GeoJournal (2014) 79:129–136
DOI 10.1007/s10708-013-9499-5

Why simulate cities?

Keith C. Clarke

Published online: 17 September 2013

Abstract This paper consists of three parts. After an introduction that stresses the historical progression of modeling methods, the motivation for urban modeling and simulation is explored, and the terms defined. Next, a meta-review of the literature is conducted, partially in an attempt to show that urban models resemble, and indeed share many overlapping issues with models in parallel fields such as economics and ecology. Lastly, the specific lessons learned from the author's fifteen-year experience developing and supporting a cellular urban growth and land use change model (SLEUTH) are shared, in the interest of making these issues generic to current and future modeling and simulation efforts. The conclusion stresses that future models face new computing power, new theoretical paradigms, vastly improved ways of visualizing simulations, and a rapidly changing audience for modeling and simulation.

This paper is derived from the keynote lecture "Why Simulate Cities? Or Lessons Learned from a Decade of Cellular Modeling with SLEUTH" delivered at the 16th International Conference on Geoinformatics and the Joint conference on GIS and Built Environment sponsored by Sun Yat-sen University and the University of Cincinnati held June 28–29, 2008 in Guangzhou, China.

K. C. Clarke (✉)
Department of Geography, University of California, Santa Barbara, CA, USA
e-mail: kclarke@geog.ucsb.edu
URL: http://www.geog.ucsb.edu/~kclarke

Keywords Urban growth modeling · SLEUTH · Simulation

Introduction

In the light of three recent book chapters examining over 10 years of the development and use of the SLEUTH cellular automata (CA) urban growth model (Clarke et al. 2007; Clarke 2008a, b), this paper attempts a far broader examination of contemporary urban simulation modeling by computer. The paper has three parts: first, the goals, purpose and value of model-building and simulation for urban regions are discussed. Second, some past and present modeling approaches are examined, in particular the paradigm of multi-agent systems (also known as Agent-Based Models), as potential inheritors of the baton in the Olympic relay race for the ideal urban model, i.e. one that is accurate, accountable, explanatory, predictive, useful (and used), and simple (enough) (Benenson 2004). Lastly, the specific lessons and limitations of SLEUTH are discussed as representative of more general issues for urban modeling, and a few words of advise given for the runners at the next urban modeling Olympic games.

Gilbert and Troitzsch (1999, p. 7) have provided a thought-provoking summary of the history of simulation modeling in the social sciences. In their view, only three sets of methods predate 1940: differential equations, stochastic processes, and game theory.

Each of these led to species of models in the later 20th century. The systems dynamics approach (e.g. Forrester models) and tools such as STELLA are direct descendents of differential equation models, and indeed still are dominant modeling approaches today. From the stochastic models came queuing models and micro-simulation models. New theoretical inputs in the 1960 s featured multi-scale modeling, cellular automata and artificial intelligence. From these and other hybrid approaches, we have seen an extraordinary resurgence of models since about 1995, not the least successful of which in the urban field have been cellular automata models (Torrens and O'Sullivan 2001) and agent-based models (Parker et al. 2003; Clifford 2008). A vast literature on these models covers the current fields of urban and regional modeling and planning, ecological modeling, integrated environmental modeling and urban geography. Yet even the contemporary scene has its critics (e.g. O'Sullivan and Haklay 2000; Couclelis 2001) and attempts at more general models based on dynamic objects (e.g. Torrens and Benenson 2005). Simulation within the built environment is seemingly at a crossroads of paradigms. After a continuous research thrust of work on the CA model SLEUTH and its refinements that has lasted since at least 1994; after over 100 applications and innumerable dissertations and planning reports; and after many sessions of pondering how to improve or modify SLEUTH, in this paper I first want to return to the roots of the model's motivation, and again pose the question "Why simulate cities" at all.

Why simulate cities?

