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# Using a cellular automaton model to forecast the effects of urban growth on habitat pattern in southern California

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**Abstract**

Land use change is one of the most important anthropogenic factors affecting terrestrial ecosystems, causing habitat loss, fragmentation, and interactions with other components of global change, such as biological invasions of non-native species. In southern California, population growth and economic expansion are the primary drivers of land use change, and the population is expected to double in 40 years. Although directly adjacent to the region's largest metropolitan area, the Santa Monica Mountains National Recreation Area (SMMNRA) remains mostly undeveloped, with 50% of the area protected as parkland. In this study, a cellular automaton (CA) model was calibrated using historical growth patterns in the region, and used to forecast three scenarios of urban growth in the SMMNRA from 2000 to 2050, with development prohibited on slopes greater than 25%, 30%, and 60% slope. Habitat pattern and extent under these scenarios was assessed using several landscape metrics, then compared to results from a GIS overlay model developed for the same region. The CA model predicted urbanization to increase from 11% of the landscape in 2000 to 26%, 35%, and 47% in 2050, respectively, for the three slope scenarios. In 2000, the majority of vegetation constituted one large, interconnected patch. With development prohibited beyond 25% and 30% slope, this patch will become, by 2050, increasingly perforated, but should stay relatively intact. However, if growth is permitted up to 60% slope, the patch breaks apart, resulting in a shift in spatial pattern dynamics on the landscape (as reflected by other landscape metrics). General growth patterns predicted by the GIS overlay model resembled those generated by the CA, but the CA model produced more patches and edge in the landscape. Because it is temporally explicit, the CA model was able to capture non-linear, emergent behavior and a phase transition in the type of growth occurring in the landscape that was not apparent in the GIS overlay predictions.


*Keywords:* Cellular automata; Habitat pattern; Landscape model; Southern California; Santa Monica Mountains; Urban growth

## 1. Introduction

Land use change is one of the most important anthropogenic factors affecting terrestrial ecosystems,

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not only because of direct habitat loss and fragmentation, but also because it interacts with many other components of global change, such as altered fire regimes and biological invasions of non-native species (Wilcox and Murphy, 1985; Noss, 1991; Soule et al., 1992; Vitousek, 1994; McGarigal and Cushman, 2002). Increased fire frequency has been attributed to ignitions at the urban–wildland interface (Keeley and Fotheringham, 2003), and biological invasions of non-native grasses can disperse out of urban areas, potentially displacing native grasslands and interacting with natural fire regimes, creating feedbacks that further increase fire frequency (D'Antonio and Vitousek, 1992).

In southern California, population growth and economic expansion are the primary drivers of land use change. Growth patterns have been fragmented, with a decentralized network of 177 interconnected communities spreading into the region's native, fire-prone shrublands (Scott, 1995). The human population in the region (16.7 million) is expected to double in the next 40 years. The great variety of physical environments in southern California supports high levels of biological diversity, as well as a large number of endemic and endangered plant and animal species, and the region is recognized as a global biodiversity 'hotspot' (Dobson et al., 1997). However, large expanses of native shrub vegetation are being lost and fragmented, and remnant stands of the coastal sage scrub plant community now provide some of the last remaining habitat for a number of endangered species (Davis et al., 1994).

A number of strategies are being developed to preserve habitat for threatened and endangered species in southern California and other regions experiencing rapid urban growth. One strategy is to convince planners to adopt the paradigm of ''smart growth'', which seeks to channel new development into existing urban areas. In addition, California's Natural Community Conservation Planning (NCCP) program was developed in 1991 to identify land for conservation in southern California that functions as critical habitat for multiple species. The secure way to preserve this habitat is for agencies such as the National Park Service to acquire the land for protection. However, high land values and competition for funding makes land acquisition challenging (Stumpf, 2000). Therefore, it is necessary to prioritize the most critical areas for protection by determining which of the regions with the highest biological value are also most at risk. Models that forecast where urban growth is likely to occur can be used to determine which of these areas are most likely to be developed.

Urban modeling became widespread in the 1960s (Wilson, 1974; Batty, 1981), and recent technological innovations (such as remote sensing and GIS) have helped the development of more sophisticated approaches that can simulate future development scenarios. However, some lack of success in Urban Growth Modeling has been attributed to incomplete understanding of the urban system (Rakodi, 2001). Because cities are open and non-linear systems, many newer modeling alternatives are founded upon complex systems theory (e.g., Gar-On Yeh and Li, 2003)

One distinction that should be considered when choosing an Urban Growth Model is the difference between complexity and complicatedness. Clarke (2004) notes that while models with multiple components and parameter requirements may be complicated, complex systems behavior can be produced with simple models, and multiple variables do not necessarily create complexity. Instead, complexity is created by non-linear behavior (Malanson, 1999). Although the science of complexity has sometimes been dismissed as lacking unification (Horgan, 1995), general properties inherent to complex systems, such as self-organization, adaptation, emergent behavior, behavioral phase changes, and surprising behavior, are widely agreed upon, and have been used to characterize the process of urban growth (Cheng et al., 2003; Batty, 1998; Couclelis, 2002).

One class of complex systems models, cellular automata (CA), has gained attention for simulating urban development (Gar-On Yeh and Li, 2003; Torrens, 2003). Although urbanization is also a top-down phenomenon (governed by policy decisions, environmental constraints, and societal trends), land development tends to spread as a bottom-up process in which broad-scale patterns, such as growth booms, emerge out of local interactions—a behavior that is well captured in CA. CA models operate on an array of identically programmed automata, or cells that exist in one of a finite number of states. Through repeated application of behavior rules, macroscale behavior emerges because of interactions between individual

cells and their neighbors (Park and Wagner, 1997; Clarke and Gaydos, 1998). CA models are also useful for simulating urban systems because they are inherently spatial, directly compatible with raster GIS (Couclelis, 2002), and temporally dynamic, with state transitions intuitively mimicking the temporal dynamics of urban change.

Detailed models that account for more of the complexity (and complicatedness) of the human–environment system also require sufficient and accurate data. Including more variables reduces the number of assumptions needed to apply the model, but also contributes to the model's uncertainty. Probably the most critical component for choosing a model is its ability to address the specific analytical needs of the project in question. The objective for choosing an Urban Growth Model for this research was to determine how future urbanization would affect the extent and spatial pattern of habitat in the Santa Monica Mountains. Because urban development is causing increased fire ignition frequency at the wildland urban interface in this region, we also required a model whose output would be compatible with a landscape-scale simulation model of fire disturbance and succession (LANDIS, He and Mladenoff, 1999), which will be the focus of future research.

A range of approaches was considered based on criteria including: data needed, data available, data compatibility, spatial/temporal scale, model complexity, model assumptions, and model realism. After ruling out other approaches (e.g., Gunter et al., 2000; Wickham et al., 2000; Jenerette and Wu, 2001), the choice was narrowed to the Clarke Urban Growth Model (UGM) (Clarke and Gaydos, 1998) and a site suitability-based GIS overlay model (the ''GIS overlay model'') that had already been developed for the Santa Monica Mountains (Swenson and Franklin (2000). Both models are driven by spatial influences on urbanization, such as slope and proximity to roads and existing infrastructure. Although the GIS overlay model had already been developed, the UGM was selected because it is a spatially and temporally explicit model capable of simulating alternate growth scenarios using a rigorous calibration process based on a performance metric.

Because of the steep terrain in the Santa Monica Mountains, most existing urbanization has occurred along canyon bottoms (Stralberg, 2000). However, increased demand for housing is putting pressure on developers to build on steeper slopes. Management agencies have recognized the potential for using slope restrictions to confine development to more desirable locations. Therefore, the UGM was used to forecast three scenarios of urban growth from 2000 to 2050, with development prohibited beyond 25%, 30%, and 60% slope. The effect of urbanization on the extent and spatial pattern of habitat was quantified over time for these scenarios using several landscape metrics. The UGM projections were also generally compared to those of the GIS overlay model to explore similarities in results between these fundamentally different approaches. Because the delineation of developed land was binary in this research, the term ''urban'' will be used to refer to developed land cover, regardless of the land use. Likewise, all non-urbanized areas in the landscape are considered wildland consisting of native vegetated habitat.

