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Modeling urban landscape dynamics: A review

Sheryl BERLING-WOLFF and Jianguo WU*

Landscape Ecology and Modeling Laboratory (LEML), School of Life Sciences, Arizona State University, Tempe, Arizona 85287–4501, USA

Reviewed here is the historical development of urban growth models, showing how different disciplines and diverse theories have come together over time to produce the models used today. This review is divided into two sections, the first section reviews the early models that are rooted in transportation and land-use planning and form the foundation on which nearly all modeling efforts are based. These models are already well documented in the literature and an overview here is sufficient. In the second section, an exploration is made into the theories and approaches that have been integrated into urban modeling efforts. The concepts are outlined and one or more contemporary examples are highlighted. These theories and approaches represent the major areas of development that exist in published work.

Key words: comparative equilibrium models; land-use and landscape planning; spatial analysis; transportation model; urban growth model.

Introduction

In the past, ecologists have typically ignored anthropogenic processes in their study of ecological systems (Pickett & Cadenasso 1995; Pickett & Rogers 1997). However, it has become clear that such processes can no longer be ignored, as there are no areas left in this world that are completely untouched by human influence. Urban growth affects ecological habitats when urban areas expand into the surrounding natural areas, diminishing them in size or resulting in habitat fragmentation, as well as generating damaging effects through such sources as pollution and human use (Landis *et al.* 1998). The study of urban systems must be considered integral to the study of landscapes, and urban processes must be studied in order to understand their influences and predict their impact on surrounding ecosystems (McDonnell & Pickett 1993; Foresman *et al.* 1997).

An urban growth model that can make reasonable and reliable projections about future urban growth would be of value for both scientific and educational purposes. Such a model is valuable for scientists who wish to understand how growth occurs and as an educational tool for the general public, politicians and city planners who can benefit greatly from the visualization of different growth scenarios (Wu 1998b; Strange *et al.* 1999). Other researchers could use projections from a model to study other facets of an urban system, such as, hydrology (Grimmond & Oke 1986) or species persistence (Baur & Baur 1993). For example, the effects of urban growth on drainage will drastically affect factors, such as, soil nutrient availability. Other urban ecological modelers, developing more complex and comprehensive models, can compare the forecasts to their own models (Wu & David 2002).

This paper outlines the historical development of urban growth models, showing how different disciplines and diverse theories have come together to produce the models used today. This review is divided into two sections, the first section reviews the early models that are rooted in transportation and land-use planning and form the foundation on which nearly all modeling efforts are based. These models are already well-documented in published work and an overview here is sufficient. In the second section, an exploration is made into the theories and approaches that have been integrated into urban modeling efforts. The concepts are outlined and one or more contemporary examples are highlighted. These theories and approaches represent the major areas of development that exist in published work.

Transportation and land-use planning

Roots in transportation

There were two sociopolitical developments in the late 1950s and early 1960s that created interest in urban

*Author to whom correspondence should be addressed. Email: Jingle.Wu@asu.edu

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modeling. The first was the demand for more scientifically based highway impact statements and the second was a federal governmental concern with urban problems (Putnam 1983). Increases in car ownership caused many traffic problems and planners realized the need to study these problems in a scientific, organized manner. With the introduction of the computer, the modeling revolution began. The processing capabilities provided by the new machines contributed significantly to the ability of planners to model regions and cities. Many models developed during these early times never became operational and those that did often performed rather poorly. However, many lessons were learned and frameworks were developed that have carried over into present day development (Lee 1973).

The first models used in transportation studies for transport planning were generally based on gravity theory, or linear or optimizing mathematics. Models based on gravity theory dealt with the movement of people at the aggregate level, emphasizing the effect of land-use change rather than the assignment of trips in a road network (Foot 1981). They used modified equations from Newton's theory of gravity that stated that the spatial interaction between two bodies declines in proportion with the square of the distance. It was postulated that the interaction between two cities varied directly with the size of the two cities and inversely with the square of the distance between them. Foot (1981) presents the formulation of an unconstrained gravity type model (i.e. neither origin zone totals nor destination zone totals are fixed), which was used in the earliest applications,

$$T_{ij} = G \star (P_i P_j / d_{ij}^2) \quad (1)$$

where T_{ij} is the interaction between cities i and j; P_i and P_j are the population size of cities i and j; d_{ij} is the distance between cities i and j; and G is a constant to be determined at calibration.

