation, *Comput. Environ. Urban*, 32(6):417–430, 2008 DOI: 10.1016/j.compenvurbsys.2008.09.004 (http://dx.doi.org/10.1016/j.compenvurbsys.2008.09.004)

A. T. Crooks and A. B. Hailegiorgis, An agent-based modeling approach applied to the spread of cholera, *Environ. Modell. Softw.*, 62:164–177, 2014 DOI: 10.1016/j.envsoft.2014.08.027 (http://dx.doi.org/10.1016/j.envsoft.2014.08.027)

A. T. Crooks and A. Heppenstall, Introduction to agent-based modeling, in A. Heppenstall et al. (eds.), *Agent-Based*

Models of Geographical Systems, Springer, pp. 85–108, 2012

V. Darley and A. V. Outkin, NASDAQ *Market Simulation: Insights on a Major Market from the Science of Complex Adaptive Systems*, World Scientific Publishing, 2007

J. Epstein, Modeling to contain pandemics, *Nature*, 460:687, 2009 DOI: 10.1038/460687a (http://dx.doi.org/10.1038/460687a)

S. Eubank et al., Modeling disease outbreaks in realistic urban social networks, *Nature*, 429:180–184, 2004 DOI: 10.1038/nature02541 (http://dx.doi.org/10.1038/nature02541)

A. S. Fotheringham and M. E, O'Kelly, *Spatial Interaction Models: Formulations and Applications*, Springer, 1989

N. Gilbert and K. G. Troitzsch, Simulation for the Social Scientist, 2d ed., Open University Press, 2005

S. Guerin and F. Carrera, Sand on fire: An interactive tangible 3D platform for the modeling and management of wildfires, *WIT Trans. Ecol. Environ.*, 137:57–68, 2010 DOI: 10.2495/FIVA100061 (http://dx.doi.org/10.2495/FIVA100061)

T. Hagerstrand, *Innovation Diffusion as a Spatial Process*, The University of Chicago Press, 1967

D. Helbing and S. Balietti, How to do agent-based simulations in the future: From modeling social mechanisms to emergent phenomena and interactive systems design, *Santa Fe Institute, Working Paper 11-06-024*, Sante Fe, NM, 2011

A. Heppenstall, N. Malleson, and A. T. Crooks, “Space, the final frontier”: How good are agent-based models at simulating individuals and space in cities? *Systems*, 4(1):9, 2016 DOI: 10.3390/systems4010009 (http://dx.doi.org/10.3390/systems4010009)

A. J. Heppenstall et al., *Agent-Based Models of Geographical Systems*, Springer, 2012

R. Lempert, Agent-based modeling as organizational and public policy simulators, *Proc. Natl. Acad. Sci. USA*, 99(Suppl 3):7195–7196, 2002 DOI: 10.1073/pnas.072079399 (http://dx.doi.org/10.1073/pnas.072079399)

N. Malleson et al., Using an agent-based crime simulation to predict the effects of urban regeneration on individual household burglary risk, *Environ. Plann. B Plann. Des.*, 40(3):405–426, 2013 DOI: 10.1068/b38057 (http://dx.doi.org/10.1068/b38057)

M. J. North et al., Multiscale agent-based consumer market modeling, *Complexity*, 15(5):37–47, 2010 DOI: 10.1002/cplx.20304 (http://dx.doi.org/10.1002/cplx.20304)

D. O'Sullivan et al., Agent-based models—Because they're worth it?, in A. J. Heppenstall et al. (eds.), *Agent-Based Models of Geographical Systems*, Springer, 2012

T. C. Schelling, Dynamic models of segregation, *J. Math. Sociol.*, 1(1):143–186, 1971

F. Seibel and C. Thomas, Manifest destiny: Adaptive cargo routing at Southwest Airlines, *Perspect. Business Innovation*, 4:27–33, 2000

Y. Sugiyama et al., Traffic jams without bottlenecks—Experimental evidence for the physical mechanism of the formation of a jam, *New J. Phys.*, 10:033001, 2008 DOI: 10.1088/1367-2630/10/3/033001 (http://dx.doi.org/10.1088/1367-2630/10/3/033001)

A. G. Wilson, *Urban and Regional Models in Geography and Planning*, Wiley, 1974

M. Batty, *The New Science of Cities*, MIT Press, 2013

I. Benenson and P. M. Torrens, *Geosimulation: Automata-Based Modeling of Urban Phenomena*, Wiley, 2004

C. Cioffi-Revilla, *Introduction to Computational Social Science: Principles and Applications*, Springer, 2014

J. M. Epstein and R. Axtell, *Growing Artificial Societies: Social Science from the Bottom Up*, MIT Press, 1996

H. R. Gimblett (ed.), *Integrating Geographic Information Systems and Agent-Based Modeling Techniques for Simulating Social and Ecological Processes*, Oxford University Press, 2002

D. C. Parker et al., Multi-agent systems for the simulation of land-use and land-cover change: A review, *Ann. Assoc. Am. Geogr.*, 93(2):314–337, 2003 DOI: 10.1111/1467–8306.9302004 (http://dx.doi.org/10.1111/1467–8306.9302004)

S. F. Railsback and V. Grimm, *Agent-Based and Individual-Based Modeling: A Practical Introduction*, Princeton University Press, 2011

Additional Readings

A Science of Cities (http://www.complexcity.info)

Dr. Andrew Crooks: GIS and Agent-based Modeling (http://www.gisagents.org)

OpenABM (https://www.openabm.org)