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Modeling urban landscape dynamics: A case study in Phoenix, USA

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Abstract. Urbanization has profoundly transformed many landscapes throughout the world, and the ecological consequences of this transformation are yet to be fully understood. To understand the ecology of urban systems, it is necessary to quantify the spatial and temporal patterns of urbanization, which often requires dynamic modeling and spatial analysis. In this paper, we describe an urban growth model, the Phoenix Urban Growth Model (PHX-UGM), illustrate a series of model calibration and evaluation methods, and present scenario-based simulation analyses of the future development patterns of the Phoenix metropolitan region. PHX-UGM is a spatially explicit urban landscape model and is a modified version of the Human-Induced Land Transformations (HILT) model originally developed for the San Francisco Bay Area. Using land use and other data collected for the Phoenix area, existing growth rules were selectively modified and new rules were added to help examine key ecological and social factors. We used multiple methods and a multi-scale approach for model calibration and evaluation. The results of the different evaluation methods showed that the model performed reasonably well at a certain range of spatial resolutions (120–480 m). When fine-scale data are available and when landscape structural details are desirable, the 120-m grain size should be used. However, at finer levels the noise and uncertainty in input data and the exponentially increased computational requirements would considerably reduce the usefulness and accuracy of the model. At the other extreme, model projections with too coarse a spatial resolution would be of little use at the local and regional scales. A series of scenario analyses suggest that the Metropolitan Phoenix area will soon be densely populated demographically and highly fragmented ecologically unless dramatic actions are to be taken soon to significantly slow down the population growth. Also, there will be an urban morphological threshold over which drastic changes in certain aspects of landscape pattern occur. Specifically, the scenarios indicate that, as large patches of open lands (including protected lands, parks and available desert lands) begin to break up, patch diversity declines due partly to the loss of agricultural lands, and the overall landscape shape complexity also decreases because of the predominance of urban lands. It seems that reaching such a threshold can be delayed, but not avoided, if the population in the Phoenix metropolitan region continues to grow. PHX-UGM can be used as a tool for exploring the outcome of different urban planning strategies, and the methods illustrated in this paper can be used for evaluating other urban models.

Keywords: urbanization, urban growth models, model evaluation, land use change modeling, Phoenix

Introduction

Urbanization has become an environmental problem of global importance. Although the absolute amount of urbanized land is still a few percent of the earth's land surface, the impacts of urbanization on biodiversity, ecosystem fluxes, and environmental quality are profound and pervasive (Breuste *et al.*, 1998; Pickett *et al.*, 2001). Urban growth affects the ecology of cities in a number of ways, such as eliminating and fragmenting native habitats, modifying local climate conditions, and generating anthropogenic pollutants. It is widely recognized that the spatial pattern of a landscape affects ecological processes (Turner, 1989; Wu and Loucks, 1995). Understanding the reciprocal relationship between spatial pattern and ecological processes is at the heart of landscape ecology (Pickett and Cadenasso, 1995; Wu and Hobbs, 2002). Urban landscapes exhibit the most conspicuous spatial heterogeneity of all landscapes, and the spatial form a city takes affects physical, ecological and sociological processes within (Pickett *et al.*, 1997; Zipperer *et al.*, 2000; Wu and David, 2002). A landscape ecological perspective for urban ecosystems is not only appropriate, but imperative as well. The study of urban ecosystems needs to be considered in a landscape context, and the patterns and processes of urbanization should be integrated if the ecology of cities is to be fully understood (Foresman *et al.*, 1997; Wu and David, 2002).

An important first step to understanding the ecology of cities is to adequately quantify the urban landscape pattern and project its spatiotemporal dynamics. Urban growth models play an instrumental role in this process. Urban modeling started in the 1950s and has experienced ups and downs in the past several decades (Lee, 1973, 1994; Harris, 1994). Several approaches to modeling urban growth have been developed by urban planners, geographers, and ecologists, and have been periodically reviewed (e.g., Batty, 1979, 1994; Harris, 1985; Wegener, 1994; Berling-Wolff and Wu, 2004; Guhathakurta, 2003). Since the 1980s, one of the most widely used modeling approaches in urban studies involves cellular automata (CA). Cellular automata are systems of cells interacting in simple ways but generating complex overall behavior. 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

$$A = \langle L, Q, l, f \rangle \tag{1}$$

A cell may be in any one of several discrete states defined by Q, and a set of transition rules, f, determines the future state of each cell as a function of the states of the neighboring cells. Time is discrete and all cells are updated at each time interval. Cellular automata are well suited to investigations of urban morphology due to their spatially explicit nature and capability of generating complex patterns. Indeed, many contemporary urban growth models in the literature are based on a CA framework. In general, CA is a powerful approach to modeling open, complex, self-organizing systems that emphasizes the way in which locally made decisions give rise to global patterns (Wu, 1998; Wu and David, 2002). Couclelis (1985) suggested that the classic cell-space models are not appropriate for studying specific urban systems, but rather should only be used to understand the driving forces that shape urban form. However, CA-based models have recently been applied to specific cities (e.g., Batty *et al.*, 1989; White and Engelen, 1993, 1994; Batty and Xie, 1994).

To simulate the urban growth of the Phoenix metropolitan area, we have adapted an existing urban growth model, the Human-Induced Land Transformations (HILT) model, which was originally developed for the San Francisco Bay Area (Clarke *et al.*, 1997; Kirtland *et al.*, 1994). To make HILT applicable to Phoenix, a number of substantial changes had to be made. To distinguish the significantly modified version of HILT tailored for Phoenix from the original, we have named it PHX-UGM (Phoenix Urban Growth Model). In this paper, we discuss the structure and evaluation of PHX-UGM, and present the results of a scenario-based analysis of the future development of the Phoenix metropolitan region.

The Phoenix metropolitan area

The Phoenix metropolitan area is located in the State of Arizona, U.S.A., the northern part of the Sonoran desert in the American southwest. Phoenix has recently become the fastest growing major city in the United States, and this rapid urban expansion has substantially altered the composition and spatial structure of the landscape (Wu *et al.*, 2000, 2002; Jenerette and Wu, 2001; Luck and Wu, 2002). Habitation in the central Arizona area began several thousands of years ago with the Hohokam native people. That civilization disappeared long ago, but eventually others (typically ranchers and farmers) came and re-settled the area. The rapid growth of the region began after World War II when agricultural interests tapped into ground and canal water so that continuous year-round farming could be supported (Gammage, 1998) and when air conditioners became readily available to make life comfortable. In the intervening years, the area has shifted from a mostly agricultural community to an industrial and commercial center. In 1985, farmers used 89% of Arizona water and produced 2% of the area's income. Cities used 7% of the water and produced 95% of the income.

Certain characteristics are apparent in the spatial development of the Phoenix metropolitan area that distinguishe it from other cities (Morrison Institute for Public Policy, 2000). First, the population density has been increasing even as the urban extent increases. Second, the region's center is holding; both population and employment rose in the regional center, avoiding the decay many cities have experienced. Third, the Phoenix metropolitan area has managed to maintain a balance among its major cities with respect to housing values, jobs and retail activity. Fourth, people and businesses keep coming; the Phoenix area has shown exponential growth over the last 50 years. Some urban morphological features of the Phoenix metropolitan area are also noteworthy. For example, new developments tend to be found only close to the urban fringe; expanding urbanization has left numerous non-urban/agricultural remnants scattered within the growing core area; there is mostly flat, open land available in all directions from the urban core with old, unpaved farm roads providing access to these areas. While there are large Native American reservations located to the east and south, these are some distance from the urban core and thus have exerted little influence on the direction of expansion.

Model structure

The HILT model

PHX-UGM is a modified version of the Human-Induced Land Transformations (HILT) model which was originally developed by Clarke *et al.* (1997) to simulate regional urbanization patterns in the San Francisco Bay Area. The model has since been applied in different urban areas, including the Washington DC/Baltimore area and Albuquerque, New Mexico.