The early transportation models generally had a 'trip' focus – the urban area was represented as a transport network and the flow and assignment of trips to the transport network was modeled (Foot 1981). This was the first step in the application of discrete/random choice theory in locational analysis (Harris 1985), the idea that trips and traffic in the city resulted mainly from decisions at the individual household level, which could be modeled mathematically.

As stated, most early transportation models were based on gravity theory and sought to integrate different activity systems according to spatial distributions obtained through interaction functions analogous to Newton's gravitational theories. One landmark effort, upon which many contemporary models are based, was the Lowry model (Harris 1985) that embedded spatial interaction equations in a demographic–economic framework (Batty 1994). Lowry iteratively applied a journey-to-work function of the gravity type to distribute workers employed in basic industries in workplace zone j among residence zones i, and an analogous journey-to-shop function to distribute population serving workers to residence zones. To complete the model, maximum density and minimum employment constraints were applied to produce a clustering of population serving jobs. Inputs to the model included employment information and travel costs and the resulting outputs were estimates of employment and population by geographic areas. Kain (1987) presented a formulation of the Lowry journey-to-work function as:

$$P_{ij} = (C)_{ij}^{-1.32R} \quad (2)$$

where P_{ij} is the proportion of workers employed at j living at i; C_{ij} is the distance from zone j to i; and R is the number of residence zones at that distance. While the early transportation models were considered successful in their technological achievements, the human behaviors that were modeled were usually more descriptive than theoretically based and these early models were generally used only for urban planning to compare alternative planning policies (Harris 1985). In fact, the greatest deficiency of models based on gravity theory was their lack of underlying economic or behavioral theory (Berechman & Small 1988).

Kain (1987) reviews several models that were modifications and enhancements to the Lowry model. One notable extension to the Lowry model was by Anas (1986) who extended it to reflect economic equilibrium. He combined ideas of market clearing and economic behavior with discrete choice, connecting gravity models and linear programming (Harris 1985; Anas 1986).

Models of location of activities

City planners were interested in models of locational activities, such as, housing and residential choice, business location, industrial location, and public service locations. Several early models incorporated central place theory, a theory based on the assumption that every household visits the closest center that can satisfy the purpose of the trip. This theory purportedly explains the sizes and functional distribution of cities within a region and subcenters within a metropolitan area. However, as this theory applied only to limited economic sectors and its rigidly deterministic consumer behavior patterns were unrealistic, it was generally discredited. Harris (1985) describes some attempts by later modelers to incorporate more realistic behavioral assumptions and some randomness to central place theory based models.

In an effort to simulate the operation of urban markets, a class of models was developed that used linear programming techniques to predict residential locations. These eclectic empiric-econometric or deterministic economic equilibrium models incorporated an economic theory of land-use, asserting that households trade off higher site costs for lower commuting costs. One well-known model was the Herbert-Stevens deterministic equilibrium model, based on linear statistical relations and urban econometrics. On the demand side: each household has a 'bid–rent function' that describes the most it would pay to live at each possible location and still have a given level of satisfaction (utility). On the supply side: each location is rented to the highest bidder. Equilibrium occurs when all households of a given type are equally well off and levels of utility have adjusted so that each household occupies exactly one site (Berechman & Small 1988). However, as it contained no spatial representations, the prevailing opinion was that it was not suitable for analysis of rapidly growing areas (Kain 1987; Batty 1994). Foot (1981) presented a formulation for the Herbert-Stevens model that distributes land-use activities over a region by deriving a set of linear equations of the form

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i} + \dots \quad (3)$$

where b_o, b_1, b_2, ... are constants and X_{1i}, X_{2i}, ... are independent variables that explain the variation. These variables of socioeconomic and land-use activities are derived from input collected from each zone.

Others began to look at behavioral choice models, called utility maximizing or random choice utility models. In these types of models, the problem of choice is formulated in terms of individual decision-makers selecting from a set of discrete alternatives. The utility of each alternative, to the chooser, is comprised of: a deterministic component, the explainable portion of behavior and is held in common with all other individuals of the same type; and a random component, representing the individual (Putnam 1986). These two components model individual choice behaviors, expressed in probabilistic terms using multinomial logit formulas. Putnam (1986) presented the formulation of a random choice utility model as

$$U_{ij}^{\star} = U_{ij} + \varepsilon_{ij} \quad (4)$$

where $U_{ij}^{\star}$ is the perceived utility of alternative i to decision maker j; U_{ij} is the deterministic component of utility common to all decision makers of type j; and ε_{ij} is the stochastic component of utility representing individual choice.

