

# Scale in Remote Sensing and GIS

Edited by

**Dale A. Quattrochi**

National Aeronautics and Space Administration

Huntsville, Alabama

and

**Michael F. Goodchild**

University of California

Santa Barbara, California



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Cover: Color composite image of processed Landsat Thematic Mapper image recorded September 14, 1989 over the central Amazon River approximately 50 km upstream from the town of Óbidos and 650 km downstream from the town of Manaus. The record flood of 1989 has receded approximately 2 m, the floodplain is draining, and flow is from left to right (west to east) in the main channel which is 4 to 6 km wide. The color of the main channel (red) indicates relatively high suspended-sediment concentrations in the water. The dark blue color indicates relatively clear water, and blue-green indicates tropical forest. Image processing completed by A. K. Mertes, Department of Geography, University of California, Santa Barbara. Raw image provided by R. Almeida Filho of INPE, Brazil.

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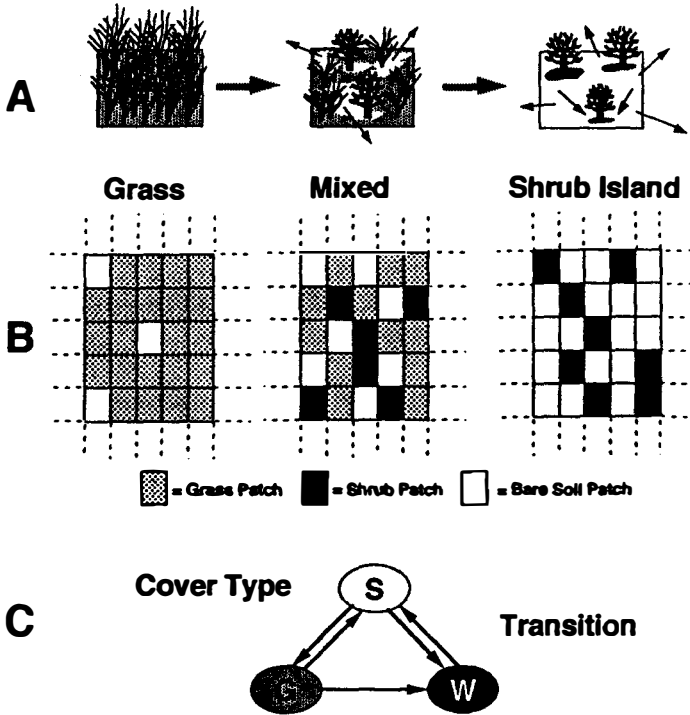
## CHAPTER 10

# Modeling Effects of Spatial Pattern, Drought, and Grazing on Rates of Rangeland Degradation: A Combined Markov and Cellular Automaton Approach

Habin Li and James F. Reynolds

### INTRODUCTION

Schlesinger et al. (1990) proposed a functional hypothesis for desertification, suggesting that changes in ecosystem function at the transition zone between arid and semiarid regions are best understood and predicted in terms of the spatial and temporal distribution of soil resources. This hypothesis emerged out of studies carried out in the Jornada Basin of southern New Mexico, where large regions of semiarid grasslands have been virtually replaced by arid shrublands during the last century (e.g., Buffington and Herbel, 1965; York and Dick-Peddie, 1969). The expansion of shrub communities has been attributed to various allogenic and autogenic factors operating at spatial scales ranging from the patch to the landscape (reviewed in Reynolds et al., 1996). *Allogenic* factors include climate change, fire suppression, overgrazing, and elevated levels of atmospheric CO<sub>2</sub> concentrations. Undisturbed grasslands of the Jornada Basin were characterized by a relatively uniform spatial distribution of water, nutrients, and other soil resources (Figure 1). During desertification, which may have been triggered by allogenic factors operating to favor shrubs over grasses, there was an increase in the spatial and temporal heterogeneity of soil resources, which promotes the invasion of shrubs. *Autogenic* factors, which operate at the patch scale, further contribute to this heterogeneity. For example, soil resources tend to accumulate under the shrubs, because wind and water remove soil resources from the inter-shrub spaces, the infiltration of rainfall to the soil profile is confined to the area directly beneath shrub canopies, and the cycling



**Figure 1** A schematic representation of landscape-scale vegetation dynamics during desertification. (A) Pictorial representation. (B) Cellular representation (i.e., spatial configuration). (C) Markov representation (i.e., a state-and-transition model) where S stands for soil, G for grass, and W for shrub.

of plant nutrients is progressively confined to the zone beneath shrubs, leading to the development of the classic "islands of fertility" in deserts (Figure 1).

We have initiated a number of modeling studies to understand the relative importance of autogenic vs. allogenic factors in desertification. To date, our models have focused largely on patch-scale dynamics (Reynolds et al., 1996). A landscape model of vegetation dynamics will allow us to address some questions at a more appropriate scale. Since aridland vegetation often consists of clearly defined discrete states (Westoby et al., 1989; Hobbs, 1994), we believe that vegetation dynamics in the context of desertification may be best represented by a state-and-transition model, i.e., vegetation is treated as a mosaic of discrete states and changes are multidirectional, instead of "ordered" and unidirectional.

A new approach to modeling vegetation dynamics as a state-and-transition system is to combine Markov models with cellular automaton models (e.g., Silvertown et al., 1992; Colasanti and Grime, 1993; Hobbs, 1994; Wiegand et al., 1995). A Markov process is the traditional model for vegetation dynamics over time that does not consider spatial configuration of the system (e.g., Horn, 1975; Turner, 1987). A cellular automaton is an approach that explores how simple rules of local patch processes can generate complex landscape behaviors in space and time (e.g., Wol-

fram, 1984; Caswell and Etter, 1993). The hybrid Markov-cellular automaton model (hereafter, referred to as M-CA) simulates vegetation dynamics as a spatially and temporally discrete system. Temporal dynamics are controlled by the transition probabilities among these states (i.e., a Markov process) (e.g., Horn, 1975; Turner, 1987; McAuliffe, 1988; Silvertown et al., 1992), whereas spatial dynamics are controlled by local rules determined either by neighborhood configuration (i.e., a cellular automaton) or by its association with the transition probabilities (e.g., Hogeweg, 1988; Silvertown et al., 1992; Caswell and Etter, 1993; Colasanti and Grime, 1993). A major advantage of the M-CA approach is that GIS and remote sensing data may be efficiently incorporated because the model can be built with a time series of GIS data and run with initial conditions defined by GIS data (Hobbs, 1994). Integrative M-CA models have been applied to studies of species competition and plant community dynamics (Silvertown et al., 1992; Wiegand et al., 1995) and gypsy moth outbreaks (Zhou and Liebhold, 1995). The M-CA approach has not been used to model complex vegetation dynamics at the landscape scale, although Hobbs (1994) proposed that it offers great potential.