The discipline of geography, like many sciences, has a long tradition of modeling (Chorley and Haggett 1967). Geographical models are inherently spatial models in that they contain at least data about spatial primitives, location in *x*, *y* and *z* or the equivalent. The rise of GIS has increasingly formalized the way that geographical space, spatial patterns and spatial relations are represented inside the computer (Longley et al. 2005). More recently, calls have been made and prototype systems designed to integrate both time and space in a more dynamic modeling framework for land change science (An and Brown 2008). Similarly, there has been strong interest in simulation in Geography. But there is an important and subtle difference between modeling and simulation, and we begin with definitions of these terms.

The abstraction of a system into a model involves building a theoretical construct that represents a phenomenon or object with a set of variables and relationships among the set members. Changes in the relations over time and space are referred to as processes, and models are created to allow reasoning within a logical framework about these processes, and so contribute to scientific theory. Spatial modeling then involves the abstraction of space and spatial relations. Models can simply represent, i.e. lines and zones as vectors and rasters in GIS, they can formalize relations, such as the 9 intersection relations of Egenhofer and Franzosa (1995), they can suggest structure and form, e.g. Homer Hoyt's radial sector model of urban form (Hoyt 1939) or they can hypothesize time-space relations, such as SLEUTH modeling urban growth and land use change. Consequently a model is an abstraction that captures a simplified version of a reality, such that information can be gleaned about reality from the formalization inherent in the model.

Simulation has been defined as the imitative representation of the functioning of one system or process by means of the functioning of another (Merriam-Webster Dictionary). Thus simulation operationalizes a model. This is usually done by expressing the model as a program or process, and invoking the process using real or contrived test data as input. These data for spatial models often take the form of digital maps for some region of interest, but we normally also simulate data about the world from data hardwired into the model, the latter are considered parameters, factors, controls or limits. These data can be from published sources, measured phenomena or rates, derived by trial-and-error, or can even be ad hoc (and undocumented). Gilbert and Troitzsch (1999) noted that simulation is a particular type of modeling. Since experiments are possible when a process is formalized, then a simulation becomes a vehicle through which to explore both a model (e.g. by sensitivity testing) and the world that it represents. Simulations that use models allow development of explanations beyond the prediction of specific results.

Both models and simulations are inherently simplifications. It is impossible to build context or process without a degree of simplification or, as social science calls it, reduction. There are excellent arguments for making models as simple as possible yet not so simple that they fail to capture the complexity and complicatedness of the system in question (Clarke 2004; Batty and Torrens 2001). It is no coincidence that the generation of models based on complex systems theory, which include cellular automata and agent-based models, are able to capture very complex behavior with only simple models, an enormous advantage in simulation. Thus from the point of view of simulation, reductionism is advantageous, because models can be created that are of value in simulation, yet are easily formalized or coded.

Models and simulations can easily cope with virtually all of the mathematics associated with models based on differential equations. Using pseudo-random number generators, they can deal with the stochastic nature of random processes and game theoretic models. A stream of evolving methods has assisted in dealing with ill-defined problems, such as fuzzy set theory, and model convergence, such as simulated annealing. There have been equivalent suites of methods that enhance model fitting and calibration, such as genetic algorithms. Models have been constructed that are top-down, e.g. modeling dynamics based on quantities and rates, and bottom-up, e.g. cellular automata. They are also increasingly able to apply to both micro and macro scales, often by scaling up from the disaggregated to the aggregate. In planning, models can also be engaged into the process of scenario generation and choice.

Simulation's principal advantage is that experiments are cheaper, faster and safer *in silico* that in reality. This is especially important in urban geography. Humankind is unprepared and unwilling to build entire experimental cities, make daily adjustments to transportation networks, or change personal habits and income. Once built, a city becomes a reality and further experiments are moot. Yet without harming anyone, or costing very much money or inconvenience, digital cities can be contorted beyond human expectations. Even completely artificial cities can form, evolve and instruct. When simulations are complete, they can explain behavior, forecast futures, automate human capabilities, train professionals and users, and even entertain us. Yet of these, it is arguable that the greatest value of simulations is their ability to formalize systems, and so discover new structures, forms and processes.

