

# Alternative model formulations for a stochastic simulation of landscape change

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## Abstract

Two stochastic model formulations, one using pixel-based transitions and the other patch-based, were compared by running simulations where the amount of information on which transitions were based was increased. Both model types adequately represented changes in the proportion of the landscape occupied by different land cover types. However, the pixel-based model underestimated contagion and overestimated the amount of edge. The patch-based model overestimated contagion and underestimated edge. Overall, the estimates more closely approximated the expected and the variances decreased as more information was added to the models. As expected, the model that most closely simulated the spatial pattern of the landscape was a 5-data-layer patch-based model that also included ownership boundaries as an additional layer. The simulation methods described provide a means to integrate socioeconomic and ecological information into a spatially-explicit transition model of landscape change and to simulate change at a scale similar to that occurring in a landscape.

## Introduction

Spatially explicit stochastic simulation of land use/land cover changes in human-influenced landscapes remains challenging. Although a variety of approaches have been used (Burnham 1973; Hall *et al.* 1988; Parks 1990; Turner 1987, 1988), there has been little evaluation of the relative benefits of the different simulation methods. In this paper, two methods of implementing transitions in a spatially explicit stochastic model of landscape change are examined. These methods are pixel-based and patch-based. In the pixel-based model, change is evaluated separately for each pixel. In the patch-based model, patches are first defined by a set of rules that cluster pixels based on their category values and neighboring pixels. The pixels that de-

fine a patch are then evaluated for change as a unit, rather than having the changes simulated separately on each pixel within the patch. Thus, the difference between the two formulations is the scale at which change is simulated within defined homogeneous units. The amount of information used to define patches and characterize pixels may vary, and we hypothesize that, as the amount of information increases, the spatial pattern of a simulated landscape should approach the expected. The goals of this paper are (1) to evaluate alternative formulations of a stochastic spatially-explicit landscape-change model and (2) to explore the effect of increasing the amount of information used in either formulation on the simulation result.

Traditionally, transitions were implemented on a pixel-by-pixel basis (*e.g.*, Lippe *et al.* 1985; Turner

1987, 1988). Pixel-based models adequately reflect aggregate changes in the landscape, such as the total area undergoing transition, but do not represent the spatial qualities of these changes very well (Turner 1987). After experimenting with models that incorporated neighborhood effects, Turner (1988) concluded that the pixel-based approach potentially can represent the spatial qualities of the landscape if sufficient information was incorporated. However, the improvement in agreement between simulated and actual landscapes when different levels of information are included has not been explored.

Patch-based stochastic landscape-change models are a more recent development. One example is a model that simulates the impacts of deforestation in Rondonia, Brazil (Dale *et al.* 1992; Southworth *et al.* 1992). This model simulates occupation of lots, farming practices, and emigration of families that move to Rondonia. Patches are defined as land parcels. Unoccupied land parcels are assigned a probability-of-occupancy based on soil quality for agriculture, lot size, and distance and access to markets. Probability-based transitions for each patch include land occupation; tenure on a specific tract; time and area in production of annual crops, perennial crops and pasture; and coalescence of pasture lands. Such patch-based models show great promise as a stochastic landscape-change modeling approach because the scale of transition, as defined by the patches, more closely resembles that of the actual landscape than in the pixel-based models. However, the behavior of patch-based stochastic landscape-change models and their comparison to pixel-based models has not been investigated.

### Overview of the Modeling Approach

The model used in this analysis is a spatially-explicit stochastic simulator that is designed to simulate landscape change by integrating socioeconomic and ecological variables (Lee *et al.* 1992). Integration is accomplished by representing all socioeconomic and ecological variables as gridded maps. Individual maps represent a single data theme that describe either physical attributes of the landscape (land

cover, slope, soil type), spatial features (distance relationships, adjacency rules), results of socioeconomic and ecological processes (changes in real estate values, species abundance, erosion), or land-ownership characteristics (tract size, shape, and history). Pixels in each map are assigned to one of the discrete categories used to describe that data theme. For example, categories for a vegetation data theme might be 1 for irrigated agriculture, 2 for rangeland, 3 for coniferous forest, and so on. The maps are overlaid to form a composite map. The categories from each data layer in this composite map are represented as a string of characters called a landscape-condition label. Each character of this label is a category from one of the original maps. For example, if the label for a pixel from the composite map was 3264, the first position (4) (moving from right to left) might be a vegetation-cover category, the second position (6) soils, the third position (2) land-ownership class, and so on.