In this chapter, we present a M-CA model of interactions between (1) spatial patterning of vegetation, (2) drought, and (3) cattle grazing in a landscape context. Ultimately, we are interested in addressing the question: Can we predict landscape *processes* based on landscape *patterns* in arid regions? Our M-CA approach utilizes a model structure that is more complex than those of Silvertown et al. (1992) or Colasanti and Grime (1993). We show the usefulness of the M-CA modeling approach as well as its limitations, and discuss how GIS data can be readily used within this framework to assist environmental assessment and management decisions. Our long-term goal is to develop a spatial modeling framework for scaling process models of desert ecosystems to larger spatial and temporal scales that are appropriate for studying desertification (e.g., Reynolds et al., 1996).

## MODEL DESCRIPTION

### Functional Groups

To simplify the spatial representation of desert landscapes, we recognize two functional groups of plants: grasses and shrubs, following Reynolds et al. (in press). A landscape is composed of a number of cells, each of which may be occupied by one of the three cover types: bare soil (S), grass (G), and woody shrub (W) (Figure 1).

### Markov Model

The Markov model is based on transition probabilities among the three states (i.e., cover types). Transition probabilities define the potential of change from one state to another and, in this study, we assume that drought and/or grazing modify these probabilities (Table 1). We also assume that no transition occurs from shrub to grass (i.e., Figure 1, Table 1). This assumption is consistent with many empirical studies on the Jornada. For example, a considerable effort has been made by range

**Table 1** The Transition Matrices Under Four Combinations of Drought and Grazing Conditions

| Drought | Grazing |       |       |       |   |       |       |       |
|---------|---------|-------|-------|-------|---|-------|-------|-------|
|         |         | No    |       |       |   | Yes   |       |       |
| No      | S       | 0.950 | 0.025 | 0.025 | S | 0.900 | 0.050 | 0.050 |
|         | G       | 0.025 | 0.975 | 0.000 | G | 0.050 | 0.950 | 0.000 |
|         | W       | 0.025 | 0.000 | 0.975 | W | 0.050 | 0.000 | 0.950 |
| Yes     | S       | 0.900 | 0.030 | 0.070 | S | 0.870 | 0.020 | 0.110 |
|         | G       | 0.120 | 0.880 | 0.000 | G | 0.180 | 0.820 | 0.000 |
|         | W       | 0.100 | 0.000 | 0.900 | W | 0.130 | 0.000 | 0.870 |

*Note:* It is assumed that both drought and grazing can affect transition probabilities. S stands for soil, G for grass, and W for woody shrub.

managers to reverse the trend of increasing shrubiness on rangelands by eradicating shrubs, thereby reducing competition with grasses (Abernathy and Herbel, 1963; Herbel et al., 1983). However, the Jornada Basin remains predominately shrubland and the "brush problem" has increased (Hennessy et al., 1983). Markov models represent landscape dynamics in an aggregated and non-spatial way, i.e., they focus on changes only in the proportions of cover types. Markov models have been successfully used to study dynamics of vegetation composition over time (e.g., Horn, 1975; Turner, 1987).

### Cellular Automaton Model

In the cellular automaton model, we assume that for any cover type to "take over" a target cell, this cover type must have already occupied at least one of the four neighbors of the target cell. We call this the "localized interaction" assumption. The cellular automaton model incorporates this assumption into two neighborhood effect modes. The first neighborhood effect mode (CA1) is based on the number and cover types of the four neighboring cells and is used as a scalar to modify the transition probabilities in the M-CA model (see Eq. 1 below). The second neighborhood effect mode (CA2) follows traditional cellular automata and is defined by 7 transition rules for a total of 15 spatial configurations (in Table 2). Cellular automaton models have shown great potential for generating complex patterns with simple rules (e.g., Wolfram, 1984), although they have been criticized for lacking ecological mechanisms (e.g., Molofsky, 1994; but see Silvertown et al., 1992; Colasanti and Grime, 1993; Wiegand et al., 1995).

### Markov-Cellular Automaton Model (M-CA)

The M-CA model is event-driven (Hobbs, 1994). In this preliminary version, the major trigger is the occurrence of droughts, although other events (e.g., years with extraordinary precipitation) may also be used. We assume that vegetation change should be more likely to occur in a drought year due to the increased intensity of both inter- and intra-specific competition for the decreased resource availability

**Table 2** Cellular automaton rules for drought years based on neighborhood configurations (CA2)

| Case | Cellular automaton rule           |                        |
|------|-----------------------------------|------------------------|
|      | If neighborhood configuration is: | Then transition to:    |
| 1    | 3 or 4 Shrub                      | Soil                   |
| 2    | 2 Shrub                           | Shrub                  |
| 3a   | 4 Grass (no grazing)              | Grass or Soil          |
| 3b   | 4 Grass (grazing)                 | Grass or Soil or Shrub |
| 4a   | 3 Grass (no grazing)              | Grass                  |
| 4b   | 3 Grass (grazing)                 | Grass or Shrub         |
| 5    | 4 Soil                            | Soil                   |
| 6    | 1 Shrub                           | Shrub or Soil          |
| 7a   | 1-2 Grass, 0 Shrub (no grazing)   | Grass or Soil          |
| 7b   | 1-2 Grass, 0 Shrub (grazing)      | Grass or Soil or Shrub |

*Note:* The total number of neighborhood configurations is 15 (i.e., all combinations of the three cover types in the four-neighbor neighborhood). When two cover types can both take over a cell under the rules #3, #4, #6, and #7, it is decided randomly. Under grazing, the rules are modified to include transitions to shrub (i.e., cases #3b, #4b, and #7b). These cellular automaton rules are based on some assumptions. For example, it is assumed that grasses will die due to inter-specific competition if there is at least one shrub neighbor (i.e., cases #1, #2, and #6). It is also assumed that, similar to the self-thinning phenomenon in forests, shrubs and grasses will die due to intra-specific competition if they have too many neighbors of their own species (i.e., cases #1 and #3a). Another assumption used is that any cover type surrounded by soil will become soil due to poor environmental conditions (i.e., case #5).