Brewer (1973) reviewed several community renewal programs that used large-scale models including those used in San Francisco (1962) and Pittsburgh (1960). One of the first was the simulation model of the urban housing market for San Francisco's community renewal program (Brewer 1973). Harris examined models that were in use at the time in retail, housing and manufacturing locations as well as other areas (Harris 1968). Ohls and Hutchinson (1975) examined 12 surveys that had been done during the previous decade, considering only those models that described land-use (housing, commercial and industrial) and urban development processes in metropolitan areas.

Integrated land-use/transportation models

It was soon apparent that transportation modeling without consideration of land-use was inadequate. By the late 1960s, numerous integrated land-use/transportation models were being developed and some models became operational. The Detroit Metropolitan Area Transportation Study (1955–1956) and the Chicago Area Transportation Study (CATS 1960) were the most influential (Berechman and Small 1988). These were adapted versions of the Urban Transportation Planning (UTP) model, which was based on the idea that future travel predictions could be derived from forecasts of future land-use, intimately connecting travel networks and land-use.

According to Berechman and Small (1988), the Integrated Transportation and Land-Use Package (ITLUP) model was one of the first to fully integrate land-use and transportation network models (Putnam 1983). Its major deficiency was that it contained neither demand nor supply functions nor a price mechanism for achieving market equilibrium (Berechman & Small 1988). This was followed by Anas's (1986) CATLAS model that was well rooted in economic theory, containing four behavioral submodels based on multinomial logit equations (Berechman & Small 1988).

By 1970, the entropy maximizing approach was applied to transportation and urban spatial models. This approach described human behavior with techniques derived for the analysis of molecular behavior, finding the most probable distribution (the maximum entropy) subject to minimum information and specific constraints (Harris 1985; Putnam 1986). As a result, different forms of residential location models, previously considered separate entities, were shown to be related. Additionally, it was demonstrated that by combining the spatial interaction models derived from this approach with transportation models using linear programming, these two approaches could be unified (Putnam 1986).

Foot (1981) presented a formulation for a doubly constrained entropy-maximizing model, where the distribution of trips T_{ij} between cities i and j is subject to three conditions:

$$\begin{aligned} \sum_j T_{ij} &= O_i \\ \sum_j T_{ij} &= D_j \\ \sum_i \sum_j T_{ij} c_{ij} &= C \end{aligned} \tag{5}$$

The origin zone totals O_i and destination zone totals D_j are fixed levels of activity and there is an overall total travel cost C for the system, where c_{ij} is the cost of each trip between i and j. The entropy maximization procedure involves maximizing the function (Equation 6) subject to the constraints (Equation 5)

$$Q = \frac{(\sum i \sum j T_{ij})!}{\Pi i \Pi j (T_{ij}!)} \tag{6}$$

determining the most probable distribution. Maximizing the logarithm of Equation 6 can be interpreted as the entropy of the system.

The transition period in urban modeling

In 1973, Lee published his 'requiem' foretelling the ultimate failure of large-scale urban models because of numerous fundamental flaws. They were complicated, expensive, and lacking an underlying theoretical base; they were too coarse for urban planners but still required vast amounts of data; there was a discrepancy between the claimed behaviors and the equations used. By the mid-1970s, numerous failures led to the near demise of large-scale urban models as interest waned and government funding dried up (Lee 1973).

Internationally, many research centers continued to build transportation models, but scaled-down, less general versions. Many of these smaller scale models, based on Lowry extensions, were used successfully in practical planning situations (Foot 1981). Batty (1979) reviewed the progress, successes and failures of large-scale urban modeling. He saw failure from the perspective of theory and practice but success in terms of the development of modeling-skills.

The apparent lack of coordinated effort, both in conceptual and methodological terms, suggested a lack of agreement about the basic foundations of urban and regional modeling and demonstrated a need for greater unification of urban and regional theory (Oppenheim 1986; Putnam 1986). Early modeling efforts tried to capture the totality of the system in a single model. The complexity of urban systems necessitated dividing the system into subsystems for ease of understanding and, as most models avoided dealing with the links between the subsystems, they were limited in their ability to model responses to changes within the system (Harris 1968). Clearly, if modelers were going to be successful in capturing the totality of the system, a disaggregate modular approach was required (Harris 1985).