The model's parameters are represented as a matrix of transition probabilities. These probabilities govern changes in landscape elements (land cover in the simulations reported below) by reflecting the economic, sociological, and ecological influences on landscape structure and function, and their values will vary depending upon what data layers are included in a simulation. Individual rows in the matrix represent probabilities of transition from one land-cover category to any possible category for a given landscape condition label. As more data layers are included in the composite map, the greater the number of unique landscape condition labels and the larger the transition matrix.

To conduct the simulation, the landscape condition labels in the composite map are matched with equivalent landscape-condition values in the transition matrix. The corresponding set of transition probabilities are applied, and the resulting land cover category is assigned to the appropriate pixel. When all transitions have been simulated, the result is a new map of land cover.

### Methods

To compare pixel-based and patch-based transition models, we used a data base that is supplied with

the geographic information system GRASS (Geographical Resources Analysis System). This data base, called Spearfish, covers two topographic 1:24,000 quadrangles (Spearfish and Deadwood North) in western South Dakota. The data represent an area of 26,600 ha and have a pixel size of 100 m.

We modified the Spearfish data base as follows to create six spatial data themes: (1) VEGCOVER 1, the initial vegetation cover map used in the model, was created by reclassifying the Spearfish *vegetation* map into four categories (irrigated agriculture, forest, range, and disturbed/unvegetated); (2) OWNERCLASS, the type of owner, *e.g.*, federal, state, private or Native American, was modified from the Spearfish *owner* map by reclassifying a portion of private land to state ownership and a section of federal land to Native American; (3) LANDUSE, which represents the actual use to which the land is put, was reclassified from the Spearfish *land use* map to create 5 categories (general private or federal, residential, commercial, industrial, and special use); (4) DISTROAD, the distance to the nearest road, was generated by converting the Spearfish vector-data layer *roads.vect* to raster, determining the distance from each pixel to the nearest road by using the *r.cost* utility in GRASS, and then classifying a pixel as being either near (■ 1 km) or far (> 1 km) from a road; (5) DISTCULT, proximity (near or far) to the nearest cultural center, was generated by establishing the distance from each pixel to the nearest of five designated cultural centers by locating the nearest road and then travelling along the road to the nearest cultural center; and (6) OWNERBOUND, the boundaries of individual private, state, or Native American ownerships or National Forest Stands, was generated by overlaying the LANDUSE layer with the Spearfish *fields* (individual farm boundaries), *owner*, *soils*, and *soil-texture* data layers. The OWNERBOUND map layer contained 4123 individual ownership tracts.

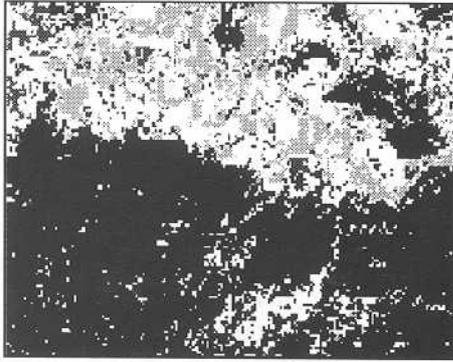
Simulations were designed to (1) compare pixel-based, patch-based, and ownership-based transition models and (2) evaluate the effect of incorporating differing amounts of information about the landscape into the model. In the pixel-based

formulation, the potential change from one cover type to another was evaluated separately for each pixel. In the patch-based formulation, the potential change from one cover type to another was evaluated separately on each patch. The ownership-based transition model was a patch-based formulation that included the ownership boundaries in the demarcation of patches. Patches were defined as contiguous pixels (adjacent vertically and horizontally) with identical landscape condition labels. Different patches with the same landscape condition label were then made unique by assigning them a patch identification number (PIN). In this implementation of the model, the PIN differentiates private ownership boundaries if non-federal land and management units (*i.e.*, National Forest stand) if federal land. When assigned a PIN, each patch is referred to as a management patch.

