FORUM

Complexity in Urban Development and Management

Historical Overview and Opportunities

Timothy M. Baynes

Keywords:

agent-based modeling
cellular automata
cities
decision making
industrial ecology
network

Summary

Systems dynamics, cellular automata, agent-based modeling, and network analyses have been used in population, land use, and transport planning models. An overview of complex systems science as applied to urban development is presented, and examples are given of where the problems of housing people and anticipating their movements have been addressed with complex approaches, sometimes in concert with deterministic, large-scale urban models. Planning for cities today has additional environmental and social priorities in common with many topics that concern industrial ecology. The research agenda suggested here is that this, too, can be enriched with complex systems thinking and models to complement the often static assessment of environmental performance and better inform decision processes.

Address correspondence to:
Timothy M. Baynes
Commonwealth Scientific and Industrial Research Organisation
Sustainable Ecosystems Division
Urban Systems Program
P.O. Box 310
North Ryde NSW 1670
Australia
tim.baynes@csiro.au
www.csiro.au/people/Tim.Baynes/html

DOI: 10.1111/j.1530-9290.2009.00123.x

Volume 13, Number 2

Introduction

Complexity theory and complex systems science (CSS) constitute a relatively new field of research concerned with understanding systems characterized by nonlinear behavior, feedbacks, self-organization, irreducibility, and emergent properties, in which the whole is not only more than but also different from the sum of its parts (Anderson 1972; Bertalanffy 1972).

An introduction to complexity concepts and general examples can be found in books by Johnson (2001), Miller and Page (2007), Barabási (2002), Holland (1998), and Strogatz (2003). Complexity has also been embraced in the field of ecology (see, e.g., Gunderson and Holling [2002] or Solé and Bascompte [2006]). In sympathy with an ongoing interest in the ecology of cities (Grimm et al. 2008), there appears to be a natural opportunity for the transfer of complexity thinking to ecological descriptions of urban function and development.

Cities as a whole may be considered as emergent entities existing near a critical point of self-organization, far from equilibrium and qualitatively different from their constituent residents and subsystems. Kay and Schneider (1994) refer to such systems as self-organizing holarchic open (SOHO) systems, although perhaps they are summarized best by the Zen-like, visual metaphor of Holland (1995, 1–2): "Like a standing wave in front of a rock in a fast-moving stream, a city is a pattern in time. No single constituent remains in place but the city persists."

In subsequent sections, CSS approaches are presented: systems thinking, cellular automata (CA), agent-based models (ABMs), and network analysis as applied in the urban domain. Examples of the application of these approaches are given.

The thesis discussed at the end of this overview is that studies in urban complexity have historically focused on population, land use change, and transport. Although these are still relevant to industrial ecology, the field could be expanded to encompass other priorities of urban management, which now include food and water security, energy supply, and climate-changing emissions.

Complexity Thinking and Cities: A Very Short History

The City as a Problem of Organized Complexity

Throughout history, there has been a variety of manifestations and conceptions of the city (Mumford 1961), but probably the first explicit recognition of spontaneous complex order in the form and dynamics of cities was in the book *Death and Life of American Cities*, by Jane Jacobs (1961). Jacobs asked, rhetorically, "What kind of a problem is a city?" Her answer was remarkable for its insight and subtlety. She proposed that a city is a problem in "organized complexity." This was a clear reference to an article written by Warren Weaver (1948), who classified three types of problems for science: simple problems, problems of disorganized complexity, and those of organized complexity.

Simple problems are the ones that can be reduced into smaller divisions, each of which a person can solve independently to achieve a solution to the aggregate. Classical physics and engineering are full of these simple types of problems. In industrial ecology, we see examples in life cycle assessment, material and energy accounting, and some stocks and flows models.

Problems of disorganized complexity involve the passive interactions of many homogenous components but without coherence. We see these sorts of problems in describing the behavior of gases in physics and in markets with a large number of buyers and sellers. One can describe such problems by averaging over the behavior of populations, and insight into the dynamics of the system can be found through statistical techniques.

The basic assumption behind simple problems and disorganized complex problems is that the system being described seeks equilibrium and that this can essentially be approached with reductionist, deterministic methods. The problems of organized complexity are characterized by heterogeneity, coherent local interactions, irreducibility, and persistent disequilibrium. Deterministic approaches and statistics cannot adequately represent the diversity or importance of interactions and dynamics that lead to aggregate observations in organized complex systems.

From Determinism to System Dynamics

More than 50 years ago, deterministic descriptions of city form and function abounded in economic location theory, as well as in the writings of Christaller (1933) and Losch (1943)—who built on von Thünen's (1826) concept of land use depending on different market actors being able to pay rent at locations of increasing distance from a city center. Given the monocentric and apparently stable morphology of industrialized cities up to that time, it is perhaps no surprise that this location theory surmised that it was sufficient to describe cities with a static, cross-sectional depiction of urban form (see also Alonso [1964]).

In the 1960s, the increasing availability of motorized transport and augmented urban populations produced problems of expanding residential development and unanticipated traffic problems. Jacobs (1961) was not alone in her assessment of cities as problems of organized complexity. Christopher Alexander (1964) also recognized the bottom-up evolution of city systems and the implications for urban design. The suggestion was that planning and management approaches needed to be as organic as the city itself (Alexander 1964).

In the United States, the National League of Cities and the U.S. Conference of Mayors (1968) referred to the situation as a "crisis." John F. Collins, mayor of Boston from 1960 to 1967, declared, "The plight of American cities is so grave and complex that it clearly defies simple remedies" (preface to Forrester 1969, vii).

Planners sought operational models of cities that could explore more sophisticated scenarios, and the initial efforts to supply such analyses derived from location theories, with enhancements from economics and social physics, such as gravitational models to describe movements of people, as in the example by Lowry (1964).

