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AN ABSTRACT OF THE THESIS OF

Habin Li for the degree of Doctor of Philosophy in Forest Ecology presented on September 5, 1989.

Title: Spatio-temporal Pattern Analysis of Managed Forest Landscapes: A Simulation Approach

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Jerry F. Franklin

This study dealt with research problems at the landscape level. The objectives of this thesis were to develop tools to study and characterize landscapes and to interface with a geographic information system (GIS), to evaluate landscape indices, and to examine development of forest cutting patterns under different cutting methods and explore alternative forest management strategies.

A computer program was developed for simulation and analysis of landscape patterns. The primary applications of the computer program were (1) to quantify spatial patterns of landscapes, (2) to perform experiments with different silvicultural strategies and forecast the consequences of management activities, (3) to examine the behavior of landscape indices without having a large number of landscape samples, (4) to interface with and to complement GIS in terms of ecological analysis, and (5) to

serve as a base on which GIS-related landscape models could built.

Many extant landscape indices were reviewed, and some new indices proposed. Each was evaluated in terms of its ability to distinguish four test synthetic landscapes with distinct spatial patterns. Fractal dimension, patchiness index, dispersal index, and two fragmentation indices (i.e., the forest interior area and the largest forest patch size) appeared to be most sensitive to spatial variations among the test landscape mosaics, and may be most useful to study and quantify the landscape pattern. On the other hand, some commonly-used landscape indices, contagion and dominance, could not distinguish variations in distinct landscape patterns.

The simulation program and the landscape indices were then used to study landscape patterns generated by different forest cutting methods. The results indicated that different cutting designs may produce landscapes with distinct characteristics. Landscapes were clearly less fragmented when larger sizes of cut-units were used. When a stream system was included in the landscape structure, the behavior of many landscape characteristics changed. The results suggested that simple landscape models (i.e., the checkerboard model and random model) may lead to misleading interpretations of landscape patterns.

Spatio-temporal Pattern Analysis of Managed Forest Landscapes: A Simulation Approach

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I am grateful to Dr. Robert H. Gardner for his permitting me to use, in LSPA, some subroutines and algorithms therein of his percolation program. His help was the most critical to my research.

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CHAPTER I

INTRODUCTION

Background

Judicious management of forest landscapes for both commodities (e.g., timber production) and ecological values (e.g., wildlife) is an important challenge (Franklin and Maser 1988, Franklin 1989). Timber production has been and continues to be one of the most important components of the economy in the Pacific Northwest region. However, as forest cutting proceeds, fragmentation of old-growth forest landscapes intensifies and the viability of ecosystems may be endangered. One important consequence of forest fragmentation is deterioration of forest ecosystems, as evidenced, for example, by the loss of plant and animal species (Lovejoy et al. 1983).

The decision-making process is increasingly complex for the forest resource managers. Their predicament is society's demands for multi-purpose use of finite forest resources. The present economies of some local communities depend greatly on timber production, whereas maintenance of biological diversity and viability of forest ecosystems is also mandated by laws.

Landscape ecology can provide a theoretical base for forest pattern management (e.g., Franklin and Forman 1987). Landscape ecology is a newly-emerged interdisciplinary field synthesized from ecology, geography, forestry, wildlife management, and landscape planning. "Landscape ecology basically studies how a heterogeneous combination of ecosystems is structured, functions and changes in a landscape" (Forman and Godron 1986). It is at the landscape level where forest management activities are carried out, where biological diversity and cumulative effects issues emerge, and large-scale ecological processes take place. In practice, federal agencies, such as the USDA Forest Service, very often direct their management schemes at the landscape level. For example, questions about forest cutting pattern, population dynamics of widely-ranged wildlife species or disturbances like wildfire can only be addressed appropriately at the landscape level. Advances in landscape ecological research not only provide insight into forest management strategies (e.g., Franklin and Forman 1987), but also provide ways of assessing the effects of management activities on ecosystems.

The development of landscape ecology depends, in part, upon the development of sophisticated techniques with which a landscape can be measured and analyzed. First, the determination of spatial and temporal patterns of landscapes is important in both theoretical landscape ecology and resource management (Risser et al. 1984, O'Neill et al. 1988). Methods to characterize, analyze and model spatial and temporal patterns of landscapes are needed as a first step in the investigation of landscape functions and processes. Second, landscape models are needed to address problems which may not be adequately or appropriately addressed by empirical studies because of large time and space scales (e.g., cutting pattern development of forest landscapes or forest fragmentation). Spatially-explicit landscape models which utilize patch location and configuration are not well developed, but are needed (Baker 1989).

1. Forest cutting pattern and fragmentation

Forest fragmentation occurs when the forest matrix is broken into many small patches, when the forest interior habitat area shrinks, when the size of the largest forest patch decreases, or when forest patches are isolated. The current staggered-setting system of forest pattern management involves maximum dispersion of cut-units in a forest landscape. This has been challenged (Franklin and Forman 1987). Franklin and Forman (1987) examined the staggered-setting clearcut system using the newly-emerged perspectives of landscape ecology. They hypothesize that continued implementation of the staggered-setting clearcut system could result in the intensification of forest fragmentation, in degradation in wildlife habitats, and in increased susceptibility of residual forest patches to disturbances. Although the staggered-setting method has some benefits, they argued that it should be reconsidered due to changed technologies, perspectives, and societal demands. In addition, the appropriateness of the method should be reassessed in light of the dramatic change of the landscape from extensive forest to patchy mosaic. They suggest that cutting units be spatially aggregated and cut-unit sizes be increased. They argue that the alternative method may have economic and ecological advantages (e.g., improvement in protection of species diversity and reduction of catastrophic disturbance frequency).

The hypotheses proposed by Franklin and Forman (1987) need testing. Different approaches to distribution of cutting units create different landscape patterns, but how forest landscapes develop, given a certain approach and effects of distribution, is still in question.

2. Computer simulation of landscape patterns

Evaluation of the effects of fragmentation created by different cutting methods is an urgent but difficult task because of the temporal and spatial scales involved (Burgess and Sharpe 1981, Verner et al. 1986, Baker 1989). Three approaches could be used: experimentation, chronological study, and computer simulation. In the experimental approach, forest cutting patterns can be developed for different cutting methods under similar environmental conditions, and changes in landscape characteristics be monitored over a long period of time (e.g., Lovejoy et al. 1983). The major limitation of this approach is the long time period required to obtain results; management options would be limited by the time results of experimentation are available. Another major limitation is the difficulty in finding a suitable large piece of land for the experiment (Perry 1988, Baker 1989); even if land is available, lack of experimental controls and difficulties of replication in large-scale field studies may make it difficult to interpret results. Furthermore, the cost of carrying out such a large-scale experiment is high. As a result, the experimental approach is generally not feasible (but see Lovejoy et al. 1983).

The chronological approach investigates fragmentation effects by studying some selected forest areas with different degrees of fragmentation. This is analogous with methods most often used in vegetation succession studies (e.g., Mueller-Dombois and Ellenberg 1974). The chronological approach is also limited by lack of controls and difficulties in finding appropriate study sites.

In contrast to the other approaches, computer simulation may provide a rapid, controlled evaluation, and a timely "testing" ground unavailable now in field or laboratory studies. Computer simulation is the process of designing a mathematical-logical model of a real system (in this case, forest landscapes) and experimenting with this model on a computer (Pritsker 1987). These experiments permit inferences to be made about the system without building, disturbing or destroying the object under study. With the help of computer simulation, forest cutting patterns can be generated according to certain cutting methods, and fragmentation effects can be studied under controlled conditions over time. The main limitation of computer simulation is that the reliability of results obtained are highly dependent upon the accuracy of the models used and the assumptions made. However, computer simulation may be the only feasible approach in many cases.

Generation and analysis of landscape patterns is a spatial problem. The commonly-used tool for handling and manipulation of spatial data is a geographic information system (GIS). A GIS is composed of specialized computer software and hardware with four processing functions: computer mapping, spatial data-base management, spatial statistics, and cartographic modeling (Berry 1986). The use of GIS in ecological research will increase due to the strong interest of ecologists in spatial patterns at the landscape level (Burrough 1986, Baker 1989) and due to the spatial nature of problems in resource management. However, present GIS is limited in terms of ecological analysis, because GIS was not originally designed for ecologists. In addition, spatial statistics installed in a GIS are restricted to simple descriptive statistics and map overlays. Thus specific tools are needed to perform ecological analysis of landscape patterns using GIS or other types of spatial data (Baker 1989).

3. Landscape Indices

Landscape indices, used to characterize landscape patterns, have been studied by landscape ecologists for their theoretical value (Krummel et al. 1987, O'Neill et al. 1988) and used for establishing guidelines for resource management (Romme 1982, Romme and Knight 1982). As O'Neill et al. (1988) have pointed out, the general use of landscape indices is "to quantify landscape patterns so that relationships between landscape structure and landscape functions and processes can be established by linking those indices with ecological phenomena at the landscape level". Generally speaking, landscape indices are simple, quantitative, comparable, and easy to obtain. The past few years has witnessed increasing use of landscape indices by landscape ecologists as well as land managers (e.g., O'Neill et al. 1988).

Before landscape indices are used, they should be evaluated against landscapes with known characteristics. Many landscape indices have been proposed (e.g., Pielou

1975, Romme 1982, Krummel et al. 1987, O'Neill et al. 1988). Each has been designed to reveal information on a particular attribute of landscape mosaics. However, what each index actually reveals has not been demonstrated in a "controlled" environment. For example, spatial pattern is an important emergent property of landscapes which distinguishes one landscape from the other. Some landscape indices do not distinguish landscapes with different spatial patterns. A misinterpretation of an index can result in poor management decisions and science. A revaluation of the landscape indices is warranted.

Objectives and Thesis Organization

The objectives of this thesis are three-fold: (1) to develop a computer program for simulation and analysis of spatial patterns of landscapes (LSPA), (2) to review, propose and evaluate landscape indices, and (3) to examine the development of forest cutting patterns under different cutting methods and assess their consequent impacts on forest ecosystems.

The dissertation is composed of five chapters and written in the manuscript format. Chapter one provides background information on the problems addressed, the techniques used, and the relevant literature on those problems and techniques. Chapter two documents the structure, functions and applications of LSPA. In chapter three many landscape indices are reviewed and some new ones proposed; they are all evaluated using landscapes with known characteristics that were generated by LSPA. Chapter four deals with development of forest cutting patterns. Differences in landscape patterns created by different cutting methods are quantified, using the simulation approach, and effects of different landscape patterns on landscape functions and processes are assessed indirectly by modeling. The principal results of the research and discussion of future research needs are summarized in chapter 5.

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CHAPTER II

LSPA: A COMPUTER PROGRAM FOR SIMULATION AND ANALYSIS OF SPATIAL PATTERNS OF LANDSCAPE MOSAICS

Abstract

A computer program was developed for simulation and analysis of landscape patterns. The program had four basic functions: to generate landscape patterns, to measure basic landscape parameters, to calculate landscape indices, and to perform spatial statistical analysis on landscape patterns. The primary applications of the computer program were (1) to quantify spatial patterns of landscapes, (2) to perform experiments with different cutting methods and forecast the consequences of management activities, (3) to examine the behavior of landscape indices without having a large sample of landscapes, (4) to interface with and to complement geographic information systems in terms of ecological analysis, and (5) to serve as a base on which geographic information system related landscape models could be built.

Introduction

Forest fragmentation is a major issue in forest management of the Pacific Northwest region. Timber harvest, a major cause of fragmentation, is economically important to local communities, while conservation of biological diversity is mandated by laws. Assessment of fragmentation effects is a difficult task because of the magnitude of the temporal and spatial scales involved (Perry 1988, Baker 1989, but also see Lovejoy et al. 1983). Furthermore, the chronological approach to investigation of fragmentation effects, based on study of selected forest areas with different degrees of fragmentation, is also limited due to lack of controls.

These difficulties suggest that computer simulation may be one promising solution to the problem. Computer simulation is the process of designing a mathematical-logical model of a real system (in this case, forest landscapes) and experimenting with this model on a computer (Pritsker 1987). Hence, these experiments permit inferences about systems to be drawn without building, disturbing, or destroying them. With the help of computer simulation, forest cutting patterns can be generated according to specified scenarios, and then fragmentation effects over time can be studied in "controlled" conditions.

A computer program for landscape spatial pattern analysis (LSPA) was developed to address spatial problems in landscape ecological research in general, and to investigate forest fragmentation in particular. The program has two main functions: simulation and analysis of landscape patterns. LSPA (1) generates landscape patterns for different rules of forest cutting patterns, (2) measures basic parameters of landscape structure, (3) calculates many indices of landscape characteristics, and (4) performs spatial statistical analysis on the landscape pattern. Some subroutines for parameter measurement were adopted from the percolation program developed by Robert Gardner[1] with permission. The simulation and analytical parts of LSPA are independent. Hence, the analytical part of LSPA can be used to interface with a GIS and to analyze real landscapes (e.g., landscape maps stored in GIS). LSPA is grid-based and in Fortran, and runs on IBM PC.

The Basic Structure of LSPA

LSPA is composed of (1) initial inputs of simulation parameters, (2) simulators of landscape patterns, (3) measurement of basic parameters of landscape structure, (4) calculation of landscape indices, (5) spatial statistics, and (6) outputs of results of simulation and analysis (Figure II.1).

LSPA is partially interactive. To perform a simulation run, the user is asked to input some basic parameters, such as the dimensions of a landscape (i.e., the numbers of rows and columns), the number of replications for assessment of simulation variances, the number of time steps (or habitat

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(available with LSPA) before they can be analyzed by LSPA.

A few input parameters require some explanation. The "mean patch size" is not the actual average patch size in a landscape, but is a parameter used to determine sizes of individual patches generated by some landscape simulators. The size of a patch in some models is determined by adding (or substracting) a random number to (or from) the "mean patch size". The scalar is required for transforming pixel units of landscape indices to real units, such as kilometers, meters, and hectares. When an existing digital map of a landscape is analyzed, the coding of element types should be from 0 for the matrix (e.g., forest), through 1, 2, and up to 30 for other patch types, and coding should be consecutive (i.e., no missing codes between 0 and the largest code number). When landscape indices such as relative patchiness, dispersal, and fire susceptibility indices are needed, more information must be input from data files. A dissimilarity matrix is required for relative patchiness, a habitat suitability matrix for dispersal index, and a matrix of fire probability for fire susceptibility index (see Appendix II.2).

LSPA is basically composed of two parts: simulation and analysis of landscape patterns. In the simulation part, LSPA has nine models available to generate landscape patterns: a random pixel model, a random patch model, a maximum dispersion model with one-pixel patches, maximum (available with LSPA) before they can be analyzed by LSPA.

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LSPA is basically composed of two parts: simulation and analysis of landscape patterns. In the simulation part, LSPA has nine models available to generate landscape patterns: a random pixel model, a random patch model, a maximum dispersion model with one-pixel patches, maximum dispersion models with patches of 4 or 9 pixels, a model mimicking the staggered-setting clearcut system, a partial aggregation model, progressive cutting models with a single-nucleus or with four-nuclei, and a strip-cut model. A percolation model (Gardner et al. 1987) was also examined in LSPA. The percolation model is a random pixel model without memory of the pattern at previous time step. The percolation model produces landscapes with almost the same values of landscape indices as the random pixel model does, and it is, therefore, not included in LSPA.

In the analysis part, LSPA measures some basic parameters of landscape structure, calculates landscape indices, and performs spatial statistical analysis on the landscape pattern. The basic parameters measured in LSPA are patch size, edge length, edge-to-edge inter-patch distance, and edge length between any two types of patches. These basic parameters are used later to calculate of landscape indices.

Landscape indices are used to characterize landscape maps. Landscape indices calculated in LSPA are: (1) the descriptive measures of landscape mosaics, including number of patches (e.g., forest vs. clearcut), patch density, mean patch size, total area, total edge, edge density (i.e., edge length per unit area), and cutting percentage at each time interval (or proportion of one habitat type); (2) patch shape measure, including mean fractal dimension of individual patches, fractal dimension for total edge and size, mean shape index, area-weighted shape index, and Patten's habitat edge diversity (Patten 1975); (3) measures from inter-patch distance, including mean inter-patch distance, proximity index, nearest neighbor index (Clark and Evans 1954, Haggett et al. 1977); (4) landscape diversity measures, including richness, evenness (dominance), contagion, patchiness, fractal, and connectivity (Romme 1982, O'Neill et al. 1988a); and (5) fragmentation measures, including number of patches (or patch density), patch shape, the largest patch size, interior habitat area, patch isolation, and contrast of landscape mosaics.

Several spatial statistical methods are also installed in some versions of LSPA, such as joins-count statistic for spatial autocorrelation test (Cliff and Ord 1981, Unwin 1981) and semivariogram (Burrough 1981, 1986, Webster 1985, Robertson 1987). These spatial statistical methods are important because landscape ecological research requires more sophisticated, spatially explicit techniques to deal with spatial problems (e.g., forest fragmentation). However, emphasized now in LSPA are those techniques which analyze the most commonly-used nominal data (e.g., data from landscape maps). Given the nature, scale and resolution of landscape problems, however, the methods currently installed in LSPA may be sufficient in many cases.

LSPA can output results on screen and in an ASCII file. The outputs of LSPA include: a matrix of a landscape map with pixel-values being codes of patch types, a corresponding letter-tuned graphic output of landscape maps, information on individual patches (e.g., size and perimeter), a summary table of landscape indices, results of spatial statistical tests, and descriptive statistics (i.e., mean and standard deviation) on all landscape measures at each time step for replications at the end of simulation (Appendix II.3).

There are four versions of LSPA, categorized by two factors: (1) whether synthetic or real landscape data are used and (2) whether clearcuts of different ages are considered different patch types. Version one (LSPA1x) has landscape simulators and considers clearcut age in analysis. This version is useful for studying development of forest cutting patterns and examining performance of landscape indices, but it is limited on PCs to landscapes of dimensions about 50 by 50 pixels (200 by 200 for the other three versions). Version two (LSPA2x) has no landscape simulators and performs analysis with consideration of age difference among clearcuts. LSPA2x primarily analyzes real landscape maps for any relevant fields, such as forest management, remote sensing and wildlife ecology. The dimensions of landscapes which can be analyzed with LSPA2x are about 200 by 200 pixels. Version three and four (LSPA3x, LSPA4x) treat all clearcuts as one type of landscape elements, and therefore have two patch types only: forest and clearcut. LSPA3x does both simulation and analysis, while LSPA4x only has analytical function and is a by-product of LSPA3x. Some landscape indices (e.g., landscape diversity indices) are not calculated in versions three and four. Discussions in this documentation are primarily about LSPA1x, but are closely related to the other three versions.

Landscape Simulators

Nine models are available in LSPA to generate landscape mosaics based on different rules. Some of the models were developed to mimic different cutting schemes, while others were designed for comparison (e.g., the maximum dispersion random model). Most of the models are stochastic. A few common assumptions are made for all the models: (1) once a pixel is cut, it is no longer available for consideration of cutting because the total length of model run is less than the rotation length; (2) a new type of patch is introduced at each time step, because clearcut patches cut at different time steps are regarded as different patch types; (3) cutting at a time step is terminated when the total number of cut-pixels is larger than or equal to the number defined by the cutting rate; (4) the size of a patch is determined, for the patch models (i.e., the random patch, staggered-setting, and partial aggregation models) by adding or substracting a random number to the predetermined "mean patch size" (an input parameter), but patch size cannot be less than or equal to zero; and (5) patterns which are not created by cutting are not considered, except stream (or road) systems. In addition to the five assumptions, each model is constrained by its own assumptions. Specific assumptions used by each landscape model are discussed below.

1. Random pixel model: a null model

The random pixel model is used as a null model for comparative purposes. The random pixel model generates landscapes according to the following rules or assumptions (Figure II.2): (1) At each time step, every pixel has a fixed, equal probability to be cut; a random number generator is used to determine which pixels are cut. (2) One pixel is cut for each search. Two or more adjacent pixels cut in the same time step are regarded as one patch. The random pixel landscape generator is a neutral model similar to the percolation model (Gardner et al. 1987). The differences between the two models are that the random pixel model may have more than two types of patches in the synthetic landscapes and has to save the landscape mosaic generated at simulation time "t" on which the landscape mosaic at time "t+1" is generated. The two models result in almost identical values for most landscape indices despite the restriction built in the random pixel model.

2. Random patch model: a null model

The random patch model is similar to the random pixel model except that the random patch model creates a patch (a group of pixels) for one search instead of a single pixel (Figure II.3). The advantage of this model over the random pixel model is that it is more comparable to other models because those other models are basically patch models of some kinds. Two assumptions are made in the random patch model. First, the starting pixel is randomly located from which other pixels of a patch are generated by a random walk model (Figure II.4). This implies that the search direction, and therefore the patch shape, is randomly determined. Second, if a search for more pixels of a patch is "trapped" (i.e., no pixels are available for cutting in the neighborhood), the search is terminated and the patch saved, and then a new starting pixel is randomly chosen for the next patch.

3. Maximum dispersion model

The maximum dispersion model is a simplified staggered setting model (Franklin and Forman 1987), and it generates landscapes with maximum forest fragmentation (Figure II.5). Four assumptions are made for the maximum dispersion model. First, cut-pixels at each time step are distributed as evenly and with as much dispersion as possible. Figure

II.6 illustrates the searching algorithm. Second, when there is no true center pixel, a "pseudo-center" is defined as the upper-left for a 4-pixel square center or the upper (or left) pixel for a 2-pixel center. Third, only one pixel is cut at each search resulting in one-pixel clearcut patches until about 50% cut-over. Fourth, at later simulation time steps, it is desirable to search for the cells jointed with the fewest number of neighbor cut-cells (i.e., to cut pixels with zero neighbor cut-cell first, and then those with 1, 2, 3 and up to 4 neighboring cut-pixels).

A multi-pixel maximum dispersion model is developed to generate maximum dispersion landscapes with multi-pixel square patches. This model generates square patches of 4 or 9-pixels in order to make the maximum dispersion model comparable to other multi-pixel patch models. For the multi-pixel maximum dispersion model, additional pixels of a patch are cut around the first pixel so that a cut-unit remains a square patch. The flowchart of this multi-pixel maximum dispersion model is similar to that of the staggered-setting model discussed below. The only difference between the two models is that a square patch generator is used instead of a restricted random walk patch generator (see Figure II.7).

4. Staggered-setting clearcut model

Figure II.1: The basic structure of LSPA.

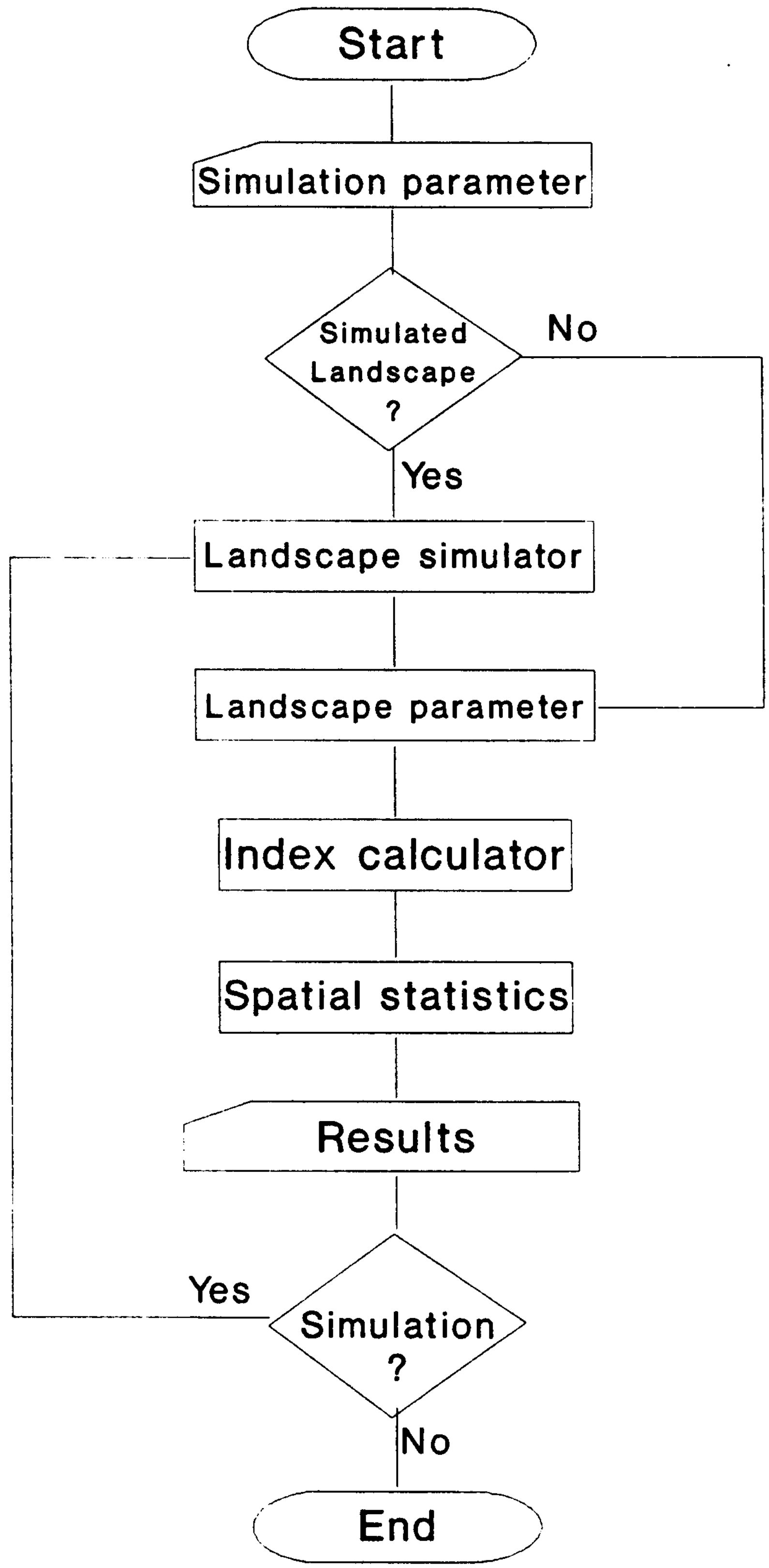


Figure II.2: The flowchart of the random pixel model.

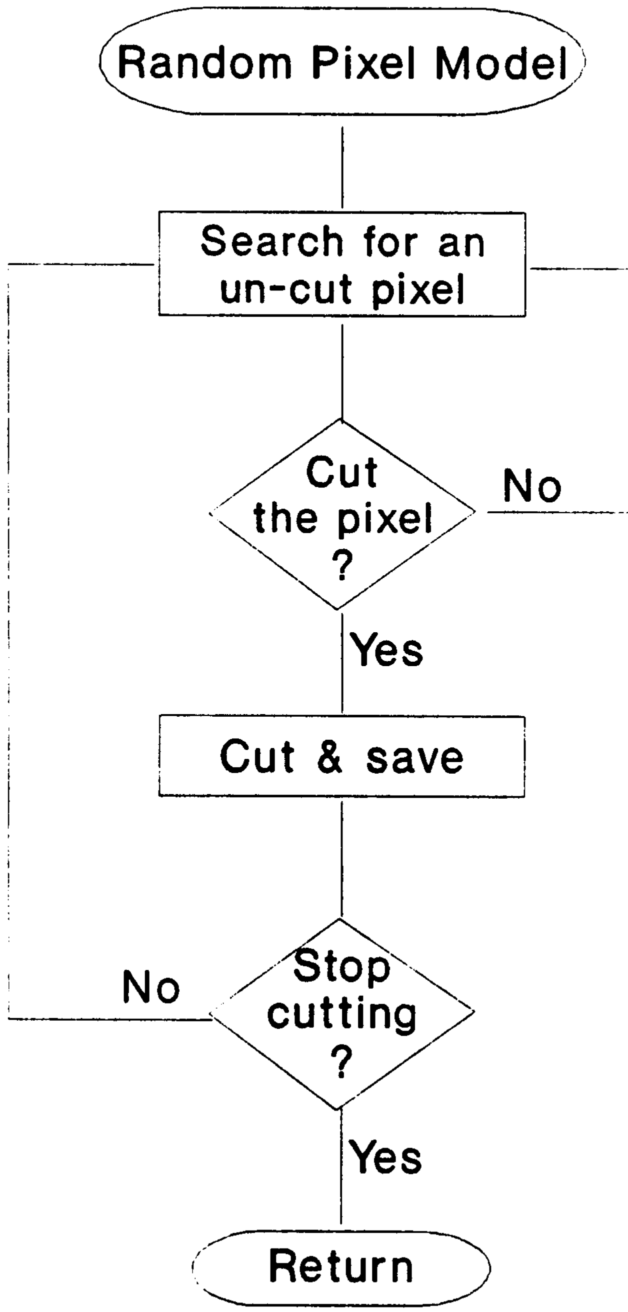
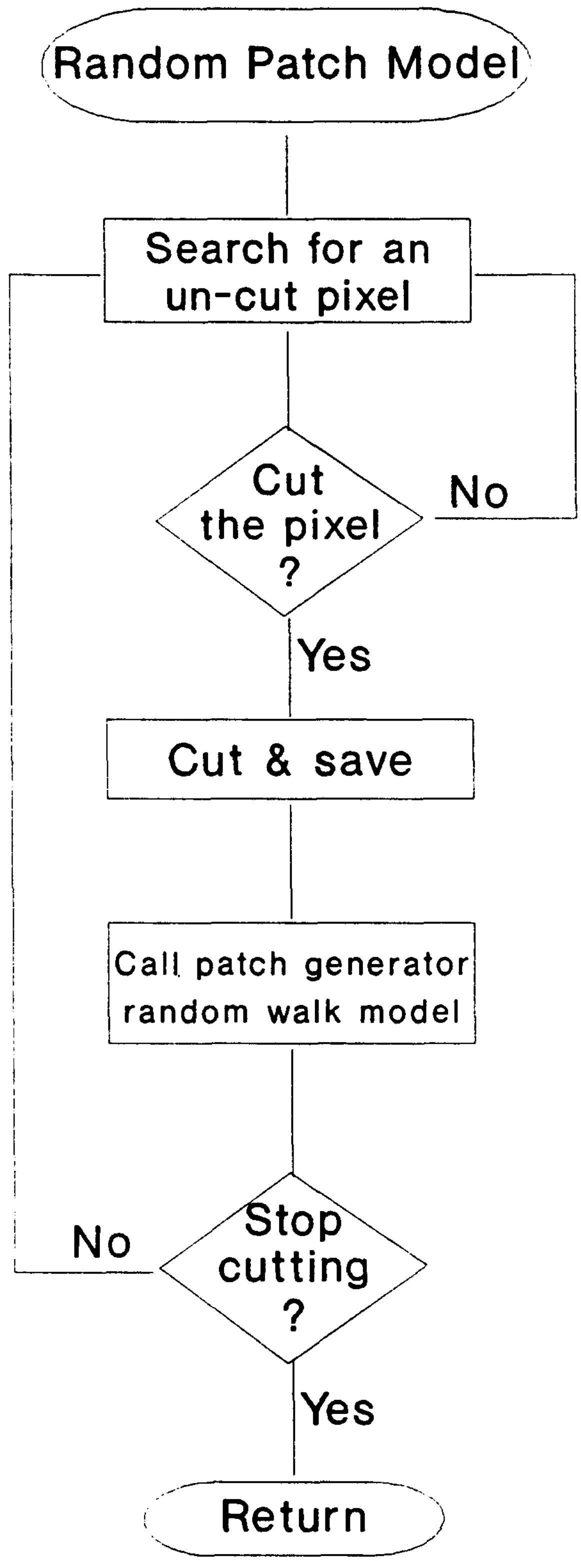


Figure II.3: The flowchart of the random patch model.



