COMPARING PATCH- AND SURFACE-BASED METRICS OF PATCHINESS AND ABRUPTNESS ON SIMULATED ECOTONES

By

Mark Allen Bowersox

A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

MASTER OF ARTS

Department of Geography

1999

ABSTRACT

Comparing patch- and surface-based metrics of patchiness and abruptness on simulated ecotones

By

Mark Allen Bowersox

The use of landscape metrics to infer ecological process at alpine treeline requires knowledge of metric sensitivity to specific ecotone characteristics. In this study, a set of patch-based metrics was compared with a set of surface-based metrics to assess their suitability as patchiness and/or abruptness quantifiers of simulated ecotone landscapes. A simulation produced 25 groups of ecotones that vary systematically in their degree of patchiness and abruptness. Factorial ANOVA was used to evaluate metric sensitivity to the known differences among the simulated groups. Indices of metric suitability based on the ANOVA results were developed and used to rank the metrics in order of their suitability. Metrics from each set were suitable as patchiness and abruptness quantifiers, but the patch-based metrics were on average more suitable for both characteristics than the surface-based metrics. Both sets of metrics were more consistent as abruptness metrics than they were as patchiness metrics. Specific recommendations of which metrics to use for patchiness and abruptness were made. The results of this research are meaningful to applications dealing with ecotones that rely on the interpretation of patch- or surface-based metrics.

To my parents, Thomas and Karen Bowersox

ACKNOWLEDGMENTS

First and foremost, I would like to thank Dr. Daniel Brown for helping me develop the topic of this research and for providing continual oversight and support through its completion. I am glad I had the opportunity to work with him. In the summer of 1999 Dr. Brown accepted a position in the School of Natural Resources and Environment at the University of Michigan. Upon his move, Dr. Judy Olson took over as the chair of my committee but Dr. Brown remained my primary advisor. I wish to thank Dr. Olson for being so accommodating, for her constant willingness to brainstorm ideas, and for her guidance in general. Dr. Randall Schaetzl provided a helpful review of my thesis, but more importantly I would like to thank him for his honest criticism and encouraging praise. Thank you to Geoffrey Jacquez and Susan Maruca of BioMedware for the use of their GEM software and their suggestions on my methodology. My sincere appreciation goes to my lab mates Scott Drzyzga, Geoffrey Duh, and Brad Shellito for taking the time to assist me with my day-to-day problems no matter how busy they were. In addition to those mentioned above, I would also like to recognize Julie Colby, Paul Rindfleisch, Colleen Garrity and Yushuang Zhou for their support as friends and colleagues. I am grateful to my friend Seamus Mooney for providing me with a place to stay and work. Last but by no means least, I wish to thank Courtney Abeln for being my inspiration and for her ever-present consolation and patience.

TABLE OF CONTENTS

LIST OF TABLES VII

LIST OF FIGURES IX

LIST OF ABBREVIATIONS XI

INTRODUCTION 1
- Alpine treeline ecotones 1
- Patch-based metrics 3
- Surface-based metrics 6
- Objectives and Research Questions 9

METHODOLOGY 11
- Simulation 11
- Calculating patch-based metrics 23
- Calculating surface-based metrics 26
  - Choosing threshold values 28
  - Subgraph statistics and hypothesized function 29
  - Cumulative boundary elements 32
- Data summary 34
- Analysis of Variance 36
  - Main effects 38
  - Interaction Effects 38
  - Simple effects 40
  - Metric suitability ranking 43

RESULTS 45
- Patch-based metric ANOVA results 45
  - Patch-based metrics ranked by simple effects 52
  - Patch-based metric suitability ranking 54
- Surface-based metrics ANOVA results 56
  - Subgraph statistics 56
  - Cumulative boundary elements 70
  - Surface-based metrics ranked by simple effects 72
  - Surface-based suitability ranking 75
- Patch-based suitability vs. Surface-based suitability 77

DISCUSSION AND CONCLUSIONS 81
- Research Questions Revisited 81
- Considerations 87
- Summary 89

APPENDIX A 91
- Bonferroni Comparisons for patch-based metrics 91

APPENDIX B 100
Bonferroni comparisons for surface-based metrics 100

APPENDIX C 109
Bonferroni Comparisons for the CBE metric 109

APPENDIX D 112
Source Code 112
Simdeterm.c 112
Matrix.aml 115
Gemit.aml 118
Connect2.c 122
Dispersion.c 129

