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A qualitative spatial model of hardwood rangeland state-and-transition dynamics

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Abstract

We present a method for computerizing the transition rules of a state-and-transition model and then linking this model to a geographic information system. The resulting simulation characterizes rangeland vegetation dynamics in space and time. The method makes use of an expert system, a computer program that forms logical chains of transition rules. Simulation using state-and-transition rules, sometimes called qualitative simulation, has the disadvantage that it is less precise than traditional numerical simulation. However, it may have the advantage of being able to generate more robust simulation of complex vegetation communities. We demonstrate the application of the method by constructing a model of hardwood rangeland in the western foothills of the Sierra Nevada. The model is tested by comparison with historic black-and-white aerial photographs. The model is found to agree generally with the observed data but to differ substantially in some locations. Implications of this difference are discussed.

Resumen

Presentamos un método para computarizar las reglas de transición de un modelo de estados y transición y enlazamos este modelo a un sistema de información geográfica. La simulación resultante caracteriza en espacio y tiempo la din mica de la vegetación del pastizal. El método utiliza un sistema experto, que es un programa de computación que forma cadenas lógicas de las reglas de transición. La simulación usando reglas de estado de transición, a veces llamada cualitativa, tiene la desventaja de que es menos precisa que la simulación númerica tradicional. Sin embargo, tiene la ventaja de ser capaz de generar una simulación mas sólida para comunidades vegetales complejas. Demostramos la aplicación del método construyendo un modelo del pastizal "hardwood" al pie de la montaña del lado oeste de la Sierra Nevada. El modelo es probado por comparación de fotografías aéreas históricas en blanco y negro. Se encontró que el modelo genealmente concuerda con los datos observados; sin embargo, difiere substancialmente en algunas localidades. Se discuten las implicaciones acerca de esta diferencia

Key Words: geographic information systems, simulation models, vegetation dynamics

The state-and-transition model, introduced to range science by Westoby et al. (1989), has potential to be useful in summarizing information about vegetation dynamics. State-and-transition models in range management have generally been implemented through simple printed flowcharts, but they can be directly implemented on a computer using expert system methodologies (Noble 1987). Expert systems are a type of computer program that forms logical chains of transition rules. Starfield and his collaborators (Starfield and Bleloch 1983 Starfield et al. 1989) have developed expert system-based ecosystem models comprised of discrete states together with rules to describe the transitions between states. These models are used to forecast the response of these ecosystems to various forms and magnitudes of disturbance.

Computer implementation of state-and-transition models offers a number of advantages. One is that the exercise of writing the transition rules in precise logical form imposes a high level of rigor and precision on the model. A second is that using the computer to keep track of logical relationships opens the way for more complex qualitative models that include some degree of mechanism. A third is that it offers the potential for introducing explicit representation of spatial effects through the linkage with a geographic information system (GIS). This explicit representation of spatial variability is essential in an explanatory model that is to be used as a management tool (Grice and Macleod 1994). The use of GIS and cartographic modeling (Tomlin 1990) provides a natural linkage between spatial and temporal processes in the model. In this paper we introduce a methodology for implementing state-and-transition models as computer simulations and linking them with geographic information systems.

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Materials and Methods

Simulation methodology

The simulation methodology is based on establishing a correspondence between the rules of a rule-based expert system (Noble 1987, Plant and Stone 1991) and the transition rules of a state-and-transition model. We use the QTIP (Qualitative Temporal Inference Program) expert system (Plant 1997) to encode the model's transition rules. The QTIP incorporates qualitative (i.e., non-numerical) simulation based on concepts originally developed for mechanical and electrical systems (de Kleer and Brown 1984, Kuipers 1986, Whitehead and Roach 1990). The most important aspect of qualitative simulation is that the variables take on ordinal rather than rational or interval values (Stevens 1946). The QTIP was originally developed for the qualitative modeling of crop production systems (Plant and Loomis 1991). The important feature of the program for application to state-and-transition modeling is that it combines an expert system with dynamic simulation of system behavior. The QTIP uses an event-based simulation (Langran 1992), which means that the time variable jumps in chronological sequence from one event to the next rather than changing in fixed steps. The state-and-transition model is linked with a GIS through an algorithm that alternates between spatial steps and dynamic steps. The spatial model is laid out as a grid of square cells in a raster-based GIS. Spatial steps are carried out in the Idrisi GIS (The Idrisi Project, Clark University, Worcester, Mass.). The specific GIS software is not critical, however. We used Idrisi because it is a simple raster-based system that functions very well and because a large data set of Idrisi files has been assembled for the study site. At each time step, for each cell the program calls on the GIS to determine the spatial relationships between that cell and the rest of the cells in the model (e.g., proximity to the nearest cell with a high level of shrubs). Following this GIS spatial analysis, the program uses the QTIP dynamic simulation to process state-transition rules, generating a prediction of the state of the cell at a later time. This process is repeated for every raster cell at each time step.

