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Research Article

Analysis and simulation of land-use change in the central Arizona – Phoenix region, USA

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Abstract

To understand how urbanization has transformed the desert landscape in the central Arizona – Phoenix region of the United States, we conducted a series of spatial analyses of the land-use pattern from 1912–1995. The results of the spatial analysis show that the extent of urban area has increased exponentially for the past 83 years, and this urban expansion is correlated with the increase in population size for the same period of time. The accelerating urbanization process has increased the degree of fragmentation and structural complexity of the desert landscape. To simulate land-use change we developed a Markov-cellular automata model. Model parameters and neighborhood rules were obtained both empirically and with a modified genetic algorithm. Land-use maps for 1975 and 1995 were used to implement the model at two distinct spatial scales with a time step of one year. Model performance was evaluated using Monte-Carlo confidence interval estimation for selected landscape pattern indices. The coarse-scale model simulated the statistical patterns of the landscape at a higher accuracy than the fine-scale model. The empirically derived parameter set poorly simulated land-use change as compared to the optimized parameter set. In summary, our results showed that landscape pattern metrics (patch density, edge density, fractal dimension, contagion) together were able to effectively capture the trend in land-use associated with urbanization for this region. The Markov-cellular automata parameterized by a modified genetic algorithm reasonably replicated the change in land-use pattern.

Introduction

To understand the structure, function, and dynamics of ecosystems it is necessary to integrate both ecological and human processes. As a result of human activities, pervasive ecological changes have occurred at local, regional, and global scales. The change in land cover through the appropriation of natural landscapes to provide for human needs is one such process (Vitousek 1994). While the ecological and sociological effects of land conversion for agricultural uses have been studied (Riebsame et al. 1994), the effects of land conversion for human habitation, or urbanization, is less understood (Pickett et al. 1997). Urbanization is the general process of city growth; native land cover is appropriated for industrial, commercial, residential, and other land uses associated with human demands. As human population increases and as increasing proportions of people move to urban environments, the number and size of urbanized areas will also increase globally (Simpson 1993; Cohen 1995). The importance of these particularly human-dominated landscapes in controlling global biospheric processes will be magnified.

The dynamic spatial configuration resulting from human appropriation of regional landscapes can have a variety of ecological effects. A direct effect of urbanization is the alteration of local ecological processes through the modification of land cover. For example, converting desert to residential land cover alters many environmental parameters, such as soil physical and chemical properties, water availability, vegetation, and associated animal and microbial communities. Additionally, urbanization alters the spatial configuration of land-cover patterns within a region. New land-cover types are juxtaposed within increasingly fragmented native land-cover types. Changes in the structure of the landscape can have ecological effects such as modifying nutrient transport and transformation (Peterjohn and Correll 1984; Hobbs 1993) and affecting species persistence and biodiversity (Fahrig and Merriam 1985; Wu et al. 1993; Dale et al. 1994b; With and Crist 1995).

In this study we examined how urbanization has affected the landscape pattern of the central Arizona – Phoenix region by analyzing the spatial extent of urbanization and landscape structural complexity. Changes in land-use patterns are particularly important to many arid-lands that are rapidly becoming urbanized or converted to agricultural uses (Warren et al. 1996; Lal 2000). To describe the effect of urbanization on the structure of the landscape in this region the temporal change in selected spatial pattern indices was examined. The influences of a potential socio-economic driver, population size, and an environmental constraint, topography, on development of land-use patterns were also considered. We used population size as a simple surrogate for the multitude of social variables that can be important in urbanization patterns. Topographic patterns have the potential to directly limit the locations of urbanization by making some places inaccessible or unstable for buildings.

In addition to analyzing the pattern of land-use change, a spatially explicit model for simulating land-use change was developed. Our modeling objective was to simulate spatial patterns of land-use change at a temporal resolution of a single year. A model at an annual time step facilitates the future integration of land use change with ecosystem and community dynamic process models. To accomplish this we created a Markov-cellular automata derivative. In this model spatially-explicit transition probabilities of land-use changes were dependent upon land-use at a location and neighborhood influences. Similar frameworks have become popular for describing land-use change in a spatially explicit context (Turner 1987, 1988; Baker 1989; Flamm and Turner 1994; Dale et al. 1994a; Kirtland et al. 1994; Clarke et al. 1997; Wu 1998). While land-use change results from influences at a range of scales, new urban development often is extended from existing urbanized areas. Cellular automata are appropriate for modeling processes where neighborhood influences dominate system dynamics. The basis for using cellular automata is the accretive nature of human developments. In contrast to models maximizing a detailed realistic depiction of the mechanistic processes involved in urbanization (e.g., Landis 1995), a cellular automata model maximizes generality of land-use dynamics.

This model requires a down-scaling from the temporal resolution of our data, 20 years. How such scale translations are achieved has become a recent focus of ecological research (Allen and Starr 1982; O'Neill et al. 1986; Wu and Loucks 1995; Wu 1999). Because of the interdependence of time and space, we examined the effects of spatial scale on model performance by iterating the model at both a coarse and a fine scale. While much research has been conducted on scale in the analysis of patterns (Wu et al. 1997), little research has been conducted to specifically examine the role of scale in models. Thus, one of the aims of this study was to evaluate model performance at different spatial scales.

We examined the abilities of direct extrapolation as well as statistical optimization to achieve this scale translation. Our statistical optimization is an application of an inverse modeling approach to estimate model parameters. Inverse modeling provides information about a system's variables by determining the set of parameters that produce the best correspondence with data (Hilbourn and Mangel 1997). This approach is becoming widely used for deriving information from satellite imagery (Asner et al. 1998), ground water dynamics (Poeter and Hill 1997), and atmospheric mixing (Gloor et al. 2000).

Combining the analysis of patterns with simulation modeling allows for a richer understanding of land-use change in the central Arizona – Phoenix region. In this paper, we will show that patterns of urbanization can be assessed and trajectories projected both through a statistical extrapolation of the historical trend and through simulation modeling.

Study area and data description

The extent of the study area was delimited by a 68.5 km $\times$ 88.75 km boundary centered on the city of Phoenix, AZ, USA. An extensive research program, the Central Arizona – Phoenix Long Term Ecological Research (CAP–LTER), was recently established in this region to study the ecology of the urban en-