HILT is a self-modifying cellular automaton urban growth model that simulates a one-way transition from a non-urban category to an urban category. It involves (1) converting space to a grid, (2) establishing an initial set of conditions, (3) establishing a set of transition rules that are applied for each iteration, and (4) recursively applying the rules (figure 1). Four different types of urban growth are distinguished in HILT: spontaneous, diffusive, organic and road influenced (Clarke *et al.*, 1997). For spontaneous neighborhood growth,

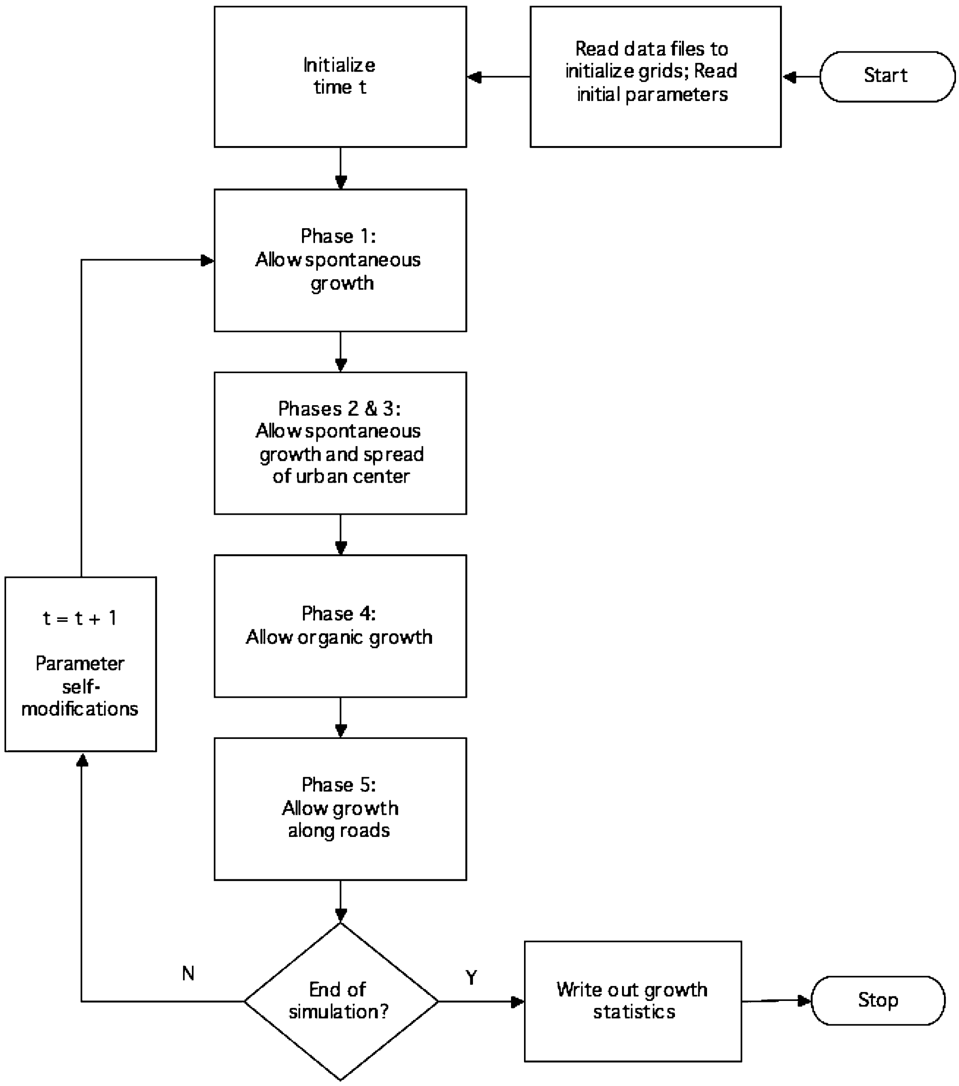

Figure 1. Flowchart of the HILT model, showing the five phases through which urbanization is simulated (based on the descriptions in Clarke *et al.* (1997)).

a randomly selected cell may become a new urban center, simulating the development of urban settlements in undeveloped areas. This growth type reflects the number of new centers that will be created—new center startups. For diffusive growth, a spontaneously urbanized cell (above) may develop into a spreading urban center even though it may not lie near an already established urban area—new center growth. For organic growth, a random cell may become urbanized if some of its neighbors are already urbanized—expansion of existing urban areas. Finally, for road influenced growth, urbanization may expand along road corridors, simulating the development seen in newly accessible areas.

The urban growth rules in HILT involve selecting a location, investigating the spatial properties of the neighboring cells, and urbanizing the cell under consideration based on a set of weighted probabilities. A neighborhood in this model is determined by the 8-neighbor rule. There are five factors that control the behavior of the system: (1) a Diffusion Coefficient that determines the overall dispersiveness of the distribution both of single grid cells and in the movement of new settlements outward through the road system, (2) a Breed Coefficient that determines how likely a newly generated detached settlement is to begin its own growth cycle, (3) a Spread Coefficient that controls how much normal outward "organic" expansion takes place within the system, (4) a Slope Resistance factor that influences the likelihood of settlement extending up steeper slopes, and (5) a Road Gravity factor that has the effect of attracting new settlements onto the existing road system if they fall within a given distance of a road (Clarke *et al.*, 1997). HILT is a self-modifying CA because the rules and parameters themselves are allowed to change to different, prescribed settings when the urban growth rate exceeds or drops below some critical value (Clarke *et al.*, 1997). Self-modification of the parameters is allowed through an additional set of rules. These rules are designed to fit the form of urban growth such as those observed in the San Francisco Bay Area. If growth in a year exceeds the critical high value, the Diffusion, Spread and Breed Coefficients are increased, encouraging diffusive, organic and road influenced growth, respectively. As the urban areas enlarge to cover more of the cellular grid space, these factors are decreased to prevent exponential growth. If the growth rate falls below the critical low value, these variables are decreased to cause a tapering off of growth. As the road network is enlarged, the Road Gravity factor is increased to create a wider band of development around the roads. Finally, as available land decreases, the Slope Resistance factor decreases to allow development higher on hillsides.

The four types of growth are implemented in the model through five sequential phases (figure 1). After initialization of the cellular grid, execution begins. During each subsequent time step (one year), each phase of the model is executed once. At completion of the run, output statistics and resulting images are recorded. Self-modification of the variables occurs before beginning the next cycle. Phase 1 models a simple diffusive process where a random cell on the map is selected and converted to urban, representing the possibility of occasional new small development springing up (extent of development limited to grain size) outside the urban core area. Once a random point has been selected, the slope at that location is used to determine either that it will not be urbanized or may yet be considered. If it is still under consideration, a random number (1–100) is selected; if that number is less than the Diffusion Coefficient, the cell becomes urbanized. Generally, the slighter the cell's slope, the less likely it will be rejected outright, and the higher the Diffusion Coefficient, the more likely it will be urbanized. Phases 2 and 3 are combined to represent random new developments spreading into several cells from booming development—a representative of a large development springing up. Again, a location is randomly selected and a random number (1–100) is generated. If the random number is less than the Breed Coefficient, the cell is being considered for urbanization. As in Phase 1, the slope at that location is used to determine whether to reject it outright, and if not, the cell is urbanized. Thus, the Breed Coefficient limits the number of cells to be considered and the slope limits the cells actually selected.

Phase 3 is applied only to those cells urbanized in phase 2. Once the cell has been urbanized, a random neighbor (8-neighbor rule) is selected. If the cell is not rejected outright based on the slope at that location, that cell is urbanized also. This spread is repeated 3 times, urbanizing up to 4 cells in one pass. Phase 4 represents the spread of existing urban areas into adjacent non-urbanized land. For a randomly selected cell neighboring an existing urban area, if a random number (1–100) is less than the Spread Coefficient, if at least 4 of its neighbors are also urban, and if the slope is allowable, it is urbanized. Phase 5 represents the spread of urbanization along transportation corridors. Some of the cells that were urbanized in the last time step are selected randomly based on the Diffusion Coefficient. One of these cells is selected at random, and if a cell of type "road" exists nearby, a walk is taken along the road (a cell to cell traverse, staying on the road cells) for the distance of 2 * Diffusion Coefficient. Once traveling has stopped, if the endpoint cell is not rejected outright based on the slope, the cell is urbanized. The Diffusion Coefficient limits the number of cells to be considered as starting points for road traversal as well as the distance traveled along the road. The Road Gravity parameter limits the distance for which a neighboring road will be searched. Again, the flatter the slope, the more likely a cell is urbanized.

There are four major types of data used within the HILT model: (1) land-use data, (2) slope, (3) transportation and (4) protected lands. Land-use data and protected lands are used to determine the initial cell values at the start of simulation. The slope associated with each grid cell is used to determine the likelihood of urban growth development along hillsides, and the road information is used to influence the urbanization along transportation corridors (which in Phoenix tends to parallel the water distribution system).

