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A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications

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Abstract

Ecological systems are generally considered among the most complex because they are characterized by a large number of diverse components, nonlinear interactions, scale multiplicity, and spatial heterogeneity. Hierarchy theory, as well as empirical evidence, suggests that complexity often takes the form of modularity in structure and functionality. Therefore, a hierarchical perspective can be essential to understanding complex ecological systems. But, how can such hierarchical approach help us with modeling spatially heterogeneous, nonlinear dynamic systems like landscapes, be they natural or human-dominated? In this paper, we present a spatially explicit hierarchical modeling approach to studying the patterns and processes of heterogeneous landscapes. We first discuss the theoretical basis for the modeling approach—the hierarchical patch dynamics (HPD) paradigm and the scaling ladder strategy, and then describe the general structure of a hierarchical urban landscape model (HPDM-PHX) which is developed using this modeling approach. In addition, we introduce a hierarchical patch dynamics modeling platform (HPD-MP), a software package that is designed to facilitate the development of spatial hierarchical models. We then illustrate the utility of HPD-MP through two examples: a hierarchical cellular automata model of land use change and a spatial multi-species population dynamics model. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Complex systems modeling; Hierarchical patch dynamics; Hierarchical modeling; Scaling; Urban landscape ecology

1. Introduction

Ecological systems are characterized by diversity, heterogeneity and complexity. Complexity often results from the nonlinear interactions among a large number of system components which frequently lead to emergent properties, unexpected dynamics, and characteristics of self-organization (Jørgensen, 1995; Prigogine, 1997; Levin, 1999). The study of complexity has a history of at least several decades, ranging from physical, biological, and to social sciences, and a recent resurgence of interest in complexity issues is evident as new theories and methods have mushroomed in the past few decades (see Wu and Marceau, this issue and references cited therein). One of the most intriguing and widely-cited theories in the science of complexity is self-organized criticality (SOC; Bak et al., 1988; Bak, 1996). According to the theory of SOC, large interactive systems naturally evolve toward a self-organized critical state in which a minor event can lead to a

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cascading catastrophe. When a system is at the self-organized critical state, the frequency and magnitude of events follow a power law distribution, and this may be viewed as a statistically stable, internally controlled state with no characteristic scale within the system. At this point, events are correlated across all scales exhibiting a statistical fractal pattern in spatial structure. Bak and Chen (1991) claimed that SOC may explain the dynamics of a wide range of natural and human-related phenomena, including earthquakes, ecosystems, and social and economic processes. Furthermore, the title, as well as the content, of Bak's (1996) book even suggested that SOC was the mechanism of 'How Nature Works'.

However, while it is extremely intriguing, SOC does not seem adequate for explaining the great diversity of ecological phenomena (Levin, 1999). Of course, it is not surprising that simple statistical analyses may reveal that some ecological variables in certain ecosystems exhibit power–law relationships (e.g. Jørgensen et al., 1998; Solé et al., 1999). However, the existence of a power–law relationship alone is not adequate to prove that a system is at the self-organized critical state because diverse mechanisms may result in such a relationship in both physical and ecological systems (Raup, 1997; Jensen, 1998; Kirchner and Weil, 1998; Levin, 1999). SOC de-emphasizes or completely ignores the existence of multiple-scale constraints and their significance in influencing system dynamics. Bak (1996) asserted that all complex self-organizing systems move themselves to the self-organized critical state just like a sandpile. To the frantically enthusiastic SOC advocates, top-down constraints in controlling system dynamics do not seem to be important. In this regard, SOC appears to represent an extreme reductionist view. Interestingly, Bak and Chen (1991) claimed that SOC was 'the only model or mathematical description that has led to a holistic theory for dynamic systems'. It is evident from the above discussion, however, that the implications of the theory of self-organized criticality for ecological systems are in sharp contrast with hierarchy theory or any holistic systems theory.

In general, ecological systems are not, and do not behave like, sandpiles. Levin (1999) argued that heterogeneity, nonlinearity, hierarchical organization, and flows are four key elements of complex adaptive systems, like ecosystems, that allow for self-organization to occur. That is, CAS typically become organized hierarchically into structural arrangements through non-linear between-component interactions, and these structural arrangements determine, and are reinforced by, the flows of energy, materials and information among the heterogeneous components. Levin (1999) further suggested that SOC and modular structure represent the two ends of a continuum along which most ecosystems are found in the middle. While we agree with Levin's postulation in general, we dare to speculate that the majority of ecosystems, especially once well-developed, are hierarchically structured, so that component diversity, spatial heterogeneity, process efficiency, and system stability are simultaneously accommodated. Simon (1962) convincingly argued that 'complexity frequently takes the form of hierarchy, and that hierarchic systems have some common properties that are independent of their specific content.' In other words, hierarchy is a central structural scheme of the architecture of complexity, and often manifests itself in the form of modularity in nature.

Why are complex systems usually hierarchically organized? For biological and ecological systems, a hierarchical architecture tends to evolve faster, allow for more stability, and thus is favored by natural selection (Simon, 1962; Whyte et al., 1969; Pattee, 1973; Salthe, 1985; O'Neill et al., 1986). Although not all hierarchical systems are stable, the construction of a complex system using a hierarchical approach is likely to be more successful than otherwise as suggested by the watchmaker parable (Simon, 1962; Müller, 1992; Wu, 1999). In evolutionary biology it is well documented that complexity is built upon existing complexity. This is also frequently the case in the business world, the political arena, and the engineering disciplines. For example, to build complex, yet stable and efficient software, computer software engineers have developed the object-oriented paradigm, which is based on the decomposition principle of hierarchy theory (Booch, 1994). In general, successful human problem-solving procedures are hierarchical, too. It has been argued that a non-hierarchical complex system cannot be fully described, and even if it could, it would be incomprehensible (Simon, 1962; Newell and Simon, 1972). In ecology, the hierarchies we construct inevitably result from the interactions between the inherent characteristics of the system under study and the observer who studies the system. While there is no absolute objectivity, how closely a constructed hierarchy corresponds to the structure of the real system significantly affects the usefulness and power of using a hierarchical approach.

In a sense, a hierarchical approach is a way of breaking down complexity and a process of discovering or rendering order. To do so, a number of hierarchical modeling methods have been developed in different disciplines (see Wu 1999 for a review). However, the problem of spatial heterogeneity and the need for spatial explicitness present grand challenges to the application of hierarchy theory in modeling ecological systems. Based on the hierarchical patch dynamics (HPD) paradigm (Wu and Loucks, 1995; Wu, 1999), we present a spatially explicit hierarchical modeling approach to studying complex ecological systems and a modeling software platform that was designed to facilitate the development of HPD models. Not to be confused with specific modeling methods such as cellular automata, genetic algorithms, and Markov chains, the spatial HPD modeling approach is a multiple-scale methodology for studying complex systems that can bring different modeling techniques together in a coherent manner.

2. Theoretical basis for the spatially explicit hierarchical modeling approach

The theoretical basis for the spatially explicit hierarchical modeling approach is the hierarchical patch dynamics paradigm (HPDP), which emerges out of the integration between hierarchy theory and patch dynamics (Wu and Loucks, 1995; Wu, 1999). The following is a brief discussion of the major elements of HPDP and their ecological implications.

2.1. Hierarchy theory

Hierarchy theory emerged from a diversity of studies in various disciplines, including management science, economics, psychology, biology, ecology, and systems science (Simon, 1962, 1973; Koestler, 1967; Whyte et al., 1969; Pattee, 1973; Overton, 1975; McIntire and Colby, 1978). It has been significantly refined and expanded in the context of evolutionary biology and ecology by a series of books published in the past two decades (Allen and Starr, 1982; Salthe, 1985; O'Neill et al., 1986; Ahl and Allen, 1996). Thus, major developments in hierarchy theory are relatively recent, although the concepts of 'levels' of organization and 'hierarchy' date back to ancient times (Wilson, 1969). Much of the theory is only pertinent to nested hierarchies in which lower-level components are completely contained by the next higher level, although some general attributes are found in both nested and non-nested hierarchical systems (Valentine and May, 1996; Wu, 1999).