## 2. Methods

### 2.1. Study area

The Santa Monica Mountain National Recreation Area (SMMNRA) is an administrative unit that encompasses approximately 60,000 ha of land bordered to the south by the Pacific Ocean, to the north by suburban communities, to the west by agriculture and rural communities, and to the east by the Los Angeles metropolitan area (Fig. 1). The Santa Monica Mountains are a rugged east–west trending range with a Mediterranean climate, characterized by cool, wet winters, and warm, dry summers. The SMMNRA protects the largest expanse of coastal Mediterranean ecosystem in the United States, and supports tremendous biodiversity with approximately 1000 different plant species falling into at least nine distinct plant communities (Dale, 2000). The major vegetation types in the mountains include chaparral (approximately 60% of the study area); coastal sage scrub (approximately 25% of the study area) on low-elevation coastal slopes; oak woodland on northern slopes with deep soils; riparian woodland; and (primarily exotic) grasslands (Radtke et al., 1982). The mountains are also home to 50 mammal, 384 bird, and 36 herpetofauna species. The SMMNRA has an

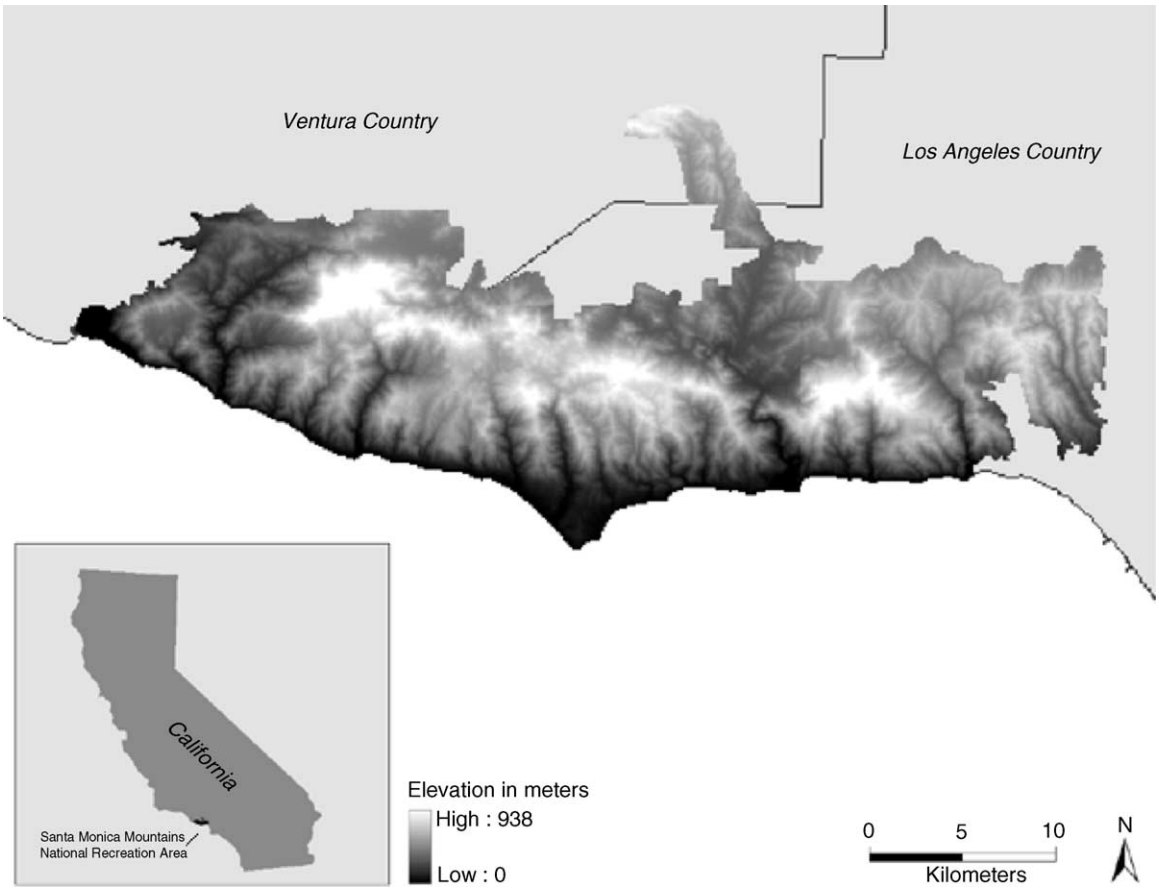


Fig. 1. The Santa Monica Mountains in southern California.

active fire regime characteristic of Mediterranean-type ecosystems. More than 28,000 hectares have burned since 1990, and some areas have burned up to eight times over the last century; and during that time period, most fire ignitions have been human-caused. Therefore, despite fire suppression efforts, fire-related losses and expenditures are steadily increasing due to urban expansion into the hazardous wildland environment (Keeley, 2002).

Approximately half of the land within the administrative boundary is publicly owned and protected, and jurisdiction is shared between diverse governmental entities including California State Parks, the National Park Service, the city of Malibu, Ventura and Los Angeles Counties, as well as local public parklands. Of the approximately 50% of the land that is privately owned, about 25% is developed. Based on 2000 census data, residents of the SMMNRA are generally wealthy with median annual incomes more than US$ 100,000, and many of the residences are retirement or second homes. However, commercial and residential development is increasing. Approximately 6% of the nation's total population lives within an hour drive of the park.

The California Coastal Commission (CCC), which has permit authority for the majority of the study area, conducted a comprehensive analysis of land development patterns and permitting in the Santa Monica Mountains from 1975 to 1996. Development approved in the land use plans for the region would allow current urban land to double. The report identified constraints and negative cumulative impacts that could result from this future urban development. Among the areas considered sensitive, from which development should

Table 1
Sequential growth types and controlling coefficients in the UGM, after Jantz et al. (2003)

| Growth cycle order | Growth type | Controlling coefficient | Description |
|---|---|---|---|
| 1 | Spontaneous | Dispersion, slope resistance | Randomly selects cells for new growth |
| 2 | Diffusive | Breed, slope resistance | Expansion from cells urbanized in spontaneous growth |
| 3 | Organic | Spread, slope resistance | Expansion from existing settlements |
| 4 | Road-influenced | Road gravity, dispersion, breed, and slope resistance | Growth along transportation network |

be ‘‘constrained’’, were those with slopes greater than 30% for Ventura County and greater than 25% for LA County.

### 2.2. The Urban Growth Model (UGM)

The UGM is a CA model that predicts the spatial extent of urban expansion based on repeated application of growth rules and weighted probabilities that promote or inhibit growth. As with other CA models, the UGM predictions begin with a set of initial conditions describing the current state of the system, including slope, urban extent, transportation, and portions of the landscape that are excluded from development. The model operates through a series of nested loops in which the outer loop retains cumulative statistics for the growth history, and the inner loop executes growth rules for a single year. Four types of growth occur in the model, and the probabilities of these growth types occurring are a function of five growth control coefficients that affect the behavior of the system (Table 1). The growth types are applied sequentially, one cell at a time, and the entire grid is updated after annual iterations to form the basis for growth in the succeeding year. First, ‘‘spontaneous growth’’ occurs, which is the random selection and urbanization of isolated cells; next, ‘‘diffusive growth’’ determines whether those cells just urbanized from spontaneous growth will become new urban centers; ‘‘organic growth’’ is the most common type of growth, and simulates expansion from existing settlements; and ‘‘road-influenced growth’’ is based on the tendency for growth to occur near transportation corridors.

