Chapter 20
Urban Geosimulation

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Abstract The field of geosimulation represents one of the most innovative attempts to revitalize the usefulness and application of spatial modeling. With its generative emphasis on micro-dynamics of complex systems and its flexible treatment of space, time, pattern, and process, it marks a significant departure from traditionally employed coarse, static approaches. The primacy of geography in geosimulation also represents a departure for spatial simulation from its reliance on modeling methods borrowed from economics and physics, which were often ported to spatial applications because of tractability, but without consideration of the suitability of the fit. Research in geosimulation, while still nascent in its development, has been particularly active in urban applications, where the technique has considerably expanded the range of questions and ideas that can be explored in simulation. This chapter reviews the origins of urban geosimulation, discusses the state-of-the-art relative to urban applications, and speculates about potential future avenues of inquiry in the field.

20.1 Introduction

Geosimulation represents an innovative approach to constructing spatial simulations, building on the successes of previous generations of spatial simulation within the relatively unique context of a conventional era of 'big data', rapid advances in computing hardware and software, the convergence of modeling and simulation technologies across applications, and the growing utility of Geographic Information Science (Torrens 2010). Geosimulation has been developed in several disciplines, although much of its usefulness has been proven for *urban applications*. In essence, the geosimulation approach is characterized by information processing, and in that

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way, it is no different than most conventional computer simulation schemes. However, the novelty, in geosimulation, is in using *geography* to map information processing directly to individual system elements and the processes that determine their dynamics in a massively interactive systems context, such that complete, realistic models of complex phenomena can be built, generatively, from the spatial atoms that comprise them. The emphasis in establishing such mappings, is on how geography – geographic processes, patterns, and context – can enable and advance more useful information processing.

In this chapter, I will describe the development of geosimulation for urban applications: its origins in the early introduction of computing to urban modeling in the 1970s, an overview of the current state-of-the-art, and a discussion of potential future avenues for research and development in the field.

20.2 The Origins of Geosimulation

The *premise* for geosimulation has quite a distinguished history. It dates back to Alan Turing's ideas for the digital computer, which were pioneered in his efforts to design devices that could crack the German Enigma code during World War II. In his original paper, Turing (1936, 1938) introduced the idea for an automaton (a term which had historically been associated with anthropomorphized but mechanical *machines*) that, given enough storage, power, and the right rule-set could automatically and efficiently compute solutions to mathematical problems. His later development of the idea to ascribe machine intelligence to such devices (Turing 1950) established the origins for modern-day artificial intelligence. Turing's use of neighborhood filters for information processing in these ideas was of key relevance to geography. Turing originally suggested that information processing could be treated as a quadruple of interacting factors: a serialized set of cells as containers for data on a tape-like manifold; state information which described data in the context of its unique location in space and time along the tape; a tape-reading head that could shift cell-by-cell along the tape to interpret neighboring state information on adjacent cells; and a table of rules that determined how states and neighbors should be contextualized. This introduced some core geographical concepts – space-time, relationships between pattern and process, action-by-proximity, neighborhood filtering, and perhaps even the trained eye of the geographer – into the early evolution of information processing.

The significance was not lost on geographers and the idea of using automata to formally treat geography in computer models of spatial process surfaced as early as the field began. Indeed, Waldo Tobler's (1970) concise expression of one of the tenets of exploration in the geographical sciences, the idea that near things are related to each other, neatly encapsulates the core components of Turing's automata and the heuristic was at the foundation of one of the first examples of automata modeling (and geosimulation), Tobler's model of the urbanization of Detroit. Other early examples included the land-use transition models developed by Chapin and

GeoSimulation

Geosimulation is a new field in the geographical sciences that involves the exploration of geographic problems using computation as the principle form of research inquiry as well as employing the computer as a laboratory for testing hypotheses.

This page describes some of my work in the area and links to various other related simulation projects (some of which I am involved with, and others in which I am not).

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You can always email me if you have any questions or queries.

Fig. 20.1 The geosimulation.com website in 1999, complete with horrendous graphics, as befitting web design of the time

Weiss (1962), an urbanization model introduced by Nakajima (1977), and Peter Allen's work on modeling settlement hierarchy (Allen and Sanglier 1979).

The actual *term* geosimulation was introduced by Torrens in 1999 to describe efforts underway at the time in the Centre for Advanced Spatial Analysis (CASA) at University College London to build a next generation of spatial simulation methods, which were essentially building on the foundation introduced by Chapin, Weiss, and Tobler decades before. In a time before the popularity of Weblogs, Torrens launched a Website, http://www.geosimulation.com (later, .org) devoted to the topic (Fig. 20.1). Torrens outlined the idea for geosimulation in a talk at the 2000 Geocomputation meeting in Greenwich co-authored with David O'Sullivan (Torrens and O'Sullivan 2000). This was further developed in a 2004 special issue of the journal, *Computers, Environment and Urban Systems* by Torrens and Itzhak Benenson (Benenson and Torrens 2004b), who also co-authored a book on the topic, which was published in 2004 (Benenson and Torrens 2004a).

Many people at CASA were doing work in this area at the time, following the interests of Michael Batty and Yichun Xie in developing new forms of urban modeling around cellular automata (CA) (Batty and Xie 1994). Michael was building several extensions of the idea, for urbanization (Batty 1997a, b, 1999, 2001; Batty et al. 1999; Batty and Xie 1997) and movement of walkers within (Batty et al. 1998) and around (Batty et al. 2003) built spaces. Bin Jiang was collaborating with Michael on CA models for pedestrian simulation (Batty and Jiang 1999); David O'Sullivan was researching graph-based CA for gentrification modeling (O'Sullivan 2001); and Torsten Schelhorn, Muki Haklay, and David O'Sullivan were building the STREETS movement model for town centers (Schelhorn et al. 1999).