Major modifications to HILT

We tested the applicability of HILT for the Phoenix region without any modification to the model structure by running the model from 1975 to 1995 with mid-range default parameter values. Land use data of 1975 and 1995 were used for model initialization, calibration and evaluation (see the following sections for more detail on running such simulations). These simulations produced only a fraction of the actual urban growth in the region. Then, we increased the parameters to their maximum values, but the model still significantly underestimated the urban growth. Our error analysis showed that 88% of the cells predicted as urban (this includes both seed and converted cells) were correct (user's accuracy), but that only 33% of the urban growth was actually generated by the model (producer's accuracy). Clearly, the model, without modification, was not able to adequately simulate the urban growth in the Phoenix metropolitan area. We realized that some new components needed to be added, and several aspects of the model must be substantially changed before HILT could be used for our research purposes.

HILT includes only 3 cell types: urban, non-urban and exclusions. We added one new cell state, agriculture. The agriculture-to-urban transition has been an important part of the urbanization in the Phoenix area, and it was necessary to be modeled explicitly for many research purposes. Cells may change from non-urbanized or agriculture to urbanized, but urban and excluded cells never change to any other type. We combined recreation and non-privately owned lands that are restricted from development into one single category, excluded lands.

One notable characteristic of the Phoenix area is the leapfrog type of development, leaving remnant patches around and within neighborhoods and increasing landscape fragmentation. To capture this phenomenon, we modified HILT to allow for neighborhoods to be defined as wider bands of cells around a central cell rather than just the traditional 8-neighbor rule. Another striking characteristic of the Phoenix area is that urban growth has been taking place at an exponential rate. HILT used self-modifying rules to prevent just such behavior. We replaced the growth controlling variables with a human population growth model derived by empirical data (figure 2), so that the total area of new urbanized cells each year is directly influenced by population growth. To improve the prediction accuracy, the exponential population model was applied over relatively short periods (1912–1934–1955–1975–1995) for which both population size and density data existed. During program execution, once the population is estimated, the number of cells that needed to be urbanized in the current year is computed. Based on current density statistics, the model repeatedly runs through the five phases of growth until all the new urban cells have been allocated.

To allow greater flexibility in experimenting with the growth rules and to simplify the procedures for changing runtime options, numerous code modifications were made to allow command line input and to utilize conditional compilation options. These changes eased the

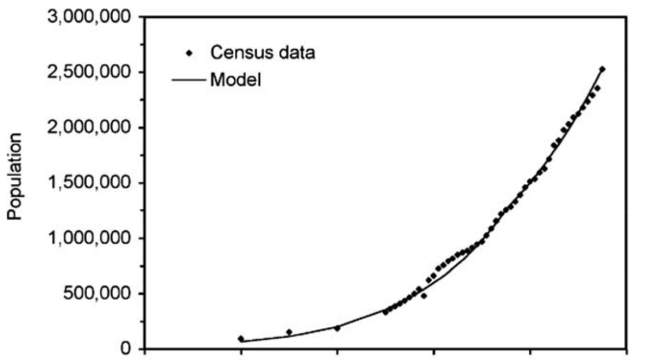

Figure 2. Population growth in the Phoenix metropolitan area. Dots are census data, and the line is the prediction from the exponential human population model, $P = P_0 e^{rt}$. Note that the model was applied separately for four time periods (1912–1934–1955–1975–1995).

effort of experimentation with different grain sizes (for multi-scale analysis), simulation start dates, and rule modifications. Several supporting utilities were also developed to facilitate data preparation and the new methods of calibration and analysis (see below). Grid images for input were created by ArcView and results were written out and stored in an ArcView compatible format for ease of display.

Model parameterization and calibration

The extent of the study area is delimited by a 68.5 km $\times$ 88.75 km boundary centered on the Phoenix metropolitan area, as defined by CAP-LTER. The major data input used for parameterizing PHX-UGM included land-use maps for 1975 and 1995 with four classes: undeveloped desert, urbanized areas, recreation areas, and agriculture (Knowles-Yanez *et al.*, 1999), maps of land ownership and 1978 road data layers obtained from the CAP-LTER database, and topographic information derived from the United States Geological Survey (USGS) digital elevation models (DEMs). All vector-based data files were converted into raster format using ArcView. An important reason for choosing the land use data of 1975 and 1995 was that the rate of urbanization during this time period was extraordinary: urban land use increased from 7% in 1975 to 18% of the total area in 1995 (Knowles-Yanez *et al.*, 1999).

It is impossible to directly validate the model projections of future growth because we simply do not have the data. However, we can calibrate the model so that it describes, as accurately as possible, what has already happened. Then, based on past trends, we can project likely future patterns. This retrospective approach has inherent problems for studying complex self-organizing systems whose future, by definition, can not be predicted by its past (Wu and Marceau, 2002). However, we believe that this traditional modeling approach in combination with scenario-based analysis can still provide valuable insights about how urban landscapes may develop. Before such exploratory attempts, however, the model must be able to reproduce the known system behavior reasonably well. This often involves model calibration (or tuning), the process in which certain model parameters and constants are adjusted so that the agreement between model output and observations is improved. As described above, several variables control the probability for a cell to be urbanized (e.g. Diffusion Coefficient, Breed Coefficient, Spread Coefficient and Slope Resistance) and the distance along a road that urban development may take place (e.g. Road Gravity). Additionally, PHX-UGM has two new variables NEI_HOOD and NEI_RQMT that define the "neighborhood" and the number of neighbors that must be urbanized to consider urbanizing a new cell. The goal of calibrating the model is to find the combination of settings that yield the most satisfactory results.

We followed the two calibration phases built in HILT: a visual version for general pattern comparison and a more computationally efficient batch version for quantitative evaluation. The visual phase is used to establish meaningful ranges of values as well as to verify that growth is proceeding within reasonable bounds, while the second phase involves a variety of statistical measures. Based on preliminary sensitivity analysis, we selected only a small set of parameters for model calibration, including Diffusion, Breed, Spread, and Road Gravity. There were 1024 different combinations run in total. The performance was evaluated using the Lee-Sallee value as described in Clarke *et al.* (1997).

Model evaluation

Model evaluation is an important part of the modeling process although model "validation" for complex systems is extremely difficult or impossible (Oreskes *et al.*, 1994; Rykiel, 1996; Wu and Marceau, 2002). We based our model evaluation on the empirical land use map compiled using remote sensing and survey data for 1995, although we understood that the empirical map itself inevitably had errors. To facilitate model evaluation, we used two different versions of PHX-UGM, one for visual inspection with graphic output, and the other for quantitative evaluation. The visual inspection produced a qualitative comparison of the general growth pattern between the simulated and empirical maps. For quantitative evaluation, we used several methods to determine the accuracy of model projections. To examine possible scale effects (Jelinski and Wu, 1996; Wu *et al.*, 2002; Wu, 2004), we ran the model at five different grain sizes, most of which are multiples of the TM resolution (60, 120, 240, 480, and 1000 m), with input data also corresponding to those grain sizes. The rasterization of the land use maps at these different specified resolutions was implemented following the majority rule using the ArcView GIS (geographic information systems). We were not able to conduct the same simulations at the resolution of 30 m because of excessive computational demands. Figure 3 is a visual comparison between the 1995 empirical land use map and a simulated land use map for the same year. In the following, we shall focus on the results of three quantitative model evaluation methods: (1) error matrix, (2) multiple resolution goodness-of-fit, and (3) landscape metrics.

Error matrix

A commonly used method to evaluate mapping accuracy is to construct an error matrix. The error matrix is a table that counts both the number of correctly identified and misidentified cells. From the error matrix, one can compute the user's accuracy—the percentage of cells identified as urban on the model output map that were actually urban on the empirical map—and the producer's accuracy—the percentage of urban cells on the empirical map that were correctly projected on the model output map (Congalton and Green, 1999). For the 5 grain sizes of 1000, 480, 240, 120, and 60 m^2, the user's accuracy for the urban class was 77, 74, 72, 72, and 66%, and the producer's accuracy for the urban class was 77, 72, 72, 74, and 77%. The overall average accuracy, the ratio of the correctly identified cells of all classes to the total number of cells, was 79, 78, 76, 77, and 75% at the 5 grain sizes. Thus, the overall and user's accuracy declined at coarser spatial resolutions. Based on visual comparison of the error maps that were produced by overlaying the simulated with empirical maps (not shown here), we found that, as grain size decreased, more spontaneous development occurred outside the core urban area, producing many scattered small patches. Additionally, more development occurred along the roads than is observed in the empirical data.