Fiqure II.4: The flowchart of the random walk model.

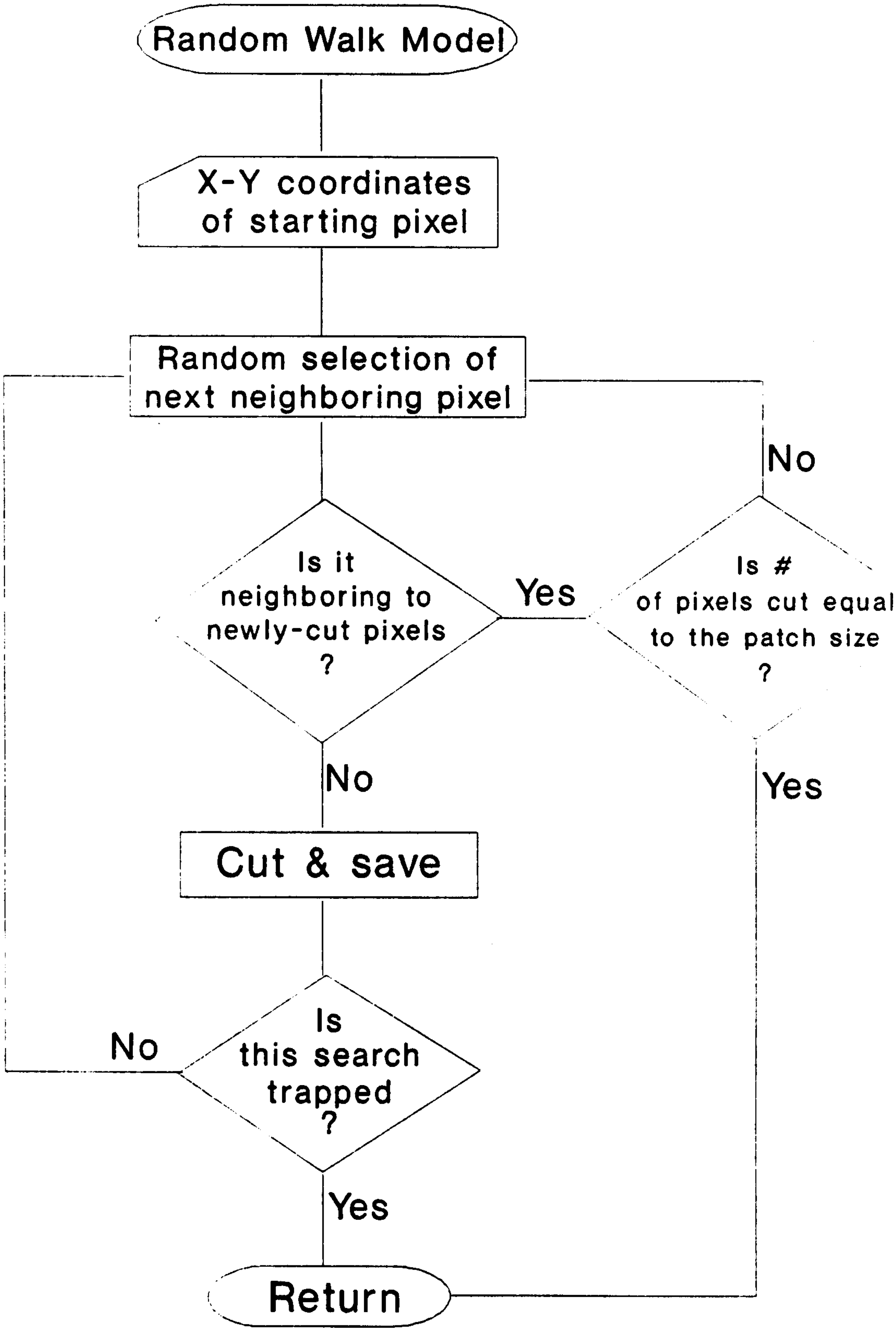


Figure II.5: The flowchart of the maximum dispersion model.

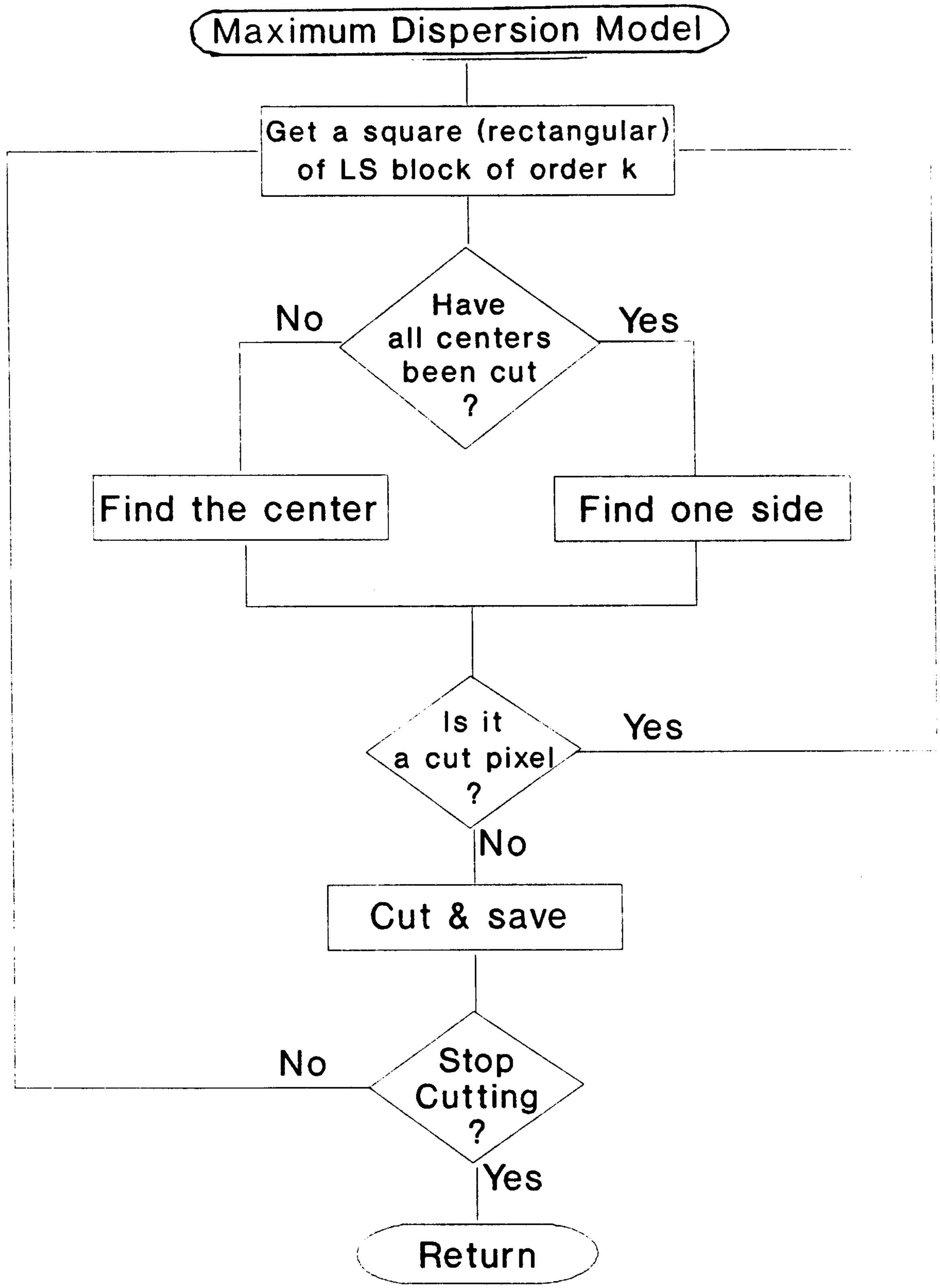


Figure II.6: Example of the searching algorithm of the maximum dispersion model. This model landscape is 13 by 13; cutting rate is 4%; numbers stand for the time step when the pixels are cut. Cutting starts at the center (7,7), then the four corners followed by the four side pixels, and new centers, for example pixel (4,4), and new sides, for example pixel (1,4). See text for more explanation.

	01	02	03	04	05	06	07	08	09	10	11	12	13
1	1	0	0	2	0	0	1	0	0	3	0	0	1
2	0	4	0	0	4	0	0	4	0	0	5	0	0
3	0	0	6	0	0	0	0	0	0	0	0	0	0
4	3	0	0	2	0	0	3	0	0	2	0	0	3
5	0	5	0	0	5	0	0	5	0	0	5	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	1	0	0	3	0	0	1	0	0	3	0	0	2
8	0	5	0	0	5	0	0	6	0	0	6	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0
10	3	0	0	2	0	0	4	0	0	2	0	0	4
11	0	6	0	0	6	0	0	6	0	0	6	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0
13	1	0	0	4	0	0	2	0	0	4	0	0	1

Figure II.7: The flowchart of the staggered-setting model.

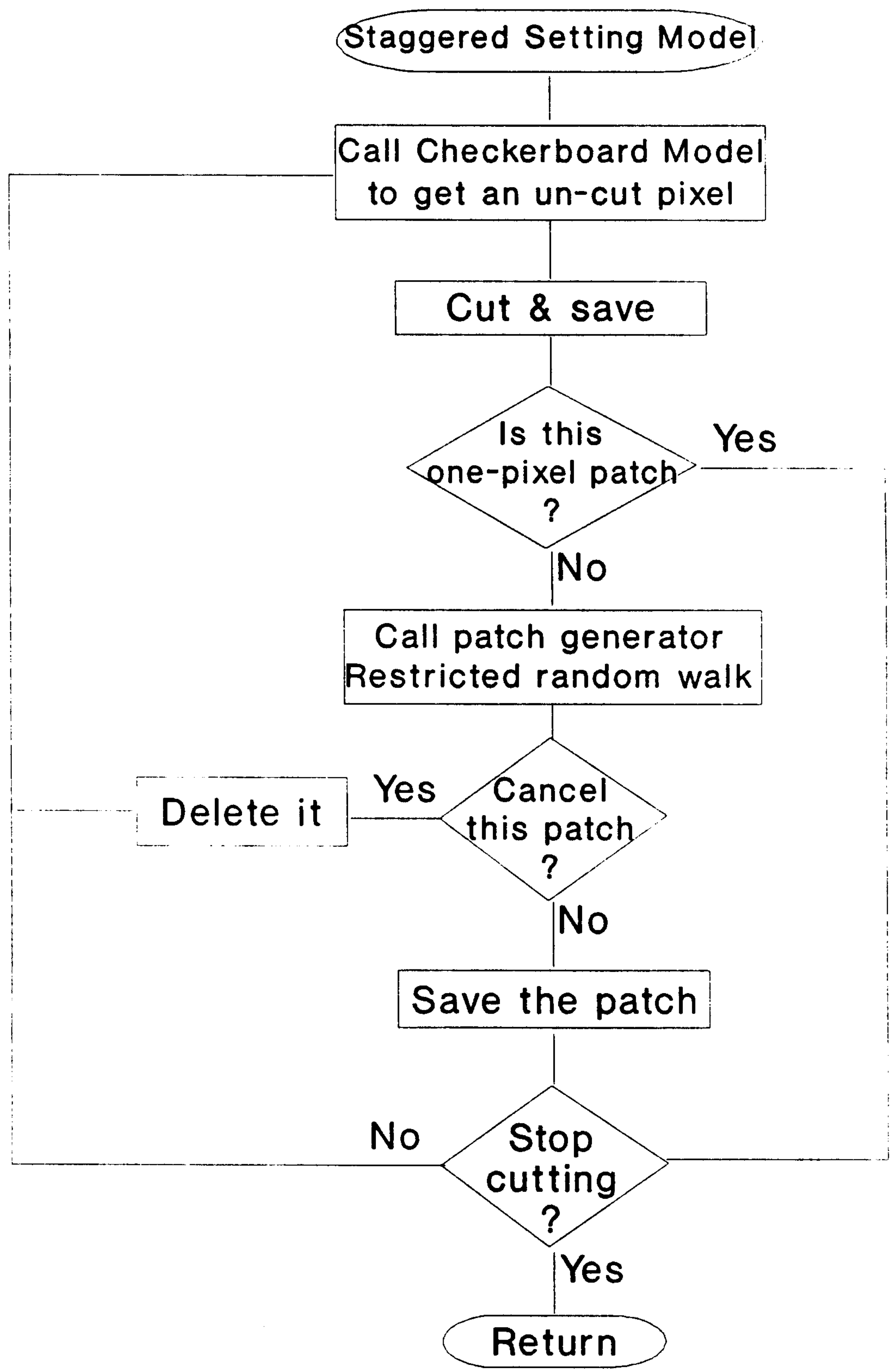
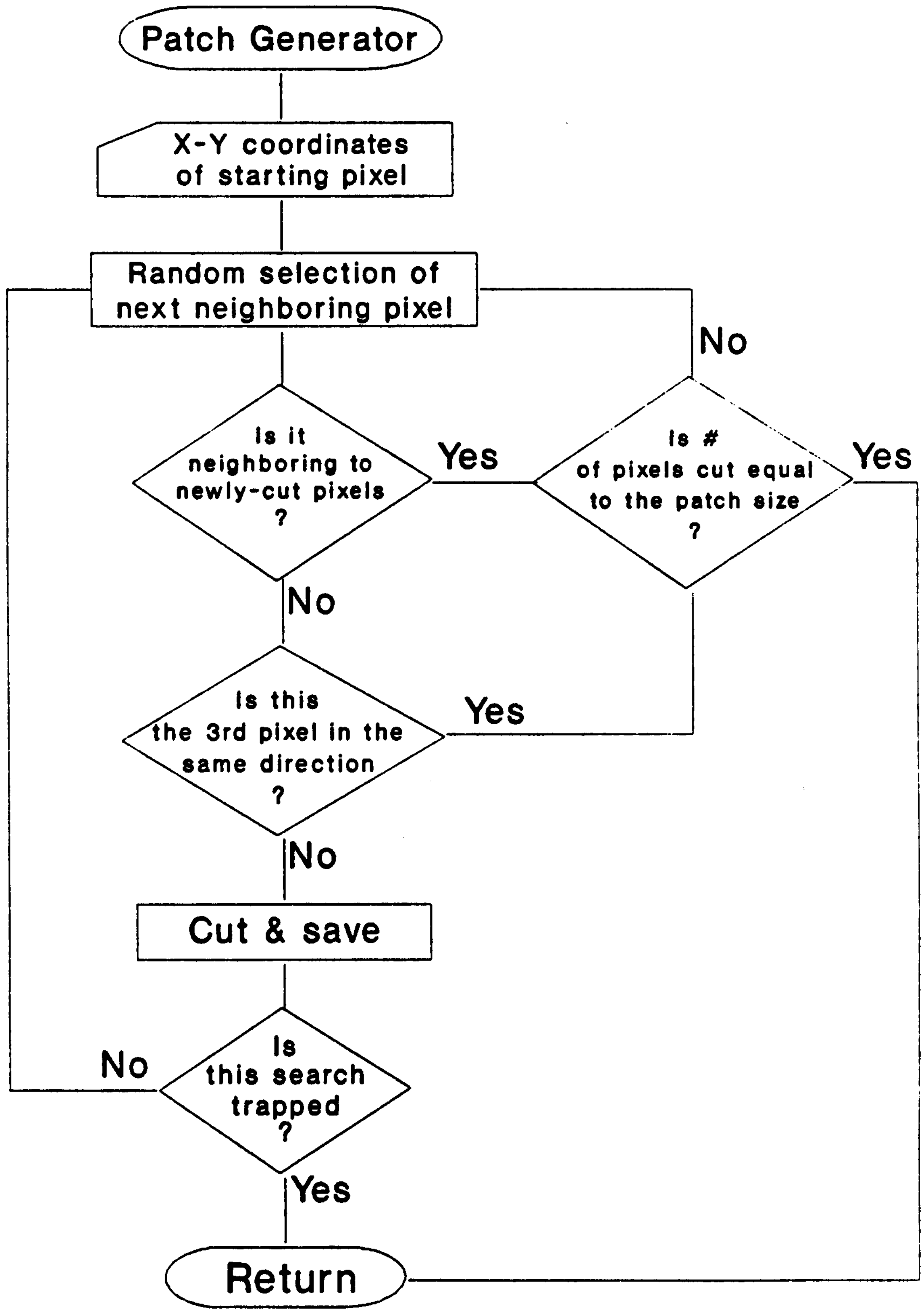


Figure II.8: The flowchart of the restricted random walk model.



The staggered-setting model mimics the clearcutting system commonly-used on the federal forest lands in the Pacific Northwest region. This model generates landscapes with high degree of fragmentation (Figure II.7). Three assumptions are made. First, the algorithm used in the maximum dispersion model is adopted to locate the first pixel of a patch from which the patch is developed. Second, the patch generator is a restricted random model (Figure II.8), that is, the patch size and search direction are determined randomly with two restrictions: (a) no more than 3 pixels are cut, for one search, in a row in the same direction, and (b) no pixels of two patches generated at the same time step may join with each other. Third, if a search for more pixels of a patch is "trapped", one of the two options is executed: (a) terminate the search and save the patch if the number of pixels cut for this patch is larger than half of the predetermined number or (b) terminate the search and delete the patch.

5. Partial aggregation clearcut model

The partial aggregation model is a modification of the staggered-setting model. The partial aggregation model is the alternative silviculture approach which has been proposed to replace the staggered-setting approach (Eubanks[2], personal communication). The assumptions used

2. Steve Eubanks was the Blue River District ranger, the Willamette National Forest, and is now with the Recreation Office, USDA Forest Service, Washington D.C..

are: (1) The landscape matrix is divided into 4 quadrats. One of the quadrats is randomly chosen and cutting is kept within it until it is almost impossible to find space to put in another cut unit, and then another quadrat is randomly chosen for cutting. (2) Within each quadrat, the first pixel of a patch is randomly located; from it the patch is developed, using a patch-generator similar to the one used in the staggered-setting model, or using a self-affinity patch generator, which creates less irregularly-shaped patches because the search for pixels is forced to move towards the pixels already cut for the patch. (3) A piece (or several pieces) of forest land can be set aside as a reserve which is unavailable for cutting. This is used as an option.

6. Progressive cutting model

The progressive cutting model generates landscapes with the highest aggregation of patches and the least fragmentation. The model operates following the rules below. (1) A starting pixel is randomly selected, and then the search extends outwards in all directions. (2) For each time step, only one search direction is chosen randomly. The minimum and maximum row (or column) numbers in the existing patch are used to control the cutting range; a belt of pixels constrained by these extreme control numbers are then cut in the selected direction. One piece of land is generally cut at each time step.

A variation of this model is the progressive cutting model with four nuclei. This modified model has four starting points instead of one. After random selection of the four starting points, the 4-nuclei progressive model operates in the same way as the one-nucleus model except that the modified model cuts, for each nucleus, one-forth of the total number of pixels to be cut at one time step.

7. Strip-cut model

The strip-cut model generates linear cut-units. The resultant landscape is similar to that generated by the progressive model: high aggregation and low fragmentation. The model requires that strip length be input by the user; the strip width on the other hand is a function of the strip length and the cutting rate. Cutting starts from the upper-left corner and proceeds to the right. When cutting reaches the border of the landscape, the cutting goes from the upper-left to the bottom; when it reaches the border, cutting switches back to left-to-right again, and then to upper-to-bottom.

8. Supplementary models

Two supplementary models, stream and road generators, are designed to assist in creating more realistic landscapes. Both the stream and the road generators are self-avoiding random walk models (e.g., Smart et al. 1967, Smart and Moruzzi 1971). The models are used to create a stream or road system in a synthetic landscape. Because of the scale problem, a stream or road pixel usually means that a stream channel or road meanders through this pixel. The model assumes: (1) The model initiates randomly at a single pixel, and develops a linear system of pixels continuously with a width of only one pixel. (2) Stream channels or road branches can randomly change direction but never go backward. When a stream channel or a road branch steps out of boundary or meets another branch, it starts from the original point again; it terminates when it goes out off boundary. (3) No loop-type of channel is allowed in the case of streams, but loop-type road systems are allowed.

<u>Basic Landscape Parameters</u>

The landscape parameters measured by LSPA are (1) patch size, (2) edge length of a patch, including outer and inner edges, (3) the edge-to-edge inter-patch distance (i.e., the first order nearest neighbor distance), and (4) edge length between any pair of different patch types. The size of a patch is measured by counting the number of pixels making up the patch. The so-called "rook's rule" is used to delineate patches, that is, only pixels of the same type with joint common sides are regarded as belonging to the same patch. A patch has an inner edge where there are "holes" (i.e., patches of other types) inside the patch. The outer edge and inner edge are measured separately and the sum of the two is usually used in calculation of landscape indices. The inter-patch distance is the distance from an edge pixel of the target patch to an edge pixel of a nearest patch of the same type. The edge length between different patch types is measured collectively for any pair of two types of patches. For example, the number of pixels of patch type i adjacent to patch type j is counted and then converted to the number of pixel sides shared by these two types of patches. After measurement, the pixel units (i.e., the number of pixels or pixel sides) of those basic parameters are transformed into real units (i.e., hectares for patch size, kilometers or meters for edge length and distance), using the appropriate scalar provided by the user.

Landscape Indices in LSPA

1. Basic information on patches

The basic information on patches is composed of the descriptive measures of landscape mosaics: the number of patches of each type, patch density, the mean patch size, total area, total edge, edge density (the ratio of total edge to total area), and proportion of the total area in a patch type when real landscape maps (e.g., from GIS) are studied. Another set of patch measures critical to special habitats (e.g., old-growth forests) are size, edge, and shape of the largest patch (Gardner et al. 1987).

2. Patch shape measures

Patch shape is a good indicator of habitat suitability because many species may respond to it (Forman and Godron 1986, Buechner 1989). LSPA uses two types of indices to quantify patch shape: a patch shape index (SI) and a shape index based on fractal dimension of patch shape (FSI). Both utilize the same information: size and edge length of patches. The patch shape index measures the departure of the edge-size relationship from that of a simple standard geometric unit, such as a circle or a square (Patten 1975). A square patch is defined in LSPA as the standard with an SI value of one. This choice is made because the raster formed data are used in LSPA. The equation of SI for an individual patch is defined here as:

$$SI(i) = 0.25\ P(i)\ [A(i)]^{-1/2} \quad ,$$

where SI(i) is the shape index of patch i, P(i) is the perimeter (i.e., edge) of patch i, and A is the area of patch i. The higher the SI value, the more irregular the shape of a patch. Three derivatives of this general shape index are also used in LSPA to quantify patch shape in a landscape mosaic: the arithmetic mean SI (MSI), area-weighted mean SI (ASI), and overall landscape SI (LSI). The equations of the three shape indices are:

$$MSI = \sum\ SI(i)\ /\ T \ ,$$

$$ASI = \sum\ A(i)\ SI(i)\ /\ A \ ,$$

$$LSI = 0.25\ P\ (A)^{-1/2} \quad ,$$

where T is the number of patches, A is the total area of patches, and P is the total edge length of patches. Both MSI and ASI are averages, but MSI gives each patch the same weight, while ASI uses patch size as a weighting factor and thus assumes that larger patches have greater effect. LSI is Patten's habitat edge diversity index (Patten 1975) and is a function of total area and total edge.

The fractal dimension of patch shape also measures irregularity of patch shapes. More discussion about fractal dimension is given in the section on landscape indices. The equation of a patch shape index using fractal (FSI) is:

$$FSI = D - 1.0 ,$$

where D is the fractal dimension of patch shape. This new index of patch shape, FSI, is proposed here because FSI has fractal properties (e.g., scale-invariance) since it is a function of the fractal dimension. Thus FSI reveals information different from that of SI. FSI ranges from 0 for regularly-shaped patches (i.e., squares) to 1 for highly irregular patch shapes. FSI rather than fractal dimension is used because its values can be regarded as relative values (i.e., from 0 to 1).

3. Measures using inter-patch distance

Inter-patch distance is mainly used for detecting pattern and quantifying patch connectivity or isolation. As a pattern detector, a measure from inter-patch distance indicates whether patches in a landscape are randomly distributed. One example of measures of this type is the nearest neighbor index (Clark and Evans 1954, Unwin 1981):

$$NNI = MNND / ENND ,$$

$$MNND = 0.5 \ (d)^{-1/2} \quad ,$$

where NNI is nearest neighbor index, MNND is the mean nearest neighbor distance, ENND is the expected mean nearest neighbor distance under Poisson (random) distribution, and d is the density of the given type of patches in landscape. NNI ranges from 0 (for a perfect cluster pattern), through 1.0 (for a random pattern), and up to 2.149 (for a perfect dispersed or regular pattern). A test of significance can be performed because the standard deviation of ENND (SD) is known (Clark and Evans 1954):

$$SD = 0.26136 \ (N \ d)^{-1/2} .$$

Note, however, this test may not be valid in the present case due to the modification of the nearest neighbor index. However, some modifications must be made because NNI was originally designed for point pattern detection. Because area pattern and edge-to-edge inter-patch distance are measured in LSPA, d in the above equation is redefined as the proportion of area of patches of one type to the total area of the landscape, and the maximum NNI value is then less than 2.149.

The index of clumping, I, (David and Moore 1954, Pielou 1978) is another distance measure:

$$I = (V / m) - 1 ,$$

where I is the index of clumping, V is the variance and m the mean of sample count data (e.g., the number of individuals in plots). The index I is a measure of aggregation of individual species in a community. This index is modified here for use in landscape characterization. The modified equation of I has the same form as the one above, but the two parameters are changed:

$$V = \sum (NND(i) - MNND)^2 / (N-1) ,$$

$$m = MNND = \sum NND(i) / N ,$$

where V and m are variance and mean of nearest neighbor distance respectively, and all the other terms are the same as discussed above. Notice that a distance measure is used in the above equation instead of the sample frequency data originally proposed for the index. The modification assumes that the patch distribution in space has a Poisson (i.e., random) distribution if the distribution of distances of patches to their nearest neighbors is random. In theory, the range of the index of clumping has no limits. A value of zero indicates a possible random distribution, and positive and negative values indicate possible regular and aggregated distributions, respectively. A test of significance of two samples was also given by David and Moore (1954):

$$w = 0.5 \log[(V_1/m_1) / (V_2/m_2)],$$

$$t = 2.5 (N-1)^{-1/2} ,$$

where w is the test statistic, V_1 and V_2 are the variances of samples 1 and 2, respectively, m_1 and m_2 are the means of samples 1 and 2, respectively, and t the test threshold. If w falls outside the range of -t and t, the two samples are said to be significantly different at 95% confidence level (Davis and Moore 1954). Although this index was also designed for point pattern analysis, it can be used in patch pattern analysis because it does not have an area component in the equation. The modified index of clumping is preferred to the nearest neighbor index because it allows a test of significance of two landscapes without requiring the variance of the index I itself. This index has not been used in landscape context.

Many other indices, such as Lloyd's index of patchiness and Morisita's index of dispersion (see Pielou 1978), can be used as spatial measures, but the difficulty in interpreting results may reduce their usefulness in landscape ecological research.

Distance measures are also used in landscape ecology as a way to quantify connectivity or isolation (Forman and Godron 1986, Fahrig and Merriam 1985). However, those indices of connectivity listed in Forman and Godron (1986) are not used in LSPA due to difficulties of obtaining certain required information such as the information about the nearest neighbor patches. The mean inter-patch distance, the nearest neighbor, and proximity indices are installed in LSPA. Mean inter-patch distance is the arithmetic mean of the first order nearest neighbor distances of individual patches. Proximity index (PX) is an inverse function of the nearest neighbor distance with patch size as weight:

$$PX = \sum \{[A(i)/NND(i)] \,/\, [\sum A(i)/NND(i)]^2\},$$

where A(i) is the area of patch i, and NND(i) is the distance of patch i to its nearest neighbor. A higher value of PX means that patches are more aggregated.