According to hierarchy theory, complex systems have both a vertical structure that is composed of levels and a horizontal structure that consists of holons (Fig. 1). Hierarchical levels are separated, fundamentally, by different characteristic rates of processes (e.g. behavioral frequencies, relaxation time, cycle time, or response time). Higher levels are characterized by slower and larger entities (or low-frequency events) whereas lower levels by faster and smaller entities (or high-frequency events). Generally speaking, the relationship between two adjacent levels is asymmetric: the upper level exerts constraints (e.g. as boundary conditions) to the lower level, whereas the lower provides initiating conditions to the upper. On the other hand, the relationship between subsystems (holons) at each level is relatively symmetric in that they interact in both directions. The interactions among components within the same holon are more strongly and more frequently than those between holons.

These characteristics of hierarchical structure can be explained by virtue of 'loose vertical coupling', permitting the distinction between levels, and 'loose horizontal coupling', allowing the separation between subsystems (holons) at each level

(Simon, 1973). The existence of vertical and horizontal loose couplings is the fundamental reason for the decomposability of complex systems (i.e. the feasibility of a system to be disassembled into levels and holons without a significant loss of information). System decomposition (i.e. the process of separating and ordering system components according to their temporal and spatial scales) represent one of the most essential tenets of hierarchy theory. While the word 'loose' suggests 'decomposable', 'coupling' implies interactions among components. Complete decomposability only occurs when between-component interactions do not exist, and thus complex systems are usually nearly decomposable (Simon, 1962, 1973). According to the principle of decomposition, for a given study that is focused on a particular level, constraints from higher levels are expressed as constants, boundary conditions, or driving functions whereas the rapid dynamics at lower levels are filtered (smoothed out) and only manifest as averages or equilibrium values. One of the most important implications of vertical decomposition is that the short-term dynamics of subsystems can be effectively and justifiably studied in isolation by ignoring the between-subsystem interactions that operate on significantly longer time scales. On the other hand, the long-term dynamics of the entire system is predominantly determined by slow processes. However, it must be noted that occasional exceptions to this general rule do exist as certain nonlinear effects penetrate through several levels above or below (so-called perturbing transitivities by Salthe, 1991; also see O'Neill et al., 1991a).

Unfortunately, misinterpretations of the term 'hierarchy' and hierarchy theory may have been a major reason for a lot of confusions about, and

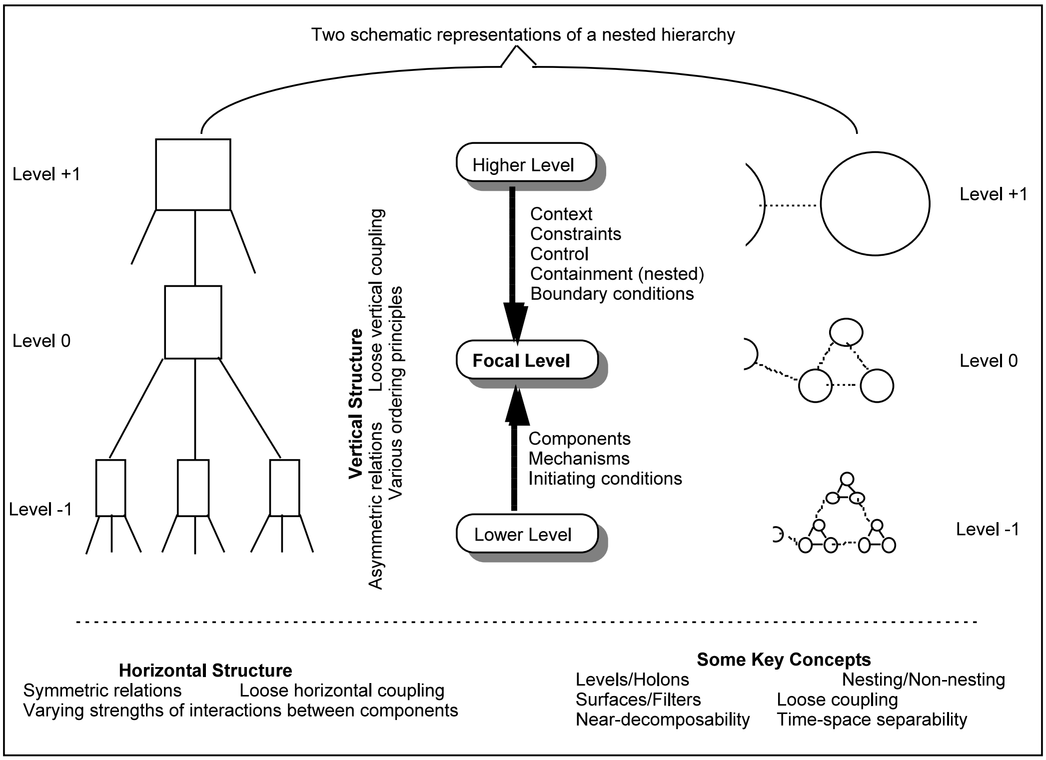

Fig. 1. Illustration of the major concepts in hierarchy theory (modified from Wu, 1999 and references cited therein). Much of the theory is only pertinent to nested hierarchies although some general attributes are found in both nested and non-nested hierarchical systems (Valentine and May, 1996; Wu, 1999).

resistance against, hierarchy theory within and outside the scientific community. Thus, it seems necessary to point out that hierarchy, as used in the scientific context, does not always refer to a system that is rigidly controlled by overwhelming top-down constraints and in which bottom-up effects generated by local interactions are insignificant. Certainly, hierarchy theory does not suggest this, either. As discussed earlier, hierarchy theory emphasizes both top-down and bottom-up perspectives. While dominance hierarchies do exist in natural, social, and engineered systems (Whyte et al., 1969), the local dynamics of, and interactions among, components are fundamental to the very existence of any functioning hierarchies. Indeed, the relative importance or relationship between top-down constraints and bottom-up forces in determining system dynamics is a key to understanding most if not all complex systems. Neither does hierarchy theory imply inflexibility or a lack of diversity and creativity. On the contrary, an appropriate hierarchical, dynamic structure not only provides opportunities for diversity, flexibility, and creativity, but also for higher efficiency and stability that are difficult to obtain in non-hierarchical complex systems.

2.2. Hierarchical structure of landscapes

Landscapes are spatially nested hierarchies and can be effectively studied as such (Woldenberg, 1979; Woodmansee, 1990; Reynolds and Wu, 1999; Blaschke, 2001; Hay et al., 2001). For example, Woodcock and Harward (1992) described a forested landscape as a spatial hierarchy: individual trees form distinctive forest stands that in turn constitute different forest types. Wu and Levin (1994) modeled a serpentine grassland as a dynamic spatial hierarchy of patches. Reynolds et al. (1996) demonstrated that the arctic tundra landscapes in Alaska could be effectively studied as spatially nested hierarchies. The lowest hierarchical level and the smallest landscape spatial unit correspond to the individual plant, whose functioning is determined by numerous interactions between the plant and its immediate abiotic and biotic environments. At a coarser spatial scale, plants, soil, and associated local microbial and faunal communities comprise relatively homogeneous ‘patch’ ecosystems, which in turn form ‘integrated flow systems’—distinctive hydrological units. Then, the landscape is a mixture of integrated flow systems that make up the scale of interest.