Multiple resolution goodness-of-fit

The error matrix method is based on a single-scale, cell-to-cell comparison, and may produce biased estimates of mapping accuracy (Shao *et al.*, 2003). Turner *et al.* (1989)

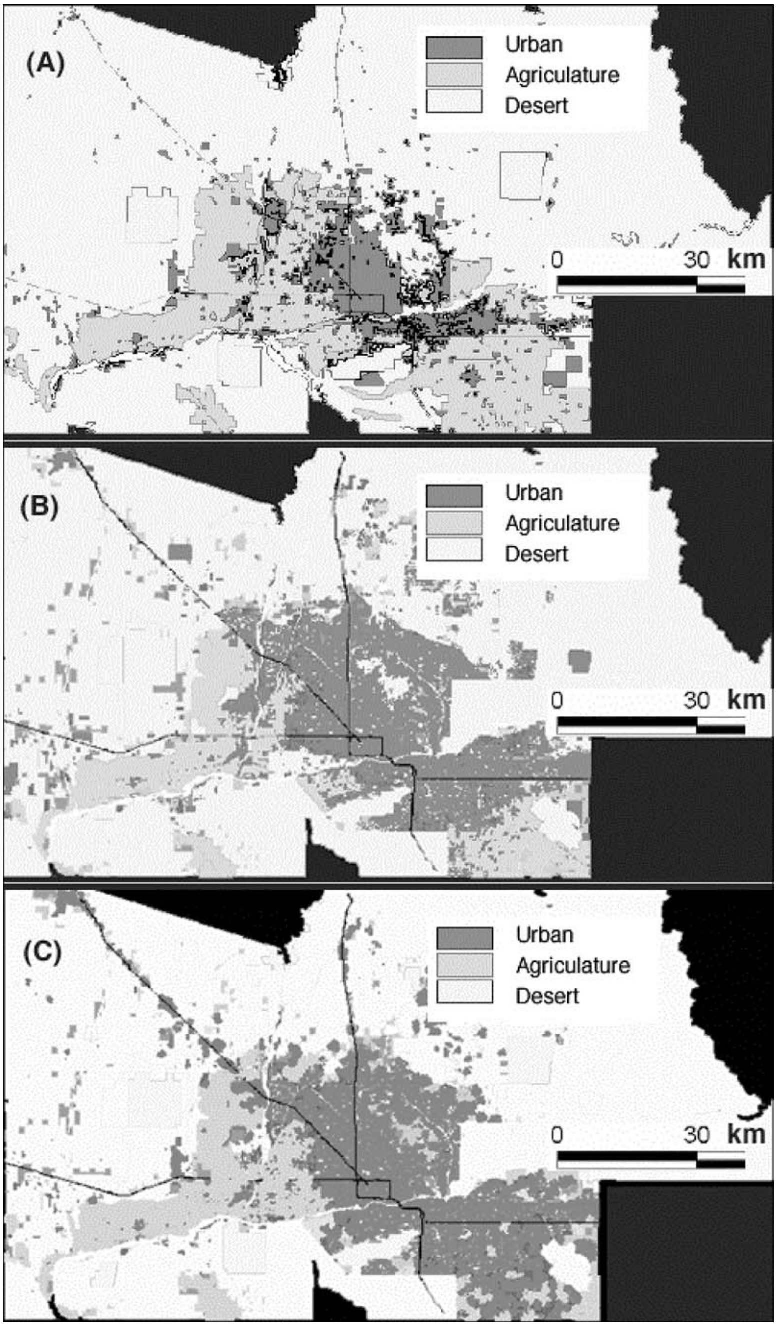

Figure 3. The land use maps of the Phoenix metropolitan area in 1975 and 1995: (A) empirical map of 1975 compiled from survey data, (B) empirical map of 1995 compiled from remote sensing and survey data, and (C) simulated map from PHX-UGM with a grain size of 120 m.

indicated that comparison at one single resolution was not adequate for evaluating spatial models and thus suggested a multiple-resolution measure, or a multi-scale goodness-of-fit. This method requires intensive resampling with a moving window whose size is increased progressively. The average goodness-of-fit is repetitively calculated at each window size. The formula for the fit at a particular sampling window size, F_w, is (Turner *et al.*, 1989):

$$F_w = \frac{\sum_{s=1}^{t_w} \left[1 - \frac{\sum_{i=1}^{P} [a_{1i} - a_{2i}]}{2w^2}\right]s}{t_w} \tag{2}$$

where w is the linear dimension of the (square) sampling window, a_{ki} ($k = 1, 2$; referring to the two maps to be compared) is the number of cells of category i in scene k in the sampling window, P is the number of different categories in the sampling window, s denotes the moving window that slides through the map one cell at a time, and t_w is the total number of sampling windows in the map for window size w. If two maps are identical, $F_w = 1$, and it remains 1 for all sampling window sizes (w); if two maps have the same proportions of cover types, but very different spatial pattern, F_w will increase gradually with the window size; if the spatial patterns of the two maps are slightly different, F_w will increase rapidly at first and soon start to approach 1 (Turner *et al.*, 1989).

We selected seven window sizes (1×1, 2×2, 4×4, 8×8, 16×16, 32×32, and 64×64 pixels), and a multi-scale goodness-of-fit plot was accordingly constructed (figure 4). In all cases, F_w increased rapidly first and then tended to approach the maximum value of 1 (figure 4a). While the overall goodness-of-fit was quite high for all window sizes (due partly to the large proportion of desert area), the mean value of F_w (averaged over all window sizes) varied among the five different grain sizes (figure 4b). To quantify the differences, we had 30 simulation runs at each grain size and then computed the mean goodness-of-fit over all sampling window sizes for each grain size. This result suggested the existence of a limited range of grain sizes (i.e., 120–480 meters) for which the overall fit of the model was higher.

Landscape indices

Error matrix and multiple resolution goodness-of-fit are valuable for assessing the accuracy of spatial models, but it is difficult to determine how well the spatial patterns of the modeled and empirical maps match each other. However, the model accuracy in terms of spatial patterns may be important ecologically and technically, and can be assessed using landscape indices (Turner *et al.*, 1989). Landscape ecologists have developed and applied a suite of indices to quantify spatial patterns in the past two decades (O'Neill *et al.*, 1988; Turner *et al.*, 1991; Gustafson, 1998; Wu *et al.*, 2002). We used FRAGSTATS, a landscape analysis package developed by McGarigal and Marks (1995), to compute the values of 18 selected metrics at different grain sizes (Wu *et al.*, 2002; Wu, 2004). However, to reduce redundancy we report the results of only 6 metrics: number of patches (NP), edge density (ED), mean patch size (MPS), patch size coefficient of variation

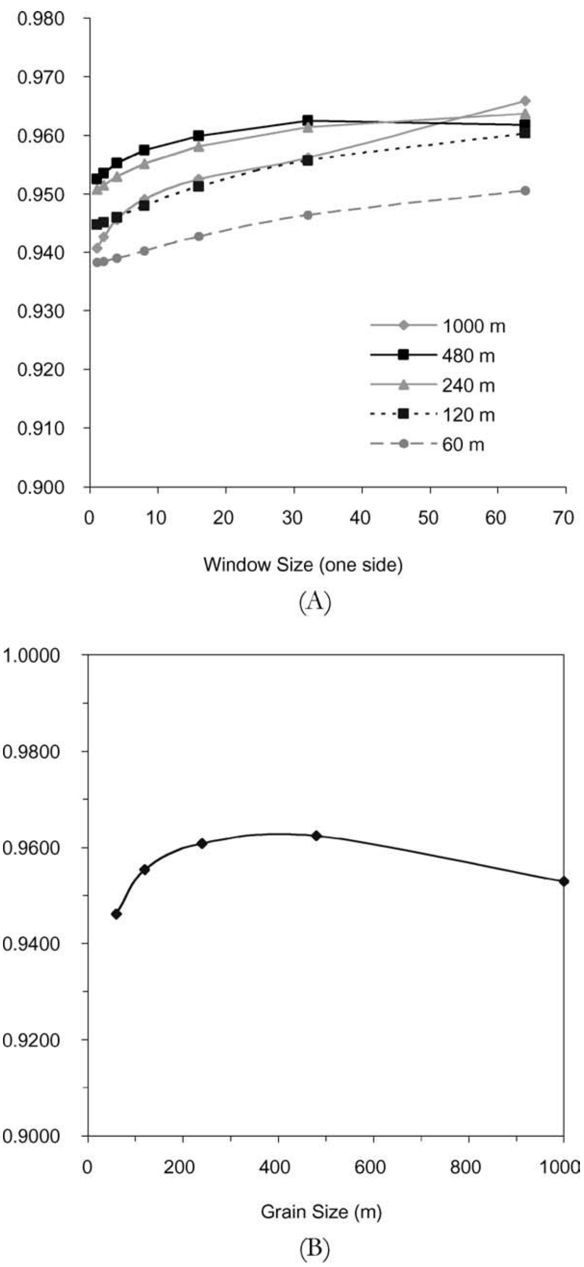

Figure 4. Multiple-scale goodness-of-fit, the $F_w - w$ plot (A), and the means of F_w (B) for the PHX-UGM model at five different grain sizes. Each model projection shown here was the best performer of 30 sample runs for each grain size.