The concept of management patches is founded on the premise that land use is impacted by socioeconomic factors in addition to ecological processes. Landscape processes occur within and across boundaries designated by humans. As owner differ, so may the land use occurring among ownership tracts, even to portions of the landscape that appear identical. The management patch does not necessarily predicate what type of transition will take place, but rather, how many contiguous pixels can change state simultaneously.

Results of simulations using the pixel-, patch-, and ownership-based formulations of the landscape-change model were compared to a projected vegetation cover map (VEGCOVER2) of Spearfish (Fig. 1). This projected map was generated by applying a transition matrix that considered the six data themes listed above. The probabilities in this matrix were designated arbitrarily and were chosen to reflect a tendency toward increased urban development and forest harvesting. The strongest weights for vegetation-cover change caused by urban development or forest harvesting were for those cells nearest to a road or cultural area. The smallest weights were for those cells furthest from a road or cultural area. Vegetation-cover changes caused by either of these two land uses were assigned to the disturbed/unvegetated category. Thus, VEGCOVER1 represented the beginning

## VEGCOVER1



■ Forest  
 ■ Disturbed/unvegetated

## VEGCOVER2



■ Rangeland  
 □ Irrigated agriculture

Fig. 1. Maps representing vegetation cover of Spearfish, South Dakota for the beginning landscape (VEGCOVER1) and the landscape at a new point in time (VEGCOVER2). VEGCOVER2 was produced by applying a transition matrix to VEGCOVER1. This matrix assumed increased urban development and forest harvesting.

land cover in our simulations and VEGCOVER2 represented the landscape at the next time step.

To explore the effect of different amounts of information incorporated into a simulation, five transition probability matrices were constructed. Each matrix was based on a different number of data themes, beginning with one layer and adding one until all five were included. The first matrix considered only vegetation cover (VEGCOVER1) to estimate the probability of vegetation cover type  $i$  changing to cover type  $j$ . The order that the remaining data themes were appended was determined randomly. The two-data theme matrix consisted of VEGCOVER1 and OWNERCLASS and estimated the probability of vegetation-cover type  $i$  in ownership class  $k$  moving to cover type  $j$ . The remaining data layers appended were LANDUSE (3 data themes), then DISTROAD (4), and finally DISTCULT (5). The data layer OWNERBOUND had no effect on the transition probabilities and therefore, was not included in their derivation. Note that as more information was added, each pixel was described in greater detail, and patch size decreased.

Probabilities for each matrix were derived empirically by calculating net changes (in units of num-

bers of pixels) in vegetation-cover type between the VEGCOVER1 and VEGCOVER2 maps. Probabilities were calculated using only those data layers included in their respective matrix. For example, the two-data-layer matrix consisted of probabilities of vegetation-cover transition for all combinations of ownership class and vegetation type that can exist for a pixel in its respective map.

Simulations, applying these five transition matrices as treatments, were conducted with both the pixel-based and patch-based model formulations for 1 time step. The ownership-based model used only the five-data-layer transition matrix. Each treatment was replicated 10 times for the pixel-based and ownership-based simulations and 20 times for the patch-based simulations. Additional replicates of the patch-based model were necessary to account for their greater variability. All simulations were begun using the VEGCOVER1 map, and the simulated landscape changes were compared to the VEGCOVER2 map. The source code for the model was written in "C" and was executed on a SUN SPARC II workstation running UNIX system V.

Several measures of landscape pattern were calculated on the simulated maps by using the spatial

