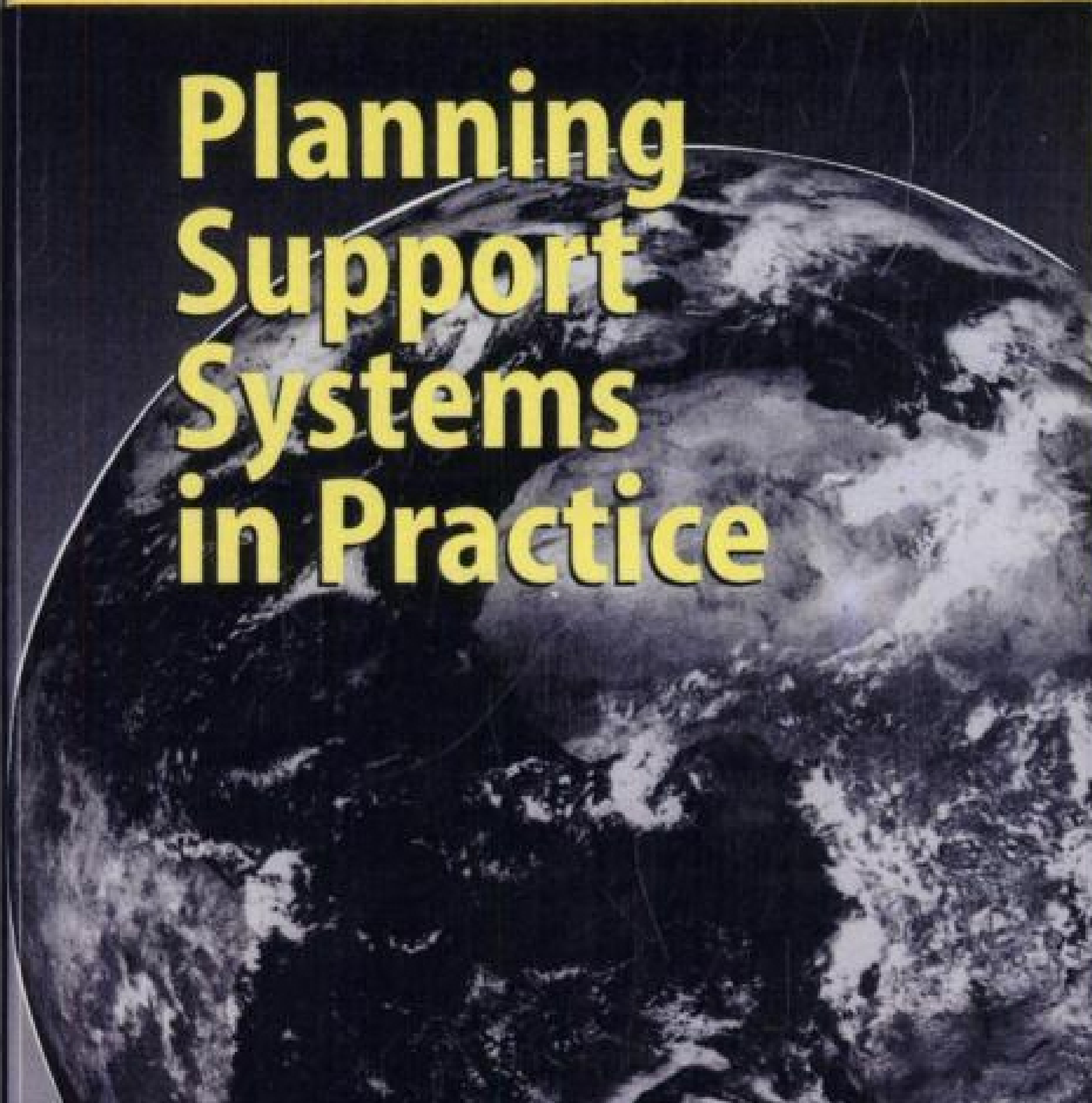
S. Geertman · J. Stillwell
Editors

Planning Support Systems in Practice



ADVANCES IN SPATIAL SCIENCE

Stan Geertman
John Stillwell
Editors

Planning Support Systems in Practice

With 181 Figures
and 38 Tables

Springer

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Cellular Automata and Multi-Agent Systems as Planning Support Tools

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'Traditional' urban simulation models have a number of weaknesses that limit their suitability as planning support tools. However, a 'new wave' of models is currently under development in academic circles, and it is beginning to find application in practical contexts. Based around two simulation techniques that have origins in artificial life and artificial intelligence—cellular automata and multi-agent systems—it offers great potential for planning support tools, with the capacity to simulate individual households and units of the built environment in a truly dynamic, realistic, and highly flexible manner. This chapter presents an overview of 'traditional' land-use and transport models as planning support tools and examines their fragilities before reviewing a 'new wave' of urban models. Additionally, it considers the challenges facing the use of new techniques in operational models.

1 Introduction

In the early 1970s, the field of urban simulation was all but written-off as a failure. Douglas Lee's article, 'Requiem for large-scale models', published in the *Journal of the American Institute of Planners* (Lee 1973), served as a harbinger of doom for a generation of urban simulation models applied in planning contexts. (If you really want to make a name for yourself in academic circles, publish a paper declaring the demise of your discipline!) Lee provided a broad justification for retiring large-scale urban models as planning support systems (PSS) and many of his arguments were appropriate at the time. To some extent, the challenges posed in his article were muted by subsequent developments in computer hardware, computer software, dataware, new simulation techniques, and important breakthroughs in our understanding of cities. But several important weaknesses remained with urban models used as planning support tools, and without much in the way of a viable empirical alternative for supporting decisions in cities, urban planning and management agencies continued to use those technologies to assist them in their duties despite the flaws associated with the models.