Table 1. List of landscape metrics used for the evaluation of PHX-UGM (modified from Wu *et al.*, 2002)

Landscape metric	Abbreviation	Description
Number of patches	NP	The total number of patches in the landscape.
Edge density	ED	The total length of all edge segments per hectare for the class or landscape of consideration (unit: m/ha).
Mean patch size	MPS	The average area of all patches in the landscape (unit: ha).
Patch size coefficient of variation	PSCV	The standard deviation of patch size divided by mean patch size for the entire landscape (unit: percentage).
Area-weighted mean patch shape index	AWMSI	Mean patch shape index weighted by relative patch size: $\mathrm{AWMSI} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[\left(\frac{0.25 P_{ij}}{\sqrt{a_{ij}}} \left(\frac{a_{ij}}{A} \right) \right) \right]$ where P_{ij} and a_{ij} are the perimeter and area of patch ij, respectively, A is the total area of the landscape, m is the number of patch types, and n is the total number of patches of type i (unitless).
Double-log fractal dimension	DLFD	The fractal dimension for the entire landscape which is equal to 2 divided by the slope of the regression line between the logarithm of patch area and the logarithm of patch perimeter: $\mathrm{DLFD} = \dfrac{2}{\left[\dfrac{\left[N \sum_{i=1}^{m} \sum_{j=1}^{n} (\ln(P_{ij}) \ln(a_{ij})) \right] - \left[\left(\sum_{i=1}^{m} \sum_{j=1}^{n} \ln(a_{ij}) \right) \right]}{\left(N \sum_{i=1}^{m} \sum_{j=1}^{n} (\ln(P_{ij}^2)) \right) - \left(\sum_{i=1}^{m} \sum_{j=1}^{n} (\ln(P_{ij})) \right)^2} \right]}$ where P_{ij} and a_{ij} are the perimeter and area of patch ij, respectively, m is the number of patch types, n is the total number of patches of type i, and N is the total number of patches in the landscape (unitless).

(PSCV), area-weighted mean patch shape index (AWMSI), and double-log fractal dimension (DLFD). Detailed definitions of these 6 metrics are given in Table 1. These metrics can be computed at both the landscape level (i.e., considering all land use types in the landscape) and the class level (i.e., considering only one individual land use type each time). We compared the simulated with empirical maps at both levels, but focused only on the urban land use type at the class level because of our particular interest in urban growth.

Due to the stochastic nature of the model, the spatial patterns of different simulation runs with the same parameter set differed in certain ways. Thus, to make a meaningful comparison between the model output and the empirical map, we needed to determine the minimum number of runs for computing the means of the selected metrics for each of the five grain sizes at which the model was run. This was done using the formula recommended by Grant *et al.* (1997):

$$n \geq 2(\sigma/\delta)^2 \left[t_{\alpha,\gamma} + t_{2(1-P),\gamma} \right]^2 \quad (3)$$

where n is the number of runs, σ is the estimated standard deviation of model runs, δ is the smallest difference between the predicted and observed values of a variable of interest that we desire to detect, γ is the degrees of freedom of the sample standard deviation with b groups of samples and n samples per group (or $\gamma = b(n-1)$), α is the significance level, P is the desired probability that a difference will be found to be significant if it is as small as δ and $t_{\alpha,\gamma}$ and $t_{2(1-P),\gamma}$ are values from a two-tailed t-table with γ degrees of freedom corresponding to probabilities of α and $2(1-P)$, respectively. One cannot solve for n directly because γ is a function of n. Instead, one guesses a value of n, calculates γ, then solves the equation for n. If the calculated n is not equal to the guessed n, a different value of n is guessed accordingly and the procedure repeats. Here, an estimate of the variability of selected sampling items (in this case landscape indices) needs to be obtained by running 30 baseline simulations and calculating the sample variance. The minimum number of runs required to compute the mean of each of the 6 selected metrics is listed in Table 2. At the landscape level, the minimum number of runs tended to increase with increasing grain size (i.e., decreasing resolution), but such a trend was absent at the class level (Table 2). Instead, the finest and coarsest grain sizes required the largest number of runs for deriving meaningful means of the metrics. To simplify the simulation procedures, we derived the means of all the metrics based on 30 simulation runs, which was larger than the minimum number of runs for most landscape metrics (except NP and MPS) at all grain sizes based on Eq. 3.

Figure 5 shows the results of the six landscape metrics computed for both the whole landscape including all land use types and the urban class only. The relative differences between the model and data at each grain size are listed in Table 3. In general, two kinds of scale effects were apparent: (1) the values of the landscape metrics changed with grain size (Wu, 2004), and (2) the agreement between the model and the empirical data also varied with grain size. For a given metric, these scale effects showed similar patterns at the urban class and the whole landscape levels, but model accuracy measured by these metrics was consistently higher at the landscape level than the class level (Table 3). Specifically, the values of the number of patches, edge density, and patch size coefficient of variation decreased with grain size, and the discrepancy between the model and data measured by these metrics was greatest at the 60 m grain size, smallest at the 120 m grain size, and moderate to small for larger grain sizes (figures 5a–d, g–h; Table 3). The average shape of individual patches (AWMSI) showed a similar pattern without the dramatically large discrepancy at the finest grain size (figures 5i–j). In contrast, the mean size of individual patches (MPS) and the shape complexity of the whole landscape (DLFD) tended to increase with grain size, and so did the model errors represented by these metrics (figures 5e–f, k–l).

Projecting future urban growth of Phoenix

A major goal of this study was to explore how the Phoenix urban landscape would change in the future. To achieve this goal, we designed three development scenarios based on the current political climate and the desires of the residents, and then ran simulations to examine how these scenarios led to different future development patterns. The sources of information for developing these scenarios include the Maricopa County Comprehensive

Table 2. The minimum number of runs for computing the means of the six landscape metrics, at both the landscape and class (urban) levels, for the five grain sizes at which the model was run. A value of >30 indicates that we ran the model up to 30 times, and still could not determine the minimum number of runs for computing the means of the selected metrics

		Minimum number of runs needed for computing the mean	
Landscape metric	Model grain size	Whole landscape	Urban class only
Number of patches (NP)	1000 m	10	>30
	480 m	5	>30
	240 m	5	>30
	120 m	5	>30
	60 m	10	15
Edge density (ED)	1000 m	5	20
	480 m	5	10
	240 m	5	5
	120 m	5	5
	60 m	5	5
Mean patch size (MPS)	1000 m	10	>30
	480 m	5	>30
	240 m	5	>30
	120 m	5	>30
	60 m	10	15
Patch size coefficient of variation (PSCV)	1000 m	10	20
	480 m	5	20
	240 m	5	15
	120 m	5	15
	60 m	10	10
Area-weighted mean patch shape index (AWMSI)	1000 m	5	25
	480 m	5	20
	240 m	5	15
	120 m	5	15
	60 m	10	15
Double-log fractal dimension (DLFD)	1000 m	5	10
	480 m	5	5
	240 m	5	5
	120 m	5	5
	60 m	5	5

Plan (Maricopa, 1997), an analysis of a recent local growth limitation initiative (Gordon *et al.*, 2000), and other studies (Lee *et al.*, 1998; Landis *et al.*, 1998; Ellfman, 1997). A grain size of 480 meters was selected for the scenarios because of the reasonable balance between overall model accuracy and computational demands.