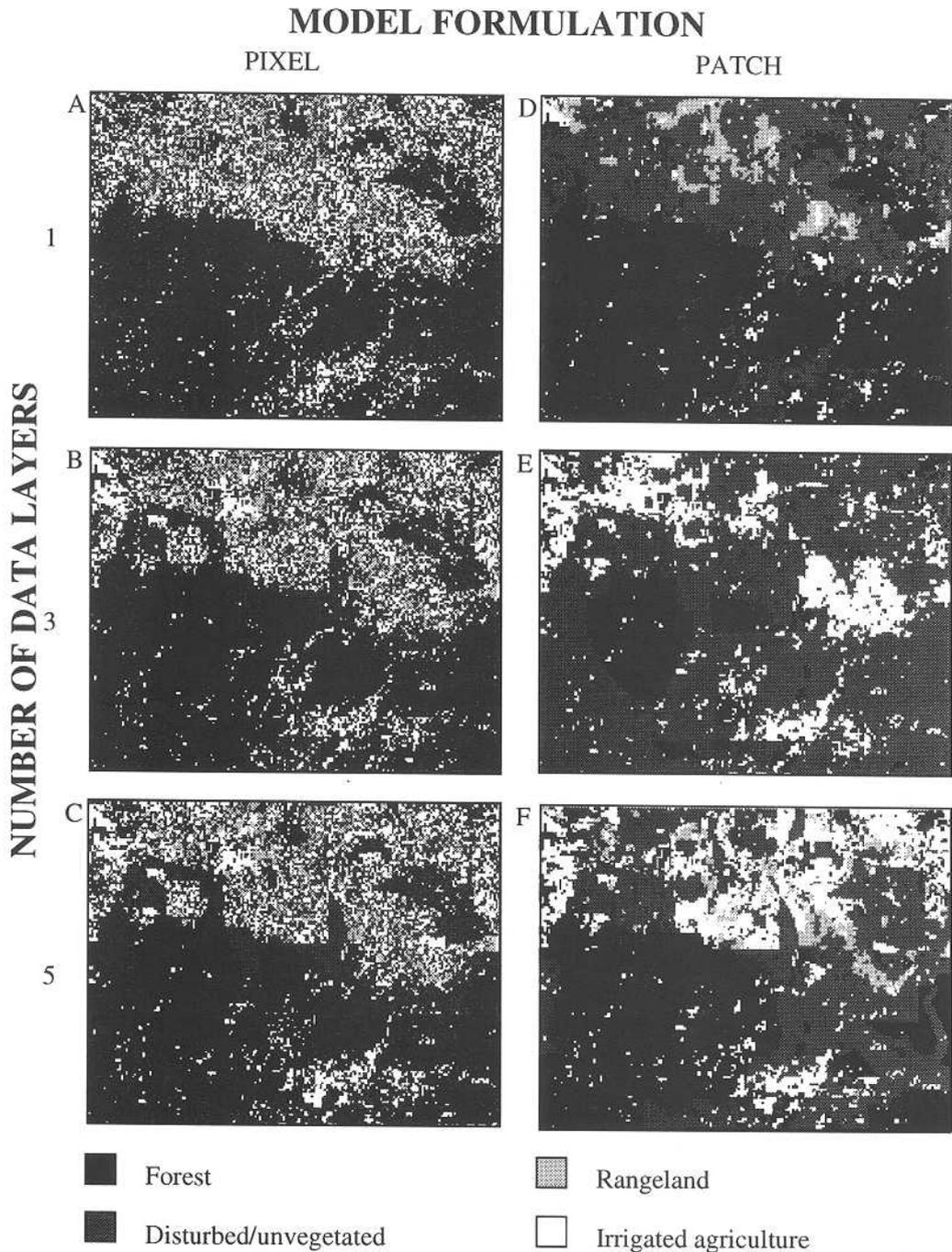


Fig. 2. Maps of simulated vegetation cover for pixel-based (A,B,C) and patch-based (D,E,F) models at three levels of information detail; 1 (vegetation cover only), 3 (vegetation cover, ownership class, and landuse), and 5 (vegetation cover, ownership class, landuse, distance to the nearest road, and distance to the nearest cultural center).

analysis program, SPAN (Turner 1990), and were used to compare the simulated maps with VEGCOVER2. As an aggregate measure, the pro-

portion of the landscape in each cover type was calculated. Percent agreement was used to evaluate the precise locations of the transitions and was cal-