Several other groups were also developing the essential components of urban geosimulation in parallel at other sites. In North America, Keith Clarke's group at the University of California, Santa Barbara had long been developing an extensible urban growth model based on CA and his ideas for deltatrons (Clarke 1997; Clarke and Gaydos 1998; Clarke et al. 2007). This, perhaps, built on earlier work in applying CA to wildfire modeling (Clarke et al. 1994). Helen Couclelis, also at Santa Barbara, had experimented with CA modeling in the 1980s (Couclelis 1985) and her interest in the intersection between CA and GIS was revived around this time (Couclelis 1997; Takeyama and Couclelis 1997). Geographer, Michel Phipps (1989) at the University of Ottawa, developed the idea for the neighborhood coherence principle – initially used in biology, not urban analysis – using cellular automata. In the early-2000s, the land-use and land cover change modeling community in North America also began to pick-up CA modeling as a mechanism for developing what they referred to as spatially-explicit models, continuing the tradition started by Chapin and Weiss in the 1960s (Manson 2000; Brown et al. 2003; Evans and Kelley 2004; Lim et al. 2002). However, this work was mostly focused on *non-urban* areas, where ecologically significant canopies manifested as land cover.

In Europe, Roger White, at the Memorial University of Newfoundland was developing what would become the MURBANDY models (Engelen et al. 2002) with Guy Engelen and colleagues at the Research Institute for Knowledge Systems (RIKS) in the Netherlands (Engelen et al. 1995; White and Engelen 1994, 1997). From the outset, these were developed with the intention of becoming operational planning support systems (White and Engelen 1993). Denise Pumain and Lena Sanders at the Université Paris I were building the original SIMPOP model of demographic geography based around agent automata (Sanders et al. 1997). Itzhak Benenson and Portugali at Tel Aviv University were also working on urban segregation models based on the idea of agents in CA cells (Benenson 1998; Portugali 2000), echoing the idea of the "particle in a cell" (p. 99) introduced by Gipps and Marksjö (1985). Chris Webster and Fulong Wu were also building CA models of urban growth at Cardiff University, using fuzzy approaches and linguistic rule-sets (Webster and Wu 1998; Wu 1996). Ferdinando Semboloni at the University of Florence was developing 2.5 dimensional (land-use and height) urbanization models based on CA functionality (Semboloni 1997; 2000). Peter Mandl at Alpen-Adria Universitat in Austria was pursuing CA modeling research and adopted the term geosimulation for his work (Mandl 2000). Harry Timmermans and Jan Dijkstra at the Delft University of Technology in the Netherlands were also developing CA-based pedestrian models at the time (Dijkstra et al. 2000). Related work was ongoing in European physics and biophysics research, with some crossover in urban applications (Nagel and Schrekenberg 1995; Schweitzer 1997; Helbing and Molnár 1995; Ermentrout and Edelstein-Keshet 1993). Transport modelers in Europe had also begun to look at CA as a vehicle for simulating pedestrian traffic along streetscapes (Blue and Adler 2001), following early influential work by Gipps and Marksjö (1985).

In Asia, Anthony Gar-On Yeh and Xia Li at the University of Hong Kong were developing CA models of urbanization with GIS output functionality

(Li and Yeh 2000). Takashi Arai's group at the Tokyo University of Science was also developing well-calibrated CA models of urbanization on the basis of the White & Engelen model (Arai and Akiyama 2004).

In Australia, Robert Itami had long been developing agent automata models of hikers' movement along trails (Itami 1988), which although not urban was one of the first (as far as I know, *the* first) introductions of *agent* automata in geography. Martin Bell at the University of Adelaide developed a CA-like graphic model of urbanization that was coupled to geographic information systems (GIS) and that considered adjacency rules (Bell et al. 1999). Doug Ward, Stewart Phinn, and Alan Murray, then at the University of Queensland, also developed a CA-based urbanization model, which considered the role of road-building in fostering urban growth (Ward et al. 2000).

CA models rely on checking the information contained in automata through neighborhood filters and so geography featured implicitly in many of these models. Similarly, many of the models relied on GIS for data management and for visualizing model output. However, *geographical science*, which sits at the heart of the geosimulation approach, was not necessarily treated *explicitly* in the models. The contribution of geosimulation is mainly in reawakening interest in the developments introduced by early pioneers in the 1960s and 1970s, but also in infusing anew the idea of using geography to advance urban simulation amid more recent developments in computing technology. In this sense, geosimulation also draws upon the early work of Stan Openshaw in developing the field of geocomputation at the University of Leeds (Openshaw et al. 1987; Batty 1998) at the intersection of computing (rather than simply using computers) and geography (Longley et al. 1998).

Geography-specific automata modeling actually forms a smaller sub-set of the activity I have just described. Early work by Waldo Tobler really exemplifies a *dedicated* geographic consideration of the utility of employing automata for spatial modeling. His initial paper on the topic introduced variable neighborhood considerations as a vehicle for exploring the relationship between action and distance (Tobler 1979), perhaps following from his interest in automated cartography and projections (Tobler 1959). Later work by Couclelis extended geographic ideas, exploring the fundamental nature of information-gathering in geographic automata (Takeyama and Couclelis 1997). Similar ideas had been pursued by Phipps, in examining the utility of the neighborhood as a vehicle for spatial interaction (Phipps 1989). Clarke's careful exploration of sufficient geographic (and GIS) processes for the SLEUTH model (Clarke and Gaydos 1998) was also critical in laying the foundation for the development of dedicated geographic algorithms for urban automata: an area of research which still does not enjoy the attention that it deserves (Torrens and O'Sullivan 2000). Although not specifically urban, Robert Itami's work on ascribing spatial cognition as artificial intelligence for agent automata was pioneering in its early exploration of the role of spatial intelligence in allying automata models to human geography (Itami 2002, 1988). Recently, Bernard Moulin's group at Université Laval have developed a series of geosimulation applications, ranging from shopping behavior (Ali and Moulin 2005) and crowd modeling (Moulin et al. 2003) to disease propagation (Bouden et al. 2008).