The growth control coefficients have values that can range from 0 to 100, and each of their initial values are derived through model calibration. These values evolve during the course of model runs as a function of a second hierarchy of growth rules that cause the model to ‘‘self-modify’’. The self-modification rules, established a priori, control the rate of growth to more realistically simulate how urban development occurs over time (e.g., to prevent linear growth and to simulate the S-curve-type growth rate typical of urban expansion). Specifically, critical threshold values are set so that unusually high or low growth rates lead to either a slowing down or a speeding up of urban expansion through slight alteration of the dispersion, spread, and breed growth-control parameters.

In addition, although growth is generally more likely to occur on flatter terrain than on steep slopes, as the percentage of land available for development decreases, the model will decrease the slope resistance coefficient based on a slope sensitivity parameter established a priori, allowing growth to occur on steeper terrain. Furthermore, the ‘‘critical slope threshold’’ specifies a degree of slope beyond which growth cannot occur.

### 2.3. UGM data preparation

The calibration of the UGM statistically and spatially associates future urban growth with historic growth patterns in the study area; therefore, four data layers of historical urban extent and two data layers of road networks were created as model inputs. To create the historical data set, aerial photographs of the entire study area for 1947 and 1976/1977 were acquired from the University of California Santa Barbara (UCSB) Map and Image Library (MIL), and digital orthorectified quarter quadrangles (DOQQs) for 1989 and 2000 were acquired from the U.S. Geological Survey (via the National Park Service) (Table 2). After scanning all the airphotos, the 1976/1977 photos were registered to the 1989 DOQQ, and the 1947 photos were registered to the 1976/1977 photos. Due to the

Table 2
Spatial data used to calibrate the UGM

| Data | Source | Resolution/scale | Date |
|---|---|---|---|
| Airphotos | UCSB/MIL[a] | 1:24000 | 1947 |
| Airphotos | UCSB/MIL | 1:24000 | 1976/1977 |
| DOQQs[b] | USGS/NPS[c] | 1:12000/1 m | 1989 |
| DOQQs | USGS/NPS | 1:12000/1 m | 2000 |
| Roads | NPS/Thomas Bros. | 1:24000 | Current to 2001 |
| DEM | USGS/NPS | 10 m | N/A |
| Land use | SCAG[d] | 1:24000 | 1990/1993 |
| Property tracts | NPS | 1:24000 | 2002 |

[a] University of California, Santa Barbara Map and Imagery Library.
[b] Digital orthophoto quarter quads.
[c] United States Geological Survey/National Park Service.
[d] Southern California Association of Governments.

mountainous terrain in the Santa Monica Mountains, ERDAS Imagine/Orthobase™ (ERDAS, 1997) was chosen to register the images because the software corrects for terrain displacement using a digital elevation model (DEM).

The airphotos were mosaicked, and urban extent was delineated for all four dates using onscreen digitizing. To begin the digitizing process, all areas classified as urban (Anderson level I, Anderson et al., 1976) in the 1993 land use coverage (Table 2) were extracted and overlaid on the 2000 DOQQ. To create the urban extent layer for 2000, the land use coverage was then edited based on airphoto interpretation (e.g., additional urban areas were added, and erroneously classified urban areas were deleted). All land use types with built structures, as well as golf courses, were delineated as urban, and roads within urban areas were subsumed into the urban extent. Otherwise, the roads were part of the separate transportation layers. After creating the 2000 layer, urban areas were then successively deleted to create urban extent layers for each of the earlier dates (1947 and 2000 shown in Fig. 2).

The original transportation data were created by Thomas Brothers, including roads from 1990 (Los Angeles County) and 1995 (Ventura County). The National Park Service updated this coverage to include roads as current as 2001. To create the 1947 coverage, roads were deleted from the 2001 coverage using heads-up digitizing and airphoto interpretation of the 1947 image mosaic (Fig. 2).

Other data created for model input included a layer of slope in percentage, derived from a DEM, and a binary "excluded land" layer to specify areas prohibited from development. A property-ownership-coverage (Table 2) was used to select all protected parklands (regardless of ownership), and then convert those areas into a layer of (100%) excluded land (Fig. 2). Although land is protected under diverse ownership, it exists within the administrative boundaries of the National Recreation Area owned by the NPS. Together with the Santa Monica Mountains Conservancy, the NPS is working to protect more land. Therefore, no development was anticipated in these excluded areas over the next 50 years.

Because the UGM requires *.gif images as input, and because the calibration of the model occurred in four phases at different resolutions, all coverages were converted to grids at 240 m, 120 m, 60 m, and 30 m; then they were transformed into *.gif images by first converting them to *.tifs in ARC/INFO™.

### 2.4. UGM calibration and predictions

The "brute force" calibration process for the UGM is based on a combination of Monte Carlo techniques and hindcasting, and is described extensively elsewhere (e.g., Clarke and Gaydos, 1998; Silva and Clarke, 2002). Hindcasting is a method used to explain patterns observed up to the time and place where the original data were gathered (Morrison et al., 1992). In the case of the UGM, hindcasting fits simulated data to historical data with the assumption that calibrating the model to the growth patterns in the past can be used to reasonably forecast into that regions' future (Clarke et al., 1997). The key to this process involves systematic manipulation of the five growth control coefficients (described previously, Table 1) to find the unique combination of values that best fits the simulated to the observed historical data.

Although improving the calibration process has been the subject of recent work (e.g., Yang and Lo, 2003; Goldstein, 2004), the methods used for this research followed the standard procedures as described in Clarke and Gaydos (1998). The calibration occurred in four separate phases that iteratively searched for the best coefficient combination by stepping through the calibration space (all of the $101^5$ possible combinations of the coefficients) using progressively smaller ranges of values at progressively

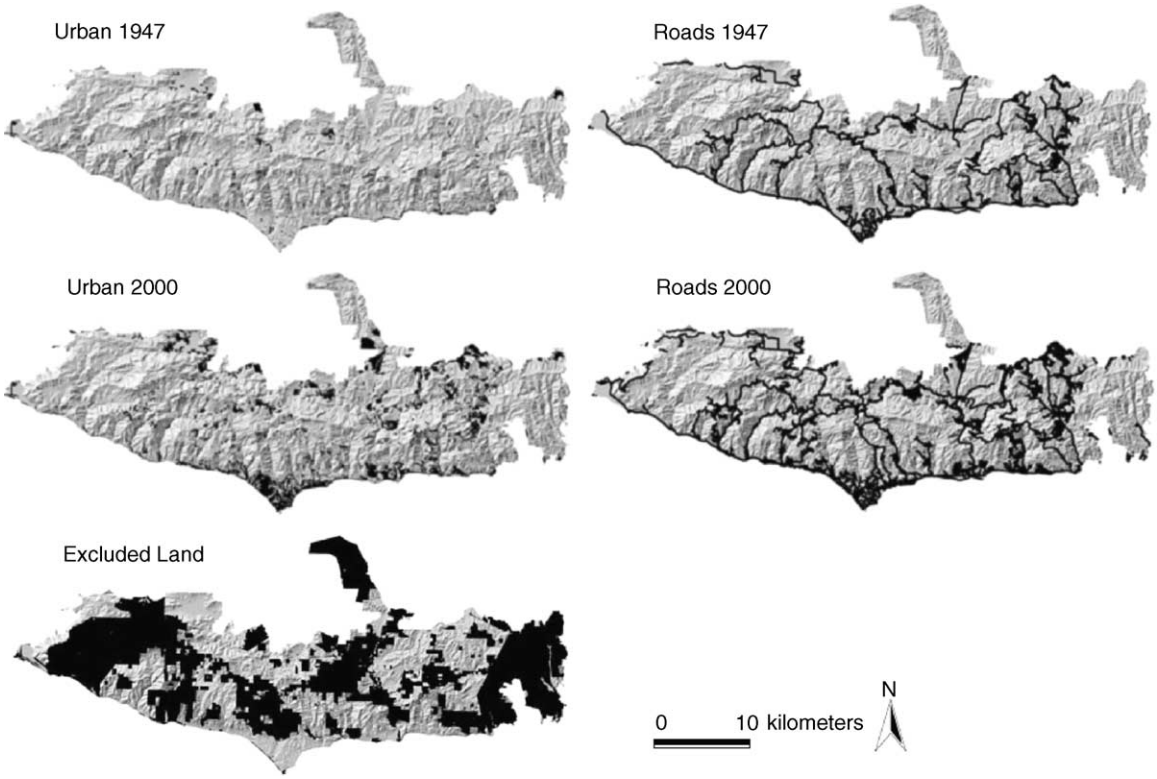


Fig. 2. Input data layers for the Urban Growth Model: urban development and road networks in 1947 and 2000, and land excluded from development (in black).