BIBLIOGRAPHY 135

LIST OF TABLES

TABLE 1. MATRIX OF SIMULATION GROUPS. 16

TABLE 2. DESCRIPTIVE STATISTICS AND MORAN'S I SPATIAL AUTOCORRELATION COEFFICIENT FOR THE SIMULATED ECOTONES, SUMMARIZED BY ECOTONE GROUP 20

TABLE 3. PATCH-BASED METRICS AND HYPOTHESIZED FUNCTION. ADAPTED FROM MCGARIAGAL AND MARKS (1993). 24

TABLE 4. SUBGRAPH STATISTICS AND HYPOTHESIZED FUNCTION. 31

TABLE 5. MAIN AND INTERACTION EFFECTS FOR FACTORIAL ANOVA ON PATCH-BASED METRICS. 46

TABLE 6. SIMPLE EFFECTS RESULTS FOR ANOVA ON PATCH-BASED METRICS. MAXIMUM OMEGA SQUARED VALUES ARE IN BOLD, MINIMUM ARE UNDERLINED. AN "NS" INDICATES AN ANOVA THAT WAS NOT SIGNIFICANT. 47

TABLE 7. PATCH-BASED METRICS RANKED BY SINGLE-FACTOR OMEGA SQUARED VALUES. 53

TABLE 8. PATCH-BASED METRICS RANKED BY PATCHINESS AND ABRUPTNESS SUITABILITY SCORES. 55

TABLE 9. MAIN AND INTERACTION EFFECTS RESULTS FOR ANOVA ON LEVEL 1 SUBGRAPH STATISTICS. SIGNIFICANCE IS FOR $\alpha = 0.01$. A "NS" INDICATES THAT THE VARIATION IN THE SOURCE WAS NOT SIGNIFICANT DIFFERENT. 60

TABLE 10. MAIN AND INTERACTION EFFECTS RESULTS FOR ANOVA ON LEVEL 9 SUBGRAPH STATISTICS. SIGNIFICANCE IS FOR $\alpha = 0.01$. A "NS" INDICATES THAT THE VARIATION IN THE SOURCE WAS NOT SIGNIFICANT DIFFERENT. 64

TABLE 11. OMEGA SQUARED VALUES FOR EACH SINGLE-FACTOR ANOVA FOR EACH SUBGRAPH STATISTIC. MAXIMUM OMEGA SQUARED VALUES ARE IN BOLD, MINIMUM ARE UNDERLINED. AN "NS" INDICATES AN ANOVA THAT WAS NOT SIGNIFICANT. 65

TABLE 12. MAIN AND INTERACTION EFFECTS FOR ANOVA ON THE CUMULATIVE BOUNDARY ELEMENTS METRIC. AN "NS" INDICATES THAT THE VARIATION IN THE SOURCE WAS NOT SIGNIFICANT DIFFERENT. 71

TABLE 13. SIMPLE EFFECTS RESULTS FOR ANOVA ON THE CUMULATIVE BOUNDARY ELEMENTS METRIC. THE MAXIMUM OMEGA SQUARED VALUE IS IN BOLD; THE MINIMUM IS UNDERLINED. AN "NS" INDICATES AN ANOVA THAT WAS NOT SIGNIFICANT 71

TABLE 14. SURFACE-BASED METRICS RANKED BY SINGLE-FACTOR OMEGA SQUARED VALUES 74

TABLE 15. SURFACE-BASED METRICS RANKED BY PATCHINESS AND ABRUPTNESS SUITABILITY SCORES. 76

TABLE 16. PATCH- AND SURFACE-BASED METRICS RANKED ACCORDING TO PATCHINESS SUITABILITY SCORES. PATCH-BASED METRICS ARE UNDERLINED. 78

TABLE 17. PATCH- AND SURFACE-BASED METRICS RANKED ACCORDING TO ABRUPTNESS SUITABILITY SCORES. PATCH-BASED METRICS ARE UNDERLINED. 79