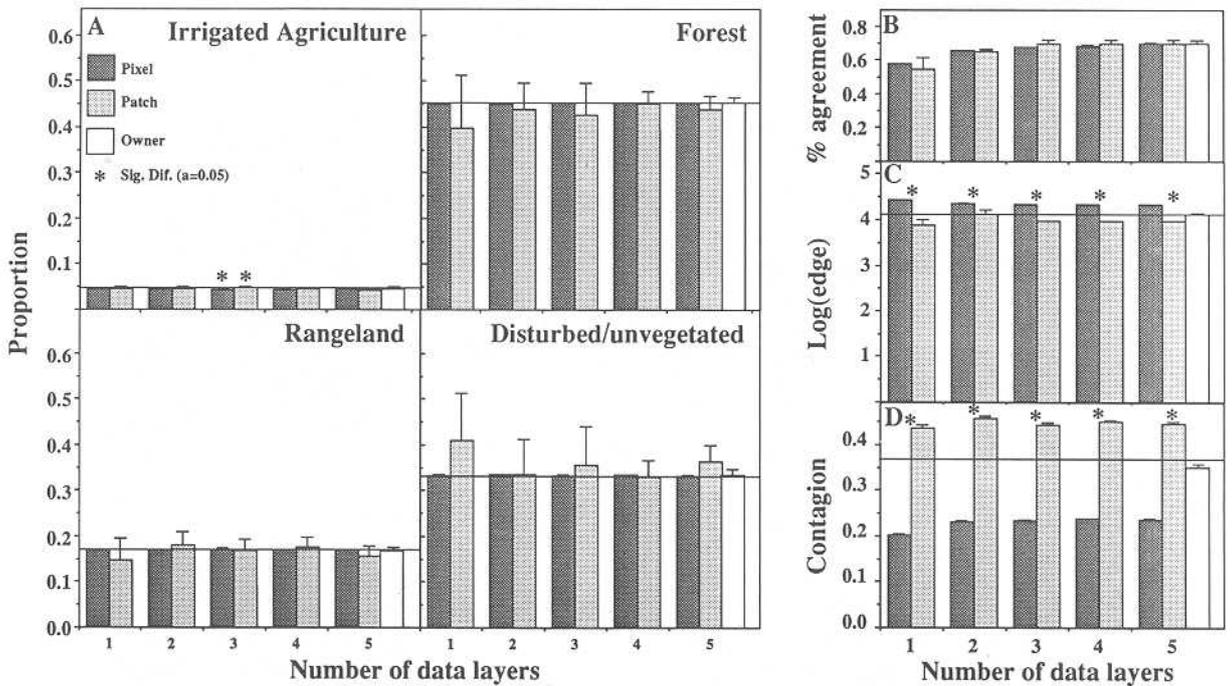


Fig. 3. Results of T-tests, assuming unequal variances, for comparing means of pixel- and patch-based models at each informational level. A, proportion cover for the four vegetation-cover types; B, pixel-by-pixel percent agreement; C, edge; and D, contagion. The horizontal line represents the corresponding value calculated from VEGCOVER2. The errors bars are the 95% confidence intervals. (\* =  $P < t_{\alpha,05}$ ;  $df_{\text{pixel vs patch}} = 19$ ;  $df_{\text{pixel vs owner}} = 9.3$ ;  $df_{\text{patch vs owner}} = 19$ .)

culated by overlaying VEGCOVER2 with the simulated maps and then comparing them pixel by pixel. To quantify attributes of the spatial pattern, we used contagion (O'Neill *et al.* 1988, Turner and Ruscher 1990) and the total amount of edge between cover types. Contagion measures the extent to which cover types are aggregated or fragmented. Edge provides a measure that integrates across the number and sizes of patches. Means and standard deviations were calculated for these descriptors for each treatment. Means of pixel- and patch-based models result were compared by calculating t-statistics that assumed unequal variances;  $P \geq t_{\alpha} 0.05$  (Steel and Torrie 1960). At the 5-data layer treatment, we compared the pixel, patch, and ownership models. Ninety-five percent confidence intervals were used to evaluate how closely the simulations estimated the values measured in VEGCOVER2. The analysis of information content used a Duncan's multiple range test on the means ( $P \geq t_{\alpha} 0.05$ ) and a series of F-tests ( $F \geq t_{\alpha}$

0.05) to compare the variances within each simulation type.

## Results

The structure of landscapes simulated by the pixel- and patch-based formulations and by using varying levels of information differed considerably (Fig. 2). In the pixel-based simulations, pixels that underwent transition tended to coalesce into patches as more information was added into the model. In the patch-based model, transitions tended to get more dispersed because patches decreased in size as more information was added. The patch-based model also generated some dramatic changes in the landscape (Figure 2e), whereas spatially-extensive shifts of land cover did not occur with the pixel-based models.