4. Landscape diversity measures

Landscape diversity is defined as a measure of the variability and complexity of landscape mosaics (Li and Franklin 1988). It is a function of either the composition or configuration of landscape elements or both (Li and Franklin 1988). Landscape composition refers to both the number of landscape element types and the proportion of those types in landscapes, while landscape configuration is concerned with the spatial pattern of patches in landscape mosaics. Five components of landscape diversity have been recognized (Romme 1982, O'Neill et al. 1988a, Li and Franklin 1988): (1) richness, (2) evenness (or dominance), (3) patchiness (or contagion), (4) fractal dimension, and (5) connectivity (or isolation).

Richness is the total number of different landscape element types in a landscape mosaic. The relative richness index (R) is defined as (Romme 1982):

$$R = 100\ (T\ /\ T_{max})\ ,$$

where T is the number of different ecosystem types present, and T_{max} the maximum possible number of different types. R is a percentage.

Evenness measures the equitability of distributions (preferably area-weighted) of landscape element types in a landscape mosaic. Romme's relative evenness index (E) is given as (Romme 1982):

$$E = 100\ (H\ /\ H_{max})\ ,$$

$$H = -\log[\Sigma\quad P(i)]^2\ ,$$

$$H_{max} = \log(T)\ ,$$

where H is the modified Simpson's index, H_{max} the maximum possible value of H with T patch types, and P(i) the proportion of patch type i in a landscape. E is also a percentage.

Dominance measures the extent to which one or a few landscape elements dominate the landscape, and is inversely related to evenness. Dominance index (D1) is given as (O'Neill et al. 1988a):

$$D1 = \log(T) + \Sigma\quad P(i)\ \log[P(i)]$$

where T is the total number of patch types, and P(i) the proportion of the grid pixels in patch type i. Higher values of D1 indicate that one or very few patch types dominate the landscape.

Patchiness measures the extent of contrast between neighboring landscape element types in a landscape mosaic.

Romme's relative patchiness index (PT) is given by (Romme 1982):

$$PT = 100 \sum \sum E(i,j)\ D(i,j)\ /\ N_b\ ,$$

where E(i,j) is the number of boundaries (edge) between patch type i and j, D(i,j) the dissimilarity value for type i and type j, N_b the total number of boundaries. The dissimilarity matrix, D(i,j), of landscape elements can be obtained either subjectively (e.g., by expert judgment) or objectively (e.g., using scores of the first ordination axis or other dissimilarity measures). An example of the dissimilarity matrix is displayed in Appendix II.2. A higher value of PT indicates the presence of many habitat types in juxtaposition with other habitat types. The result is a high contrast and highly dissected landscape.

Contagion measures the extent to which landscape elements are aggregated or clumped (O'Neill et al. 1988a). Contagion index is modified due to an error in the original equation and the new equation is given here as:

$$RC = - \sum \sum P(i,j) \log[P(i,j)]\ /\ [2\ T \log(T)]\ ,$$

where RC is the relative contagion index, T the total number of patch types, and P(i,j) the probability of a grid cell of patch type i being found adjacent to a grid cell of patch type j. Higher values of RC usually reflect landscapes having only a few large, contiguous patches, whereas lower values reflect landscapes with many small patches (O'Neill et al. 1988a). Contagion is similar to

Pielou's mosaic's spatial diversity index (Pielou 1975), but differs in that Pielou's index requires a transect sampling to obtain some parameters for calculation. Conceptually, contagion is inversely related to patchiness, but contagion is expressed in probability terms, while patchiness incorporates information on first-order neighbor contrast, by using the dissimilarity matrix.

Connectivity measures the contiguity of the matrix (or patches of the same kind) in a landscape mosaic (Merriam 1984, Li and Franklin 1988). Connectivity can be measured either from geometry of landscape structure as discussed in previous sections, or from landscape functions, for example, in terms of what wildlife species perceive. The latter is termed dispersal index.

The dispersal index is a specific type of connectivity index calculated from the hypothetical or assumed viewpoint of animals. This index is proposed because connectivity should be a species (or process, such as material flow) specific measure because species may respond differently to the same landscape structure. Dispersal index measures the ease with which a hypothetical species can move within a landscape mosaic. To calculate this index, a hypothetical species is put in a landscape mosaic and allowed to move through the landscape. The information on landscape structure, from the species' perspective, is recorded in the course of species movement and then used to calculate dispersal index. A random walk model is used to define the manner in which a hypothetical species moves in landscape mosaics. This is a simple model, and more sophisticated models of animal movement can be constructed so that the movement of a particular species can be mimicked according to its behavioral characteristics. It is likely that the mesh size (i.e., area of a pixel) of the landscape at which species responses are assessed may exert great influence on this type of landscape indices. Dispersal index is calculated using a habitat suitability matrix (Appendix II.2), which is constructed from literature on wildlife habitat selection. Two hypothetical species, an edge species and an interior species, are studied in this paper. The differences between the two types of species are reflected in those habitat measures. The dispersal index (DP) is calculated by:

$$DP = \sum \sum MHS(i,j)\ K(i,j)\ /\ S\ ,$$

$$MHS(i,j) = HS[t(i),t(j)]\ ,$$

where MHS(i,j,k) is the value of habitat suitability at pixel (i,j), K(i,j) the species movement vector (i.e., coordinates of movement), S the total number of moves, and HS[t(i),t(j)] the habitat suitability value for habitat t(i) with a neighbor habitat t(j).

The fractal dimension of patch shape measures the irregularity of patch shape (Mandelbrot 1982). A higher value of fractal indicates that a landscape has more irregularly-shaped patches. Three derivatives of fractals of patch shape are used in LSPA: an overall landscape fractal (LFR), a mean fractal of individual patches (MFR), and a fractal obtained from double-log regression (DFR). Their equations are given below:

$$LFR = 2 \log(P/4.0) / \log(A) ,$$

$$MFR = \sum FR(i) / T ,$$

$$FR(i) = 2 \log[P(i)/4.0] / \log[A(i)] ,$$

$$DFR = 2 / SLP ,$$

where P is the total edge, A is the total area of patches (Robert Gardner, personal communication, see footnote 1), T is the number of patches, FR(i) the fractal dimension of patch i, P(i) the perimeter (i.e., edge) of patch i, A(i) the area of patch i, and SLP is the slope of double-logarithmic regression of area on edge of individual patches (Burrough 1986). LFR and DFR can be considered as the fractal dimension of the entire landscape, whereas MFR describes individual patches. The difference between LFR and DFR is not clear except that they are obtained from different methods and yield different values. These fractals can be calculated for either patches of one type or patches of all types.

5. Fragmentation measures

Fragmentation can be regarded as one component of landscape diversity. Landscape diversity and fragmentation are discussed separately because fragmentation itself is an important research subject in resource management (Burgess and Sharpe 1981, Harris 1984, Verner et al. 1986). Forest fragmentation occurs when: the number of forest "islands" increases; the shapes of forest "islands" become more irregular; the area of forest interior area shrinks; and/or forest corridors are broken and forest patches are isolated. A fragmentation index measures the extent to which a habitat type of interest is fragmented at a particular time. Four facets of fragmentation are recognized here: (1) number (or density) of remnant forest "islands", (2) shape of remnant forest "islands", (3) size variation of remnant forest "islands", and (4) forest interior area. Landscape diversity can be used to characterize fragmentation, especially connectivity (or isolation) and patchiness.

The fragmentation indices are scaled to vary from 0 to 1. On the one hand, a value of 1 indicates that a forest landscape is completely fragmented in terms of a particular landscape characteristic. For example, the fragmentation of the number of forest patches reaches 1 (i.e., 100%) when the landscape is 50% cut-over in a maximum dispersion pattern (see Franklin and Forman 1987). On the other hand, a value of 0 represents the least fragmentation. For example, when the strip-cut model starts from one side of the landscape and progresses to the other side, there is no fragmentation in terms of connectivity or the number of forest patches (e.g., Haila 1986). The equations of fragmentation indices of different aspects are given below.

(1) Fragmentation index of the number of forest patches:

$$FGN1 = (N_p - 1) / N_c \text{ or}$$

$$FGN2 = MPS \; (N_f - 1) / N_c \; ,$$

where FGN1 and FGN2 are the fragmentation indices of the number of forest patches, MPS the "mean patch size" (an input parameter), N_p the total number of patches of all types, N_f the number of forest patches, and N_c the total number of pixels. FGN1 is a modification of the fragmentation index proposed by Monmonier (1974, also see Haggett et al. 1977), while FGN2 is a variation of FGN1. Based on previous simulation results, FGN2 is a better index when the matrix is regnant, that is, the landscape mosaic is not fully developed (e.g., forest landscapes in the Pacific Northwest).

(2) Fragmentation index of forest patch shape:

$$FGS1 = 1 - 1 / MSI \text{ or}$$

$$FGS2 = 1 - 1 / ASI \text{ or}$$

$$FSI = FR - 1.0 \; ,$$

where FGS1 and FGS2 are the fragmentation indices of forest patch shape, and MSI, ASI, FSI and FR were discussed in the previous section.

(3) Fragmentation index of the largest forest patch size:

$$FGL = (1 - A_1 / A) \; ,$$

where FGL is the fragmentation index of the largest forest patch size, A_l the area of the largest forest patch, and A the total area of forest. A variation of FGL is an index for the size of the largest "compact" forest patch:

$$FGC = (1 - A_c / A) ,$$

where FGC is the fragmentation index of the largest compact forest area, and A_c the area of the largest compacted forest patch, which is determined by blocking all the narrow forest corridors and then measuring the largest forest "patch" left. The width of forest corridors for blocking is defined by the user (the default is 2).

(4) Fragmentation index of forest interior area:

$$FGI = 1.0 - A_i / A ,$$

where FGI is the fragmentation index of forest interior area, and A_i is the interior forest area. A_i is calculated by considering the scale of edge effect to be one pixel and substracting this amount from the total forest area.

Spatial Statistics

1. Autocorrelation

Autocorrelation, the spatial (or temporal) dependency among data points in a sample, can be measured by the joins-count statistic (Cliff and Ord 1981, Unwin 1981). Only the binary joins-count statistic is installed in LSPA (versions 3 and 4), although similar methods exist for analyzing ordered or colored maps with more than two elements (Cliff and Ord 1981). Suppose that there are only two landscape elements: forest (F) and clearcut (C); the proportion of F is p and the proportion of C is q (q=1-p). A join is defined as the border between two adjacent pixels. Therefore, a FC join is the one between a forest pixel and a clearcut pixel, and a FF (or CC) join is the one between two pixels of the same type. The joins-count method determines if the pattern is random by testing the observed joins-counts against the expected with known variance (Cliff and Ord 1981, Unwin 1981). For example, in the case of the FC joins for free sampling (i.e., an infinite landscape),

$$MEAN(FC) = 2\ k\ p\ q\ ,$$

$$VAR(FC) = 2(k + m)\ p\ q - 4(k + 2m)\ p^2\ q^2\ ,$$

$$k = 4 + 3(NROW+NCOL-4) + 2[(NROW-2)\ (NCOL-2)]\ ,$$

$$m = 8 + 6(NROW+NCOL-4) + 6[(NROW-2)\ (NCOL-2)]\ ,$$

where MEAN(FC) is the expected joins between forest and clearcut, VAR(FC) is the variance of the expected joins of FC, NROW and NCOL are the dimensions of the landscape (i.e., numbers of rows and columns). A z-test is then performed to see if the pattern can be formed by a random process; if not, spatial autocorrelation exists. More detailed discussion of the joins-count method can be found in Cliff and Ord (1981).

2. Semivariogram

Semivariogram is a technique to study spatial variation and spatial dependency. The mathematical definition of semivariogram is given as:

$$r(h)=E\{[x(z) - x(z+h)]^2\}/2 ,$$

where $r(h)$ is the measure of semivariance, $x(z)$ the value of property x at location z, h the lag distance and $E\{[x(z)-x(z+h)]^2\}$ the expected square difference between values of samples separated by lag distance h. By definition, semivariogram is a measure of variance of the sample value x at location $(z+h)$ from the sample value x at location z. Conceptually, $r(h)$ has the following properties (Matheron 1963, Burgess and Webster 1980): (1) $r(h)$ is a measure of similarity between points at a given distance (h) apart; (2) The more alike are the points, the smaller is $r(h)$; (3) In general, $r(h)$ is an increasing function of h; and (4) $r(h)$ is not only dependent upon the length h, but also upon the direction of the vector h. The graph of $r(h)$ against h is called the semivariogram. Further analysis is usually performed on graphs of this kind. A typical semivariogram is shown in Figure II.9b. Semivariogram increases, as h increases, from zero to a constant value b called the sill which approximately equals the sample variance. The value a on the h axis is called the range and is the value of lag distance h at which the semivariance reaches the sill. The range represents the distance beyond which samples are not correlated. Sometimes, $r(h)$ does not equal to zero as h approaches to zero (Figure II.9a). This is called the nugget effect (e.g., constant c in Figure II.9b) which expresses the micro-variability of a property at a scale smaller than the sampling interval, or the measurement error, or both (Gutjahr 1985, Trangmar et al. 1985). These parameters (i.e., a, b and c) can be estimated by the least square fit of regression models (Webster 1985). The commonly used one is the spherical model, defined as:

$$r(h) = c + d\,[\,3h/2a - (h/a)^3/2\,], \qquad \text{for } 0<h<=a,$$

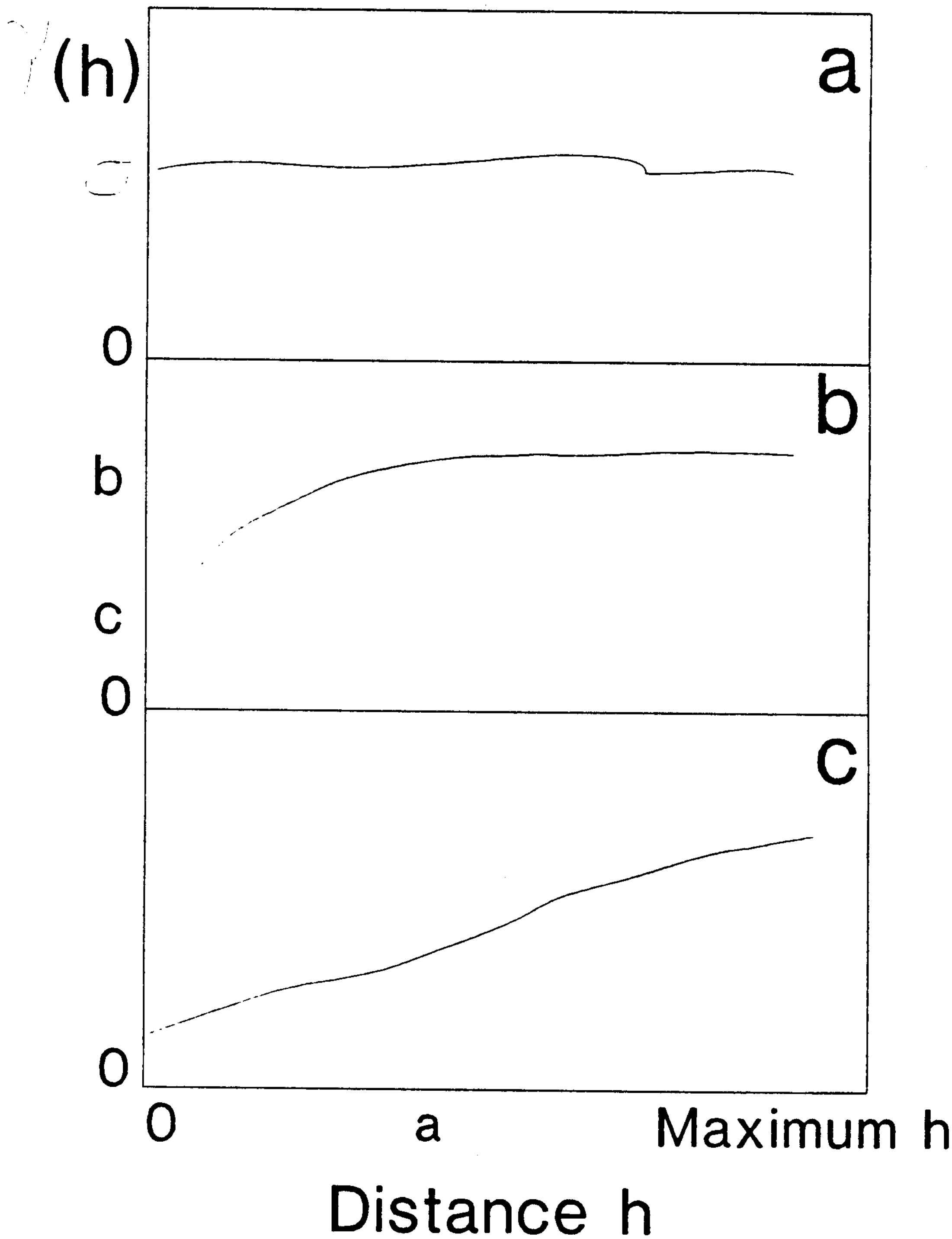
$$r(h) = c + d = b, \qquad \text{for } h>a,$$

$$r(h) = c, \qquad \text{for } h=0,$$

where a, b, c and h are the range, the sill, the nugget effect and the lag distance respectively, and d (d=b-c) is a regression constant which defines the sill b.

The behavior (or shape) of semivariogram is the key to interpretation of spatial pattern using semivariogram. Some of the conceptual behaviors of semivariogram are displayed in Figure II.9a-c. If r(h) remains essentially constant for all the values of h>0 (Figure II.9a), it indicates that observations are spatially independent (i.e., a random pattern). If, for all the values of h>0, r(h) increases and approaches a constant (Figure II.9b), the observations are spatially dependent within a spatial area that can be characterized as a single domain. If, as h increases, r(h) continues to increase (Figure 9c), then it indicates that area being sampled continually changes and is not comprised of a single domain. Usually, data are transformed (e.g., a logarithmic transformation) before

Figure II.9: Illustration of the semivariogram.
See text for discussion.



analyzed by semivariogram. This is only for the purpose of stabilizing variance, but not for normality, because semivariogram does not require data with a normal distribution (Gutjahr 1985, Shumway 1985). Other methods for adjusting non-stationary data include detrending, using linear or nonlinear regression, and differencing. Data for analysis of semivariogram or other geostatistical methods are usually collected by regular grid sampling or transact sampling with evenly-spaced sample points. Even-spacing is preferred, but not always required.

Landscape Models

Three landscape models were developed to perform more sophisticated analyses on landscape patterns: a fire spread simulator, a percolation detector, and a species movement model. Models similar to the first two cases have been developed and used previously in landscape ecological research (e.g., Gardner et al. 1987, Turner et al. 1989). The species movement model is only a prototype. These landscape models are used to link landscape structure to landscape functions and processes. Because much of ecological research is centered on function, this should be a useful tool for the investigation of landscape problems (Franklin and Maser 1988).

The fire spread simulator was designed to assess the effects of landscape pattern on fire spread. The following scenario is assumed: (1) Lightening occurs randomly in a landscape, and fire starts at one or more pixels. The probability of a lightening strike is subjectively assigned to each patch (i.e., stand) type, for example, using the fuel succession model by Agee and Huff (1987). (2) The probabilities of fire spreading outward are assigned by stand types (Agee and Huff 1987). (3) During each simulation day, fire at each burning pixel can go against the wind by 1 pixel, parallel to wind direction by 2 pixels, and with the wind by 4 pixels for a low intensity fire. For high intensity fire the figures double. Wind direction may randomly change on a daily base. (4) Streams can function as fire breaks to low intensity fires. (5) Burned pixels can not be burned again. To assess effects of landscape patterning or spatial heterogeneity on fire spread, the number of simulation days needed for a fire to spread out off the boundary of the landscape, the number of fires burned out inside the landscape, and the percent landscape burned are measured. A fire susceptibility index (FS) is constructed using those data:

$$FS = 100\ (DY + BT + PCT)\ /\ 3\ ,$$

$$DY = (NROW\ /\ (2\ FIN\ DAY)\ ,$$

Where NROW is the landscape dimension (i.e., the number of rows), FIN the fire spread parameter (equal to 4 for low intensity fire, 8 for high intensity fire), DAY the mean number of simulation days for fires to spread out of the landscape, BT the mean percent of fires which have not burned out inside, and PCT the mean percent landscape burned. For each synthetic landscape, the mean measurement of FS of 30 fires is used.

The species movement model was developed to measure connectivity of landscape mosaics and to indirectly assess effects of landscape patterns on landscape functions and processes. The dispersal index calculated from this model has been discussed in a previous section.

The percolation model was also developed to assess connectivity of landscapes. It has been used to simulate fire spread (MacKay and Jan 1984, Stauffer 1985, Turner et al. 1989), and to study species movement across landscapes (Gardner et al 1987, O'Neill et al. 1988b). This model can certainly be used to measure connectivity of landscape mosaics, but a good index from the model is still lacking.

Applications of LSPA

Remote sensing and GIS are important data sources in both landscape ecology and resource management. Their importance will increase because the technological development in both remote sensing and GIS will provide greater coverage and higher quality of spatial data. Many ecological problems caused by human activities are large-scaled and their investigations will consequently require more utilization of remotely sensed spatial data (Burrough 1986, Hall et al. 1987, 1988). Furthermore, remote sensing allows for the study of landscape change over time (Burrough 1986, Hall et al. 1987), and facilities the measurement of such landscape parameters as patch size and edge length. Hence, tools to use this kind of data to address problems in landscape ecology and resource management are needed. LSPA is one such tool which can use both remote sensing and GIS data.

LSPA is a useful tool to study spatial patterns of landscapes, and particularly to evaluate the development of forest cutting patterns. The applications of LSPA are as follows. (1) LSPA can quantify spatial patterns of landscapes; (2) LSPA can forecast consequences of management activities; (3) LSPA can examine behavior of landscape indices without a large sample of landscapes; (4) LSPA can interface with GIS and complement GIS in terms of spatial statistical analysis; and (5) LSPA can be used as a base on which to build GIS (or remote sensing data) related landscape models.

LSPA is useful in quantifying landscape patterns. Landscape indices are most effective in this regard. Landscape indices characterize landscape structure so as to provide a common ground to study landscape functions and processes. Other spatial statistical techniques in LSPA are also useful, especially the semivariogram which can analyze interval or ratio data and which is the most powerful method for spatial analysis.

LSPA is useful in experimenting with different silvicultural strategies and forecasting the consequences of management activities. Long-term experimentation on effects of different silvicultural strategies is difficult to conduct due to the magnitude of the system involved. Furthermore, most questions emerged from landscape management need answering today; any delay would be costly and thus not allowed. The fragmentation issue is a good example. LSPA provides land managers with an alternative approach because simulation is in most cases the only scientific approach to studying those problems.

LSPA is useful in examining the behavior of primary indices of landscape patterns without excessive digitizing needs. Many landscape indices have been proposed to characterize landscape structure. We need to know what a landscape index reveals, how it behaves under various conditions, and how its values can be interpreted. Only then can an index be used properly. However, a large number of landscape samples are often not available. LSPA can generates synthetic landscapes with known characteristics, and therefore provides a way to study behavior of landscape indices. In addition, comparison of landscapes is usually desirable; we want to know whether a difference in values of an index between two or more landscapes is statistically significant. LSPA can also estimate variances of landscape indices, which may be difficult to obtain, so that statistical tests (e.g., t-test) can be performed.

LSPA is also useful in interfacing with GIS and complementing GIS in terms of spatial statistical analysis. Although many statistical analyses of ecological problems can be done using GIS in conjunction with a standard statistical package, it is often frustrating to transform GIS data into an ASCCI form, reorganize them into certain format, and then transport them into the statistical package and do analyses. The major problems are that (1) the time involved with data handling outside GIS and statistical formulation could be tremendous and (2) some data (e.g., inter-patch distance) may not be explicitly generated in GIS. Certain ecological analyses are much easier to do when available in LSPA. Both some GIS functions and analytical methods are installed in LSPA. The data required to run LSPA in conjunction with GIS are landscape maps in raster form, which can be obtained from GIS with little difficulty.

Finally, LSPA is useful in serving as a base upon which GIS-related landscape models can be built. To use models to address landscape problems is an important and sometimes the only feasible approach in landscape ecology and land management. How to build landscape models, however, is still an open question. I believe that the top-down (i.e., from context to mechanism) approach, which has the capacity of using remote sensing or GIS data, should be the dominant one in landscape ecology. First, remote sensing and GIS are principal data sources in both landscape ecology and resource management, and their importance will greatly increase with advances in remote sensing technologies (both data collection and data processing) and with increase of data available in GIS. Second, most landscape problems are spatial in nature, and therefore successful landscape models should be able to deal with spatial data or have spatial components. Third, when dealing with large-scale problems, not all details are necessary and thus should not be modeled. For example, single tree dynamics have little effect on landscape stability. Finally, top-down models do not require large amount of data, can produce results relatively quickly, and can identify future research directions.

It should be pointed out that LSPA has some limitations. First, most landscape simulators in LSPA are specifically designed for generating forest cutting patterns; modifications may be needed if other types of land-use patterns are of interest. Second, the matrix size in the simulation part of LSPA is limited to 50 by 50 pixels. Third, LSPA is basically designed to analyze nominal landscape maps. Finally, the process models (e.g., the fire spread model and the species movement model) are still prototypes, and more work has to be done before they can be used as effective tools in resource management.

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CHAPTER III

INDICES TO QUANTIFY SPATIAL PATTERNS OF LANDSCAPE MOSAICS AND THEIR EVALUATION WITH KNOWN SYNTHETIC LANDSCAPES

Abstract

Several landscape indices were reviewed or proposed. Four synthetic landscapes were generated by a computer simulation program specifically designed for the analysis of spatial patterns of landscapes. The simulation parameters were kept the same except for the spatial pattern. The landscape indices were evaluated in this controlled environment. Spatial pattern was emphasized in the evaluation because it is one important emergent property of landscapes. The major result of the study was that patchiness index, fractal dimension, connectivity, and fragmentation indices, such as forest interior area and the largest forest patch size, could best distinguish spatial variations in landscape structure, whereas contagion and dominance failed to do so.

Introduction

It is desirable to have quantitative and objective descriptions of landscape characteristics, such as forest fragmentation and landscape diversity, since intuitive evaluation of those characteristics of landscapes are often used in research and decision-making for resource management. Landscape indices provide effective tools to characterize spatial pattern or other attributes related to landscape structure (Romme 1982, O'Neill et al. 1988). Landscape indices "quantify landscape patterns so that relationships between landscape structure and landscape functions and processes can be established by linking those indices with ecological phenomena at the landscape level" (O'Neill et al. 1988). However, landscape structure (e.g., spatial pattern) has to be detected and characterized first before studying the underlying processes which form the pattern. Generally speaking, landscape indices should be simple, quantitative, comparable, and easy to obtain. The past few years has witnessed increasing use of landscape indices by landscape ecologists as well as land managers (e.g., Romme 1982, O'Neill et al. 1988).

Landscape diversity is defined as a measure of variability and complexity of landscape mosaics (Li and Franklin 1988). Many landscape diversity indices have been used in landscape ecological research and resource management. They can be characterized as: (1) richness, (2) evenness (or dominance), (3) patchiness (or contagion), (4) fractal dimension, (5) connectivity (or isolation), and (6) fragmentation. Romme (1982) proposed three landscape diversity indices: relative richness, relative evenness, and relative patchiness. O'Neill et al. (1988) proposed three additional indices for landscape diversity:

dominance, contagion and fractal dimension. These are the most widely-used landscape indices today. Connectivity and fragmentation indices were introduced to describe landscape diversity here. In general, a single index is insufficient to fully characterize landscape diversity (Pielou 1975) because each category of indices describes landscape mosaics from a different perspective. For this reason several diversity indices are often used together to depict landscape patterns.

Before being applied, landscape indices should be evaluated against landscapes with known characteristics. Each of the landscape indices mentioned above describes a particular aspect of landscape mosaics, but what each index reveals has not been demonstrated in a "controlled" environment. For example, the three landscape indices proposed by O'Neill et al. (1988) have been examined using a large array of real landscapes from the Eastern United States, but their ability to capture variations in landscape structure has not been demonstrated. Some landscape indices were neither designed for nor capable of distinguishing landscapes with different spatial patterns. Spatial pattern is a key emergent property of landscape mosaics whose study distinguishes landscape ecology from other fields of ecology (Risser et al. 1984, Forman and Godron 1986, Urban et al. 1987), and therefore should be emphasized in landscape characterization. The application and interpretation of landscape indices should be executed with care and discretion because they could be misleading if improperly used. A revaluation of landscape indices is warranted.

The objectives of this paper are to review, propose and evaluate landscape indices. Synthetic landscapes were generated by four simulation models in such a way that all the landscape parameters were kept the same except the spatial pattern of landscape mosaics. The four synthetic landscapes differ greatly in spatial pattern: ranging from typical regular distribution, to random distribution, and then to maximum aggregation of patches. Landscape indices were evaluated in this controlled environment by examining the behavior of the indices among the four synthetic landscapes. The two criteria used in this chapter to determine whether a landscape index is useful in spatial pattern discrimination were: (1) ability to detect differences in landscape structure, and (2) utility in making clear ecological interpretations. A new category of landscape indices were developed to quantify forest fragmentation. Additionally, some indices of connectivity were proposed. The following landscape indices were evaluated in this paper: dominance, contagion, patchiness, fractal dimension, connectivity indices (i.e., proximity and dispersal), and fragmentation indices (i.e., the forest interior area and the largest forest patch size). This study indicated that patchiness, fractal, connectivity and fragmentation indices were capable of distinguishing landscapes with distinct spatial patterns, whereas contagion and dominance failed to do so.

Methods

1. The simulation program

The data of landscape maps used in this paper to evaluate landscape indices were from synthetic landscapes generated by a computer simulation program for Landscape Spatial Pattern Analysis (LSPA). Calculation of the landscape indices were also carried out by LSPA. Some subroutines in the part of parameter measurement were adopted from the percolation program developed by Robert H. Gardner[1] with permission (also see Gardner et al. 1987). The data of synthetic landscapes were in raster form.