(e.g., water, nutrients). At each time step, each cell is checked to see if a transition will take place (i.e., Markov model at work). If "yes," one of the two neighborhood effect modes is invoked: CA1 in a normal year or CA2 in a drought year. Table 3 describes the factors, the model components and their use in M-CA. In a normal year, M-CA is similar to Silvertown et al. (1992), and the new cover type of a target cell (i,j) is determined as:

$$C(i,j) = k \quad \text{if} \quad RN \geq T(m,k) \cdot NE(k)/4 \quad (1)$$

where  $C(i,j)$  is the cover type of cell (i,j),  $T(m,k)$  is the transition probability from cover type m to k (Table 1),  $NE(k)$  is the number of neighboring cells of cover type k,  $NE(k)/4$  is the neighborhood effect function (CA1), and  $RN$  is a random number with a uniform distribution. It is assumed that the probability that a target cell will be occupied by a certain cover type increases as the number of neighboring cells already occupied by this cover type increases. We use the weight of 4 in Eq. 1 because each cell is assumed to have four neighbors (i.e., the rook's rule). In a drought year, M-CA uses the transition rules in Table 2 to update the state of each cell (CA2). Following the notation of Wolfram (1984), M-CA in a drought year is given by:

**Table 3** Summary of the Factors, the Model Components, and Their Use in the M-CA Model Simulation

| Factor   | Model component |                       |                    | Model execution        |                         |
|----------|-----------------|-----------------------|--------------------|------------------------|-------------------------|
|          | Markov<br>(M)   | Cellular<br>automaton |                    | Normal year<br>(M-CA1) | Drought year<br>(M-CA2) |
|          |                 | (CA1)                 | (CA2)              |                        |                         |
| Drought  | Table 1         | —                     | —                  | Table 1                | Table 1                 |
| Grazing  | Table 1         | —                     | —                  | Table 1                | Table 1                 |
| Neighbor | —               | Eq. 1                 | Eq. 2 &<br>Table 2 | Eq. 1                  | Eq. 2 &<br>Table 2      |

$$a_{(i,j)}^{(t)} = F \left[ a_{(i-1,j)}^{(t-1)}, a_{(i+1,j)}^{(t-1)}, a_{(i,j)}^{(t-1)}, a_{(i,j-1)}^{(t-1)}, a_{(i,j+1)}^{(t-1)} \right] \quad (2)$$

where  $a_{(i,j)}^{(t)}$  is the value of cell (i,j) in a two-dimensional cellular automaton at time step t, and F is an arbitrary function that specifies the cellular automaton rules (CA2 in Table 2). The principal feature of the combined Markov-cellular approach is that it overcomes some of the limitations that these models have individually.

### Effects of Drought

We define a drought when annual rainfall deviates more than one standard deviation from the long-term mean. In this study, we consider only the presence and absence of droughts and, thus, the drought frequency. A drought "regime" is therefore defined by a time series of drought and normal years. This is modeled as a Bernoulli random process, which generates a sequence of independent Bernoulli trials of a binary experiment (Gardner, 1986):

$$D(t) = \begin{cases} 1 & \text{when } 0 < RN \leq P_d \text{ (for drought years)} \\ 0 & \text{when } P_d < RN \leq 1 \text{ (for normal years)} \end{cases} \quad (3)$$

with

$$P_d = P\{D = \text{Drought}\} = 1/N \quad (4)$$

where D(t) is the time series of drought,  $P_d$  is the probability of drought, N is the drought return interval (i.e., a drought every N years on average), and RN is a random number of a uniform distribution.

### Effects of Grazing

The effects of grazing on vegetation are complex and we make a number of simplifying assumptions. Brown and Archer (1989) suggested that a lack of seed availability may have limited shrub invasion to grasslands in the southwestern U.S. before the introduction of domestic livestock. We incorporate grazing as (1) a factor

that modifies the transition probabilities (see Table 1), reflecting the negative impact of heavy grazing on grass, and (2) a condition in which the localized interaction assumption is relaxed for shrubs. In the latter case, we assume that heavy grazing increases seed dispersal and survival and, ultimately, establishment of shrub species. To relax the localized interaction assumption, modifications are made to the neighborhood effect functions in the M-CA model. This is accomplished by allowing transitions to shrub even when there are no shrub neighbors. For CA1, when no shrub neighbors are present, a new, arbitrarily chosen weight of 5 (compared to the weight of 4 in Eq. 1) is used to allow transition to shrub as if there were a fifth neighbor, a shrub. For CA2, transitions to shrub are added to the transition rules (i.e., cases #3b, #4b, and #7b in Table 2) when no shrub neighbors are present. Grazing effects can be manipulated by changing the weight in CA1 and the probability of transition to shrub in CA2.

## SIMULATION EXPERIMENT

### Effects of Spatial Pattern

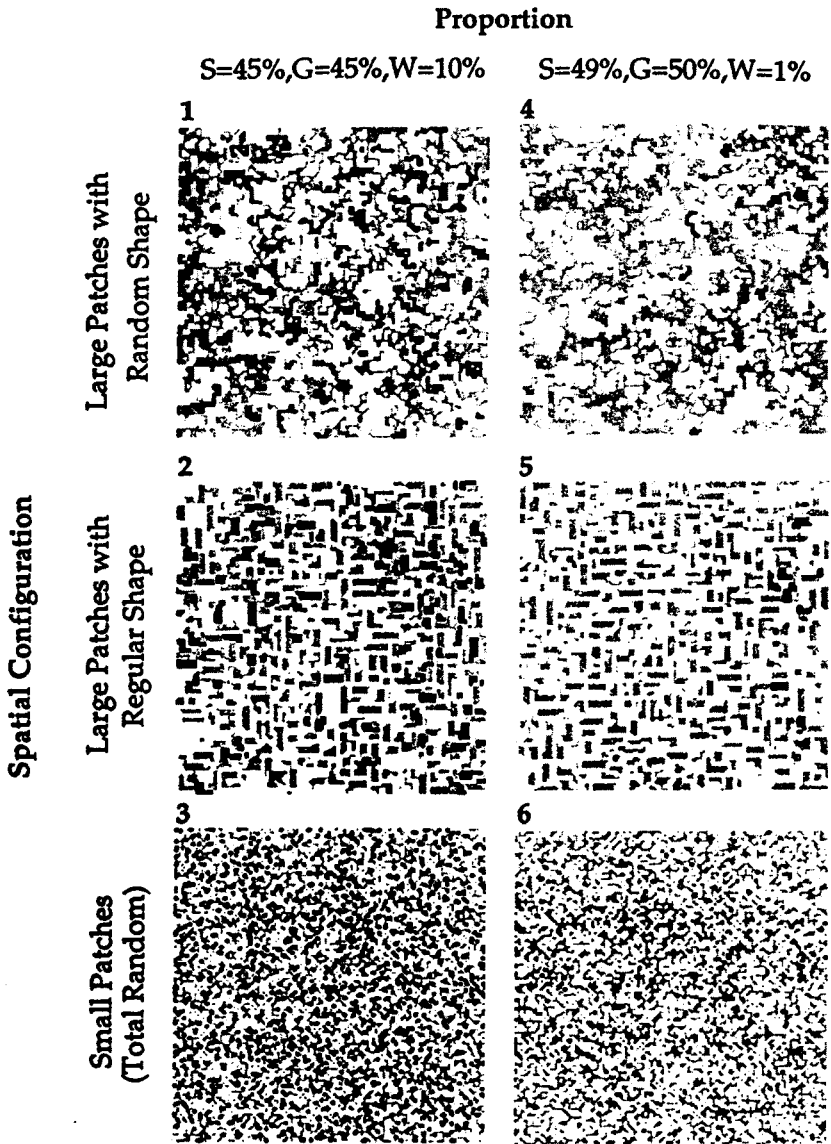
Does landscape pattern affect the rate of degradation from a grass- to shrub-dominated system (Figure 1)? We considered both landscape composition (e.g., proportions) and configuration (e.g., patch size and shape) in generating initial landscape pattern maps for the simulation experiment reported here. We used two sets of proportions of the cover types for soil, grass, and shrub: 45%–45%–10% and 49%–50%–1%. We also used three spatial configurations that correspond to three combinations of patch size and shape: (1) large patches with random shape; (2) large patches with regular shape; and (3) small patches (total random). The pattern simulation program, SHAPC (Li and Reynolds, 1994, 1995), was used to generate six initial maps (see Figure 2).