Cities are the focus of human society, and the dominant home of the majority of humankind. With the global population approaching 7 billion, never has the amount and extent of the world's urban areas been so great. Yet cities vary by place, they pave land and create extra run-off, they alter natural habitats and ecosystems, they boom and decline over the ages, indeed they are agents of global change (Mills 2007). They are also centers of cultural innovation and decay, disease and cures, learning and social pathology, crime and punishment (Canclini 1997). That we need to model and simulate every aspect of cities is obvious, because without the knowledge created our homes would be far less worthwhile and enduring. But *how* to model, and *how* to simulate? And what should we do with our simulations when we have them?

The competitors

The number of models created over the history of urban modeling is immense. "Urban modeling also has had eras of models based on paradigms that have fallen into and out of favor" (Clarke 2008a). While many past models are now obsolete, they nevertheless have often led to new generations of models that overcame their initial limitations and weaknesses. There is also a tendency to explore with research models that are new and promising, rather than improve models that have given satisfactory results in the past. Of course, both approaches are necessary.

The boundaries of what counts as an urban model is confusing. Many consider urban modeling a subset of land change science, where land use and land cover change models deal with such drivers as deforestation and agricultural expansion (Lambin and Geist 2006). From this perspective, two reviews of specific models and their approaches were Agarwal (2002) and Gaunt and Jackson (2003). The 50 years tradition of systems dynamics modeling (Moody 1970) was recently surveyed (Forrester 2007). Many of the first generation of urban computational models came from this tradition, and suffered from the problems of early generation computing (Klosterman 1994). Similarly, there are models aimed primarily toward land suitability analysis in the tradition of HcHarg's *Design with Nature*, (Collins et al. 2001); models which include economic drivers (Irwin and Geoghegan 2001); and the ubiquitous cellular models (Batty and

Xie 1994). Perhaps less well known outside of ecology are the spatial process models of succession and invasion of plants and animal species termed landscape dynamics modeling (Perry and Enwright 2006; Berling-Wolff and Wu 2004), where agent-based models (known as individual-based models in ecology) have also had considerable impact. The field of transportation modeling also regularly influences urban modeling, especially in the increasingly-active field at the intersection of land use and transportation demand forecasting. Chang (2006) makes a classification of these models based on their locational characteristics, form of decision-making, and degree on interaction similar to that of Agarwal et al. (2002).

Curiously, especially given the extraordinary size of the literature on urban modeling (all of the above citations are literature reviews or model surveys), relatively little attention by comparison has been devoted to the role of visualization in modeling (Simpson 2001). The assumption is commonly made that GIS supplies a model with data, and then re-ingests the results and makes them visible. Nevertheless, model outcomes are often scenarios with measured and unmeasured uncertainty. While model outputs have become more sophisticated, so too have the visualization methods. Some urban modeling systems (e.g. CommunityViz, and What-If) have engaged this visual model approach, most have not. Considering the great increase in accessibility to viewing tools such as GoogleEarth and Virtual Globe, with 3D modeling and much flexibility, the role of the direct use of visualization of simulations in planning and decision-making remains somewhat unexplored outside of specific contexts, such as homeland security and gaming.

In this paper I consider the lessons learned from years of working with the SLEUTH model, yet it is important to understand that SLEUTH is only one of many choices when cellular models are considered. These models include Logistic-CA (Wu and Webster 1998), CA using artificial neural networks such as ANN-CA (Li and Yeh 2002 and decision-tree CA (Li and Yeh 2004). In some cases, these models have been compared (e.g. Irwin and Geoghegan 2001; Almeida et al. 2003).