Of course, much of the geography that finds its way into urban automata filters through GIS. Many of the urban automata modeling schemes built in the 1990s and early-2000s had components that *connected* to GIS. Usually, this was for simple data input and cartographic visualization of results. Many CA models, for example, would read-in polygonal, raster, or graph lattices as a cellular structure for automata. Similarly, the graphic user interface (GUI) components of GIS were often used to visualize model output cartographically, allowing for on-screen querying of results through brushing and other geovisualization procedures. For some time, there was debate about whether urban automata models should be run within standard GIS toolboxes (Wagner 1997; Batty et al. 1999; Park and Wagner 1997) and automata-based extensions for commercial GIS software were developed (Strout and Li 2006; Brown et al. 2005), as were GIS input-output functionality for popular open source (Dibble and Feldman 2004) or freeware automata model development packages (Blikstein et al. 2005). Similarly, there was debate about whether the two should be loose-coupled or tight-coupled (Brown et al. 2005; Clarke and Gaydos 1998; Torrens and Benenson 2005).

20.3 Geosimulation: A Primer

Geosimulation goes beyond issues of getting GIS data in and out of simulations. However, at its core, it deals with flexible handling of geographic information through process modeling (Torrens 2009) and matching those processes as realistically as possible to ideas, theory, hypotheses, or knowns of the system being considered. Geosimulation has several key components in interfacing geography with information processing generally and automata particularly.

First, traditional treatment of geographical units as average, spatially-modifiable geographical units, or (statistically) mean individuals (Openshaw 1983) in spatial modeling is expanded in geosimulation. This coarse approach is instead replaced with a regard for spatially non-modifiable entities, replete with individual descriptions and independent functionality. If spatial aggregates are indeed treated in simulation, they are handled generatively (Epstein 2006), as being built from the bottom up through assembly of individual entities and their connecting interactions for the purposes of producing aggregate behavior, phenomena, processes, or structures. This introduces a significant advantage as it allows for exploration of the genesis of spatial phenomena as the 'atoms' of the process. Additionally, it permits for the emergence of complexity from these assemblies across complicated mechanisms such as non-linearity, path-dependence, self-organization, feedback, scaling, bifurcation, fractality, and so on (O'Sullivan 2004).

Second, geosimulated entities are usually endowed with autonomy and independence in their behavior, even when collaborating or conflicting. This individuality is important as it shifts the attention in model-building and in exploring simulations to treatment of singular behavior in the context of larger systems (O'Sullivan and Haklay 2000). It also marks a departure from physics-based or economics-based modeling methods, from which spatial modeling has traditionally pilfered, in that the behavior of entities in simulation is not necessarily considered as being homogenous across the system, i.e., the spatial uniqueness of the behavior and the unique geography of its context matters, whether spatial, temporal, social, technical, environmental, built, economic, and so on. Moreover, these behaviors are not considered as being static within a simulation. Even if a transition rule is applied mechanically in the same way for each modeled entity, the unique experience of that entity will infuse the rule with unique information, producing variation in outcomes over space and time. This sort of sensitivity to micro-specification is one of the hallmarks of complexity studies (Arthur 1990). The computational flexibility of geosimulation also means that the approach is agnostic in its consideration of the sorts of behaviors, phenomena, agency, or processes that it can handle.

Third, geosimulations are usually designed as event-driven systems, as compared to the traditional approach of building time-driven (or even cross-sectional) models. Specifically, geosimulations generally treat interactions among modeled entities as events, with discrete bundles of change in space-time. These could be one-off events, or cyclical, seasonal, chain reactions, serials, and so on. They can also be considered synchronously or asynchronously among entities and spaces within the simulation. Treatment of timing in this manner has a number of advantages. It allows for representation of entities' internal 'clocks' (whether these are actual, mechanical within a simulation, or conceptual). This allows, for example, for the 'thought calculus' of a modeled entity to be worked through before it produces an interaction within the simulation, and for diversity in these calculi to be reconciled and scheduled parsimoniously across many interacting entities. When put together to form a system, update of modeled entities' clocks may be flexibly defined and the methodology can reconcile diverse temporal scales. Events can also be constructed heterogeneously per simulated entity with the result that the characteristic timing of a process, phenomenon, thought, collaboration, conflict, and so on can be represented in simulation. In essence, this allows for the treatment of entities at both their spatial and temporal atoms of behavior or process.

Fourth, geosimulation has a natural symbiosis with Geographic Information Science, GIS, spatial analysis, and related geospatial technologies. This connection to Geographic Information Science extends to spatial data models, including entity-relationship, object-oriented, raster, graph, hierarchical and so on. It also allies automata with spatial data access heuristics. This is perhaps not surprising, given the origins of geosimulation in *information processing* and the fundamental consideration of space, time, process, and neighborhood in relating information dynamics within the automata framework. It is, however, quite a significant development over traditional spatial modeling approaches, which quite often were designed for reading-in variables and parameters, but not for handling input data, output results, and the internal information processing dynamics of simulation with dedicated data models. Fundamentally, it increases the opportunities for information diffusion and interaction in models.

Fifth, with origins in the birth of digital computing, geosimulation is comfortably allied with computer science with the result that geosimulation models can be docked with other forms of computational modeling, including computer graphics and animation (Torrens 2007a), parallel and high-performance computing (Guan et al. 2006; Phipps and Langlois 1997), artificial neural networks (Li and Yeh 2002), Bayesian computing (Kocabas and Dragi evi 2006), swarm optimization (Liu et al. 2007), evolutionary computation (Manson 2005), and so on.

Sixth, because of its fundamental emphasis on dynamics and interaction, geosimulation is well-suited to representing complexity in simulation, and associated phenomena of feedback and path-dependence, non-linearity, emergence, fractality, allometry, bifurcation, autopoiesis, self-organization, and so on (see Batty (2005) for an overview).