Reynolds and Wu (1999) argued that complex landscapes have structural and functional units at different scales on both theoretical and empirical bases (also see Wu and Levin, 1994, 1997; Wu and Loucks, 1995). Landscapes can be perceived as near-decomposable, nested spatial hierarchies, in which hierarchical levels correspond to structural and functional units at distinct spatial and temporal scales. The process of identifying structural and functional units involves finding the characteristic scales of ecological processes of interest and decomposing landscape systems accordingly. The objectives of doing so are twofold: (1) to break down the complexity of landscapes by providing a hierarchical structure to them; and (2) to identify multiple-scale patterns and processes as well as top-down constraints and bottom–up mechanisms. While simplification is an imperative step toward understanding, the explicit consideration of scale multiplicity, which is closely related to hierarchical properties of landscapes, is a key to successful simplifications of complex systems.

2.3. Hierarchical patch dynamic and the scaling ladder approach

Spatial patchiness is ubiquitous in ecological systems. The theory of patch dynamics, assuming that ecological systems are dynamic patch mosaics, studies the structure, function and dynamics of patchy systems with an emphasis on their emergent properties that arise from interactions at the patch level (Levin and Paine, 1974; Pickett and White, 1985; Wu and Levin, 1994, 1997; Pickett et al., 1999). On the one hand, hierarchy theory provides useful guidelines for ‘decomposing’ complex systems and focuses on a ‘vertical’ perspective. On the other hand, patch dynamics deals explicitly with the spatial heterogeneity and its change, an apparent ‘horizontal’ or landscape perspective (Wu, 1999, 2000). The hierarchical patch dynamics (HPD) paradigm integrates hier-

Table 1
Main tenets of hierarchical patch dynamics paradigm (modified from Wu and Loucks, 1995 and Wu, 1999).

Ecological systems are spatially nested patch hierarchies, in which larger patches are made of smaller patches.
Dynamics of an ecological system can be studied as the composite dynamics of individual patches and their interactions at adjacent hierarchical levels.
Pattern and process are scale dependent, and they are interactive when operating in the same domain of scale in space and time.
Non-equilibrium and stochastic processes are not only common, but also essential for the structure and functioning of ecological systems.
Ecological stability frequently takes the form of meta-stability that is achieved through structural and functional redundancy and incorporation in space and time.

archy theory and patch dynamics, and emphasizes the dynamic relationship among pattern, process, and scale in a landscape context (Table 1). As a result of the integration of the two perspectives, HPD unites structural and functional components of a spatially extended system, like a landscape, into a coherent hierarchical framework.

The relationship between pattern and process is scale dependent. In view of hierarchical patch dynamics, pattern and process are only interactive when both of them operate on the same or similar spatiotemporal scales. When a spatial pattern is more or less static relative to the process under study, only the effect of pattern on process, not process on pattern, needs to be considered. When a spatial pattern changes much faster than the process under study, only the spatially filtered average property is relevant to the pattern and process relationship. In neither of these two cases does a reciprocal relationship exist between pattern and process. However, when a spatial pattern and an ecological process operate at similar rates in the same spatial domain, their relationship may (but not necessarily) become interactive—by definition, reciprocal. For example, few would imagine that centimeter-scale grass clumping patterns could directly affect the behavior of eagles, even though these fine-grained patterns certainly influence the movement of beetles. On one hand, landforms cover large geographic areas and change on geological time scales; thus, landforms substantially constrain, but are not significantly affected by, ecological processes such as community and ecosystem dynamics (Rowe, 1988; Swanson et al., 1988). On the other hand, landforms interact with regional climatic regimes (Rowe, 1988), and the leaf-level photosynthetic processes affect and are affected by the spatial pattern of micrometeorological conditions surrounding individual leaves (Baldocchi, 1993; Wu et al., 2000a). Regional climate patterns surely affect the latent heat fluxes over a landscape, but contribute little to the understanding of the photosynthetic process of individual leaves. Some biochemists may wish that their precise understanding of rubisco's carbon-fixing mechanisms could somehow be directly extrapolated to the global scale, so that the biospheric responses to elevated CO_2 could be equally well predicted in the same way. Unfortunately, this is absurdly unrealistic because of the scale separation of several orders of magnitude in space and time between the enzyme molecule and the planet. In other words, non-linearity, emergent properties, and spatiotemporal heterogeneity in the real world suggest that such a scaling strategy is theoretically flawed and practically formidable.

In an attempt to develop a methodology for studying the relationship among pattern, process and scale and for extrapolating information across heterogeneous landscapes, Wu (1999) proposed an HPD multiple-scale modeling and scaling strategy-the scaling ladder approach. The HPD scaling ladder approach is composed of three steps: (1) identifying appropriate patch hierarchies. Ecological processes always interact with spatial patterns, but not all spatial patterns matter to ecological processes. In complex ecological systems, reliable spatial scaling must be based on an adequate account for the spatial heterogeneity of the landscape (e.g. spatially explicit or statistical representations). Thus, it is immensely helpful to be able to identify the spatial patterns—the patch hierarchies—that are relevant to the ecological processes of interest. The identified patch hierarchies can serve as 'scaling ladders' that facilitate multi-scale modeling and spatial scaling. To identify patch hierarchies is to decompose complex spatial systems. In general, decomposing a complex system may invoke a top-down (partitioning) or bottom-up (aggregation) scheme or both (Fig. 2). A top-down approach identifies levels and holons by progressively partitioning the entire system downscale, whereas a bottom-up scheme involves successively aggregating or grouping similar entities upscale. A number of quantitative methods in spatial pattern analysis exist for identifying patch hierarchies. For example, variability usually changes abruptly when pattern and process shift their characteristic domains of scale across a heterogeneous landscape. These conspicuous changes reveal scale breaks that may be