finer resolutions. As the model iterated through these combinations of coefficient values, the simulated growth was compared to the growth in the years for which the historic data sets were available using a number of Pearson $r^2$ statistics. These statistics helped to determine the goodness of fit between the actual and predicted data by comparing, for example, the number of urban pixels; number of edges (urban adjacent to non-urban); number of separate clusters (calculated with an image processing routine that erodes urban cluster edges until all separate blobs collapse into one pixel, and then counting those pixels (Clarke and Gaydos, 1998); spatial correspondence was determined through a modified Lee–Sallee shape index (the ratio of intersection over the union).

The coarsest phase of calibration was initiated with the full range of possible values (0–100) for each coefficient, stepping through the calibration space at increments of 25, at a resolution of 240 m. An automated calibration routine (see Clarke and Gaydos, 1998; Silva and Clarke, 2002) was used to run multiple simulations from 1947 to 2000 (the earliest through the latest dates of historic data) using each possible ($5^5$) combination of coefficients (e.g., each of the five coefficients had five possible values when stepping from 0 to 100 at increments of 25). Simulations for each coefficient combination were repeated for four Monte Carlo iterations so that the statistical tests could be averaged, allowing confidence limits to be placed on predicted spatial patterns. The method for selecting the best range of coefficients to use for each successive phase of the calibration was to sort the statistics output log file based on three measures: the product (all of the fit scores multiplied together), the Lee–Sallee shape index, and the modeled urbanization for the final year/actual urbanization for the final year. The top 10 scores for these measures were compared, and the coefficient combinations that most frequently produced the maximum scores were used to initialize each subsequent phase of calibration. Because of the

self-modifying properties of the UGM, the coefficient parameters used to initialize simulations may be slightly altered by the end of the model runs. Therefore, the best coefficient combination selected from the final phase of calibration, known as the ''derive coefficients'', was used to run the model through the historical data for 100 Monte Carlo iterations. The average terminating coefficient values from these runs (the ''prediction coefficients'') were then used to seed the model for prediction.

Given the steep terrain in the Santa Monica Mountains (approximately 30% of the land has slopes greater than 40%), three different growth scenarios were developed based on critical slope values. Because the CCC report identified areas with slopes greater than 30% or 25% for Ventura and LA Counties as sensitive to development, and because development, nevertheless, tends to occur on slopes steeper than that predictions were run from 2000 to 2050 using critical slope threshold values of 25%, 30%, and 60%. Each scenario was replicated with 100 Monte Carlo iterations, allowing the generation of variance estimates and the development of probability images. Annual probabilistic images of urban growth were thresholded at 95% or greater likelihood of development to develop binary model output.

### 2.5. Landscape pattern analysis

Predicting ecological response to changing landscape heterogeneity is complex due to differences in species habitat preferences, difficulties in distinguishing the effects of habitat loss from fragmentation, and the variability of landscape patterns and processes over time. However, several direct and general landscape metrics can be calculated that not only serve as the basis for deriving other indices, but are also related to myriad ecological processes (Gustafson, 1998). These metrics are useful for monitoring change in landscape structure over time as well as for comparing different landscapes (Turner, 1989). Because the objective of this research was to forecast the impact of different urban development scenarios on habitat extent and patterns, and to generally compare those scenarios to the GIS overlay model, these general landscape-level metrics (Table 3) were chosen to quantify model output using FRAGSTATS Version 3 (McGarigal et al., 2002).

One of most important components in a landscape is the area of its patches because most species have minimum area requirements (Beier, 1993). The positive relationship between habitat area and species richness is well documented (e.g., Gleason, 1922), and one principle of reserve design is that preserving habitat patches large enough to support species with large area requirements will protect other species under this ''umbrella'' (Noss, 1990).

Core area/interior habitat represents the portion of habitat patches that is farther than a specified distance from the patch boundary. Because species composition and abundance is typically different at or near the perimeter of habitat patches than away from the perimeter (Forman and Godron, 1986), core area may better represent habitat availability than absolute area in fragmented landscapes. Using a 100 m buffer width (as in Swenson and Franklin, 2000), the total core area, number of patches containing core area, and mean of core areas for all patches were calculated. Increased urbanization was expected to reduce total core area and fragment the landscape into small, dispersed patches, thus resulting in a higher number of patches with smaller mean core areas.

Table 3
Landscape Metrics used in the analysis

| Metric | Description |
|---|---|
| Total core area (TCA) | TCA equals the sum of the area of all (interior) natural vegetation located within a 100 m buffer of patch edge. Hectares |
| Number of distinct core patches, NDCA (NDCA $\geq$ 1, no limit) | NDCA is the number of patches in the landscape that contain habitat within 100 m of the patch edge. |
| Mean core patch area, CORE_MN (ha) | CORE_MN equals TCA divided by NDCA |
| Total Edge, TE (km) | TE is the sum of all edge lengths in the landscape |
| Number of patches (NP) vegetation (NP $\geq$ 1, no limit) | NP equals the total number of patches of natural vegetation in the landscape |
| Largest patch index, LPI (%) (0–100) | LPI equals the percent of the landscape occupied by the largest patch |

Another indicator of habitat quality is the amount of edge between landscape elements. Edge affects the movement of organisms across boundaries, alters the structure and composition of vegetation, and influences different species based on habitat preferences (Turner, 1989; McGarigal et al., 2002). Smaller habitat patches tend to have a higher edge-to-interior ratio; therefore, fragmentation can increase the amount of edge in a landscape (Pearson, 2002). Total edge (urban adjacent to non-urban) and the number of habitat patches were calculated with the expectation that both would increase (edge as a function of the number of habitat patches) with urbanization.

When habitat is distributed over few large patches, the landscape is more highly connected. Connectivity is important for processes such as migration, seed dispersal, and competition (Green, 1994). Currently, a single, large patch of uninterrupted vegetation dominates the Santa Monica Mountains landscape. Therefore, the largest patch index (LPI), a measure of the percentage of the landscape occupied by the largest patch, was calculated to evaluate how that patch would fragment under the different urbanization scenarios. The LPI was expected to decrease with increased urban growth.

To prepare the annual UGM output for landscape pattern analysis, all *.gif images were converted to *.tif images, a format accepted by ARC/INFO. An Arc Macro Language (AML) script was created to automatically convert the images to ArcGrids so they could be reclassified for use in FRAGSTATS. All natural vegetation was considered one class, and all urban or water areas were designated background, but were included in overall landscape area calculation. Grid cells outside of the study area boundary were also designated background, but these areas were excluded from area calculations. Landscape metrics were calculated on grids for each year of the UGM output for all three scenarios

### 2.6. Comparison with the GIS overlay model

The GIS overlay model (Swenson and Franklin, 2000) used a static, site suitability approach with four variations to project different development patterns in the Santa Monica Mountains from 5 years to 25 years forward. The projected dates for the predicted growth were estimated from previous development rates for the region. Development likelihood was assumed based on an overlay of five equally weighted Boolean (or binary) GIS data layers, leading to a rank of five ordinal categories. Values of 3, 4, or 5 were assumed to have a ‘‘medium to high’’ likelihood of development. Growth was more likely in areas that were: on more level slopes, in areas of proposed development, in areas zoned for high density development, located near roads, or located near existing development. The two major model variations were the Standard Development scenario and the Maximum Development scenario. In the Standard Development scenario, points were randomly selected from medium or high likelihood classes, and ownership tracts in which the points fell became developed. In the Maximum Development scenario, all ownership tracts that partially or completely coincided with areas of medium or high likelihood classes became developed.