20.4 Geographic Automata as a Vehicle for Geosimulation

The introduction of *geographic automata* has perhaps represented the most explicit conventional treatment of geosimulation. Development of the idea has come from a variety of sources, mostly organized around geographic CA, with extended (usually derived from GIS and spatial analysis) geographic functionality for relating cells to other cells through neighborhood filters. Often, these are developed to handle specific cellular geometries, such as layered rasters (Takeyama and Couclelis 1997), vectors (Moreno et al. 2008; Stevens and Dragi evi 2007), and graphs (networks) (Dibble and Feldman 2004; O'Sullivan 2001). Other approaches have used the geographic attributes of CA to accelerate computing in simulation (Guan et al. 2006; Liu et al. 2007).

The development if *geographically-enabled* CA has introduced fantastic geographic functionality to urban automata models, but in many ways they are extensions of existing CA approaches through spatial analysis. In the early-2000s, Torrens (2001) introduced a dedicated geographic automata system (GAS), designed to treat geography inherently in an automata framework. Starting with a basic, stripped-down automaton with processing capability (states, input, state transition), the approach infused geographic functionality into the basic working elements of the automaton. This included dedicated processing capabilities for space-time movement, malleable location conventions, dedicated neighborhood process rules that dictate how neighborhood filters should transform over space and time, and ontology of spatial primitives. In a paper with Itzhak Benenson (Torrens and Benenson 2005), Torrens demonstrated the concept with a working demonstration of the classic Schelling/Sakoda segregation model (Sakoda 1971; Schelling 1971), worked as a GAS, and a review of how all urban automata models at the time could be accommodated in the framework. The GAS framework goes beyond simply allying automata models with GIS, as it allows the model-designer to infuse core geographic principles into the essential functionality of the automata. These geographic primitives can then be used to build spatial entities or phenomena from the bottom-up. In essence, knowledge is created in model-building and simulation by experimenting with the geographical building-blocks of geographic complexity, from first principles.

Torrens has since published a series of demonstrations of the approach for urban geosimulation, including models of urbanization (Torrens 2006a), suburban sprawl (Torrens 2006b), residential location behavior (Torrens 2007b), gentrification dynamics (Torrens and Nara 2007), and behavioral geography (Torrens 2007a). Itzhak Benenson also developed the idea into a software package (Benenson et al. 2006).

The GAS framework has also been adopted for geosimulation in other fields. Shawn Laffan at the University of Queensland and Michael Ward at Texas A&M have developed a series of infection propagation models for veterinary studies using geographic automata (Doran and Laffan 2005; Ward et al. 2007; Laffan et al. 2007). Shen and colleagues (2009) have used geosimulation and geographic automata for land-use modeling. Hammam and colleagues (2007) developed an extended concept for geographic automata with geometry displacement. A series of related concepts for geographic automata have also been developed by Moreno and Marceau, with at least partial inspiration from the GAS approach (Moreno et al. 2008, 2009).

20.5 Epilog: The Future of Urban Geosimulation

The field of geosimulation is still quite nascent and developments are almost inextricably tied to the emergence of new forms of modeling and simulation in science generally. The emergence of new forms of dataware for modeling and simulation and the growth in computational social science around those developments could have a transformative impact on the future research trajectory for urban geosimulation. In particular, a set of promising avenues for future research are relevant.

The first is the development of semantic search on the Web (Berners-Lee et al. 2001), semantic computing (Egenhofer 2002), and the evolution of the "GeoWeb" (Elwood 2010; Haklay et al. 2008). The basic components of geosimulation are naturally amenable to ontological representation, which lends geosimulation interoperability with semantic computing. Coupled with the popularity of semantic approaches, there has been a recent swelling in the volume, availability, and semantic organization of geographic information on the Web. Already, applications that use geosimulation-like process functions are being used to extract and interpret space-time data on the Web or data generated using mobile devices tethered to the Web. These include so-called predestination models (Krumm and Horvitz 2007) that couple geosimulation-like modeling with location-based services to provide application to users of mobile devices based on their position in space and time and models of their (and others') past trajectories (Torrens 2010). Indeed, there exists great potential for the development of more sophisticated semantically-operable and Web-enabled geosimulation processing services, which can feed on a steady stream of newly-emerging geographic information (Goodchild 2007). The emergence of geoagents as Web-scraping tools has already shifted Geographic Information Science in this direction (Yu and Peuquet 2009; Zhang and Tsou 2009).

Geosimulation-like schemes are also being introduced in computer graphics research, specifically to endow synthetic characters in special effects and games with realistic behavioral geography (Pelechano et al. 2008). Thus far, the spatial intelligence afforded these synthetic (usually automata-based) characters has been relatively simple, but significant advances are being made, in ascribing them realistic vision (Terzopoulous et al. 1994), activity (Paris and Donikian 2009), behavior (Ulicny and Thalmann 2003), collective geography (Nieuwenhuisen et al. 2007), and even emotions (Badler et al. 2002). Cross-fertilization of ideas between computer graphics and geosimulation could catalyze significant gains in the computability of geosimulation models (which developers of computer graphics often excel at) while maintaining rich behavioral fidelity (which geographers often excel at). Several geographers have already made initial forays into this area from the perspective of Geographic Information Science, geovisualization (Crooks et al. 2009), and geosimulation (Torrens 2007a).

There also remains a relatively untapped potential for connecting urban geosimulation with geodemographics and related business intelligence. Geodemographics, as a field of study, concerns itself with classifying and grouping consumers based on the geography of their activity patterns and spending habits (Singleton and Longley 2009; Harris et al. 2005). It is used widely and practically in marketing and business analysis, for political polling, consumer testing, advertising, and actuarial analysis. Much of the spatial analysis used in geodemographics is relatively primitive, however, and would benefit substantially from the infusion of geosimulation, which would allow for more sophisticated models of individuals and their space-time activity and behavior to be developed (Kurose et al. 2001; Hui et al. 2009). Given the basis for geodemographics in data-collection and data-generation (Longley and Harris 1999), there also exists potential for calibration of geosimulation models. Of course, the potential for unwelcome uses of such systems and function creep beyond simple customer analysis is great (Dobson and Fisher 2003).