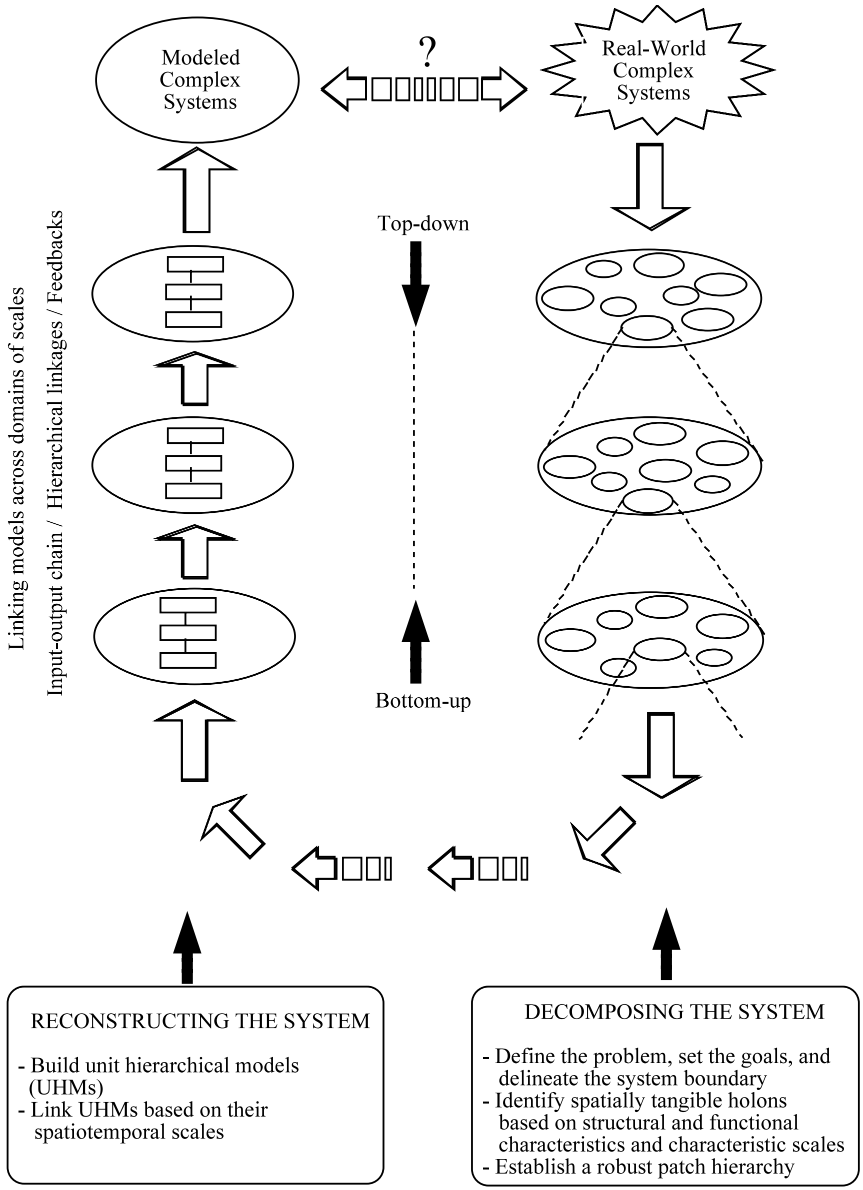

Fig. 2. Illustration of the process of decomposing a complex system to find an appropriate patch hierarchy and building hierarchical models.

indicative of hierarchical levels (e.g. O'Neill et al., 1991b; Cullinan et al., 1997; Wu et al., 2000b).

(2) Making observations and developing models at focal levels. Once an appropriate patch hierarchy is established, ecological processes can be studied at focal levels (corresponding to characteristic domains of scale), by properly choosing grain size (sampling interval or spatial resolution) and extent (study duration or area). There are always many factors affecting a given ecological process, but usually only a few are dominant for a given spatiotemporal domain of scale (Holling, 1992). Thus, a process-relevant patch hierarchy effectively groups these factors into relatively separate regions according to their characteristic scales in space and time. It is crucial to understand the role of scale in making observations. The phenomena of interest are only observable at the appropriate scale of observation. Simon (1973) explained well how temporal scale should be chosen by dividing system behaviors into high, medium, and low ranges of characteristic frequencies. The medium range corresponds to the focal level. If the total time span for a study is T, and if the temporal resolution of the observation (or time interval between measurements) is τ, the behavior of the system that is much faster than $1/\tau$ (high frequency events) appears to be noise, and its meaning (signal) to the focal level is revealed by its statistical averages. On the other hand, system dynamics that are much slower than $1/T$ (low frequency events) will not be observed and can be treated as constants at the focal level. This principle remains equally valid for the relationship between system dynamics and characteristic spatial scales where T and τ are the spatial extent and grain size of the observation, respectively. The above argument provides the essential theoretical basis for adopting the so-called triadic structure of hierarchy in research. That is, when one studies a phenomenon at a particular hierarchical level (level x), the mechanistic understanding comes from the next lower level (level $x-1$), whereas the significance of that phenomenon is revealed at the next higher level (level $x+1$).

(3) Extrapolating information across the domains of scale hierarchically. Scaling or extrapolating information across scales (or levels) over spatially heterogeneous landscapes has proven to be a formidable task because of complex pattern–process interactions. The most salient aspect of this complexity is the non-linearity in time and space that is the fundamental source of emergent properties. Thus, a major role of a patch hierarchy identified in step one is to serve as a scaling ladder that is composed of the domains of scale relevant to a particular study. Scaling can be accomplished by changing the grain size and extent of models along the patch hierarchy (Fig. 3). While a variety of specific scaling techniques can be applied here (e.g. Iwasa et al., 1987, 1989; Ehleringer and Field, 1993; van Gardingen et al., 1997; Jarvis, 1995; see Wu, 1999 for a review), a general approach is to link models along the scaling ladder that are built individually around distinctive focal levels. One of the most sensible ways of doing so is to use the output of lower-level models as the input to upper-level models. Sometimes, the input may take the form of response curves or surfaces that are generated using statistical methods based on the output from a lower-level model (e.g. Reynolds et al., 1993). Similarly, such hierarchical scaling can be implemented from top down—using the output of higher-level models to constrain or drive lower-level models. This top-down approach has become increasingly appealing and feasible as remote sensing data, with high temporal and spatial resolutions, are readily available over large geographic areas.

3. A hierarchical patch dynamics model of the Phoenix urban landscape (HPDM-PHX)

In this section, we demonstrate how to implement the hierarchical patch dynamics paradigm and the scaling ladder approach in modeling complex ecological systems through an example, the hierarchical patch dynamics model for the Phoenix urban landscape (HPDM-PHX). This example is a part of our on-going modeling efforts associated with the Central Arizona-Phoenix Long-Term Ecological Research (CAP-LTER) and related research projects. Although the system under study is an urban landscape, the spa-

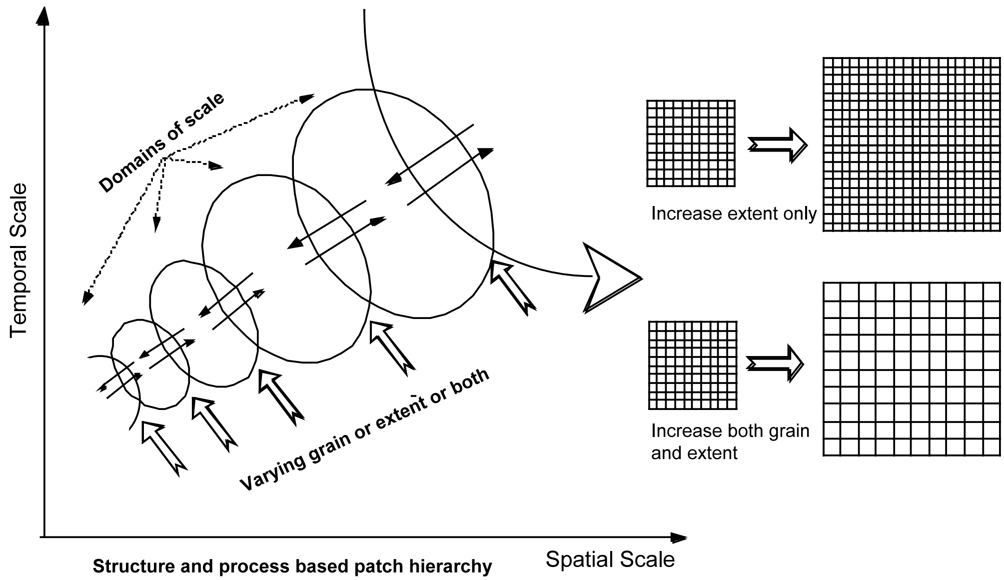

Fig. 3. Illustration of hierarchical scaling or extrapolating information along a hierarchical scaling ladder. Scaling up or down can be implemented by changing model grain size and extent successively across domains of scale.

tially explicit hierarchical modeling approach is general, and can be used for other complex ecological systems.

3.1. Background

Urbanization has drastically transformed natural landscapes everywhere throughout the world, inevitably exerting profound effects on the structure and function of ecosystems. In particular, the conversion of natural and agricultural areas to highly artificially modified urban land uses has been taking place at an astonishing rate. According to the United Nations, the world urban population was only a few percent of the global population in the 1800s, but increased to nearly 30% in 1950 and reached 50% in 2000. It has been projected that 60% of the world population will live in urban areas by 2025.

Land use and land cover changes associated with urbanization significantly affect the composition of plant communities by fragmenting the landscape, removing and introducing species, and altering water, carbon, and nutrient pathways. Although urban areas represent arguably the most important habitats for humans, they are among the least understood ecosystems of all, and urban ecology has not been considered part of the mainstream ecology worldwide (Collins et al., 2000). It is true that ecological studies in urban areas have a long history that dates back to the early 1900s or even earlier (Breuste et al., 1998). Also, much research has been done to understand spatial pattern and urban dynamics by geographers and social scientists with little or only superficial consideration of ecology in and around cities. However, a full understanding of how urban ecosystems work does not come from isolated, disciplinary studies, be they ecological, sociological, or geographic. The urban whole is larger than the sum of its biotic and abiotic parts. The ecology of urban systems as integrated wholes needs new and integrative perspectives (Pickett et al., 1997, Zipperer et al., 2000).