Berechman and Small (1988) noted that rapidly growing urban areas developed their own patterns of agglomeration and centrality, which were very different from the patterns that inspired the land-use models familiar to urban planners. Population and employment were shifting to the suburbs, and with the economic independence gained in these areas, they now contained many of the features formerly associated with city life. Berechman and Small (1988) argued that the different characteristics of modern cities and land-use changes needed different kinds of models.

Integration of new theories and approaches

The second half of this paper investigates some of the techniques, approaches and theories that have been applied to urban growth models. Several examples are mentioned but it should be noted that these techniques, approaches and theories are not mutually exclusive. In fact, many contemporary models combine several of the techniques and approaches listed here. By the late 1970s and early 1980s, the computer revolution was making great strides. Processing power was increasing, memory prices were dropping, and software was becoming cheaper and more powerful. Urban models began to grow again, but one lesson was learned – that modularity was going to be a key to success. New mathematical and economic theories were being developed, and computers made previously unsolvable problems, such as, partial differential equations, solvable. Modelers began to build modular models that could apply different theories and different mathematics to different parts of the problem.

Dynamic modelling techniques

Early models were typically static or comparative equilibrium models, based on theories stating that social systems tend to converge to a stable equilibrium. Static equilibrium models deal with data for one point in time and the model operates as though the system is in a state of equilibrium. The predictions provide information on the equilibrium situation at some future date. Comparative equilibrium models deal with incremental changes during a particular time period. There were also some quasi-dynamic models that carry out recursive predictions, making a series of predictive runs where the output for one point in time becomes input to the following prediction. None were ideal approaches since cities are complex, self-organizing, evolving systems and rarely, if ever, in equilibrium (White & Engelen 1993).

Forrester (1961) introduced his industrial dynamics in 1961, for simulating industrial processes in firms. He attempted to apply this idea to the complexity of urban systems with a differential equation model of an abstract city. Forrester's model had little empirical content and ignored the spatial dimension of urban dynamics. According to Lee (1973), Forrester's conceptions about public programs were flawed and it was incorrect to offer his model as a generalized model of a city. It contained irrelevant complexity and, although Forrester claimed otherwise, it was of no use for public policy because it had only a single response built in. However, Forrester's model played an important role in introducing the dynamic view of urban systems. Several modelers (Kain, Babcock, Batty) modified Forrester's model and contributed new insights (Bertuglia *et al.* 1987). But it was the Lowry model, with extensions and modifications making it more useful, which gained acceptance and found widespread use as a framework for future developments.

It wasn't until the late 1970s that models with dynamic features began to appear more frequently in published work. Economists attempted to describe the dynamics of social systems and modelers began to consider the temporal dimension of social phenomena. New developments in the biosciences with respect to the behavior of complex systems as well as new mathematical techniques, such as, spatial dynamics, catastrophe and bifurcation theory provided better tools for researchers to model dynamic behaviors (Harris 1985; Wegener *et al.* 1986). Clearly, the ability to model the dynamic aspects of a system would lead to more realistic models and hence have a more general application.

Significantly contributing to dynamic modeling was the Brussels School approach (Allen & Sanglier 1978, 1979). It was based on the concept of self-organization through random perturbations as found at the molecular level in physical or biological systems. Activities, described similarly to those of the Lowry model, evolve in time according to a non-linear growth dynamic (Bertuglia *et al.* 1987)

$$X_i = \varepsilon_i[D_i - X_i]X_i \qquad (7)$$

where X_i is an activity X in zone I; D_i is the carrying capacity for activity X in zone i and ε_i is the proportionality factor. In this formulation, the carrying capacity for an activity in any given zone is defined as a function of the values of the other activities in the other zones according to certain economic and spatial relations (Bertuglia *et al.* 1987). This model was significant because it considered stochastic elements in the formation of urban spatial patterns.

Allen and Sanglier (1978, 1979) developed a dynamic version of central place theory based on the mutual interaction of the spatial distributions of population and employment opportunities. Deterministic equations represented population growth, economic functions of growth and decay, and market potential, modeling the qualitative changes in the spatial organization of a region. Chen (1996) improved on this model by presenting a simulation model of non-linear dynamic urban growth in which he included equations to represent demand-side considerations, microeconomic foundations, agglomeration effects and land prices. However, the inability of this approach to distinguish between growth and decline led to doubts about its ability to model urban evolution (Wegener *et al.* 1986).