Lessons from SLEUTH: toward superior models

SLEUTH, named for its data input layers (slope, land use, exclusions, urban extents, transportation and a hillshade visualization) is a land use change model that couples within computer code two cellular automata, one to simulate the spread of urban areas and the other to simulate changes among other land uses. The model assumes that multiple time-slices of digital map information are available for the study area, and requires the files to use a naming convention and a common format. A script then directs the model to read these data, and to run the cellular automaton. Historical data are used to calibrate the model by hind-casting. This part of the modeling, the calibration, is time-consuming and immensely computationally intensive, as the model uses brute force computing, i.e. for the five parameters that control the cellular automaton behavior, each of which can vary from 0 to 100, every combination and permutation are computed and their results matched by regression against the real historical data. Computing all combinations (100^5), is not tractable, so a phased approach is used to successively improve on results and close in on the "best" values. The behavior types include diffusive growth, organic growth, new growth centers, road-influenced growth and differential reaction to topographic slopes. The control parameters interact within a single model run, and so permit non-linear feedbacks. Lastly, to reduce model uncertainty, the calibration and forecasting phases both use Monte Carlo simulation, and build uncertainty forecasts.

In the prior discussions of SLEUTH, we focused on limitations with regard to modeling land use change (Clarke 2008a) and on limitations of the model itself as an approach (Clarke 2008b). To summarize, the best aspects of SLEUTH were that it works reasonably well, but also is easily available, open source, and has a degree of support through the SLEUTH website and through two discussion forums. The last aspect should not be underestimated. Access to the model's designers, and to other users of the model, have greatly assisted new users with the learning curve. This was especially important when users were unfamiliar with the model's programming environment (unix) or language (C). Such cross-application knowledge permitted comparisons of the model in different environments, including a web-based results depository and research comparing calibration results (Gazulis and Clarke 2006). The model was also compared against other models in an attempt to measure the effectiveness of spatial models (Pontius et al. 2008). Such comparison or meta-modeling is highly desirable in future work, as also is forensic modeling. Forensic modeling is the examination of past forecasts in places where events have now arrived at the extent of the original forecasts, e.g. a 1970 plan forecasting growth to 2005. Such work is better than mere calibration, it is a true validation of the modeling approach.

In terms of calibration, SLEUTH demanded years of attention to the process. If a model is to be credible for forecasting, it should be able to replicate past measured urban behavior to an accuracy that is acceptable to the model's users. Unfortunately, in many places where urbanization is proceeding at unprecedented rates, such as in China's Pearl River Delta, long term prior behavior (i.e. before remote sensing) may be poorly measured, and vastly different from the behavior to be expected in the future. Some issues of calibration include: scale sensitivity, i.e. how well does the model's results cross spatial scales (Jantz and Goetz 2005); temporal sensitivity, i.e. how sensitive is the model to the length, frequency, and irregularity of the spacing of time-slices used as both input data and outputs; and sequencing, i.e. does the model update annually, once, synchronously in space, or asynchronously in space? Also of concern is the level of aggregation involved. For example, if a model uses a hierarchical land use classification, are the results at the highest level of class aggregation better than those at lower levels (Dietzel and Clarke 2006)? Lastly, any stochastic model is ultimately dependent on the rigor of its computational pseudo-random number generator (Van Niel and Laffan 2003). High performance, parallel, and grid computing applications of models make it essential to question values that are assumed to be random, because of periodic cycling and non-randomness of values that are assumed random. The bottom line is that models that have not undergone rigorous sensitivity testing should be regarded as research-grade, and not ready for full scale application and use until such testing is complete.

A long term measure of the utility of a model is how its formalizations have discovered or revealed drivers, behaviors or relations that were not apparent at the time of model construction. Such a property has been termed emergence (Holland 1997; Gilbert and Troitzsch 1999), and in SLEUTH was the case for several observations. The clustering of settlements at places where highways intersect, for example, was not programmed into the model, but happened anyway. The critical nature of topographic slope in steering growth, the growing power-law settlement size distribution (as predicted by theory), and the dominance of allometric growth were all unexpected. Also a surprise was when comparing cities by their calibration settings, some cities would never have been able to grow at all other than in their specific geographical setting, e.g. on a river, a highway, or before a mountain pass (Gazulis and Clarke 2006). The formalization of SLEUTH, done by painstakingly testing the behavior rules, revealed the effective drivers of growth to be transportation routes, availability of flat land for growth, and the degree of dispersal of the prior settlement pattern.