In the southwest US, the Phoenix metropolitan area in particular, urbanization has profoundly changed the desert landscape. In fact, Phoenix has become the sixth largest city with the highest population growth rate in the United States. To understand the interactions between urbanization and ecological conditions, we have been developing models based on the hierarchical patch dynamics paradigm to simulate the pattern and process of urban growth and its ecological consequences. This section describes the general structure of the hierarchical patch dynamics model for the Phoenix metropolitan landscape (HPDM-PHX). The main goal of the current version of HPDM-PHX is to develop an understanding of how urbanization affects ecosystem productivity and biogeochemical cycles at local and regional scales.

3.2. General model structure of the HPDM-PHX

A spatially nested patch hierarchy is used for HPDM-PHX, which consists of local ecosystems, local landscapes, and the regional landscape (Figs. 4 and 5). In the case of modeling ecosystem processes, this patch hierarchy is essentially a hierarchical implementation of the ecosystem functional type (EFT) concept (Reynolds et al., 1997; Reynolds and Wu, 1999). Local ecosystems correspond to land cover types that have a relatively homogeneous vegetation–soil complex within (e.g. cotton fields, urban centers, residential areas, parks, creosote bush-dominated desert communities). The land cover EFTs are readily detectable from air photos and remote sensing data (e.g. Landsat TM images), and largely correspond to the categories of the Anderson et al.'s (1976) level II classes. A local landscape is a patch mosaic of local ecosystems, in which spatial patterns emerge. Local landscapes are characterized by dominant land cover types, and several different types can thus be recognized (e.g. urban, rural, agricultural, and natural landscapes). Thus, the structure and function of a landscape EFT is a function of its (non-spatial) composition and (spatial) configuration. Finally, the regional EFT is a mixture of local landscapes, and characterized by climate, geomorphology, hydrology, soils, and vegetation at the regional scale. Because the EFT concept emphasizes ecosystem attributes and processes such as primary productivity, biogeochemistry, and hydrology, it gives concrete meanings to patches and thus reinforces the less tangible functional aspect of the hierarchical patch dynamics paradigm.

Scale	Major Characteristics
Regional Landscape	• Composed of different types of local landscapes • Heterogeneous in ecosystem structure and function • Characterized by the dominant biome and land use pattern at the regional scale (e.g., an urbanized desert region vs. an agricultural grassland region)
Local Landscape	• Composed of different land use and land cover types • Heterogeneous in ecosystem structure and function • Characterized by dominant land use types, such as urban landscapes, rural landscapes, agricultural landscapes, and natural desert landscapes
Local Ecosystem	• Relatively homogeneous vegetation-soil complexes • Readily detectable from air photos and remote sensing data (e.g., Landsat TM images) • Largely corresponding to Anderson et al.'s (1976) Level II classes

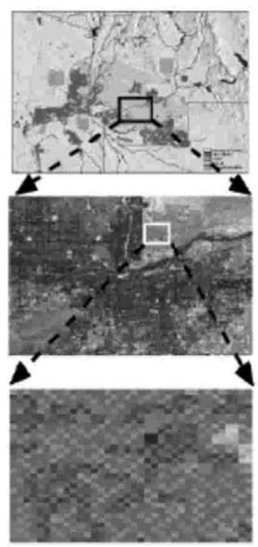

Fig. 4. Hierarchical ecosystem functional types (EFTs) for the Phoenix metropolitan area. The EFT hierarchy consists of local ecosystems, local landscapes, and the region. Each of these hierarchical levels is characterized by a set of distinct structural and functional features.

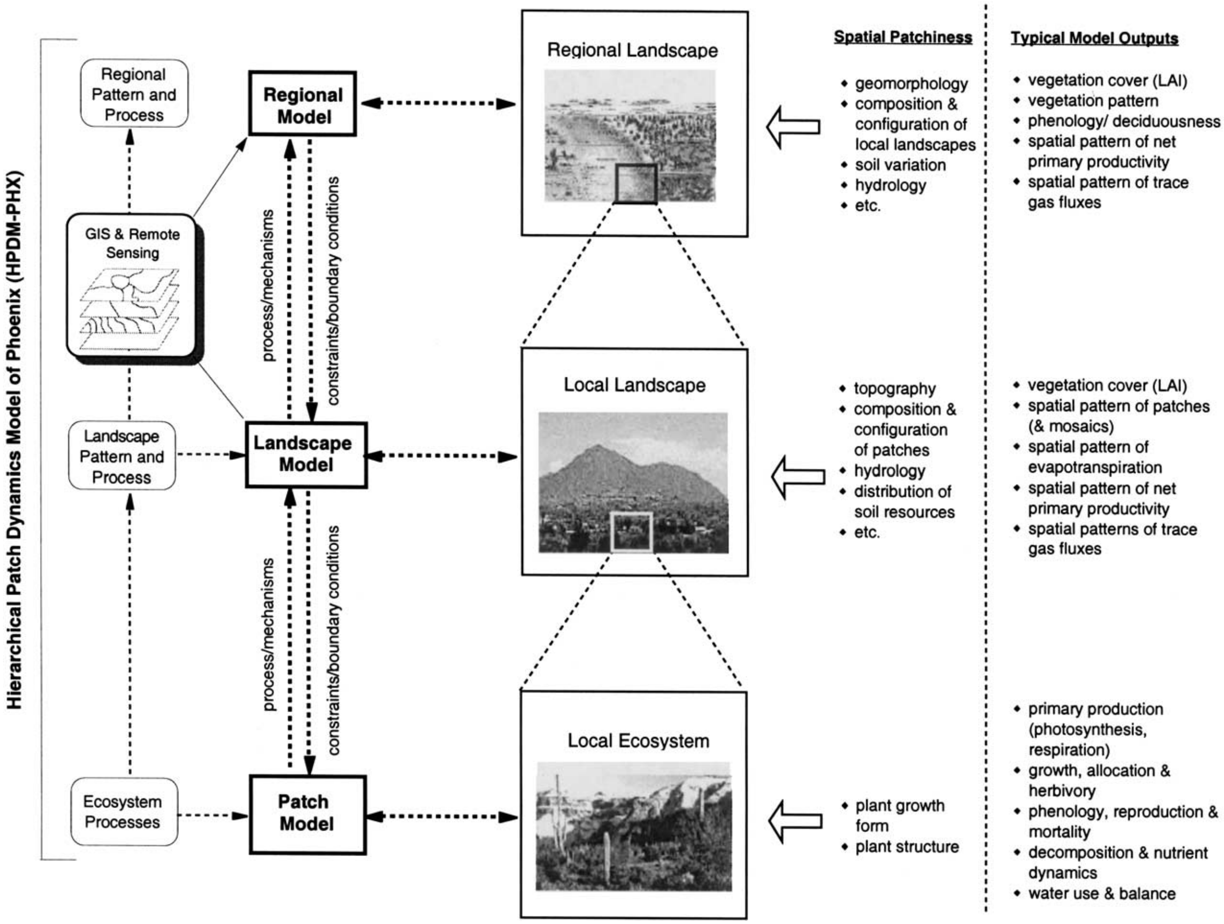

Fig. 5. Diagrammatic representation of the basic structure of the hierarchical patch dynamics model of the Phoenix urban landscape (HPD-PHX).