Cellular automata

It was widely recognized that actual growth patterns were represented by a variety of factors and functions; the question became how to structure a model so that this complexity could be modeled and studied. This led to a notable contribution to dynamic modeling, the incorporation of the cellular automaton structural framework. Cellular automata are not new. They were developed by the physicist Stanislaw Marcin Ulam in the 1940s and were used by John Von Neumann to investigate self-reproducing systems (White & Engelen 1993). Cellular automata are systems of cells interacting in a simple way but displaying complex overall behavior. These models can generate very complex structures including fractals, and can be used to explore a wide range of fundamental theoretical issues in dynamics and evolution (White & Engelen 1993). Cellular automaton is an approach to modeling open, complex, self-organizing systems that emphasizes the way in which locally made decisions give rise to global patterns (Wu 1998a).

A cellular automaton (A) is defined by a lattice (L); a state space (Q); a neighborhood template (l); and a local transition function (f) expressed in set notation as:

$$A =< L,\ Q,\ \ell,\ f > \qquad (8)$$

A cell may be in any one of several discrete states defined by Q, and a set of transition rules, f, determines the state of each cell as a function of the state of the cells adjacent to it. Time is discrete and all cells are updated at each time interval. White and Engelen (1993) noted that cellular automata models have been used in a variety of different fields. Many contemporary urban growth models in published work are based on a cellular automaton framework and several will be used as examples in the following sections.

Spatial analysis

Spatial analysis (SA) embraces a whole cluster of techniques and models that apply formal, usually quantitative, methods to systems in which the prime variables of interest vary significantly across space (Longley & Batty 1996). The lattice framework of a cellular automaton model lends itself to analysis by spatial analysis techniques. Spatial analysis, which developed rapidly in the 1980s and 1990s, was essentially based on the notion of adapting standard statistical theory, much of it linear, to handle changes in assumptions caused by the introduction of space (Rossi *et al.* 1992). One of the main concerns of SA became the search for methods for measuring spatial autocorrelation in data and adapting linear statistical models to account for it. Scale and aggregation, discreteness and continuity, were issues that served to make SA distinct from other kinds of mathematical analyses.

Again, it was the computer revolution with its faster and more powerful processing abilities that enabled the integration of SA into urban modeling. Many SA techniques required the use of a computer because of the vast computational power needed and the huge quantities of spatial data used. Landis *et al.* (1998), in the California Urban and Biodiversity Analysis (CURBA) Model, included a spatial analysis module that measured habitat change and fragmentation to compare alternative policy options. As we shall see in the next section, the use of spatial analysis on geographic information systems data has increased urban modeling capabilities tremendously.

Geographic information systems and visualization techniques

Geographic information systems (GIS) are a combination of hardware and GIS software used to manipulate, store, retrieve, view, and analyze spatial data. All features in a spatial database are comprised of graphic elements (points, lines, or polygons) linked to a table that uniquely identifies each feature and its location in a coordinate system. Data can be mapped and analyzed, and linked to attribute data in one-to-one or many-to-one relationships (Mills 2001). Geographic information systems trace their roots to computer cartography and other fields, such as, landscape architecture (Longley & Batty 1996). Geographic information systems have emerged within the past 20 years due to cheap computer memory and disk storage, faster processing speeds and the availability of desktop hardware and GIS software. There were two major consequences of computer and GIS development: (i) model planning systems could become more user friendly and accessible; and (ii) researchers could approach problems that previously were considered analytically intractable (Wilson 1998).

The availability of desktop computers and GIS software has changed the way many urban planners and managers do their jobs (Lee *et al.* 1998). The introduction of GIS has already changed the way we measure and model the size and shape of cities. Increased processing capabilities, combined with the wide range of data sources available due to the integration of remote sensing technology, has allowed users to analyze complex spatial landscape features (Mesev *et al.* 1996). Fotheringham and Rogerson (1993) outlined some of the major problems in the analysis of spatial data and indicated ways in which GIS could assist in understanding and perhaps even circumventing these problems. As more sophisticated spatial analysis techniques become integrated with GIS, we are likely to see many of their theories put into practice. Sui (1998) reviews the practices, problems and prospects of GIS-based urban modeling.

As computers increased the complexity of spatial modeling and analysis, methods for visualization became necessary to evaluate the model output. Visualization not only enables users to absorb data in a more manageable form but is also a valuable aid in the identification of spatial patterns. It can be difficult for people to effectively understand the meaning behind model predictions and estimations without visual representation (Batty 1992). Numerous applications have been developed to provide visual displays of GIS data. Batty (1992) developed an application to demonstrate how graphics could help a user visualize urban processes, with the goal of influencing the way developers build models for urban analysis and forecasting and the ways they communicate results. It was based on an enhanced gravity type residential location model that linked demographic and economic activity sectors. Others used GIS to develop models with graphic displays that allow for the inclusion of spatial change processes, such as, cellular growth and diffusion (Batty & Xie 1994; Clarke *et al.* 1997; Landis *et al.* 1998). Development in a GIS/visual environment was also undertaken by: Birkin (1996) modeling retail locations; Densham (1996) demonstrating visual interactive locational analysis; and Macmillan (1996) investigating game-type simulation models.