In recent years, however, a confluence of several related and distinct developments across disciplinary boundaries has provided the foundation for a new generation of urban simulation models with the capacity to revolutionize our capabilities for simulating cities. Models have been developed in academic circles that enable users to simulate the complex dynamics of urban systems at the level of individual households and buildings, in some cases approximating real time representations. Moreover, these simulations have begun to migrate from the confines of the laboratory and into real world applications.

This chapter presents an overview of 'traditional' urban simulation models and discusses their weaknesses before reviewing a 'new wave' of urban models. Additionally, it considers the challenges facing the use of new techniques—cellular automata and multi-agent systems—as operational planning support tools.

2 'Traditional' urban models

The conceptual framework for a 'traditional' urban model is outlined in figure 1. The figure illustrates the general land-use and transport model that was (and in many cases still is) used as a planning support tool by city planning and management agencies. Generally, these models are comprised of several sub-components. Cities are usually simulated from two distinct standpoints: land-use (with sub-models for land supply, land demand, and mechanisms for reconciling the two) and transport (with sub-models for potential demand and trip generation, trip distribution, modal split, and trip assignment). In recognition of the fact that several relationships exist between land-use and transport in the real world, the simulations of land-use and transport are commonly linked via some connecting mechanisms. 'Traditional' simulations are most commonly devised as combinations of spatial interaction models, spatial (or discrete) choice models, and simple functional statements.

Spatial interaction models (also known as gravity models) allow us to predict the size and direction of flows through urban spaces using independent variables that measure some structural properties of the area being modeled. The models are commonly used to assign activities to locations in land-use simulations and to model trip generation and assign trips to routes in transport simulations. For example, the geography of journey-to-work flows might be modeled using structural variables such as the distribution of workers, the distribution of employment, and the costs of traveling to work. Spatial interaction models are formulated based on Newton's laws concerning gravitational attraction. Newton

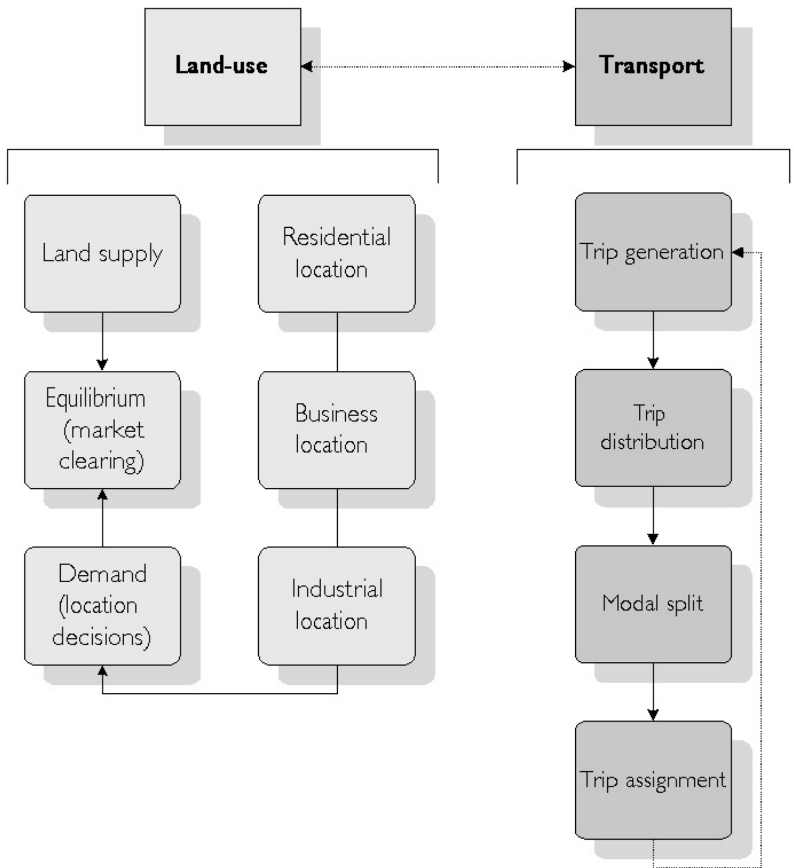

Figure 1. *The structure of a 'traditional' land-use and transport model.*

asserted that the force of attraction between two bodies (F_{ij}) is the product of their masses (m_i, m_j) divided by the square of the distance between them (d_{ij}^2):

$$F_{ij} = G \cdot \frac{m_i m_j}{d_{ij}^2} \quad \text{(i)}$$

Where G is a constant: gravity. In urban models this translates to:

$$T_{ij} = k \cdot \frac{W_i W_j}{d_{ij}^{\alpha}} \quad \text{(ii)}$$

Put simply, the above equation represents flows as the result of push and pull factors. Specifically, the flow between two places is considered to be a function of the ability of an origin (i) (e.g., a residential neighborhood) to generate flows (e.g., trips), the capacity of a destination (j) to attract these flows (e.g., through employment), the distance over which the flow must pass (d_{ij}), and some weighting mechanism that discourages flows over long distances: a distance-decay effect (α). In the above equation, k is a scaling constant; it needs to be included because the independent variables W_i and W_j are not measured in units of flow (Thomas and Huggett 1980).

Significant variations on this basic description of the gravity model include the production-constrained model, the attraction-constrained model, the production-attraction-constrained model, and the entropy-maximizing model (Torrens 2000b). The motivation behind applying these enhancements to the basic framework is to provide some form of balancing or accounting in the predictions that the model makes. To put it another way, constraints straightjacket a model into compliance with known data.