References

Ali, W., & Moulin, B. (2005). 2D-3D MultiAgent GeoSimulation with knowledge-based agents of customers' shopping behavior in a shopping mall. *Lecture Notes in Computer Science, 3693*, 445–458.

Allen, P. M., & Sanglier, M. (1979). A dynamic model of growth in a central place system. *Geographical Analysis, 11*(3), 256–272.

Arai, T., & Akiyama, T. (2004). Empirical analysis of the land use transition potential in a CA based land use model application to the Tokyo Metropolitan Region. *Computers, Environment and Urban Systems, 28*(1/2), 65–84.

Arthur, W. B. (1990, February). Positive feedbacks in the economy. *Scientific American*, pp. 80–85.

Badler, N., Allbeck, J., Liwei, Z., & Byuan, M. (2002). Representing and parameterizing agent behaviors. In *Proceedings of computer animation* (pp. 133–143). Geneva: IEEE Computer Society.

Batty, M. (1997a). Cellular automata and urban form: A primer. *Journal of the American Planning Association, 63*(2), 266–274.

Batty, M. (1997b). Possible urban automata. *Environment and Planning B, 24*, 175–192.

Batty, M. (1998). GeoComputation using cellular automata. In P. A. Longley, S. M. Brooks, R. McDonnell, & B. Macmillan (Eds.), *Geocomputation: A primer* (pp. 96–129). Chichester: Wiley.

Batty, M. (1999). *Multi-agent approaches to urban development dynamics*. London: Centre for Advanced Spatial Analysis, University College London.

Batty, M. (2001). Polynucleated urban landscapes. *Urban Studies, 38*(4), 635–655.

Batty, M. (2005). *Cities and complexity: Understanding cities with cellular automata, agent-based models, and fractals*. Cambridge: The MIT Press.

Batty, M., Desyllas, J., & Duxbury, E. (2003). The discrete dynamics of small-scale spatial events: Agent-based models of mobility in carnivals and street parades. *International Journal of Geographical Information Science, 17*(7), 673–697.

Batty, M., & Jiang, B. (1999). *Multi-agent simulation: New approaches to exploring space-time dynamics within GIS* (CASA Working Paper 10). London: Centre for Advanced Spatial Analysis (CASA), University College London.

Batty, M., Jiang, B., & Thurstain-Goodwin, M. (1998). *Local movement: Agent-based models of pedestrian flows* (CASA Working Paper 4). London: Centre for Advanced Spatial Analysis (CASA), University College London.

Batty, M., & Xie, Y. (1994). From cells to cities. *Environment and Planning B, 21*, s31–s48.

Batty, M., & Xie, Y. (1997). Possible urban automata. *Environment and Planning B, 24*(2), 175–192.

Batty, M., Xie, Y., & Sun, Z. (1999). Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems, 23*(3), 205–233.

Bell, M., Dean, C., & Blake, M. (1999). A model for forecasting the location of fringe urbanisation, with GIS and 3D visualisation. In P. Rizzo (Ed.), *Proceedings of the sixth international conference on computers in urban planning and urban management (CUPUM)*, Venice, CD-ROM.

Benenson, I. (1998). Multi-agent simulations of residential dynamics in the city. *Computers, Environment and Urban Systems, 22*(1), 25–42.

Benenson, I., Birfur, S., & Kharbash, V. (2006). Geographic Automata Systems and the OBEUS software for their implementation. In J. Portugali (Ed.), *Complex artificial environments* (pp. 137–153). Berlin: Springer.

Benenson, I., & Torrens, P. M. (2004a). *Geosimulation: Automata-based modeling of urban phenomena*. London: Wiley.

Benenson, I., & Torrens, P. M. (2004b). Geosimulation: Object-based modeling of urban phenomena. *Computers, Environment and Urban Systems, 28*(1/2), 1–8.

Berners-Lee, T., Hendler, J., & Lassila, O. (2001). The semantic Web. *Scientific American, 284*(5), 34–44.

Blikstein, P., Abrahamson, D., & Wilensky, U. (2005). NetLogo: Where we are, where we're going. In M. Eisenberg & A. Eisenberg (Eds.), *Proceedings of the Annual Meeting of Interaction Design & Children*, Boulder, CO, June 8–10.

Blue, V., & Adler, J. (2001). Cellular automata microsimulation for modeling bi-directional pedestrian walkways. *Transportation Research Part B, 35*, 293–312.

Bouden, M., Moulin, B., & Gosselin, P. (2008). The geosimulation of West Nile virus propagation: A multi-agent and climate sensitive tool for risk management in public health. *International Journal of Health Geographics*, *7*(35), Online.

Brown, D. G., Page, S. E., Riolo, R. L., & Rand, W. (2003). Agent based and analytical modeling to evaluate the effectiveness of greenbelts. *Environmental Modelling and Software, 19*(12), 1097–1109.

Brown, D. G., Riolo, R., Robinson, D. T., North, M. J., & Rand, W. (2005). Spatial process and data models: Toward integration of agent-based models and GIS. *Journal of Geographical Systems, 7*(1), 25–47.

Chapin, F. S., & Weiss, S. F. (1962). *Factors influencing land development. An urban studies research monograph*. Chapel Hill: Center for Urban and Regional Studies, Institute for Research in Social Science, University of North Carolina.

Clarke, K. (1997). *Land transition modeling with deltatrons* [Online]. Department of Geography, University of California, Santa Barbara. Accessed January 1, 2000. Available from http://www.geog.ucsb.edu/~kclarke/Papers/deltatron.html

Clarke, K. C., Brass, J. A., & Riggan, P. J. (1994). A cellular automata model of wildfire propagation and extinction. *Photogrammetric Engineering and Remote Sensing, 60*(11), 1355–1367.

Clarke, K. C., & Gaydos, L. (1998). Loose coupling a cellular automaton model and GIS: Long-term growth prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science, 12*(7), 699–714.