At the local ecosystem level, we use modified versions of two ecosystem process models: CENTURY, a general model of terrestrial biogeochemistry originally developed for the Great Plains grassland ecosystem by Parton et al. (1987, 1988) and PALS, a patch-level arid ecosystem simulator developed by Reynolds and his associates for the Jornada basin, New Mexico (Reynolds et al., 1993, 1997). CENTURY simulates the long-term dynamics of carbon, nitrogen, phosphorus, sulfur, and plant production and has been tested for a number of grassland ecosystems worldwide (Parton et al., 1993). PALS simulates carbon, water, nitrogen, and phosphorus cycles, and takes into account variations in patch type, plant characteristics, soil resources, and climatic factors. The abiotic components of PALS include micrometeorological conditions (e.g. temperature and moisture within and above the canopy) and soil properties (e.g. water flux, nutrients, and temperature). PALS is well-suited to explore questions related to nutrient cycling and has been parameterized for the Jornada LTER site, the California chaparral, and a grassland in Kansas (Reynolds et al., 1997; Reynolds and Wu, 1999). We use these two ecosystem models in parallel for the following reasons. CENTURY and PALS represent different levels of mechanistic details in simulating ecosystem processes, and thus comparing them can help us understand what details can be ignored in the process of scaling up from the local ecosystem to the region. Model comparisons also provide a means for increasing our confidence in estimating ecological variables especially when data are rarely available (Schimel et al. 1997). Moreover, ecosystem models that are tailored for different land cover types found in the Phoenix metropolitan area can be more effectively developed based on CENTURY and PALS.

While our land cover change (sub)model in HPDM-PHX shares some of the similarities of the Markov-cellular automata approach (e.g. Li and Reynolds, 1997), it is integrated directly with the ecosystem model. The regional model is the integration of various component landscapes with explicit consideration of their horizontal interactions (Fig. 5). The land cover change model is driven by local rules and top-down constraints which are in turn influenced by socioeconomic processes in the region. Changes in landscape pattern then result in changes in ecosystem processes at both local and regional scales. Although the effects of land use and land cover change on ecological processes are often more obvious and dominant than the feedback of changed ecological conditions to land use decisions, the latter does exist and will become more important as urbanization continues to progress. While still on-going, our model evaluation process involves several steps: (1) to assess the reasonableness of the model structure and the interpretability of functional relationships within HPDM-PHX; (2) to simulate ecosystem processes across a gradient of land cover types; (3) to evaluate the correspondence between model behavior and empirically observed patterns at local ecosystem, landscape, and regional scales; and (4) to conduct a series of sensitivity and uncertainty analysis to HPDM-PHX.

4. Developing a hierarchical patch dynamics modeling platform (HPD-MP)

Constructing and evaluating hierarchical patch dynamics models like HPDM-PHX can be technically complex in terms of programming, data handling, and model linkage and interface. To facilitate the development of such models, therefore, we have been building an HPD-based modeling platform (HPD-MP). In this section we describe the general structure of HPD-MP, and illustrate how it is being used in our effort to develop HPDM-PHX.

4.1. Description of HPD-MP

The hierarchical patch dynamics modeling platform is designed to facilitate spatially explicit hierarchical modeling by taking a 'fine-grained' approach to program interoperability. Practically speaking, this means that we begin by approaching modeling problems from a programmer's view point: first developing necessary objects (or modules) and application programming interfaces (APIs), and then using them to further develop tools and utilities that allow users to develop models with a minimal amount of programming. The fine-grained approach differs from 'coarse-grained' methods that adopt existing modeling and data management tools (e.g. simulation and GIS packages) via common interchange linkages and languages (e.g. COM, DCOM, CORBA, XML). While these two approaches represent different modeling perspectives, they are not mutually exclusive. By taking a fine-grained approach, HPD-MP provides a high degree of flexibility that allows for modeling a variety of complex systems and a high level of user-friendliness that eases its applications.

The hierarchical patch dynamics modeling platform consists of software libraries, algorithms, data converters, and a series of tools and utilities for model development and integration. All these components are organized into two levels within HPD-MP (Fig. 6). The API/Data Format level gives users the flexibility to develop new objects, tools and utilities in C^{++} and to build models from ground up. The Tools/Utilities level allows users to develop models using tools and utilities provided by HPD-MP, and to link them with other models and data management tools external to HPD-MP. An application programming interface (API) is simply a set of routines, protocols, and tools for building software applications. It serves as a software interface for other programs

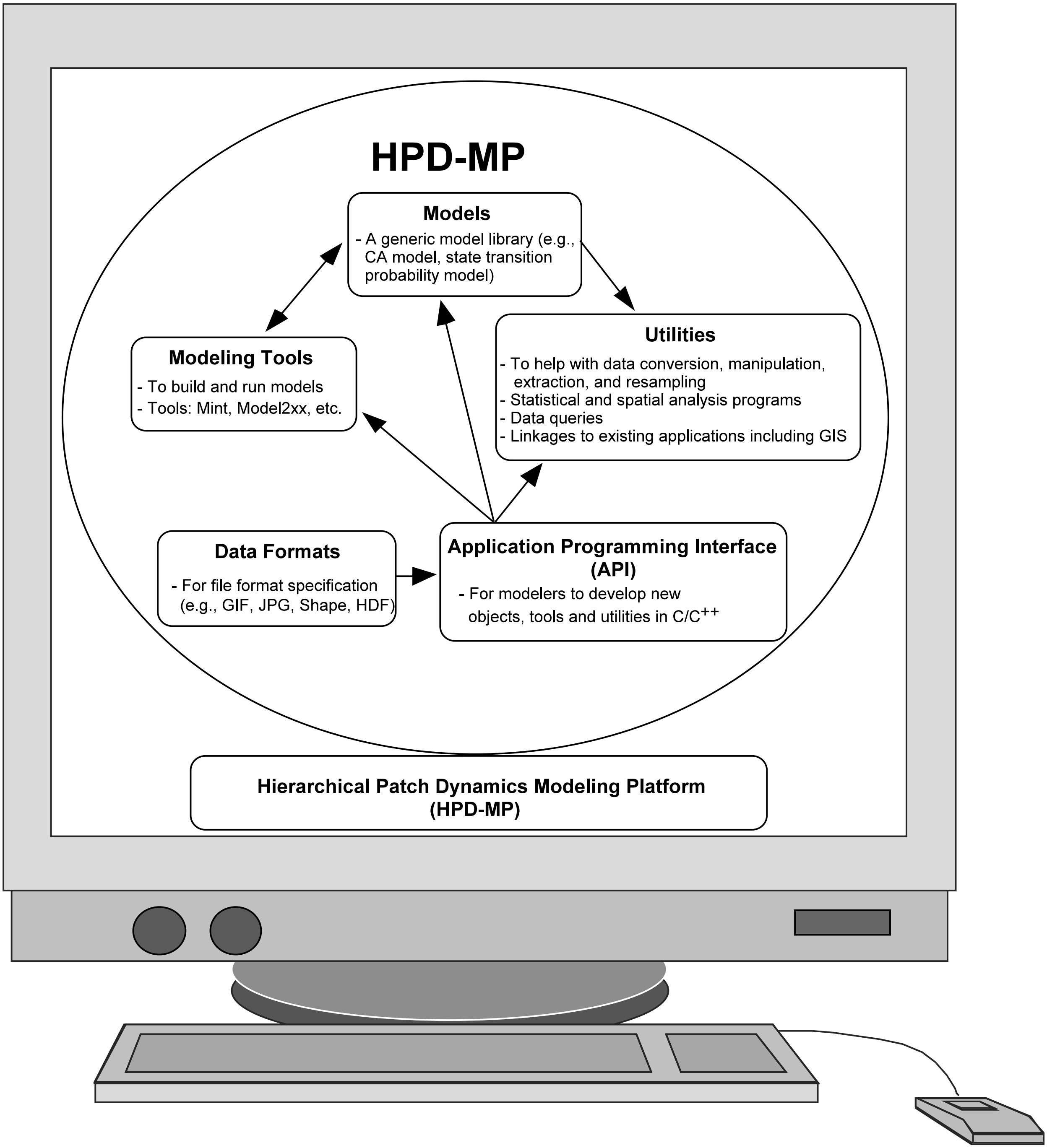

Fig. 6. Illustration of the structure of the hierarchical patch dynamics modeling platform (HPD-MP), showing the major components and their relationship.

such as image manipulation routines, and makes it easier to develop applications by providing necessary building blocks.