LIST OF FIGURES

FIGURE 1. FIVE DETERMINISTIC SURFACES USED TO SIMULATE ABRUPTNESS. CONTROL OVER THE ABRUPTNESS OF EACH SURFACE WAS ACCOMPLISHED BY ALTERING THE SLOPE PARAMETER OF THE FUNCTION THE SURFACES WERE MODELED AFTER. THE BRIGHTNESS OF THE SURFACE SHADING REPRESENTS THE STRENGTH OF TREE PRESENCE. 14

FIGURE 2. FIVE PERTURBATION SURFACES USED TO SIMULATE PATCHINESS. PATCHINESS WAS CONTROLLED BY ALTERING THE DEGREE OF SMOOTHING TO WHICH EACH PERTURBATION SURFACE WAS SUBJECTED. THE BRIGHTNESS OF THE SURFACE SHADING REPRESENTS THE STRENGTH OF TREE PRESENCE 15

FIGURE 3. AN EXAMPLE OF THE SIMULATED ECOTONE SURFACES FROM EACH OF THE 25 GROUPS. EACH SURFACE IS THE RESULT OF ADDING A PERTURBATION SURFACE OF A GIVEN PATCHINESS LEVEL TO A DETERMINISTIC SURFACE OF A GIVEN ABRUPTNESS LEVEL. THE BRIGHTNESS OF THE SURFACE SHADING REPRESENTS THE STRENGTH OF TREE PRESENCE. 18

FIGURE 4. AN EXAMPLE OF THE SIMULATED ECOTONE SURFACES THAT HAVE BEEN CLASSIFIED INTO TREE PRESENCE/ABSENCE FROM EACH OF THE 25 GROUPS. BLACK REPRESENTS TREE PRESENCE, WHITE REPRESENTS TREE ABSENCE (I.E., TUNDRA SPECIES, ROCK, AND BARE SOIL). 19

FIGURE 5. MEAN MORAN'S I SPATIAL AUTOCORRELATION COEFFICIENT FOR EACH GROUP OF SIMULATED ECOTONE SURFACES. THE VARIATION IN SPATIAL AUTOCORRELATION BETWEEN GROUPS WAS USED AS EVIDENCE THAT THE SIMULATION PRODUCED ECOTONE SURFACES THAT WERE DIFFERENT WITH REGARD TO SPATIAL PATTERN. 22

FIGURE 6. DEPICTION OF THE CUMULATIVE BOUNDARY ELEMENTS METRIC FOR AN ECOTONE OF LOW ABRUPTNESS VS. AN ECOTONE OF HIGH ABRUPTNESS. THE CHART IN THE CENTER ILLUSTRATES THE DIFFERENCE IN THE BOUNDARY ELEMENT RESPONSE CURVES OF THE TWO ECOTONES. MAPS OF THE BOUNDARY ELEMENTS FOR EACH ECOTONE AT 20 ROC SLICE LEVELS ARE SHOWN ABOVE AND BELOW THE CHART. BOUNDARY ELEMENTS ARE SHOWN IN BLACK. 35

FIGURE 7. MEAN COEFFICIENT OF VARIATION OF THE 8 SUBGRAPH STATISTICS BY ROC SLICE LEVEL. THE COEFFICIENT OF VARIATION

SUMMARIZED THE POTENTIAL AMOUNT OF INFORMATION AVAILABLE THAT COULD BE USED TO DISTINGUISH DIFFERENCES AMONG THE 1250 ECOTONES. 57

FIGURE 8. AN EXAMPLE FROM EACH OF THE 25 GROUPS OF THE SUBGRAPH MAPS CREATED FROM THE LATTICE DELINEATION THAT USED SLICE LEVEL 1 AS THE GRADIENT THRESHOLD. AREAS OF HOMOGENEOUS COLOR REPRESENT INDIVIDUAL SUBGRAPHS OR SINGLETONS. 58

FIGURE 9. AN EXAMPLE FROM EACH OF THE 25 GROUPS OF THE SUBGRAPH MAPS CREATED FROM THE LATTICE DELINEATION THAT USED SLICE LEVEL 9 AS THE GRADIENT THRESHOLD. AREAS OF HOMOGENEOUS COLOR REPRESENT INDIVIDUAL SUBGRAPHS OR SINGLETONS. 59