Three scenarios

Scenario 1 represented the continuation of development status quo. Developers continued to provide large, single-family dwellings as the market demands, and the density and growth rates remained at the 1995 rates. Recreation areas , particularly parks, are an important part of urban development. Using 2002 statistics of the current population, number of parks and average park size for Peoria (one city in the Phoenix metropolitan area), we derived parameters for modeling park creation in a fast developing city in this region. Specifically, the model

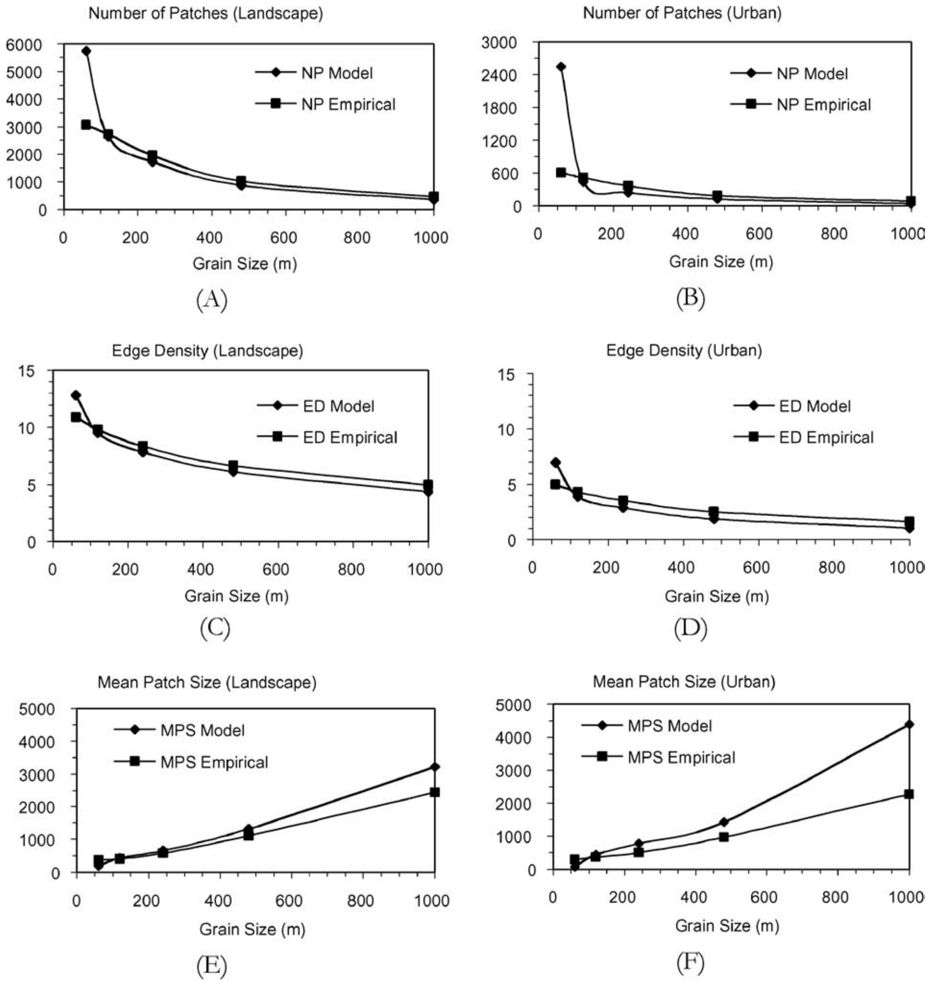

Figure 5. Comparison of the spatial patterns between the empirical and simulated maps using landscape metrics at the whole landscape level (A, C, E, G, I, K) and the urban class level (B, D, F, H, J, L).

(*Continued on next page*).

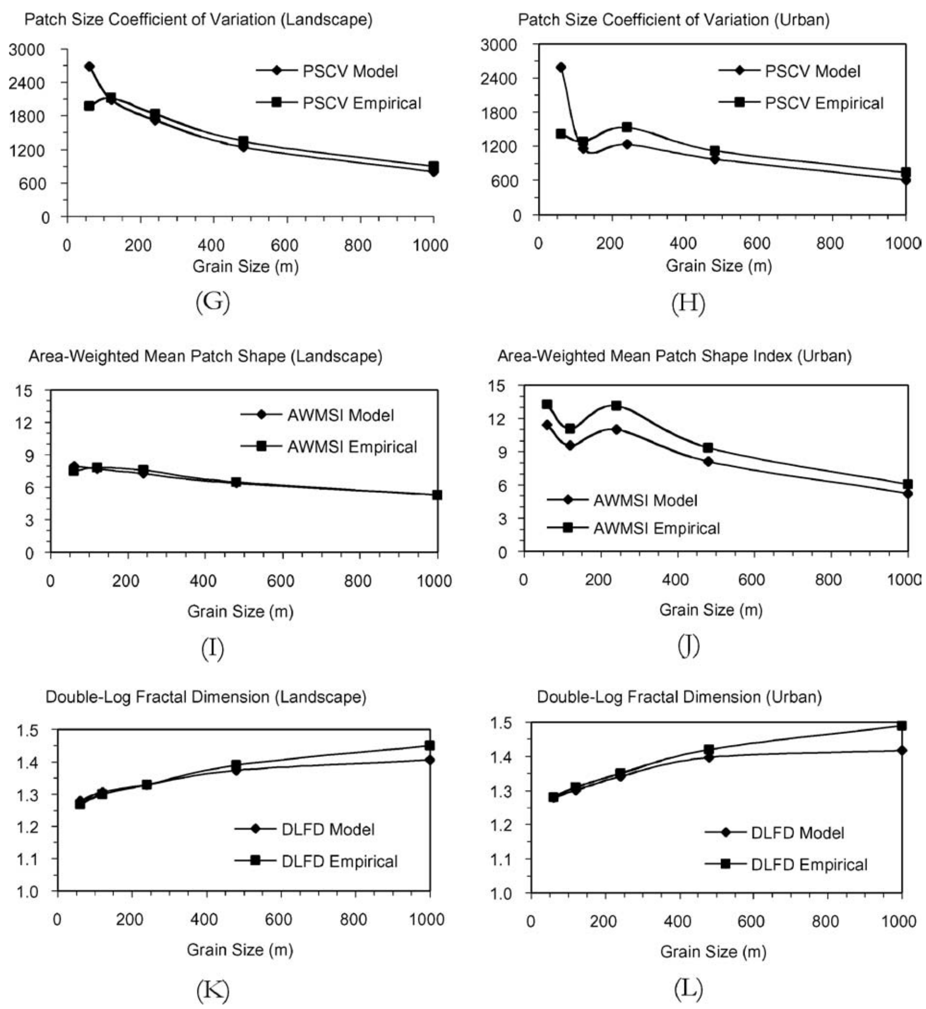

Figure 5. (*Continued*).

created parks at an average rate of one new park cell for every 74 new urban cells. The new park was placed next to a newly urbanized cell if there was not already a park within a radius of 7 cells (approximately 2 miles). Another important issue for future urban development in the Phoenix area is the disposition of state trust land. Current Arizona legislation requires that state trust land be sold to the highest bidder, effectively encouraging developers to buy the lands for development. There is a movement locally to turn some state trust lands into parks, but this would require an amendment of the state law. In this scenario, all state trust lands were assumed to be sold to developers and opened to development in 2007.

Table 3. Comparison of the simulated and empirical maps using landscape metrics at both the landscape and class (urban) levels. Numbers in bold in each row represents the smallest difference among the five grain sizes

Landscape metric		% Difference between the simulated and empirical maps [Grain sSize (meters)] 60	120	240	480	1000
Number of patches (NP)	Landscape	87	**−3**	−11	−16	−24
	Class	320	**−14**	−34	−34	−48
Edge density (ED)	Landscape	17	**−3**	−6	−8	−12
	Class	40	**−10**	−18	−27	−37
Mean patch size (MPS)	Landscape	−46	**4**	13	19	32
	Class	−72	**21**	53	46	93
Patch size coefficient of Variation (PSCV)	Landscape	36	**−2**	−6	−7	−11
	Class	82	**−10**	−20	−13	−17
Area-weighted mean patch shape index (AWMSI)	Landscape	6	−1	−4	−2	**0.04**
	Class	−14	−14	−16	−14	**−13**
Double-log fractal dimension (DLFD)	Landscape	**1**	**1**	0	**−1**	−3
	Class	**−0.1**	−1	−1	−2	−5

The comprehensive plan for Maricopa County encourages infill within existing development, the incorporation of more multi-family dwellings, and the preservation of lands with slope greater than 15%. To simulate this situation, Scenario 2 represented a more managed approach to urban growth. Population density was increased by 10% over 10 years (starting in 2002) to represent infill and the decrease in proportion of single-family dwellings, and population growth rate was decreased by 5% over 10 years (starting in 2002) to represent the decreased desirability of the crowded area. Parks were created as in Scenario 1, and only 50% of state trust lands were opened to development in 2007, with the other 50% left as protected open spaces.