Spatial choice models represent a behavioral approach to urban simulation. They are also used to simulate elements of the scheme outlined in figure 1. They are commonly applied to the simulation of location decisions on the land-use side and to modal choice in transport simulation. In some instances, the technique is also applied to simulating development decisions on the supply-side. Spatial choice models use various assumptions to simulate decision-making or spatial choice in urban contexts, commonly on an aggregate level. First, decision-making is assumed to take place from a discrete set of choice alternatives. Second, choices are assumed to be made in such a way that the most utility, or satisfaction, is yielded. In an urban sense this might represent a household making a location decision amongst a set of given locations that a city has to offer so that a combination of utilities is maximized (e.g., cost, amenities, quality of the school system, etc.). Third, it is assumed that choices are made in a probabilistic fashion—decision-makers have a likelihood of making certain choices. Fourth, it is assumed that the utility of a decision can be divided into two components: one measuring 'strict utility': the fixed and measurable attributes of utility, and the other dealing with 'stochastic utility': an error or disturbance term that reflects the unobserved attributes of a given decision (De la Barra 1989).

There are several variants on this general theme. The most general, the discrete choice model, is expressed mathematically as:

$$P_{ik} = \Pr\left(V_{ik} + E_{ik} > V_{ij} + E_{ij}\right) \quad \forall k \neq j,\ j = 1,\ldots,n \tag{iii}$$

Where P_{ik} is the probability of an individual (i) choosing an option k from a given choice set. V_{ik} and V_{ij} are the 'strict utility' components of an individual's (i) choices of k and j respectively and E_{ik} and E_{ij} are the stochastic elements of the utility calculation for choices k and j. Additional elements may be added to this formula to weight the probability calculation, e.g., variables representing the socio-economic characteristics of a decision-maker.

The logit model is a variant of this. It is devised by making assumptions regarding the random component of utility (E_{ij}), e.g., assuming that individuals evaluate every available alternative to their decision before settling on an optimal one (the non-hierarchical logit model) or that decision-makers make choices sequentially, rather than wading through every available option at once (the nested or hierarchical logit model). Space is introduced into these models by simply adding it as an additional choice variable. Mathematically, the model is expressed as:

$$P_{is} = \frac{\exp\left(V_{is}\right)\cdot\left[\sum_{k\in s}^{n}\exp\left(V_{ik}\right)\right]^{\sigma}}{\sum_{s}^{n}\exp\left(V_{is}\right)\cdot\left[\sum_{k\in s}^{n}\exp\left(V_{ik}\right)\right]^{\sigma}} \tag{iv}$$

Where P_{is} is the probability that a decision-maker *i* will select a particular spatial cluster s to focus its decision in; $\sum_{k \in s}^{n} \exp(V_{ik})$ is termed an 'inclusive value' and describes the attractiveness of a cluster as a function of the individual alternatives available within that cluster (Fotheringham and O'Kelly 1989); and σ represents the extent to which decision-makers process their information hierarchically, and ranges in value from zero to one, with $\sigma = 1$ denoting decision-makers who do not process their information hierarchically at all.

Once a decision-maker has selected a given spatial cluster, s, to narrow her choice set, all that remains is for an option (or alternative), k, to be settled upon. The likelihood of a decision-maker selecting a particular alternative k, within the selected spatial cluster s, is then calculated as:

$$P_{ik \in s} = \frac{\exp(V_{ik})}{\sum_{k \in s}^{n} \exp(V_{ik})} \quad \forall k \in s \tag{v}$$

In addition, the probability of a decision-maker selecting k *from the set of all alternatives* is:

$$P_{ik} = P_{is} P_{ik \in s} \tag{vi}$$

Between them, spatial interaction and spatial choice models comprise the bulk of material underpinning land-use and transport models as planning support tools. In his 1994 review of operational modeling, Wegener identified twelve models that he considered to be state-of-the-art. Of those, ten were formulated predominantly as discrete choice models (Wegener 1994). More recently, a similar review by the U.S. Environmental Protection Agency (U.S. Environmental Protection Agency 2000) identified 22 operational models and, once again, discrete choice models featured most prominently (figure 2). Despite their popularity, however, these techniques have several weaknesses.