### Characterization of Landscape Dynamics

Landscape dynamics were measured by changes in % cover of grass and shrub. Changes in landscape configurations were monitored by a number of landscape indices, including contagion, edge density, and joint-count (Cliff and Ord, 1981; Li and Reynolds, 1993). We assume that the overall rate of degradation probability is a function of proportions of cover types and spatial configurations of patches (i.e., effects of pattern on process). We used relative change in % cover of grass as an indicator to assess the degree of degradation, that is,

$$\Delta C(t) = [G(t) - G(t_0)]/G(t_0) \quad (5)$$

where  $\Delta C(t)$  is the relative change in % cover of grass at time  $t$ ,  $G(t_0)$  is the initial % grass cover, and  $G(t)$  is % cover of grass at time  $t$ . A plot of  $\Delta C$  against a landscape index (e.g., edge density) may depict how degradation probability changes under different conditions.



**Figure 2** The six initial maps of different spatial patterns used in the simulation experiment. For composition, maps 1, 2 and 3 on the left column have proportions of 45%, 45%, and 10% for soil, grass and shrub, respectively, whereas maps 4, 5 and 6 on the right have proportions of 49%, 50%, and 1% for the three cover types. For spatial configuration, maps 1 and 4 on the upper row are landscapes with large random-shaped patches, maps 2 and 5 on the middle row with large regular-shaped patches, and maps 3 and 6 on the bottom row with small patches (i.e., total random). Each map is represented by a regular lattice of  $100 \times 100$  cells.

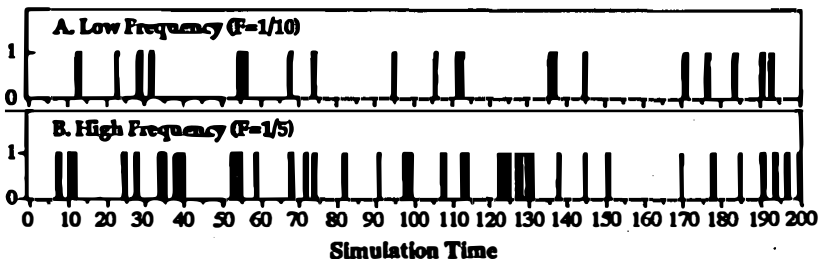
## Simulation Conditions

A total of 24 simulation conditions was used (Table 4). We considered three factors: drought regime, grazing level, and spatial pattern over a 200-year period (time step = 1 year). The two drought regimes used were a low frequency and a high frequency drought series with return intervals of 10 and 5 years, respectively (Figure 3). Grazing level was set to either presence or absence of heavy grazing. For the four combinations of drought and grazing levels, different transition probabilities were used (Table 1). Spatial patterns of landscapes were represented by the six initial maps discussed above (Figure 2). For each of the initial maps, a regular lattice of  $100 \times 100$  cells was used with a buffer zone of 5 pixels wide to reduce potential edge effects on results. In addition, a stochastic factor of up to 5% was applied to the transition probabilities at each iteration of the simulation.

**Table 4** Factors Used in the Simulation Experiments: Drought, Grazing, and Spatial Configuration

| Factor                | No. of levels | Description                                                                                         |
|-----------------------|---------------|-----------------------------------------------------------------------------------------------------|
| Drought regime        | 2             | Low vs. high frequency                                                                              |
| Grazing               | 2             | Grazing vs. no grazing                                                                              |
| Spatial configuration | 6             | Distinct initial maps                                                                               |
| Proportion            | (2)           | 45%–45%–10%<br>49%–50%–1%                                                                           |
| Patch size and shape  | (3)           | Large patches with random shape<br>Large patches with regular shape<br>Small patches (total random) |

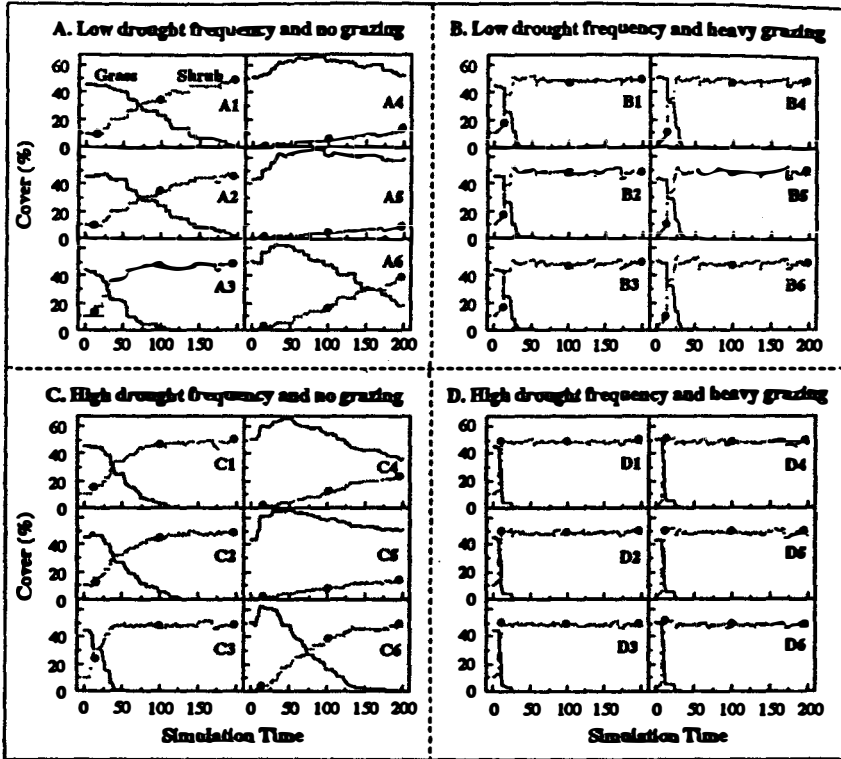
*Note:* Proportions are for soil, grass, and shrub, respectively.