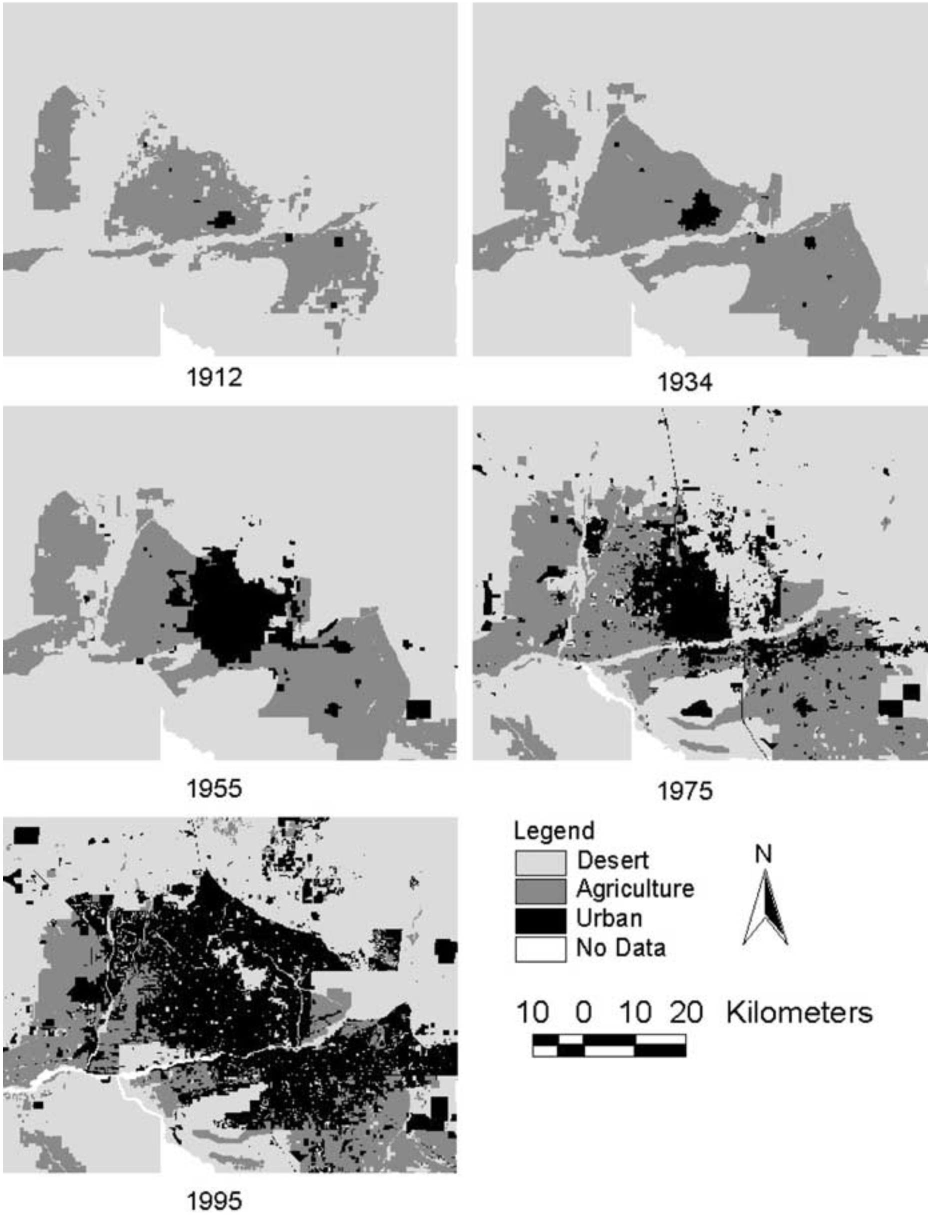

Figure 1. The historical reconstruction maps of the central Arizona region. The distribution of urban (black), agriculture (dark gray), and desert land (light gray) cover types are shown for five different years: 1912, 1934, 1955, 1975, 1995.

vironment. This region exists on a sedimentary plain surrounded by remnant mountains, some of which exist inside the currently urbanized area of central Arizona. These few remnant mountains provide essentially all the topographic heterogeneity within the central Arizona–Phoenix region. The climate of this region is characterized as hot and dry (summer daily mean maximum = 40 °C, mean annual precipitation = 18 cm). Human habitation in this region began several thousand years ago with the rise of the Hohokam civilization. The population at that time may have reached 50 000 inhabitants at its height followed by a decline due to unknown causes (Redman 1992). The central Arizona region did not again support this number of inhabitants until 1920. The current revival of the central Arizona urbanized region began as an agricultural center that tapped into ground and surface water to support continuous farming throughout

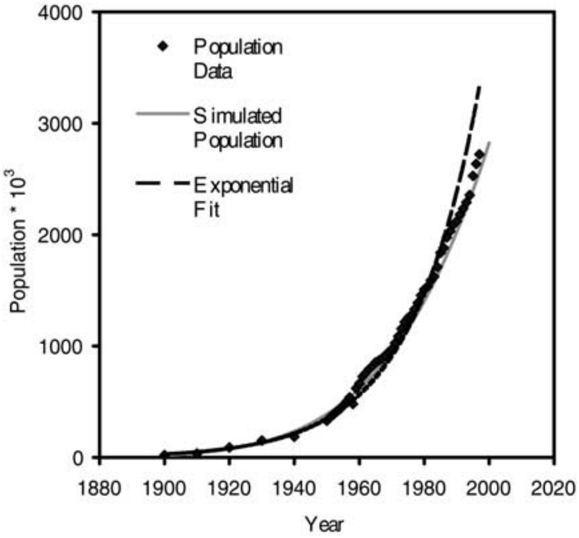

Figure 2. Population data for the central Arizona–Phoenix region (points) and the fitted simulation model of population growth (line). For comparison, a fitted exponential statistical model is also shown (dashed line).

the year (Gammage 1998). Currently this region is changing into an industrial and commercial center of the southwestern United States. As population has increased, so has the extent of urban development at the expense of agricultural and desert lands.

To analyze the change in land-use pattern, five reconstructed land-use maps from 1912, 1934, 1955, 1975, and 1995, of the central Arizona region were obtained (Knowles-Yanez et al. 1999) (Figure 1). These maps classified land use into three separate classes: urban, agriculture, and undeveloped desert; no additional classes or linear features such as roads or utility infrastructure were included. The data were compiled primarily from USGS topographic maps and land-use/land cover data, Salt River Project irrigation maps, and Maricopa Association of Government Existing Land-Use data in addition to more specialized sources. Coupled with land-use maps, topographic and census data were obtained. Topographic information was obtained from a USGS digital elevation model (DEM).

Population records were obtained from the Maricopa Association of Governments, a quasi-political organization that has documented population growth since 1912. The population record was interpolated to an annual time step with a single-state dynamical population model fitted to the data. Population change was modeled as:

$$\mathrm{dPop/dt} = \mathrm{Pop}_{t-1} + (\mathrm{NetMigration}_t + \mathrm{Birth}_t - \mathrm{Death}_t)\,\mathrm{dt},$$

where Net Migration and Birth were density-dependent functions with linearly decreasing coefficients and death was a density-dependent function with a constant coefficient. This model fit the data better than a statistically based exponential regression, and provided a more mechanistic description of population growth for extrapolation purposes (Figure 2).