The simulated proportions of the landscape occupied by different cover types were not significantly different for the pixel, patch, and ownership

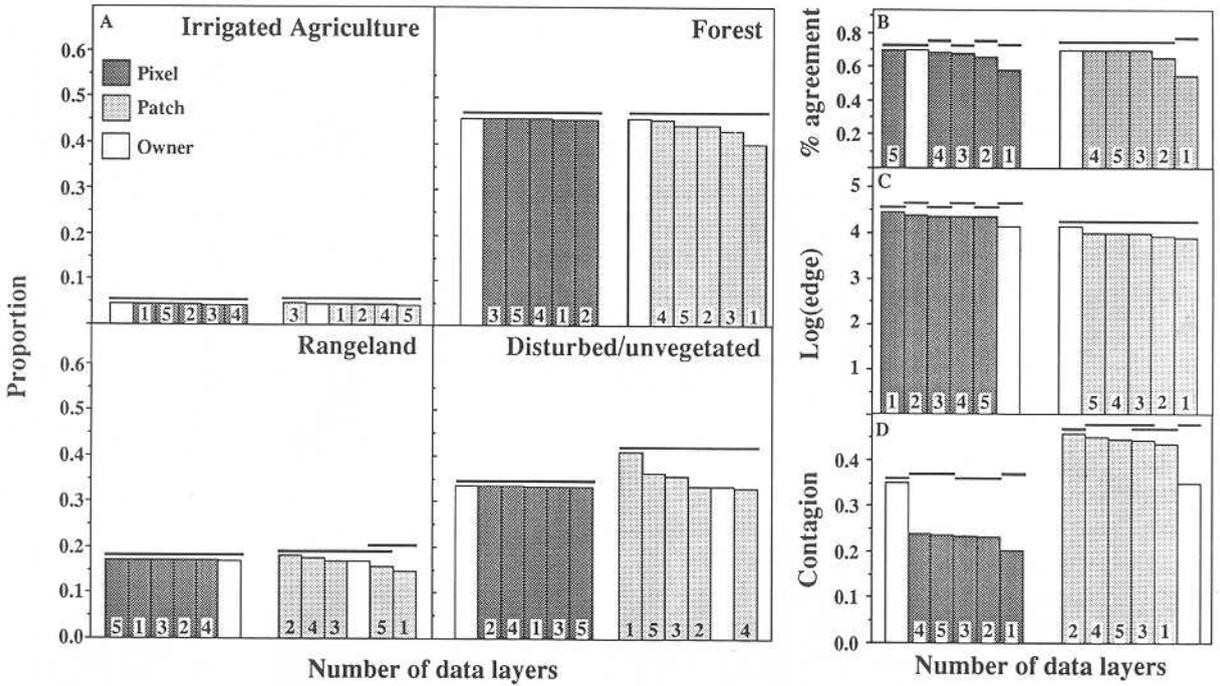


Fig. 4. Results of a Duncan's multiple range test to evaluate the effect of increasing the amount of information into the models on the mean. A, proportion cover for the four vegetation-cover types; B, pixel-by-pixel percent agreement; C, edge; and D, contagion ( $P < t_{\alpha,05}$ ;  $df_{\text{pixel}} = 54$ ;  $df_{\text{patch}} = 104$ ).

models (Fig. 3a) and the confidence limits of the mean always contained the values for VEGCOVER2. Thus, at the scale of the entire landscape, all model types adequately simulated change. However, the variance associated with the means differed by model type, with the patch-based model having the greatest variance. The pixel-by-pixel percent agreement between simulated maps and VEGCOVER2 also tended not to differ between the model formulations (Fig. 3b). These results were expected because the transition matrices were derived from differences between VEGCOVER1 and VEGCOVER2.

In almost all cases, edge and contagion differed significantly between the pixel, patch, and ownership models at all treatment levels (Fig. 3c, d). The pixel-based models underestimated contagion and overestimated edge, *i.e.*, they produced a more fragmented landscape pattern. In contrast, the patch-based models overestimated contagion and underestimated edge, producing a more clumped landscape pattern.

As expected, the simulated proportions of the landscape in different cover types did not change significantly with the addition of information (Fig. 4a). Adding information did influence which pixels change state. This influence was reflected as an increase in percent agreement and improvements in the measures of contagion and amount of edge (Fig. 4b,c,d). In the pixel-based model, mean edge decreased and mean contagion increased as more information was added. In the patch-based model, mean contagion decreased as more information was added, but there was no significant differences for mean edge. These results indicate that the amount of information can affect how well the model represents the spatial quality of landscape change.