LSPA was designed specifically for simulation and analysis of spatial patterns in landscapes. LSPA could: (1) generate landscape patterns for different forest cutting designs; (2) measure basic parameters of landscape structure; (3) calculate indices of landscape characteristics; and (4) perform spatial statistical analysis on the landscape pattern. The primary uses of

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without a large sample of landscapes, and to interface with

LSPA were to experiment with different forest cutting patterns, to examine the behavior of landscape indices geographic information systems (GIS) and to complement GIS in terms of spatial statistical analysis.

The dimensions of synthetic landscapes were chosen to be 34 by 34 pixels. The cutting rate for each of the ten simulation time steps was seven percent. Ten replicates of simulation runs were performed to assess the variability of all variables used in LSPA. This relatively small number of replications were used because of small variations in most of the variables indicated by the results of previous simulation runs (see Appendix III.1). The mean clearcut patch size was about 4 pixels.

Four simulation models were used to generate landscape patterns: (1) a maximum dispersion model, that is, a modified model of the "checkerboard model" of Franklin and Forman (1987), (2) a random patch model, (3) a partial aggregation model, and (4) a progressive cutting model with one nucleus. Three common assumptions were made in all the four models. First, a previously cut-pixel was not available for later cutting. Second, the cutting rate at each time step was fixed (i.e., 7%). Third, patches cut at two different time steps were regarded as two different types of landscape elements, that is, a new type of patch was introduced at each time step.

In addition to the three common assumptions, each model had its own constraints. The random patch model assumed a random distribution of cut-units in landscapes. In this model each un-cut pixel had an equal probability to be cut as the first pixel of a patch. After random selection of the first pixel, other contiguous pixels of the patch were determined by a random walk model (i.e., each search direction is randomly determined); the size of each cut-unit was determined by adding (or substracting) a random number to the "mean patch size", which was input as a simulation parameter at the beginning of a simulation run. The maximum dispersion model placed cut-pixels as evenly spaced and dispersed as possible. A square patch of four pixels were cut as one cut-unit at each search. For the partial aggregation model, a piece of forest land was set aside as a reserve unavailable for cutting; the landscape matrix was divided into 4 pieces, and cut-units were confined to one of the four quadrats until it was almost exhausted. In each of the four landscape quadrats, cutting was done in such a way that the first pixel of a patch was chosen randomly and then a restricted random walk model was used to create the patch. The two restrictions to the random walk model were: (1) no more than 3 pixels were cut in a row in the same direction, and (2) no pixels of two patches, generated at the same time step, may join each other. The number of the pixels in a patch was randomly determined as in the random patch model. The progressive cutting model assumed that cutting started at one point from which cutting extends outward. A more detailed discussion of the four models can be found in Li (in preparation).

The simulation was performed for the four models using the same landscape parameters except the spatial pattern. Each model generated a landscape with distinct spatial pattern and degree of fragmentation (see Figure III.1). The maximum dispersion model created landscapes which had higher contrast, were more patchy, and were the most fragmented. The progressive model generated landscapes which were the most aggregated and the least fragmented. The random patch and partial aggregation models were intermediate between the maximum dispersion and progressive models, with the random model yielding landscape index values closer to those of the maximum dispersion model. The differences in spatial pattern among the four synthetic landscapes made it possible to evaluate the performance of different landscape indices in a controlled environment by examining the behavior of the indices obtained from those known landscapes.

2. Landscape diversity indices

Landscape diversity is a function of either composition or configuration of landscape elements, or both. Landscape composition refers to both the number of landscape element types and the distribution among those types, while landscape configuration is concerned with the spatial pattern of patches in landscape mosaics. Configuration of landscape mosaics should be emphasized because spatial pattern is one of the important emergent properties of landscapes. Mathematical definitions and basic properties of landscape diversity indices are given below.

Dominance measures the extent to which one or a few landscape elements dominate the landscape. The equation is given as:

$$D1 = \log(T) + \sum P(i) \log[P(i)]$$

where D1 is the dominance index, T the total number of land use categories, P(i) the proportion of the grid pixels in land use i (O'Neill et al. 1988). Higher values of D1 indicate that one or very few patch types dominate the landscape. Dominance is inversely related to evenness. Dominance (or evenness) has been studied intensively in relation to species diversity and most of the comments and criticisms made about it (e.g., Hurlbert 1971) can be applied to its counterpart in landscape diversity.

Patchiness measures the contrast of neighboring landscape element types in a landscape mosaic, and is expressed by:

$$PT = 100 \sum \sum E(i,j)\ D(i,j) \ /\ N_b\ ,$$

where PT is the relative patchiness index, E(i,j) the number of boundaries (i.e., edge) between patch types i and j, $D(i,j)$ the dissimilarity value for patch types i and j, and N_b the total number of boundaries (Romme 1982). A higher value of patchiness index means that the landscape has higher contrast between adjacent patches and is highly dissected. The dissimilarity matrix (i.e., $D(i,j)$ in the above equation) of landscape elements, required for calculation of patchiness, can be obtained either subjectively (e.g., by expert judgment) or objectively (e.g., using scores of the first ordination axis or other dissimilarity measures). A subjective dissimilarity matrix, with a dissimilarity value of 100% for forest and the most-recently-cut clearcut patches, was used in this study. Patchiness has a spatial component because it incorporates information on the first-order neighbor contrast.

Contagion measures the extent to which landscape elements are aggregated or clumped, and is given by:

$$D2 = 2\,T\log(T) + \sum\sum P(i,j)\log[P(i,j)]\ ,$$

where D2 is the contagion index, T the total number of patch types in a landscape mosaic, and $P(i,j)$ the probability of patch type i adjacent to type j. According to O'Neill et al. (1988), higher values of contagion may result from landscapes with a few large, contiguous patches, whereas lower values generally characterize landscapes with many small patches. Contagion is similar to Pielou's mosaic's spatial diversity index (Pielou 1975), but Pielou's index requires a transect sampling to obtain a few parameters for its calculation. Conceptually, contagion is inversely related to patchiness.

Fractal dimension is used to measure irregularity or spatial variation of a natural phenomenon (Mandelbrot 1983, Burrough 1983, 1986, Milne 1988, and O'Neill et al. 1988, De Cola 1989). There are many ways to calculate fractals (cf., Burrough 1983, 1986, Milne 1988). If variability of patch shape is of interest or if only patch shape data are available, the method described by O'Neill et al. (1988, also see Burrough 1986) may be used:

$$D = 2 / SLP ,$$

$$\log[A(i)] = C + SLP \log[P(i)] ,$$

where D is the fractal dimension, SLP the slope of a double-log regression of are on edge of patches, A(i) and P(i) area and perimeter of patch i respectively, and C the regression coefficient. On the other hand, if landscape properties other than patch shape are of interest and if their interval or ratio data can be obtained, the semivariogram method (Burrough 1983, 1986) should be used:

$$D = (4 - SP) / 2 ,$$

$$\log[r(h)] = C + SP \log(h) ,$$

where D is fractal dimension, SP the slope of a double-log regression of semivariance (i.e., r(h)) on corresponding distance (i.e., h). A simpler method to calculate fractal is (R.H. Gardner, personal communication, see footnote 1):

$$D = 2 \log(EDGE/4) / \log(AREA) ,$$

where D is the fractal index, EDGE the edge length of a patch (or of patches of the same type in the whole landscape), and AREA the area of a patch (or patches of the same type in the whole landscape). This method and the double-logarithm regression method were used in this chapter. A higher fractal value indicates either more irregularly-shaped patches and/or greater spatial variation.

Connectivity measures the contiguousness of the matrix, or patches of the same kind, in a landscape mosaic (Li and Franklin 1988). This definition of connectivity differs from that given by Forman and Godron (1986). They define connectivity as a measure of connectedness of a corridor network (also Fahrig and Merriam 1985). However, the difficulty to construct the corridor network limits the use of their connectivity concept in analysis of landscape patterns. Connectivity is an important attribute of landscape mosaics and may exert great influence on flows of energy, materials and species between landscape elements, as well as on spread of disturbance (Forman and Godron 1986). Studies of small mammal population dynamics have indicated that connectivity is a crucial factor to species survival in a landscape (Merriam 1984, Fahrig and Merriam 1985, Lefkovitch and Fahrig 1985). Landscapes with higher values of connectivity may have higher probability for species to move or for energy and materials to flow among patches.

Connectivity can be measured either from the geometry of landscape structure or from landscape functions (e.g., from eyes of a hypothetical species). The former is termed in this paper "proximity index" and the latter "dispersal index". Basically, proximity index is an inverse function of the nearest neighbor distance:

$$PX = \sum \{[A(i)/NND(i)] / [\sum A(i)/NND(i)]\}^2 ,$$

where PX is the proximity index, A(i) the area of patch i, and NND(i) the edge-to-edge distance from patch i to its nearest neighbor. Area is used as a weighting factor; larger patches have more influence on connectivity of landscapes. However, connectivity should be a species (or process) specific measure because different species (e.g., edge species vs. interior species) will not respond similarly to a landscape mosaic. Thus, properties of species behavior (or flux of materials or spread of disturbances) should be taken into account in measures of connectivity if they are to be functionally meaningful (Magurran 1988).

I propose a dispersal index, a connectivity index related to species movement, to quantify the functional connectivity. Dispersal index measures the ease that a hypothetical species can move within a landscape.

$$DP = \sum \sum MHS(i,j)\ K(i,j) / S ,$$

$$MHS(i,j) = HS[t(i),t(j)] ,$$

where DP is the dispersal index, i and j ther geographic location index variable, MHS(i,j,k) the value of habitat suitability at pixel (i,j), K(i,j) the species movement vector (i.e., coordinates), HS[t(i),t(j)] the habitat suitability value for habitat t(i) with a neighbor habitat t(j), and S the total number of moves. The habitat suitability matrix used by the dispersal index was constructed by judgment developed from the literature on wildlife habitat selection. Two hypothetical species were studied in this paper, edge species (e.g., elk) and interior species (e.g., spotted owl). The differences between the two types of species were reflected in the habitat suitability matrix. For example, an edge pixel is considered as a good habitat for an edge species but not a suitable habitat for an interior species. A random walk model was used to define the manner in which a hypothetical species moves in the landscape. This is a highly simplified model. More sophisticated models of animal movement can be constructed which can mimic the movement of a particular species according to observed behavioral characteristics.

Fragmentation is one component of landscape diversity because it describes an important aspect of spatial patterns of landscapes, that is, forest fragmentation. Forest fragmentation occurs when: the number of forest "islands" increases; the shapes of forest "islands" become more irregular; the size variation of forest "islands" decreases; the area of forest interior habitats shrinks; or corridors are broken and patches are isolated. Fragmentation index measures the extent to which the matrix or a patch type of interest is fragmented at a particular time. Five facets of fragmentation are recognized here: (1) number (or density) of remnant forest "islands", (2) shape of remnant forest "islands", (3) size variation of remnant forest "islands", (4) size of the largest forest "island" or the largest compact forest area, and (5) total forest interior area. Other landscape diversity indices can also be used to describe fragmentation, especially connectivity (or isolation) of forest "islands" and patchiness.

Only the forest interior area and the size of the largest forest patch fragmentation indices were discussed in this paper. The formulas of the two fragmentation indices are similar in form:

$$FGI = 1 - A_i / A ,$$

$$FGL = 1 - A_l / A ,$$

where FGI and FGL are fragmentation indices of the total forest interior area and the largest forest patch size respectively, A_i and A_l the total forest interior area and the largest forest patch size respectively, and A the total area of a forest landscape. The formulas of the fragmentation indices were scaled in such a way that every index of fragmentation varies from 0 to 1. A value of 1 indicates that a forest landscape is completely fragmented in terms of that particular landscape characteristic, while a value of 0 represents the least fragmentation.

Results and Discussion

To evaluate their effectiveness in characterizing and contrasting landscapes, all landscape indices were plotted against the percentage of landscape cut-over. The behavior of each landscape index was evaluated by examining its trends along both the cutting gradient and the fragmentation gradient established by the four simulation models.

The dominance index did not capture the spatial variations of patch distributions among the synthetic landscapes (Figure III.2). This suggests that dominance could not adequately measure spatial patterns of landscape mosaics and therefore should not be used for this propose. Dominance is basically an information index which does not have a spatial component. The initial increase of dominance indicates that dominance should not be used when the number of patch types is too small.

Contagion also failed to distinguish the four landscapes (Figure III.3a). In addition, contagion increased almost linearly with increase of landscape cut-over percentage (Figure III.3a). This contradicts the definition of the contagion index. Contagion should decrease as cutting proceeds because a few large contiguous forest patches prevail in the landscapes at earlier simulation time steps, and the forest matrix is broken into many smaller patches at later stages. The failure of contagion is because the spatial component of contagion is actually in the second term of the equation and thus changes in contiguity is reflected by changes in the second term. The inclusion of the first term made the original equation erroneous because the equation really measures the opposite of contagion. Therefore, the contagion index has to be modified (O'Neill[2] personal communication). The equation of the modified contagion, called relative contagion (RC), is give by:

$$RC = - \sum \sum P(i,j) \log[P(i,j)] / [2\ T \log(t)] ,$$

where all the terms in the equation are the same as those in the original contagion equation. The relative contagion index did capture some differences in the four models and also in the landscapes with different patch sizes (Figure III.3b). This index of contagion should be used instead of the one originally given.

Patchiness clearly distinguished the different

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with the random model being closer to the maximum landscapes and reflected the fragmentation gradient established by the models (Figure III.4). Patchiness values for the progressive model remained low even though the percentage of landscape cut-over increased, while patchiness values for the maximum dispersion model increased and were the highest. Patchiness values of the random and partial aggregation models were intermediate dispersion model. Patchiness for the maximum dispersion model increased at first, peaked at about 50 percent landscape cut-over, and then leveled off. Patchiness for the random and partial aggregation models displayed the same trend, but peaked at about 30 percent landscape cut-over.

Fractal dimension also captured spatial variations in landscape mosaics and that relative positions of fractal curves for the four models reflected the fragmentation gradient (Figure III.5a and 5b). The fractal dimension in Figure III.5a was calculated from the relationship between total area and total edge of forest patches, while the fractal in Figure III.5b was calculated from the double-log regression of edge on size of forest patches (Burrough 1986, Milne 1988, and O'Neill et al. 1988). Fractal values for the progressive cutting model (Figure III.5a) were significantly different from those for the other three models, and remained low as the cutting developed. This is because the progressive model generates landscapes with more regularly-shaped forest patches and with the least fragmentation. The partial aggregation model differed from the maximum dispersion and random models but not dramatically (Figure III.5a). The maximum dispersion and random models yielded higher fractal values because they create more edge and more irregularly-shaped of forest patches. Similar trends were observed in Figure III.5b, but the differences of fractal values among the four models were more pronounced between 20% to 60% of landscape cut-over. In contrast to the monotonic increase in Figure III.5a, fractal values in Figure III.5b leveled off (e.g., the random patch and partial aggregation models) or showed a decrease after a certain point of landscape cut-over (e.g., 45% for the maximum dispersion model) had been reached. This result suggests that fractals calculated using different methods may differ not only in value but also in behavior through landscape pattern development.

The proximity index, calculated from the nearest neighbor distance between patches, revealed information on spatial structure of landscape mosaics (Figure III.6). The forest patches in the progressive model remained connected in spite of the steady increase of landscape cut-over. Proximity for the maximum dispersion model also remained high before 35%, but dropped off dramatically after 35%. The random and partial aggregation models showed decreasing connectivity with increase of landscape cut-over. In addition, the relative positions of the last three models switched at about 45-55% landscape cut-over (Figure III.6). This was in accordance with the visual observation of the synthetic landscapes. The forest matrix of the maximum dispersion landscape was nibbled but was still in one piece before 35% of cut-over; 4-pixel forest patches started to emerge after 35% until 50% when the forest matrix no longer existed (i.e., all 4-pixel patches). In the meantime, the random and partial aggregation landscapes had a few small forest patches at earlier time steps (which yielded lower values of proximity) but their forest matrices remained at later time steps.

Dispersal indices failed to distinguish the four landscapes for interior species (Figure III.7a), but worked well for edge species (Figure III.7b). Dispersal index for interior species steadily decreased along the cutting gradient, because of reduction of the interior forest habitats (Figure III.7a). The failure of the index to separate the four landscapes may be because the species movement model used here was not valid for interior species due to the assumptions made. Dispersal index for edge species increased with increase of landscape cut-over, and its values for the four landscapes reflected the fragmentation gradient (Figure III.7b). Because no information on corridors and barriers to the hypothetical

Figure III.1: Map illustrations of the four models. Landscape maps at three time steps (i.e., 3, 5 and 7) are displayed for each of the four models. Shade symbols (from light to dark) represent clearcut ages (from young to old). Forest is coded as blank. Dimensions of landscape maps are 30 by 30 pixels, and cutting rate is 7%.
a1: maximum dispersion model at time step 3.
a2: maximum dispersion model at time step 5.
a3: maximum dispersion model at time step 7.
b1: Random patch model at time step 3.
b2: Random patch model at time step 5.
b3: Random patch model at time step 7.
c1: partial aggregation model at time step 3.
c2: partial aggregation model at time step 5.
c3: partial aggregation model at time step 7.
d1: Progressive cutting model at time step 3.
d2: Progressive cutting model at time step 5.
d3: Progressive cutting model at time step 7.

Figure III.1a: The maximum dispersion model.

a1

a2

a3

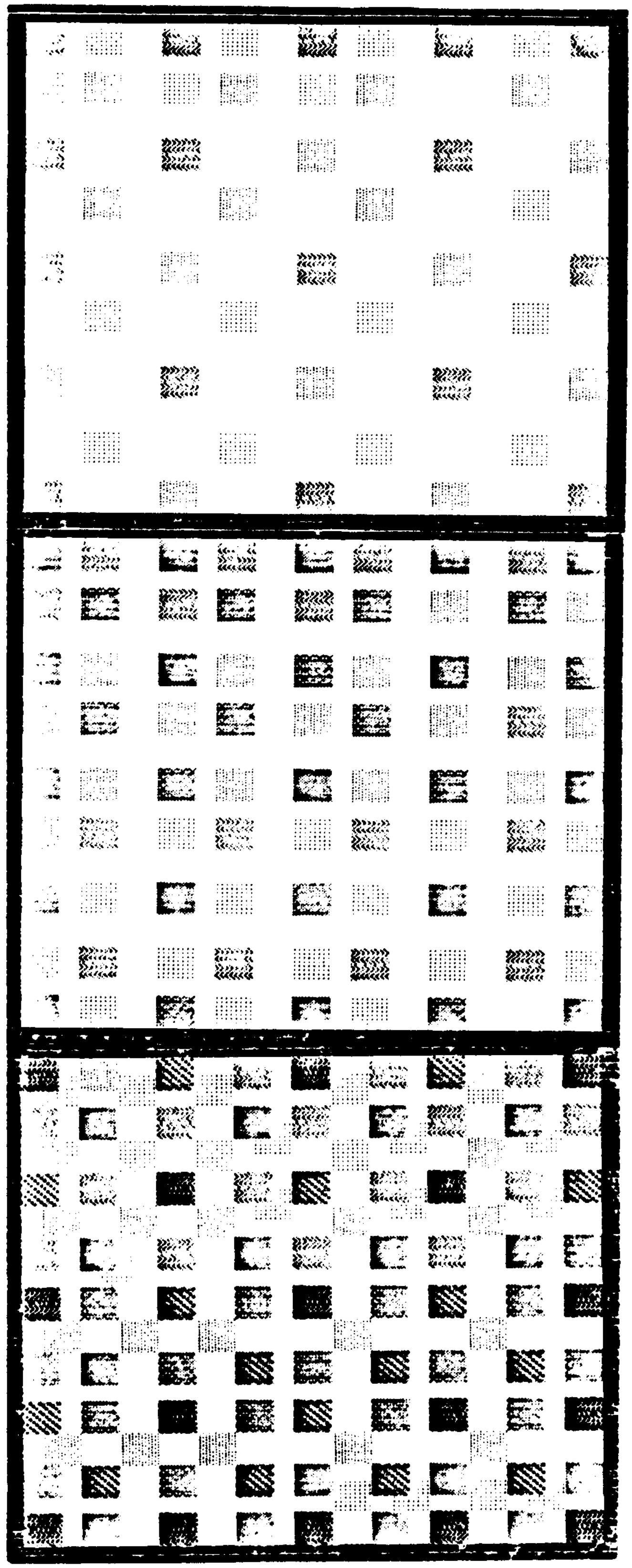


Figure III.1b: The random model.

b1

b2

b3

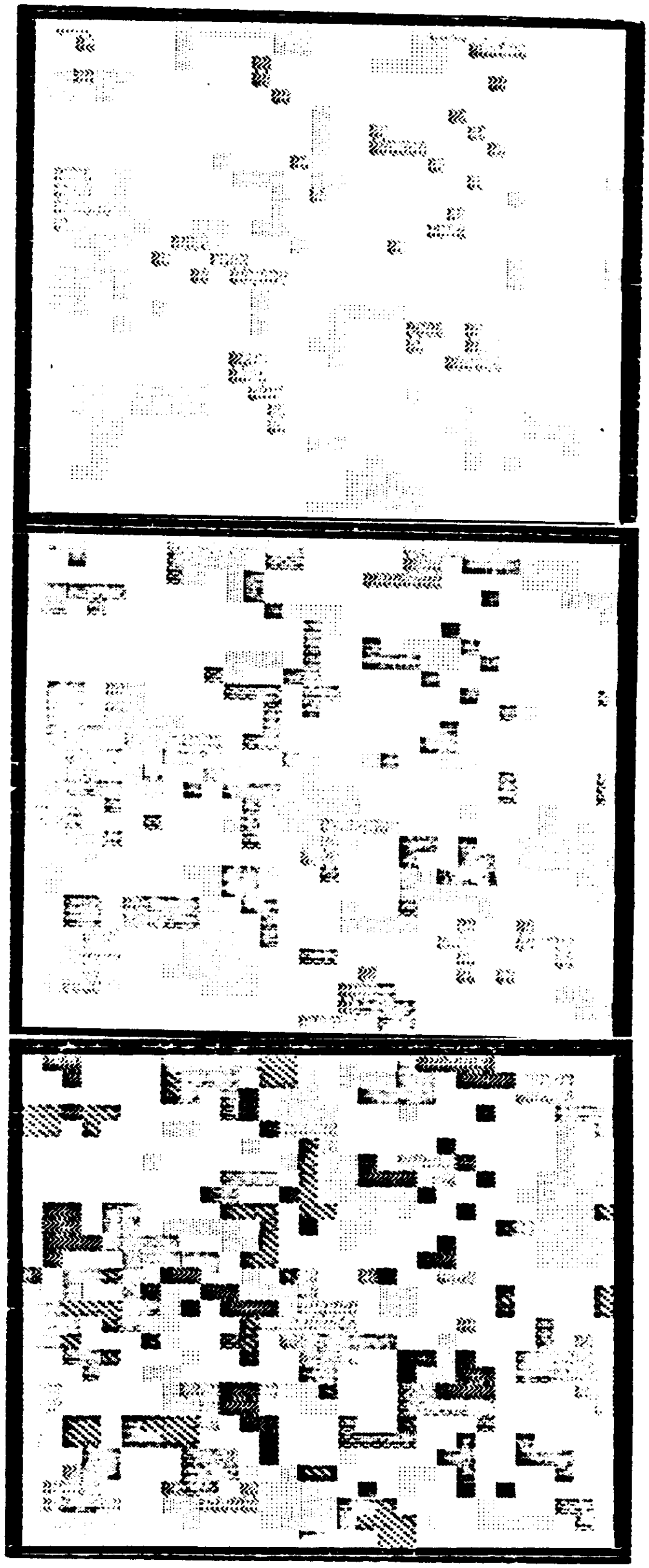


Figure III.1c: The partial aggregation model.

Figure III.1d: The progressive cutting model.

d1

d2

d3

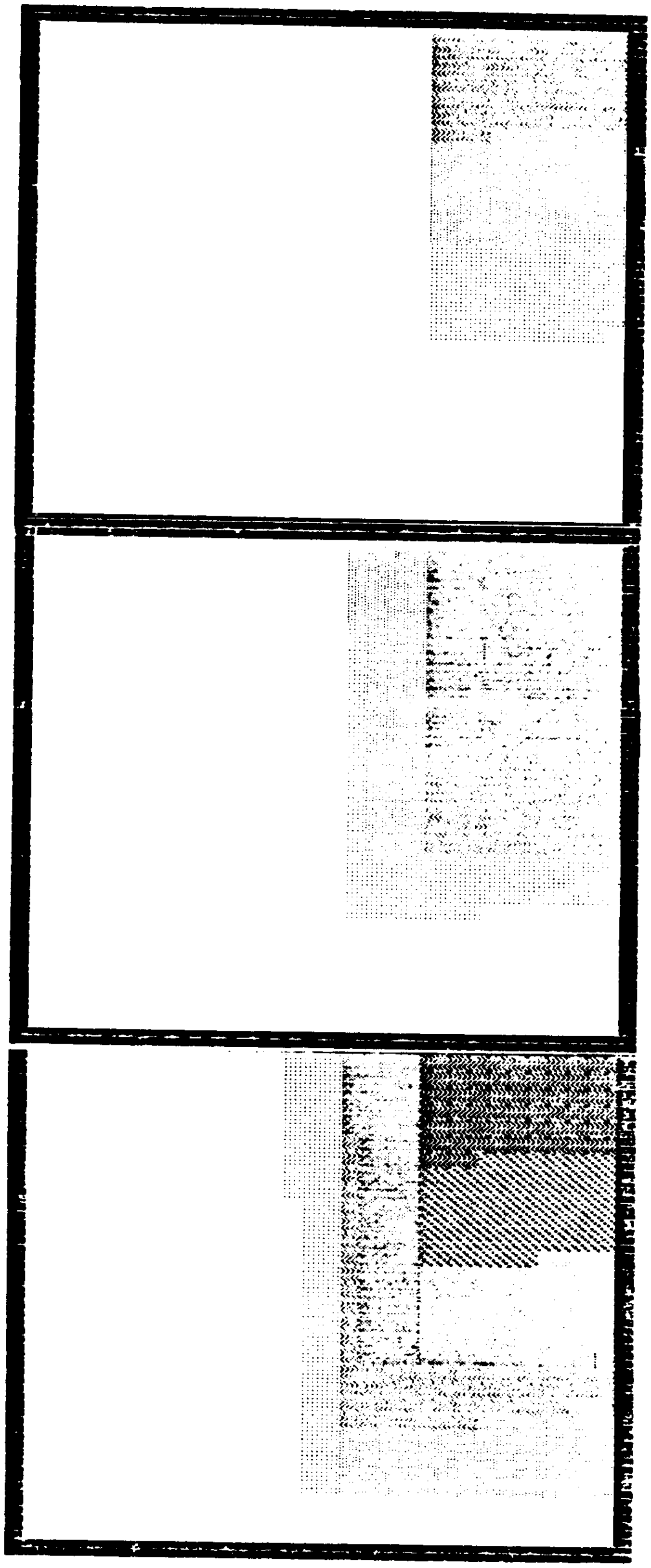


Figure III.2: Changes of dominance index along the cutting gradient and among the four synthetic landscapes.

The four curves represent different landscapes generated by the four simulation models:
the maximum dispersion model (chck),
the random patch model (rand),
the partial aggregation model (mfrg), and
the progressive cutting model (prog).

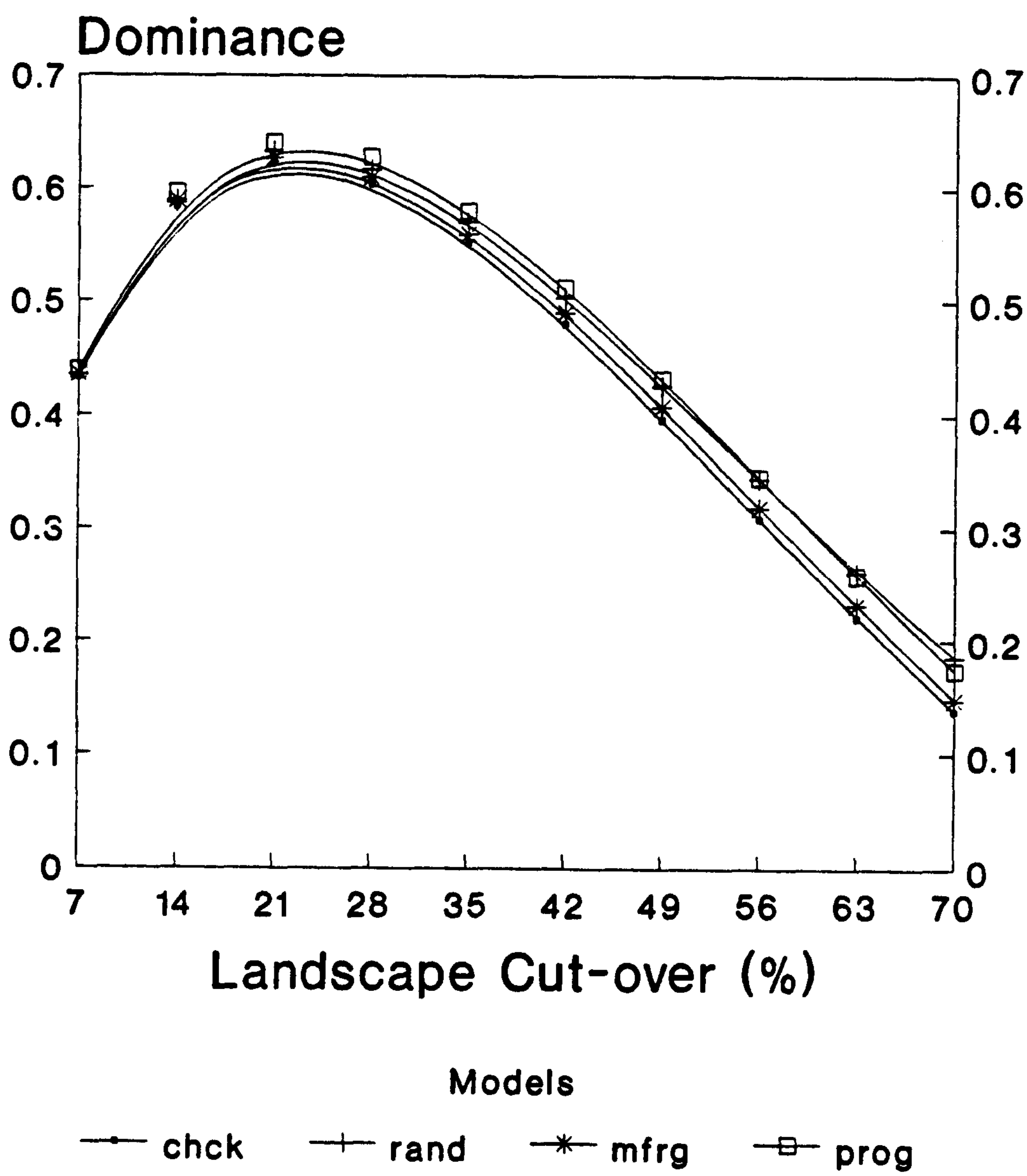


Figure III.3: Changes of contagion indices along the cutting gradient and among the four synthetic landscapes.