LIST OF ABBREVIATIONS

Simulation

p	patchiness
a	abruptness
t	type (of alpine treeline ecotone; defined by levels of a and p)

Patch-based metrics

AWMPFD	area-weighted mean patch fractal dimension
AWMSI	area-weighted mean shape index
CONTAG	contagion
LPI	largest patch index
MPS	mean patch size
NP	number of patches
PSCV	patch size coefficient of variation
TE	total edge

Surface-based metrics

BEs	number of boundary elements
Disp	subgraph dispersion
L_{max}	maximum subgraph length
L_{mean}	mean subgraph length
L_{min}	minimum subgraph length
L_{stdv}	standard deviation of subgraph length
N	number of subgraphs
NS	number of singletons
CBE	cumulative boundary elements

Suitability score

S_{ME}	main effect sensitivity
S_{SE}	simple effects sensitivity
C_E	external consistency
C_I	internal consistency

Miscellaneous

NDVI	normalized difference vegetation index
LAI	leaf area index
GNP	Glacier National Park
TM	Thematic Mapper
ROC	rate of change

INTRODUCTION

Ecotones are zones of transition between adjacent ecological systems. They have a set of characteristics uniquely defined by space and time scales and by the strength of the interactions between adjacent ecological systems (Holland, 1988). Conceptual consideration of ecotones began in the 1930's. However, it was not until the 1970's that ecotones became recognized as dynamic landscape entities that deserve separate attention (Risser, 1995). Ecotones under the above definition include what are referred to as edges (Orloci and Orloci, 1990), transitional areas (Kent et al., 1997) and boundaries (Wiens et al., 1985) but unlike definitions of these three terms, the definition of an ecotone does not specify that the transition must be distinct. An ecotone may be distinct or less obvious and may be highly heterogeneous or less heterogeneous depending on the ecological processes acting on it.

Alpine treeline ecotones

The alpine treeline ecotone occurs along an increasingly stressful altitudinal gradient and forms the zone of transition between lower-elevation sub-alpine forest and high-elevation alpine tundra. There is a threshold within this ecotone above which the potential for tree species establishment and growth is zero (Armand, 1985). As the threshold is approached, tree species' growth form and patterns of occurrence begin to change. Generally, the stature and abundance of trees decreases as altitude and environmental stress increases. At treeline, krummholz, shrub-like formations of tree species, become more conspicuous and occupy the less environmentally stressful sites often creating a patchy landscape. Other components of alpine treeline such as tundra species, rock, and bare soil are found adjacent to krummholz patches in the matrix of the alpine treeline landscape.

Variation in the spatial arrangement or pattern of the ecotone components presumably occurs because of differences in ecological processes acting upon them. In order to decipher which spatial patterns are representative of specific ecological processes, reliable data on spatial pattern must first be collected.

This research focuses on the measurement of two characteristics of spatial pattern thought to be representative of specific ecological processes at treeline: patchiness and abruptness. The impetus for this investigation came from the early stages of research conducted by Malanson and Brown (1997) at alpine treeline in Glacier National Park, MT. They required a suitable methodology to measure ecotone patchiness and abruptness in order to establish a link between spatial pattern and ecological process. The goal here is to investigate two methodologies and determine which is the most suitable for quantifying ecotone patchiness and abruptness.

Ecotone *patchiness* is defined as spatial heterogeneity or unconformity; an ecotone is patchy when neighboring areas are frequently dissimilar. Processes that may be responsible for creating patchy patterns include natural and human disturbance (Krummel et al., 1987) and differential species establishment due to an uneven distribution of nutrient-rich sites (Stevens and Fox, 1991) or seed rain (Malanson, 1997).

Abruptness is a measure of the rate at which one ecological system changes to another across the ecotone; abrupt alpine treeline ecotones change rapidly from trees to alpine tundra while gradual ecotones are characterized by slower transitions. Abrupt ecotones that occur along a gradual environmental gradient suggest the presence ecological processes such as species competition (Armand, 1992; Malanson and Butler, 1994), and positive feedback mechanisms (Wilson and Agnew 1992; Malanson, 1997). These processes prohibit the species at treeline from exhibiting change consistent with the change in environmental gradient.