The predicted results from the Standard and Maximum Development scenarios were clipped to the same boundary and classified identically to the UGM output, then analyzed with the same landscape metrics. Because of the static nature of the GIS overlay model, grids from the two dates of each UGM slope scenario that had the closest total area of natural vegetation as the Standard and Maximum Development scenarios of the GIS overlay model were selected for comparison.

## 3. Results

### 3.1. UGM calibration and simulations

The UGM was successfully calibrated to the historical data set, resulting in a selection of final coefficients to use for prediction (Table 4). During the predictions, the self-modifying properties of the UGM resulted in similar changes in the values of the growth coefficients for all three of the slope scenarios (Fig. 3). For the first 30 years, the breed and spread coefficients were at the maximum values possible, the slope coefficient was at the lowest value possible, and the diffusion and road gravity coefficients gradually increased at mid-range. In the middle of the 2030s, however, the breed, spread, and diffusion coefficients bottomed out to 0, slope increased to 100, and the road gravity coefficient declined, but remained at a mid-

Table 4
Coefficients used for UGM calibration and prediction in the Santa Monica Mountains

| Resolution | 240 m (99 × 231) | 120 m (198 × 461) | 60 m (397 × 922) | 30 m (793 × 1844) | Derive coefficient | Prediction coefficient |
|---|---|---|---|---|---|---|
| Diffusion | | | | | | |
| Start | 0 | 0 | 5 | 15 | 19 | 31 |
| Step | 25 | 5 | 5 | 2 | | |
| Stop | 100 | 25 | 25 | 25 | | |
| Breed | | | | | | |
| Start | 0 | 0 | 45 | 63 | 69 | 100 |
| Step | 25 | 15 | 6 | 3 | | |
| Stop | 100 | 75 | 75 | 75 | | |
| Spread | | | | | | |
| Start | 0 | 50 | 60 | 66 | 82 | 100 |
| Step | 25 | 10 | 6 | 4 | | |
| Stop | 100 | 100 | 90 | 86 | | |
| Slope | | | | | | |
| Start | 0 | 25 | 55 | 55 | 55 | 1 |
| Step | 25 | 15 | 9 | 2 | | |
| Stop | 100 | 100 | 100 | 65 | | |
| Road gravity | | | | | | |
| Start | 0 | 0 | 0 | 0 | 25 | 33 |
| Step | 25 | 25 | 25 | 25 | | |
| Stop | 100 | 100 | 100 | 100 | | |

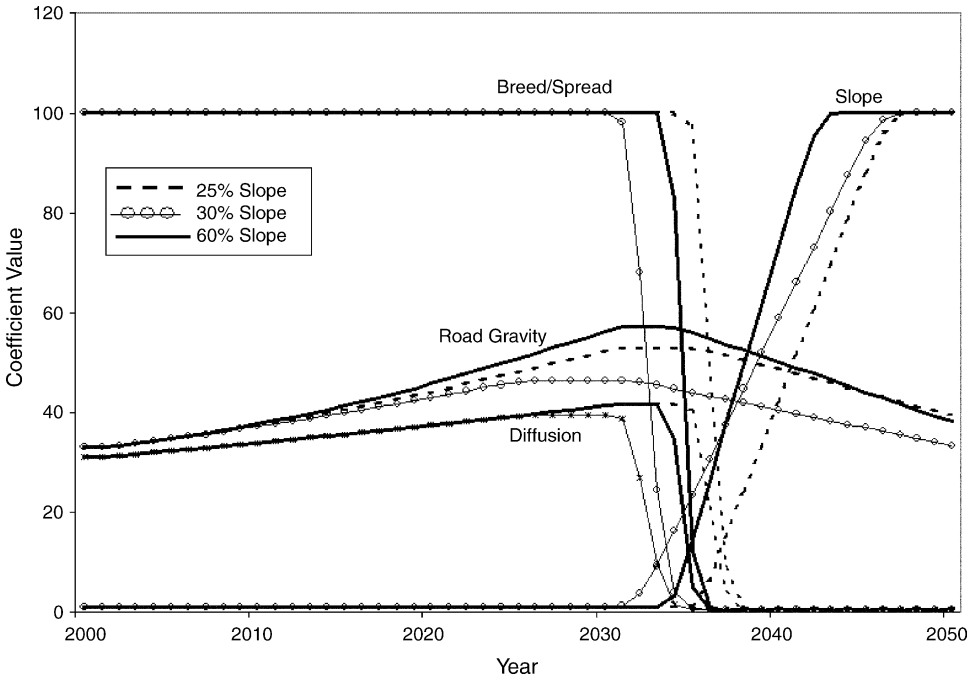


Fig. 3. UGM self-modification of growth coefficients (range 0–100) from 2000 to 2050 with development prohibited beyond 25%, 30%, and 60% slope.

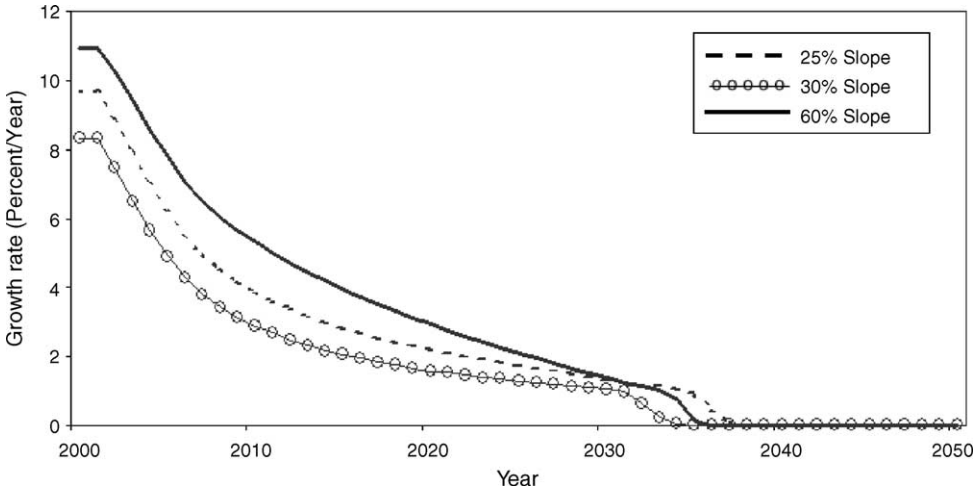


Fig. 4. Predicted growth rate of urbanization in the Santa Monica Mountains from 2000 to 2050 with development prohibited beyond 25%, 30%, and 60% slope.

range. These transitions occurred most rapidly at 25% slope, and were the slowest at 30% slope, with 60% slope falling in between.

Throughout most of the 50-year simulations, urban growth was predicted to occur faster at higher critical slope thresholds (Fig. 4). However, the growth rate drops to nearly 0% in the 60% slope scenario faster than it does in the 30% slope scenario. In all three scenarios, less than 1 ha per year will be developed by approximately 2040.

At the beginning of the simulations (year 2000), 11% (6380 ha) of the landscape was urban. However, only 50% (28,967 ha) of the landscape was available to be urbanized due to the protected parks that were excluded from development (Table 5). When accounting for the portion of the landscape with slopes above the three critical slope thresholds, the area of developable land in the initial conditions predictably decreased with tighter slope restrictions, though only slightly at 60%. At the end of the simulations, the remaining amount of developable land was highest at 30%, but the differences between scenarios were not substantial. However, greater proportions of the initial developable area were urbanized with higher critical slope thresholds. Substantially, more area of land became urban (thus, decreasing the total core area of natural vegetation) when development was allowed at higher-degree slopes (Table 5, Figs. 5 and 6A).