We demonstrate the algorithm by applying it to an existing state-and-transition model of the hardwood rangelands of the western foothills of the Sierra Nevada in California. The output of the model is compared with hardwood vegetation dynamics at a study site located at the University of California Sierra Foothill Research and Extension Center (SFREC) (latitude 39˚16'N, longitude 121˚16'W), at elevation approximately 1,000 meters. Soils are predominantly Auburn rocky loam, which is a member of the loamy, oxidic, thermic Ruptic-Lithic Xerochrepts, and Sobrante very rocky loam, which is a member of the fine-loamy, mixed, thermic Mollic Haploxeralfs. In this region the overstory is dominated by blue oak (*Quercus douglasii* H. and A.) in association with other oak species and with foothill pine (*Pinus sabiniana* Douglas). The understory includes a number of native shrub species, e.g., ceanothus (*Ceanothus* spp.) and poison oak (*Toxicodendron diversilobum* (Torrey & A. Gray) E. Greene). The groundcover, which formerly was dominated by native perennial bunchgrasses, now consists primarily of introduced Mediterranean annual grasses (e.g., wild oat, *Avena fatua* L., soft chess, *Bromus mollis* L.) and forbs (e.g., filaree, *Erodium* spp.). The region's climate is Mediterranean, with hot, dry summers and cool, wet winters but with little frost.

The purpose of this paper is to present the methodology rather than to develop a detailed simulation of a particular site or sites. We therefore use a model made by combining 2 existing state-and-transition models that have been independently constructed for hardwood rangelands in this region (George et al. 1992, Huntsinger and Bartolome 1992). These models are similar in their classification of states. The model of George et al. (1992) contains more detail in its description of groundcover and that of Huntsinger and Bartolome contains a more detailed description of the oak/shrub understory states. To test the model, we compare its output with a data set drawn from a sequence of 5 black-and-white aerial photographs taken between 1952 and 1993 of the study site.

The simulation methodology is presented in 2 stages. The first stage describes the dynamic component of the model. This involves the development of the state-and-transition model and the translation of its transition rules into a knowledge base for the qualitative simulation model. The second stage presents the spatial component of the model. This involves linking the transition rules of the QTIP knowledge base with the analysis modules of the Idrisi GIS.

The Dynamic Component

The qualitative simulation model is based on the principle that each of the model variables takes on categorical values that may be either ordinal or nominal (Stevens 1946). Ordinal values have an ordered relationship (e.g., *high, moderate,* and *low*). Nominal values have no such ordering (e.g., *sandy, rocky,* and *loamy*). The method replaces traditional dynamic equations with expert system rules phrased so that the direction of cause and effect parallels the direction of inference in the rule (Plant 1997). For example, if a moderate or high fire causes groundcover to be low due to burning then this would be phrased as

If *fire_level* ≥ *moderate*
Then *groundcover* = *low*.

Each step of the dynamic simulation process involves testing all the rules and implementing any that apply. This process is repeated cyclically until no new conclusions can be drawn (this is called *forward chaining*, cf. Plant and Stone 1991). For example, if the rule base contained a second rule stating

If *groundcover* = *low*
Then *seed_production* = *low*

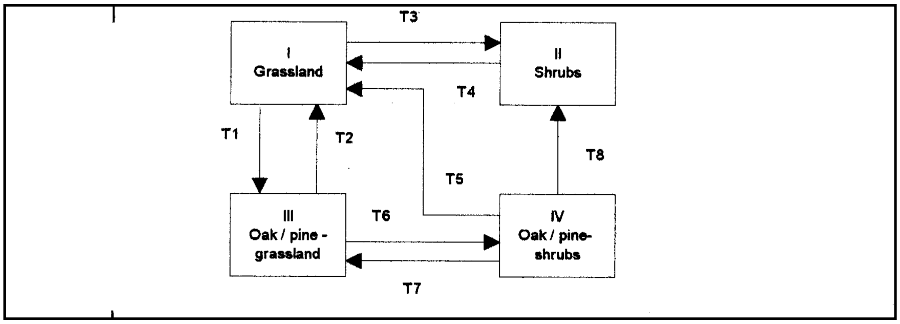
and if input data included a value of *moderate* for *fire_level*, then the forward chaining process would first use the first rule to generate the value *low* for *groundcover* and then use the second rule to generate the value *low* for *seed_production*. Dynamics are introduced into the model by incorporating the capability to alter values at a later time as described below.

Figure 1 shows the hardwood rangeland state-and-transition model with the catalog of transitions, expressed in the descriptive form proposed by Westoby et al. (1989). The transition descriptions have been slightly simplified from the original papers of George et al. (1992) and Huntsinger and Bartolome (1992) to facilitate translation into computer form. The model emphasizes the dynamics of the long-lived shrub and tree life forms that dominate these ecosystems.

The first step in converting this state-and-transition model into a qualitative simulation model is to establish the variables and their range of values. Table 1 lists the full set of variables in the model. The variables characterizing the vegetation are: (1) *groundcover*, the level of cover of the herbaceous groundcover, (2) *shrubs*, the understory shrub cover level, (3) *saplings*, the cover of immature trees, (4) *overstory*, the cover of mature trees, and (5) *litter_level*, characterizing the amount of herbaceous material left at the end of the growing season. There are 4 variables characterizing the 4 external inputs simulated in the model: *fire_level*, *grazing_level*, *herbicide_applied*, and *tree_cutting*. Finally, there are 2 fixed-value parameters, *soil_texture* and *soil_depth*.

Each of the variables describing vegetation may take on 1 of the values *high*, *moderate*, or *low*. The 3 variables *groundcover*, *shrubs*, and *overstory* play a special role in the qualitative model since they determine the location's state in the state-and-transition model. There are 8 possible combinations of *high* and *low* values among the 3 vegetation types. However, only 4 of these are possible in a real state since *groundcover* and *shrubs* are assumed to be mutually exclusive so that they cannot both remain *high* or *low* in the same cell. (A location that consisted of bare rock could have both values *low* at the same time in a stable state, but such a location would not take on any other values and so may be ignored in this discussion). Each of the 4 possible combinations of values is interpreted as one of the states in the state-and-transition model as shown in Table 2. The values of *litter_level*, *herbicide_applied*, *tree_cutting*, *grazing_level*, and *soil_depth* are also *high*, *moderate*, or *low*. The variable *soil_texture* may be either *rocky_loam* or *very_rocky*, reflecting the 2 soil textures found at the test site. The variable *fire_level* may take on 1 of the 4 values *none*, *grass_fire*, *shrub_fire*, and *crown_fire*.