Planning models expanded in detail and scope to represent more and more aspects of a city, although often they contained many elements of the "simple" approaches that assume cities are essentially at equilibrium. The computer models that were favored by centralized planning had (and have) much value in resolving those issues that are amenable to deterministic mathematics—for example, the aggregate housing demand and servicing requirements. As Lee (1973) has observed, however, they were taken up operationally with varying enthusiasm.

Shortly after the 1968 U.S. Conference of Mayors, urban complexity appeared in Forrester's catalytic 1969 book *Urban Dynamics*. In a dedicated chapter titled "Notes on Complex Systems," he observed that the high number of equations with feedbacks governing state variables "can be expected to exhibit . . . devious behaviour" (Forrester 1969, 109).

Forrester's (1969) systems model was possibly the first coherent model of a city with feedbacks that operated through time. Using Boston as a case study, he modeled the salient variables of residential population, housing, employment, land use, transportation, and governance. The important distinction between this and the efforts that had gone before was that Forrester's model was manifestly dynamic.

Forrester's (1969) starting assumptions were based on continuous change, and his mathematics involved feedbacks among 20 equations of state. In fact, such was his concentration on the mechanics of change that Forrester neglected to represent space in his model other than in aggregate terms. The important thing was the recognition and description of feedbacks and delays that can lead to unanticipated equilibrium or the sort of sustained disequilibrium referred to by Holland (1995) earlier in this article.

Following this example, more spatially specific models appeared that emphasized temporal feedbacks (Batty 1971). Wilson (1981) used nonlinear logistic growth algorithms in a spatially explicit model to demonstrate the emergence of retail areas. Other complexity theories and methods came to be of interest in urban research, such as dissipative structures (Allen and Sanglier 1981) and catastrophe theory (Clarke and Wilson 1983).

The uptake of temporal feedbacks in operational urban modeling has been variable. Some large-scale urban models, such as MEPLAN (Echenique 1985) and TOPAZ (Brotchie et al. 1980), made more use of microeconomics, optimization algorithms, and the same sort of feedbacks found in input–output analysis.

Cellular Automata (CA) and Spatial Modeling

Appearing at about the same time as Forrester's (1969) systems dynamics was Schelling's (1969) cellular automata model of segregation. His schema was a grid neighborhood of cells, each with two possible states. Each cell altered its own binary state in response to the current states of its neighbors, according to rules about how many neighbors it could tolerate that were the same as or opposite to itself. This game was so trivial that it could be worked out iteratively with pencil and paper, but it produced global patterns of segregation. Although this was an abstracted CA demonstration, there is evidence of a fundamental validity in the observations of social segregation today and in Engels's (1995) historic description of the seemingly spontaneous economic segregation of people in the residential areas of 19th century Manchester, England.[1]

CA can be constructed with much more sophisticated attributes, and one of the first instances of the direct application of CA to represent urban development was by Tobler (1970), who used cellular spaces[2] to develop a spatial model of Detroit's demographic development. Couclelis (1989) also used ideas of local interactions in her study of growth in Los Angeles, and researchers have experimented with dynamic models to make use of CA. Arthur (1988) developed simple CA models of monocentric urban agglomeration based on returns to scale algorithms.

It was not until the early 1990s that a synergy of readily available computing power and widely communicated concepts of chaos, fractals, and complexity produced investigations such as those of White and Engelen (1993), who used CA to model emergent density patterns and nonlinearities based on urban development in Cincinnati, Milwaukee, Houston, and Atlanta. Langlois and Phipps (1995) also demonstrated emergent segregation of different land use types. Krugman's (1996) model employed the idea of centripetal and centrifugal potentials for activity, which enabled simulations of polycentric agglomeration.

CA models emphasize local spatial change to complement the temporal process priorities of systems dynamics. Any integration of CA into theories of urban dynamics, however, has to recognize the success of nonlocal, action-at-a-distance descriptions, such as concentric growth and gravitation. It is likely that localized spatial behavior and long-range effects are interdependent, and there is no reason why the two should not be consistent with one another (Batty 2005).

Where to Next?

The above, greatly abridged history clearly concentrates on the physics and economics of urban population, housing, land use, and transport. The modern decision maker also has concerns about complex issues of material, energy, waste, emissions, and water flows. Spiegelman (2003) proposes complex systems theory as a useful framework for industrial ecology to address such profoundly interconnected issues, and the argument here is that the current work on urban complexity can be extended to include these topics.

Although CSS in the urban arena has had a halting development, stymied by a lack of unifying theory and data and distracted by the demands of more immediate and pragmatic planning problems, the last 20 years have seen the confluence of ideas and sufficient computing power to represent the organized complexity of cities. There exists a significant body of academic research poised for application, and it is encouraging to see the acquisition of data to support the modeling and simulation task (Bettencourt et al. 2007; Alberverio et al. 2008).

The results of Bettencourt and colleagues (2007) are particularly intriguing, because they suggest that aggregate scaling relationships in cities may derive from the social and physical microdynamics. Extending the ideas of allotropic scaling, Bettencourt and colleagues surveyed the statistics from 295 Chinese, 361 North American, and more than 400 European cities and found that 20 key social, economic, and physical variables seem to scale as a function of city size according to a simple relationship:

$$Y(t) = Y_0 N(t)^{\beta} \quad (1)$$

where $Y(t)$ represents measures of material resources (energy or infrastructure) or social activity (wealth, crime, patents) at time t. Y_0 is a normalization constant, $N(t)$ denotes the population and is incorporated into the exponent, and β is the dynamics of the urban system.

The authors found that physical aspects of a city scaled sublinearly ($\beta < 1$) with respect to size, which suggests the familiar returns to scale dynamic, but, more interesting, socioeconomic indicators scaled superlinearly ($\beta > 1$). This, the authors concluded, indicates that social interactions are strong drivers of research and development, innovation, gross domestic product (GDP), and the spread of disease in cities. These are the aggregate signs that, through a multitude of interactions, the city is more than the sum of its parts.

Complex Approaches and Their Application

The exercise of modeling cities can hardly be separated from the influence of the requirements of planning, and this connection has historically led to an ad hoc, pragmatic development of ideas and methods. What follows is an overview of some complex systems approaches, with discussion of the limitations and the potential applications for managing urban change.