See Figure III.2 for more information about the legends.

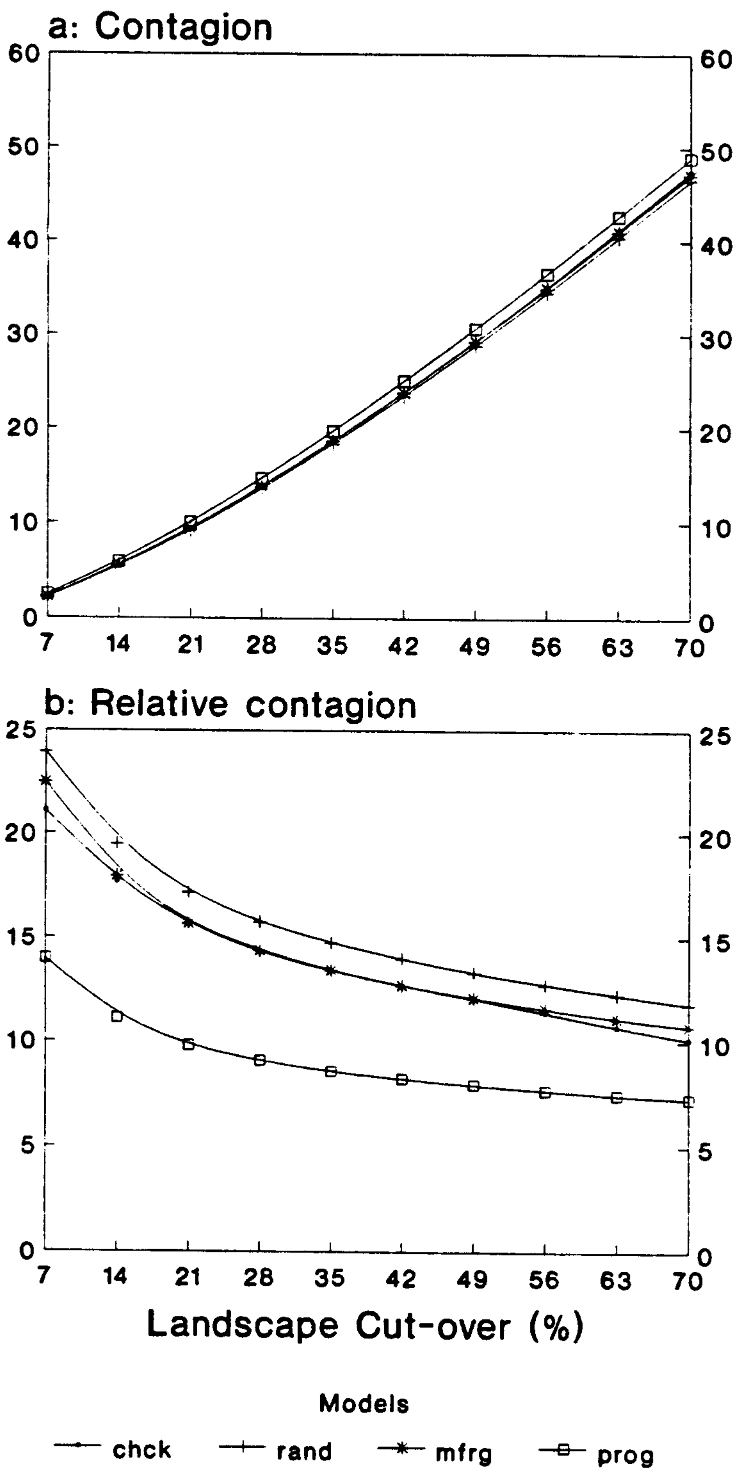


Figure III.4: Changes of patchiness indices along the cutting gradient and among the four synthetic landscapes.

See Figure III.2 for more information about the legends.

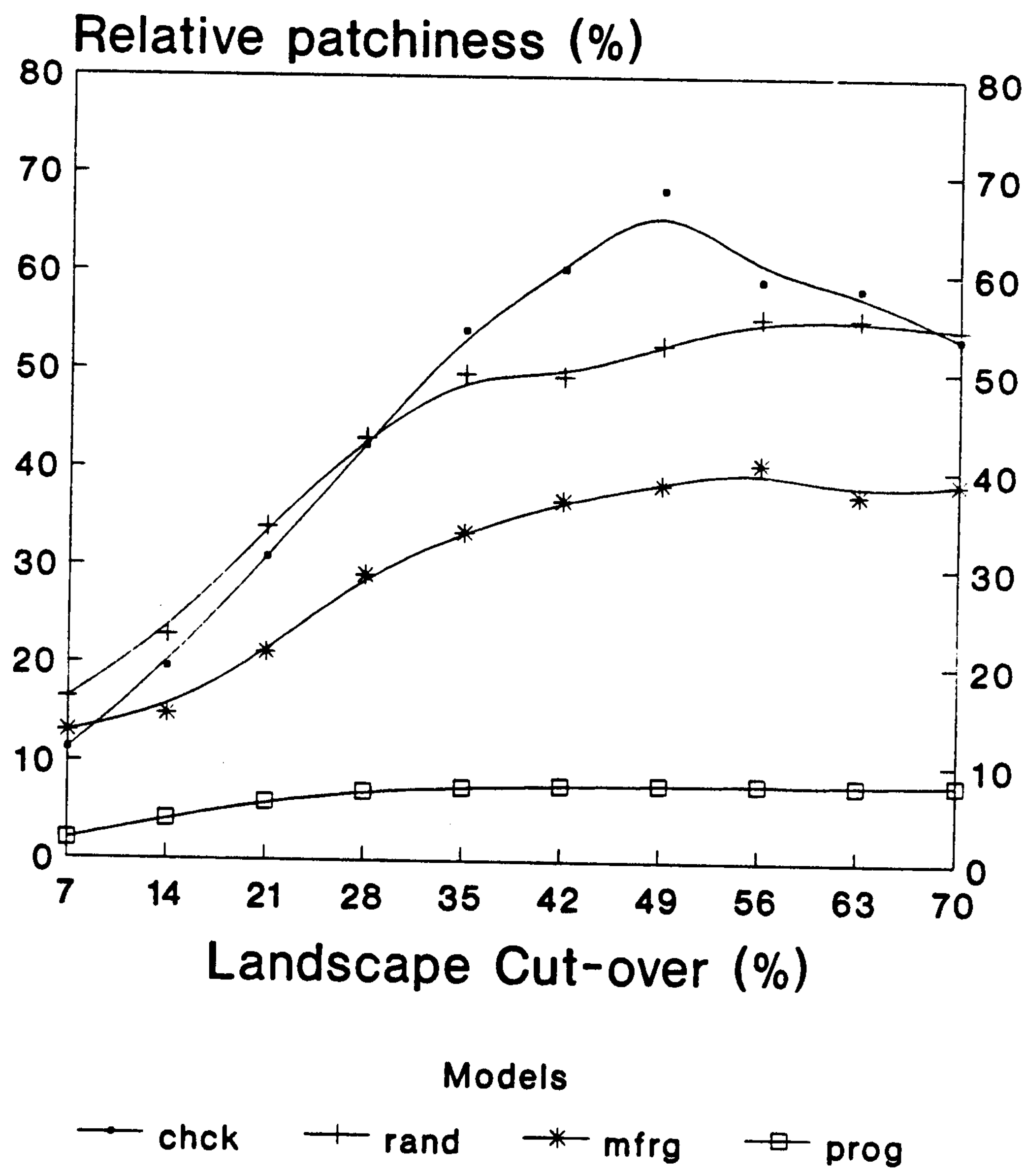


Figure III.5: Changes of fractal dimension along the cutting gradient and among the four synthetic landscapes.

See Figure III.2 for more information about the legends.

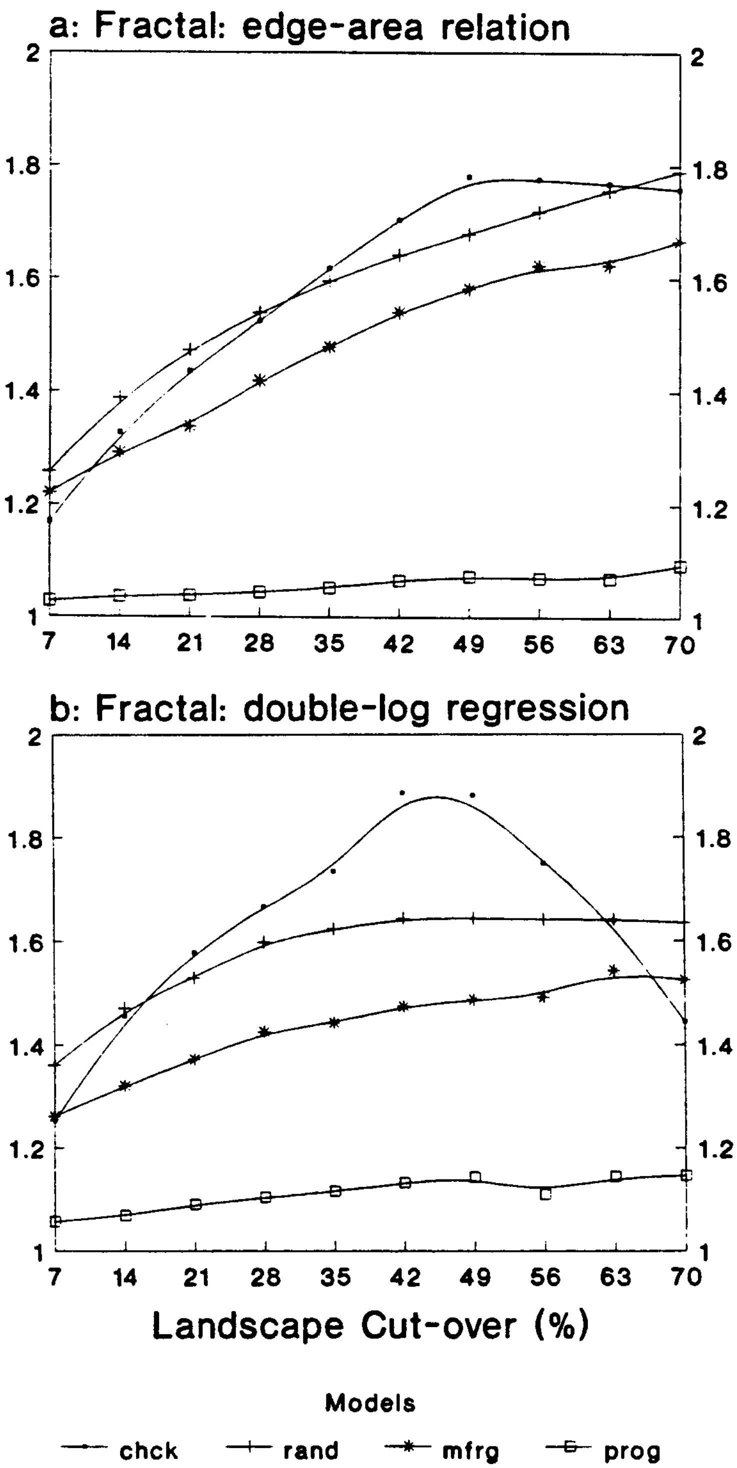


Figure III.6: Changes of proximity index along the cutting gradient and among the four synthetic landscapes.

See Figure III.2 for more information about the legends.

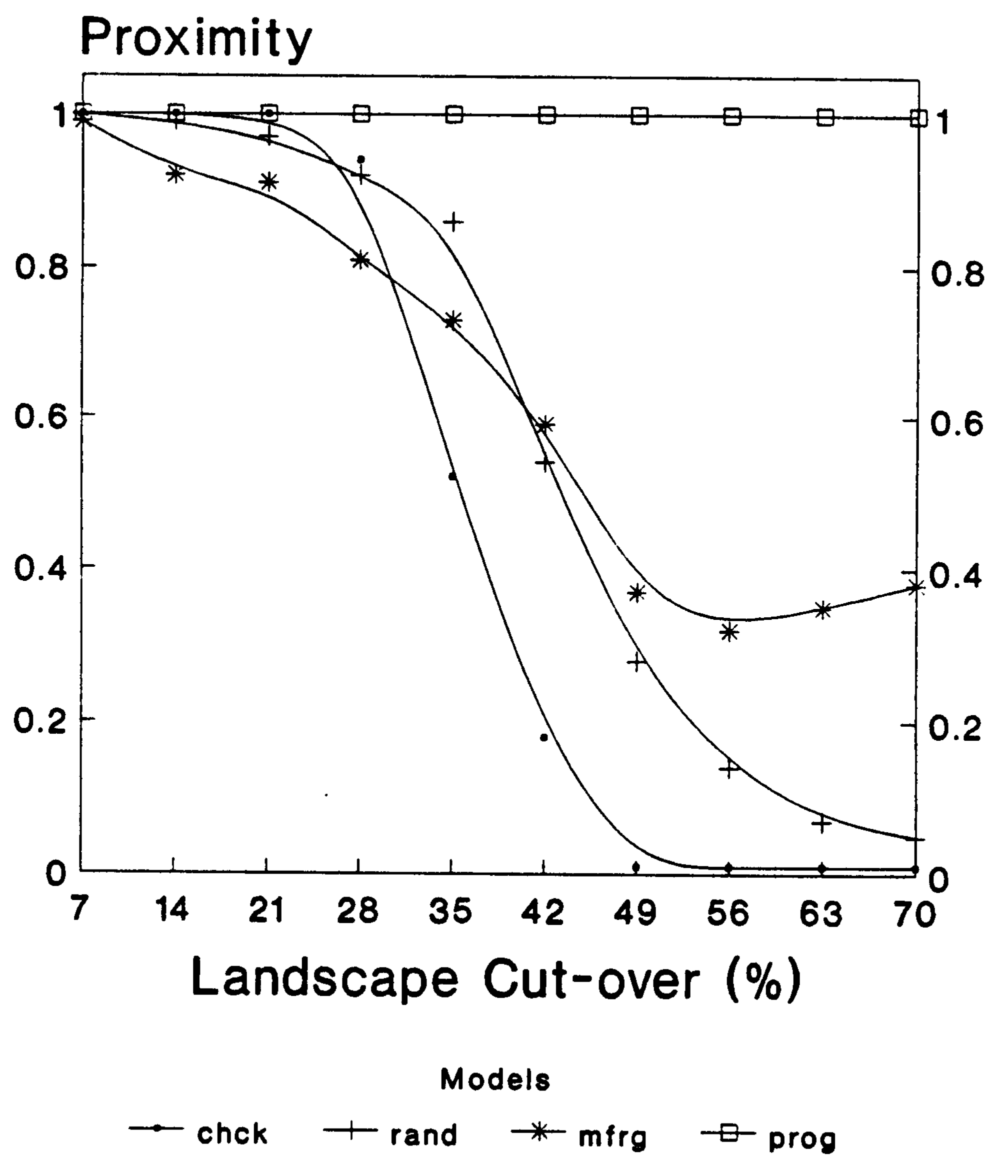


Figure III.7: Changes of dispersal indices along the cutting gradient and among the four synthetic landscapes.

See Figure III.2 for more information about the legends.

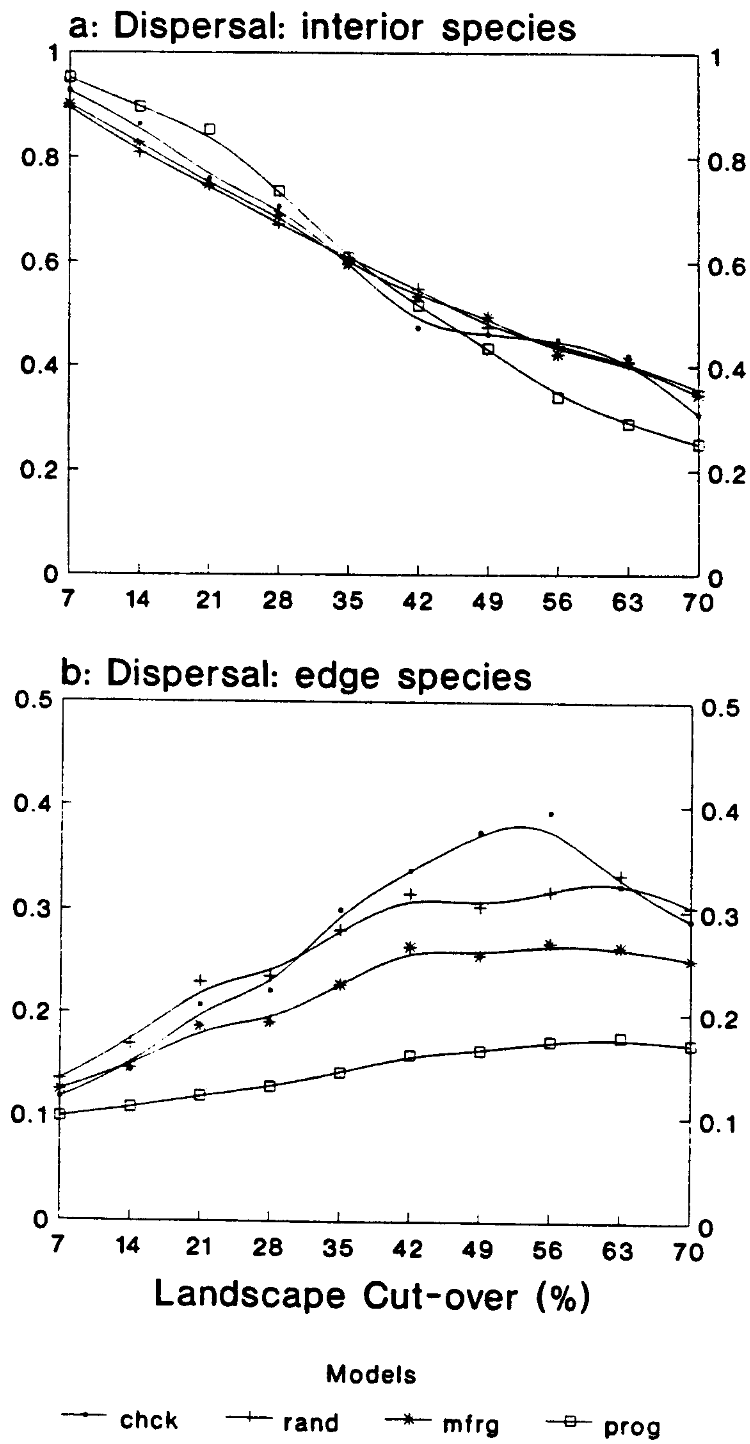
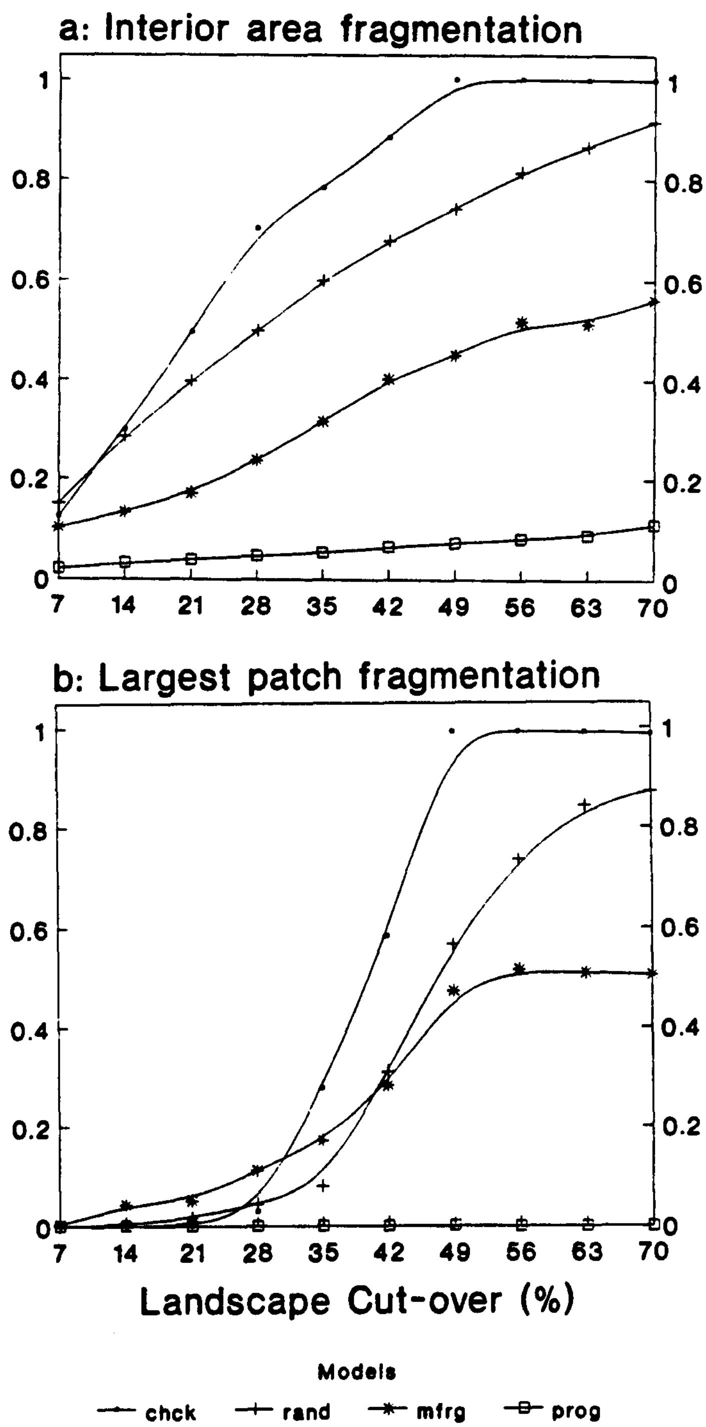


Figure III.8: Changes of fragmentation indices along the cutting gradient and among the four synthetic landscapes.

See Figure III.2 for more information about the legends.



species was used in this paper, the dispersal index obtained here was really an estimate of the mean habitat suitability of a landscape mosaic to the hypothetical edge species. However, the sampling theme was designed to mimic species movement in a landscape mosaic. The assumption that species movement follows a random walk model may not be realistic, but it suits the purpose because the model was designed not to determine how a species moves in a landscape mosaic, but to examine the effects of landscape patterning on wildlife species dispersal in landscape mosaics.

Two fragmentation indices, the forest interior area and the size of the largest forest patch, appeared to be most useful to detect differences in spatial pattern among landscapes (Figure III.8a and 8b). The fragmentation index of forest interior habitat area steadily increased along the forest cutting gradient and clearly distinguished the four simulated landscapes (Figure III.8a). The fragmentation index of the largest forest patch size also showed a steady increase with increase of landscape cut-over (Figure III.8b), but did not separate the four synthetic landscapes until 50% of the landscape is cut-over. The fragmentation index of the largest forest patch size failed to depict differences among the four synthetic landscapes because it incorporates no information about edges and because the forest matrix remained intact before

50%. The result suggests that this index should not be used to quantify fragmentation when landscape cut-over percentage is under 50%.

Forest fragmentation is an important issue in resource management (Harris 1984, Verner et al. 1986). Quantitative description of this landscape characteristic can help land managers assess fragmentation effects and make management plans. In management of forest landscapes, the major consideration is the fragmentation of old-growth forests. In this paper, fragmentation always refers to that of natural forests. However, analogy can be made to other types of patches, as in wildlife habitat studies.

Interestingly, in most cases, the random model yielded values of landscape indices which were between values for the maximum dispersion model (i.e., regular pattern) and for the partial aggregation model and the progressive model (i.e., aggregated pattern). This suggests that those landscape indices worked well because the results agreed with the general theory on spatial pattern that adding constraints to the landscape structure leads to departure from random pattern (e.g., Ludwig and Reynolds 1988).

It is important to know the meaning of differences between values of a landscape index for different landscape mosaics, especially when comparison of two real landscapes is desirable. Although it is difficult to evaluate the statistical significance of differences between two values, some rules of thumb can be generated from the results displayed in the above figures. For example, a difference of about 20% in patchiness (Figure III.4) or a difference of 0.1 in fragmentation index of forest interior area (Figure III.8a) may result from two entirely different landscapes; if half of the extreme values can be used as a rule of thumb, a 10% difference in patchiness, or an 0.05 difference in fragmentation of forest interior area, should indicate a significant difference of two landscapes of interest. Another approach is to regard the standard deviations of these landscape indices obtained from the simulation replications as the population parameters, and then to do a statistical test like the t-test, using those standard deviations, to determine if a difference of an index for two landscapes is significant. The underlying assumption is that the standard deviations of those landscape indices obtained by simulation are good estimates of the true population parameters.

The landscape indices examined above may be well correlated (Appendix III.2). The correlation coefficient ranges from 0.75 to 0.99. This indicates, as expected, that there is redundancy in the information of the landscape structure presented by those landscape indices.

Summary and Conclusions

Several commonly-used landscape indices were reviewed and some new indices proposed in this paper. These landscape indices were evaluated in terms of their ability to distinguish the four synthetic landscapes created by the four simulation models. The two criteria used to evaluate landscape indices were the ability to capture the spatial variations in landscape mosaics and the utility to interpret results ecologically. Spatial pattern was emphasized because it is an important, emergent property of landscape mosaics. Visual observation indicated that the four synthetic landscapes had different spatial patterns.

The landscape indices examined varied markedly in their ability to distinguish landscapes with distinct spatial patterns. Fractal dimension, patchiness, and dispersal index detected the spatial variation of landscape mosaics, and are recommended when spatial pattern of landscape mosaics is of interest. On the other hand, two commonly-used landscape indices, contagion and dominance did not distinguish the spatial variations of distinct landscape patterns. Therefore, the usage of those landscape indices is limited. Fragmentation indices, such as the forest interior area and the largest forest patch size, also captured differences in landscape patterns. Furthermore, they are more practical with direct applications to resource management. They should be used when forest fragmentation is concerned.

Although forest cutting pattern was emphasized by the simulation models used in this paper, the results obtained should be applicable to any landscapes. This study involved progressive forest cutting pattern development with certain characteristics, such as patch size, shape, development rate, and alternative patterns. Clearcuts generated at different simulation time steps were regarded as different patch types; hence, there were more than two types of patches in the landscape except at time one. By simulation, landscape pattern was heavily altered, distinctive vegetation patterns were created, and various approaches to pattern management were used. This provided a useful test case for landscape studies which may not be feasible otherwise.

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CHAPTER IV

DEVELOPMENT OF FOREST CUTTING PATTERNS UNDER DIFFERENT SILVICULTURAL STRATEGIES: A SIMULATION APPROACH

Abstract

Different forest cutting methods were studied and contrasted using a simulation program to generate and quantify landscape geometry for different forest cutting patterns. Different cutting designs produce landscapes with distinct spatial and temporal patterns. Cutting patterns employing larger cut-units led to less forest edge and less fragmented landscapes. Aggregation of cut-units mitigated fragmentation effects and resulted in more gradual changes of landscape indices compared to dispersion of cut-units. When a stream system was included in the landscape structure, the behavior of many landscape characteristics changed. The results suggested that simple landscape models (i.e., the maximum dispersion and random models) may lead to misleading interpretations of landscape patterns.

Introduction

Fragmentation of natural Douglas-fir forests on federal lands in the Pacific Northwest has intensified in the past two decades (Burgess and Sharpe 1981, Harris 1984, Verner et al. 1986). The widely-used forest cutting strategy on

USDA Forest Service lands in the Pacific Northwest is the so-called staggered-setting clearcut system. Franklin and Forman (1987) examined the staggered-setting clearcut system from the perspectives of landscape ecology. They hypothesize that continued implementation of the staggered-setting clearcut system could result in intensification in fragmentation of natural forests, in degradation in wildlife habitats, and in increased susceptibility of residual natural forests patches to disturbances. Although the staggered-setting system has some advantages, they argue that it should be re-evaluated in response to changes in technology, perspectives, and societal demands. They suggest that cutting units be aggregated, large blocks of forest habitat be retained until later in the cutting cycle, and larger clearcut units be used (but leaving some live trees within cutting units). They believe this proposed system to have economic and ecological advantages (e.g., improvement in protection of species diversity and reduction of catastrophic disturbance frequency).