Methods of landscape analysis and modeling

A series of spatial analyses was carried out on each of the land-use maps. This analysis began by rasterizing the landscape into 250 × 250 m pixels (for a total of 274 × 355 pixels). Each pixel was classified by a majority rule criterion, based on the areal distribution of land use classes on the base vector maps. The choice of grain size and aggregation method both strongly influence the results of a spatial analysis (Jelinski and Wu 1997). Because we were not addressing a specific ecological process, we chose the 250 × 250 m scale as a compromise between fine and large scale processes. Following rasterization, a statistical analysis of the landscape was conducted to examine the temporal change in the land-use pattern of the central Arizona region. Proportional area of each land-use class relative to the 1912 map provided one index of land-use change. To quantify change in landscape structural complexity we examined selected metrics for the entire landscape, including number of patches, edge density (the number of adjacencies between distinct land-use classes per hectare), fractal dimension (a measure of the structural complexity of the landscape), and contagion (a measure of landscape configuration). These metrics were computed from the rasterized land-use maps using the Fragstats software package (McGarigal and Marks 1995). This suite of spatial pattern metrics captures ecologically relevant aspects of spatial pattern such as fragmentation (number of patches and contagion), patch shape (fractal dimension), and amount of edges between contrasting patch types (edge density and contagion).

To examine relationships between potential socio-economic drivers and environmental constraints, land-use patterns were correlated with population size and topography. We compared the area classified as urbanized in each image to the interpolated population size generated by the population growth model. To examine the potential constraints of topography, we estimated the mean slope of each land-use class by overlaying the DEM onto each land-use map.

To simulate the temporal sequence of the changing land-use pattern we developed a probabilistic cellular automata simulation model. Cellular automata have been widely used for modeling spatially explicit phenomena in ecology (Hogeweg 1988). A cellular automata is a model embedded on a landscape rasterized into discrete cells. During each time step the current state of each individual cell is updated based on rules, either deterministic or probabilistic, which are dependent on the state of the focal cell and neighboring cells. The neighborhood and transition rules are defined *a priori*.

To examine the effects of spatial scale on the performance of the model, we conducted simulations at the coarse grain size used in the spatial analysis, 250 m^2 pixels, and at a finer scale of 75 m^2 pixels. To obtain the fine scale data we again rasterized the original vector maps at the finer resolution using the same procedures as described earlier.

We implemented the cellular automata in two-dimensional space on the rasterized pixels of the 1975 land-use map. Based on our analysis of the pattern of land-use change, we developed an initial set of transition rules that projected from one temporal sequence to the next at an annual time step. To account for the dual role of desert as an available area for urbanization as well as non-developable land, a political land-use class, desert park, was created. This class differentiated between protected desert parks within the urban perimeter from open desert outside the urban perimeter. As shown in the current land-use pattern, desert remnant patches are common elements on the landscape. Our inspection of the 1975 and 1995 maps showed that some of the desert remnants were urbanized during this time interval; thus not all desert patches within the city are protected. In initializing the model a random set of desert cells within the urban boundary was chosen to discriminate between the desert parks that were prevented from further change and those which were allowed to change. These transition rules allowed desert and agricultural land-use types to change to either urban or desert park, both of which are dependent upon the number of urban neighbors of the focal cell.

During each time step, the number of neighbors for each non-urban cell was calculated based on an eight-neighbor rule, which counts both diagonal and adjacent cells. Probability of a cell changing was based on the number of urban neighbors; this probability was also dependent on the state of the focal cell, which allowed for differentiation of urban and agricultural cells. Land-use change in this model occurs on a yearly time step, a finer resolution than the 20-year time step of the available data. Following the determination of land-use change probabilities, a realization of this probability was simulated. Of the sites changing, a random subset of sites were allocated to a desert remnant class. All other sites that changed were urbanized. The procedures are summarized in a flow chart for a single simulation (Figure 3).

Transition probabilities for the model were determined using both a linear interpolation method and an optimization algorithm. The linear interpolation method derived transition probabilities from an overlay of the 1975 and 1995 temporal images. The probability that a cell with *n* urban neighbors would become urbanized was computed by dividing the number of all cells with *n* urban neighbors$_{t-1}$ that became urbanized$_t$, by the total number of non-urban cells with *n* urban neighbors$_{t-1}$. To scale the transition probabilities to an annual time step, each transition probability was divided by the time interval between the images, 20 years.

Additionally, we determined transition probabilities by optimizing the model parameters to the spatial characteristics of the 1995 land-use map. To simplify this we generated a class modification function allowing agricultural to urban transition probabilities to be represented as a function of the desert to urban transition probabilities. The class modifying rule multiplies the transition probability for a cell with *n* urban neighbors by a power decay function based on the number of neighbors for the agriculture class. Based on analyses of the pattern of urbanization, agricultural land had a higher probability of forming isolated urban sites with less accretive growth. The decay function was designed to incorporate this characteristic by increasing the probability of change for agricultural cells with only a few urban neighbors while decreasing the change probability for agricultural cells with many urban neighbors.

To optimize the parameter set we used a modified genetic algorithm (GA). A GA is a generic method for identifying solutions to problems that cannot be determined analytically due to system complexity. This process optimizes a set of parameters through iterative mutation and selection of the more appropriate parameter sets (Mitchell 1996; Mitchell and Taylor 1999). This technique utilized a genome consisting of eleven

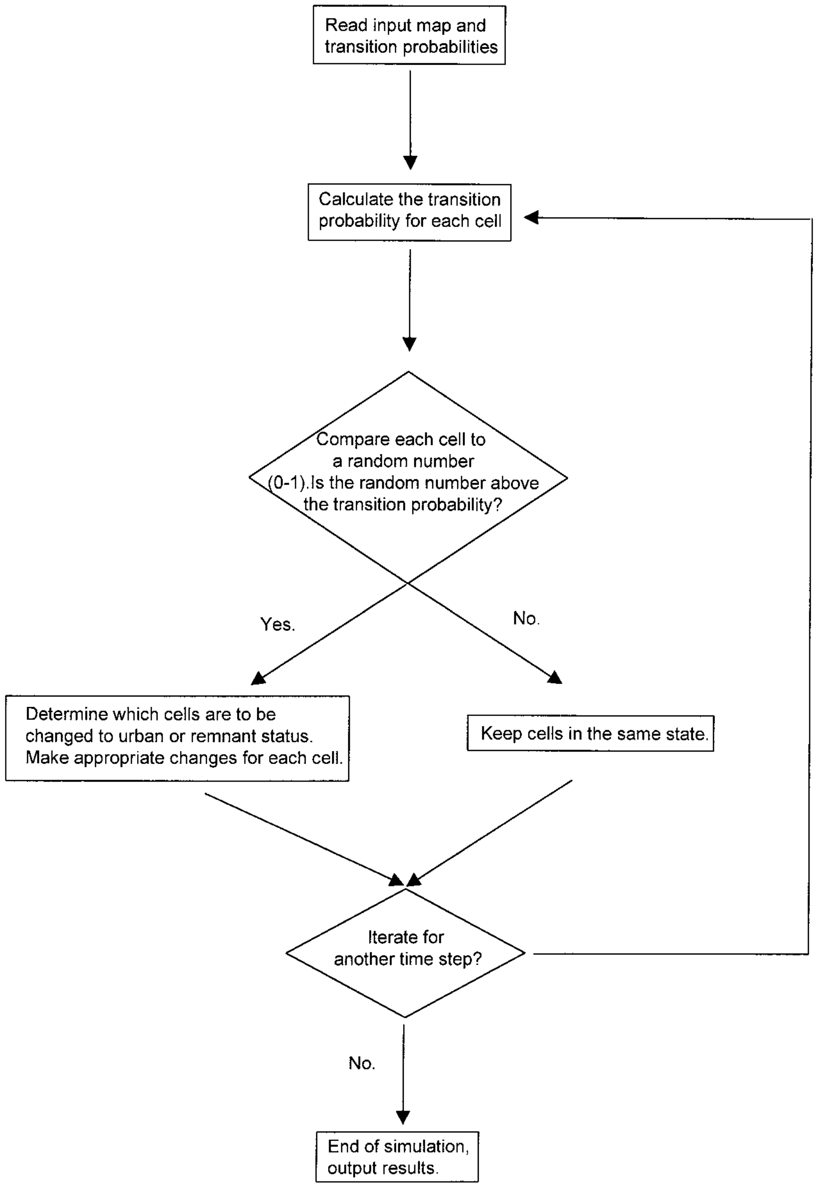

Figure 3. Flow chart for the implementation of the land use change model.