Another consequence of SLEUTH was the realization that only rarely is one urban model used in isolation. SLEUTH has been coupled with models of landfill siting, urban heat islands, species distributions, hydrology, climate change, and even long term fire regime (Clarke et al. 2007). This coupled modeling approach, whether at the data input level, or using the so-called tight coupling, is now understood as a highly effective, indeed superior approach. Linking models in systems is far more possible using grid computing, common and open architectures, and in distributed systems. So far, the many attempts to build modeling systems have been successful only for prototyping such systems (e.g. REPAST and SWARM). Open computing is far more likely to yield coupled modeling solutions, and much will be possible when the vision of cyberinfrastructure becomes fact.

There are negatives in the lessons learned too. Nowhere in my career plans did I expect to be working on a single model for about 15 years. Development of any model takes time. But development of a model that works, reliably gives accurate and justifiable results, runs on supercomputers with massive data sets (and on student PCs with insufficient memory), and its sustenance through over 100 applications is almost a full time occupation by itself. The model has cost the United States government and the National Science foundation approximately a million dollars. Yet it is sensitive to time resolution and spacing, geographical scale and resolution, and the classification schema applied to land use. It is not capable of determining the interior structure of cities, nor is it capable of creating density estimates within them. There is an accounting for, but no explicit model of uncertainty in the model. The most common critique of the model is that it is "supply-side", i.e. it makes no estimates of the many demand attributes that urban geographers and planners crave (households, trips, incomes, jobs, land markets, etc.) My response is that these features were deliberately left out to concentrate on form and dynamics, and that I was satisfied to be able to model "where" and not "why." If needed, they can be included in coupled models where SLEUTH is one of many components. Coupling with agent-based models seems an exciting possibility.

The unexplored dimensions of SLEUTH include more use of visualizations on the results, what constants might also have been variables, exactly how changes in transportation impact growth, how dynamic probabilities of land use change could be included, and how sensitive the model's assumptions about topographic slope are (they could be tied to engineering and soils data about building construction, for example). On the more theoretical front, a factor of importance in cross scale modeling is the time a change propagation "wave" takes to get from any point in the model space to the most distant places (Dietzel et al. 2005). This obviously impacts rates of change, but also concerns the nature of time and update within the model formalization. For example, if only a Moore neighborhood updates in one time cycle, then change will take many cycles to get from one edge of the map to the other, but if update is asynchronous, then in theory a change could propagate across the map space in one time cycle, a very different process indeed. One might call this phenomenon the persistence of memory. In CA models, there is assumed to be no memory at all, although the land use component of SLEUTH violates this assumption. And lastly, the self-modification element of SLEUTH was necessary to emulate the real inclination of cities to boom and bust, grow in spurts and then slow down or decline. If this mechanism were fully understood, it may be possible to model the decline and fall of civilizations, both today and those of the past.

Another important lesson learned from SLEUTH is that models have product life cycles. Whether the model is used primarily for research, or becomes a tool for planning is an important distinction, especially in how the model needs to be reported and supported. In the earliest work, advances were in getting the model to support single applications, yet every success led to more of a need for testing, automation and more computer speed. As of today, four distinct versions of the model are supported, each with a different flavor: a PC version, a version for parallel computers and the Cray memory model, a production version and a prototype. Each, of course, has to give exactly the same results on the same data, a truly challenging task. Including test data and results proved very important, as did the user discussion forums. Of course, without web-based documentation, the model might not have lasted more than a couple of years.