The hypotheses proposed by Franklin and Forman (1987) need testing, and a broader range of landscape patterns should be examined in terms of their ecological and other consequences. Different cutting methods do create different landscapes, but specifics are still poorly known. This study examines how different forest cutting patterns may affect forest landscape structure and dynamics in terms of forest fragmentation and other structural features. The specific objectives were: to determine the spatial and temporal patterns of forest landscapes created by different simulation models using different rules for choosing location of successive cut-units, to study effects of increase of clearcut sizes on landscape structure, and to examine possible effects of geomorphic constraints (i.e., inclusion of a stream network in synthetic landscapes) on simulation results. Possible ecological effects of large cut-units containing living trees, snags and downed logs (hereafter referred to as "structurally heterogeneous large cut") were also studied.

Computer simulation was used in this study because the two alternatives, experimental and chronological approaches, were not feasible due to expense, time requirements, lack of experimental controls, and difficulties of finding suitable study sites (Perry 1988, Baker 1989). The major advantage of the computer simulation approach is that specific forest cutting patterns can be generated in order to study fragmentation effects in controlled conditions over time. This approach can also produce timely results needed now in design of new landscape management strategies. The main limitation of computer simulation is that the reliability of results obtained are highly dependent upon the degree to which the models reflect reality. However, computer simulation may be the only feasible approach in many cases.

Methods

1. The computer program (LSPA) and the simulation runs

Data from synthetic landscapes generated by a computer simulation program (LSPA) were used in this study. LSPA (1) generates structural landscape patterns for different cutting methods; (2) measures basic parameters of landscape structure; (3) calculates various indices of landscape characteristics; and (4) performs spatial statistical analysis on the landscape pattern.

The specific models used to generate synthetic landscape patterns were a random patch model, a maximum dispersion model, a staggered-setting model, a partial aggregation model, and a progressive cutting model. Each model was based on its own assumptions. The random patch model assumed a random distribution of cut-units in landscapes. In this model each un-cut pixel had equal probability of being cut as the first pixel of a patch. After selection of the first pixel, contiguous pixels to be cut to form the patch were determined by a random walk model (i.e., each search direction is randomly determined); the size of each cut-unit was determined by adding a random number to the "mean patch size", which was input as a simulation parameter at the beginning of a simulation run.

The maximum dispersion model placed cut-pixels as evenly spaced and dispersed as possible. A square patch of 4 pixels was cut as one cut-unit at each search. The staggered-setting model used two assumptions: First, the algorithm of the maximum dispersion model was adopted to locate the first pixel of a patch from which the patch was developed. Second, the patch generator was a restricted random model, that is, the patch size and search direction were determined randomly with two restrictions: (a) no more than 3 pixels are cut in a row in the same direction, and (b) no pixels of two patches generated at the same time step may join. For the partial aggregation model, the landscape matrix was divided into 4 pieces, and cut-units were confined to one of the four blocks until it was almost exhausted. In each of the four landscape blocks, the first pixel of a cutting patch was chosen randomly and then the restricted random walk model, discussed above, was used to create the patch. The number of the pixels in a patch was randomly determined as in the staggered-setting model. A reserve area of 10% of the total landscape was used, but later simulation without a reserve area indicated that this made little difference for the partial aggregation model. The progressive cutting model assumed that cutting started at one point from which cutting extends outward. A more detailed discussion of the four models can be found in Li (in preparation).

aggregation models were run another three times: (1) with cut-units of 16-pixel mean clearcut patch, (2) with a 4-pixel mean clearcut patch size and the inclusion of a stream network (stream pixels were prevented from cutting), and (3) with the structurally heterogeneous large cut of a 16-pixel mean cut-unit size. The first run was used to examine changes in landscape characteristics along the cutting gradient and among the five models. A contrast between the first run (i.e., with 4-pixel average cut-unit size) and the second run (i.e., with 16-pixel average cut-unit size) permitted study of the effects of cut-unit sizes on landscape characteristics. A comparison between the first run (i.e., without the stream network) and the third run (i.e., with the stream network) was used to assess the effects of geomorphic constraint (i.e., the stream network) on simulation results. The fourth run was compared to the second run to study effects of the heterogeneous large cut on landscape structure (see discussion below).

2. Landscape indices

Many landscape indices (Table 1) were used in this study to quantify changes in landscapes structure as forest cutting proceeds. Some of them were used by Franklin and Forman (1987), some were proposed for analysis of landscape patterns in general (Romme 1982, O'Neill et al. 1988), and some were developed in my research. Indices used here include: (1) basic landscape parameters, (2) fragmentation

Table IV.1: The equations of the landscape measures used.

Landscape Measure	Equations*
Forest edge density	ED = P / A
Forest patch shape	ASI = Σ SI(i) A(i) / A
	SI(i) = 0.25 P(i) / A(i)
Interior area fragmentation	FGI = 1 - Ai / A
Largest patch fragmentation	FGL = 1 - Al / A
Largest compact fragmentation	FGC = 1 - Ac / A
Patchiness	PT = 100 Σ Σ E(i,j) D(i,j) / Nb

* P is the total edge length,
A is the total area,
SI(i) is shape index of patch i,
P(i) is edge length of patch i,
A(i) is area of patch i,
Ai is the total forest interior area,
Al is the size of the largest forest patch,
Ac is the largest compact forest area,
E(i,j) is edge between patch type i and patch type j,
D(i,j) is the dissimilarity value of patch types i and j,
Nb is the maximum edge length possible in a landscape.

indices, (3) landscape diversity indices. Edge density (i.e., edge length per unit area) was used rather than total edge length because edge density is not affected by the size of study areas. The area-weighted patch shape index was used rather than the arithmetic mean shape index because it was assumed that larger patches should be more important to characterize a landscape. The scale of edge effects was chosen as one pixel and the total forest interior area was calculated by substracting a rim of 1 pixel from around the boundary of forest patches. The largest "compact forest area" was calculated by blocking all the narrow forest corridors (less than or equal to 2 pixels wide) and then measuring the largest forest area left. The largest compact forest area was assumed to represent the likelihood of the future management options in forest landscapes.

The patchiness index was used to examine indirectly the effect of the structurally heterogeneous large cut in this paper. In simulation of the heterogeneous large cut, the dissimilarity matrix required for calculation of the patchiness was modified: the dissimilarity values of all pairs of patch types were reduced by 0.05. This was an arbitrary figure which assumes that the heterogeneous large cut-over should reduce the dissimilarity between any pair of patch types. A comparison of this heterogeneous large cut to the clean big cut (i.e., the second simulation run) was made to simulate some effects of the heterogeneity in cut-units.

Results

The landscape indices were plotted against landscape cut-over percentage to examine how they change with development of forest cutting patterns. Different models or different simulation runs were compared on the basis of the landscape characteristics such as forest edge density, area-weighted shape index of forest patches, fragmentation indices, and patchiness index.

1. Spatial and temporal patterns

Edge density displayed bell-shaped curves with increased cutting except for the progressive model (Figure IV.1a). Edge density for the maximum dispersion model showed a linear increase first, peaked at 50% of landscape cut-over, and then started to decrease linearly, in accordance with Franklin and Forman (1987). The landscapes generated by the random, staggered-setting, and partial aggregation models had nearly the same trend, but edge densities did not change as dramatically as the maximum dispersion model (Figure IV.1a). Edge density varied little for the progressive model. In addition, the staggered-setting and random models had similar values of edge densities throughout development of cutting pattern.

As cutting proceeded, the area-weighted mean shape index (ASI) of forest patches first increased, peaked, and then declined (Figure IV.2b). A higher value of ASI may characterize landscapes with more irregularly-shaped patches. ASI for the maximum dispersion model peaked at 30% and dropped to the lowest at 50% cut-over when all the forest patches were basically 4-pixel square patches. ASI for both the random and staggered-setting models peaked at 35% cut-over and then dropped dramatically. ASI for the partial aggregation model displayed a moderate change with a small peak at 40% cut-over. ASI for the progressive model remained unchanged.

Fragmentation indices of forest interior area (FGI), largest forest patch size (FGL), and largest forest compact area (FGC) appeared to be useful indices for distinguishing landscapes generated by different models. The steady increase of FGI was due to an almost linear decrease in total interior area (Figure IV.1c). When the landscape generated by the partial aggregation model was about 50% fragmented in terms of FGI at 50% cut-over, the landscape for the maximum dispersion model was already 100% fragmented (i.e., no interior area left), while FGI for the random and staggered-setting models reached about 80%. FGL started to differ among the models at 35% cut-over (Figure IV.1d). FGL for the maximum dispersion and partial aggregation models reached maxima at 50% cut-over, but FGL for the former was 100% fragmented while FGL for the latter was only 50% fragmented. Changes in FGC were even more dramatic (Figure IV.1e): the maximum dispersion model amounted to maximum FGC at 14% cut-over, and the random and staggered-setting models arrived almost at maximum FGC at about 35% cut-over when FGC for the partial aggregation model was still low. The progressive model had the lowest value for all the three fragmentation indices (Figures IV.1c, 1d, and 1e).

The patchiness index (PT) showed little difference among the maximum dispersion, random and staggered-setting models until 30% cut-over after which the maximum dispersion model diverged from the other two models (Figure IV.1f). PT for the maximum dispersion model peaked at 50% and then decreased. PT for the random and staggered-setting models displayed a slow increase after 35% and then leveled off at 50% cut-over; those two models showed little difference. PT for the partial aggregation model increased first and leveled off also at 50% cut-over (Figure IV.1f), while PT for the progressive model changed little (Figure IV.1f). Therefore, in real landscapes fragmentation in terms of neighboring contrast may reach the maximum earlier than Franklin and Forman (1987) predicted. The results also suggest that contrast of landscape mosaics may remain constant after landscape cut-over percentage reaches a certain point, even although new patches are still being introduced.

2. Effects of clearcut patch size

The mean patch size of clearcuts had a great influence on landscape characteristics (Figure IV.2a-2f). Use of larger cut-units consistently produced landscapes with lower edge densities (Figure IV.2a). Interestingly, edge density for the partial aggregation model did not change much with the cut-over percentage regardless of cut-unit sizes. The landscapes with larger cut-units had lower values of ASI (Figure IV.2b), but the differences only occurred before 50% cut-over. In addition, ASI for the partial aggregation model with larger cut-units changed little with increased cutting. The use of larger clearcut patches generally resulted in landscapes with less fragmentation and lower values of patchiness (Figure IV.2c-2f).

3. Effects of inclusion of a stream network

When the stream system was included in landscapes, edge density increased compared to the landscapes without a stream network (Figure IV.3a). However, the increase in edge density diminished at about 40-50% of cut-over, and then the edge density curves reversed relative position so that the landscapes with streams began to have lower edge densities (Figure IV.3a). The higher edge density before 40% landscape cut-over was expected because of the addition

Figure IV.1: Comparison of landscape indices along the cutting gradient and among the five synthetic landscape types.
The five curves represent different landscapes generated by the five simulation models:
the maximum dispersion model (chck),
the random patch model (rand),
the staggered-setting model (stag),
the partial aggregation model (mfrg), and
the progressive cutting model (prog).

a: Forest edge density
b: Area-weighted shape index of forest patches
c: Forest interior area fragmentation index
d: Largest forest patch size fragmentation index
e: Largest compact forest area fragmentation index
f: Patchiness index

Figure IV.1a

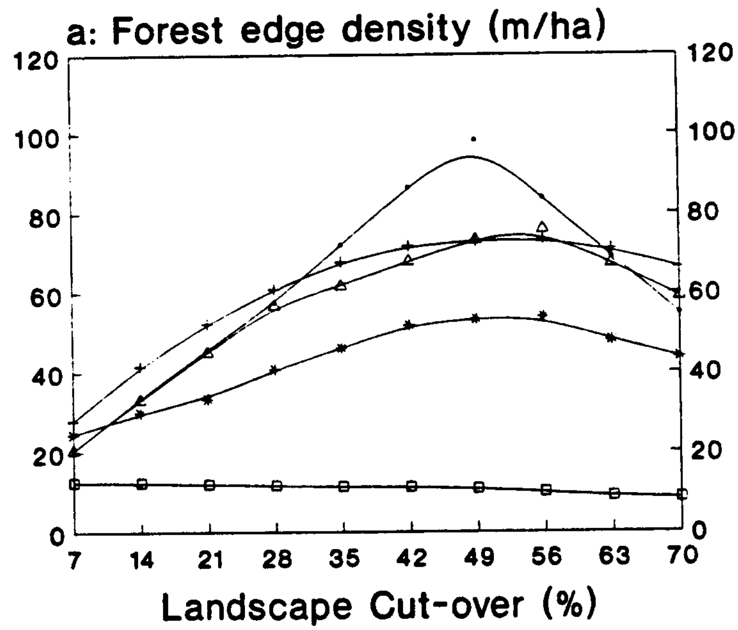


Figure IV.1b

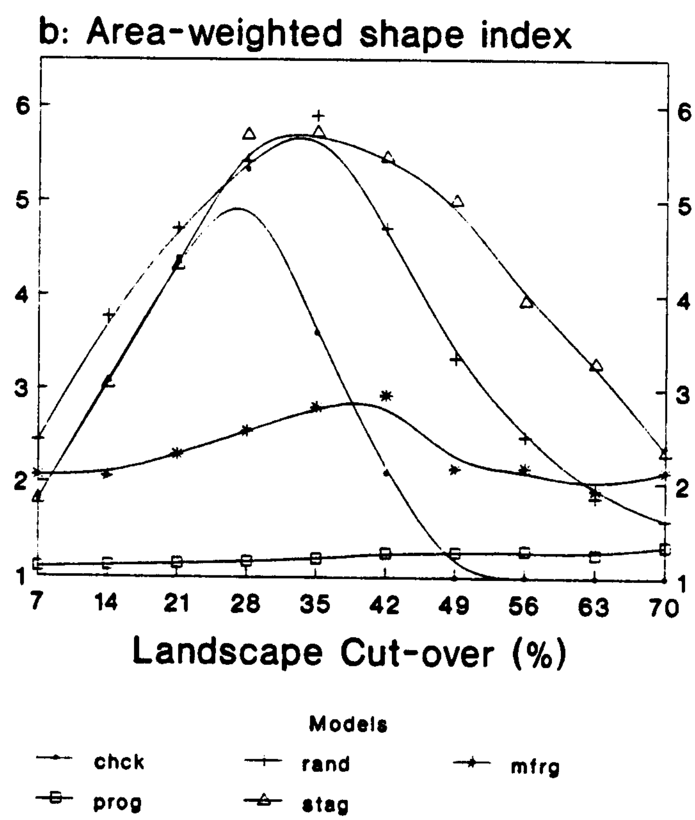


Figure IV.1c

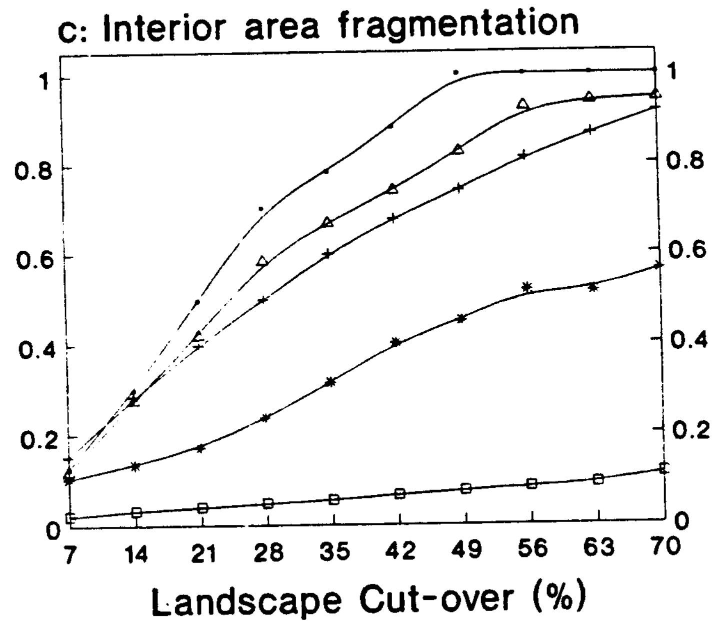


Figure IV.1d

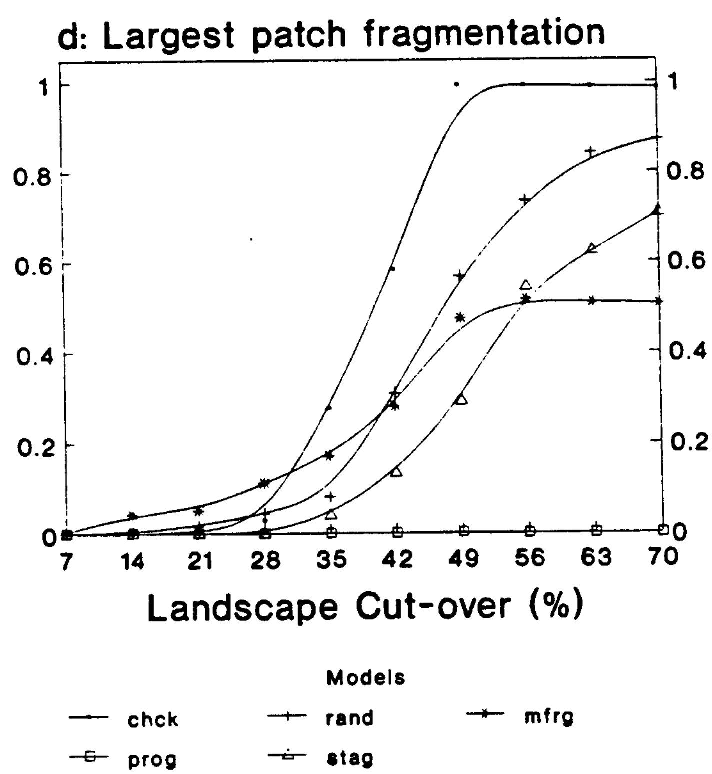


Figure IV.1e

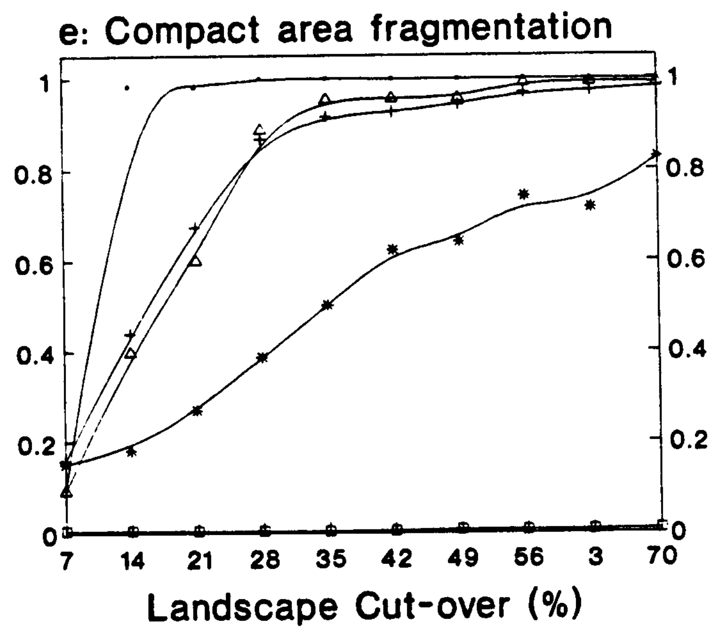


Figure IV.1f

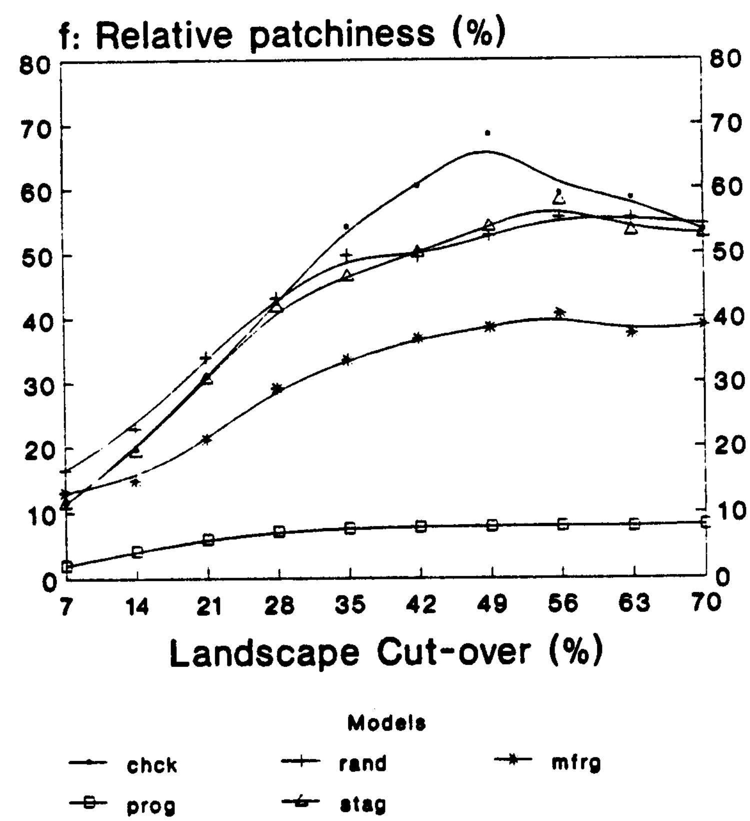


Figure IV.2: Comparison of landscape indices among landscapes with different cut-unit sizes.

ran1 and mfg1 stand for the landscapes with 4-pixel mean clearcut patch size generated by the random patch and partial aggregation models, respectively; ran2 and mfg2 stand for the landscapes with 16-pixel mean clearcut units generated by the random and partial aggregation models, respectively.

a: Forest edge density
b: Area-weighted shape index of forest patches
c: Forest interior area fragmentation index
d: Largest forest patch size fragmentation index
e: Largest compact forest area fragmentation index
f: Patchiness index

Figure IV.2a

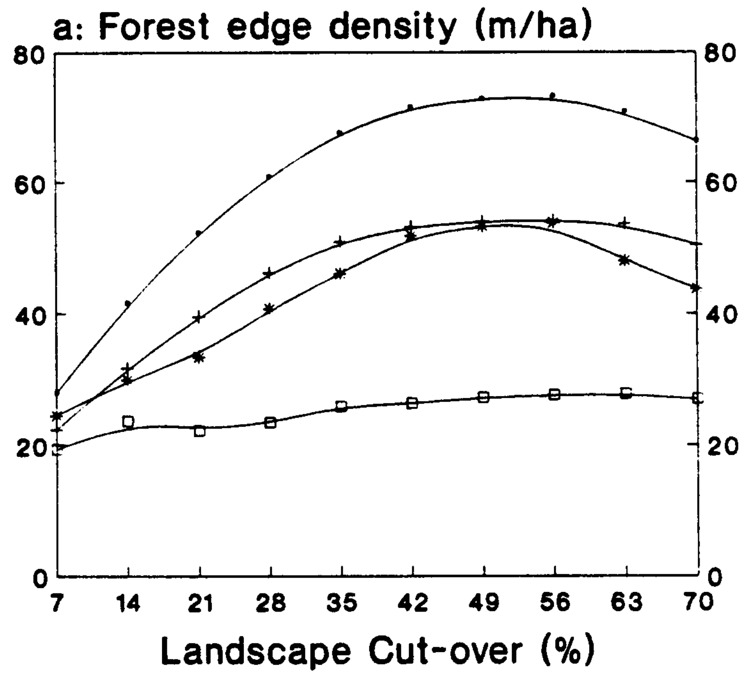


Figure IV.2b

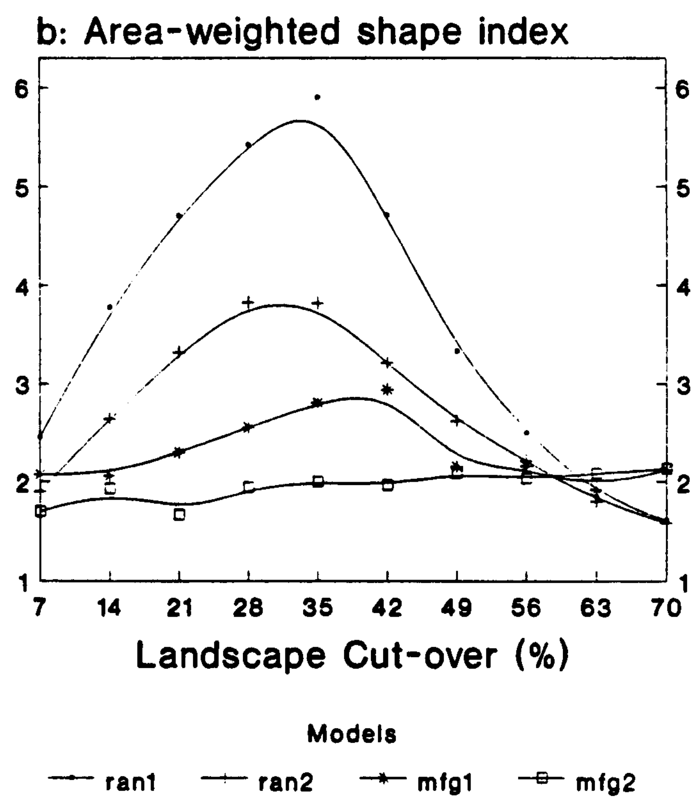


Figure IV.2c

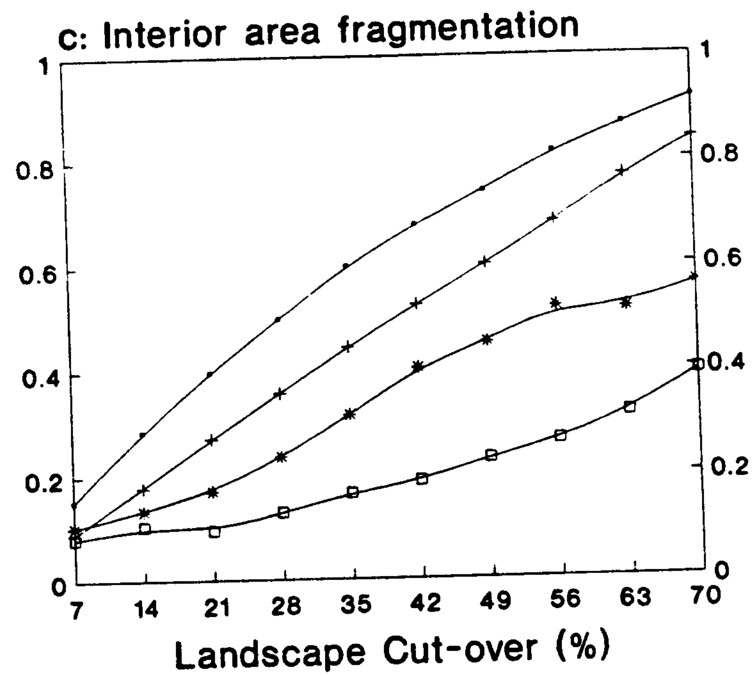


Figure IV.2d

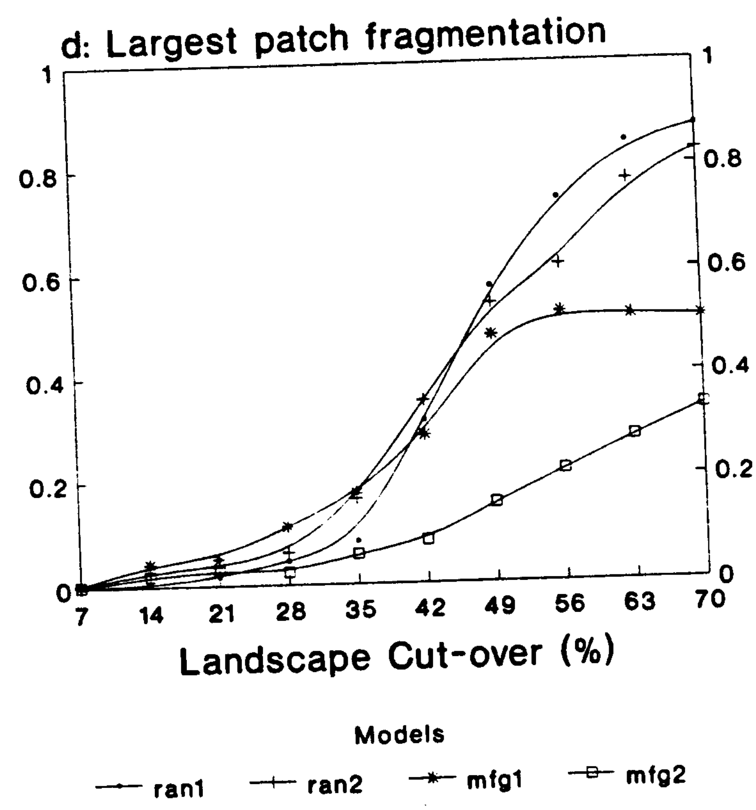


Figure IV.2e

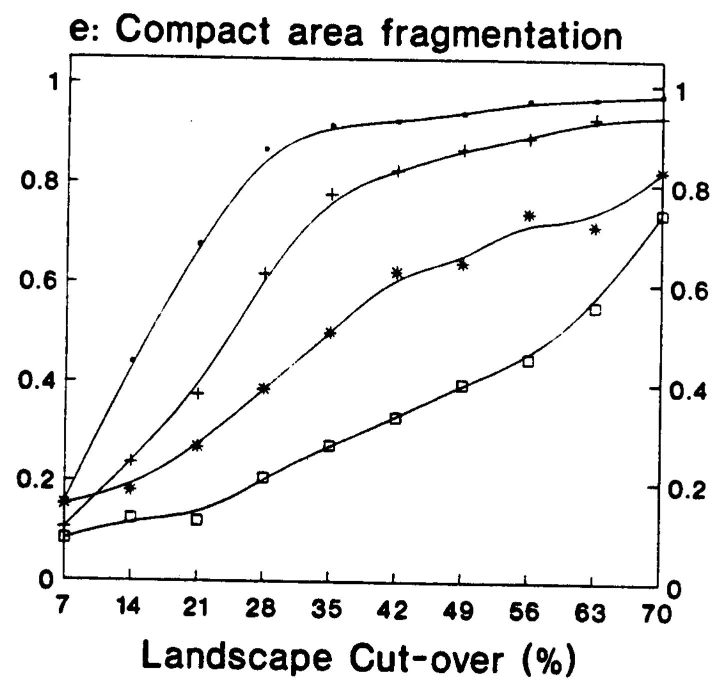


Figure IV.2f

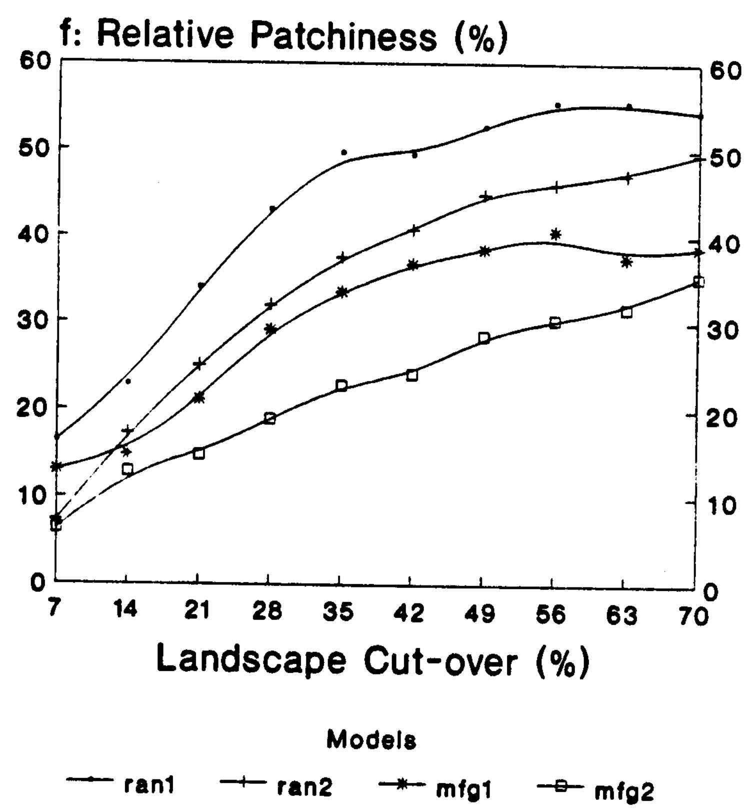


Figure IV.3: Comparison of landscape indices between landscapes with and without a stream network.