System dynamics models, described earlier, can generate global structures consistent with actual cities, and, by far, they represent the type of model most favored for operational use. Nonetheless, Gilbert and Troitzsch (2000) identify four limitations: Micro-level dynamics and qualitative information are poorly represented, parameters can often be too aggregate, and emergent global outcomes may not always be easily anticipated. These shortcomings are addressed to some extent in later sections on cellular automata and agent-based models.

There are certainly other methods, such as genetic algorithms, fractal analysis,[3] game theory, and neural networks, that could also be said to be aligned with CSS and have an association with urban systems. For those interested in further reading about urban complexity, please refer to three very useful books: *Cities and Complexity*, by M. Batty (2005); *Self-Organisation and the City*, by J. Portugali (1999); and *The Dynamics of Complex Urban Systems*, edited by Albeverio and colleagues (2008).

Networks: Approach

Networks are made up of nodes that represent some entity, agent, or physical object and connections (or "edges" in graph theory) that represent the relationships between them. Connections could represent actual physical links or nonphysical chains of influence. Urban networks occur in the physical networks of transport systems, water delivery, telecommunications, and electricity transmission and also in social networks and the parallel hierarchies of governance, the law, finance, and business (Barabási 2002; Carrington et al. 2005). Some basic types of networks are shown in figure 1.

Regular networks have a uniform distribution of connections, something that can be seen in the grid pattern of the road plan in many American cities. In random networks, the probability $P(k)$ that a node will have k connections follows a Poisson distribution (Erdős and Rényi 1960). Small-world networks include the possibility of long-range connections that bring together nodes that would otherwise have a greater separation across many more nodes (Watts and Strogatz 1998). "Scale-free" networks are described by Barabási and Albert (1999) and are characterized by a small number of extremely popular nodes and a much larger number of less well-connected nodes. The probability that a node in a scale-free network interacts with k other nodes decays as a power law, $P(k) \sim k^{-\gamma}$, and a surprising number of real-world networks display scale-free properties, which may arise from an evolution of systems in which new nodes are preferentially added to existing popular nodes. Some aggregate observations, such as Zipf's (1949) law for city size, also display power law relationships. Zipf found that population P_r of a city ranked r, in a list of cities within a set boundary, could be predicted from the formula $P_r \approx P_1/r$, where P_1 is the population of the largest city in the set.[4] Gabaix (1999) proposes that this phenomenon is repeated over a range of scales, also applying to popular districts or suburbs.

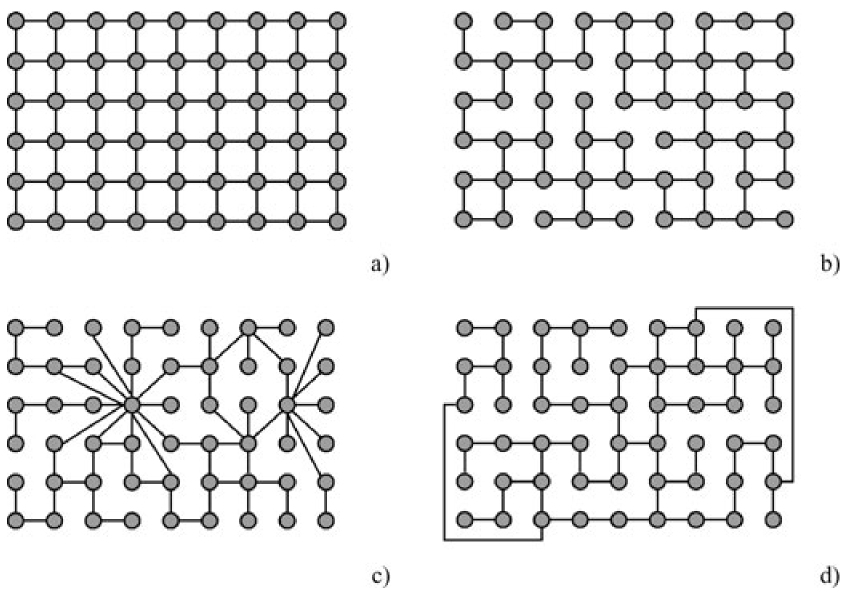

Figure 1 Examples of (a) regular, (b) random, (c) scale-free, and (d) "small-world" networks.

Scale-free networks have a great strength that is simultaneously a great weakness. Possessing a very few, vital nodes that connect many others means that scale-free networks are resilient to the random attack or removal of any particular node or link. A targeted attack on those specific, important nodes, however, could stop the whole system from functioning.

Networks are a powerful tool for representing a relatively stable arrangement of interaction. When nodes are mobile and able to disconnect and recombine over long ranges, the utility of network descriptions decreases. In this case, ABMs may be more appropriate, and this is discussed later.

Networks: Application

System dynamics and networks have some conceptual structural similarities: the components of systems dynamics models can be mapped to a network description of links and nodes, and the following examples could also be phrased in terms of systems dynamics.

Networks are a feature of ecological systems, and several studies have appeared about network characteristics of industrial ecologies. Ashton (2008) found that social network analysis was useful in clarifying the relationships in an industrial ecosystem. Hardy and Graedel (2002) examined the connectance of a limited number of real and some hypothetical industrial ecosystems as food webs.

Connectance, C, is the proportion of possible links between nodes within a network. It is related to the statistical distribution of connections and is given by the following formula, where L is the number of directed links and N is the number of nodes in the network:

$$C = 2L/[N(N+1)] \tag{2}$$

It might be presumed that greater connectance in an industrial ecosystem means more closed production—consumption loops. Simply increasing connectance may be naive, however, as additional links might not close loops or have feedback directions, and they might have greatly varying strengths. Meadows (1999) suggests that generating connectance and information flows where none existed before is a powerful way to intervene in a complex system, but increased connectance in industrial ecosystems does not necessarily imply more stability or improved environmental performance (Hardy and Graedel 2002).