**Figure 3** The two time series of droughts used in the simulation experiment. Drought is modeled here as a discrete-time random process of a binary Bernoulli experiment. A value of 0 indicates a normal year, whereas a value of 1 (as represented by a vertical bar) denotes a drought year. These two time series of droughts are generated with drought return intervals of 10 and 5 years, respectively.

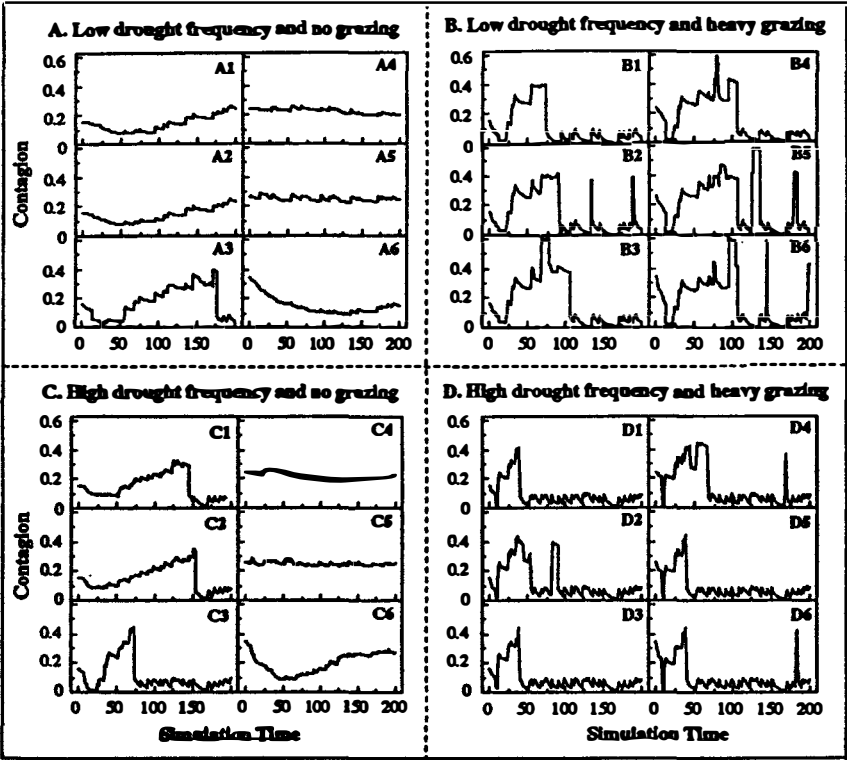
## RESULTS

The results are presented in a series of factorial plots constructed for all 24 simulation runs: the dynamics of % cover of grass and shrub (Figure 4), the response



**Figure 4** The dynamics of % cover of grass (solid lines) and shrub (shaded lines with dots) over 200 years for the 24 simulation runs. The four boxes (i.e., A, B, C, and D) represent the four combinations of two drought and two grazing levels. Inside each box, six panels (labeled 1 to 6) are displayed for the results of the six initial maps arranged in the same layout as in Figure 2. In general, grass cover decreases over time, whereas shrub cover increases.

curves of contagion and joint-count indices to vegetation dynamics (Figures 5, 6), and the effects of initial edge density on degradation potential (Figure 7). The first two factors (drought and grazing) have two levels each and, thus, form a  $2 \times 2$  table (Figures 4 to 7); the four boxes in this  $2 \times 2$  table are labeled as: (A) for low frequency drought and no grazing; (B) for low frequency drought and heavy grazing; (C) for high frequency drought and no grazing; and (D) for high frequency drought and heavy grazing. The initial spatial pattern has six levels (i.e., the six initial maps), which are arranged similarly to Figure 2 and are labeled as 1 to 6 (Figures 4 to 6). Each panel in Figures 4 to 6 displays plots of the landscape measures against simulation time. For example, a panel labeled A1 in Figure 4 represents dynamics of % cover of grass and shrub in a simulation with low frequency drought, without grazing, and with large and random-shaped patches of the proportions of 45%–45%–10% of soil, grass, and shrub. Figure 7 also uses the  $2 \times 2$  factorial plot of drought and grazing, but displays only two panels in each box that represent the two sets of proportions of cover types. In Figure 7, initial edge density is used as



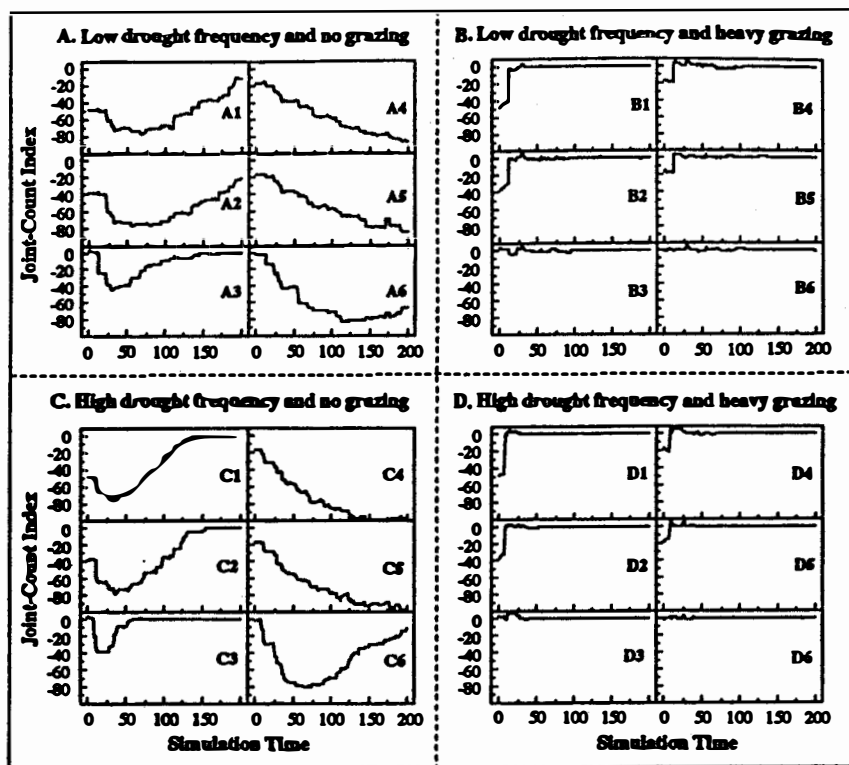
**Figure 5** The response curves of contagion index for the 24 simulation runs. Contagion Index measures the extent to which patches of the same cover type are aggregated. The figure layout is the same as that in Figure 4.