genes, nine describing the transition probabilities for the number of urban neighbors (0–8) and two describing the power decay function distinguishing agriculture and desert land use classes. The fitness of any particular genotype (parameter set) was determined by the correspondence between equally weighted indices of the model output and data. We chose the following spatial indices: patch number, edge density, fractal dimension, mean nearest neighbor, and contagion for the entire landscape, and % landscape, number of patches, edge density, fractal dimension, and mean nearest neighbor for each land-use class. Because the model is stochastic, the mean fitness from five iterations was used to estimate the fitness of a genotype. Initial transition probabilities for the optimization algorithm were determined based on a perceived graphical fitting between model output and the 1995 data set (Hilbourn and Mangel 1997). This iterative approach identified parameter sets that modeled the land use change between 1975–1995 in a visually realistic manner. Initializing the GA with this set of parameters should decrease the search time required to find optimal pa-

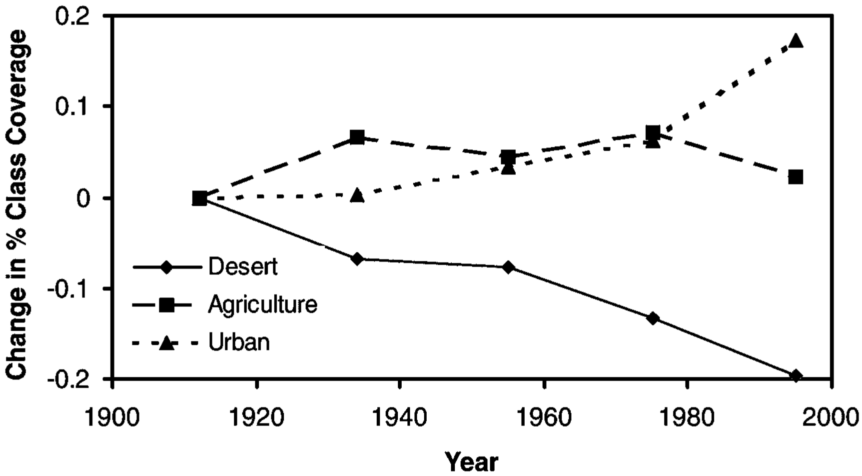

Figure 4. Change in the percent class coverage of the study region from the 1912 values.

rameter sets. The initial genotype was denoted the parent genotype, from which a single mutant offspring was generated. A single mutation was generated by altering a randomly chosen gene by ±5%. If the mean fitness of the mutant was higher than that of the parent it became the new parent from which further mutants were generated. This process was iterated for 3000 generations.

One of the problems frequently encountered by optimization techniques in multi-dimensional parameter spaces is the occurrence of relatively low-fitness local optima (Kauffman 1993). Local optima are genotypes superior to all one mutant neighbors; a ±5% change in any gene results in a genotype with a lower fitness. In general, as problem complexity increases, the number of local optima increases. To escape the local optima, periodic high mutation events were used. If the GA could not find a more fit mutant within 25 generations (the number of possible one-mutant neighbors is 24), the GA saved the current parameter set and made a 'long jump' by changing a random number of parameters by ±20%. This technique is similar to the method of simulated annealing. The new parent should be sufficiently far away in parameter space from the previous local optima whereby new optima can be found.

Comparisons between the model output and the 1995 map were made by examining the correspondence of selected spatial pattern indices. Differences between the model and data were determined through a Monte-Carlo confidence interval estimation technique (Buckland 1984). Confidence limits were derived from one hundred iterations of the model and the computation of landscape indices for each iteration. If the 1995 data pattern statistics exceeded the 95% confidence limits for values of the model output, the model projection was statistically different from the data. Otherwise the model generated a pattern exhibiting statistical similarity to the data. This method of model evaluation utilizes multiple spatial pattern indices and incorporates Monte-Carlo techniques to derive statistical estimates of performance. However, even with the increase in statistical rigor provided by the Monte-Carlo method, evaluating the ecological equivalence between the simulated pattern and the real pattern is difficult and is dependent upon the processes of interest (Turner et al. 1989).

Results

Pattern analysis

The rapid expansion of urbanized area within the central Arizona region was evident. Urban area increased exponentially since 1912 ($r^2 = 0.97$ for absolute areal coverage). Concomitant with the urban expansion was a substantial decrease in desert area. Agriculture land has exhibited a varied response since 1912, initially increasing and later decreasing back towards the 1912 extent (Figure 4). In addition to changes in the proportion of land-use types, urbanization also increased the structural complexity of the landscape (Figure 5). Fragmentation has occurred at increasing rates for both the entire landscape and for each individual land-use type.

The extent of urban area was linearly correlated with population size ($r^2 = 0.99$) (Figure 6). An