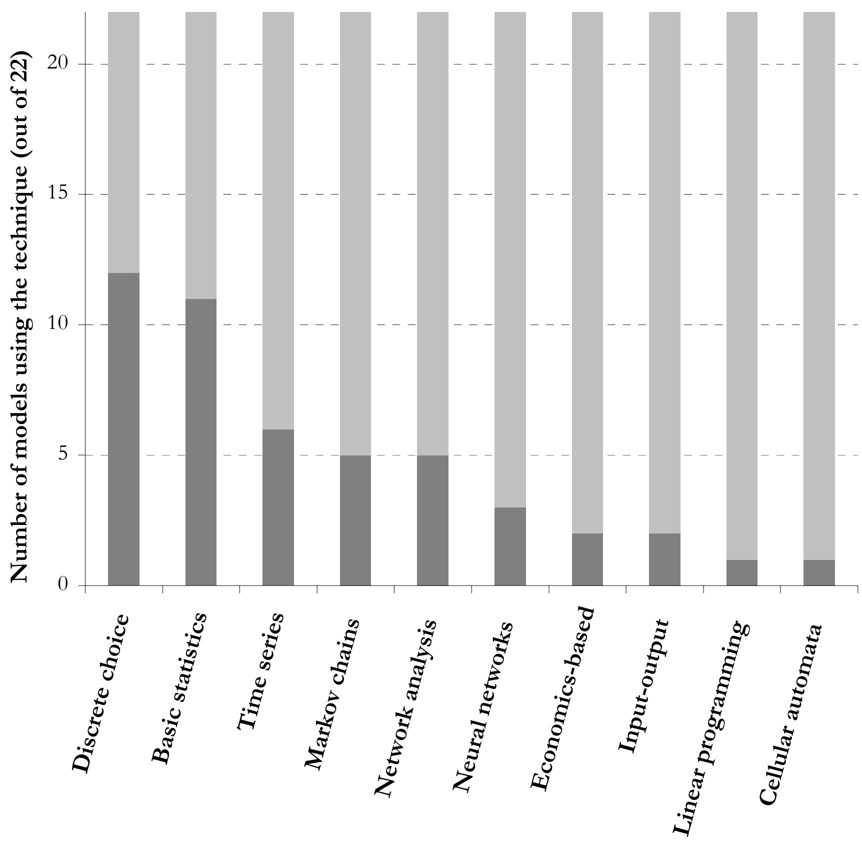

Figure 2. *Common simulation techniques underpinning operational land-use and transport models. (Source: data from U.S. EPA 2000, Appendix A.)*

2.1 Criticisms of the traditional approach

As mentioned in the introduction, 'traditional' approaches to urban simulation have come under heavy criticism over the years. Lee (1973) provided one of the most well known articles documenting their failures; another influential one was written by Sayer (1979). Several of the complaints forwarded in those papers were resolved over time, simply through innovation in computer hardware, software, data capture techniques, and the development of new methodologies (see Batty 1994; Harris 1994; Klosterman 1994). While the models may be regarded as reasonably successful for providing a very general simulation framework for planning support, they have some important weaknesses and any success achieved with their application is tempered by the lack of an available alternative. The assumption that flows of people in an urban system—whether for travel or migration—take place in manners akin to those described by Newton is a simplification. Furthermore, spatial interaction models convey only one form of spatial interaction and not everything in a city passes through urban space as a flow. Spatial choice models offered somewhat of an improvement over gravity models by introducing decision-making, but retained weaknesses. It is widely understood that the distinctions between choice categories may often be fuzzy rather than discrete; spatial choice models do not commonly accommodate this. In addition, the treatment of space as a simple choice variable in a utility calculation is severely limiting. Several other, more generic weaknesses of 'traditional' models can be identified: a poor treatment of dynamics, weak attention to detail, shortcomings in usability, and a lack of realism.

Urban systems are highly dynamic. Models should be able to capture that property, but dynamics are often poorly represented in urban simulations. *Cross-sectional* data are commonly used as a proxy for dynamics. These data are collected for a single period in time: a snapshot. Other models are developed with *longitudinal* data, offering a series of snapshots, often separated by long periods of time with little information about the intervening period, e.g., data from the Census, which is commonly reported on a ten-year basis. While longitudinal data are much richer in the information they convey, they still constitute a weak proxy for dynamics—a lot can happen in a city in ten years! Consider the chart represented in figure 2. In this instance, were we to use two snapshots as the basis for explaining dynamics in a model of the stock market—say, September 1998 to September 2001—we would be looking to explain a flat market: the values at the start and end of the time period are essentially identical at around $1500. The processes that yield market stability are much different from those that generate the sort of volatility that a more fine-scaled examination of the period would reveal. Any results derived from a model designed to explain stability would be wholly inappropriate in this case. The same may well be true for urban models calibrated with longitudinal data.

Figure 3. *The NASDAQ composite index for a five-year period.*

'Traditional' models are often weak in handling detail. For the most part, this is due to a lack of data available at fine-scale spatial resolutions. 'Traditional' models generally adopt the Traffic Analysis Zone (TAZ) as a minimum level of spatial resolution. TAZs are aggregate levels of geography: a medium-size city would be divided into just a few hundred TAZs, for example. From this level of geography, one can only *infer* information at the level of individuals or entity-level geographies of urban space and to do so invokes issues of ecological fallacy and modifiable areal unit problems (Openshaw 1983). At the heart of the Modifiable Areal Unit Problem is the issue that there are almost an infinite number of spatial objects that can be defined and modified for any given area of inquiry but few, if any, modifiable entities. Census data, for example, are collected in many cases for spatially non-modifiable entities (e.g., people, households) and are reported across spatially modifiable units (e.g., counties, ZIP code geographies, census tracts and block groups). Ecological fallacy is a closely related problem. An ecological fallacy occurs when it is inferred that results based on aggregate data can be applied to the individuals who form the aggregated group. 'Traditional' models also represent discrete socioeconomic groupings in a city in a relatively aggregated manner. Household and employment categories are often divided into a handful of classifications. Microsimulation models have gone some way toward disaggregating the groupings represented in simulations, but they are still a long way from an accurate representation of the variety and diversity of people and activities in an urban system. This lack of detail can, in some cases, be regarded as a serious limitation of 'traditional' models because many of the processes that take place in urban systems operate at finer resolutions.

It is vitally important that urban models intended for use as PSS are developed with the end-user in mind. In particular, models should be developed in such a way that makes them easier for decision-makers and the public to digest. Usability has long been a concern in other areas of applied science (e.g., human-computer interaction in computing), but has often been weakly addressed in urban simulation. In many cases, users perceive simulations as 'black boxes': inputs are fed into the model and the results of calculations and operations are output, but the inner workings of the model may remain a mystery. This acts as a barrier to the efficient and appropriate use of models as decision support systems and impairs the ability of models to serve as exploratory tools. The strengthening of linkages between models and Geographic Information Systems (GIS) has helped somewhat in the area of usability, particularly with the communication and interpretation of results, but the need for an interactive environment for directly manipulating models still remains largely unrealized in operational contexts.