X-axis, and simulation time as a covarying factor reflected by the five curves inside each panel.

Drought effects can be evaluated by comparing panels in box A to those in box C (or B to D) in Figures 4, 5, 6 and 7. Similarly, grazing effects can be evaluated by comparing panels in box A to those in box B (or C to D) in Figures 4, 5, 6 and 7. Effects of spatial patterns of landscapes can be assessed by simply comparing the six panels in each of the four boxes in Figures 4 to 6, or by directly examining changes of degradation probability with initial edge density in Figure 7. In addition, six simulated maps at time 40 under the conditions of low drought frequency and no grazing are shown in Figure 8 to illustrate vegetation dynamics under different conditions.

**Drought Effects**

Drought frequency strongly affects the rate of degradation (i.e., comparing A to C in Figure 4). For example, under no grazing and with initial map 1, grass cover dropped below the 1% mark in about 120 years under a high frequency drought regime (Figure 4 C1), compared to 200 years with a low frequency (Figure 4 A1).



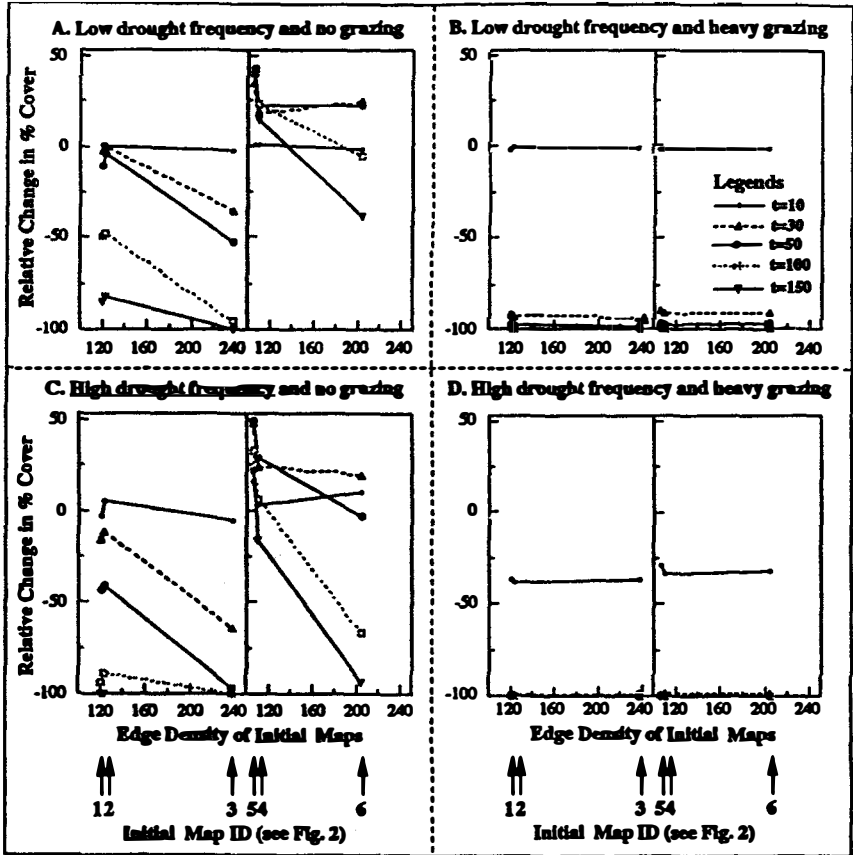
**Figure 6** The response curves of joint-count index for the 24 simulation runs. The joint-count index represents spatial autocorrelation between shrub and grass. The figure layout is the same as that in Figure 4.

The two landscape indices and the degradation potential plots also show different responses between the two drought regimes under no grazing conditions (i.e., comparison between A and C in Figures 5 to 7). However, the presence of heavy grazing greatly obscures these effects (i.e., B and D in Figure 4; discussed below). Drought is important in initiating rangeland degradation, as well as sustaining the degradation process.

### Grazing Effects

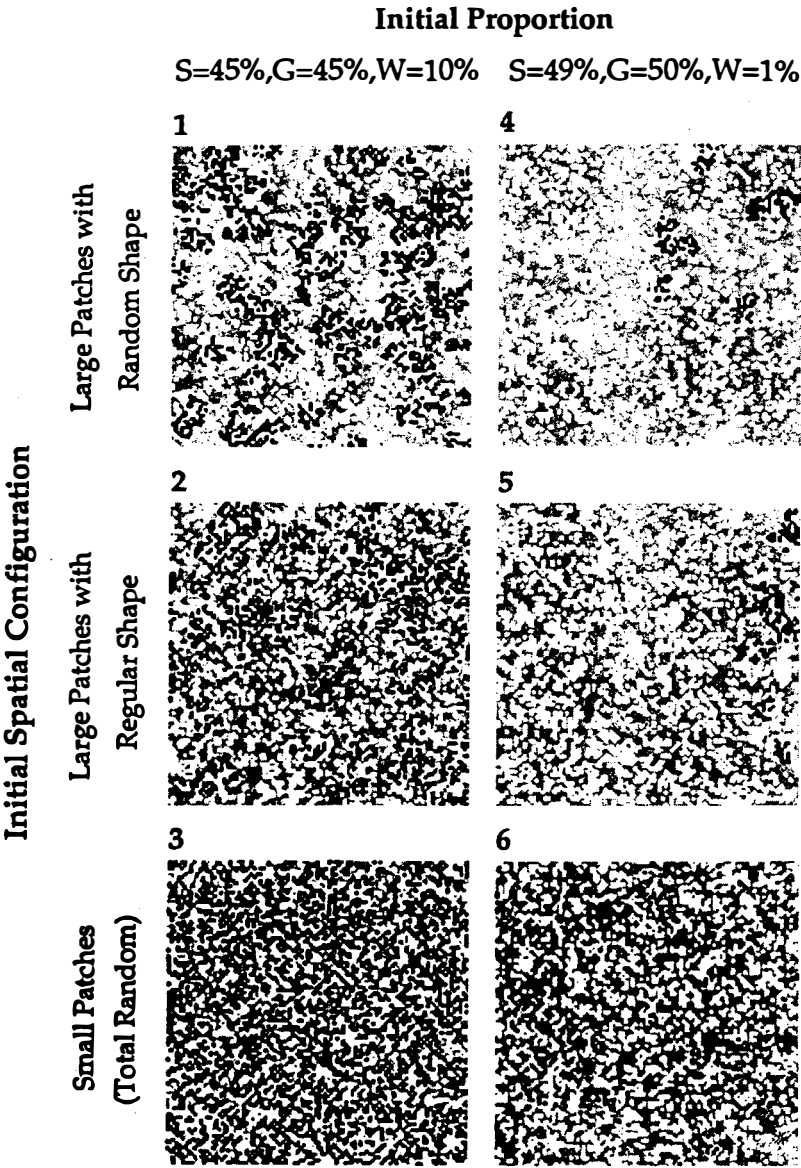
Grazing — modeled here as increased shrub seed dispersal and establishment — also exerts strong effects on the rate of degradation. Grass cover dropped below the 1% mark within ca. 50 time steps for all simulation conditions with grazing (i.e., B and D in Figure 4). The presence of grazing also causes significant differences in the response curves of the two landscape indices and the degradation potential plots (i.e., comparison between A and B, or C and D in Figures 5 to 7).