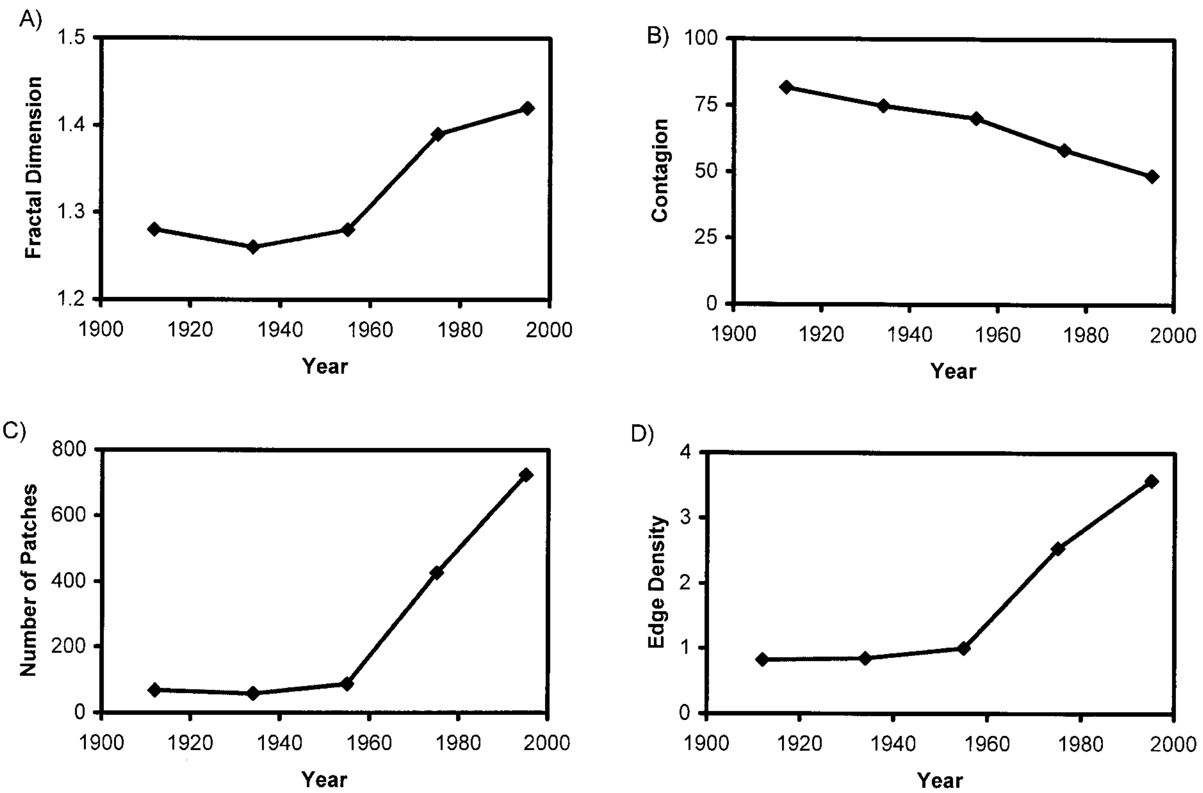

Figure 5. Changes in 4 landscape indices, (A) fractal dimension, (B) contagion, (C) number of patches, and (D) edge density (meters/hectare), for the central Arizona region from 1912 to 1995.

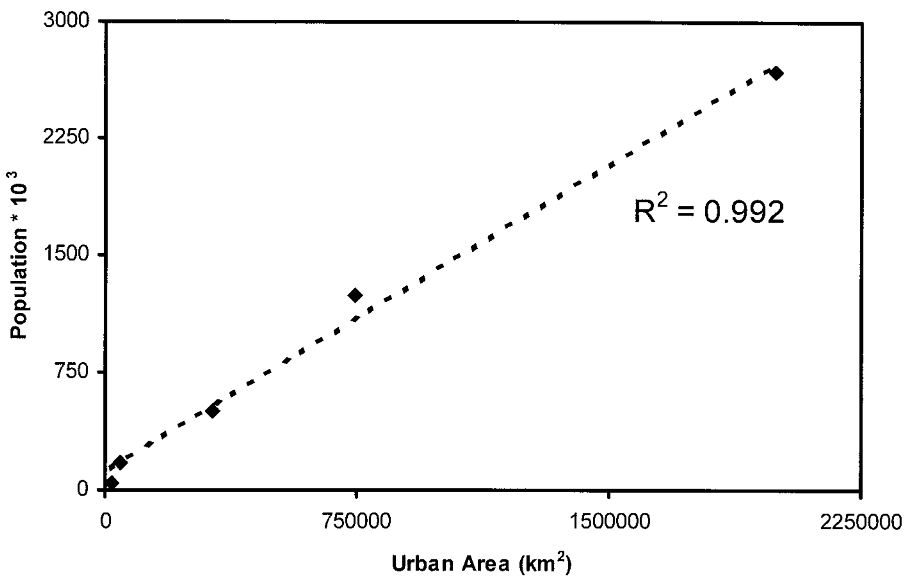

Figure 6. Correlation between urban area and interpolated population size from 1912 to 1995 in the central Arizona region.

extrapolation of the population model with the relationship between urban area and population projects that the entire study site will be urbanized by the year 2030. In contrast, the proposed environmental constraint, topography, does not seem to limit the distribution of urban expansion (Figure 7). This is shown by the net increase in the average slope of urbanized land – as the city grows out, it also climbs up.

Modeling results

A study of the genetic algorithm behavior can be useful for understanding the complexity of characterizing land-use dynamics. As expected, the fitness landscape, the fitness mapped to all locations in parameter space, is wrought with many low-fitness local optima. For the coarse-scale model a mean difference of 10% between the initial parameters and the 1995 data was observed. After 3000 generations, 50 local optima were found with a mean difference between selected 1995 data of 7.5% (max = 10.7%, min = 5.4%). The best parameter set was found at generation 2028.

The four model parameter sets: optimized parameters at a coarse scale, empirical parameters at a coarse scale, optimized parameters at a fine scale, and empirical parameters at a fine scale, differed substantially (Figure 8). Models based on the empirically derived parameters generated patterns with many disconnected urban patches. In the fine-scale model, this resulted in rapid urbanization of the entire region. This pattern resulted from a higher probability of urbanization at lower numbers of urban neighbors. The optimized parameters produced a map that did not have this problem. The differences between the empirical and optimized parameter sets did not follow a simple pattern (Figure 9). In general, the empirically derived transition probabilities were lower than the optimized set for the desert land-use class, while the opposite was true for the agriculture land-use class.

Using a Monte-Carlo confidence interval estimate allowed comparison between the optimized model parameters and the actual 1995 map for both coarse and fine scale models (Figure 10). Statistical quantification is unnecessary to determine the inappropriateness of the empirically derived parameters. The optimized parameter set for the coarse-scale model output was statistically similar to the 1995 data for a variety of landscape indices. The fine-scale model, in contrast, generated a less congruent pattern.

Using the coarse-scale model with optimized parameters a projection for an additional 20 years to the year 2015 was made (Figure 11). Projected urban extent by the land use model was less than that generated by the population-based extrapolation. This land-use change model projects that the entire study area, excepting the protected desert remnants, will be urbanized by the year 2038 (average of five model runs).

Discussion

Statistical Analysis

Urban development in the central Arizona–Phoenix region has altered the composition and configuration of the regional landscape between 1912–1995. Native desert and agricultural patch types have been displaced by urban patch types. Increases in patch shape complexity, the number of patches and edges have substantially altered this part of the Sonoran Desert landscape. These structural changes can affect ecological processes in a variety of ways. Species that cannot adequately function in edge areas will be hampered by these landscape changes, while exotic species will have more contact with the native communities potentially increasing invasion rates. In addition, fragmentation of patches can reduce landscape connectivity thereby breaking a metapopulation into several isolated populations. This may further lead to localized extinctions of floral and faunal groups. Fragmentation of the landscape may also alter transport and transformation of biotically reactive elements such as nitrogen and phosphorus.

Because information on potential corridors and barriers were not included, these results show a pattern of landscape change resulting solely from land conversion. A contrasting approach to examine the change in landscape structure would be to examine the temporal development of linear corridors and barriers, such as the road and canal network. Linear features like these can have important ecological effects, in many cases similar to those due to land-use change (Forman and Alexander 1998). Comparisons between landscape change resulting from land-use conversions and the development of linear features could provide alternative, yet complementary views of urbanization.