Spatially explicit models often have to deal with questions similar to those in computational geometry (CG). For example, is a given point inside, on, or outside a polygon? What is the surface area of a polygon or higher dimensional object? Do two geometric objects intersect? If so, what are the intersection and union of these objects? What are the nearest neighbors of a given object? To deal with these computational problems, HPD-MP incorporates a number of CG algorithms and methods (O'Rourke, 1998; de Berg et al., 2000).

When contemplating a modeling project we are often confronted with the choice between raster and vector data. While tradeoffs of choosing one over the other are well documented and understood, specific data formats (e.g. DEM, GIS coverages, digitized aerial photos) have no common application programming interfaces (APIs) that deal with both raster and vector data interchangeably, much less with some mechanisms through which spatial queries can be readily made. To overcome this problem, HPD-MP contains utilities to read and translate between a variety of data formats. The Hierarchical Data Format (HDF; Brown et al., 1993; Schmidt, 2000) is used as a base for information interchange because it can handle large (greater than 2 gigabytes) and multidimensional data sets, permits the use of both vector and rater data layers within the same file, and allows user-definable data types. In addition, we also use the ImageMagick Studio image processing libraries (http://magick.imagemagick.org) to provide a transparent interface to read and write over 60 different common image formats. This capability of HPD-MP greatly facilitates I/O and visualization processes. For example, the data and image processing facilities are not only convenient for developing utilities like converting ARC GRID and SHAPE files (yet to be implemented), but also allow for the automatic generation of output into common image formats like GIF and JPEG.

There are three basic ways to use HPD-MP: (1) to use the existing tools and utilities, as well as prebuilt models provided by the platform to run simulations by simply specifying model parameters and input data; (2) to use high-level modeling tools and utilities provided by the platform to develop models for user-defined problems; and (3) to develop new objects or modules using a programming language (e.g. C^{++}) and, at the same time, take advantage of the capabilities of the existing tools and utilities. Currently, HPD-MP includes several high-level utilities, including MINT—a model interpreter that reads in and runs an existing model (e.g. STELLA equations; HPS, 1996), MODEL2XX—a utility to translate various modeling languages (e.g. STELLA) into stand-alone programs in C^{++} (and JAVA in future), HPD_STATS—a collection of statistical routines and tools for spatial analysis, and DATA_CONV—a data converter that supports a number of data formats, including ImageMagick Studio, HDF, and ArcInfo/ArcView.

4.2. Examples of using HPD-MP

As a demonstration of HPD-MP, we present two examples here: (1) a land use change model for the Phoenix area; and (2) a spatial multi-species population dynamics model. These examples here are used only for the purpose of illustrating the use of HPD-MP. A thorough evaluation of the structure and behavior of these models is not intended, therefore.

4.2.1. A hierarchical stochastic cellular automata model of land use change

The land use change model is a hierarchical stochastic cellular automata model. Stochastic cellular automata (CA) typically model the state transition probability as a function of only local or neighborhood rules. These local-interactions are assumed to be the only driving forces to generate the global pattern of system dynamics. However, in real-world phenomena, local-interactions are frequently modified by patterns and factors at broader scales that act as top-down constraints or driving functions. These may either be spatially fixed (as in the case of property ownership boundaries and zoning ordinance restrictions) or variable (such as domains of influence or the land use change due to the proximity to roads). They are important in simulating observed land use change patterns. HPD-MP was used to facilitate such multiple-scale modeling whereby local processes may be modified by top-down constraints or driving functions and, at the same time, bottom-up propagation of information is allowed to hierarchically link interactions between scales.

Specifically, we modeled the land use change in the Phoenix area by explicitly considering local urban growth factors, domains of urbanization influence, and effects of ownership (Fig. 7). The transition probability between different land use types (urban, agriculture, and desert) was treated as a function of the three groups of factors at different spatial scales, i.e. $P_{\text{change}} = \mathbf{f}$ (local rules, domain of influence, ownership). The domains of influence were intended to reflect heterogeneous urbanization situations between the scale corresponding to the pixel size and the entire region. In reality, they may modify land use transition probabilities through legal and zoning restrictions. As a first approximation we assumed that these domains of influence operated independently of the local-scale processes. The data used to parameterize the model were historic land-use maps from CAP-LTER (Knowles-Yanez et al., 1999). In an earlier study, Jenerette and Wu (2001) had used

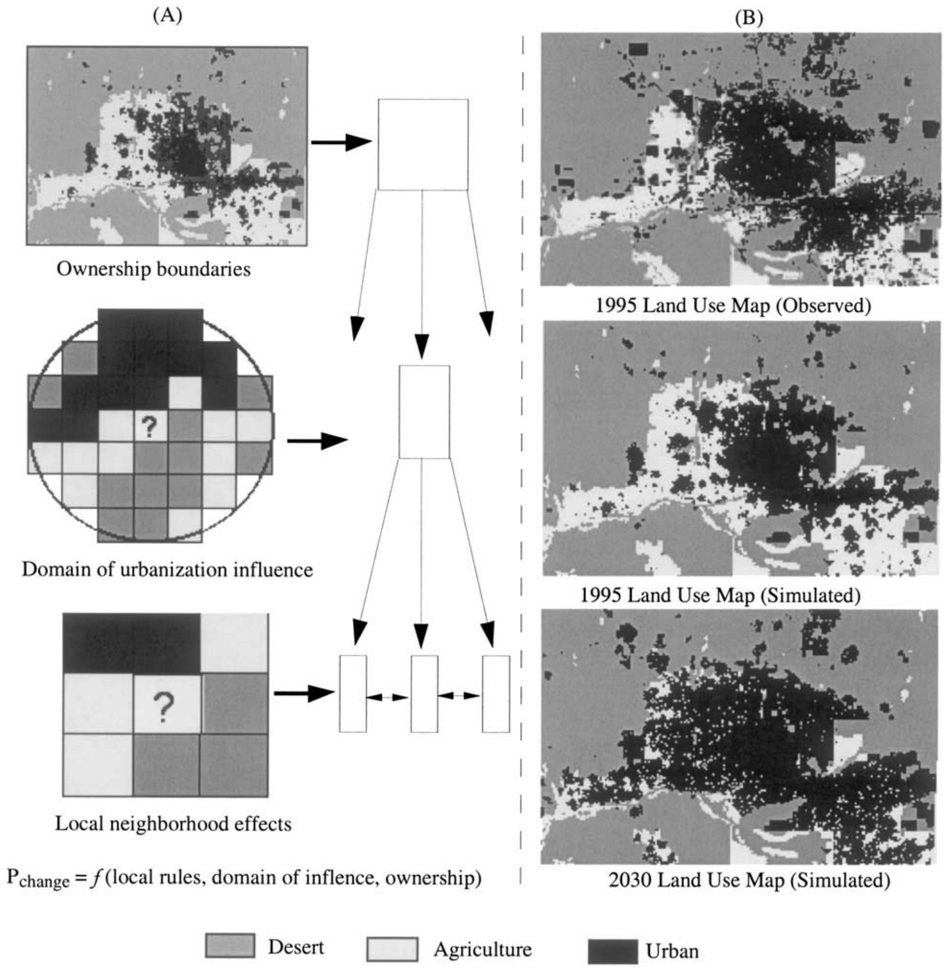

Fig. 7. Illustration of the hierarchical structure of the stochastic CA model of land use change in Phoenix (A), and a comparison between observed and simulated land use patterns (B).

this data set (for years 1975 and 1995) to develop a cellular automata urban growth model using a genetic algorithm (GA) optimization approach. In this study, we adopted the optimized parameter set from Jenerette and Wu (2001) for the initial values of land use change transition probabilities at the pixel size of 250 by 250 m (same as in Jenerette and Wu, 2001). Ownership information was obtained from a 1988 data set provided by the Arizona Land Resource Information System (ALRIS).