The full QTIP knowledge base interpreting the state-and-transition model is available at the world wide web given at the end of the paper. The model is written in the QTIP knowledge base syntax, which is based on the computer language LISP (Winston and Horn 1981). A complete description of this syntax is given by Plant



Transition 1 (Grassland to oak/pine - grassland). This transition is sufficiently rare that it is not included in the catalog of Huntsinger and Bartolome (1992). Protection from grazing and fire facilitates overstory regrowth in situations where such regrowth is possible. Foothill pine establishes an overstory in about 20 years. Oak overstory, if it is established at all, takes about 50 years to mature. Herbaceous understory remains present. Overstory establishment is inhibited by dense litter mat that prevents seed contact with soil, and by shallow or infertile soil.

Transition 2. (Oak/pine-grassland to grassland). Drought, crown fire, herbicide application, or cutting remove overstory trees and leave herbaceous groundcover.

Transition 3 (Grassland to shrub). Protection from grazing and fire facilitates shrub invasion where conditions favor such invasion. Shrub establishment is favored by rocky soil, even in the presence of grazing. Therefore, this transition often takes place in regions that were previously dominated by shrubs but underwent transition to grassland (Transitions 4, 5, or 7). Shrubs become dominant in 10 to 20 years. Herbaceous understory declines as shrub cover increases.

Transition 4 (Shrub to grassland). Wildfire or controlled burning remove shrubs and groundcover. Groundcover is re-established in the succeeding year from residual and dispersed seed.

Transition 5 (Oak/pine - shrub to grassland). Drought or crown fire remove both trees and shrubs. Herbicide application or cutting remove overstory trees and, in combination with lower intensity fire, lead to establishment of herbaceous groundcover.

Transition 6 (Oak/pine - grassland to oak/pine - shrub). This transition occurs over a span of decades, if at all. Protection from fire and grazing facilitates this transition in areas where it is possible. As with Transition 3, this transition often takes place in regions where the understory was previously dominated by shrubs but underwent transition to grassland.

Transition 7. (Oak/pine -shrub to oak/pine - grassland). Shrub fire removes shrub understory and may kill pines. Herbaceous groundcover established in succeeding year from residual and dispersed seed.

Transition 8. (Oak/pine - shrub to shrub). Herbicide application or cutting removes trees. If shrub understory is left intact it will remain stable.

Fig. 1. State-and-transition description of vegetation dynamics of blue oak woodland in the western foothills of the Sierra Nev., based on a synthesis of existing state-and-transition models of George et al. (1992) and Huntsinger and Bartolome (1992).

Table 1. List of parameters and variables used in the state-and-transition model for hardwood rangeland.

Vegetation layers	External inputs	Fixed parameters
overstory	fire_level	soil_depth
saplings	grazing_level	soil_texture
shrubs	herbicide_applied	
groundcover	tree_cutting	
litter_level		

Table 2. Correspondence between values of variables in the model and states of the state-and-transition model for hardwood rangelands.

State	groundcover	shrubs	overstory
I. Grassland	*high*	*low*	*low*
II. Shrubs	*low*	*high*	*low*
III. Oak/pine- grassland	*high*	*low*	*high*
IV. Oak/pine- Shrubs	*low*	*high*	*high*

(1997), but the rules are self-explanatory. Each rule is numbered according to the transition it interprets. For example, rule T3&6.4 (i.e., the fourth rule used in transitions 3 and 6) has the following form:

(Rule T3&6.4
if(soil_type/=very_rocky)
shrubs = low)
(grazing_level=low)
(litter_level)=low)
(dist_shrubs=low)
then (predict shrubs moderate plus
time 5 prob 0.2))

Transitions 3 and 6 involve shrub invasion. The transition rule states that if the soil texture is not *very rocky*, and if the current grazing level is low but the litter level is also low (as would occur, for example, after a grass fire), and if the current shrub level is low but there are shrubs nearby, then there is a 20% chance that a moderate level of shrubs will be present on the site in 5 years. The value of 20% was determined by our own experience and observations from historical aerial photos at the SFREC. Other rules in the knowledge have a similar structure. Each rule is a statement of cause and effect in the sense that if the parameters have the values indicated in the "if" part of the rule, then this will cause the effect shown in the "then" part of the rule. The probabilistic component of the rule is implemented by selecting a random number on the interval 0 to 1. If the number is between 0 and 0.2, the transition is implemented, otherwise not.

A single time step of the model consists of successively running through the rules as described above. If the test of the "if" part of a rule is passed, the "then" part is implemented. If the implementation involves an event that occurs at a later time, as is the case with Rule T3&6.4 above, then this transition is placed in a chronologically ordered "event queue." All the rules in the knowledge base are cyclically tested until no new transitions are generated. At this point the time step is complete for that raster cell. If any events have been placed in the event queue, after all raster cells are processed the system updates its time to the value of the next occurring event and the transition is implemented. The spatial portion of the algorithm is carried out, and the process is then repeated with the new parameter values.