ran1 and mfg1 stand for the landscapes without a stream network generated by the random and partial aggregation models, respectively; ran3 and mfg3 stand for the landscapes with a stream network generated by the random and partial aggregation models, respectively.

a: Forest edge density
b: Area-weighted shape index of forest patches
c: Patchiness index

Figure IV.3a

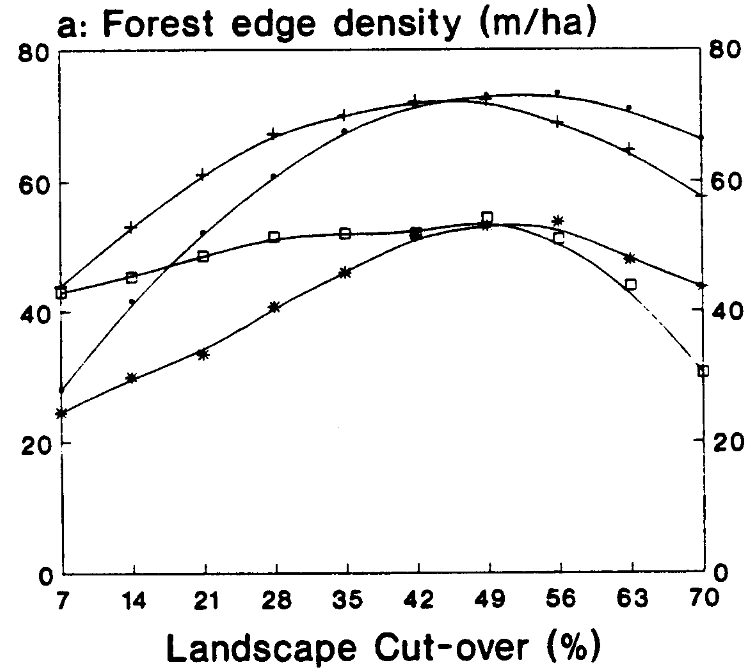


Figure IV.3b

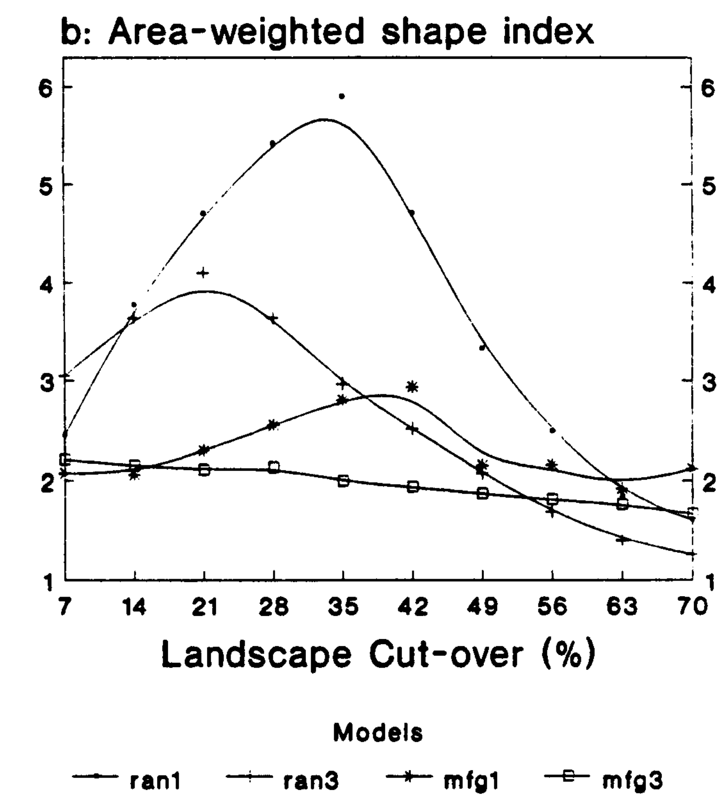


Figure IV.3c

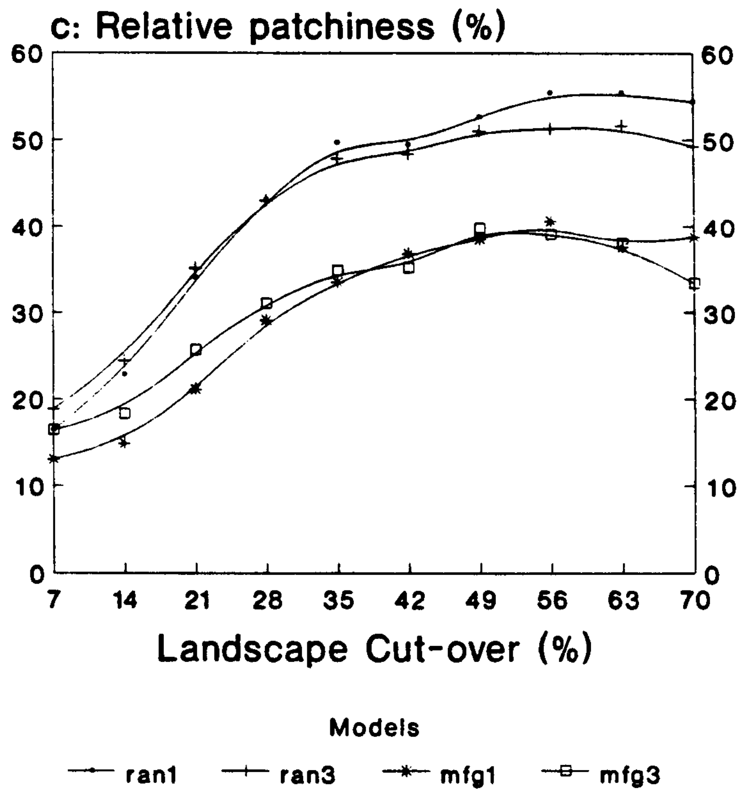
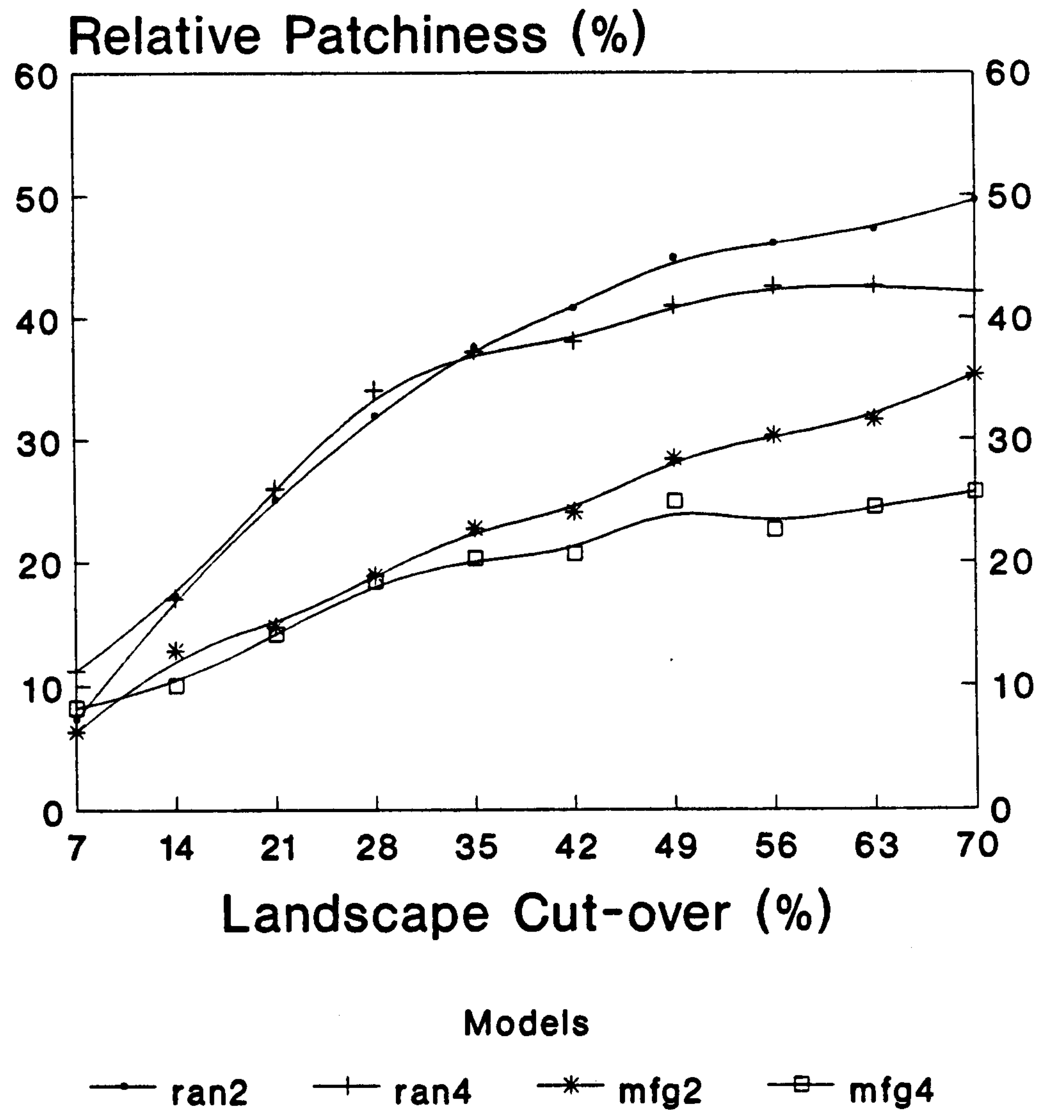

c: Relative patchiness (%)
60
50
40
30
20
10
0
7
14
21
28
35
42
49
56
63
70
Landscape Cut-over (%)
Models
ran1
ran3
mfg1
mfg3

Figure IV.4: Comparison of patchiness index between landscapes generated by the structurally heterogeneous large cut (ran4 and mfg4) and landscapes generated by the clean big cut (ran2 and mfg2). The two models used were the random and partial aggregation models.



of edges created by streams. However, the reason for the later switch was unclear. The landscapes with streams differed in ASI from those without streams, most profoundly for the random model (Figure IV.3b). The landscapes with streams had lower ASI values. In contrast, the inclusion of streams had little effects on PT (Figure IV.3c), because the dissimilarity values between stream pixels and clearcut pixels were assumed to be similar to those between forest and clearcut.

4. Assessment of the large heterogeneous cut

The structurally heterogeneous large cut was indirectly assessed in this study by using the patchiness index, which can reflect differences between the structurally heterogeneous large cut and the clean clearcut. Patchiness values for the heterogeneous large cut were lower compared to the clean clearcut after 35-40% cut-over (Figure IV.4). Patchiness started to show differences at 40% for the random model and at 35% for the partial aggregation model, and the differences were increasing. This was due to the cumulative effects of retention of trees and snags in the structurally heterogeneous large cut through the simulation time.

Discussion

Different cutting methods produce landscapes with distinct characteristics. For example, the maximum dispersion model created a landscape with maximum fragmentation: more edge density, more irregularly shaped forest patches, less interior forest area, and more patchy. In contrast, the progressive model created a landscape with the least fragmentation for all the landscape measures. The landscape generated by the partial aggregation model showed considerably less fragmentation than the maximum dispersion, random, and staggered-setting models for almost all the landscape measures.

In most cases, values of landscape indices yielded by the random model were between values for the maximum dispersion model (i.e., regular pattern) and those for the partial aggregation and progressive models (i.e., aggregated pattern). This suggests that those landscape indices worked well because the results agreed with the general theory on spatial pattern that adding constraints to the landscape structure leads to departure from random pattern (e.g., Ludwig and Reynolds 1988).

The temporal patterns of forest landscapes under different cutting methods varied markedly as evidenced by the behavior of the landscape indices along the forest cutting gradient. For example, for the maximum dispersion model, fragmentation accelerated after 25-30% of the landscape was cut, as many forest patches began to emerge; fragmentation reached maximum at about 50% cut-over (e.g., with the highest edge density and the least forest interior area), just as Franklin and Forman (1987) predicted. Additionally, changes in the maximum dispersion landscape were more dramatic. The staggered-setting and random models followed the same trends as the maximum dispersion model. In contrast, the partial aggregation model tended to display a more gradual development of fragmentation, and the progressive model usually showed little change.

Changes of many landscape characteristics may not be observable before 25-30% (or sometimes 50%) landscape cut-over as indicated by the fact that many landscape indices did not differentiate distinct synthetic landscapes before certain points along the cutting gradient. This implies that there may be some thresholds of pattern development along the forest cutting gradient, and only after those thresholds are exceeded does forest fragmentation become conspicuous. It is interesting that in many areas of forest management we are just arriving at about 30% cut-over point and getting uptight about what we see.

The simulation results consistently showed the departure of the more realistic model (i.e., the partial aggregation model) from the simple models (i.e., the maximum dispersion and random models). The simple models not only displayed greater changes in spatial patterns, but also exhibited more dramatic changes in temporal patterns, and in some cases demonstrated divergent trends. Although this study identified the usefulness of simple landscape models, the results of those models should be considered with caution.

The results observed for the staggered-setting model may seem to contradict the above statement. The landscapes of the staggered-setting model seemed strikingly similar to the maximum dispersion landscape in many landscape measures and even more so to the random landscape. However, the staggered-setting model was also a simple model. This model was such a modification of the maximum dispersion model that the size and shape of clearcut units were allowed to vary to an extent, but the locations of the first pixels of cut-units were primarily kept unchanged from the maximum dispersion model. Therefore, the staggered-setting model actually mimicked the "ideal" situation of the staggered setting clearcut system when there were no constraints (e.g., geomorphic setting and development of road system). However, those constraints in reality may shape the cutting pattern considerably. For example, cutting usually follows the development of a road system. In contrast to the staggered-setting model, the partial aggregation model incorporated some constraints in simulation: cutting started and concentrated in one part of the landscape, and then moved to another part as if the road system was developed first in one part of the landscape and then another. Furthermore, the effect of generating irregularly-shaped patches by the staggered-setting model was shown in the results as indicated by its difference from the maximum dispersion model in terms of many landscape measures. Addition of constraints drove the staggered-setting model from the maximum dispersion model and closer to the random model.

The use of larger cut-units to lessen fragmentation effects has been suggested (Franklin and Forman 1987), but its ecological and hydrological consequences have not been demonstrated in field studies. In this study, landscapes were clearly less fragmented when larger sizes of cut-units were used, as demonstrated by two simulation runs with different cut-unit sizes for the random and partial aggregation models. For example, the landscapes with larger cut-units had more forest interior area and less forest edge. This result supports the observations of Franklin and Forman (1987) that larger cut-units may have ecological benefits.

Effects of structural heterogeneity in cut-units was indirectly investigated using some landscape indices. The patchiness index reflected the effects of the structurally heterogeneous cutting on landscape structure, and indicated less fragmentation in landscapes in which retention of live and dead trees in cut-units was practiced. However, more functional information must be incorporated in future field and modeling exercises.

The general order of fragmentation for the five models (from high to low) was: the maximum dispersion, random and staggered-setting, partial aggregation, and progressive models. FGI and FGC consistently discriminated landscapes produced by different models and landscapes with different cut-unit sizes, while FGL did not distinguish those landscapes until about 35-50% of cut-over (Figures IV.1c, 1d, and 1e). However, FGC is strongly affected by the scale of the simulation models (i.e., the dimensions of landscapes); its values should be lower, if, for example, the simulations were run for landscapes of 100 by 100 pixels rather than the 34 by 34 matrix in the simulation runs used here. FGI is affected not only by the landscape dimensions, but also by the scale of edge effects used in the models. In contrast, FGL may be more robust.

The modeling exercise discussed above did not consider landscape features other than the forest cutting pattern. However, landscape features, such as topography, stream systems, and spatial heterogeneity which naturally occurs in forest landscapes, may have profound effects in managed forest landscapes. Since inclusion of all the information presents great difficulties in landscape modeling, this study employed a stream model in one of the simulation runs. Behavior of many landscape characteristics changes when a stream system was included in the landscape structure. For example, when streams were considered, edge density for the partial aggregation model dropped sharply after a gradual increase (Figure IV.3a), and the area-weighted mean shape index showed little effect of the forest cutting development (Figure IV.3b). The results suggest that simplified landscape models may yield misleading conclusions about landscape patterns.

Changes in landscape patterns discussed in this study were possible structure changes as forest cutting proceeds. The effects of changes in certain landscape structural characteristics on certain landscape functions are extremely important in interpretation of the results presented here. Research is strongly needed to establish the relationships between landscape structure and landscape functions and processes.

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Chapter V

Summary and Conclusion

Many critical questions in landscape ecological research and problems in resource management are spatial in nature. Landscape ecology is a discipline which emphasizes study of spatial heterogeneity. A landscape is by definition a heterogeneous system, and spatial pattern is one of the important emergent properties of landscapes. Tools capable of resolving spatial variations are needed to characterize and analyze landscape structure for a variety of purposes. For example, habitat fragmentation has become one of the most important issues in resource management. However, assessing fragmentation effects is difficult because of the magnitude of the temporal and spatial scales. Existing tools are somewhat limited. GIS is a good tool to handle spatial data, but GIS functions may not meet requirements of many landscape ecological studies. For example, GIS is not a good tool for landscape simulation, and spatial statistics installed in a GIS are often restricted to simple descriptive statistics and map overlays. Thus additional tools are needed to perform landscape simulations and ecological analyses of landscape patterns in conjunction with using GIS data or other types of spatial data (e.g., remote sensing imagery). Simulation and analysis of landscape patterns by computer may sometimes become the only feasible approach.

A computer program for simulation and analysis of landscape spatial patterns (LSPA) was developed to address spatial problems and needs for application in landscape ecological research. The simulation was used to investigate forest fragmentation in the Pacific Northwest region. LSPA could prove useful in both landscape ecological research and resource management. LSPA has two main functions: simulation and analysis of landscape patterns. The simulation and analytical functions of LSPA are independent; hence, the two functions may be used separately. The analytical function of of LSPA can be used to characterize real landscapes and to interface with GIS (i.e., to analyze landscape maps in GIS). Specifically, LSPA (1) generates landscape patterns for different cutting methods, (2) measures basic parameters of landscape structure, (3) calculates indices of landscape characteristics, and (4) performs spatial statistical analysis on the landscape pattern.

LSPA has many applications. First, LSPA is useful in quantifying spatial patterns of landscapes. LSPA provides a way for landscape ecologists and land managers to readily use a combination of techniques. Second, LSPA is useful in performing experiments with different cutting patterns and forecasting the consequences of management activities. LSPA provides land managers with an alternative approach to investigation of landscape management strategies, because simulation is, in most cases, the only feasible scientific approach to studying those problems with extensive time and space domains. Third, LSPA is useful in examining the behavior of primary indices of landscape patterns without having a large number of landscape samples. LSPA is capable of generating synthetic landscapes with known spatial and compositional characteristics, and therefore provides a "control" with which to study behavior of landscape indices. Fourth, LSPA can complement GIS in terms of spatial statistical analysis. LSPA can use existing GIS data to perform ecological analysis which may be difficult to do within GIS. Finally, LSPA can be used as a base on which GIS (or remote sensing) related landscape models are built. The use of GIS or remote sensing imagery in landscape modeling is critical because remotely sensed data are the major data sources in landscape ecological research as well as in resource management.

One method which allows statistical evaluation of the spatial characters of landscapes is the landscape index. Landscape indices provide effective, quantitative tools to characterize spatial pattern and/or other attributes related to the landscape structure. Landscape indices "quantify landscape patterns so that relationships between landscape structure and landscape functions and processes can be established by linking those indices with ecological phenomena at the landscape level" (O'Neill et al. 1988). However, landscape indices should be evaluated against landscapes with known characteristics. Each of the landscape indices describes a particular aspect of landscape mosaics. The extent and exact nature of landscape indices has not been sufficiently explored. For this reason, the study of each index in a "controlled" environment by computer is a way of evaluating its contents.

A fragmentation gradient, composed of a system of landscapes from the least to the most fragmented, was established by four simulation models which generate landscapes using different rules. All simulation parameters of those synthetic landscapes were kept the same except spatial pattern. Landscape indices were evaluated in this controlled environment by examining the behavior of the indices along the fragmentation gradient. The two criteria used in my research to determine whether a landscape index is useful in spatial pattern discrimination were: (1) the ability to detect differences in landscape structure, and (2) the utility in making clear ecological interpretations. Spatial pattern was emphasized because it is an important emergent property of landscape mosaics.

In chapter three, the extant landscape indices in the literature were discussed and reviewed. Three new indices, proximity, dispersal, and fragmentation indices, were proposed. Each was evaluated in terms of its ability to distinguish the four synthetic landscapes created by the four simulation models. The landscape indices examined varied markedly in their ability to distinguish landscapes with distinct spatial patterns. The fractal dimension, patchiness, and dispersal indices appeared to be most sensitive to spatial variations in the landscape mosaics, and may be most useful to study and quantify the landscape pattern. Two fragmentation indices, the total forest interior area and the largest forest patch size, were also capable of capturing differences in landscape patterns. Furthermore, they are practical because they have direct application in resource management. The results obtained in chapter three suggested that these indices should be used when forest fragmentation is concerned. On the other hand, some commonly-used landscape indices, such as contagion and dominance, could not distinguish changes in the spatial variations of distinct landscape patterns. Dominance did not appear to contribute new information, whereas contagion had an error in the published equation and must be modified. Therefore, the usage of those landscape indices should be limited.

The development of forest cutting patterns was studied for landscapes generated by five simulation models. The results indicated that different cutting methods may produce landscapes with distinct characteristics in both spatial and temporal patterns. For example, the maximum dispersion model created landscapes with maximum fragmentation, while the progressive cutting model created landscapes with the highest aggregation. The results obtained in this research also indicated that changes of many landscape characteristics may not be observable before 25-30% landscape cut-over, as evidenced by the failure of most landscape indices to differentiate those distinct synthetic landscapes before that point. The mean cut-unit size tended to exert great influences on the characteristics of resultant landscapes. The results indicated that landscapes were clearly less fragmented when larger sizes of cut-units were used. This result supported the claim of Franklin and Forman (1987) that larger cut-units may have ecological advantages. Furthermore, the characteristics of landscapes with streams appeared to differ from those without streams in terms of the behavior of landscape indices. This may suggest that simplified landscape models may yield misleading conclusions about landscape patterns. This was also evidenced by the divergent trends observed for the partial aggregation model (i.e., a more realistic model).

This study suggests that landscape modeling is a promising approach to investigation of problems in both landscape ecology and resource management. However, more sophisticated landscape models should be developed which have more functional components. Thus integration of models developed at different scales should prove important in landscape modeling. This study also suggests that data about landscape functions and processes are needed. Most importantly, those data should be collected in a spatial scheme and in relation to quantifiable landscape structural characteristics. Data of this sort will be very valuable in establishing the relationships between landscape structure and landscape functions and processes. Only when we understand those relationships can we infer changes in landscape functions or processes from changes in landscape structure. This is the key to the solutions of most questions in landscape ecology and resource management because it is easier to observe landscape structure changes than changes in processes and because it is possible to manipulate landscape structure in order to maintain or to obtain desirable landscape functions.

There are many implications of the results to forest management. First, the landscape ecological perspectives are important in resource management. Landscape is the level at which management plans are made, many management activities take place, and many management problems should be addressed. Only at the landscape level may we discuss and achieve ecological equilibrium, that is, a sustained forest landscape. Landscape ecology can provide resource management with sound theoretical bases. Second, forest cutting pattern should be considered in any management plans because landscapes created by different cutting methods may have profound differences in many aspects. The alternative cutting method, imitated by the partial aggregation model, may produce many desirable characteristics of forest landscapes, such as reduction of fragmentation effects and retention of large forest areas for future management options. Finally, increase of cut-unit sizes and preservation of structural heterogeneity in cut-units should be considered in silviculture practice because they may also exert great influences on landscape characteristics.

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APPENDICES

Appendix II.1: An example of the input map of real landscapes.

Note that consecutive integers are used for coding of landscape elements. The matrix (e.g., old-growth forest) is usually coded as 0. This is a 30 by 30 landscape map with 8 (from 0 to 7) patch types. -8 is the code for reserved land.

```
4 4 4-8-8 1 2 2 2 0 0 0 0 1 1 1 0 0 0 0 5 5 5 5 0 0 6 6 6 6
4 4 1-8-8 1 2 2-8-8-8-8 0 5 0 5 5 6 6 5 5 5 5 5 4 7 7 6 7 7
0 1 1-8-8-8-8-8-8-8-8 1 5 5 0 5 0 0 6 0 7 7 7 0 4 7 7 6 7 7
0 1 0 1 1-8-8-8-8-8-8 1 5 5 5 0 0 0 0 6 7 7 7 4 4 7 7 5 5 5
0 0 1 1 0-8-8-8-8-8-8 1 5 5 1 5 5 0 6 6 7 4 5 5 4 6 6 6 0 7
0 0-8-8 0-8-8-8-8-8-8-8 1 1 5 5 0 7 7 6 0 5 5 6 6 6 5 5 7 7
0-8-8-8 0-8-8 0-8-8 0-8 1 0 1 6 6 7 7 0 0 5 0 7 7 6 6 5 5 5
5-8-8-8-8-8-8-8 0-8-8-8 1 1 1 6 5 7 7 0 0 6 6 4 4 0 0 7 7 7
5 5-8-8-8-8-8-8-8-8 0 4 4 1 1 1 6 6 6 0 0 6 6 4 0 4 4 0 7 7
5-8-8-8-8-8 1 1 1 1 4 4 4 1 1 0 6 0 0 6 6 7 4 5 5 4 0 5 5 6
5 5-8-8-8 4 1 1 1 2 4 4 4 4 4 0 7 7 6 6 7 7 4 5 0 5 5 5 6 6
5 5-8-8-8 4 4 4 2 2 2 5 5 1 4 7 7 0 6 0 7 7 4 4 5 5 0 7 6 6
4 4 0-8 0 4 4 0 0 4 4 5 4 4 0 0 6 6 0 0 0 6 6 5 5 7 7 7 0 0
4 4-8-8 4 0 4 4 0 4 0 5 4 4 4 4 6 6 6 7 7 6 6 5 6 7 7 7 0 0
8-8-8 4 4 4 4 0 0 0 1 1 4 1 4 3 6 6 7 7 7 6 6 5 6 6 6 7 7 7
8 0 0 4 0 0 0 0 0 0 1 1 1 0 3 3 6 6 7 7 7 0 5 5 6 6 7 7 7 7
0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 0 0 2 2 2 3 3 3 2 2 7 7 0 2
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 0 3 0 3 3 2 2 2 2 0 2 2
0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 2 3 3 0 2 0 2 2 0 0 0 2 3
0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 2 2 0 2 2 2 3 3 3 0 0 0 3
0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 2 1 4 4 4 2 2 0 2 2 0 0 0 3
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 4 4 4 2 2 2 2 2 2 3 3 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 2 2 3 3 3 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 3 3 0 0 2 2 2 3 3 3 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 3 3 3 0 0 3 3 2 2 0 0 0 1
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 3 3 1 2 2 0 0 2 2 0 0 1 1
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 0 3 1 2 0 0 0 0 0 0 0 1 1
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 1 1 1 3 3 0 0 0 0 0 0 2
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 1 1 3 3 3 3 0 3 3 0 2 2
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 1 3 0 3 3 3 0 0 0 2 2
```

Appendix II.2: Examples of the three input matrices.