At the urban level, network analysis has been applied to electricity and transport infrastructure, but it also permits the rigorous exploration of alternatives, such as distributed generation connected to the electricity grid or novel traffic control methods (see, e.g., work by Youn [2008]). Studies of food webs abound in the ecological literature, and it may be worthwhile to use a network perspective on urban food supply systems to consider the effect of reconfigurations, such as those that have already happened in Cuba (Altieri et al. 1999).

The exploration of alternatives is the job of modeling in general, but network analysis and the other complexity science techniques are particularly suited to situations in which a multitude of interacting components produce macro-level results that can be difficult, if not impossible, to predict.

Cellular Automata (CA)

CA and agent-based modeling enable us to explicitly represent the microdynamics that are germane to urban growth and change. CA are grids of cells, each of which interacts with its neighbors as part of an iterative determination of its own state. An early popular example was John Conway's Game of Life model (see Gardner 1970). CA are a subclass of agent-based models.

Feedbacks and systems dynamics can represent the smooth changes that happen in urban systems. The advantage of discrete CA and ABMs is that they can display discontinuous change and directly represent microbehavior. The trouble is that discontinuous change at any level less than that of the whole system is difficult to verify, and those features that distinguish CA and ABMs are apt to get subsumed into the larger, more stable system dynamics of the city. Even though the assumptions that underlie ABMs and CA may be entirely reasonable and their results are often imbued with realism, it is difficult to use them to predict, and therefore they are difficult to validate. Engelen and White (2008) propose that the statistical analysis of repeated CA simulations may provide valid insight.

CA: Applications

CA simulate local spatial change based on interaction rules that represent social and economic drivers. To demonstrate the application of CA in simulating land use change, consider the following hypothetical example, which brings into play features of the other approaches mentioned previously.

Let us say that a group of suburbs becomes developed or redeveloped. Over 5 to 10 years, there are dynamic changes to land use and transport networks and also to the channels of material and energy supply and to social networks. These changes do not occur in isolation but as a result of feedbacks between these subsystems. The attractor of *access to amenity* will change or disappear if there are too many people drawn to an area, and this could drive developments in the opposite direction, toward decay, although, over a longer time scale, perhaps there is a cycle back to rejuvenation. There are also effects on neighboring or connected suburbs through links that operate on other space and time scales. This interplay of local social forces and biophysical constraints goes beyond systems dynamics and networks.

Most applications to real cities relax the strict local interaction rules for CA and employ a mix of other modeling principles. Batty and Longley (1994) incorporated the action-at-a-distance concepts with the microdynamics of cell interaction, and similar hybridization can be found in models such as UrbanSim (Waddell 2002). See also Wilson's (2000) book on urban and regional spatial modeling. The following are a selection of applications relating to real cities that in some way have used CA:

- Toulon—Meaille and Wald (1990)
- Ottawa—Langlois and Phipps (1995)
- San Francisco—Clarke and colleagues (1997)
- Rome—Colonna and colleagues (1998)
- Washington, DC—Baltimore—Clarke and Gaydos (1998)
- Guangzhou—Wu and Webster (1998)
- Lisbon—Silva and Clarke (2002)
- Vienna—Loibl and Toitzer (2003)
- Southeastern Michigan—Brown and colleagues (2008)

Although these examples *relate* to real cases, there was and is the issue of analyses getting out of academia and into operational use (Batty 2008a). CA are based on spatial interaction rules that correlate to the microdynamics of cities, and they can reproduce patterns of the same fractal dimension as cities. Colonna and colleagues (1998) trained CA to reproduce 10 years of urban growth in Rome. Even proponents of CA have said, however, that CA may be of more use for exploration and understanding than for prediction (Couclelis, 1989). There is a blurred connection between the behavior of CA and the broader dynamics of the city, and this belies a fundamental problem: understanding the connections between micro and macro processes rather than merely reproducing the patterns they make. That is not to say that CA are of less value than predictive models. It is still of interest to be aware of potentially sudden endogenous change due to local interactions that we otherwise might be blind to.

Planning for the future population and location of a city is fraught with uncertainty. Banister (2007) calls for substantial behavioral change if we are to address looming issues of fossil fuel shortages and climate change, but how much do we invest in trying to change people's behavior, and what are the returns? How are we to model and measure this? As Waddell and Ulfarsson (2004) note, efforts in this area may benefit from researchers' ability to include behavior in modeling, and CA are able to represent this at some level, although ABMs described in the next section can go further. CA may not present large planning models with more certainty, but they do give "what-if?" scenario behavioral assumptions some basis.

Agent-based Models (ABMs)

ABMs consist of many independent agents that may be heterogeneous and may represent mobile actors, such as people, animals, companies, or industries. Their actions are generally both reactive, like CA, and proactive. They may also act in conjunction with CA or a cellular space, as in the work of Portugali (1999). Perhaps most distinctively, with agents we can represent qualitative choices and also adaptation: Agents can react to and alter their environment in a recursive manner.

A useful schematic aid to understanding the relationships in ABMs is in figure 2, (modified from Batty [2005]). A_i refers to an agent, and E_j refers to an element of the landscape or environment. These components are influenced by other agents or other landscape elements, external variables, and the aggregate states of all agents (ΣA_i) and all landscape elements (ΣE_j).

ABMs have been used in the simulation of flocking behavior (Reynolds 1987), the motion of crowds (Saunders and Gero 2002; Batty 2005) and traffic flow, and in safety science (Helbing et al. 2000). Researchers have also employed ABMs to find distributed solutions to numerous architectural design problems (Gero and Brazier 2002), and ABMs have been used extensively in economics (Tesfatsion and Judd 2006). Here, I will be content to summarize Batten and Perez (2006) and say that ABMs possess the following attributes:

- an environment that bounds the agents' behavior;
- a set of passive objects that can be modified by agents (these could be CA);
- a set of autonomous agents that communicate with the environment, objects, and other agents;
- well-defined relationships between agents and objects, such as like or dislike; and
- a set of operators allowing agents to act on the objects, such as transport, divide, combine, buy, and sell.