The Spatial Component

The spatial component of the simulation process links the state-and-transition model of the previous section to the geographic information system. Parameter and variable values for the model are stored in GIS layers (these are Idrisi files, called *image files* in Idrisi terminology), with 1 layer for each parameter or variable. Each image file contains data for the grid of cells that represents the site. Each cell in an image file contains a single number that represents the value in that cell of the quantity represented by the GIS layer. The raster cells in the hardwood rangeland model are squares representing a land surface 35 m on a side. This size was selected because it is small enough to characterize relatively uniform areas but large enough that a single cell will contain more than 1 tree.

At each time step the QTIP program proceeds on a cell-by-cell basis. For each cell it first reads from the Idrisi image files the values of all the model variables in that cell. It then runs a single dynamic step of the simulation for the cell. During this step, any time a transition rule is invoked to predict a future event, QTIP creates new Idrisi image files to store that event. After the time step has been carried out for all of the cells, QTIP calls Idrisi to perform GIS operations such as distance and area calculations using the newly-written image files.

In the present hardwood rangeland model there is only 1 spatial calculation. This involves the spread of shrubs. At the spatial and temporal scale of the model, shrubs are assumed to spread more rapidly to contiguous regions so that the probability that a site with herbaceous groundcover will be invaded by shrubs is increased if there are shrubs at a nearby site. This is reflected in Rule T3&6.4, given as an example in the previous section, in which the variable *dist_shrubs* must have the value *low* for the rule to be triggered. This variable represents the distance from the cell to the nearest cell in which the variable *shrubs* has the value *high*. Idrisi computes values of the variable *dist_shrubs* for each cell during the spatial part of the simulation algorithm. This is accomplished in a 3 step process. First, a layer is constructed in which each cell is assigned a value 0 or 1 depending on whether the variable *shrubs* has the value *high* in that cell. Next, the Idrisi Distance module is used to compute the distance of each cell from the nearest high-shrub cell. Finally, these distances are reclassified as *low* if they have a value of 175 m or less.

Idrisi image files are also used to characterize external inputs to the system. Disturbances (e.g., fire, tree cutting, herbicide application, and changes in the grazing regime) are defined in image files and read by QTIP during the spatial part of the algorithm. Each disturbance is treated as an event and placed in the "event queue." Conditions after the disturbance are re-evaluated during the dynamic time step, and a forecast consistent with these new conditions is generated. If a change in value takes place in any cell, then all changes of value of that variable in that cell predicted at a later time are eliminated from the event queue. For example, if the event queue contains a transition of the *shrub* variable to *moderate* in 5 years and a fire takes place in the meantime reducing shrubs to *low* in

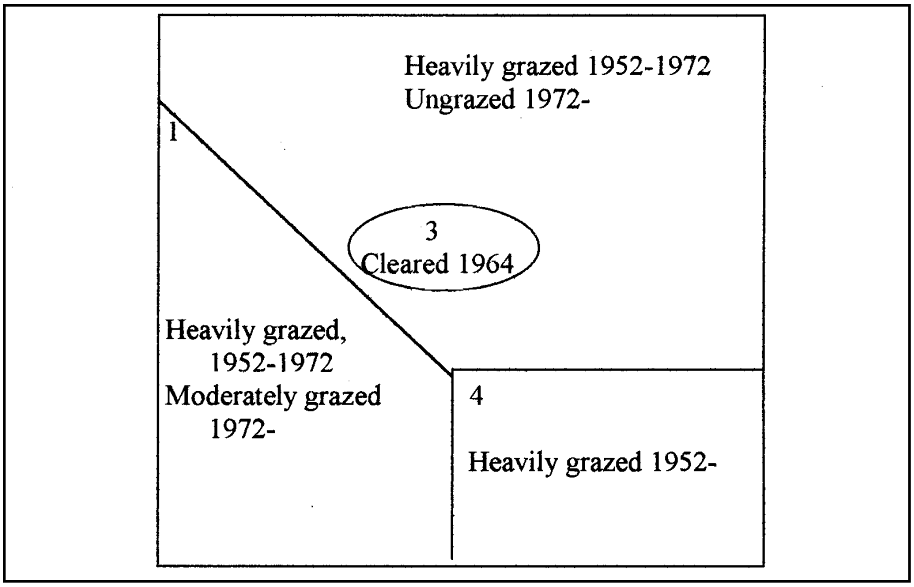


Fig. 2. Schematic map of the study site used to illustrate the state-and-transition model. Site is 700 m on a side and is located at the University of California Sierra Foothills Research and Extension Center. The site is divided into 4 areas based on grazing and clearing history.

that cell, then the shrub transition to *moderate* in that cell is removed from the queue of future events.

Comparison of model output with study site

The model was tested by comparing its simulation results with the vegetation dynamics in a 49 ha site on the Koch tract of the SFREC. The site is a square, 700 m on a side. Black and white aerial photographs including the site taken in 1952, 1972, 1984, 1989, and 1993 were obtained from the National Archives, USDA, and the WAC Corporation, Eugene, Ore. All photos were taken in May, June, July, or August. An orthophotograph of the site taken in 1978 was obtained from the US Geological Survey and was used as the base map. The photographs were georegistered to the base map using the Idrisi Resample module with approximately 20 landmarks in each photograph.