The number of distinct core area patches in the landscape increased slowly over time, particularly in the first two decades, for the 25% and 30% slope scenarios (Fig. 6B). In the middle of the 2020s, the number increased a bit faster and then leveled off in the last two decades with more core area patches at 30% slope. The mean area of those distinct core area patches decreased non-linearly during the first decade, with a more gradual decline continuing for the remainder of the simulations for the 25% and 30% slope scenarios (Fig. 6C). The core area was slightly larger in the 25% slope scenario than the 30% slope scenario.

At 60% slope, the number of patches of core area declined slightly for the first two decades, but the mean size of the core-area patches increased

Table 5
Land available for development (hectares, percent of landscape) and land urbanized in 2000 and 2050 for three slope restrictions

| Slope restriction (%) | Available 2000 | Urban 2000 | Available 2050 | Urban 2050 |
|---|---|---|---|---|
| 25 | 15187 (26%) | 6380 (11%) | 6343 (11%) | 15223 (26%) |
| 30 | 23414 (40%) | 6380 (11%) | 9396 (16%) | 20398 (35%) |
| 60 | 28965 (49%) | 6380 (11%) | 8125 (14%) | 27220 (47%) |

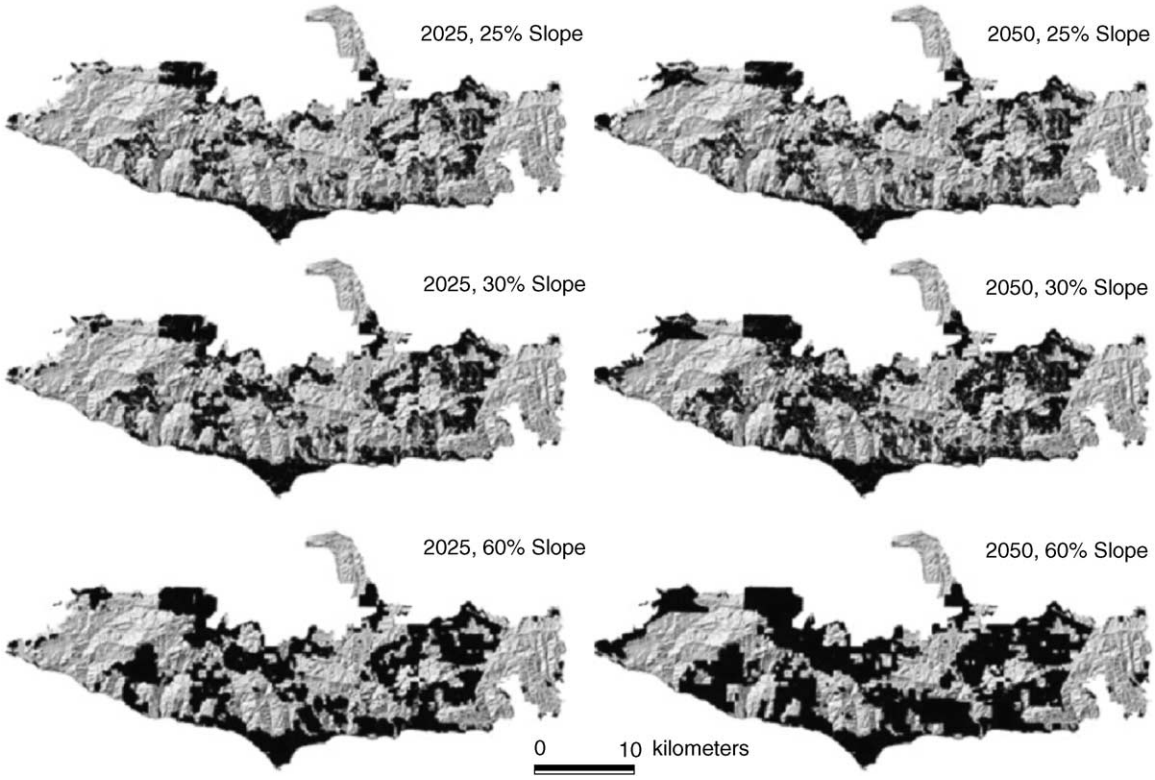


Fig. 5. Predicted urban development in the Santa Monica Mountains in 2025 and 2050 with development prohibited beyond 25%, 30%, and 60% slope.

substantially in the first decade, then declined gradually until approximately 2025 (Fig. 6B). At that time, the number of core areas increased substantially, but their mean size plummeted (Fig. 6C). Within 5 years, the number of core areas decreased again, became larger, and stabilized for the remainder of the simulations. Throughout the entire simulation, the 60% slope runs had larger, but fewer patches of core area than the 25% and 30% scenarios.

While the number of distinct core areas declined over time in the 25% and 30% slope scenarios, the total number of patches in the landscape increased substantially (Fig. 6D). In the first decade, the number of patches increased almost linearly in both scenarios, with slightly more patches at 25%. The rate of increase then slowed at the 25% slope scenario, but the number of patches in the 30% slope scenarios increased at approximately the same rate until the middle of the 2030s, resulting in almost twice as many patches in the landscape than the 25% slope scenario. Except for a temporary spike in the late 2020s for the 60% slope scenario, the number of patches declined slowly throughout the entire simulation.

The total edge in the landscape also increased progressively over time in both the 25% slope and 30% slope scenarios, but was higher in the 25% slope scenario until the middle of the 2030s (Fig. 6E). The rate of increase then slowed, and the 30% slope scenario ended up having more edge than the 25% slope scenario for the remainder of the simulations. Again, except for a temporary spike in the late 2020s, the total edge slowly declined over time for the 60% slope scenario.

The majority of vegetation existed in one large patch at the beginning of the simulations. At 25% and 30% slope, this patch became increasingly perforated, and got smaller with increased urbanization; however, the patch remained connected throughout the simulations. At 60% slope, however, the large patch eventually broke up into several disconnected patches in the middle of the 2020s (Fig. 6F).