Landscape ecology and the use of landscape metrics provides the methods necessary to develop the link between pattern and process (Turner, 1989; Forman and Godron, 1986). The approaches to developing metrics that describe landscape pattern have been divided into two categories; a categorical or *patch-based* approach and a spatially continuous or *surface-based* approach (Gustafson, 1998). This research evaluates each approach with the goal of selecting the most suitable metrics for quantifying patchiness and abruptness.

Patch-based metrics

The patch-based approach typically involves classifying satellite imagery or aerial photography to produce a map in which similar types of ecological communities or vegetation types are grouped together. These groups, referred to as classes, are represented within a raster map as contiguous clusters of cells called patches. After classification, patches are considered internally homogeneous and the boundary between patches of different classes is a distinct one. Patches from similar and different classes agglomerate over an area to form a landscape (Forman and Godron, 1986). The programs SPAN (Turner, 1990), r. le (Baker and Cai, 1992) and FRAGSTATS (McGariagal and Marks, 1993), which are compatible with geographic information systems, generate a variety of patch-based metrics that mathematically define the spatial pattern of a landscape. Patch-based metrics quantify patch density, size, shape and variability, landscape edge, core area, landscape diversity, contagion and interspersion (McGariagal and Marks, 1993). Several of these metrics are reviewed by Haines-Young and Chopping (1996) for application to forested landscapes.

Baker and Weisberg (1995), in Rocky Mountain National Park, CO and Allen and Walsh (1996), in Glacier National Park, MT applied the patch-based approach to quantify landscape pattern at alpine treeline. Both were able to discern 6 unique types of alpine treeline ecotone using cluster analysis of patch-based metric data. Patch-based metrics measuring the number of patches, patch interspersion, patch richness, and edge density were used by both studies. Baker and Weisberg (1995) also included an evenness of patch types metric and several variables describing relative amounts of different land cover types in each ecotone. Unlike Baker and Weisberg (1995), Allen and Walsh (1996) used mean landscape fractal dimension as a metric of landscape complexity. Fractal dimension quantifies the departure of a shape from Euclidean geometry or, in other words, how well a shape fills a plane (Haines-Young and Chopping, 1996).

Differences in the classification scheme used by each study make the comparison of ecotone types between studies difficult. However, the studies did find similar ecotone types. Of particular interest here is that each study found ecotone types that were best described according to their patchiness and abruptness characteristics. Baker and Weisberg (1995) found ecotones that were "long" and "short" with variable amounts of patchiness, while Allen and Walsh (1996) separated patchiness and abruptness into ecotone types that were labeled "heterogeneous" or "highly heterogeneous" and "moderately zonal" or "zonal", respectively. Results from Allen and Walsh suggest that ecotones were characterized by a certain degree of patchiness or a certain degree of abruptness, but not both. On the other hand, Baker and Weisberg suggest that patchiness and abruptness (length of ecotone) were not independent characteristics of ecotone pattern. This difference between the two studies might be attributed to regional differences in treeline at the two study areas; or it could have been a result of misinterpretation due to a lack of information concerning patch-based metric behavior in response to combinations of ecotone patchiness and abruptness.

A patch-based approach may not be the most appropriate one when attempting to quantify ecologically meaningful characteristics of ecotones. The central problem lies with the classification process necessary to compute patch-based metrics. Classification reduces the amount of information available by transforming continuous, locally variable, data into discrete classes. The patch-based approach represents an ecotone as the boundary line between adjacent patches, which is a line of zero thickness. This is particularly troublesome because even though most ecotones occur along a continuum they are represented as discrete elements resulting from a method of classification that is based on arbitrary ecological differences (Wood and Foody, 1989; Brown, 1998). At best, only the length of ecotone and the classes that it separates can be directly quantified. The patch-based approach does not allow ecotone width or ecological contrast to be calculated because this information is lost to classification (Johnston and Bonde, 1989). Also important, there is no way to represent a gradual transition between neighboring patches; all transitions between patches are represented as abrupt.

Surface-based metrics

The surface-based approach attempts to avoid the classification step and instead calculates metrics directly on a variable derived from satellite imagery, aerial photography, or other continuous field sampling approach. It is called a surface-based approach because the metrics are calculated from the distribution of a continuous variable over a two-dimensional area. Surfaces possess the mathematical property of continuity and have only one value at any point. Surfaces of ecologically relevant variables are frequently generated from satellite imagery; examples include percent vegetative cover, the Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI). The ecological surface is represented as a regularized grid where each cell of the grid contains a unique data value. In essence, the regularized grid is only an approximation of the real ecological surface.