ABMs: Applications

Nikolic and colleagues (2006) used ABMs to look at sociotechnical relationships between industries in the evolution of the industrial ecology at the Rotterdam Industrial Cluster. Why not apply the same approach to industries and actors in a city (even if they are not colocated)? Calls for a change to the flow-through structure of urban metabolism (Brunner 2007) and the execution of circular economy ideals require not only information tools that can represent the dynamics and outcomes but also tools and models to represent

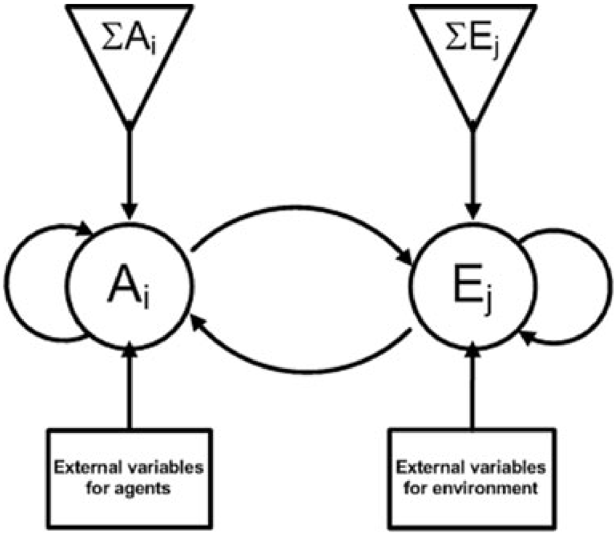

Figure 2 Schema for thinking about the relationships between agents and their landscape in agent-based models, modified after Batty (2005). A_i refers to an agent, E_j to an element of the landscape or environment. These components are influenced by other agents and landscape elements, external variables and the aggregate states of all agents (ΣA_i) and all landscape elements (ΣE_j).

behavior both in calculation and by involving the stakeholder.

Problems involving a small number of actors may not be complex, and millions of agents might be portrayed sufficiently well with statistics, but with 10 to 1,000 agents one has the propensity for organized complexity. This situation exists in a metropolitan area—for example, in the number of councils, the number of utilities, the number of government departments, or the number (types) of industries. Each of these is operating according to rules of limited awareness, limited jurisdiction, and self-interest and with selected connections to other agents. This is a classic case of the bounded rationality problems (Simon 1982) that ABMs are designed to explore.

ABMs and resource consumption are the topic of several chapters in the work by Batten and Perez (2006), and the contribution by Daniell and colleagues (2006) stands out for its relevance to urban development, albeit on a scale smaller than a suburb. Daniell and colleagues looked at a development in Adelaide, South Australia, taking into account interactions between housing development design and the behavior of residents, as measured by their waste flow, water use, and carbon dioxide (CO_2) emissions performance. They found that community interaction can have a significant effect on improving resource use behavior.

ABMs also allow us to explore the dynamics of cooperation as much as the statistics of crowd behavior. To discuss this more fully would require some elaboration on ideas from game theory, which is beyond the scope of this article, but there are some interesting developments in the use of ABM to foster greater understanding and cooperation between stakeholders. For example, ABMs have been used in "companion modeling," in which the behavior of stakeholders is simulated as a complement to participatory research in the management of water systems (Dray et al. 2006), ecosystems (Bousquet et al. 2002), and agricultural systems (Bousquet et al. 2007). There certainly seem to be opportunities for using similar companion modeling in urban management.

As with CA, there is the technical issue of obtaining data about the behavior of agents. Dray and colleagues (2006) underline that acquiring data to codify the mental models of stakeholders and other actors is, in fact, a far more substantial task than constructing the computer model.

Discussion

Part of the endeavor of making a sustainable city seems to be an implicit appeal for more self-reliance: In trying to contain waste flows and reduce energy and resource consumption, we try to recycle and use or reuse *local* resources (Grimm et al. 2008; Jacobs 1969). *Local* may be a relative term here, because this appeal can carry across scales from the household to the suburb to the city and possibly to systems of cities (Desrochers 2002; Meijers 2005). If we are trying to encourage connectivity between different land uses, between industries, communities, and governance, then we need to measure and model such characteristics.

I readily concede that CSS does not present a complete approach to measuring and modeling sustainability, but it does provide useful tools to find positive intervention in urban management. Complex systems approaches, such as ABMs and CA, can also take into account learning and behavioral responses that may be diverse and heterogeneous (and irrational), and there is the capacity to involve the stakeholder more.

A number of urban issues involve policies that may rely on complex interactions, involve feedback, or be dependent on behavioral responses. As such, the outcomes, from a policy maker's point of view, are unpredictable. Policy makers are understandably averse to uncertainty and tend to accept it only when no other options are available (hence investing in desalination rather than more decentralized solutions for water supply). The main strength of CSS is not in adding greater precision to prediction. As has been mentioned, CA and ABM approaches are difficult to validate except perhaps statistically. The strength of the complexity thinking and approaches lies in developing a better understanding of system function and complex interactions. Through this effort, informed by numerate analyses, we may anticipate the existence of thresholds and opportunities and alleviate some of the uncertainty in urban decision making, for example, about distributed energy solutions.

Apart from describing, understanding, and anticipating, there may be an active role for complexity in the spirit of urban management envisaged by Jacobs (1961) and Alexander (1964). CSS approaches may open up opportunities for policy makers to adopt more holistic and organic policies that were previously not considered. This potential is best summarized by Michael Batty (2008b, 771):

> We have only just started in earnest to build theories of how cities function as complex systems. We do know, however, that idealized geometric plans produced without any regard to urban functioning are not likely to resolve any of our current urban ills, and this new physics makes us much more aware of the limits of planning. It is likely to lead to a view that as we learn more about the functioning of such complex systems, we will interfere less, but in more appropriate ways.