Figure 2 is a simple schematic map of the site. The southeast corner, denoted area 4 in Figure 2, is privately owned. The remainder of the site was incorporated into the SFREC in 1960. The northeast portion, denoted area 2 in Figure 2, was surrounded by an exclosure in 1972, and no domestic animal grazing has occurred in this area since that time although wild herbivores still have access. Area 1 in Figure 2 has been continuously grazed since the late nineteenth century (McClaran 1986). Detailed grazing records are not available, but the grazing intensity on the SFREC has been moderate (approximately 0.7 acres/AUM) for at least the last 20 years. Grazing intensity on the privately-owned area is generally heavier. An area in the ungrazed region, denoted area 3 in Figure 2, was cleared of oak trees in 1964. Parts of the grazed area of the SFREC have been cleared more recently in 1988 and 1989. The southwest portion of the site was part of an area in which McClaran (1986) examined fire scars in tree rings in order to establish the dates at which fires had occurred. McClaran concluded that the most recent fire on the site occurred in 1944.

Locations at the site containing each of the 4 vegetation states in the state-and-transition model of Figure 1 were identified and their position determined using a differentially corrected GPS (Trimble Pro-XL, Trimble Navigation, Sunnyvale, Calif.). The locations recorded with the GPS were identified in the most recent (1993) aerial photograph and used to guide photointerpretation. Each of the aerial photographs was interpreted after mounting the photograph on a light table. Our conclusions regarding our ability to accurately interpret black-and-white photos matched those of Davis et al. (1995). Different tree species could not be distinguished at all. Individual mature trees could easily be distinguished from shrubs, but clusters of immature trees were difficult to distinguish from shrubs. In general, mature trees appeared darker than other vegetation. Shrub understory could not be reliably distinguished from herbaceous understory.

Photointerpretation was partially carried out using image processing software Paint Shop Pro (JASC, Inc., Eden Prairie, Minn.) and Adobe Photoshop (Adobe Systems, Mountain View, Calif.). The georegistered aerial photographs were subdivided into 400 square cells, each having a side length of 35 m on the ground, corresponding to the raster cells in the GIS model. For each cell a histogram of the frequency of darkness of the gray tones was constructed. Amount of dark gray in the cell was correlated to canopy cover by comparing ground-based observations with the 1993 photo. Cover was classed as *high, moderate,* or *low* based on the cover classes defined by Pillsbury et al. (1991), with their “scattered” and “low” categories lumped together as *low*. Thus, 0–33% cover was classed as *low*, 34–75% cover was classed as *moderate*, and 76–100% cover was classed as *high*. The cover classes in each cell of the 1952 photo were then estimated based on their gray level.

The 1952 photograph did not appear to contain many areas high in shrubs. Therefore, shrub cover was assumed to be generally low at the start of the simulation except in 2 areas that appear to have been high in shrubs. Soil texture data was taken from the library of Idrisi image files maintained by the SFREC. The original files, which had been digitized from SCS soil survey maps, were resampled to the model grid of 35 m on a side. Soil depth was assumed to be moderate except in those areas where rocky outcroppings could be observed on the ground.