There are several surface-based methods available to extract information on landscape pattern. Legendre and Fortin (1989) provide a thorough review of methods employing spatial autocorrelation coefficients, correlograms, variograms, spectral analysis, and the Mantel test to measure spatial pattern. Kent et al. (1997) reviews similar methods with respect to ecotone analysis.

Among the several surface-based methods available, one group focuses directly on transitional areas and relies on the concepts of edge detection. The goal of edge detection is to locate discontinuities along transects (Ludwig and Cornelius, 1987) or within two-dimensional maps (Johnston et al., 1992) using algorithms that accentuate areas with high rates of change within a given variable or set of variables mapped over the landscape. Once detected, spatially contiguous locations with high rates of change are referred to as edges or boundaries. The location, width, shape, or distribution of these edges can be used to characterize the transition.

One method of boundary detection within two-dimensional ecological data was proposed by Womble (1951) and has since been rejuvenated by Barbujani et al. (1989), Fortin (1994), and Jacquez and Maruca (1998). The method is commonly called either Wombling or lattice delineation. The method first computes a rate of change value for every point on a regularized surface (lattice). The top *k* percent of the rate of change locations are then selected from the rate of change surface, where *k* is an arbitrary threshold set by the researcher. The top *k* percent of rate of change locations are called *boundary elements*. Boundary elements are connected to one another based on an aspect threshold, also set by the researcher, to form *subgraphs*. Subgraphs represent locations where the rate of change is high and the direction of change is similar. The number of subgraphs and *singletons* (singletons consist of only one boundary element), as well as subgraph length and diameter statistics are calculated and used to measure the cohesiveness of the detected boundary.

The use of the subgraph statistics as a surface-based approach has typically focused on delineating contiguous boundaries that are statistically significant. Lattice delineation will always find locations whose rate of change is higher than others which make significance tests necessary to determine if the boundaries would occur on the basis of chance alone (Fortin, 1994). Subgraph statistics were developed specifically to determine whether the boundaries detected in the collected data differed significantly from null models based on spatial randomness (Oden et al., 1993). While the subgraph statistics have been found to be effective in determining the significance of detected boundaries (Fortin 1994; Fortin and Drapeau, 1995), less is known about how the subgraph statistics can be used to quantify specific boundary or landscape pattern. For instance, a small number of long subgraphs may indicate that an ecotone is abrupt, while a large number of shorter subgraphs may indicate the ecotone is more gradual. The subgraph statistics may also prove to be good indicators of ecotone patchiness. For example, a large number of singletons would indicate that the boundaries are not contiguous which may indicate ecotone patchiness.

One concern with the lattice delineation approach is the arbitrary nature of the rate of change threshold. Researchers have commonly used a threshold of the top 5 or 10% of the rate of change values; however this may not be optimal for all applications. A method that uses the lattice delineation approach to obtain subgraph statistics at multiple threshold levels may avoid the effects due to an ad-hoc analysis at one threshold level. For example, information on how the statistics change from one threshold level to another could constitute a unique metric. One such metric, called cumulative boundary elements, is developed and presented here. The cumulative boundary elements metric was conceived to measure ecotone abruptness alone, but it may measure patchiness as well, in which case it will not be a good abruptness quantifier because its value could indicate "patchy", "abrupt", or both.

Objectives and Research Questions

Applications of both patch- and surface-based metrics measuring the patchiness and abruptness of alpine treeline ecotones are affected by uncertainties. The goal of this research is to evaluate the two approaches in an experiment where patchiness and abruptness characteristics are controlled through a simulation of alpine treeline ecotones. This approach allows for an objective comparison between patch- and surface-based methodologies and should provide evidence of the information content and behavior of the metrics when applied to alpine treeline and ecotones in general. The experiment also allows for an examination of the interacting effects of patchiness and abruptness on each set of metrics.

A series of specific research questions was addressed involving the capability of the metrics to measure and distinguish differences in ecotone patchiness and abruptness:

- Do patch-based metrics only measure patchiness or are they capable of measuring abruptness? Which of the patch-based metrics are most suitable as patchiness metrics and which are most suitable as abruptness metrics?