The correspondence between the pattern of urban development and population size suggests that population size can be used as a coarse surrogate for a suite of

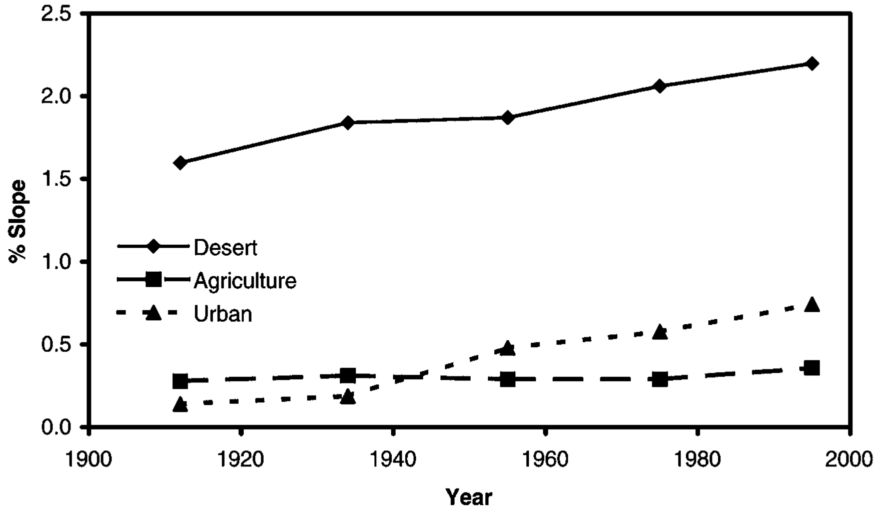

Figure 7. Mean slope for each land use class in the central Arizona region from 1912 to 1995.

socio-economic drivers in examining land-use change in the greater Phoenix, AZ region. It is likely that population dynamics of the central Arizona–Phoenix region are controlled by socio-economic factors such as job opportunities, housing costs, or educational services. While the population/urban area relationship existed for only five data points, the strength of the relationship suggests that this single variable might be an effective interface between more complex social and ecological processes. A further examination of the spatial heterogeneity of human density and its correspondence with other sociological variables should be conducted to determine the scales at which this inference is appropriate.

The failure of topography to constrain urbanization up to 1995 was surprising. In several other regions topography has been shown to be a strong determinant of land-use patterns (Chomitz and Gray 1995; Wear and Bolstad 1998) The topographic-urbanization analysis suggested that urbanization proceeded fastest on the flat valley floor. As topographically variable land became surrounded by urbanized land, the pressure to develop this land resulted in an upward encroachment of urbanization. Future studies examining this relationship in multiple regions could to clarify the generality of this relationship and factors that might regulate it.

The potential effect of errors in generating classified maps should be considered when interpreting the results of a spatial analysis. Reconstructing land-use patterns nearly always results in errors that are not readily quantified. Sources of error may include temporal aggregation (data from some sources were collected before or after the specified date), land-use classification (areas such as agricultural lands left fallow for an indeterminate number of years necessitated some subjective decisions), and rasterization (the modifiable areal unit problem; Jelinski and Wu 1996). However, these maps are the best available reconstruction of the central Arizona region and we believe the pattern of urbanization shown in these data are accurate at the scale used in this analysis.

Modeling analysis

The modeling approach we implemented generated a successful coarse-scale simulation of many statistical properties of the most recent land-use data available. Our model differs from previous models (e.g., Turner 1987, 1988; Flamm and Turner 1994) primarily in our consideration of time. Human development generally proceeds in an accretive manner – new urban area is built near existing urban sites. However, land-use maps at decadal time intervals often show urban development occurring at locations that had no urban neighbors on the previous map. This is one of the fundamental problems in our translating of spatio-temporal scales. To solve this problem while still using a model time step equal to the data interval, one may choose the site with the highest probability for transition, change that site, then recompute land-use change probabilities for the entire landscape. The time interval is completed when a set number of transitions occurs. This number could be obtained from data or from a hypothetical scenario. In contrast, we explic-

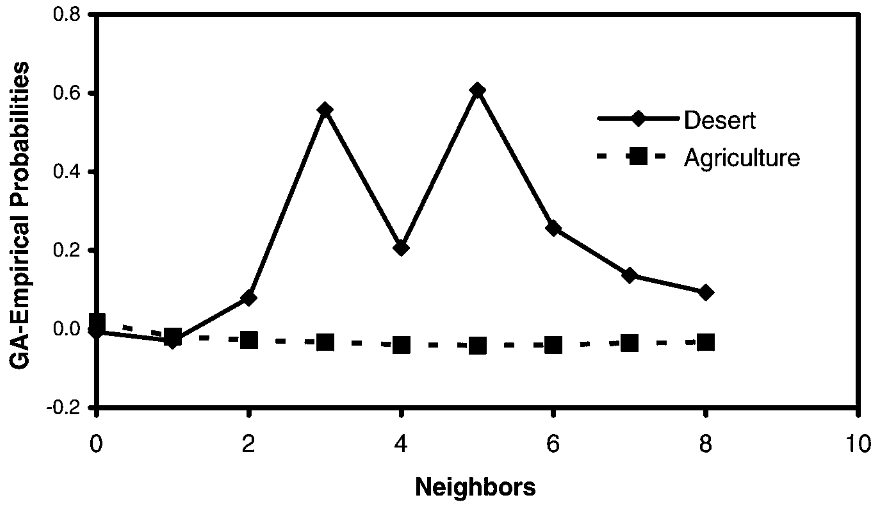

Figure 8. Difference between the empirically derived and genetic algorithm (GA) derived parameter sets for both desert and agriculture land use classes of the coarse scale model based on the number of urban neighbors.

itly modeled land-use change at a single-year interval. Downscaling time served two functions: it provided a more mechanistic interpretation of the model and it provided a hypothesis for the intervening time steps. Another utility of this temporal interpolation is that it facilitates future integration between this model and ecosystem or community models also implemented at an annual time scale.

The methods used to achieve temporal downscaling produced distinct results. The best model was not based on the empirically derived transition probabilities. This failure of the empirical approach highlights problems of translating between scales (Wu 1999). For our objectives a linear extrapolation between scales was inappropriate. This was expected based on our characterization of the neighborhood as only the eight adjacent sites. Because the growth rate of urbanization during the twenty-year interval was larger than our pixel size, an empirical measure of urbanization between 1975 and 1995 shows many cells becoming urbanized which did not have any previous urban neighbors. Examining the differences between the empirical parameter set and the optimized set suggests that no simple relationship exists between these two parameter sets – the empirical approach was not helpful in downscaling. Alternative spatial frameworks that might allow for easier downscaling include a polygon based approach (Flamm and Turner 1994; Landis 1995), a hybrid polygon–raster approach (Wallin et al. 1994) and a hierarchical approach.

The scale of resolution affected the ability of the model to simulate land use change. Previously, increased spatial resolution has been shown to both increase and decrease the performance of models (Ciret and Henderson-Sellers 1989). In our study, the coarse-scale model was better able to capture the dynamics occurring between 1975–1995. As detail is increased, the likelihood of errors also increases (Costanza and Maxwell 1994). In contrast to a fundamental spatial resolution of land-use change, a dynamic relationship between temporal and spatial scale is more plausible. Within a given unit of time particularly sized patches of land, described by a mean and variance of patch sizes, become urbanized – longer time intervals correspond to larger areas of urban expansion. This amount of urban expansion should be the appropriate spatial resolution for the temporal resolution used.