The examples include 11 patch types (or 10 simulation time steps).

(1) The dissimilarity matrix for the patchiness index.

code	0	1	2	3	4	5	6	7	8	9	10
0	0.0	1.0	0.9	0.9	0.8	0.8	0.8	0.7	0.7	0.7	0.7
1	1.0	0.0	0.3	0.3	0.4	0.5	0.6	0.6	0.6	0.7	0.7
2	0.9	0.3	0.0	0.2	0.2	0.3	0.4	0.4	0.4	0.5	0.5
3	0.9	0.3	0.2	0.0	0.1	0.2	0.2	0.3	0.3	0.3	0.4
4	0.8	0.4	0.2	0.1	0.0	0.0	0.1	0.2	0.2	0.3	0.3
5	0.8	0.5	0.3	0.2	0.0	0.0	0.0	0.0	0.1	0.2	0.2
6	0.8	0.6	0.4	0.2	0.1	0.0	0.0	0.0	0.0	0.1	0.1
7	0.7	0.6	0.4	0.3	0.2	0.0	0.0	0.0	0.0	0.0	0.1
8	0.7	0.6	0.4	0.3	0.2	0.1	0.0	0.0	0.0	0.0	0.0
9	0.7	0.7	0.5	0.3	0.3	0.2	0.1	0.0	0.0	0.0	0.0
10	0.7	0.7	0.5	0.4	0.3	0.2	0.1	0.1	0.0	0.0	0.0

(2) The habitat suitability matrix for the dispersal index.
Interior species

0	1.0	0.3	0.4	0.4	0.5	0.5	0.6	0.6	0.6	0.7	0.7
1	0.3	0.1	0.1	0.1	0.15	0.15	0.2	0.2	0.2	0.2	0.2
2	0.4	0.1	0.15	0.1	0.2	0.2	0.2	0.2	0.2	0.3	0.3
3	0.4	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3
4	0.5	0.15	0.2	0.2	0.25	0.2	0.25	0.3	0.3	0.3	0.4
5	0.5	0.15	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.4	0.4
6	0.6	0.2	0.2	0.2	0.25	0.3	0.35	0.35	0.4	0.4	0.4
7	0.6	0.2	0.2	0.3	0.3	0.3	0.35	0.4	0.4	0.4	0.5
8	0.6	0.2	0.2	0.3	0.3	0.3	0.4	0.4	0.45	0.45	0.5
9	0.7	0.2	0.3	0.3	0.3	0.4	0.4	0.4	0.45	0.5	0.5
10	0.7	0.2	0.3	0.3	0.4	0.4	0.4	0.5	0.5	0.5	0.5

Edge species

0	0.1	1.0	0.9	0.9	0.8	0.8	0.7	0.7	0.6	0.6	0.55
1	1.0	0.4	0.3	0.3	0.35	0.4	0.45	0.5	0.5	0.5	0.55
2	0.9	0.3	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.4	0.5
3	0.9	0.3	0.3	0.3	0.25	0.3	0.3	0.3	0.3	0.3	0.4
4	0.8	0.35	0.3	0.25	0.25	0.25	0.3	0.3	0.3	0.3	0.3
5	0.8	0.4	0.3	0.3	0.25	0.25	0.2	0.2	0.2	0.3	0.3
6	0.7	0.45	0.4	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2
7	0.7	0.5	0.4	0.3	0.3	0.2	0.2	0.2	0.15	0.2	0.2
8	0.6	0.5	0.4	0.3	0.3	0.2	0.2	0.15	0.15	0.15	0.15
9	0.6	0.5	0.4	0.3	0.3	0.3	0.2	0.2	0.15	0.15	0.1
10	0.55	0.55	0.5	0.4	0.3	0.3	0.2	0.2	0.15	0.1	0.1

(3) The fire probability vectors: ignition and spread.

i	0.30	0.80	0.75	0.70	0.65	0.63	0.61	0.55	0.53	0.51	0.55
s	0.50	0.70	0.70	0.70	0.65	0.65	0.65	0.63	0.62	0.61	0.60

Appendix II.3: Examples of LSPA outputs.

A. The generated landscape map for time 5 (reduced).

```
LSPA: simulation with model Min Fragm
Landscape pattern of Irep=  1  at time t=  5

0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 0 0 2 2-8-8-8 0-8-8-8 2 2 2
0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 0 2 2 0-8 0-8-8-8-8-8-8-8 2
0 0 0 0 0 0 0 0 0 0 0 0 0 3 2 2 0 0-8-8-8-8 0-8-8-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 0 3 2 2 0 0-8-8-8-8-8-8-8-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0-8-8-8-8-8 3-8-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0-8-8-8-8 3 3 3-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 3 3 3-8 0 0-8-8-8-8-8-8-8-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 3 3 3-8-8-8 0-8-8-8-8-8-8-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 2 2 2-8-8-8-8-8-8-8-8-8-8-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0-8 3 3 3 0 2 2 2 2 0-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 2 2 0 2 0 0-8-8-8-8-8
0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 3 3 3 2 3 2 2 2-8-8 3 3 3 0
0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 0 0 2 0 2 3 2 2 0-8-8 2 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 2 2 0 0 0 0 0 2 2 2 0 0 2
0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 0 2 2 2 2 0 2 2 0 2 2 0 2 2
0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 2 2 2 2 2 0 2 2 0 5 0 0 0 0 0
0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 2 2 4 4 2 2 2 2 5 5 0 0 0 0
1 0 0 0 2 0 1 1 1 0 0 0 0 5 5 5 0 5 4 5 5 3 3 5 5 5 0 3 5 5
1 0 0 0 2 0 0 0 0 0 0 0 0 5 5 0 5 5 4 5 5 3 3 5 5 0 3 3 5 5
2 0 0 0 0 0 0 0 0 0 0 0 0 5 5 0 5 5 0 3 3 3 3 5 5 0 3 3 5 5
2 0 0 0 0 0 0 0 0 0 0 0 4 4 4 3 3 3 0 3 0 3 3 5 5 0 0 4 4 4
2 0 0 0 0 0 0 0 0 0 0 0 0 0 4 4 4 3 0 0 5 5 0 0 0 0 5 5 4 5
0 0 0 0 0 1 1 0 0 0 0 0 0 0 4 4 4 0 0 5 5 5 0 0 5 0 5 5 4 5
0 0 0 0 1 1 1 0 0 0 0 0 0 4 0 0 0 0 0 0 0 0 0 3 5 5 0 5 4 5
0 1 1 0 0 0 0 0 0 1 1 0 4 4 4 0 0 0 0 4 0 0 3 3 5 5 5 0 4 5
0 1 1 0 0 0 0 2 2 1 1 0 0 0 4 4 4 5 5 4 5 5 5 3 4 4 4 5 5 0
0 1 1 1 0 0 0 0 0 1 0 0 0 0 4 5 3 5 4 4 5 5 5 0 4 4 5 5 0 4
0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 5 3 3 4 4 4 4 4 0 4 0 4 4 4 4
1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 4 4 3 4 4 3 4 0 0 0 4 4 0 4 4
1 0 0 0 0 1 2 2 2 1 1 1 0 0 4 4 0 4 4 5 3 4 0 4 4 0 4 4 3 3
0 0 0 0 1 1 1 2 2 0 1 0 4 4 4 0 0 4 0 5 5 4 0 4 0 0 5 5 3 3
0 1 1 0 1 1 1 1 0 1 1 1 4 4 4 4 3 3 0 0 0 4 4 0 3 3 5 5 3 3
0 1 1 0 0 0 0 0 0 1 1 0 0 3 3 3 3 0 5 5 0 0 0 3 3 3 5 5 5 0
0 1 1 0 0 0 0 0 0 0 0 0 0 0 3 3 3 0 5 5 5 0 0 0 0 4 4 4 4 4
```

Appendix II.3 (continued)

B. Individual patch information of forest patches

Model= Min Fragm IREP= 1 Time= 5 Map Dimension: 34 by 34
(unit=# of pixel)

#	Size	----Edges---- inner	outer	perimeter	NNDist	fractal
1	657	161	209	370	1	1.220
2	1	0	4	4	2	1.000
3	1	0	4	4	1	1.000
4	1	0	4	4	1	1.000
5	1	0	4	4	1	1.000
6	1	0	4	4	1	1.000
7	1	0	4	4	1	1.000
8	1	0	4	4	1	1.000
9	1	0	4	4	1	1.000
10	2	0	6	6	1	1.170
11	32	0	54	54	1	1.502
12	1	0	4	4	1	1.000
13	1	0	4	4	1	1.000
14	1	0	4	4	1	1.000
15	1	0	4	4	1	1.000
16	1	0	4	4	1	1.000
17	7	4	12	16	1	1.129
18	1	0	4	4	1	1.000
19	1	0	4	4	1	1.000
20	1	0	4	4	1	1.000
21	1	0	4	4	2	1.000
22	3	0	8	8	2	1.262
23	3	0	8	8	1	1.262
24	1	0	4	4	1	1.000
25	1	0	4	4	1	1.000
26	1	0	4	4	1	1.000
27	11	0	22	22	1	1.422
28	1	0	4	4	1	1.000
29	2	0	6	6	1	1.170
30	1	0	4	4	4	1.000

Appendix II.3 (continued)

C. Summary table for all the landscape indices of forest

Landscape dimension is: 34 by 34 (units: ha or km)

SUMMARY OF LANDSCAPE CHARACTERISTICS FOR FOREST LAND	
Number of Patches	30
Total Forest Area (ha)	739.000
Mean Patch Size (ha)	24.633
Sdv of Patch Size (ha)	119.581
Size of Lrgst Patch (ha)	657.000
Forest Interior Area	478.000
Edge Density (m/ha)	50.000
Fractal of All Edge	1.506
Mean Fractal of a Patch	1.071
Fractal of Patch Shape	1.552
Mean Shape Index	1.187
Area-weighted MSI	3.396
Percent Forest Remained	63.927
Mean N.Neighbor Distance	0.120
Nearest Neighbor Index	1.919
Proximity Index	0.800
Index of Clumping	19.116
Fragmentation Index 2	0.100
Fragmentation Index 3	0.157
Fragmentation Index 4	0.705
Fragmentation Index 5	0.688
Fragm:Largest Patch Size	0.111
Fragm:For. Interior Area	0.353
Fragm: Lgst Compact Size	0.598
Shape Index of Lst Patch	3.609
Perimeter of Lgst Patch	37.000
Lgst Compact Patch Size	297.000

D. Individual patch information of clearcut patches

Model= Min Fragm IREP= 1 Time= 5 Map Dimension: 34 by 34
(unit=# of pixel)

		-----Edges-----				
#	Size	inner	outer	perimeter	NNDist	fractal
1	5	0	10	10	5	1.139
2	9	3	13	16	1	1.073
3	5	0	10	10	1	1.139
4	5	0	10	10	2	1.139
5	8	0	14	14	1	1.205
6	5	0	10	10	2	1.139
7	16	4	24	28	1	1.292
8	11	0	20	20	2	1.342
9	8	0	14	14	2	1.205
10	5	0	10	10	1	1.139
11	6	0	10	10	2	1.023

Appendix II.3 (continued)

E. Summary table for all the landscape indices of clearcut

Landscape dimension is: 34 by 34 (units: ha or km)

SUMMARY OF LANDSCAPE CHARACTERISTICS FOR CLEARCUT PATCH 1	
Number of Patches	11
Total Areas Cut (ha)	83.000
Mean Patch Size (ha)	7.545
Sdv of Patch Size (ha)	3.475
Size of Lrgst Patch (ha)	16.000
Edge Density (m/ha)	13.149
Fractal of All Edge	1.646
Mean Fractal of a Patch	1.167
Fractal of Patch Shape	1.894
Mean Shape Index	1.243
Area-weighted MSI	1.331
Percent Landscape Cut	7.180
Mean N.Neighbor Distance	0.182
Nearest Neighbor Index	0.974
Proximity Index	0.137
Index of Clumping	20.023
Shape Index of Lst Patch	1.750

F. Edge information

Edges between Patches of Different Ages (in meter)

Total Edge of Age 0 with age of	1	===	12700.0
Total Edge of Age 0 with age of	2	===	11500.0
Total Edge of Age 0 with age of	3	===	9400.0
Total Edge of Age 0 with age of	4	===	8300.0
Total Edge of Age 0 with age of	5	===	7400.0
Total Edge of Age 1 with age of	2	===	1000.0
Total Edge of Age 1 with age of	4	===	100.0
Total Edge of Age 2 with age of	3	===	1800.0
Total Edge of Age 2 with age of	4	===	400.0
Total Edge of Age 2 with age of	5	===	400.0
Total Edge of Age 3 with age of	4	===	2500.0
Total Edge of Age 3 with age of	5	===	2900.0
Total Edge of Age 4 with age of	5	===	4700.0
Total edge among clearcuts is:			13800.0

Appendix II.3 (concluded)

G. Diversity indices

Diversity Indices for Rep 1 and Time	5
Relative Richness Index	30.0000
Relative Evenness Index	46.4963
Relative Patchiness Index	36.6765
Dominance Index	0.5574
Contagion Index	18.5928
Contagion Index	13.5262
Dispersal: Interior Spp	0.6244
Dispersal: Edge Spp	0.2555
Fire susceptibility	7.1947

H. Statistics for simulation replications

STATISTICS OF LS CHARACTERISTICS FOR FOREST LAND

TIME	LANDSCAPE INDICES	MEAN	SDV
1	Number of Patches	1.5000	0.7071
1	Total Forest Area (ha)	1073.5000	2.1213
1	Mean Patch Size (ha)	805.5000	381.1306
1	Size of Lrgst Patch (ha)	1073.0000	2.8284
1	Forest Interior Area	955.0000	2.8284
1	Edge Density (m/ha)	24.1349	0.1218
1	Fractal of All Edge	1.2165	0.0018
1	Mean Fractal of a Patch	1.0363	0.0292
1	Fractal of Patch Shape	1.2465	0.0441
1	Mean Shape Index	1.8370	0.3999
1	Area-weighted MSI	2.1136	0.0087
1	Percent Forest Remained	92.8633	0.1830
1	Mean N.Neighbor Distance	5.0750	6.9650
1	Nearest Neighbor Index	1.4445	2.0428
1	Proximity Index	0.9981	0.0027
1	Index of Clumping	19.0833	0.1181
1	Relative Richness Index	10.0000	0.0000
1	Relative Evenness Index	20.5142	0.5232
1	Relative Patchiness Index	12.7731	0.2377
1	Dominance Index	0.4360	0.0047
1	Contagion Index	2.1542	0.0079
1	Contagion Index	22.3053	0.2854
1	Dispersal: Interior Spp	0.9110	0.0142
1	Dispersal: Edge Spp	0.1234	0.0020
1	Fire Susceptibility Index	9.6142	0.4967
1	Fragm:Largest Patch Size	0.0005	0.0007
1	Fragm:For. Interior Area	0.1104	0.0009
1	Fragm: Lgst Compact Size	0.1863	0.0194

Appendix II.4: Values of landscape indices calculated for a "real" forest landscape.

LSPA was used to characterize two landscape maps provided by Dr. Miles Hemstrom of USDA Forest Services. The data set was composed of two digital (raster) landscape maps (produced from ARC/INFO) from the Blue River District, Willamette National Forest. The data for 1968, 1978 and 1988 were observed, resulting from the actual cutting; the data for the future years were projections made for two cutting schemes: the staggered-setting and partial aggregation (previously termed as minimum fragmentation) clearcut systems. The projection was done by the planning staff of the Blue River District, and therefore the data could be regarded as "real" landscape data. Values of landscape properties or indices in the first three decades should have been the same for the two approaches, and the slight discrepancies may result from errors of data transformation (from vector to raster) and, to a less extent, from errors of digitizing. This work was done to examine potential differences between two cutting approaches. However, only some physical variables (e.g., total forest area, mean patch size and cutting percent) were calculated through GIS. The variables in the table below stand for the following landscape properties or indices:

pcnt	percentage of remaining forest (%)
npt	number of patches
pdn	forest patch density (#/100ha)
ted	total forest edge (km)
edn	forest edge density (m/ha)
mps	mean forest patch size (ha)
tfa	total forest area (ha)
lps	size of the largest forest patch (ha)
ihps	total forest interior area (ha)
ear	mean edge-to-area ratio (m/ha)
fr	fractal of total forest area and edge
dfr	fractal from edge-area regression of forest patches
prx	proximity index
awsi	area-weighted mean shape index
patc	patchiness index
dom	dominance index
cont	contagion index
fgl	fragmentation index of largest forest patch size
fgi	fragmentation index of forest interior area
fgc	fragmentation index of largest compact forest area

Appendix II.4 (continued)

The Staggered-setting Landscape

year	pcnt	npt	pdn	ted	edn	mps	tfa	lps	ihps
1968	98.0	1	.01	51.2	7.2	6940.5	6940.5	6940.5	6691.2
1978	93.4	1	.01	91.9	13.0	6617.6	6617.6	6617.6	5807.4
1988	87.6	7	.10	145.1	20.5	886.7	6206.8	6189.8	4847.0
1998	83.9	8	.11	172.0	24.3	742.6	5940.5	5920.7	4266.3
2008	80.0	13	.18	190.9	27.0	435.8	5665.7	5626.1	3909.3
2018	75.2	21	.30	200.0	28.2	253.6	5325.8	5144.5	3560.9

year	ear	fr	dfr	prx	awsi	patc	dom	cont	fgl	fgi	fgc
1968	0.00	1.11	1.11	1.00	1.54	7.7	.60	3.6	.000	.036	.001
1978	2.33	1.27	1.27	1.00	2.82	14.7	.82	6.5	.000	.122	.015
1988	3.48	1.40	1.46	0.97	4.47	31.8	.89	10.2	.003	.219	.093
1998	3.56	1.45	1.52	0.96	5.42	40.0	.95	14.6	.003	.282	.560
2008	3.63	1.49	1.56	0.96	6.03	44.4	.98	19.4	.007	.310	.549
2018	3.36	1.51	1.57	0.82	5.94	42.4	.95	24.6	.034	.331	.655

The Partial Aggregation Landscape

year	pcnt	npt	pdn	ted	edn	mps	tfa	lps	ihps
1968	98.1	1	.01	50.8	7.2	6946.2	6946.2	6946.2	6696.9
1978	93.9	1	.01	90.9	12.8	6648.7	6648.7	6648.7	5855.5
1988	87.8	6	.08	144.8	20.4	6221.0	6221.0	6206.8	4858.4
1998	83.0	15	.21	153.2	21.6	391.7	5875.4	5813.0	4507.1
2008	78.0	19	.27	156.5	22.1	290.9	5526.9	5410.8	4192.6
2018	72.5	21	.30	145.8	20.6	244.6	5136.0	5022.7	3923.5

year	ear	fr	dfr	prx	awsi	patc	dom	cont	fgl	fgi	fgc
1968	0.00	1.11	1.11	1.00	1.52	7.5	.60	3.6	.000	.036	.001
1978	2.38	1.26	1.26	1.00	2.79	14.6	.83	6.6	.000	.119	.008
1988	3.40	1.40	1.46	0.98	4.48	31.4	.89	10.2	.002	.219	.091
1998	3.36	1.42	1.48	0.94	4.59	34.2	.93	14.6	.011	.233	.140
2008	3.43	1.44	1.51	0.93	4.59	35.7	.92	19.4	.021	.241	.126
2018	3.44	1.43	1.49	0.93	4.37	31.7	.88	24.6	.022	.236	.093

Appendix II.4 (continued)

The two approaches produced different landscapes. Forest edge showed clear difference between the two landscapes. For example, at the year of 2018, edge density would be 28 meters per hectare for the staggered-setting landscape, but only 20 meters per hectare for the partial aggregation landscape. Many other physical variables also appeared to differentiate the two landscapes, but the differences may not be as profound. There were also clear differences in landscape indices, such as the patchiness index, fractal, area-weighted shape index and fragmentation index of the largest compact forest area. Those landscape indices not only reflected the differences in physical variables between the two approaches, but also characterized the change in spatial pattern of clearcut patches, which was really the most important difference between the two cutting schemes. The results supports the speculation that alternative landscape management strategies (e.g., aggregation of cut-units) may better meet requirements of management objectives because of alleviation of fragmentation effects by the alternatives.

Appendix III.1: Means and standard deviations of landscape indices calculated from 100 simulation replications.

Note that, for a given T, the first line is the means and the second the standard deviations. The abbreviations of index names are defined below:

T	Simulation time step
FR	Fractal dimension of total edge-area relation
DFR	Fractal dimension of double-log regression
PX	Proximity index
PT	Relative patchiness index
CT	Contagion index
DIS1	Dispersal index for interior species
DIS2	Dispersal index for edge species
FGL	Fragmentation index of the largest forest patch size
FGI	Fragmentation index of forest interior area
FGC	Fragmentation index of largest compacted forest area

Random Patch Model

T	FR	DFR	PT	CT	DIS1	DIS2	FGL	FGI	FGC
1	1.273	1.378	28.256	2.757	0.898	0.133	0.001	0.151	0.161
1	0.011	0.056	1.625	0.042	0.026	0.008	0.001	0.009	0.019
2	1.403	1.485	35.193	5.709	0.824	0.164	0.004	0.284	0.442
2	0.011	0.039	1.862	0.057	0.034	0.011	0.004	0.016	0.113
3	1.490	1.570	49.759	9.511	0.746	0.229	0.010	0.403	0.756
3	0.011	0.015	2.364	0.049	0.035	0.017	0.007	0.021	0.100
4	1.557	1.631	59.503	13.892	0.668	0.236	0.034	0.510	0.884
4	0.011	0.021	2.502	0.051	0.038	0.017	0.032	0.024	0.052
5	1.610	1.658	65.343	18.772	0.604	0.283	0.103	0.602	0.931
5	0.010	0.026	2.349	0.060	0.037	0.017	0.080	0.025	0.029
6	1.657	1.659	62.851	24.080	0.552	0.312	0.324	0.685	0.953
6	0.011	0.025	2.373	0.052	0.034	0.015	0.158	0.025	0.022
7	1.698	1.651	64.517	29.763	0.488	0.313	0.596	0.757	0.966
7	0.011	0.025	2.295	0.060	0.033	0.016	0.149	0.025	0.017
8	1.736	1.648	64.450	35.773	0.444	0.323	0.754	0.820	0.975
8	0.010	0.025	2.341	0.062	0.033	0.013	0.107	0.026	0.012
9	1.770	1.643	61.589	42.094	0.413	0.331	0.846	0.870	0.979
9	0.010	0.023	2.285	0.060	0.026	0.014	0.065	0.023	0.012
10	1.805	1.646	57.487	48.705	0.358	0.310	0.893	0.914	0.983
10	0.009	0.022	2.288	0.066	0.021	0.013	0.042	0.018	0.008

Appendix III.1 (continued)

Minimum Fragmentation Model

T	FR	DFR	PT	CT	DIS1	DIS2	FGL	FGI	FGC
1	1.232	1.294	19.293	2.991	0.829	0.117	0.003	0.102	0.145
1	0.010	0.052	1.169	0.040	0.054	0.013	0.004	0.014	0.034
2	1.300	1.333	18.482	6.166	0.755	0.140	0.040	0.128	0.162
2	0.023	0.056	2.933	0.078	0.062	0.017	0.026	0.024	0.053
3	1.363	1.386	27.450	10.119	0.690	0.181	0.058	0.184	0.296
3	0.050	0.073	6.075	0.137	0.070	0.030	0.050	0.049	0.175
4	1.431	1.442	33.478	14.627	0.611	0.185	0.119	0.237	0.413
4	0.031	0.049	4.488	0.177	0.066	0.018	0.107	0.045	0.162
5	1.480	1.472	37.720	19.557	0.563	0.217	0.174	0.295	0.488
5	0.043	0.069	7.092	0.163	0.072	0.029	0.121	0.069	0.155
6	1.530	1.498	38.983	24.886	0.490	0.248	0.272	0.359	0.550
6	0.045	0.062	5.747	0.199	0.059	0.030	0.147	0.068	0.119
7	1.575	1.516	41.153	30.550	0.423	0.242	0.352	0.419	0.606
7	0.043	0.064	6.691	0.206	0.052	0.024	0.135	0.095	0.138
8	1.621	1.543	43.566	36.527	0.386	0.260	0.423	0.499	0.708
8	0.057	0.073	7.787	0.215	0.051	0.030	0.148	0.125	0.165
9	1.672	1.571	43.074	42.792	0.347	0.270	0.504	0.578	0.801
9	0.056	0.065	6.164	0.239	0.040	0.027	0.152	0.104	0.137
10	1.709	1.577	39.435	49.338	0.282	0.249	0.550	0.600	0.834
10	0.033	0.034	3.082	0.207	0.029	0.019	0.117	0.060	0.075

Progressive Cutting Model

T	FR	DFR	PT	CT	DIS1	DIS2	FGL	FGI	FGC
1	1.027	1.052	3.377	3.449	0.960	0.099	0.000	0.018	0.004
1	0.012	0.024	0.511	0.023	0.022	0.001	0.000	0.003	0.003
2	1.041	1.078	4.011	6.914	0.885	0.106	0.000	0.028	0.006
2	0.020	0.037	0.512	0.037	0.058	0.005	0.000	0.004	0.005
3	1.043	1.081	4.534	11.129	0.825	0.121	0.000	0.034	0.006
3	0.027	0.048	0.652	0.041	0.079	0.011	0.000	0.006	0.006
4	1.050	1.094	5.242	15.862	0.725	0.127	0.000	0.041	0.006
4	0.032	0.057	0.854	0.054	0.108	0.016	0.000	0.007	0.008
5	1.054	1.097	5.372	21.015	0.626	0.137	0.000	0.047	0.006
5	0.036	0.068	0.779	0.060	0.114	0.017	0.001	0.008	0.010
6	1.064	1.111	5.693	26.502	0.524	0.157	0.000	0.054	0.008
6	0.044	0.085	0.868	0.068	0.110	0.020	0.001	0.011	0.015
7	1.070	1.105	5.789	32.287	0.436	0.159	0.001	0.063	0.009
7	0.051	0.130	0.999	0.077	0.093	0.020	0.004	0.015	0.016
8	1.076	1.135	5.950	38.335	0.346	0.171	0.000	0.072	0.009
8	0.061	0.101	1.388	0.086	0.067	0.014	0.000	0.020	0.020
9	1.086	1.152	5.694	44.618	0.311	0.174	0.000	0.085	0.011
9	0.067	0.108	1.260	0.086	0.062	0.016	0.000	0.026	0.027
10	1.093	1.147	5.526	51.117	0.257	0.167	0.003	0.099	0.017
10	0.066	0.134	1.224	0.078	0.039	0.014	0.026	0.028	0.049

Appendix III.2: Correlation analysis on landscape indices

A correlation analysis of some landscape indices was done for the random patch and partial aggregation models. In the correlation matrices below, the first line for a variable was the value of the correlation coefficient, and the second line was the significance level. However, the existence of autocorrelation among data points (i.e., time-series type of data) violates the independence assumption of correlation analysis. The correlation among landscape indices may still exist, but the correlation coefficients could change. The variables in the correlation matrices stand for the following landscape indices:

PT	patchiness index
D2	contagion index
RC	relative contagion index
FR	fractal of total forest area and edge
EDIS	dispersal index of edge species
PX	proximity index
FGL	fragmentation index of largest patch size
FGI	fragmentation index of forest interior area

A Correlation Matrix of Landscape Indices:
The Random Patch Model

	PT	D2	RC	FR	EDIS	PX	FGL	FGI
PT	1.000	.875	-.976	.971	.977	-.802	.962	.766
	.000	.001	.000	.000	.000	.005	.000	.010
D2	.878	1.000	-.883	.953	.869	-.966	.972	.965
	.001	.000	.001	.000	.001	.000	.000	.000
RC	-.976	-.883	1.000	-.983	-.962	.802	-.964	-.773
	.000	.001	.000	.000	.000	.005	.000	.009
FR	.971	.953	-.983	1.000	.961	-.889	.996	.868
	.000	.000	.000	.000	.000	.001	.000	.001
EDIS	.977	.869	-.962	.961	1.000	-.820	.954	.779
	.000	.001	.000	.000	.000	.004	.000	.008
PX	-.802	-.966	.802	-.889	-.820	1.000	-.921	-.995
	.005	.000	.005	.001	.004	.000	.000	.000
FGL	.962	.972	-.964	.996	.954	-.921	1.000	.901
	.000	.000	.000	.000	.000	.000	.000	.000
FGI	.766	.965	-.773	.868	.779	-.995	.901	1.000
	.010	.000	.009	.001	.008	.000	.000	.000

Appendix III.2 (continued)

A Correlation Matrix of Landscape Indices:
The Partial Aggregation Model

	PT	D2	RC	FR	EDIS	PX	FGL	FGI
PT	1.000	.883	-.943	.970	.977	-.918	.942	.891
	.000	.001	.000	.000	.000	.000	.000	.001
D2	.883	1.000	-.874	.966	.875	-.948	.981	.959
	.001	.000	.001	.000	.001	.000	.000	.000
RC	-.943	-.874	1.000	-.948	-.944	.863	-.897	-.840
	.000	.001	.000	.000	.000	.001	.000	.002
FR	.970	.966	-.948	1.000	.959	-.964	.990	.954
	.000	.000	.000	.000	.000	.000	.000	.000
EDIS	.977	.875	-.944	.959	1.000	-.915	.936	.889
	.000	.001	.000	.000	.000	.000	.000	.001
PX	-.918	-.948	.863	-.964	-.915	1.000	-.980	-.997
	.000	.000	.001	.000	.000	.000	.000	.000
FGL	.942	.981	-.897	.990	.936	-.980	1.000	.978
	.000	.000	.000	.000	.000	.000	.000	.000
FGI	.891	.959	-.840	.954	.889	-.997	.978	1.000
	.001	.000	.002	.000	.001	.000	.000	.000