The variance in the proportions of the landscape in different cover types across replicates within each treatment was lowest for the pixel-based model, highest for the patch model, and intermediate for the ownership model (Fig. 5a). These variances related directly to the scale of the changes occurring in the landscape, being smallest in the pixel

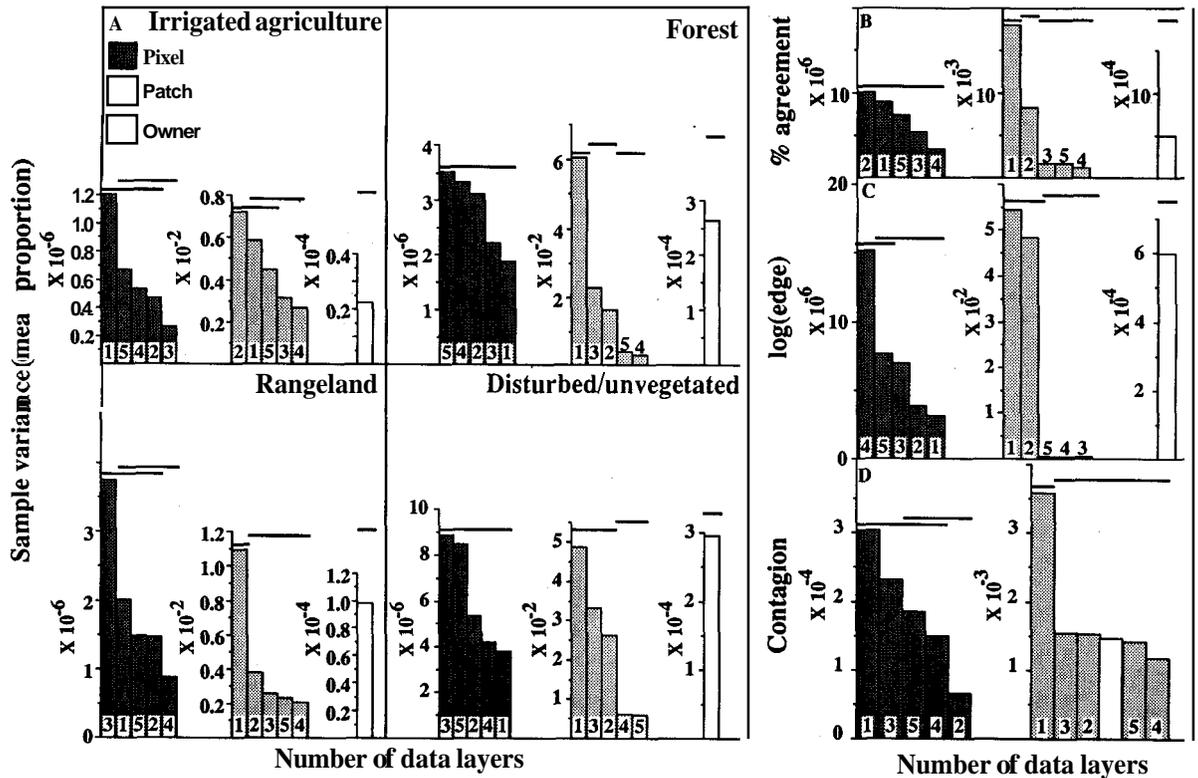


Fig. 5. Results of a series of F-tests to evaluate the effect of increasing the amount of information into the models on the variance. A, proportion cover for the four vegetation-cover types; B, pixel-by-pixel percent agreement; C, edge; and D, contagion ( $P < F_{\alpha, 0.05}$ ;  $df_{\text{pixel}} = 9, 9$ ;  $df_{\text{patch vs owner}} = 9, 9$ ;  $df_{\text{owner}} = 19, 19$ ).

model and largest in the patch model. The addition of information in the model formulations did not yield obvious changes in variance as it did with the means. The variance in the 4 and 5-data layer treatments for both model types were never significantly different from each other, and usually significantly different from those treatments with the lowest number of data layers. The relationship between variance and informational content was weaker still with percent agreement, contagion, and edge, but significant difference between the 4 and 5 data layer simulations and those with the least amount of information were present most of the time (Fig. 5b–d).