The incorporation of GIS, spatial analysis and visualization techniques have greatly influenced the ways models are now being used in urban planning. As these methods are taught in schools and used in workplaces, there will be an increase in the number of applications in the field of urban growth models.

Ecological processes

In the 1930s, biological theorists thought of cities as multispecies ecosystems (Wegener *et al.* 1986). Early urban system modelers saw a similarity between such ecosystems and retail locations and incorporated equations previously used to model multispecies ecosystems (Wilson 1998). These early attempts were not very successful but more recent modelers have begun to incorporate other ecological concepts in their models. Bertuglia *et al.* (1987) cited several transportation/land-use studies derived from ecological modeling, specifically with respect to species competition.

Numerous modelers have incorporated ecological parameters into growth rules for cellular automata (Landis 1995; Clarke *et al.* 1997; Cogan *et al.* 1997; Landis *et al.* 1998; Lee *et al.* 1998). For example, Landis and Zhang (1998) modeled the role of policy/planning alternatives as they affect population growth and urban development relating to environmental impacts. In the first and second generations of the California Urban Futures Model, random-utility theory was used to predict generalized location and travel choices for households. The rules applied to growth were based on policy decisions regarding ecologically sensitive lands. A cellular automaton was used to represent spatial change processes and a GIS provided vast amounts of land data and a visual interface (Landis 1995; Landis & Zhang 1998). Landis *et al.* (1998) further extended this idea in the California Urban and Biodiversity Analysis (CURBA) Model. This model included more extensive procedures for simulating the effects of alternative development and conservation policies on the amount and pattern of urban growth and by including more extensive data layers regarding habitat types, biodiversity and other natural factors.

The incorporation of ecological theories with urban modeling has provided urban planners, managers, urban ecologists and others the opportunity to try out alternative public policies and evaluate the changes in both urban and ecosystem form and function. The inclusion of GIS and its visualization capabilities facilitates understanding by the general public and can help generate public support for projects.

Fractal urban form

Fractals can be used to describe the complexity of natural patterns and the changes in these patterns with changes in scale (Gardner 1998). Most contemporary urban models are based on relationships linking location, density, and urban evolution, but the application of rules of fractal geometry and laws of particle physics have yielded some new models in which the growth processes are tied to the geometry of the system. Early versions of these models were based on the physics of certain particle clusters that manifested spatial self-similarity across a wide range of scales and whose structure was subject to scaling laws consistent with ideas in fractal geometry. These models were collectively known as diffusion-limited aggregation (DLA) models (Batty *et al.* 1989). The structures generated were familiar tree-like forms or dendrites, grown from a seed, manifesting self-similarity of form across several scales. Diffusion-limited aggregation growth starts with a bounded circular region with a single seed fixed at its center. New particles are launched, one at a time, from a circular boundary that is at least three times the radius of the existing cluster. After the launch, the particle begins a random walk around the lattice. Either the particle moves outside the boundary and is destroyed or it eventually approaches the neighborhood of an already fixed particle, sticks, and the cluster is extended (Batty *et al.* 1989).

Batty *et al.* (1989) developed a DLA simulation model along with a variety of measures of structure and dynamics. Two measures of the change in density were used to estimate the dimensions of the structure (Equation 9 and Equation 10); these measures are specified in terms of the radius around the seed point at the center of the lattice:

$$\Delta\rho(R) = \rho(R) - \rho(R-1) = \frac{N(R)}{S(R)} - \frac{N(R-1)}{S(R-1)} \quad (9)$$

where $\rho(R)$ is the density of particles associated with all distances up to R; N(R) is the cumulative number of particles at all distances up to radius R; S(R) is the total number of lattice points around each point up to radius R; and

$$Q(R) = \frac{\Delta N(R)}{\Delta S(R)} = \frac{n(R)}{s(R)} \quad (10)$$

where N(R) and S(R) are defined as in Equation 9, n(R) is the total number of particles at distance R; and s(R) is the number of lattice points at distance R. The growth dynamics are represented by the order in which the particles stick to the cluster along with their location on the lattice. The equation used to analyze the dynamics over time and space was given as follows:

$$n(R,T) = \sum_{t=1}^{T} n(R,t) = \sum_{r=1}^{R} n(r,T) = \sum_{t=1}^{T}\sum_{r=1}^{R} n(r,t) \quad (11)$$

where t is a single time period; T is the total of all time; r is a single band radius; R is the sum of all radii; and n is the number of particles at a given distance. Batty *et al.* (1989) applied these measures to a small town in England to evaluate the approach and the new techniques. Their study suggested that there was potential in extending the analogy between DLA and urban form and that research should continue.