Conclusion

The urban growth that SLEUTH was designed to model has continued unabated, indeed even accelerated, during the model's life cycle. Yet out of the new research on feedbacks, climate responses, and congestion, has come a new paradigm that has had a powerful impact on planning. The economics and geographical consequences of sprawl are now universally seen as disadvantageous to humankind. The "new urbanism" school of planning seeks instead to build at higher densities in more central locations, to promote mixed use rather than uniform zoning, to develop where transportation is available, such as in transportation corridors, and to try to minimize the need for people to move beyond a small interior zone in a city for shopping and employment. With the recent surge in the price of petroleum, this approach makes more sense today than ever before.

Yet also, the very nature of urban development is changing. The era of unplanned, haphazard and individual growth that CA simulate so well is giving way to larger and larger planned and phased developments, that often involve land trades. For example, a developer will be given the rights to build on part of a land acquisition at higher densities if some of the land is left undisturbed or as parks, if businesses and services are integrated into the plan, and if housing is set aside for low income residents. In rural areas, many states and countries now use land conservation trusts and easements, sometimes even private purchase, to conserve sensitive habitat or areas of great natural beauty, or to protect farming, especially on the most fertile and productive soils (Onsted 2006). Energy reduction, conservation-based irrigation plans, and green communities are now beginning to appear as alternatives to the growth-centered approaches of the past. To be relevant, future modeling and simulation of cities must at the least incorporate these features, or risk irrelevance.

Lastly, the audience for urban models and simulations is changing. Especially young people are far more visual, and more internet-savvy, and so expect data and information in different ways, even beyond the simple 2-D maps of GIS. This new group of consumers is spatially aware, familiar with visual simulation, video games and contributed internet content, such as in the GoogleEarth community. Perhaps at last there will be a convergence between simulations for entertainment, and those for planning and research, as the eye becomes the direct analyst of the number, and no longer seeks structure in tables, charts and graphs. These new users will have their own social, economic and demographic questions for which the next generation of models will provide answers.

This is an auspicious time at which to embark on new models and approaches. Never before has the suite of geospatial technologies and socio-economic data collection schema been so powerful and of such potential (Lo 2007). Integrated modeling approaches can select from the best existing models to build coupled systems of models that bridge entire disciplines (Clarke et al. 2002), and use common and open-source tools to do so. Meta-modeling, using more than one model to measure confidence in results, is becoming more commonplace, for now in climate science but increasingly in social science models. And lastly, geocomputation, high-performance and grid computing are on the edge of creating computationally tractable answers to previously unsolvable modeling and simulation problems (Guan 2008).

Why simulate cities then? Ultimately, because urban models and the simulations they build provide an inexpensive and effective way to prevent poor urban design, to anticipate problems as cities grow and land uses change, and perhaps to make our world more sustainable. Urban modeling is indeed at the threshold of paradigmatic change, as the resurgence of modeling meets the power of the next generation of computing, and of new and different users. Clearly there is much to be gained by coupling existing models, rather than trying to build the mother-of-all-models, that may or may not explain everything. There is also a strong case for making better use of the models and model results that we already have; for visualizing them better, making them more accessible to decision-makers and the public, and for validating their results. And lastly, the needs of sustainable urbanism have in many ways moved the finish-line for urban modeling. Simulation has an extraordinary role to play in the future of planning and urban geography, and if we are successful, in creating a sustainable future for us all.

References

Agarwal, C., Green, G. M., Grove, J. M., Evans, T. P., & Schweik, C. M. (2002). *A review and assessment of land-use change models: Dynamics of space, time, and human choice. General technical report NE-297*. Newton Square, PA: US Department of Agriculture, Forest Service, Northeastern Research Station.

Almeida, C., Batty, M., Monteiro, A. M., et al. (2003). Stochastic cellular automata modelling of urban land use dynamics: Empirical development and estimation. *Computers, Environment and Urban Systems, 27*(5), 481–509.

An, L., & Brown, D. (2008). Survival analysis in land change science: Integrating with GIScience to address temporal complexities. *Annals of the Association of American Geographers, 98*(2), 323–344.