Clarke, K. C., Gazulis, N., Dietzel, C., & Goldstein, N. C. (2007). A decade of SLEUTHing: Lessons learned from applications of a cellular automaton land use change model. In P. Fisher (Ed.), *Classics in IJGIS: Twenty years of the International Journal of Geographical Information Science and Systems* (pp. 413–427). Boca Raton: CRC Press.

Couclelis, H. (1985). Cellular worlds: A framework for modeling micro-macro dynamics. *Environment and Planning A, 17*, 585–596.

Couclelis, H. (1997). From cellular automata to urban models: New principles for model development and implementation. *Environment and Planning B, 24*, 165–174.

Crooks, A., Hudson-Smith, A., & Dearden J. (2009). Agent street: An environment for exploring agent-based models in second life. *Journal of Artificial Societies and Social Simulation*, *12*(4). http://jasss.soc.surrey.ac.uk/12/4/10.html

Dibble, C. & Feldman, P. G. (2004). The GeoGraph 3D computational laboratory: network and terrain landscapes for RePast. *Journal of Artificial Societies and Social Simulation*, *7*(1). http://jasss.soc.surrey.ac.uk/7/1/7.html

Dijkstra, J., Timmermans, H. J. P., & Jessurun, A. J. (2000). A multi-agent cellular automata system for visualising simulated pedestrian activity. In S. Bandini & T. Worsch (Eds.), *Theoretical and practical issues on cellular automata* (pp. 29–36). London: Springer.

Dobson, J., & Fisher, P. (2003). Geoslavery. *IEEE Technology and Society Magazine, 22*(1), 47–52.

Doran, R. J., & Laffan, S. W. (2005). Simulating the spatial dynamics of foot and mouth disease outbreaks in feral pigs and livestock in Queensland, Australia, using a susceptible-infected-recovered cellular automata model. *Preventive Veterinary Medicine, 70*(1–2), 133–152.

Egenhofer, M. J. (2002). Toward the semantic geospatial web. In K. Makki & N. Pissinou (Eds.), *Proceedings of the tenth ACM international symposium on advances in Geographic Information Systems,* McLean, VA (pp. 1–4). New York: ACM Press.

Elwood, S. (2010). Geographic information science: Emerging research on the societal implications of the geospatial web. *Progress in Human Geography, 34*(3), 349–357.

Engelen, G., White, R., & Uljee, I. (2002). *The MURBANDY and MOLAND models for Dublin*. Maastricht: Research Institute for Knowledge Systems (RIKS) BV.

Engelen, G., White, R., Uljee, I., & Drazan, P. (1995). Using cellular automata for integrated modelling of socio-environmental systems. *Environmental Monitoring and Assessment, 30*, 203–214.

Epstein, J. M. (2006). *Generative social science: Studies in agent-based computational modeling*. Princeton: Princeton University Press.

Ermentrout, G. B., & Edelstein-Keshet, L. (1993). Cellular automata approaches to biological modeling. *Journal of Theoretical Biology, 160*, 97–133.

Evans, T. P., & Kelley, H. (2004). Multi-scale analysis of a household level agent-based model of landcover change. *Journal of Environmental Management, 72*(1–2), 57–72.

Gipps, P. G., & Marksjö, B. (1985). A microsimulation model for pedestrian flows. *Mathemathics and Computers in Simulation, 27*, 95–105.

Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal, 69*(4), 211–221.

Guan, Q., Clarke, K. C., & Zhang, T. (2006). *Calibrating a parallel geographic cellular automata model*. Presented at AutoCarto 2006, Vancouver, WA, June, 2006.

Haklay, M., Singleton, A., & Parker, C. (2008). Web mapping 2.0: The neogeography of the GeoWeb. *Geography Compass, 2*(6), 2011–2039.

Hammam, Y., Moore, A., & Whigham, P. (2007). The dynamic geometry of geographical vector agents. *Computers, Environment and Urban Systems, 31*(5), 502–519.

Harris, R., Sleight, P., & Webber, R. (2005). *Geodemographics, GIS and neighbourhood targeting*. Chichester: Wiley.

Helbing, D., & Molnár, P. (1995). Social force model for pedestrian dynamics. *Physical Review E, 51*, 4282–4286.

Hui, S. K., Fader, P. S., & Bradlow, E. T. (2009). Path data in marketing: An integrative framework and prospectus for model building. *Marketing Science, 28*(2), 320–335.

Itami, R. (1988). Cellular worlds: Models for dynamic conception of landscapes. *Landscape Architecture, 78*(5), 52–57.

Itami, R. (2002). Mobile agents with spatial intelligence. In H. R. Gimblett (Ed.), *Integrating Geographic Information Systems and agent-based modeling for simulating social and ecological processes* (pp. 191–210). Oxford: Oxford University Press.

Kocabas, V., & Dragićević, S. (2006). Coupling Bayesian networks with GIS-based cellular automata for modeling land use change. *Lecture Notes in Computer Science, 4197*, 217–233.

Krumm, J., & Horvitz, E. (2007). Predestination: Where do you want to go today? *IEEE Computer, 40*(4), 105–107.

Kurose, S., Borgers, A. W. J., & Timmermans, H. J. P. (2001). Classifying pedestrian shopping behaviour according to implied heuristic choice rules. *Environment and Planning B, 28*(3), 405–418.

Laffan, S. W., Lubarsky, E., Ward, M. P., & Highfield, L. D. (2007). A Geographic Automata System for modelling disease outbreaks. In L. Oxley & D. Kulasiri (Eds.), *Proceedings of the MODSIM 2007 International Congress on Modelling and Simulation,* Canterbury, NZ (pp. 1252–1257).

Li, X., & Yeh, A. G.-O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science, 14*(2), 131–152.

Li, X., & Yeh, A. G.-O. (2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science, 16*(4), 323–343.