White and Engelen (1993), however, found that this DLA process did not correspond to any actual urban growth processes, so they developed a model that generated fractal patterns of land-use through the use of rules of spatial behavior. They combined a cellular automaton approach that incorporated the ideas of evolution, self-organization and fractal geometry. Transition potentials were calculated for all allowed transitions for each iteration, representing the behavior of the agents of land-use change, forming the basis of the transition rules in the model. The transition potential for each cell was calculated as a weighted sum as follows:

$$P_{ij} = S\left(1 + \sum_{h,d,k} m_{kd} I_{hd}\right) \tag{12}$$

where P_{ij} is the transition potential from state i to state j; m_{kd} is the weighting parameter applied to cells in state k in distance zone d; h is the index of cells within a given distance zone. I_{hd} equals 1 if the state of cell h = k; $I_{hd} = 0$ otherwise, and S is a stochastic disturbance term given by:

$$S = 1 + ((-\ln R)^{\alpha}) \tag{13}$$

where R is a uniform random variate between 0 and 1 and α is a parameter that allows control of the size of the stochastic perturbation. They demonstrated that the cellular approach made it possible to achieve a high level of spatial detail and realism and that the results could be linked directly to general theories of structural evolution.

Makse *et al.* (1998) developed a model based on a modification of percolation theory and cluster analysis. Percolation theory describes the way a set of sites connects to form a cluster within a system and the properties of the cluster resulting from the way it grows. In general percolation theory, a random number is defined for every site $r = (i, j)$ in a square lattice of $L \times L$ sites. This is called the occupancy variable $\mu(r)$. The $\mu(r)$ values are uncorrelated to a uniform probability distribution between 0 and 1. A site is occupied if $\mu(r)$ is smaller than the occupancy probability p, a fixed quantity at every site. The authors introduced correlation using a modification of the Fourier filtering method to get $\eta(r)$, the correlated occupancy variables.

The mathematical model developed by Makse *et al.* (1998) related the physical form of a city and the system within which it existed, to the locational decisions of its population, applying statistical physics to urban growth phenomenon. They considered 'development units' to represent buildings, people and resources and these were added to the cluster in a similar fashion to percolation. They relaxed the assumption that the concentration is constant for all points and assigned occupancy probabilities to development units to represent the urban population density at a particular site. This example illustrated how theories from the physical and chemical sciences could help explain different sets of natural phenomena. By modifying percolation theory to include the fact that the elements forming clusters are not statistically independent but autocorrelated, Makse *et al.* (1998) demonstrated that the results were morphologies that qualitatively and quantitatively resembled individual cities and systems of cities.

Ecological energetics

Ecological energetics states that the existence and maintenance of an urban region depends on the flow of goods and services into, out of, and within the city (Huang 1998). Because most cities rely on energy and materials that are imported in the form of food or other renewable resources, it has been hypothesized that evolutionary changes in urban form strongly depend on these exogenous energy inputs as well as internally self-organized behavior. The energetics approach viewed urbanization as a change in the source and amount of energy flow from the rural to the urban core, providing a conceptual link between urbanization and natural environments.

Huang (1998) developed a model that incorporated the theory of ecological energetics and hierarchy into a systems-based approach to urban modeling. In order to thread together the human economy and a natural system, energy was used as a common denominator because it is a basic functional characteristic of the ecosystem. The spatial organization of cities in the landscape is often represented as a hierarchy because living systems tend to organize into characteristic hierarchical layers from small scale to large scale processes. Huang's dynamic simulation model used the energy circuit language and ideas from systems ecology theory. The underlying theme throughout was the effect of energetic flows on urban zonation and how different zones organized hierarchically.