Batty, M., & Torrens, P. M. (2001). *Modeling complexity: The Limits to prediction*. 12th European colloquium on quantitative and theoretical geography. St-Valery-en-Caux, France, September 7–11, 2001.

Batty, M., & Xie, Y. (1994). From cells to cities. *Environment and Planning B, 21*(7), 31–48.

Benenson, I. (2004). Chapter 4. Agent-based modeling: From individual residential choice to urban residential dynamics. In M. F. Goodchild & D. G. Janelle (Eds.), *Spatially integrated social science: Examples in best practice* (pp. 67–95). Oxford: Oxford University Press.

Berling-Wolff, S., & Wu, J. (2004). Modeling urban landscape dynamics: A review. *Ecological Research, 19*, 119–129.

Canclini, N. G. (1997). Urban cultures at the end of the century: The anthropological perspective. *International Social Science Journal, 49*(3), 345.

Chang, J. (2006). Models of the relationship between transport and land-use: A review. *Transport Reviews, 26*(3), 325–350.

Chorley, R. J., & Haggett, P. (Eds.). (1967). *Models in geography*. London: Methuen.

Clarke, K. C. (2004). The limits of simplicity: Toward geocomputational honesty in urban modeling. In P. Atkinson, G. Foody, S. Darby, & F. Wu (Eds.), *Geodynamics*. Florida: CRC Press.

Clarke, K. C. (2008a). Mapping and modelling land use change: An application of the SLEUTH model. In C. Pettit, W. Cartwright, I. Bishop, K. Lowell, D. Pullar, & D. Duncan (Eds.), *Landscape analysis and visualisation: Spatial models for natural resource management and planning* (pp. 353–366). Berlin: Springer.

Clarke, K. C. (2008b). A decade of cellular urban modeling with SLEUTH: Unresolved issues and problems. In R. K. Brail (Ed.), *Planning support systems for cities and regions*. Cambridge, MA: Lincoln Institute of Land Policy.

Clarke, K. C., Gazulis, N., Dietzel, C. K., & Goldstein, N. C. (2007). A decade of SLEUTHing: Lessons learned from applications of a cellular automaton land use change model. Chapter 16. In P. Fisher (Ed.), *Classics from IJGIS. Twenty years of the international journal of geographical information systems and science* (pp. 413–425). Boca Raton, FL: Taylor and Francis, CRC.

Clarke, K. C., Parks, B. O., & Crane, M. P. (Eds.). (2002). *Geographic information systems and environmental modeling*. Upper Saddle River, NJ: Prentice Hall.

Clifford, N. J. (2008). Models in geography revisited. *Geoforum, 39*(2), 675–686.

Collins, M. G., Steiner, F. R., & Rushman, M. J. (2001). Land-use suitability analysis in the United States: Historical development and promising technological achievements. *Environmental Management, 28*(2), 611–621.

Couclelis, H. (2001). Why I no longer work with agents: A challenge for ABMs of human-environment interactions. In D. C. Parker, T. Berger, & S. M. Manson (Eds.), *Meeting the challenge of complexity, proceedings of a special workshop on land-use/land-cover change October 4–7, 2001*. Irvine, CA: CIPEC Collaborative Report CCR-3.

Dietzel, C., & Clarke, K. C. (2006). The effect of disaggregating land use categories in cellular automata during model calibration and forecasting. *Computers, Environment and Urban Systems, 30*(1), 78–101.

Dietzel, C., Oguz, H., Hemphill, J. J., Clarke, K. C., & Gazulis, N. (2005). Diffusion and coalescence of the Houston Metropolitan Area: evidence supporting a new urban theory. *Environment and Planning-B, Planning and Design, 32*(2), 231–236.

Egenhofer, M. J., & Franzosa, R. D. (1995). On the equivalence of topological relations. *International Journal of Geographical Information Systems, 9*(2), 133–152.

Forrester, J. W. (2007). System dynamics—A personal view of the first 50 years. *System Dynamics Review, 23*(2–3), 345–358.