Conclusion

There is a nascent community of practice emerging at the juncture of computer science, geography, economics, ecology, and urban studies. Simultaneously, there is the widespread acknowledgement of complex systemic issues of the social and physical metabolism of cities. This is particularly so for the newly industrialized, fast-growing cities in developing countries and also the spread of established cities in developed nations (Roberts and Kanaley 2006; Bai 2007; Grimm et al. 2008).

Reporting about urban performance and sustainability that concentrates on presenting aggregate data does not necessarily present us with a better appreciation of urban dynamics, offer intervention points, or help address dynamic problems. Recognizing and modeling interaction typologies (system, network, and agent) presents a way forward. In this regard, there are opportunities to use the strengths of CSS models and methods to gain insight into urban dynamics and thus better inform planning and management decisions. This may be achieved through complex approaches that produce measures of system performance or, at the higher level of analysis of the system itself, through identification of malign feedbacks or points where benign feedbacks and interactions might be encouraged.

Microdynamics can have an impact at the system level through their aggregate effect but also because they may influence urban change iteratively through local connections and feedbacks. CSS has strengths in representing and analyzing such features of organized complexity that arise in problems of social and ecological systems, although its value may be more exploratory rather than predictive.

Many of the models and approaches described in the historical overview catered to the priorities of planning for cities in their time. This has generally been about the placement and density of housing, the provision of services to residents, the location of industry, and the development of efficient transport options. There are now additional priorities of sustainability that insist that decision makers consider other aspects of urban metabolism, such as total water and energy consumption, flows of nutrients, tons of waste to landfill, and tons of greenhouse gas emissions. The research agenda suggested here is that complex systems approaches can be fruitfully applied to the industrial ecology topics of urban function and development.

Acknowledgements

This article has benefited greatly from the input of Dr. Magnus Moglia, Dr. Lan Ding, and Ms. Jane Blackmore, all from the Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO), and this work has been supported by both CSIRO's Marine and Atmospheric Division and its Sustainable Ecosystems Division.

Notes

1. Driven by influxes of material wealth and energy, Manchester's population went from 75,281 in 1801 to 303,382 by 1851, and it is possible that these growth rates might have produced other complex dynamics. See the work by Johnson (2001) for an accessible discussion of this topic.
2. CA operate strictly with reference to a neighborhood. A cell-space allows for a relaxation of this rule, so that a given cell may be influenced by local interactions and action-at-a-distance forces, such as the gravitational analogues of social physics.
3. Fractal patterns give us an important indicator that macro-level structures and behavior are linked to forms and dynamics at much smaller scales. White and Engelen (1993) demonstrated fractal patterns in U.S cities. Although Batty (2005) allows that urban fractal patterns may reveal no more than a geometry in common with many other systems in nature, others believe that there are social and physical benefits to a fractal structure of a city (Salingaros 2005). See also the work by Batty and Longley (1994).
4. It is worth tempering the natural tendency to go looking for power law relationships everywhere in cities with the observations of Batty's (2006) "rank clocks." Batty rightly points out that cities and city-states throughout their history undergo substantial changes in population and in their relative size ranking compared to other cities in the same country and around the world. So, whereas Zipf's (1949) law may still hold, we should not deceive ourselves that the same cities occur at the same place on Zipf's power law curve or, indeed, that the exponent of that curve is stable.

References

Alberverio, S., D. Andrey, P. Giordano, and A. Vancheri, eds. 2008. *The dynamics of complex urban systems: An interdisciplinary approach*. New York: Physica-Verlag.

Alexander, C. 1964. *Notes on the synthesis of form*. Cambridge, MA: Harvard University Press.

Allen, P. M. and M. Sanglier. 1981. Urban evolution, self-organisation, and decision making. *Environment and Planning* A 13(2): 167–183.

Alonso, W. 1964. *Location and land use*. Cambridge, MA: Harvard University Press.

Altieri, M. A., N. Companioni, K. Cañizares, C. Murphy, P. Rosset, M. Bourque, and C. I. Nicholls. 1999. The greening of the "barrios": Urban agriculture for food security in Cuba. *Agriculture and Human Values* 16(2): 131–140.

Anderson, P. W. 1972. More is different. *Science* 177(4047): 393–396.

Arthur, W. B. 1988. Urban systems and historical path dependence. In *Cities and their vital systems: Infrastructure past present and future*, edited by J. H. Ausubel and R. Herman. Washington, DC: National Academy Press.

Ashton, W. 2008. Understanding the organization of industrial ecosystems: A social network approach. *Journal of Industrial Ecology* 12(1): 34–51.

Bai, X. 2007. Special issue on industrial ecology and the global impact of cities (edited by X. Bai.). *Journal of Industrial Ecology* 11(2).

Banister, D. 2007. Cities, mobility and climate change. *Journal of Industrial Ecology* 11(2): 7–10.

Barabási, A.-L. 2002. *Linked: The new science of networks*. New York: Perseus.

Barabási, A.-L. and R. Albert. 1999. Emergence of scaling in random networks. *Science* 286(5439): 509–512.

Batten, D. F. and P. Perez, eds. 2006. *Complex science for a complex world: Exploring human ecosystems with agents*. Canberra, Australia: ANUE Press.

Batty, M. 1971. Modelling cities as dynamic systems. *Nature* 231(5303): 425–428.

Batty, M. 2005. *Cities and complexity: Understanding cities with cellular automata, agent based models, and fractals*. London: MIT Press.

Batty, M. 2006. Rank clocks. *Nature* 444(7119): 592–596.

Batty, M. 2008a. Fifty years of urban modelling: Macro-statics to micro-dynamics. In *Dynamics of complex urban systems*, edited by S. Alberverio et al. New York: Physica-Verlag.

Batty, M. 2008b. The size, scale, and shape of cities. *Science* 319(5864): 769–772.

Batty, M. and P. A. Longley. 1994. *Fractal cities: A geometry of form and function*. San Diego, CA: Academic Press.