Scenario 3 represented a hard-line approach to growth management, similar to that proposed in 1997 by the Sierra Club and others in one of the local growth initiative propositions. In this scenario, population density was increased by 25% over 10 years (starting in 2002) to represent infill and the decrease in proportion of single-family dwellings, and the population growth rate was decreased by 15% over 10 years (starting in 2002) to represent the decreased desirability of the increasingly crowded area. Parks were created from 50% of the state trust lands according to the method described in Scenario 1, and the rest opened to development in 2007.

Projections

We ran the three scenarios from 1995 until the available open desert lands were all developed. (Technically, the simulation stopped when there was no longer enough land for another full year's development, rather than when every available cell was urbanized.) Table 4 lists

Table 4. Comparison of the results among 3 scenarios at the end year

Scenario	End year	Final population (million)	Final population growth rate (%)	Final population density (per cell)
Status quo	2029	8.2	3.5	296
Managed	2028	7.8	3.3	325
Ultra-managed	2033	9.0	2.9	370

some of the model output at the ending year, final population size, population growth rate, and population density per grid cell for each of the three scenarios. The available lands were projected to be filled up by 2029 with a population size of 8.18 million for Scenario 1 (continuing development status quo), by 2028 with a population size of 7.76 million for Scenario 2 (managed development), and by 2033 with a population size of 9.03 million for Scenario 3 (heavily managed development). By comparing the three different scenarios, it became evident that small increases in population density or small decreases in population growth rate would not have a significant impact on the time needed to "fill up" the Phoenix metropolitan area. The status quo scenario took one more year than the moderately managed development scenario because the latter converted 50% of the state trust lands to parks while the status quo scenario opened all trust lands for development. On the other hand, quite significant decreases in population growth rate and increases in population density prolonged the filling-up process only by 4 years, although they did allow for a significantly larger population.

Visual comparison of the urban landscape patterns generated by Scenarios 1 and 3 at an arbitrarily chosen year, 2014 (figure 6a, c) and the ending year (figure 6b, d) did not show dramatic differences in urban morphology although a closer scrutiny seemed to reveal that the heavily managed scenario created more and larger undeveloped patches in the landscape. This was due partly to the assumption that all state trust lands were opened to development in the status quo scenario, but half of them were reserved for open space in the ultra-managed scenario.

To further examine how the urbanization trajectories of the three scenarios might differ, we quantified each landscape time series using six landscape metrics: Patch Density (PD), Largest Patch Index (LPI), Mean Patch Size (MPS), Shannon's Diversity Index (SHDI), Contagion (CONT), and Double Log Landscape Fractal Dimension (DLFD). While the six landscape metrics, reflecting different aspects of landscape pattern, exhibited various patterns of temporal change, the three scenarios showed a similar trend for a given landscape metric (figure 7). The end results for all scenarios were: increases in patch density and contagion and decreases in the largest patch, mean patch size, patch diversity, and landscape fractal dimension. However, the numerical discrepancy among the three scenarios seemed to increase as urban development unfolded. It was evident from figure 7 that, over much of the simulation time, the heavily managed development scenario had the lowest values in Patch Density and Contagion and the highest values in Largest Patch Index, Mean Patch Size, Shannon Diversity Index, and Landscape Fractal Dimension. As expected, the status quo scenario showed the opposite, and the behavior of the moderately managed development

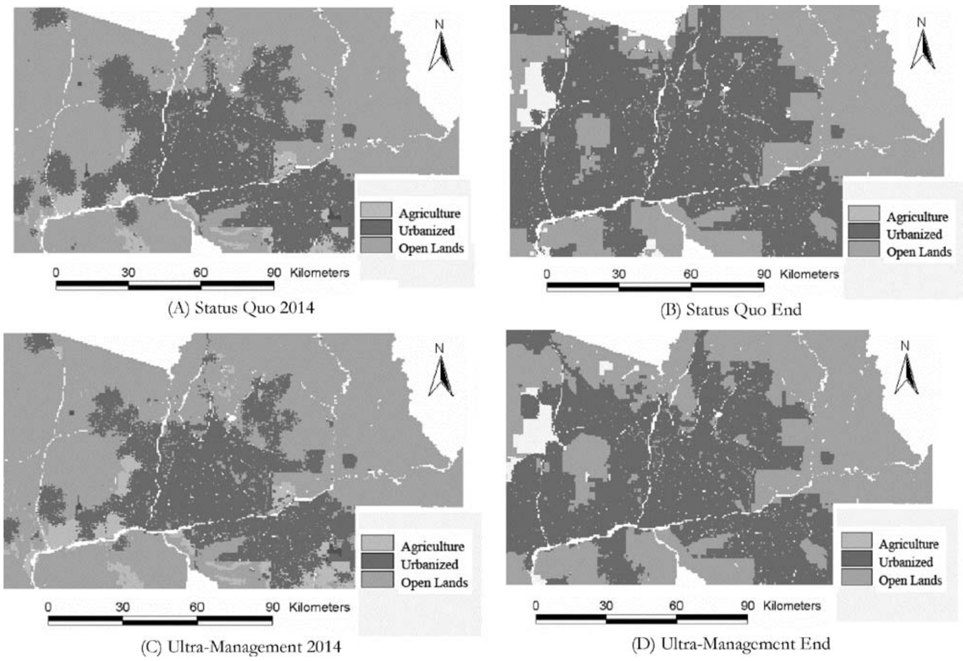

Figure 6. Model projected urban development patterns in the Phoenix metropolitan region: the status quo scenario in 2014 and 2029 (A–B), and the heavily managed development scenario in 2014 and 2033 (C–D). All simulations were conducted at the grain size of 480 m. See text for the details of the scenarios.

scenario was somewhere in between. Collectively, these changes indicated that the most intensely managed development would lead to a less fragmented landscape with more large patches and higher overall shape complexity.

An interesting and potentially important finding of the scenario analysis was that there would be an urban morphological threshold over which drastic changes in certain aspects of landscape pattern would occur. This threshold was indicated by the abrupt changes in the values of some landscape metrics (figures 7b, d, f). Specifically, large patches of open lands (including protected lands, parks and available desert lands) began to break up, patch diversity dropped due partly to the loss of agricultural lands, and the overall landscape shape complexity also decreased because of the predominance of urban lands. It seemed that none of the scenarios could avoid this threshold, but the heavily managed development scenario was able to postpone the onset of the threshold. This seems a plausible future for the Phoenix metropolitan area, and the empirical explanation may be as follows. During the early years of the simulation, much land available for development existed around current urban areas, particularly agricultural fields. As urbanization proceeded, new growth extended out from existing development, fragmenting lands near the core area but leaving the largest patches away from the center untouched. As the available lands began to fill up, growth began to spread outwards and break up the large patches of open lands. This threshold phenomenon may have significant ecological implications because open lands within and around cities