- Are the surface-based metrics able to measure patchiness? Do the surface-based metrics measure abruptness? Which of the surface-based metrics are most suitable as patchiness metrics and which are most suitable as abruptness metrics?

- How does the degree of one ecotone characteristic affect the measurement of another? Is it possible to measure the degree of patchiness at multiple degrees of abruptness and visa versa? Is metric performance dependent on the level of patchiness or abruptness? For instance, does a patchiness metric lose its ability to measure patchiness as abruptness increases?

METHODOLOGY

The research was conducted in three phases. First, ecotone surfaces with known patchiness and abruptness characteristics were simulated, classified, and organized into a matrix structure that would later allow a factorial Analysis of Variance (ANOVA) experimental design to be used. In the second phase, patch- and surface-based pattern metrics were calculated on the simulated data. The third phase included ANOVA and the interpretation of planned comparisons between groups of simulated ecotones.

Simulation

The simulation was designed to produce values of a hypothetical continuous variable for each cell in a square grid that mimicked a real world study area containing an ecotone. Simulated data were used rather than real world data to control the patchiness and abruptness characteristics of each ecotone by systematically altering the parameters of the simulation. Real world data were less advantageous because the relative degree of patchiness or abruptness between samples would not be known prior to testing the metrics on them.

The first goal of the simulation was to create ecotone data similar to what would be obtained from a LANDSAT Thematic Mapper (TM) satellite image. Inspection of alpine treeline ecotones captured in a TM scene of Glacier National Park (GNP), MT provided a visual model for the simulations. A majority of the treelines examined in the TM image had transition lengths less than approximately 600m. Transition length was defined as the distance between closed canopy forest and open alpine tundra as measured along the profile of vegetation change. The extent of the areas used in the simulations was set at $630m^2$ to accommodate the maximum transition lengths observed in the image. The simulated data set used a cell size of 30m, which corresponds to the TM cell size. The area for each simulated ecotone was approximately 40 ha which was comparable to some of the smaller two-dimensional transects used by Baker and Weisberg (1995). The GNP TM scene was consistently referred to throughout the development of the simulation to assure at the very least that the simulated ecotones visually resembled real ecotones.

The second and foremost goal of the simulation was to provide control over the degree of patchiness and abruptness assigned to each ecotone. For simulation purposes, abruptness was defined as the rate at which the surface variable changed from its maximum to its minimum across the zone of transition. High variable values represented a strong presence of trees while low variable values represented a strong presence of tundra, bare soil or rock. Abruptness was controlled using a deterministic function in the form of an "s-shaped" curve where the slope term of the function was changed to produce variable levels of abruptness. The deterministic function used was:

$$y = \text{sign}(x) \cdot |x|^{(n)} \cdot 0.5$$

Where:
y = surface variable value
x = position along transition
n = slope parameter

This function was not chosen for any known ecological significance, but rather for its ability to model a smooth transition from low values of a variable to high. In a similar fashion, Churkina and Svirezhev (1995) and Timoney et al. (1993) used sigmoid functions to mathematically model ecotones; however, their work was done at the biome scale and not a local scale, as is the case here. Other sigmoid functions were explored for use in this study but none of them were able to model transitions of varying degrees over a constant x range while holding the y range constant. The function used here is capable of modeling transitions of variable abruptness without a change in the minimum and maximum y values.

Four deterministic functions with slope parameters of 1, 0.5, 0.25 and 0.0625 were extended into two-dimensional maps resulting in four deterministic surfaces varying in their degree of abruptness. This was accomplished by mapping the value of the function over the interval $x = -1$ to $x = 1$ at 0.1 unit increments to consecutive cells in each column of the two-dimensional map. Each of the four deterministic surfaces had a surface value range of -0.5 to 0.5. Lower magnitude slope terms produced surfaces where the transition from high to low variable values was less abrupt. In fact, using a slope term of 1 produces a planar transition. A fifth deterministic surface was created manually, so that the transition between -0.5 and 0.5 occurred between two cells, which created the most abrupt surface possible. In effect, it was the deterministic function with the slope parameter set to zero. All of the surfaces lacked plan curvature while profile curvature was dictated by the parameters of the deterministic function used. Perspective views of the five deterministic surfaces are shown in Figure 1.