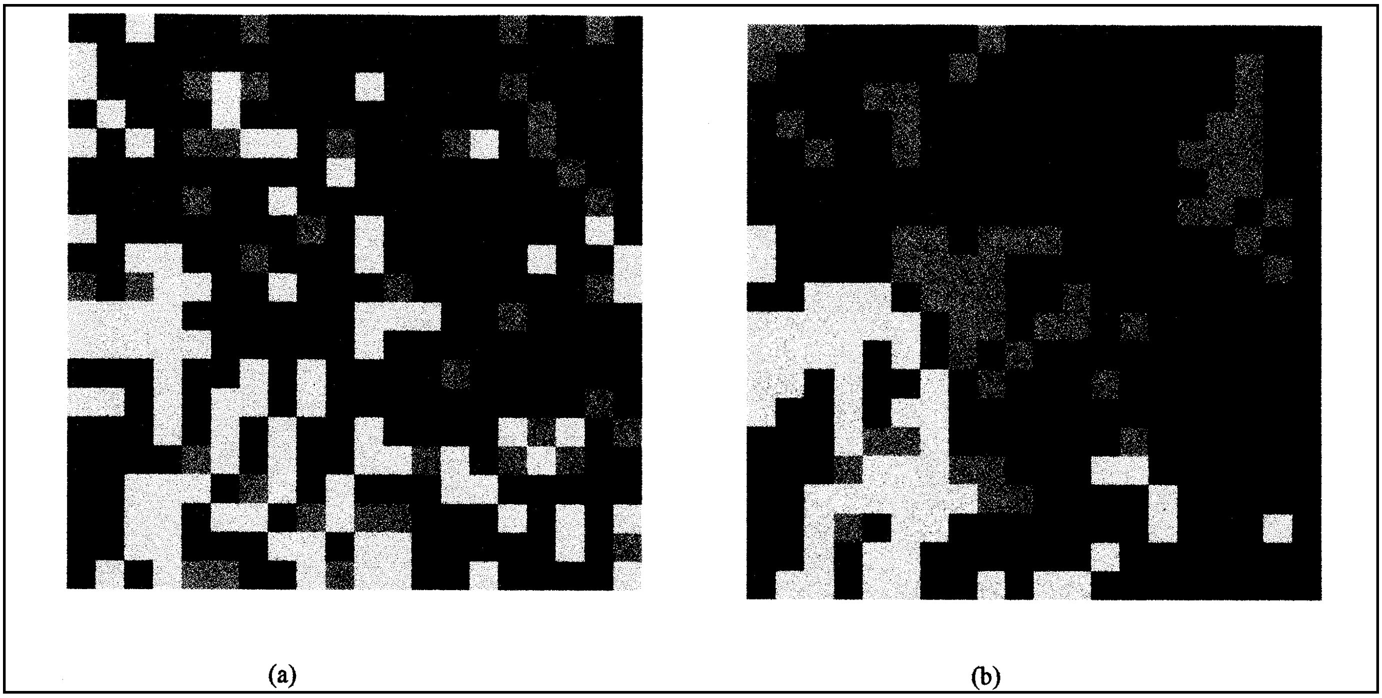


Fig. 3. (a) 1993 aerial photograph resampled to the same cell size as the model (35 m) and reclassified into categories of *low* (0–33% cover), *moderate* (34–75% cover), and *high* (76–100% cover). (b) Model output in year 41, corresponding to 1993. In both images the lightest shade corresponds to cover value of *low*, the medium shade corresponds to a cover value of *moderate*, and the darkest to shade corresponds to *high*.

The simulation process consisted of setting the model variables to values consistent with those in the 1952 photo and running the model for a simulated time of 41 years. Simulation output was compared quantitatively with the 1993 aerial photograph as follows. The photograph was resampled to the same 35 m grid as the model, so that each raster cell in the photo was assigned the gray scale value at the center of the cell. These values were then reclassified into 1 of 3 values, corresponding to *high*, *moderate,* and *low* cover. A GIS layer was then produced by subtracting the model output from the resampled, reclassified image. Cells in this resultant layer could take on one of 5 values between –2 and 2. A value of –2, for example, indicated that the photo was *low* and the model output was *high.* A value of 0 indicated no difference. The level of agreement of between the model and the 1993 photo was then indicated by the frequency histogram of the resultant GIS layer. The mean and standard deviation indicate the level of bias and the accuracy of the model, respectively. A mean and standard deviation of zero would indicate a perfect match of model output to the data.

Results

The first row of Table 3 shows the frequency histogram comparing the initial model with the data. Figure 3 shows the resampled, reclassified 1993 aerial photo and the model output of the variable *overstory* in year 1941. In all figures of model output, the light shade of gray represents cells in which *overstory* has the value *low,* the medium shade represents the value *moderate*, and the darkest shade of gray represents the value *high.*

The initial simulation results indicated fairly good general agreement. One subjectively substantial difference between the model output and the real data was that the site had several areas where tree establishment remained low over the entire simulation (these areas are also clearly visible in an earlier 1937 photo not used in this study because of its poor quality). The model had no provision to predict the existence of these areas. There are a number of possible reasons for the existence of these treeless areas including shallow soil, dense litter mats from medusahead (*Taeniatherum asperum* Nevskii) infestations, and subtle differences in soil properties such as acidity, water holding capacity, and drainage. In the absence of any evidence favoring one particular cause over another, we established a variable called *overstory_potential* and gave it the value *low* in those cells that did

Table 3. Frequency histograms of deviation of the simulation output from actual data. Histogram values indicate difference between data and model, where *high, moderate,* and *low* are valued at 2, 1, and 0 respectively. Mean and standard deviation respectively indicate level of bias and accuracy of model.

Difference	-2	-1	0	1	2	Mean	Std Dev
Original Model	0.105	0.0925	0.6675	0.0975	0.0375	-0.13	0.8631
Modified Model	0.0975	0.08	0.6625	0.1225	0.0375	-0.0775	0.8593

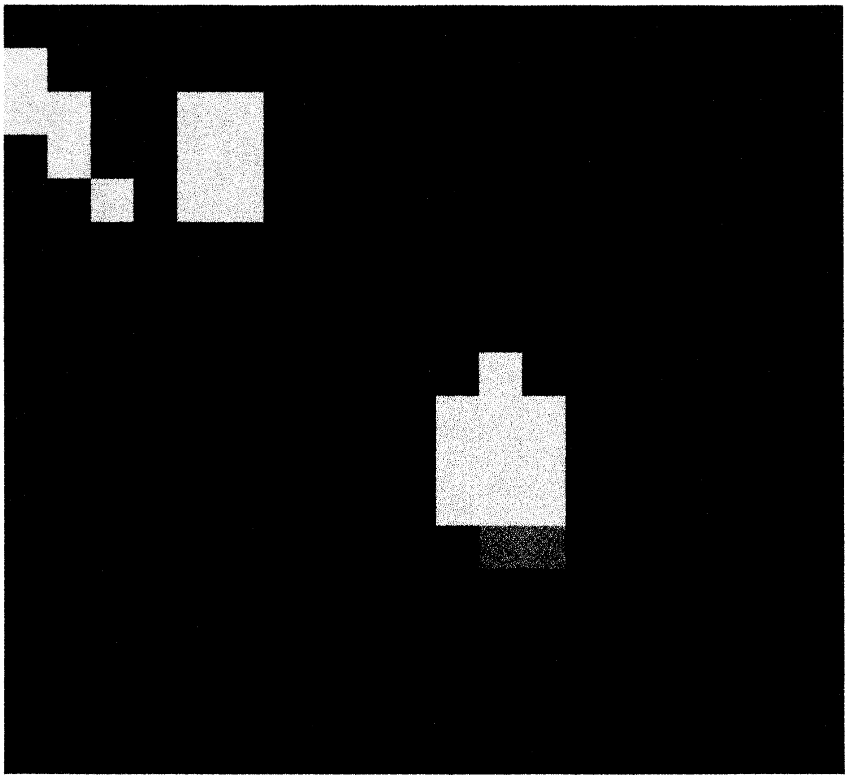


Fig. 4. Spatial distribution of the parameter *tree_potential*, introduced to induce the model output to display areas that remain treeless for at least 56 years.

not exhibit increase in canopy cover or sapling growth over the time span of the simulation. Figure 4 shows a representation of the *overstory_potential* layer used in the modified model.