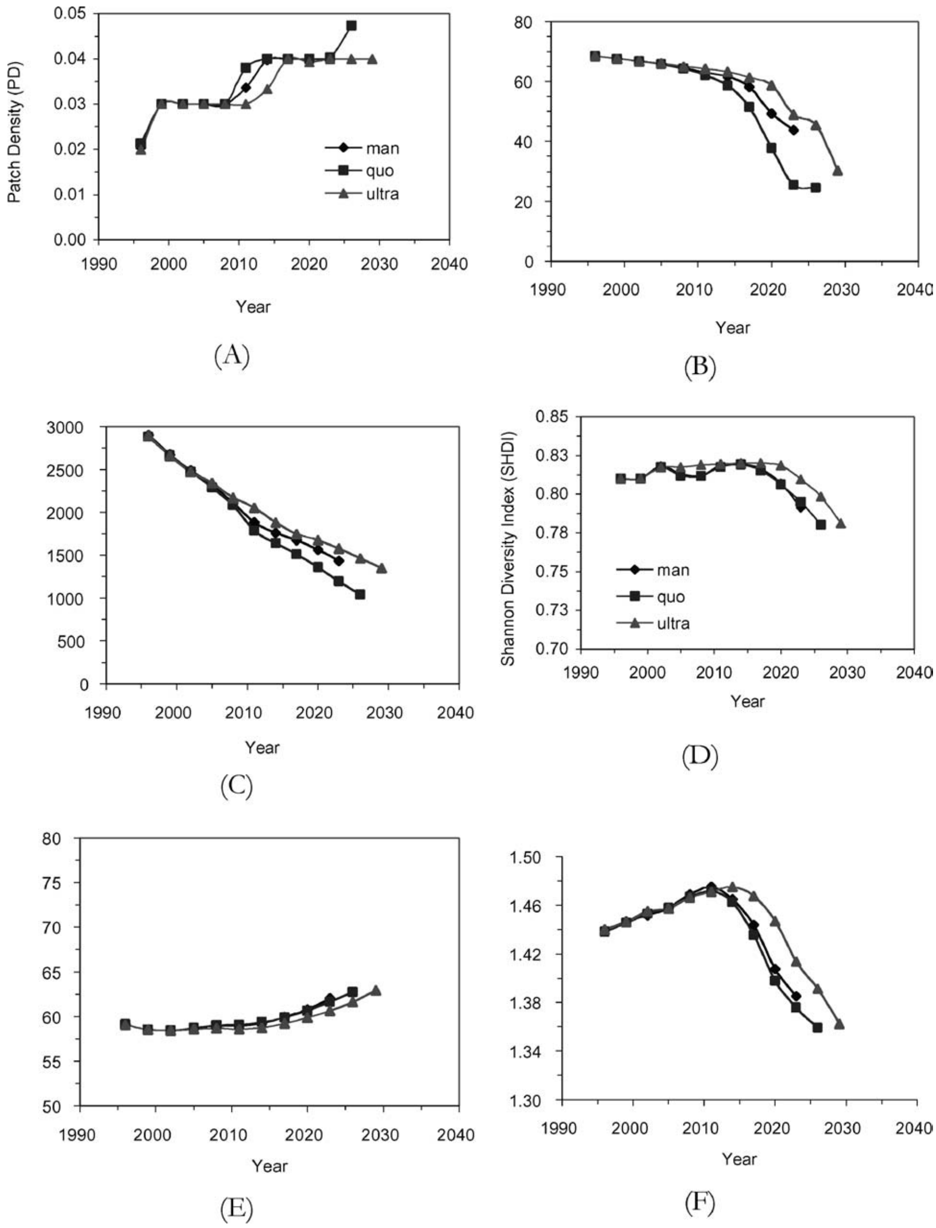

Figure 7. Comparison of the projected landscape patterns of the Phoenix metropolitan area among the three urban development scenarios: quo = status quo, man = managed development, and ultra = heavily managed development.

provide habitat and corridors for many of the native species and a range of ecosystem services.

Discussion and conclusions

Limitations of the model

The current version of the PHX-UGM model has several limitations. It includes only a few land use types and insufficient social and economic factors necessary to understand the biophysical and socioeconomic interactions in urban dynamics. The model assumes a constant population density within grid cells, and does not allow for a decreasing population density that would indicate a decaying urban core. Also, as urban development takes place, more new roads need to be created, but the current model does not project new road development. In addition, there are general limitations to the cellular automata (CA) modeling approach. CA models generally assume that large-scale patterns emerge from local-scale (or cell-level) interactions. In reality, local interactions do play an important role in urban development, but high-level constraints imposed by planners, developers and governmental agencies can also significantly shape the developed landscapes. This problem was alleviated to some extent in our model by adding some high-level constraints (e.g., land ownership, development restrictions).

It is also important to note that our model evaluation, although quite comprehensive, is not a complete "validation" of PHX-UGM. In principle, a rigorous evaluation of a model requires empirical data that were not used in model calibration. However, as with many existing land use change models, the validation data for PHX-UGM were also used for its calibration. Thus, the model evaluation was essentially to assess how successful the calibration process was, not how accurate the model prediction was. This approach has long been practiced in land use modeling, probably because of three reasons. The first is the general shortage of methodologically comparable and high quality data sets of land use change for multiple time periods. The second is the need for temporal downscaling (i.e., temporal interpolation). Land use models in many cases use as input a few maps representing the same landscape at different points of time, and one of the objectives may be to simulate the dynamics of the landscape for time periods that were not represented by the input maps (e.g., Turner, 1987; Jenerette and Wu, 2001). The third reason is the need for projections and scenario analysis. Because projections into the future can not be validated at present, a model tested on recent historical change may provide confidence for projecting into the future.

Evaluation of urban models using multiple methods

The evaluation of spatially explicit urban models like PHX-UGM is challenging in terms of both methodology and data demands. Because of the nature of spatial models, multiple methods and multiple-scale analyses should be used in the validation process of urban models. This has generally not been the case in urban modeling. In this study, we used error matrix, multiple-resolution goodness-of-fit and landscape metrics together to evaluate the model projections against empirical data. The results of the error matrix method showed that model accuracy decreased with increasing spatial resolution (i.e., decreasing grain size). This is apparently consistent with the findings in Costanza and Maxwell (1994). However, the results of multiple-resolution goodness-of-fit suggest that there is a limited range of grain sizes (i.e., 120–480 meters) within which the model performed best as measured by overall fit. The pattern analysis using landscape metrics illustrated the following findings: (1) model accuracy varied with landscape metrics under consideration, suggesting that the model simulated certain landscape atributes better than others; (2) model accuracy was dependent on the scale of analysis (grain size), suggesting landscape metrics must be analyzed at multiple scales (Wu *et al.*, 2002; Wu, 2004); and (3) there was an optimal grain size (120 m) or an optimal range of grain sizes (120–480 m) at which the model produced more accurate landscape patterns.

The different evaluation methods provided useful information on different aspects of the performance of the model. Because each method focused on different aspects, discrepancies among these methods should be expected. To answer questions such as whether the model is good enough for a specific purpose or what is the best spatial resolution of the model, one must consider the balance between overall model fit and landscape pattern accuracy, and the tradeoff between projection accuracy and structural details. Considering these factors and given the purpose of the study, we conclude that PHX-UGM would be best used at the grain size of 120–480 m. When fine-scale data are available and when landscape structural details are desirable, the 120-m grain size may be preferred. When the model grain size is too small, noise and uncertainty in input data and computational requirements significantly reduce the usefulness and accuracy of the model. When the grain size is too large, model projections would be of little use to addressing research questions at the local and regional scales. Note that several improved methods for evaluating land use models have been proposed recently (Pontius, 2002; Pontius and Batchu, 2003; Pontius *et al.*, 2003; Shao *et al.*, 2003), which should help resolve one of the most challenging problems in spatial modeling—model evaluation.

Future development of the Phoenix urban landscape

The historical development pattern in the Phoenix metropolitan area is that, as the urban fringe expanded outwards rapidly, the population density in the urban core density also increased (Morrison Institute for Public Policy, 2000). Farms have been converted to housing developments and retail super-centers, and inner city neighborhoods of single family homes have been converted to more densely populated residential areas. Our modeling results indicate that as the cities and towns in the region continue to grow, urban clusters will begin to merge into fewer and larger aggregates. Our scenario analyses suggested that, unless dramatic actions were taken to slow down the population growth, the Metropolitan Phoenix area would soon be densely populated demographically and highly fragmented ecologically. The projected time for the geographic region to be “filled up” with urban development was around 2030. An important factor to consider in future urban development planning is the urban morphological threshold as indicated in the scenario analysis. For the purpose of conserving native species and ecosystems, future development must allow for enough city parks and inner-city open lands so that a minimum habitat connectivity can be maintained. In addition, the location and spatial arrangement of parks and open spaces are also critically important. For example, these habitat patches should be situated in such a way as to create corridors in the increasingly fragmented landscape. An important value of PHX-UGM lies in its ability to incorporate different protection schemes, population growth rates and population density measures. Decision makers and land use planners may design an open space network, incorporate it into a model scenario, and then quantitatively assess habitat connectivity using landscape metrics. This may provide useful information for land-swap deals, such as trading specific state land tracts for desirable inner-city tracts to create parks.

If an ecologically healthy Phoenix urban environment is to be maintained, time is running out on many of the options still available to city planners. The residents of the Phoenix Metro area have demonstrated repeatedly that they are opposed to further increasing population density or rapid urban sprawl. Growth management initiatives have been repeatedly voted down and developers have thwarted the legislature in their efforts to create growth management legislation. These facts indicate that if the area is to continue growing and if a reasonable quality of life is to be maintained, a new mindset will need to be adopted. As our model results suggest, this would require the strict regulation and careful planning of open spaces, as well as significantly increasing population densities in the developed areas.

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