Huang (1998) focused on the spatial structure of urban zonation (urban systems components categorized into objects, activities or processes and forces) and examined the dynamics of the evolution of zonal patterns, attempting to understand the evolution of hierarchical zonation of the urban system through consideration of energetic flows. The urban economic system was described as a nonequilibrium system governed by certain nonlinear processes. Approaching regional development from an ecological energetics perspective was notable because it considered the behavior of natural systems (rather than analogy to gravitational laws or molecular behavior). It has not yet been determined, however, if ecological energetics theory can be incorporated into social theories.

Fuzzy-logic theory

Fuzzy-logic is a way of dealing with uncertainty in decision making. Wu (1998a) applied a heuristic decision-making process to the calculation of transitional probabilities for a cellular automaton by incorporating fuzzy-logic theory. He pointed out that in the case of land encroachment, a transitional decision is unlikely to be made upon explicit numerical value but rather on vague evaluative criteria. Change is an agglomeration of individual decisions and dependent upon various subjective factors and tradeoffs and the applicability of an instruction varies from cell to cell and from time to time.

A fuzzy-logic set consists of elements and their respective grades of membership in the set. Let U be a set of elements from which a single generic element is denoted by μ, the elements representing the development situation of a cell. In Wu's model, the transition rules themselves were fuzzy sets and the elements were transitional possibilities. Through the application of a function that consists of a set of instructions that determine the state transition under various circumstances, a discrete state change value was produced for each cell within the grid. An instruction I in U is a set of ordered pairs denoted by:

$$I = \{\mu, f[\mu]\} = \{\mu(S_{ij}^t, \Omega_{ij}^t), f[\mu(S_{ij}^t, \Omega_{ij}^t)]\}, \forall \mu \in U \tag{14}$$

where t is time; U is a set of elements; μ is a generic element; Ω is the development situation in the neighborhood; S is a finite set of states; $f\,[\mu]$ is the grade of membership of μ in I; and i, j are row and column, respectively. Wu (1998a) simulated several alternative land policies and demonstrated that certain risks inherent in some land policies could not be easily identified without dynamic simulation. His model was designed for use within a GIS to help managers visualize the results of the land encroachment simulation.

Neural network theory

Out of concern that a dynamic systems approach was not a natural framework for dealing with structural evolution and could not adequately explain it through a set of equations, by the 1990s modelers had begun to incorporate neural network theories into their models. Rather than adapt empiric urban theories to particular mathematical methods as most models did, this approach attempted to adapt mathematical methods to urban processes (Rodrique 1997).

Dougherty (1995) describes the common features that all neural networks share: they are composed of a number of very simple processing elements known as neurons. These elements take data in from a number of sources and compute an output dependent in some way on the values of the inputs, using an internal 'transfer function'. Neurons are joined together by weighted connections and data flows along these connections, being scaled during transmission according to the value of the weights. The neural network's functionality is very much bound up in the values of the connection weights, which can be updated over time, causing the neural network to adapt and possibly 'learn'. Learning is an iterative process where weights are adjusted until the calculated outputs correspond to the observed results resulting in a better performance, or a lesson learned, the next time.

Since real cities are almost never designed and built and then maintained as comprehensively planned units, they must 'learn' to deal with these problems by altering their structure in an appropriate way. The learning model approach provides a way of modeling the process by which a city acquires structures sufficient to solve the problems it is presented. The neural network learning model approach constituted a new technique, complementary to dynamic systems analysis, for gaining insight into the problems of structure evolution (White 1989).

White (1989) developed a neural network model and applied it to urban structures. Dougherty (1995) reviewed a variety of neural network models that have been applied to the field of transportation studies. Rodrique (1997) provided a conceptual overview of parallel computer process modeling and neural networks.

Conclusion

The early days of urban modeling were rooted in regional planning, concerned with models of transportation and location. When it was clear that transportation concerns could not be tackled without land-use considerations, integrated models began to appear. These models were based on a variety of economic and behavioral theories. By the mid-1970s, the field of urban modeling was falling into disrepute due to the poor performance and expensive failures of the large-scale, comprehensive models being attempted. Thus, regional planners began developing smaller scale models that each focused on one or a few specific questions.

As computer-processing speed increased, computer memory became cheaper, and hardware and software became available to more people, many new developments in urban modeling emerged. Dynamic system models helped to transform the field. Advances in spatial analysis and GIS to analyze and display data have been essential to urban modelers and planners. Incorporating ecological processes has expanded the use of urban models to biologists and ecologists. Theories, such as, neural networks, fuzzy-logic, fractal geometry and ecological energetics may continue to have an impact on urban models.

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