By using an inverse modeling approach to model spatial patterns, the resulting parameters can be ecologically interpreted. The better performance of the coarse-scale model suggests that this scale is more appropriate for approximating land use changes occurring over a single year. Additionally, the strength of accretive growth is approximated by the model parameters at the coarse spatio-temporal scale. In contrast, due to scale translation, the empirically derived parameters do not reproduce the spatial pattern of land use change and are not ecologically interpretable. However, because of our limited search of the infinite parameter space (nine dimensions of real values), more efficient characterizations of the fitness land-

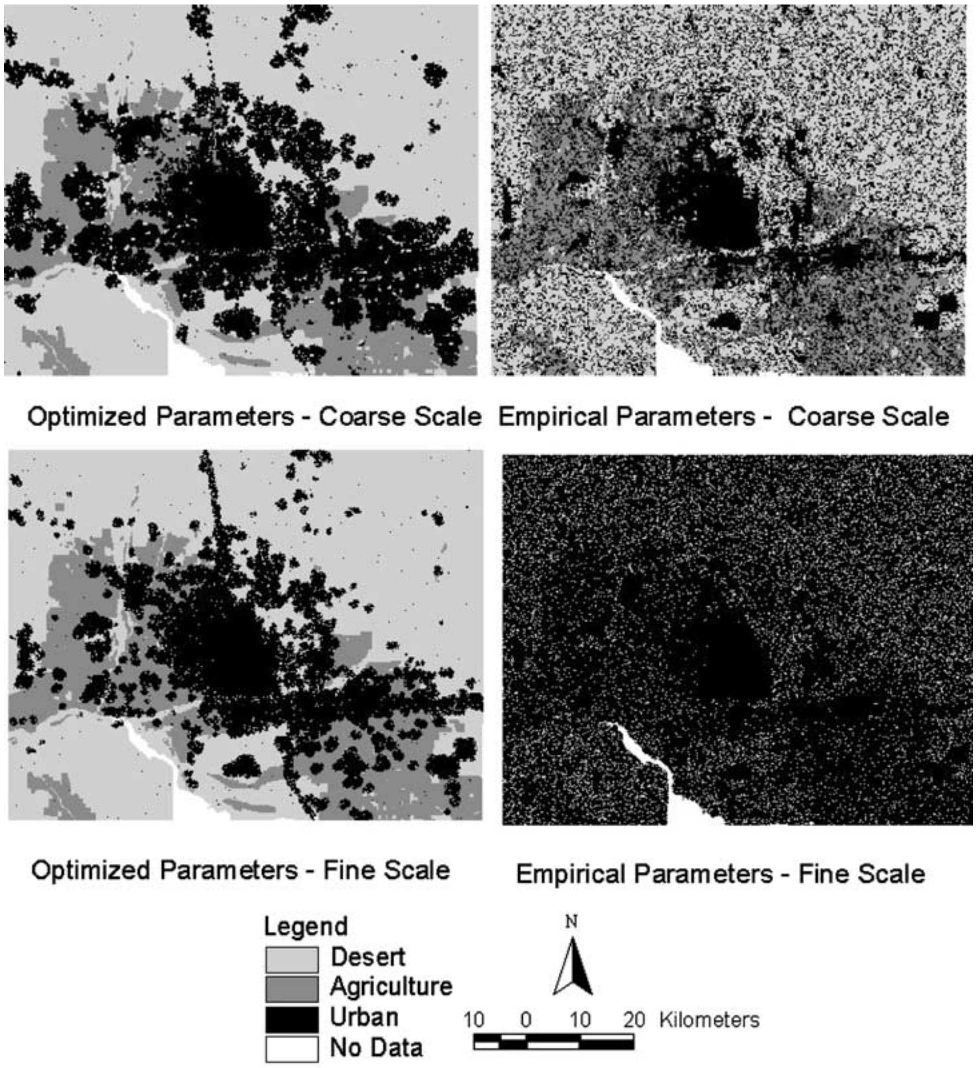

Figure 9. Results from one run of the simulation to the year 1995. All simulations were based on the 1975 data. Urban (black), agriculture (dark gray), and desert (light gray) land cover types are shown.

scape will increase the strength of applying inverse modeling to landscape dynamics.

The evaluation of a model is dependent upon the validation technique used (Rykiel 1996). In this instance, we examined the ability of the model to recreate the spatial pattern of land use change. An alternative technique is a direct pixel by pixel comparison between the simulated and real maps. For ecological processes, the absolute locations of landscape elements is likely to be less important than the overall pattern in the landscape. The spatial metrics we used to evaluate the model should be relevant to a variety of ecological processes, though any particular process will be differentially sensitive to specific aspects of spatial pattern. Because of our emphasis on the spatial pattern of landscape elements and our general modeling framework, a pixel by pixel validation technique would not have properly evaluated the model's performance. While the model succeeded in reproducing many aspects of the spatial pattern of urbanization, the exact locations of many the landscape elements were reproduced less well. Still, the relationship between locational and pattern validation of landscape-change models remains an interesting question.