Lim, K., Deadman, P. J., Moran, E., Brondizio, E., & McCracken, S. (2002). Agent-based simulations of household decision-making and land use change near Altamira, Brazil. In H. R. Gimblett (Ed.), *Integrating Geographic Information Systems and agent-based modeling techniques for simulating social and ecological processes* (pp. 277–310). New York: Oxford University Press.

Liu, X. P., Li, X., Yeh, A., He, J. Q., & Tao, J. (2007). Discovery of transition rules for geographical cellular automata by using ant colony optimization. *Science in China Series D: Earth Sciences, 50*(10), 1578–1588.

Longley, P. A., Brooks, S. M., McDonnell, R., & Macmillan, B. (1998). *Geocomputation: A primer*. London: Wiley.

Longley, P. A., & Harris, R. J. (1999). Towards a new digital data infrastructure for urban analysis and modelling. *Environment and Planning B, 26*(6), 855–878.

Mandl, P. (2000). Geo-Simulation – Experimentieren und problemlösen mit GIS-modellen. In J. Strobl, T. Blaschke, & G. Griesebner (Eds.), *Angewandte geographische informationsverarbeitung XII: Beiträge zum AGIT-Symposium Salzburg* (pp. 345–356). Heidelberg: Herbert Wichmann Verlag.

Manson, S. M. (2000). Agent-based dynamic spatial simulation of land-use/land cover change in the Yucatán Peninsula, Mexico. In *Proceedings of fourth international conference on integrating GIS and Environmental Modeling (GIS/EM4): Problems, Prospects and Research Needs*, Banff, Alberta, Canada, September 2–8, 2000.

Manson, S. M. (2005). Agent-based modeling and genetic programming for modeling land change in the Southern Yucatan Peninsular Region of Mexico. *Agriculture, Ecosystems and Environment, 111*(1), 47–62.

Moreno, N., Ménard, A., & Marceau, D. J. (2008). VecGCA: A vector-based geographic cellular automata model allowing geometric transformations of objects. *Environment and Planning B: Planning and Design, 35*(4), 647–665.

Moreno, N., Wang, F., & Marceau, D. J. (2009). Implementation of a dynamic neighborhood in a land-use vector-based cellular automata model. *Computers, Environment and Urban Systems, 33*(1), 44–54.

Moulin, B., Chaker, W., Perron, J., Pelletier, P., Hogan, J., & Gbei, E. (2003). MAGS project: Multi-agent geoSimulation and crowd simulation. *Lecture Notes in Computer Science, 2825*, 151–168.

Nagel, K., & Schrekenberg, M. (1995). *Traffic jams in stochastic cellular automata*. Los Alamos: Los Alamos National Laboratory. 95ATS089.

Nakajima, T. (1977). Application de la théorie de l'automate à la simulation de l'évolution de l'espace urbain. In *Congrès Sur La Méthodologie De L'Aménagement Et Du Dévelopment* (pp. 154–160). Montreal: Association Canadienne-Française pour L'Avancement des Sciences et Comité de Coordination des Centres de Recherches en Aménagement, Développement et Planification (CRADEP).

Nieuwenhuisen, D., Kamphuis, A., & Overmars, M. H. (2007). High quality navigation in computer games. *Science of Computer Programming, 67*(1), 91–104.

O'Sullivan, D. (2001). Exploring spatial process dynamics using irregular cellular automaton models. *Geographical Analysis, 33*(1), 1–18.

O'Sullivan, D. (2004). Complexity science and human geography. *Transactions of the Institute of British Geographers, 29*(3), 282–295.

O'Sullivan, D., & Haklay, M. (2000). Agent-based models and individualism: Is the world agent-based? *Environment and Planning A, 32*(8), 1409–1425.

Openshaw, S. (1983). *The modifiable areal unit problem*. Norwich: GeoBooks.

Openshaw, S., Charlton, M. E., Wymer, C., & Craft, A. (1987). A Mark 1 geographical analysis machine for the automated analysis of point data sets. *International Journal of Geographic Information Systems, 1*(4), 335–358.

Paris, S., & Donikian, S. (2009). Activity-driven populace: A cognitive approach to crowd simulation. *IEEE Computer Graphics and Applications, 29*(4), 34–43.

Park, S., & Wagner, D. F. (1997). Incorporating Cellular Automata simulators as analytical engines in GIS. *Transactions in GIS, 2*(3), 213–231.

Pelechano, N., Allbeck, J., & Badler, N. I. (2008). *Virtual crowds: Methods, simulation, and control*. San Rafael: Morgan & Claypool.

Phipps, M. (1989). Dynamic behavior of cellular automata under the constraint of neighborhood coherence. *Geographical Analysis, 21*, 197–215.

Phipps, M., & Langlois, A. (1997). Spatial dynamics, cellular automata, and parallel processing computers. *Environment and Planning B, 24*, 193–204.

Portugali, J. (2000). *Self-organization and the city*. Berlin: Springer.

Sakoda, J. M. (1971). The checkerboard model of social interaction. *Journal of Mathematical Sociology, 1*, 119–132.

Sanders, L., Pumain, D., Mathian, H., Guérin-Pace, F., & Bura, S. (1997). SIMPOP: A multiagent system for the study of urbanism. *Environment and Planning B, 24*, 287–305.

Schelhorn, T., O'Sullivan, D., Haklay, M., & Thurstain-Goodwin, M. (1999). *STREETS: An agent-based pedestrian model* (CASA Working Paper 9). London: University College London, Centre for Advanced Spatial Analysis.

Schelling, T. C. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology, 1*, 143–186.

Schweitzer, F. (1997). Active brownian particles: Artificial agents in physics. In T. Pöschel & L. Schimansky-Geier (Eds.), *Stochastic dynamics* (pp. 358–371). Berlin: Springer.

Semboloni, F. (1997). An urban and regional model based on cellular automata. *Environment and Planning B, 24*, 589–612.