Finally, urban models suffer from a lack of realism. Bluntly stated, cities don't really work the way that 'traditional' models would have us believe they do. There is a disparity between models and reality on a behavioral level. In particular, 'traditional' models adopt a reductionist view of urban systems. For the most part, assumptions are made that portray cities as operating from the top down. This implies dissecting cities into constituent local components from aggregate conditions in order to understand them. In many cases, this is appropriate (when studying planning constraints, large-scale infrastructure improvements, etc.), however, in other instances it is inappropriate (when studying housing demand, commuting, etc.). Many components of urban systems do not work in a top-down manner; on the contrary, aggregate conditions emerge from the bottom-up, from the interaction of large numbers of elements and entities at a local scale.

3 A 'new wave' of urban models

In recent decades, social scientists have begun to work with a new class of simulation techniques that we might term 'complexity models', 'geocomputation models', or simply 'geosimulation models'. This 'new wave' of simulation opens up exciting possibilities for simulating systems of all descriptions, and in particular the simulation of behavioral processes and the structures that they generate. While the use of computers and computation in urban simulation is by no means new, the geosimulation approach—modeling systems at the scale of individuals and entity level units of the built environment—is particularly innovative from an urban simulation standpoint and offers some significant advantages for the use of urban simulation as a planning support tool.

A number of key developments across disciplines have supported the introduction of these new techniques. Within the geographical sciences, geosimulation models have been supported by a flood of detailed geographic information that has become easily attainable in recent years. These data have been made available in a variety of media and covering phenomena that would not have been possible a relatively short time ago, e.g., multi-spectral and fine-scale resolution remotely sensed data on land-use and land cover change in urban areas. The provision of these data has been directly responsible for addressing some of the weaknesses we have just explored: a lack of detail in 'traditional' models, for example. Also, it has had indirect impacts on urban simulation by supplying new insights into how urban systems operate, thereby allowing us to develop better-informed simulations. Furthermore, GIS have been developed to store, manipulate, and display spatial data. There is now a rich tradition of use of these systems in PSS contexts.

Object-oriented (OO) programming languages such as Java and C++ have also contributed to the development of geosimulation-style models. OO approaches offer obvious advantages for the treatment of discrete entities of urban systems, e.g., land parcels, buildings, administrative zones, households, and individuals. The basic unit in OO programming is the object. Objects are associated with data and their behavior is mediated through methods (conditional statements and calculations that determine how objects should interact and evolve over the lifetime of a program run). The conceptualization of pieces of inanimate code as objects with related data and methods mimics the way that we think of real world objects ourselves: as discrete units with associated attributes and behaviors. This has several benefits for making models more flexible to build, as well as making them easier to convey and understand.

Ideas stemming from complexity studies have also been instrumental in the development of new generations of urban models. The main idea in complexity is that of emergence. In emergent systems, a small number of rules or laws, applied at a local level and among many interacting entities are capable of generating surprising complexity and often ordered patterns in aggregate form. Additionally, these systems are dynamic and change over time without the direction of a centralized executive. Complex patterns often manifest themselves in such a way that the actions of the parts do not simply sum to the activity of the whole. Essentially, this means that there is more going on in the dynamics of the system than simply aggregating little pieces into larger units. Examples of emergent systems abound. Stock markets are a good example: markets such as the New York Stock Exchange (NYSE) are comprised of millions of traders buying and selling in a bid to maximize their own individual profits. In the eighteenth century, the Scottish economist Adam Smith postulated the idea of an “invisible hand” that set the level of equilibrium between supply and demand in the market place. Individual investors in stock markets act without any centralized control, yet their activities often lead to aggregate outcomes that are relatively efficient, as efficient as if they *were* controlled. Many urban systems are also complex in this sense. From the local-scale interactive behavior (commuting, moving) of many individual objects (vehicles, people), structured and ordered patterns may emerge in the aggregate, such as peak-hour traffic congestion (Nagel, Rasmussen et al. 1996) and the large-scale spatial clustering of socioeconomic groups by residence (Benenson 1998). In urban economics, large-scale economies of agglomeration and disagglomeration have long been understood to operate from local-scale interactive dynamics (Krugman 1996). In addition, cities exhibit several of the signature characteristics of complexity, including phase transitions, fractal dimensionality and self-similarity across scales, self-organization, and emergence (Batty and Longley 1994; Allen 1997; Portugali 2000).

Complexity studies have shed new light on our thoughts regarding the inner workings of cities and have had profound impacts on our approach to urban simulation. They suggest a detailed, decentralized, and dynamic view of urban systems. They also offer a framework for considering answers to questions of the form, ‘How do cities work?’ in terms of the myriad and evolving interactions of individuals and the urban spaces that they inhabit. This is a much more *generative* approach than the reductionist view that is traditionally adopted in urban studies. Simply dissecting cities may not provide all the answers; on the contrary, there may be a need to build them up from the bottom and in doing so, we may learn a lot about how they work. As will now be explored, this may also have some direct analogies in the way we simulate cities.

3.1 The geosimulation approach

The geosimulation approach offers a unique perspective that traditional simulation has commonly lacked: a view of urban phenomena and the spatial processes that shape them as a result of the *collective dynamics* of multiple urban animate and inanimate objects. Geosimulation can be considered as an extension of traditional urban modeling in several ways.