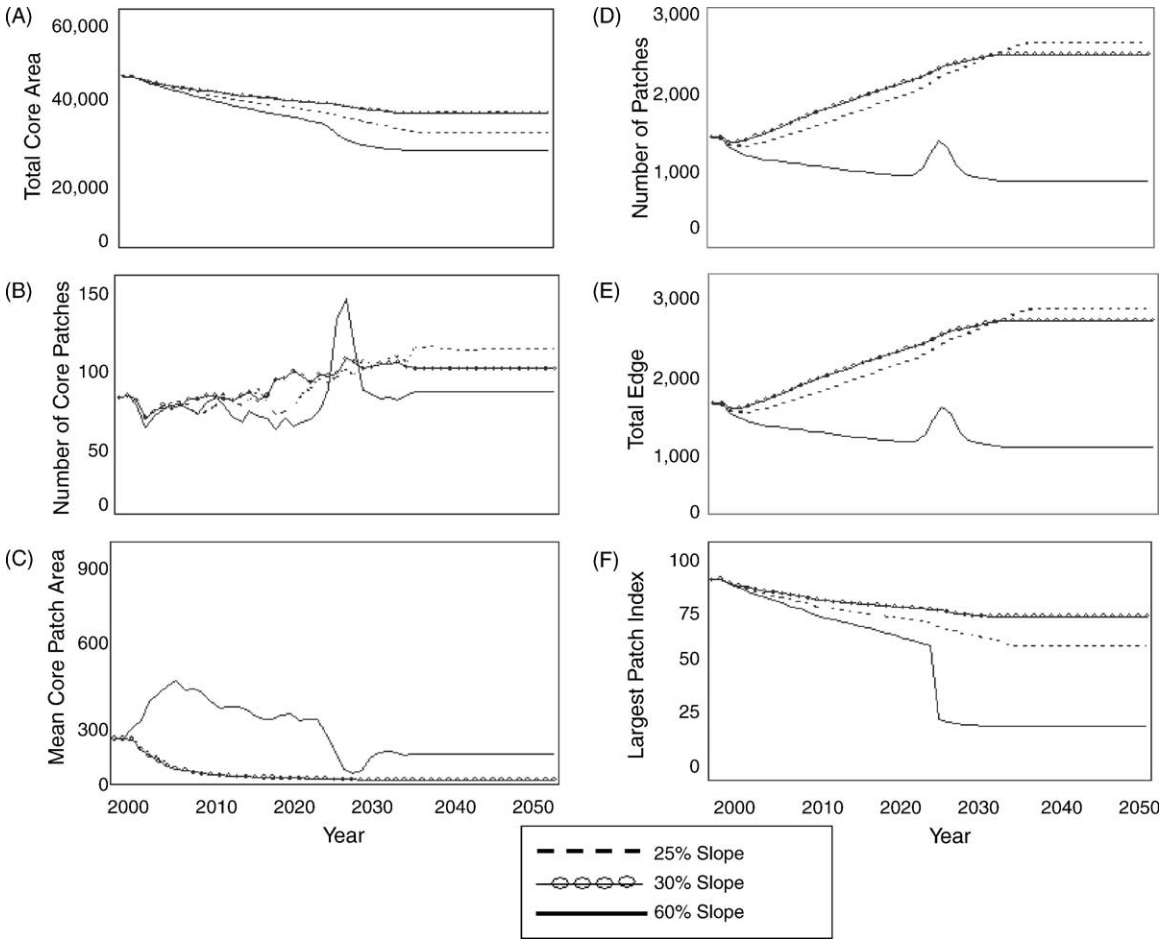


Fig. 6. Landscape metrics (see Table 3) calculated for urban growth predictions with development prohibited beyond 25%, 30%, and 60% slope: (A) total core area, (B) number of distinct core patches, (C) mean core patch area, (D) total edge, (E) number of patches, and (F) largest patch index.

### 3.2. Comparison to GIS overlay model

Landscape metrics calculated for the Standard and Maximum Development scenarios of the GIS overlay model were compared to those of the UGM predictions in the projected years with the most similar area of natural vegetation for each of the three slope scenarios (Fig. 7). For all of the landscape metrics, the direction of change created by increased urbanization (and decreased vegetation) was the same for the GIS overlay predictions and the 25% and 30% slope scenarios of the UGM predictions for those comparable years. The direction of change for comparable area in the 60% slope scenario was the same as the GIS overlay model for all of the metrics except total edge, which declined with higher urbanization. The magnitude of difference between lower and higher levels of urbanization was greater for the number of patches and total edge in the 25% and 30% slope scenarios of the UGM predictions. There were more patches and edge to begin with in the UGM model, and that number increased more dramatically with increased urban growth.

Spatially, the GIS overlay model and the UGM predicted future urban growth to occur in similar regions of the study area (Fig. 8), primarily along the coast and adjacent to major thoroughfares through the mountains. The primary difference is that the GIS

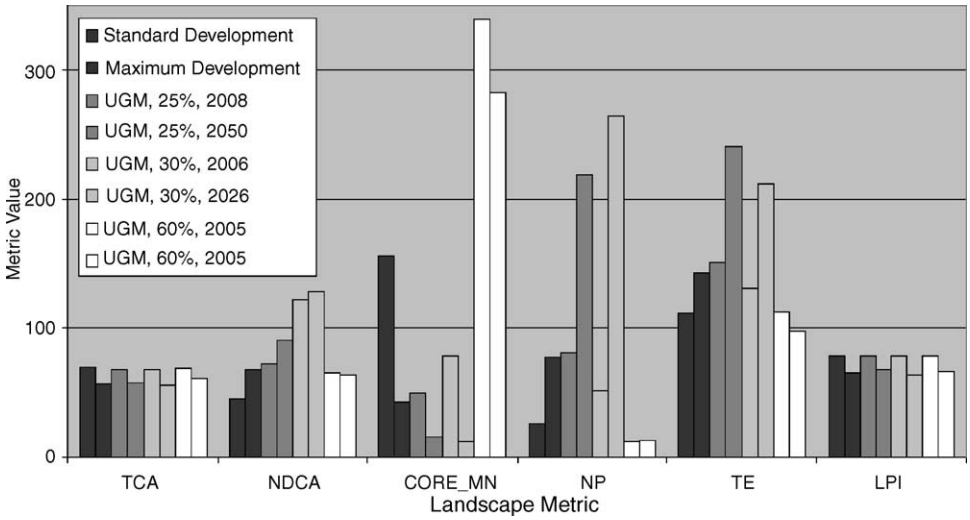


Fig. 7. Landscape metric values (Table 3) calculated for the Standard Development and Maximum Development scenarios of the GIS overlay model and the for dates with the closest corresponding total class area from the Urban Growth Model predictions when growth was prohibited beyond 25%, 30%, and 60% slope. Number of patches and total edge have been divided by 10.

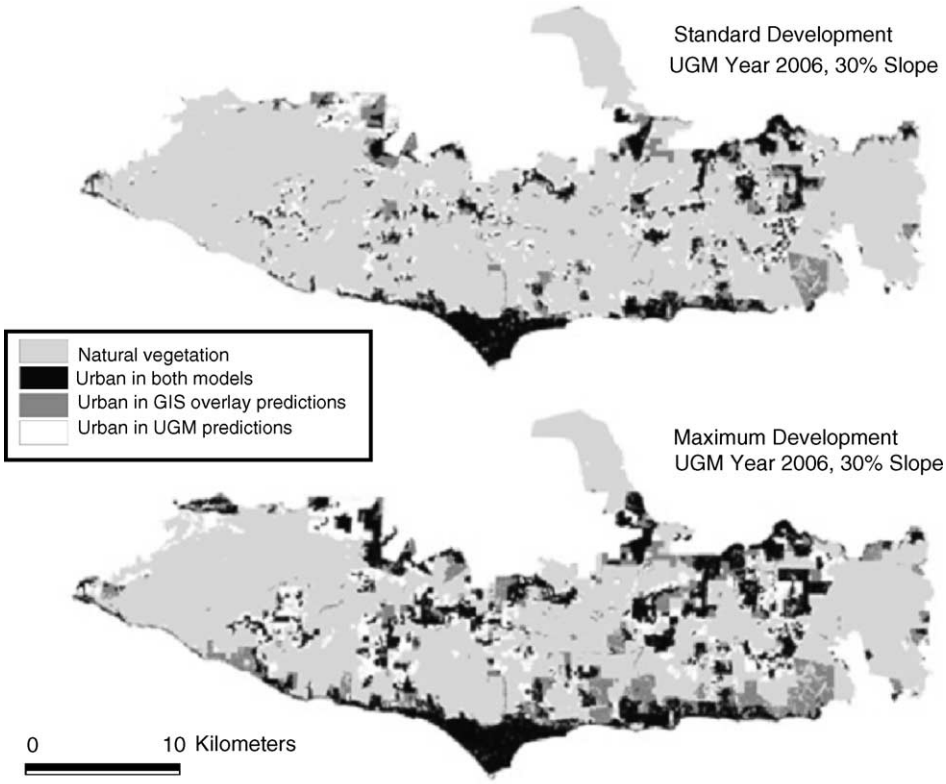


Fig. 8. Overlay of the Standard Development and Maximum Development scenarios of the GIS overlay model with the Urban Growth Model predictions that had the closest total area of remaining vegetation.

overlay model predicted more growth along the coast than the UGM, whereas the UGM predicted more growth in the interior of the mountains.

## 4. Discussion

The pace and scale of urban growth is occurring at an unprecedented rate across the globe, and the number of people living in urban areas is expected to double to more than 5 billion in the next 25 years (WRI, 1998). Consequently, Urban Growth Models are becoming critical tools for projecting where urban expansion is likely to occur. Our research objective was to predict urban growth impacts on habitat extent and pattern based on land management strategies that prohibit development beyond varying percentages of slope.