## Discussion

Pixel and patch-based approaches to stochastic spatially-explicit modeling of landscape change in human-dominated landscapes were examined.

Both approaches simulated changes in proportion cover and percent agreement equally well. However, only the patch-based model with ownership boundaries captured the complexity of the spatial pattern of the landscape. In fact, measures of spatial pattern, contagion and edge, calculated from the 5-data-layer pixel and patch simulations were often significantly different from those of the simulations that incorporated ownership boundaries.

This study demonstrated that the scale of transition must be identified if the spatial structure of a landscape is to be simulated adequately. Each model formulation implemented transitions at a different scale. In the simulations, vegetation changes occurred at scales that were either too fine (pixel-based model) or too broad (patch-based model), even when five data themes were used to construct their transition matrices. The ownership model, which served as a basis of comparison for the other formulations, succeeded because its

vegetation-cover changes used the same information (5 data themes and ownership boundaries) and, therefore, occurred at a similar scale as those that produced the VEGCOVER2 map.

Adding empirically-derived information significantly improved the representation of spatial patterns of pixel- and patch-based models. In the pixel-based model, the scale of transition that produced the VEGCOVER2 maps was being approximated through the coalescence of individual pixels with increasing information. In the patch-based model, large groups of contiguous pixels were reduced in size with added information and began to reflect the scale of change that produced VEGCOVER2. Although both pixel and patch-based models can reflect spatial patterns of landscape change, the patch-based approach can probably do so with less additional information because attributes of landscape structure are represented in patch size, shape, and juxtaposition.

Adding information to the models also decreased the variance of all measures. Variance can serve as a source of error propagation and may be of serious concern if multiple time steps are run (Gardner *et al.* 1990). For stochastic land-use models, multiple time steps in a single simulation will be a reality as dynamic transition probabilities are implemented (Lee *et al.* 1992). Therefore, future research that explores error propagation over multiple time steps remains a significant need.

This study did not attempt to evaluate the impact of each spatial data theme on the model formulations. We recognized that the content of each data theme and the order of their incorporation into the models affected the simulation results. Some of the data themes provided little information about the landscape (LANDUSE) regardless of their position in the order, while others (OWNERCLASS) were a significant addition if placed at any position. DISTROAD and DISTCULT contained some common information, so that the contributions that these data layers made depended on which was inserted into the model first. It is unlikely that our conclusions about the two model formulations would be different if the data themes were introduced into the model in a different order. To demonstrate, this we ran simulations where the data themes OWNERCLASS, LANDUSE, DIS-

TROAD, DISTCULT were incorporated into the model in the opposite order as before. The results were basically the same; no significant difference for model type and information detail for proportion cover, while the spatial measures differed by model type and information content.

Characterizing pixels and patches using landscape condition labels proved to be an extremely versatile approach. Because the landscape-condition labels were represented as character strings, the benefits of this approach included (1) the landscape-condition-label's length (*e.g.*, the amount of information used in a simulation) was not limiting; (2) adding information into the model was facile, involving simply overlaying the new map layer and appending the new category value to the end of the existing landscape-condition label of each pixel; and (3) because the patches are constructed by aggregating pixels, patch size can be delineated by any set of map layers the modeler chooses. This approach provides an avenue to address, in a spatially explicit format, socioeconomic and environmental questions at the landscape scale. By employing a landscape-condition label and patch-based transitions, this model can simulate fine-scale landscape changes at the scale of change as defined by human land use patterns. Output from this type of model could then be used to examine changes in the spatial quality of biotic (*e.g.*, species' habitat requirements) and physical variables (*e.g.*, erosion) as well as feedbacks on human decision making caused by landscape change.

In this paper, a stochastic model is presented in which ecological and socioeconomic variables are integrated to simulate landscape change. This integration is accomplished by representing all model inputs (variables and results of submodels) and conducting the simulation in a spatially-explicit manner. Since all model inputs are represented spatially, relational variables based on distance, adjacency, juxtaposition and patch shape can be derived and used as inputs as well. This approach provides a flexible environment for spatial simulation modeling and has several attributes including: (1) large-scale impacts to environmental and socioeconomic variables caused by landscape change can be evaluated and, (2) complex, landscape-level, feedback processes can be examined (Lee *et al.* 1992).

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