Gaunt, C., & Jackson, L. (2003). Models for assessing the effects of community change on land use patterns. In S. Geertman & J. Stillwell (Eds.), *Planning support systems in practice*. Berlin: Springer.

Gazulis, N., & Clarke, K. C. (2006). Exploring the DNA of our regions: Classification of outputs from the SLEUTH model. In S. El Yacoubi, B. Chapard, & S. Bandini (Eds.), *Cellular automata. Lecture notes in computer science. No. 4173*. New York: Springer.

Gilbert, N., & Troitzsch, K. G. (1999). *Simulation for the social scientist*. Guildford: Open University Press.

Guan, Q. (2008) *Parallel algorithms for geographic processing.* Ph.D. dissertation, University of California, Santa Barbara.

Holland, J. (1997). *Emergence: From chaos to order*. New York: Addison-Wesley.

Hoyt, H. (1939). *The structure and growth of residential neighborhoods in American Cities*. Washington, DC: Federal Housing Administration.

Irwin, E. G., & Geoghegan, J. (2001). Theory, data, methods: Developing spatially explicit economic models of land use change. *Agricultural Systems, 85*(1–3), 7–23.

Jantz, C. A., & Goetz, S. J. (2005). Analysis of scale dependencies in an urban land use change model. *International Journal of Geographic Information Science, 19*(2), 217–241.

Klosterman, R. E. (1994). An introduction to the literature on large-scale urban models. *Journal of the American Planning Association, 60*(1), 41–44.

Lambin, E. F., & Geist, H. J. (Eds.). (2006). *Land-use and land-cover change; local processes and global impacts*. Berlin: Springer.

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.

Li, X., & Yeh, A. G. O. (2004). Data mining of cellular automata's transition rules. *International Journal of Geographical Information Science, 18*(8), 723–744.

Lo, C. P. (2007). The application of geospatial technology to urban morphological research. *Urban Morphology, 11*(2), 81–90.

Longley, P., Goodchild, M. F., Maguire, D., & Rhind, D. (2005). *Geographic information systems and science* (2nd ed.). New York: Wiley.

Mills, G. (2007). Cities as agents of global change. *International Journal of Climatology, 27*(14), 1849–1857.

Moody, H. (1970). Urban dynamics-review of Forresters model of an urban area. *Economic Geography, 46*(4), 620–626.

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

Onsted, J. (2006). Farming on the fringe: Can tax incentives save California's farmlands? *Next American city*. http://americancity.org/magazine/article/farming-on-the-fringe-onstead/.

Parker, D. C., Manson, S. M., Janssen, M. A., Hoffmann, M. J., & Deadman, P. (2003). Multi-agent system models for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers, 93*(2), 316–340.

Perry, G. L. W., & Enwright, N. J. (2006). Spatial modelling of vegetation change in dynamic landscapes: A review of methods and applications. *Progress in Physical Geography, 30*(1), 47–72.

Pontius, R. G, Jr, Boersma, W., Castella, J. C., Clarke, K., De Nijs, T., Dietzel, C., et al. (2008). Comparing the input, output, and validation maps for several models of land change. *Annals of Regional Science, 42*(1), 11–37.

Simpson, D. M. (2001). Virtual reality and urban simulation in planning: A literature review and topical bibliography. *Journal of Planning Literature, 15*(3), 359–372.

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

Torrens, P. M., & O'Sullivan, D. (2001). Cellular automata and urban simulation: where do we go from here? *Environment and Planning B-Planning & Design, 28*(2), 163–168.

Van Niel, K., & Laffan, S. W. (2003). Gambling with randomness: The use of pseudo-random number generators in GIS. *International Journal of Geographical Information Science, 1*(1), 49–68.

Wu, F., & Webster, C. J. (1998). Simulation of land development through the integration of cellular automata and multicriteria evaluation. *Environment and Planning B, 25*(1), 103–126.