Figure 5 shows the overstory component of the simulation of the model as finally constituted. Only in those cells in which the value of *overstory_potential* was *low* was there any difference between the simulation results with the original and the modified models. In the figure each aerial photograph is matched with the corresponding model output. In both the simulation output and the data, the general tendency of the site between years 1952 and 1972 was for canopy cover to increase. Cover remained roughly constant between the years 1972 and 1993 except in areas that were cleared. The second row of Table 3 shows the frequency histogram of comparison between the model output and the resampled, reclassified aerial photo. There is little quantitative improvement, although the modified model does (since it is forced to) accurately reflect the fact that some areas on the site remain treeless. It is important, however, to recognize that the reference data set of Figure 3a, although it is constructed according to objective criteria, may itself be criticized for its accuracy of representation.

Discussion and Conclusions

As shown in Figure 3 the simulation results generally reflect the vegetation dynamics observed on the test site as interpreted through analysis of historic aerial photographs. The vegetation trends on the site fall within the pattern of vegetation dynamics observed by Davis et al. (1995). They found that there has been little or no net statewide gain or loss of canopy cover in those areas of blue oak woodland not subject to artificial vegetation loss (e.g., through urban development or clearing). They found that some areas of blue oak woodland increased in canopy cover and some declined. It should be noted that on our study site much of the increase in canopy cover was due to the increase in size of mature trees. There is little indication of substantial growth of trees from recently germinated acorns.

The simulation results presented in this paper are not a true validation test of the model. This would require replication of the comparison between model and real site on a range of randomly selected sites. The object of this paper is not to present a properly validated spatial state-and-transition model but rather to demonstrate that the methodology introduced in this paper may be useful for developing spatially explicit state-and-transition models. This methodology consists of interpreting the catalog of transitions as a set of rules in the rule base of a qualitative simulation model and of linking this qualitative model to a GIS by alternating between dynamic and spatial updating of the model variables. The qualitative simulation model is used to provide the dynamic updating and the GIS is used to provide the spatial updating.

Since vegetation communities are highly stochastic, no simulation program can predict with certainty the future course of vegetation dynamics. Markov and semi-Markov transition models have been used to study vegetation dynamics in a probabilistic sense (Callaway and Davis 1993, Scanlan 1994, Scanlan and Archer 1991). The alternating spatial and temporal step algorithm used in this paper could be applied equally well to these models to add an explicit spatial component. Within the context of qualitative models such as that discussed in this paper, there are at least 2 ways to incorporate uncertainty about the outcome of the process. One is to include an explicit uncertainty calculus in the