Under grazing, neither drought regime nor spatial pattern appears to have important effects (Figures 4 to 7). We can readily manipulate grazing effects by manipu-



**Figure 7** Relationships between the relative change in grass cover ( $\Delta C$  in Eq. 5) and the initial edge density of landscapes, based on data from the 24 simulation runs. This  $2 \times 2$  factorial plot differs from those in Figures 4 to 6. Each box has two panels that represent the two sets of proportions of cover types. Each panel shows five curves that represent the measurements taken at the five selected simulation times; as labeled in box B, upper curves usually depict results of earlier simulation times. Each curve has three points that represent the three initial maps generated with the same set of the proportions, but different spatial configurations; the six initial maps are marked at the bottom of the figure. Negative values on the Y axis mean that % cover of grass has decreased compared to its initial percentage. A general trend can be observed for simulations without grazing (i.e., Box A and C): degradation increases with an increase in initial edge density.

lating the parameter values in the two neighborhood effect modes, i.e., the weight in CA1 for normal years and the probability of transition to shrub in CA2 for drought years. Future observations on system dynamics of the Jornada desert, as well as future simulation studies, should help us determine appropriate parameter values. Model structure is also a factor in simulation studies; for example, the “relaxation” of the localized interaction assumption is responsible for the lack of spatial pattern effects under grazing.



**Figure 8** Six simulated maps at time 40 under the conditions of low drought frequency and no grazing (i.e., box A in Figure 4). These maps show clear visual and statistical differences from the initial maps in Figure 2. Shrub invasion is clearly shown; large patches of shrub are forming. In addition, these maps appear to have started the change toward randomness (see discussion in the text). The statistical differences between these maps at time 40 and the initial maps (Figure 2) are also significant, as depicted by the three landscape indices in box A's of Figures 4 to 6.

## Spatial Pattern Effects

In the absence of grazing (i.e., A and C in Figures 4 to 6), the initial proportions and the initial patch sizes — but not the initial patch shape — show strong, consistent effects on vegetation dynamics. The initial proportion of shrub and the patch sizes of shrub and grass in a landscape determine how long it may take for a landscape to degrade to shrubland. First, landscapes with high initial proportions of shrub (i.e., maps 1, 2, and 3 in Figure 2) degrade faster to shrubland than those with low proportions (i.e., maps 4, 5, and 6 in Figure 2). For example, after 190 time steps, only one landscape with a lower proportion of shrub reached the 1% grass cover mark (i.e., C6 in Figure 4). Some landscapes with the low shrub coverage did not even show much decline of grass cover after 200 time steps (e.g., A4 and A5 in Figure 4); it may take them over 800 years under such conditions (results not shown). Second, landscapes with smaller patch sizes (i.e., initial maps 3, or 6) degrade faster than those with larger patch sizes (i.e., initial maps 1 and 2, or 4 and 5). For example, the landscapes with larger patches barely reach the 1% grass cover mark at the end of simulation (A1 and A2 in Figure 4), whereas the landscape with a smaller patch size passes the same mark at around 120 time steps (A3 in Figure 4). In addition, our results agree with Silvertown et al. (1992) in that a total random landscape (e.g., our initial maps 3 and 6) shows a very rapid change in vegetation composition.

## DISCUSSION

### Effects of Pattern on Process

Relationship between pattern and process is a fundamental pursuit in ecology (e.g., Watt, 1947; Levin, 1992). Recently, studying reciprocal effects of spatial pattern on ecological processes has come to the forefront, especially in landscape ecology (e.g., Risser et al., 1984; Turner, 1989; Pickett and Cadenasso, 1995). This new development is due to the recognition that spatial heterogeneity is an important component of ecological systems at all scales (e.g., Risser et al., 1984; Turner, 1989; Levin, 1992; Pickett and Cadenasso, 1995). However, more research is needed to develop theories that predict processes from spatial patterns. This chapter presents one such attempt.

Our results suggest that spatial pattern does affect the process of desertification (at least in this modeled system). Can we predict the relative rate at which a given landscape may go through the degradation process in the Jornada Basin or other real landscapes? The answer to this question remains elusive. Figure 7 depicts a relationship between degradation potential (i.e., relative change in grass % cover, Eq. 5) and initial edge density of landscapes: the greater the initial edge density, the faster the rate of degradation. The mechanism behind spatial pattern effects should be the localized interaction assumption of our model under no grazing conditions. Landscape configuration determines the amount of the interaction front (i.e., edges between different cover types, especially shrub) in a given landscape. The amount of the interaction front is reduced when the proportion of shrubs is small, or when

shrub patch sizes are large (i.e., higher aggregation). This reduction in the interaction front slows the degradation process under the localized interaction assumption that transitions to a given cover type can take place only if the cover type exists in the neighborhood. This is why spatial pattern had little effect under grazing conditions since grazing is modeled as a cause of the relaxation of the localized interaction assumption. We conclude that the localized interaction assumption is the necessary condition for existence of spatial pattern effects.