Semboloni, F. (2000). The dynamic of an urban cellular automata model in a 3-D spatial pattern. In *Proceedings of XXI national conference aisre: Regional and urban growth in a global market*. Palermo, Italy, September 20–22.

Shen, Z., Kawakami, M., & Kawamura, I. (2009). Geosimulation model using geographic automata for simulating land-use patterns in urban partitions. *Environment and Planning B: Planning and Design, 36*(5), 802–823.

Singleton, A. D., & Longley, P. A. (2009). Geodemographics, visualisation, and social networks in applied geography. *Applied Geography, 29*(3), 289–298.

Stevens, D., & Dragićević, S. (2007). A GIS-based irregular cellular automata model of land-use change. *Environment and Planning B: Planning and Design, 34*(4), 708–724.

Strout, N., & Li, N. (2006). *What is agent analyst?* In ESRI (Ed.), Paper presented at 26th annual ESRI international user conference, San Diego, California, August 7–11.

Takeyama, M., & Couclelis, H. (1997). Map dynamics: Integrating cellular automata and GIS through Geo-Algebra. *International Journal of Geographical Information Systems, 11*(1), 73–91.

Terzopoulous, D., Tu, X., & Grzeszczuk, R. (1994). Artificial fishes: Autonomous location, perception, behavior, and learning in a simulated physical world. *Artificial Life, 1*(4), 327–351.

Tobler, W. (1959). Automation and cartography. *Geographical Review, 49*(4), 526–534.

Tobler, W. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography, 46*(2), 234–240.

Tobler, W. (1979). Cellular geography. In S. Gale & G. Ollson (Eds.), *Philosophy in geography* (pp. 379–386). Dordrecht: Kluwer.

Torrens, P. M. (2001). Cellular automata and urban simulation: Where do we go from here? *Environment and Planning B, 28*(2), 163–168.

Torrens, P. M. (2006a). Geosimulation and its application to urban growth modeling. In J. Portugali (Ed.), *Complex artificial environments* (pp. 119–134). London: Springer.

Torrens, P. M. (2006b). Simulating sprawl. *Annals of the Association of American Geographers, 96*(2), 248–275.

Torrens, P. M. (2007a). Behavioral intelligence for geospatial agents in urban environments. In T. Y. Lin, J. M. Bradshaw, M. Klusch, C. Zhang (Eds.), *Proceedings of IEEE Intelligent Agent Technology (IAT 2007),* Los Alamitos, CA (pp. 63–66). Washington, DC: IEEE.

Torrens, P. M. (2007b). A geographic automata model of residential mobility. *Environment and Planning B, 33*(2), 200–222.

Torrens, P. M. (2009). Process models and next-generation geographic information technology. In ESRI (Ed.), *GIS best practices: Essays on geography and GIS* (pp. 63–75). Redlands: ESRI Press.

Torrens, P. M. (2010). Geography and computational social science. *GeoJournal, 75*(2), 133–148.

Torrens, P. M., & Benenson, I. (2005). Geographic automata systems. *International Journal of Geographical Information Science, 19*(4), 385–412.

Torrens, P. M., & Nara, A. (2007). Modeling gentrification dynamics: A hybrid approach. *Computers, Environment and Urban Systems, 31*(3), 337–361.

Torrens, P. M., & O'Sullivan, D. (2000). Cities, cells and complexity: Developing a research agenda for urban geocomputation. In R. J. Abrahart (Ed.), *Proceedings of geocomputation 2000*, University of Greenwich, London, August 25–28, CD-ROM.

Turing, A. M. (1936). On computable numbers, with an application to the *Entscheidungsproblem*. *Proceedings of the London Mathematical Society*, Series 2, *42*(1), 230–265.

Turing, A. M. (1938). Correction to: On computable numbers, with an application to the *Entscheidungsproblem*. *Proceedings of the London Mathematical Society*, Series 2, *43*(1), 544–546.

Turing, A. (1950). Computing machinery and intelligence. *Mind, 49*, 433–460.

Ulicny, B., & Thalmann, D. (2003). Towards interactive real-time crowd behavior simulation. *Computer Graphics Forum, 21*(4), 767–775.

Wagner, D. F. (1997). Cellular automata and geographic information systems. *Environment and Planning B, 24*, 219–234.

Ward, M. P., Laffan, S. W., & Highfield, L. (2007). The potential role of wild and feral animals as reservoirs of foot-and-mouth disease. *Preventive Veterinary Medicine, 80*(1), 9–23.

Ward, D. P., Murray, A. T., & Phinn, S. R. (2000). A stochastically constrained cellular model of urban growth. *Computers, Environment and Urban Systems, 24*, 539–558.

Webster, C. J., & Wu, F. (1998). Simulations of urban growth with models of pollution property rights and subcentre formation. In A. Mumford (Ed.), *Graphics, visualisation and the social sciences: Report from workshop held May 8–9* (Advisory Group on Computer Graphics (AGOCG) Technical Report Series No. 33, pp. 113–122). Loughborough: Loughborough University Joint Information Systems Committee (JISC).

White, R., & Engelen, G. (1993). Cellular automata and fractal urban form. *Environment and Planning A, 25*, 1175–1199.

White, R., & Engelen, G. (1994). Urban systems dynamics and cellular automata: Fractal structures between order and chaos. *Chaos, Solitions & Fractals, 4*(4), 563–583.

White, R., & Engelen, G. (1997). Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning B, 24*, 235–246.

Wu, F. (1996). A linguistic cellular automata simulation approach for sustainable land development in a fast growing region. *Computers, Environment and Urban Systems, 20*, 367–387.

Yu, C., & Peuquet, D. J. (2009). A GeoAgent-based framework for knowledge-oriented representation: Embracing social rules in GIS. *International Journal of Geographical Information Science, 23*(7), 923–960.

Zhang, T., & Tsou, M.-H. (2009). Developing a grid-enabled spatial Web portal for Internet GIServices and geospatial cyberinfrastructure. *International Journal of Geographical Information Science, 23*(5), 605–630.