First, and as we have already seen, the *intellectual roots* of geosimulation differs from that of previous generations of models. Ideas from economics, physics, and engineering are still adapted to spatial contexts in urban models, but the range of inspiration is now much wider. Geosimulation models borrow from developments in several fields that were not widely considered, particularly computer science (artificial life and artificial intelligence) and natural science.

Second, the geosimulation approach differs in its depiction of *spatial units*. While traditional urban models have focused on aggregate partitions of urban space—essentially *modifiable* spatial units—geosimulation works with discrete and *spatially non-modifiable* individual objects, such as houses, lots, householders, and landowners.

The third feature relates to the portrayal of *spatial interactions*. As we saw, 'traditional' models have focused on describing flows of matter and information between aggregate spatial units. Geosimulation models contrast by concentrating on the interactive behavior of elementary geographic objects, and that interaction may take many forms: flows, distance-decay, diffusion, dispersal, action-at-a-distance, centripetal and centrifugal activity, linear and non-linear relationships, etc. If interactions are modeled at higher-level units of urban space, they are simulated in geosimulation as the outcomes of collective interactions at *micro*-scales. The choice sets used in spatial choice models also appear in geosimulation models, but in this case those rules are mediated spatially in a variety of ways, above and beyond the use of a simple choice set to represent space and geography.

The fourth characteristic is concerned with the treatment of *time*. As we saw, traditional models are essentially static. Geosimulation models, by comparison, are very dynamic and in some cases, they can approximate real time interaction within a simulation environment.

Finally, 'traditional' and geosimulation models differ in their *attitude* to urban simulation. Geosimulation could be considered as a reconsideration of the goals of simulation, with a new emphasis on building scenario-generating games—tools to think with—rather than predictive models. Various simulation scenarios can be designed, each based on different suggestions regarding factors of urban dynamics, and played through to likely conclusions before being tried in the real world. The intuitive and transparent nature of the models should facilitate discussion by model users, rather than providing prescriptive remedies based on simplified assumptions. This has obvious advantages for the application of simulation tools to PSS.

The two main techniques used to build geosimulation models for application in urban studies are cellular automata (CA) and multi-agent systems (MAS). Both CA and MAS share the traits of geosimulation models discussed above. In terms of urban simulation, CA are perhaps best used to represent the dispersal of activity and characteristics between discrete spatial units of urban infrastructure and land. MAS may be more suited to simulating urban population as collectives of individuals with associated behaviors and traits and the capacity for spatial mobility and communication.