### Scaling with Multiple-Scale Data

The effects of drought, grazing, and spatial pattern can be thought of as operating at different scales: drought at large (regional) scales, grazing at intermediate (landscape) scales, and spatial pattern at small (patch) scales. Drought and grazing affect vegetation dynamics *externally* by differentially affecting the two functional groups of plants. This is modeled by different transition probabilities (Table 1) and different neighborhood effect rules that favor shrubs (Table 3). Spatial pattern affects vegetation dynamics *internally* when local interactions define the mechanism of degradation. Spatial pattern per se is not built into the M-CA model, but is represented by the initial landscape maps used in our simulation experiment.

Scaling, i.e., to translate information from one scale to another, is a critical issue in ecology (King, 1991; Reynolds and Leadley, 1992; Ehleringer and Field, 1993). We need to study and synthesize patterns and processes ranging from individual organisms to global phenomena (e.g., Ehleringer and Field, 1993), but face the problem of lack of information at large, appropriate scales because of the difficulties in gathering such information through experimentation. One solution to this problem is to use a hierarchical modeling approach. Hierarchical models can incorporate data and relationships of ecological processes at multiple scales, and thus, provide a way of extrapolating data and models of short-term and small spatial extent to long-term and large spatial extent (e.g., Moloney et al., 1992; Reynolds et al., 1993; Wu and Loucks, 1995). For example, in discussing modeling ecosystem responses to elevated CO<sub>2</sub>, Reynolds et al. (1993) have developed a hierarchical modeling scheme based on mechanistic models at different scales. Extrapolation of CO<sub>2</sub> effects from leaf, through canopy and whole plant, to ecosystem scales, is done through a series of mechanistic models, each of which is built at a specific scale and uses the three-level hierarchical structure (i.e., lower-target-higher) to facilitate scaling (see Reynolds et al., 1993). The M-CA model presented here is a major component of the hierarchical models that we are developing for the Jornada desert.

### Limitations of the Markov-Cellular Model

A rule-based model is obviously a product of the rules employed. Selecting neighborhood rules that can successfully convey ecological knowledge is a major challenge (e.g., Caswell and Etter, 1993). This task becomes easier if a long time series of data exist (e.g., a time series of GIS maps). Process and individual-based models (e.g., Mou et al., 1993; Reynolds et al., 1996) may also help define such

rules. The transitions used here are based on an annual time step, which may be unrealistic in some situations.

We observed that all landscapes converted to an approximately random landscape, even though their initial spatial patterns may be distinct and non-random. Caswell and Etter (1993) observed a similar phenomenon with their cellular automaton model and reported that their equilibrium landscapes showed no apparent structure. We also found that some landscape indices (e.g., fractal dimension, edge density) and the 15 types of neighborhood configuration showed convergence (results not shown). We suspect that this convergence may be a result of the Markov process with a random decision-rule used in the model. There are other random processes built into the M-CA model, such as the Bernoulli process of drought regimes (Figure 3), the random decision used for some mixed neighborhood rules (Table 3), and the stochastic factor of 5% that modifies the transition probabilities. However, they are unlikely to be the sources of this problem since we observed convergence even when they were excluded. By definition, the Markov process defines future system behavior based solely on the present behavior (e.g., Gardner, 1986). So, it is highly likely that the random decision rule of Markov process leads to a common random structure, regardless of the initial conditions.

### Use of GIS Data In Markov-Cellular Modeling

GIS data have great potential for M-CA modeling, in both the model development phase and the simulation phase (Hobbs, 1994; Zhou and Liebhold, 1995). Our Markov-cellular model can use GIS data in three ways:

- (1) To define the initial configuration of landscapes (e.g., Zhou and Liebhold, 1995). This use of GIS data is straightforward. When the model is applied to a real system, a GIS map of vegetation types can be used to start the simulation. Furthermore, if GIS maps of the past and the present are both available, one may run the model with the GIS map of the past and then assess the model performance by comparing model predictions to the GIS map of the present.
- (2) To calculate transition probabilities (e.g., Zhou and Liebhold, 1995). It should not be difficult to estimate the transition probabilities from a time series of GIS maps. The problem is the availability of such GIS data at the appropriate temporal scales. However, the rapid development of GIS databases in the future should help overcome this limitation. A technical consideration should be to ensure that the GIS maps are properly geo-referenced to reduce estimation errors.
- (3) To evaluate or even determine the neighborhood rules. A vegetation map can be easily transformed into a neighborhood configuration map. For example, for our 3-state desert system, a map with 15 codes for the 15 possible neighborhood configurations can be obtained from a vegetation map with 3 codes. Thus, transitions by different neighborhood configurations can be examined with a time series of GIS maps, and the information can be used to help determine neighborhood effect rules. We have developed a simple algorithm to do this type of analysis. One difficulty that may arise with this analysis is that it requires shorter temporal scales, and, perhaps, smaller spatial scales (i.e., higher resolutions) of the GIS time series because it deals with a phenomenon of small spatial and temporal scales at the patch level.

## SUMMARY

In this chapter, we have demonstrated a new Markov-cellular model of desert vegetation dynamics. The advantages and limitations of this modeling approach are discussed. The model is used to study effects of the three factors in the desertification process: drought, grazing, and spatial pattern. Using the simulation experiment conducted with the M-CA model, we are able to show how high frequency drought, heavy grazing, and landscapes with high proportion of shrubs and high edge density would affect the degradation process. We are also able to show the interactions among the three factors. Although the effects of the three factors are, in essence, effects of model structure on results, our focus lies in the modeling framework that can be used to examine these factors under different conditions. How landscape dynamics are affected by these factors is important. However, even more important is the question: Can these effects be characterized and manipulated by the M-CA model? Our results suggest that this model can be an effective component in a hierarchical modeling framework of ecosystem dynamics at multiple scales.

Analysis and modeling of GIS data are very important to the success of applying GIS to natural resource management, but such capability is very limited in commercial GIS. This requires us to develop models that can use GIS data to produce information that is badly needed in the decision process about the environment and natural resources. We believe that the M-CA model is one such model. In general, GIS data can be used to set up the physical environments for landscape simulation (e.g., vegetation pattern, soil, hydrology). In particular, a time series of GIS data can be used to parameterize M-CA models, calculating transition probabilities and determining the neighborhood rules. It has been suggested that more studies should be designed and conducted at multiple scales in order to identify the "appropriate scale" for certain ecological processes and to better understand how these processes may be affected by factors operating at "higher" and "lower" scales (e.g., Addicott et al., 1987; Wiens, 1989; Milne, 1992). GIS, together with remote sensing data, should play a significant role in this pursuit.

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