Bertalanffy, L. V. 1972. *General systems theory*. Harmondsworth, UK: Penguin.

Bettencourt, L. M. A., J. Lobo, D. Helbing, C. Kühnert, and G. B. West. 2007. Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Science* 104(17): 7301–7306.

Bousquet, F., O. Barreteau, P. d'Aquino, M. Etienne, S. Boissau, S. Aubert, C. Le Page, D. Babin, and J. C. Castella. 2002. Multi-agent systems and role games: Collective learning processes for ecosystem management. In *Complexity and ecosystem management: The theory and practice of multi-agent systems*, edited by M. A. Janssen. Cheltenham, UK: Edward Elgar.

Bousquet, F., J. C. Castella, G. Trébuil, C. Barnaud, S. Boissau, and S. P. Kam. 2007. Using multi-agent systems in a companion modelling approach for agroecosystem management in South-east Asia. *Outlook on Agriculture* 36(1): 57–62.

Brotchie, J. F., J. W. Dickey, and R. Sharpe. 1980. *TOPAZ—General planning technique and its applications at the regional, urban and facility planning levels*, edited by B. M. and H. P. Künzi. Lecture notes in economics and mathematical systems. New York: Springer-Verlag.

Brown, D. G., D. T. Robinson, L. An, J. I. Nassauer, M. Zellner, W. Rand, R. Riolo, S. E. Page, B. Low, and Z. Wang. 2008. Exurbia from the bottom-up: Confronting empirical challenges to characterizing a complex system. *Geoforum* 39(2): 805–818.

Brunner, P. H. 2007. Reshaping urban metabolism. *Journal of Industrial Ecology* 11(2): 11–13.

Carrington, P., J. Scott, and S. Wasserman, eds. 2005. *Models and methods in social network analysis*. New York: Cambridge University Press.

Christaller, W. 1933. *Central places in Southern Germany* (translated by C. W. Baskin). Englewood Cliffs, NJ: Prentice-Hall.

Clarke, K. C., L. J. Gaydos, and S. Hoppen. 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco. *Environment and Planning* B 24: 247–261.

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

Clarke, M. and A. G. Wilson. 1983. Dynamics of urban spatial structure: Progress and problems. *Journal of Regional Science* 23(1): 1–18.

Couclelis, H. 1989. Macrostructure and microbehaviour in metropolitan areas. *Environment and Planning B* 16(2): 141–154.

Colonna, Antonio, Vittorio Di Stefano, Silvana Lombardo, Lorenzo Papini, and Giovanni A. Rabino. 1998. Learning urban cellular automata in a real world: the case study of Rome Metropolitan Area. Cellular automata: research towards industry. ACRI'98-Proceedings of the Third Conference on Cellular Automata for Research and Industry, Trieste, 7–9 October 1998. Eds. S. Bandini, R. Serra, and F. Suggi Liverani, 165–84. London: Springer.

Daniell, K. A., A. B. Kingsborough, D. J. Malovka, H. C. Sommerville, B. A. Foley, and H. R. Maier. 2006. Sustainability assessment of housing developments: A new methodology. In *Complex science for a complex world*, edited by D. F. Batten and P. Perez. Canberra, Australia: ANUE Press.

Desrochers, P. 2002. Cities and industrial symbiosis. *Journal of Industrial Ecology* 5(4): 29–44.

Dray, A., P. Perez, N. Jones, C. Le Page, P. D'Aquino, I. White, and T. Auatabu. 2006. The AtollGame experience: From knowledge engineering to a computer-assisted role playing game. *Journal of Artificial Societies and Social Simulation* 9(1): 149–158.

Echenique, M. 1985. The use of integrated land use and transport models: The cases of Sao Paulo, Brazil and Bilbao, Spain. In *The practice of transportation planning*, edited by M. Florian. Amsterdam: Elsevier.

Engelen, G. and R. W. White. 2008. Validating and calibrating integrated cellular automata based models of land use change. In *The dynamics of complex urban systems: An interdisciplinary approach*, edited by S. Alberverio et al. New York: Physica-Verlag.

Engels, F. 1885. *The condition of the working-class in England* (translated by F. Kelley). New York: Oxford University Press.

Erdős, P. and A. Rényi. 1960. Random graphs. *Publication of the Mathematical Institute of the Hungarian Academy of Science* 5: 17–61.

Forrester, J. W. 1969. *Urban dynamics*. Cambridge, MA: MIT Press.

Gabaix, X. 1999. Zipf's law for cities: An explanation. *Quarterly Journal of Economics* 114(3): 739–767.

Gardner, M. 1970. Mathematical games: The fantastic combinations of John Conway's new solitaire game "Life". *Scientific American* 223: 120–123.

Gero, J. S. and F. M. T. Brazier, eds. 2002. *Agents in design 2002*. Sydney, Australia: Key Centre of Design Computing and Cognition, University of Sydney.

Gilbert, N. and K. G. Troitzsch. 2000. *Simulation for the social scientist*. Buckingham, PA: Open University Press.

Grimm, N. B., S. H. Faeth, N. E. Golubiewski, C. L. Redman, J. Wu, X. Bai, and J. M. Briggs. 2008. Global change and the ecology of cities. *Science* 319(5864): 756–760.

Gunderson, L. and C. S. Holling. 2002. *Panarchy: Understanding transformations in human and natural systems*. Washington, DC: Island Press.

Hardy, C. and T. E. Graedel. 2002. Industrial ecosystems as foodwebs. *Journal of Industrial Ecology* 6(1): 29–38.

Helbing, D., I. Farkas, and T. Vicsek. 2000. Simulating dynamical features of escape panic. *Nature* 407(6803): 487–490.

Holland, J. H. 1995. *Hidden order: How adaptation builds complexity*. Reading, MA: Addison-Wesley.

Holland, J. H. 1998. *Emergence: From chaos to order*. Reading, MA: Perseus.

Jacobs, J. 1961. *The death and life of great American cities*. New York: Vintage/Random House.

Jacobs, J. 1969. *The economy of cities*. New York: Random House.