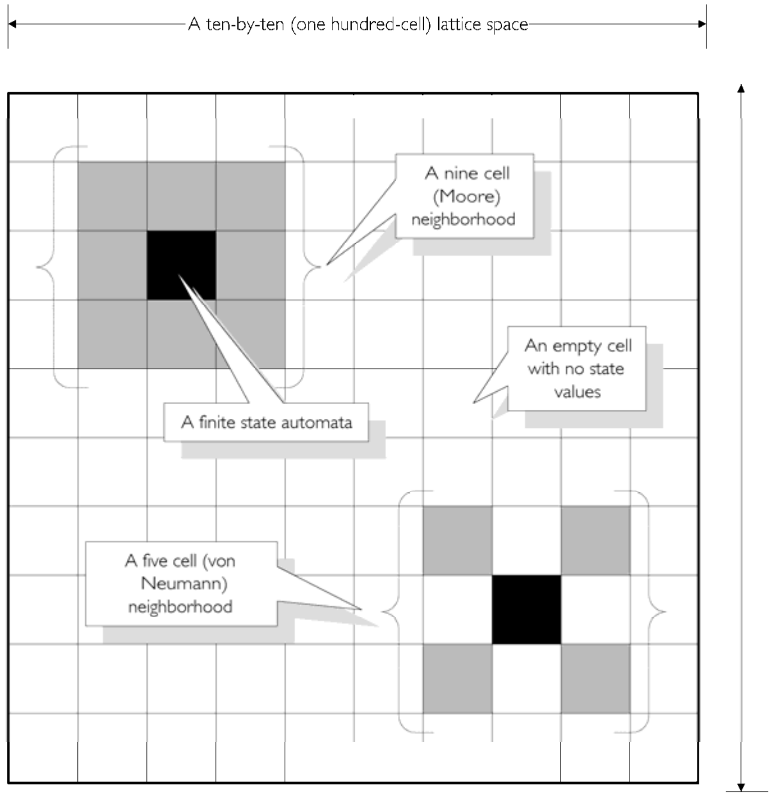

Figure 4. *The characteristics of a basic cellular automata.*

3.2 Cellular automata

Cellular automata were originally pioneered in computing (Sipper 1997) but have since seen uses in a wide variety of fields, including urban studies (see Batty, Couclelis and Eichen 1997; Torrens 2000a). A cellular automaton is a finite state machine (an engine of sorts) that exists in some form of tessellated cell-space (figure 3). The term automaton refers to a self-operating machine, but one of a very distinct nature: "An automaton is a machine that processes information, proceeding logically, inexorably performing its next action after applying data received from outside itself in light of instructions programmed within itself." (Levy 1992, p.15) Additionally, CA are *parallel* automata: more than one automaton is active at any given instance. CA are comprised of five components. The *lattice* of CA is the space in which they exist. This might be considered equivalent in an urban context to a city, an environment, a landscape, or a territory. The lattice can also be generalized to represent urban spatial structures, networks of accessibility, the physical structure of the city, etc. CA *cells* represent the discrete confines of individual automata. They are the elemental building blocks of a CA, just like individual land parcels or buildings in a city. CA cells are, at any time, in a particular *state*. The cell state offers a flexible framework for encoding attributes of a city into an urban simulation model, e.g., land-use, density, land cover, etc. *Neighborhoods* are the localized regions of a CA lattice (collections of cells), from which automata draw input. Neighborhoods in an urban CA might represent spheres of influence or activity, e.g., market catchment areas, commuting watersheds, etc. The real driving force behind CA are *transition rules*. These are simply a set of conditional statements that specify the behavior of cells as CA evolve over time. The future conditions of cells are decided based on a set of fixed rules that are evaluated on input from neighborhoods. CA rules can be devised to mirror how phenomena in real cities operate. Additionally, we might discern another component—*time*—that is generally discrete and proceeds in iterative steps. In CA, the dynamic processes of change are represented through local actions (governed by transition rules) that are applied in the immediate proximity of the various objects that comprise the system of interest (Batty, Xie et al. 1999b). Because CA are dispersive in their action through space, this can generate structures on a macro-scale.

CA offer a range of advantages for urban simulation and in several ways they remedy particular deficiencies of 'traditional' models. Whereas space is represented in a very simplistic manner in 'traditional' models (commonly as a single variable or a distance calculation), CA provide for a much richer representation. Urban systems can be represented at a variety of spatial scales simultaneously, directional elements can be introduced to mimic the way that cities develop in sectors or wedges, different distance functions can be added to characterize distance-decay, and neighborhoods can be set up hierarchically to represent action-at-a-distance. Additionally, the structure of space can be modified in a variety of ways from irregular to regular representations.

CA transition rules have been devised that mimic those of spatial interaction and spatial choice models. However, CA are highly flexible and transition rules can be devised to represent just about any process or variable you can imagine: geographical inertia, hierarchy, accessibility, suitability, potential for development, utility functions, constraints, exogenous growth, feedback effects, deterministic and probabilistic processes, etc. Importantly, they offer the potential for weaving theory and planners' knowledge and expertise directly into the cogs of model dynamics. The framework for CA (and for MAS) is not as constraining as those of 'traditional' models might be considered to be.

Additionally, CA can be designed with attention to detail. They are inherently decentralized. They are dynamic, as well as being intuitively useful and behaviorally realistic. Additionally, they have a "natural affinity" with raster data and GIS (Couclelis 1997), as well as with OO programming. CA also provide a mechanism for linking micro- and macro-approaches and for connecting patterns with the processes that produce them.

CA have been used quite widely in urban studies in recent years. The most common applications of the models are to land development, urban growth, and land-use transition. In terms of land development, CA have been used to investigate the role of density constraints in development and the spatial distribution of growth activity (Batty, Xie et al. 1999b). Other models have characterized the development process as a profit calculation, mediated through space with the use of decision-making regimes from game theory (Wu and Webster 1998). CA have also been used to simulate development as a function of demand, supply, and potential (Batty 1998).

CA models have also been applied to simulating urban growth processes, as well as specific forms of urban growth such as polycentricity (Wu 1998). CA have been used to represent the evolution of urban form through growth cycles (Batty, Xie et al. 1999b). Growth has also been modeled proceeding from historically identified 'seed' cells, using self-modifying transition rules that mimic the adaptability of cities over time (Clarke, Hoppen et al. 1997), and using predator-prey algorithms (Batty, Xie et al. 1999a). White & Engelen (2000) have developed CA models that rely on exogenously defined growth engines that reflect the position of cities in larger economic regions and economies.

CA have been quite widely applied to simulating land-use transition. Land-use dynamics have been modeled as a hierarchical process (White and Engelen 1997) and as a function of the rent-bidding power of individual sites and the externalities that they might produce (Webster, Wu et al. 1998). The role of inertia in land-use transition has also been widely investigated, as has the role of constraints such as accessibility (White 1998), density, and topological factors (Clarke, Hoppen et al. 1997).

3.3 Multi-agent systems

While CA are most suitable, in urban simulation contexts, for representing infrastructure and land, MAS are better used to model population dynamics. MAS also have origins in computer science, although their development post-dates that of CA by some years. Most commonly, MAS are used in computing as artificial intelligence systems or artificial life forms (Kurzweil 1990; Levy 1992). Additionally, there are 'species' of agents that serve as network bots, web crawlers, and spiders (Leonard 1997). Network agents are used to navigate computer information networks, to 'mine' data, retrieve it, and return it to human users. There is also a tradition of using software agents to explore entomological behavior (Bonabeau, Dorigo et al. 1999) and the actions of agents in economic systems and markets (Luna and Stefansson 2000).

Agents are quite similar to automata in their formulation but have less well-defined characteristics. They constitute pieces of software code with certain attributes (states) and behaviors (rules) (see Ferber, 1999 for a general introduction to intelligent software agents). They differ from CA mainly in their spatial mobility: agents can be designed to navigate (virtual) spaces with movement patterns that mimic those of humans, while CA are only capable of exchanging data spatially within the confines of their neighborhoods. In some senses, agents could be considered as mobile CA. Their states (e.g., occupation, income, age, etc.) describe their characteristics in the same way as in CA and they exist in some space (although this need not necessarily be a *cellular* space). Agents may have a neighborhood of influence in which they operate, but the criteria for defining that neighborhood are much more flexible than those applying to CA. Like CA, MAS are driven by transition rules that govern the behavior of the agents. These rules may be characterized as 'goals' that agents seek to satisfy (e.g., minimizing travel distance) or even 'preferences' that agents may possess (e.g., 'likes' and 'dislikes' for certain locations in space), or may be derived from their state variables.