The model was initialized with the1975 land-use map and run for 55 years with a time step of 1 year to year 2030. This period of simulation was chosen to conform to the 50-year plan initiated by the local government in 1980. The simulated land use map for 1995 was compared with the empirical map for the same year, and the two maps matched each other well (Fig. 7). The observed urbanized area was approximately 1975 km^2 while the predicted value was 1973 km^2. This high accuracy in the simulated urbanized area, however, should be of no surprise given that the original parameterization of the model, as in all other Markov chain or transition probability models of landscape change, was based on the 1975 and 1995 land use maps (Jenerette and Wu, 2001). Nevertheless, the high accuracy in spatial pattern of urban growth, attributable to the incorporation of hierarchical constraints, was noteworthy. We continued the simulation up to 2030 when a total of 3659 km^2 or roughly 69% of the total privately owned land in the study area was urbanized (Fig. 7). This example not only demonstrates the utility of HPD-MP, but also the increased accuracy and interpretability of the CA approach due to the addition of a hierarchical structure.

4.2.2. A spatial multi-species population dynamics model

While the Phoenix land use change model involves only the simulation of landscape pattern, our second example focuses on the linkage between spatial pattern and process-based models. This is a pilot model we developed to test the tools and utilities of the HPD modeling platform. Through this example we intend to illustrate some of the basic procedures for implementing process-based models, such as the ecosystem process models encapsulated in the HPDM-PHX which is currently under construction.

In the arid environment of the southwestern United States, water resources are often over-allocated, and this has resulted in devastating modification to the natural flood regimes. These natural processes are necessary to provide suitable germination sites and conditions for native plants such as willow (*Salix gooddingii*) and cottonwood (*Populus fremontii*). The modification to the flood regimes in turn has profoundly impacted native vertebrates such as birds. The modification to the natural wetland habitats has allowed a number of invasive exotics, such as salt cedar (*Tamarix ramosissima*), to become established by out-competing the native plant species. We hypothesized that one possible method to restore the natural riparian communities is to mimic the natural flood regimes with managed dam releases.

As an example of how HPD-MP can be used to develop spatial process-based models and in order to test the above hypothesis on riparian habitat restoration, we developed a plant competition model for the drought-tolerant salt cedar and the inundation-tolerant willow and cottonwood, and a suitable habitat-based bird population dynamic model. Both of these models were developed using STELLA (as are several components of HPDM-PHX under development). The plant competition model was of the Lotka–Volterra type, but explicitly incorporated the spatial variations in topography and the water table. For the purposes of demonstration, the topography was generated using Rosenbrock's (1960) multimodal mathematical function: $f(x,y) = (1-x)^2 + 100(y-x^2)^2$, where $-1.5 < x < 1.5$, $-0.5 < y < 1.5$. This function is a well-established mathematical surface and can be used to portray a generalized riverbed. The maximum difference in elevation between high and low points for the generated topographic surface was 5 m. The water table was in turn varied according to three hypothetical scenarios of water management: (1) static water level—the water level remains at a fixed height of 0.5 m (as measured from the bottom of the river channel); (2) random water level—the water level is uniformly random between 0 and 1.0 m; and (3) pulsed water level—the water level remains low in between periodic dam releases. The results of the plant competition model then produced the habitat suitability map for the bird population model. To run the STELLA models spatially, we first exported the STELLA models as finite difference equations (FDEs), and then these FDEs together with spatially-gridded information on topography and hydrology were input into HPD-MP's model interpreter (MINT) and run within each cell on the landscape. Although this was a model based on contrived data, it was interesting to notice that the periodic flood scenario produced the greatest native plant recruitment, which was in agreement with observed riparian vegetation dynamics (Middleton, 1999).

5. Discussion and conclusions

A distinctive feature of the prevailing theme in the science of complexity is that local interactions among components are essential for the organization and global dynamics of complex systems. As Mitchell et al. (1994) pointed out, 'a central goal of the sciences of complex systems is to understand the laws and mechanisms by which complicated, coherent global behavior can emerge from the collective activities of relatively simple, locally interacting components.' This view has been reinforced by the wide-spread use of such approaches as cellular automata, genetic algorithms, and agent-based modeling, all of which rely heavily on a bottom-up, rather than a top-down, perspective. While admitting that local interactions and bottom-up forces are essential, we argue that top-down constraints and hierarchical linkages are also crucial for understanding and predicting the dynamics of many, if not most, complex systems. In general, ecological systems are not sandpiles, but hierarchical patch dynamic systems with evolving structures and changing components.

Therefore, to deal with the complexity of ecological systems we advocate the hierarchical patch dynamics paradigm (Wu and Loucks, 1995; Pickett et al., 1999; Reynolds and Wu, 1999; Wu, 1999). The HPD paradigm integrates hierarchy theory and patch dynamics, and represents a spatially explicit theory of pattern, process, scale and hierarchy. Because complexity always involves multiple scales, HPD provides a sensible and powerful approach to modeling complex ecological systems and spatial scaling over heterogeneous landscapes. Scaling in ecology is inevitable for at least two important reasons (Wu, 1999; Wu and Qi, 2000). First, most environmental and resource management issues can only be dealt with effectively at broad scales whereas much of the empirical information has been collected at local scales. Second and more profoundly, to understand how ecological systems work we must be able to relate broad-scale patterns to fine-scale processes and vice versa. In both cases, transferring information between scales is indispensable. The HPD scaling-ladder strategy (Wu, 1999) provides a hierarchical way of dealing with spatial heterogeneity and modularizing nonlinearity so as to facilitate the extrapolation and translation of information across scales.

Based on the hierarchical patch dynamics paradigm and the scaling ladder concept, in this paper we have articulated a spatially hierarchical modeling approach to studying complex systems. Then, we described how this approach has been used in developing the hierarchical patch dynamics model of the Phoenix urban landscape (HPDM-PHX) that simulates the land use change and related ecosystem processes. In addition, we presented the hierarchical patch dynamics modeling platform (HPD-MP)—a software package-from which multi-scale ecological models can be developed and integrated in an efficient and coherent manner. To illustrate the utility of HPD-MP, we discussed two examples: a hierarchical stochastic CA model of land use change and a spatial population dynamics model. This modeling platform is still being developed and will be continuously refined through the development of the hierarchical patch dynamics model of the Phoenix urban landscape and related modeling projects at the Landscape Ecology and Modeling Laboratory (LEML) at Arizona State University.

The spatially explicit hierarchical modeling approach we have presented here is but one approach to modeling and understanding complex ecological systems. At a time when complexity and diversity are recognized and emphasized, pluralism in ecology is not only appropriate but also necessary. However, neither extremely reductionist nor metaphysically holistic approaches seem to be productive when dealing with such phenomena as self-organization and emergent properties. To effectively deal with complexity, we need more than simply using both approaches in parallel; we need to integrate them and produce new, more effective approaches. We believe that most such approaches are hierarchical in one way or another (Wu, 1999). In this regard, it is always refreshing and enlightening to cite Morrison (1966): 'The world is both richly strange and deeply simple. That is the truth spelled out in the graininess of reality; that is the consequence of modularity. Neither gods nor men mold clay freely; rather they form bricks.'

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