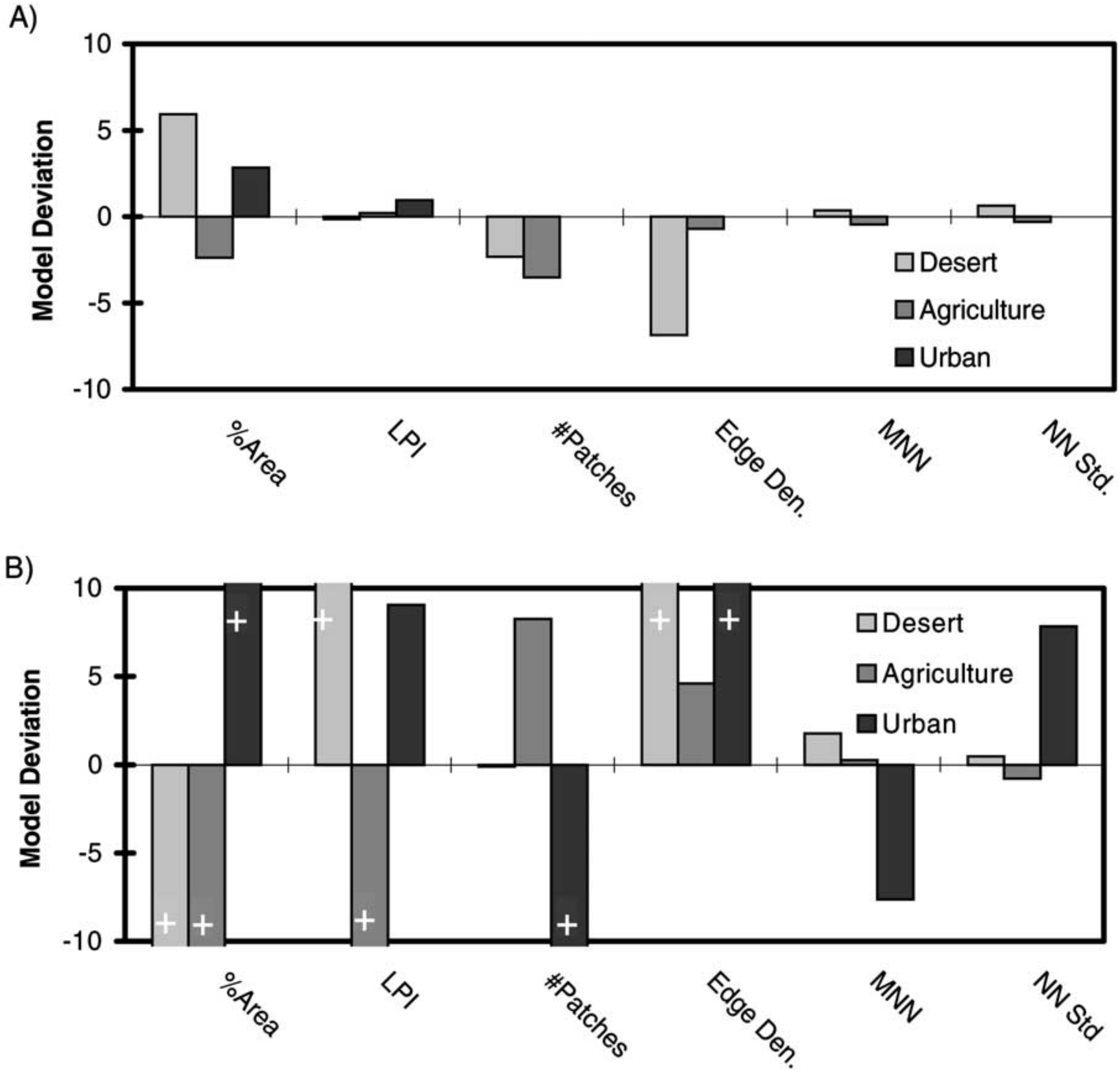

Figure 10. Deviation between the 1995 data and the model derived confidence intervals for selected class indices for the (A) coarse scale models, and (B) fine scale model. Units scaled to allow 95% confidence intervals to be represented by ± 1.0. Categories represent % Area – percent landscape area, LPI – largest patch index, #Patches – number of patches, Edge Den. – edge density, MNN – mean nearest neighbor, NN Std. – nearest neighbor standard deviation. In (B), + denotes indices which extend beyond ± 10 confidence interval units, this allows for both graphs to have the same scale and for the confidence interval band to be resolved.

Synthesis

Because human-dominated processes are probabilistic and contingent a model such as the one presented here allows examination of the entire class of land use patterns sharing the statistical properties with the current data. The ecological response to different realizations of pattern in a statistically similar landscape could be examined based on multiple realizations of the model. Alternative spatial patterns can also be generated through parameter adjustment. These alternatives can be used to find configurations of the landscape that reduce the impact of urbanization and to identify critical features of landscape pattern for maintenance of ecological processes. Potential future patterns of landscape structure can be examined by projecting the land-use pattern beyond the currently available data. The difference between the land use change

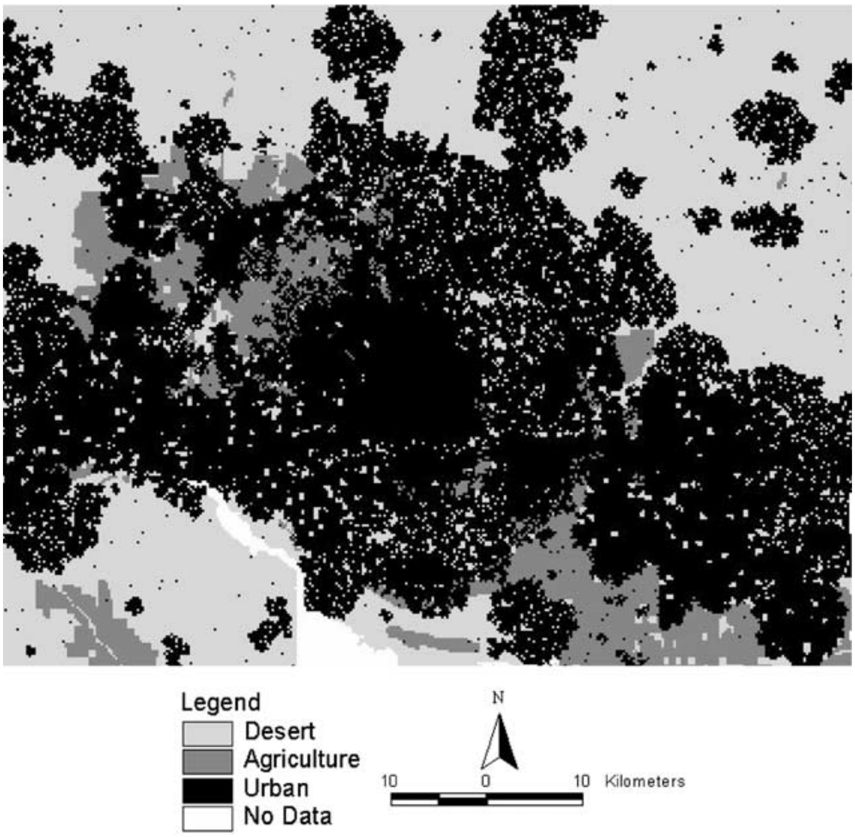

Figure 11. Model projection of greater Phoenix, AZ urbanization patterns for the year 2015. This projection is derived from the coarse grain, optimized model initialized from the 1975 data.

model and the projected population – urban area relationship was attributable to the static nature of the transition probabilities. Dynamic land-use transition probabilities would consider of the non-linear increase in human population and the correlated non-linear increase in urban extent. Based on two independent projections, if the current trend in population growth or land-change continues, almost the entire study area will be urbanized in only a few decades.

The cellular automata modeling framework is a useful simplification which requires minimal information. To implement this model we used only the mapped distribution of land use. If more information were to be used, such as the spatial distribution of socio-economic variables as well as road and utility infrastructure, alternative modeling approaches might be more appropriate. A semi-Markov model that incorporates information at a variety of scales is one powerful alternative (Turner et al. 1996; Wear et al. 1996; Wear and Bolstad 1998). However, the physical infrastructure of a city is a dynamic part of the urbanization process; i.e. the spatial patterns of roads and utilities change simultaneously with land-use change. This study shows that the simplest spatial modeling framework is able to realistically simulate many aspects of land-use change in this region.

The ecological effects of urbanization are not easily determined. Urbanization in the desert results in two broad types of change: localized changes in land cover and landscape structural change. Localized effects include increased water availability (irrigation of lawns), species changes (changes in vegetation type, tropic level changes), primary productivity (both localized increases and decreases), as well as physical disturbance and habitat engineering (housing structures, civil infrastructure). The modified genetic algorithm land-use change model can create a spatial framework for describing the pattern of urbanization. This framework can be linked to models of ecological processes to understand how ecosystems respond to the accumulation of site-specific land-use change at a regional scale.

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