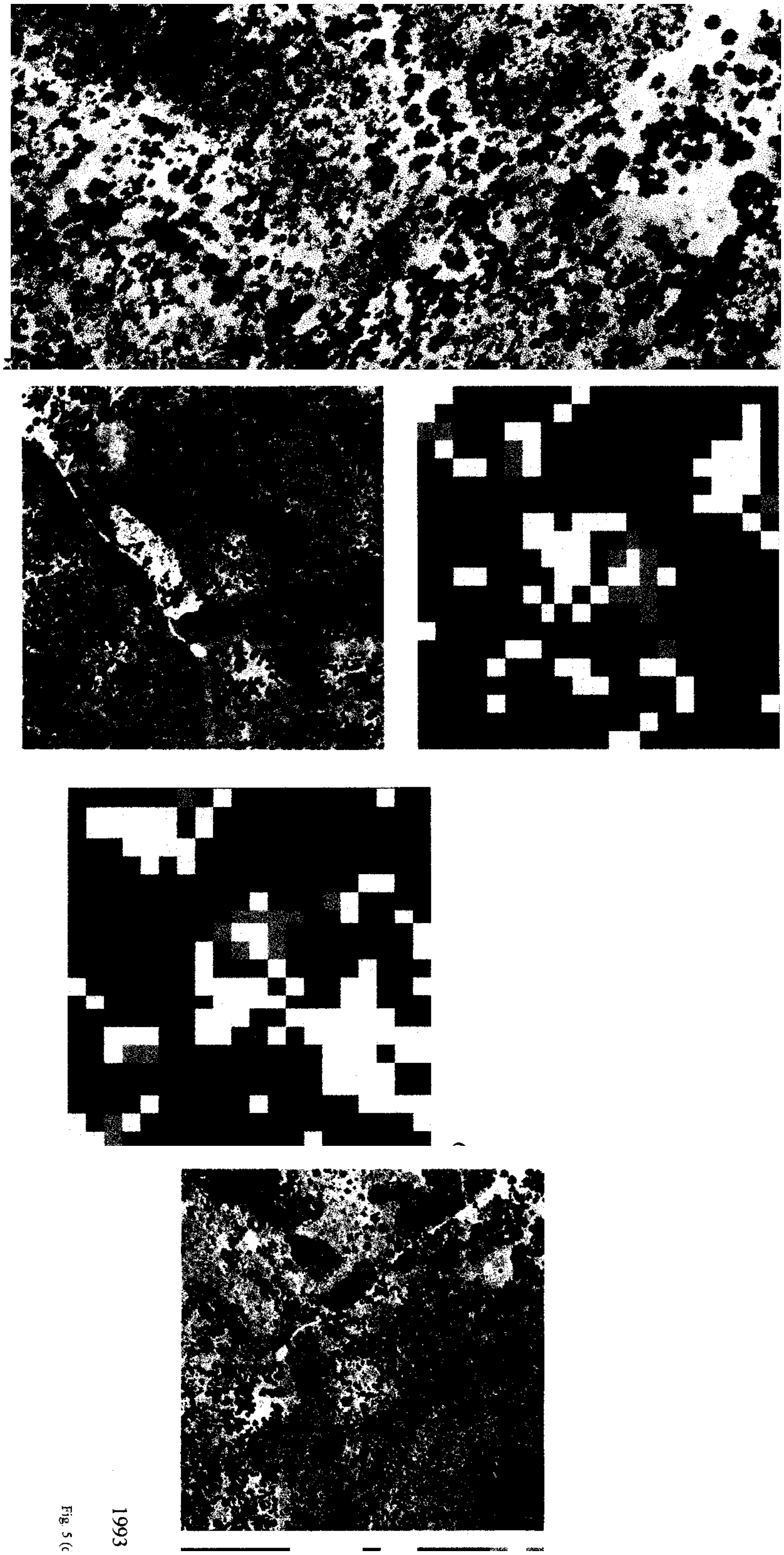


Fig. 5. Orthographically registered aerial photographs of the study site, shown next to the corresponding model output of the value of *overstory*. (a) Site in 1952, used as the initial state in the model. (b) Site in 1972. (c) Site in 1989. (d) Site in 1993. The 1993 photograph was used to calibrate the gray scale. In both images the lightest shade corresponds to cover value of *low*, the medium shade corresponds to a cover value of *moderate*, and the darkest shade corresponds to *high*.

program. This is common practice in expert system design (Plant and Stone 1991, chapter 3). In the present application the 2 most appropriate representations of uncertainty are Bayesian networks (Olson et al. 1990) and fuzzy logic (DuBois and Prade 1980). A second approach, which is taken in the QTIP program described in this paper, is to provide a framework for Monte Carlo simulation (Rubinstein 1981). In this approach, the result of an individual simulation is dependent on the value of 1 or more random variables. The simulation is run repeatedly, generating values of these random variables each time, and statistics are collected describing the distribution of the simulation results.

The methodology of qualitative simulation may be compared to more quantitative methods such as traditional simulation models (Shugart 1984) and individual-based models (Humphries et al. 1996). The qualitative simulation model has 2 primary advantages in this use over numerical population models. The first is that the qualitative model fits more naturally with the transition rules of the state-and-transition model. These transition rules are expressed in qualitative rather than quantitative terms. The forward-chaining algorithm of the dynamic step, in which rules are successively and repeatedly tested to determine whether the conditions of their “if” parts are satisfied, ensures that all rules will be invoked when it is appropriate to do so. Moreover, the QTIP program, like all rule-based expert systems, can provide a means for explaining its transitions (e.g., Plant and Stone 1991). In QTIP, each time a rule is invoked to change the value of a variable, a record of that transaction is added to a file. After a simulation run, this file can be used to assist in determining how the solution was generated.

The second advantage of qualitative simulation is that, to use the terms of Plant (1997), the qualitative model trades precision for robustness. That is, the solution of a qualitative model, since it is expressed in terms of a few discrete states rather than a continuum of numerical values, lacks the precision of a traditional numerical model. However, because each state represents a range of numerical values, and because the dynamics of the solution are controlled by a model with an inherently simpler structure, the qualitative model may be more robust than the numerical one. Traditional numerical models have been useful for deriving general principles in community ecology but have been less successful in accurately predicting the dynamics of particular ecological communities. The qualitative simulation methodology does have disadvantages. It cannot provide precise numerical estimates of observable quantities. Also, the relatively coarse, categorical description of states makes it difficult or impossible to describe some subtle processes in vegetation dynamics.

Qualitative simulation fits naturally with the state-and-transition model as a complement to GIS for spatial and dynamic simulation. This is illustrated by the ability of the simple model demonstrated here to detect spatial inconsistencies in the state-and-transition model such as the persistence of treeless areas. Westoby et al. (1989) emphasized that the primary use of the state-and-transition model is as a management tool. Grice and Macleod (1994) pointed out that most state-and-transition models have been descriptive with little or no explanatory component. If such a model is to contain an explanatory component, it must also be spatially explicit if it is to be truly useful as a management tool. Although Bellamy and Brown (1994) discussed the advantages of linkage between a state-and-transition model and a GIS, there have been few attempts to actually implement such a linkage.

The application of a computer-based, spatially explicit state-and-transition model depends on the spatial scale of the model. The model described in this paper is approximately at the scale of the individual paddock. At this scale, the model discussed in this paper would be useful to the individual ranch manager as a tool for evaluating alternative vegetation and animal management scenarios to estimate their effect on oak growth or regrowth. At a larger spatial scale, such models would be useful to policy makers as a means of estimating or visualizing the effect of alternative land use policies on vegetation dynamics. A primary value in both the small scale and the large-scale use is the possibility of enabling the manager to identify unintended consequences of management decisions.

Software Availability

The qualitative simulation model runs on any DOS-based computer with a 486 or Pentium processor. The source code is written in C and can be compiled using any common C compiler. This source code as well as the model itself is available on the Internet at

http://agronomy.ucdavis.edu/plant.

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