Johnson, S. 2001. *Emergence: The connected lives of ants, brains, cities and software*. New York: Scribner.

Kay, J. and E. D. Schneider. 1994. Embracing complexity: The challenge of the ecosystem approach. *Alternatives* 20(3): 32–38.

Krugman, P. R. 1996. *The self-organizing economy*. Cambridge, MA: Blackwell.

Langlois, A. and M. Phipps. 1995. *Cellular automata, parallelism and urban simulation—Final report on the activities of the SUAC Project*. Ottawa, Canada: Department of Geography, University of Ottawa.

Lee, D. B. 1973. Requiem for large scale models. *Journal of the American Institute of Planners* 39: 163–187.

Loibl, W. and T. Toetzer, 2003, Modeling growth and densification processes in suburban regions – simulation of landscape transition with spatial agents: Environmental Modelling & Software, v. 18, p. 553–563.

Losch, A. 1943. *The economics of location* (translated by W. H. Woglom). New Haven, CT: Yale University Press.

Lowry, I. S. 1964. *Model of Metropolis*. Memorandum RM-4035-RC. Santa Monica, CA: Rand Corporation.

Meadows, D. H. 1999. Leverage points: Places to intervene in a system. Hartland, VT: Sustainability Institute.

Meaille, R. and L. Wald. 1990. Using Geographical Information Systems and Satellite Imagery within a Numerical Simulation of Regional Urban Growth. *International Journal of Geographical Information Systems* 4: 445–456.

Meijers, E. 2005. Polycentric urban regions and the quest for synergy: Is a network of cities more than the sum of the parts? *Urban Studies* 42(4): 765–781.

Miller, J. H. and S. E. Page. 2007. *Complex adaptive systems: An introduction to computational models of social life*. Princeton, NJ: Princeton University Press.

Mumford, L. 1961. *The city in history: Its origins, its transformations, and its prospects*. New York: Harcourt, Brace and World.

Nikolic, I., G. P. J. Dijkema, K. H. van Dam, and Z. Lukszo. 2006. General methodology for action-oriented industrial ecology complex systems approach applied to the Rotterdam Industrial Cluster. In *Proceedings of the 2006 IEEE International Conference on Networking, Sensing and Control.* IEEE International Conference on Networking, Sensing and Control. published by Institute of Electrical and Electronics Engineers (IEEE). http://ieeexplore.ieee.org/xpl/RecentCon.jsp?punumber=11076 Accessed 9 March, 2009.

Portugali, J. 1999. *Self-organisation and the city*. Berlin: Springer.

Reynolds, C. W. 1987. Flocks, herds and schools: A distributed behavioural network. *Computer Graphics* 21(4): 25–34.

Roberts, B. and T. Kanaley, eds. 2006. *Urbanization and sustainability in Asia: Case studies of good practice*. Manila, Philippines: Asian Development Bank.

Salingaros, N. A. 2005. *Principles of urban structure*. Amsterdam: Techne Press.

Saunders, R. and J. S. Gero. 2002. Curious agents and situated design evaluations. In *Agents in design 2002*, edited by J. S. Gero and F. M. T. Brazier. Sydney, Australia: Key Centre of Design Computing and Cognition, University of Sydney.

Schelling, T. C. 1969. Models of segregation. *American Economic Review, Papers and Proceedings* 58(2): 488–493.

Silva, E. and K. C. Clarke. 2002. Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers the Environment and Urban Systems* 26: 525–552.

Simon, H. A. 1982. *Models of bounded rationality, economic analysis and public policy*. Vol. 1. Cambridge, MA: MIT Press.

Solé, R. V. and J. Bascompte. 2006. *Self-organization in complex ecosystems*. Princeton, NJ: Princeton University Press.

Spiegelman, J. 2003. Beyond the food web: Connections to a deeper industrial ecology. *Journal of Industrial Ecology* 7(1): 17–23.

Strogatz, S. 2003. *Sync: The emerging science of spontaneous order*. London: Penguin.

Tesfatsion, L. and K. Judd, eds. 2006. *Handbook of computational economics*. Amsterdam: North Holland.

Thünen, J. H. V. 1966. *Der Isolierte Staat in Beziehung auf Landwirtschaft und Nationalekonomie* [The Isolated State in Relationship to Agriculture and the National Economy] (translated by P. G. Hall). Oxford, UK: Pergamon.

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

Waddell, P. 2002. UrbanSim: Modelling urban development for land use, transportation and environmental planning. *Journal of the American Planning Association* 68(3): 297–314.

Waddell, P. and G. F. Ulfarsson. 2004. Introduction to urban simulation: Design and development of operational models. In *Handbook in transport: Transport geography and spatial systems*, edited by D. A. Hensher et al. Oxford, UK: Pergamon Press.

Watts, D. J. and S. H. Strogatz. 1998. Collective dynamics of "small-world" networks. *Nature* 393(6684): 440–442.

Weaver, W. 1948. Science and complexity. *American Scientist* 35: 536–541.

White, R. W. and G. Engelen. 1993. Cellular automata and fractal urban form: A cellular automata modelling approach to the evolution of urban land use patterns. *Environment and Planning* A 25(8): 1175–1193.

Wilson, A. G. 1981. *Catastrophe theory and bifurcation: Applications to urban and regional systems*. Berkeley, CA: University of California Press.

Wilson, A. G. 2000. *Complex spatial systems: The modelling foundations of urban and regional analysis*. Harlow, UK: Pearson Education.

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

Youn, H.-J., M. Gastner, and H. Jeong. 2008. Price of anarchy in transportation networks: Efficiency and optimality control. *Physical Review Letters* 101(128701): 1–4.

Zipf, G. 1949. *Human behavior and the principle of least effort*. Cambridge, MA: Addison-Wesley.

About the Author

Timothy M. Baynes is a systems analyst in the Sustainable Ecosystems Division of the Commonwealth Scientific and Industrial Research Organisation in North Ryde, New South Wales, Australia.