MAS are excellent tools for representing mobile entities in urban environments, e.g., people, households, vehicles, etc. However, their application to urban studies has not been as widespread as that of CA, although there seems to be no particular reason why this should be the case. MAS hold all of the advantages of CA, but with the additional capacity for representing a wider array of spatial processes. Like CA, MAS are easily programmed in OO environments, as well as offering advantages in terms of detail, flexibility, dynamics, usability, and behavioral realism. They have been used in urban contexts to simulate pedestrian movement in dense urban environments (Batty 2001). Here, agents are designed ‘choreographically’ with the capacity for realistic movement through space. Additionally, agents may be equipped with realistic behaviors (such as shopping habits) derived from life-like socioeconomic profiles. Another widespread application of MAS is in simulating residential location patterns. Whereas with spatial interaction and spatial choice models, residential location processes were modeled as simple flows between destinations or as aggregate-level decisions, MAS can model the process in a more life-like manner. Individual households can be represented with realistic profiles and preferences, then sent out to interact in virtual housing markets (Benenson 1999). In one example, residential location is modeled using both CA and MAS in a hybrid fashion (Torrens 2001a). Home-buying and home-owning agents negotiate the sale of properties through the help of MAS, while neighborhood effects that influence the attractiveness of certain areas of the city are simulated using a CA.

4 Epilog

Although CA and MAS models are developed, for the most part, in academic contexts, they are beginning to find their way into planning support systems. The TRANSIMS model—a CA simulation of traffic dynamics, capable of simulating interactions among hundreds of thousands of vehicles in real time—is one of the most ambitious urban simulation projects ever developed (Nagel, Beckman et al. 1999). That model is scheduled for practical application in a range of cities in the United States. The models developed by White, Engelen, and colleagues have also been used in practical contexts. In addition, Clarke’s SLEUTH model has also seen considerable application in practical contexts. However, it is unlikely that CA and MAS will be used in isolation as planning support tools. They have yet to be widely tested in planning contexts, simply because the field of research is quite new. More traditional approaches, on the other hand, have enjoyed decades of use by planners, policy makers, and urban managers. It is more likely that CA and MAS will supplement existing systems rather than supplanting them. It is here that CA and MAS can make their immediate contribution, by filling in the gaps that traditional models leave, particularly those left open at the micro-scale.

The discussion thus far has been quite optimistic about the potential of new techniques to revitalize operational simulation. The techniques themselves do certainly represent the possibility for a ‘revolution’ in the way we simulate urban systems. However, there are some imposing barriers to putting those techniques into practical use in the real world (Torrens and O'Sullivan 2001). Ironically, computing power poses one of the most pressing limitations. CA and MAS models have been developed and tested for several cities, but most are quite modest in the number of entities that they simulate. Scaling those models up to represent an entire metropolitan area, populated with individual agents numbering millions would require daunting levels of computing power. However, even here advances are being made, particularly in the use of distributed computing to provide the computational engines for detailed models. As mentioned, the TRANSIMS model at Los Alamos National Laboratories is one such example (Nagel, Beckman et al. 1999).

In addition, there are data limitations on the development of these models for practical uses. Conceptually, the idea of simulating individuals and the buildings that they inhabit is quite appealing. However, data are not widely available at the scale of the individual householder or building. In addition, there are several moral issues that arise from the use of individual-level—and often private—data in operational simulations.

Furthermore, micro-scale models, particularly dynamic and process-driven simulations, are quite difficult to calibrate, even if data are available. Organizing the models as a hybrid that interfaces with ‘traditional’ aggregate-level models allows the possibility of scaling up the simulation to meso-scales for validation purposes (Torrens 2001b). This is a reasonable solution, but ideally micro-models would be calibrated at the scale of the entity or the individual. The emphasis thus far in geosimulation modeling has been on pattern-based validation techniques: pattern recognition, and measures of match such as the chi-squared and kappa-statistics. Generally, this sort of calibration focuses on validating the patterns that CA or MAS models have generated and comparing those results with historical maps of urbanization or land-use patterns, using that as a justification for simulating ahead in time. The weaknesses of these approaches have been well documented (O'Sullivan and Torrens 2000). Some significant advances have been made in using GIS to analyze the patterns that geosimulation models generate, including some ‘fuzzy’ recognition techniques. However, much of this effort is still bogged down in pattern-based approaches, ignoring the fact that geosimulation models comprise pattern and process, form and function. Future research may therefore have to look to new process-related validation measures such as Monte Carlo averaging, spatial information statistics, and measures of complexity.

Additionally, working at the micro-scale, in some cases, reveals inadequacies in the theory of how cities work. The micro-approach betrays some theoretical gaps in our understanding of the dynamic interactions that shape our urban systems. Indeed, one of the important contributions of these models in academic terms has been in providing some justification for a ‘new urban geography’ of the micro-scale.

The point that this chapter is intended to convey, however, is that—at least methodologically and increasingly in practice—the techniques discussed here represent a move towards more theoretically sound, behaviorally realistic, and ultimately more *useful* simulation environments as planning support tools. Certainly, these simulations can be developed as proof-of-concept tools and the methodologies can be refined in academic contexts in preparation for a day in which these tools can be used to plan and manage better cities. It is also likely that several of their features will begin to see application in the real world, alongside existing ‘traditional’ models (Torrens 2001b); in fact this is already occurring. In the meantime, even as abstract tools, these simulations can do a lot for our understanding of how cities work and perhaps provide new insights into how we might construct a more sustainable urban future.

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