Not surprisingly, greater habitat loss was predicted when development was allowed to occur on steeper slopes. As evidenced by the phase transition apparent in plots of the growth control coefficients, slope-dominated growth became most critical after approximately 30 years. At that time, the amount of flatter land initially available for development had become mostly developed in all three scenarios, and slope began to drive the entire system. This phase transition occurred at similar points in time for each scenario because, although more land became urbanized with growth allowed on steeper slopes, there was also more land available for development in those scenarios. The self-modification properties of the model decrease the slope resistance coefficient based on proportion of available land as a way to realistically capture the real-life tendency to build on flatter terrain before attempting development on steep slopes. Although habitat area declined inversely with the degree of slope restrictions, allowing growth to occur almost regardless of slope in the 60% scenario resulted in fundamentally different patterns in the landscape metrics than in the 25% and 30% slope scenarios, which differed only in a matter of degree.

In the 25% and 30% slope scenarios, the mean size of the patches containing core habitat declined at a faster rate than total habitat area. Although the total number of patches and total edge in the landscape increased dramatically, the number of distinct core patches increased only slightly over time. Therefore, future landscape patterns under these scenarios are likely to be characterized by many patches too small to contain high-quality interior habitat; and the patches that do contain core habitat are expected to become smaller. This reduction in interior habitat could favor increases in species that are adept at using more disturbed, edge habitats; and species with minimum area requirements might need to depend more heavily on corridors and patch connectivity for migration.

Urbanization affected habitat patterns differently when growth was allowed up 60% slope. Although total core habitat declined substantially, the mean size of core area patches increased in the first decade, as small patches of habitat were lost first to urban growth. Then, mean size slowly decreased until approximately 2025, when the initially large, connected patch of vegetation broke into several medium patches, and mean core patch area plummeted. This abrupt change in landscape dynamics explains the temporary spikes in the number of habitat patches and total edge in the landscape, as well as the temporary drop in mean core patch area, revealing correlations that tend to be inherent in landscape metrics (Gustafson, 1998).

However, using landscape metrics together can be helpful when interpreting landscape dynamics. For example, the increase in mean core patch area in the 60% slope simulation could be misleading without other metrics to explain what was happening in the landscape. Because the total number of patches and distinct core areas declined, the mean size of remaining core patches increased because the landscape was still dominated by one large patch. The total edge also declined because the landscape was comprised of fewer patches with simpler shapes, resulting from urban infill and development saturating the available land. Unlike natural disturbances, which increase landscape complexity, human-influenced landscapes tend to exhibit simpler patterns (Turner et al., 1989).

Due to the growing number and variety of urban models, choosing an approach that is appropriate for the study in question is challenging. Although the GIS overlay model had already been completed for the study area, the more complicated UGM approach was chosen for this analysis because the model is dynamic, rigorously calibrated, and more compatible for coupling with the ecological model of disturbance and succession that we will use in future research.

Goldstein et al., 2003 used the UGM in a historic reconstruction of urban growth in Santa Barbara, CA, where the UGM performed well at simulating the general growth pattern in the city, but failed to capture the exact locations of several small new settlements. Jantz et al. (2003) reached a similar conclusion in the Baltimore–Washington metropolitan region. In another study evaluating the differential impact of future growth scenarios on wildlife habitat, output from three models, including the UGM, was intersected with predicted distribution of vertebrate species (Cogan et al., 2001). One of the models, developed by Landis and Zhang (1998) used extensive socioeconomic and physical data to predict areas of future growth. The other model was a simple 500 m buffer around existing urban areas. The UGM predicted more growth than the Landis and Zhang model, and the pattern of growth tended to occur along roads and contiguous to existing development, whereas the Landis and Zhang model predicted more isolated clusters of new development. Regardless, the two models produced similar magnitudes and rank order of impacts on vertebrate species.

In the above examples, the UGM tended to underestimate the number of separate clusters of new development, with growth more heavily attracted to roads and existing settlements. Compared to the GIS overlay model, however, the UGM predicted a patchier landscape with more total edge. Given the differences in initial conditions as well as the difference in fundamental approach, comparison between the UGM and the GIS overlay model should be interpreted with caution. In addition, because UGM calibration uniquely fits each study area to its local environment, comparison across UGM simulations may also be misleading (Silva and Clarke, 2002). However, if the UGM generally tends to underestimate patchiness in a landscape, but projected a higher number of patches and total edge than the GIS overlay model, the UGM predictions might be more realistic portrayals of future growth in the Santa Monica Mountains than the GIS overlay scenarios. One explanation for higher patchiness in the UGM model is that the GIS overlay approach used ownership tracts as minimum development units instead of grid cells. As Swenson and Franklin (2000) noted, actual development may only occur on portions of the ownership tracts.

Because of assumptions shared by the UGM and the GIS overlay model, there were also similarities in predictions for comparable years. The direction of change in landscape metrics was the same, but of different magnitudes, and the spatial pattern of the predictions overlapped in a substantial portion of the study area, primarily along major thoroughfares. Despite these similarities, the GIS overlay model, nevertheless, had some disadvantages. As a static model, it could not capture some of the intricacies in landscape change that was possible with a dynamic, temporally explicit model. Some complex system properties, such as self-organization of urban clusters that emerged from local interactions between cells and their neighbors, as well as the non-linear behavior in growth patterns, were captured in the UGM predictions, particularly when slope-dominated growth began to drive the system. In addition, no performance metric could be used to calibrate the formulations in the static model, and the different growth scenarios of the GIS overlay model were developed using independent methods. On the other hand, the use of Monte Carlo averaging to generate variance estimates on the predictions, combined with the rigor of the calibration process and repeatability of model experiments added more justification to the UGM model results. However, because the objective of both models was to identify possible consequences of alternate scenarios of future development, only the real future can validate these predictions.

## 5. Conclusion

Southern California, particularly the Los Angeles metropolitan area, has been long recognized as one of the most rapidly urbanizing, yet one of the most biologically diverse, areas in the United States (Rundel and King, 2001). Consequently, private land development has been identified as one of the key factors affecting ecological integrity in the region. A range of studies has been conducted in southern California documenting the impacts of habitat fragmentation on species richness (Tigas et al., 2003), and species including amphibians (Fisher and Case, 2000), birds (Stralberg, 2000), rodents (Bolger et al., 2000), arthopods (Suarez et al., 1998), and large carnivores (Tigas et al., 2003).

The SMMNRA, one of the few remaining places in coastal southern California with a substantial area of

connected core habitat, is home to several large carnivore species. Carnivores are critical components to biological communities, and are often used as indicator species of ecosystem health (Noss et al., 1996). At least two carnivores residing in the mountains, the bobcat and the gray fox, have demonstrated sensitivity to edge habitat at the urban–wildland interface (Sauvajot et al., 2000). One species of special concern is the mountain lion, an apex predator with a large area requirement (as much as 220,000 ha for a population), and a long-distance traveler (Beier, 1993). Because the mountain lion's survival in the SMMNRA will likely depend on its ability to disperse into and out of the mountain range, the narrow section extending to the north of the SMMNRA, Cheeseboro Canyon, is an important corridor for migration to the Los Padres National Forest. All three of the growth scenarios (as well as the GIS overlay scenarios) predicted a growing cluster of urbanization separating the main mountain range from Cheeseboro Canyon. Development completely filled in with the 60% scenario, suggesting that slope restrictions may be important for keeping parts of that corridor open.

The landscape metrics used in this analysis are broadly suggestive of the types of impacts that future urban development will have on the habitat in the Santa Monica Mountains. Although the metrics were chosen primarily for comparing multiple simulations over time, land managers could calculate additional metrics specific to different conservation strategies or to particular species' habitat preferences. Differential impacts to vegetation types could also be assessed. Owing to the convoluted boundary of the study area, however, edge effects should be taken into account when making specific ecological inferences about the effects of fragmentation.

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