1	2	3	4	5
low				high

Abruptness

Figure 1. Five deterministic surfaces used to simulate abruptness. Control over the abruptness of each surface was accomplished by altering the slope parameter of the function the surfaces were modeled after. The brightness of the surface shading represents the strength of tree presence.

Patchiness was introduced to the simulation by creating perturbation surfaces that were later added to the five deterministic surfaces. First, a surface containing normally distributed spatially random cell values was generated. The spatial randomness of the cell values produced a surface that lacked spatial autocorrelation. Positive spatial autocorrelation was then added by passing a square averaging filter over the random surface. Changing the neighborhood size of the filter effectively changed the amount of spatial autocorrelation added to the perturbations. Larger neighborhoods had a larger smoothing effect, which contributed more spatial autocorrelation. Perturbations with a high degree of spatial autocorrelation were considered less patchy. The perturbation surface without smoothing and the surfaces smoothed by neighborhoods of 2x2, 3x3, 4x4 and 5x5 cells represented five different levels of patchiness. To assure that patchiness was the only variant, the perturbation surface means and standard deviations were adjusted prior to smoothing so that they were approximately equal for all levels of patchiness after smoothing. The normally distributed spatially random surfaces were also adjusted so that cell values would range from –0.5 to 0.5 after smoothing. Examples of the perturbation surfaces for each of the five levels of patchiness are shown in Figure 2.

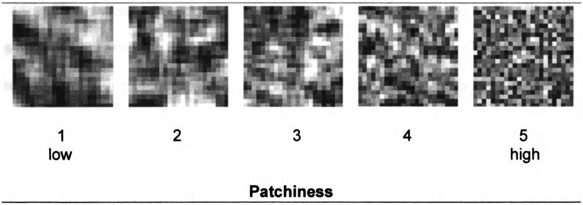


Figure 2. Five perturbation surfaces used to simulate patchiness. Patchiness was controlled by altering the degree of smoothing to which each perturbation surface was subjected. The brightness of the surface shading represents the strength of tree presence.

The final surface representation of a simulated ecotone was produced using simple map algebra. Each of the five perturbation surfaces was combined with each of the five deterministic surfaces by adding the value of each cell in the perturbation surface to the corresponding cell of the deterministic surface. In doing so, 25 unique simulated ecotone surfaces were created. Since both the perturbation and deterministic surfaces ranged from -0.5 to 0.5 the final simulated ecotone surfaces ranged from approximately -1 to 1.

All of the simulated ecotone surfaces were then transformed into binary representations of tree presence and absence to create the classified maps of alpine treeline ecotone. The classification was accomplished by mapping all surface variable values above the median surface value into a class of tree presence and all values below the median into a class of tree absence. This method assured that for each map approximately 50% of the ecotone was classified as trees and 50% as not trees.

The simulation produced 2 sets of maps, a surface set and a classified set, each representing 25 types, t_{ap}, of alpine treeline ecotones. The 25 types resulted from unique combinations of 5 levels of patchiness and 5 levels of abruptness. The simulated ecotone types are summarized in Table 1.

Table 1. Matrix of simulation groups.

		Abruptness				
		A_1	A_2	A_3	A_4	A_5
	P_1	t_{11}	t_{12}	t_{13}	t_{14}	t_{15}
	P_2	t_{21}	t_{22}	t_{23}	t_{24}	t_{25}
Patchiness	P_3	t_{31}	t_{32}	t_{33}	t_{34}	t_{35}
	P_4	t_{41}	t_{42}	t_{43}	t_{44}	t_{45}
	P_5	t_{51}	t_{52}	t_{53}	t_{54}	t_{55}

The subscript *p* denotes patchiness levels where increasing *p* corresponds to increasing patchiness and subscript *a* denotes increasing abruptness levels. For example, ecotones in t_{11} were the least patchy and least abrupt while ecotones in t_{55} were the most patchy and most abrupt. The simulation was repeated 50 times for each type (t_{ap}) in order to obtain replicates for statistical analysis. Accordingly, the 50 simulations produced 1250 randomized maps. For the remainder of this text, the 50 ecotones that were simulated to be of the same patchiness and abruptness level are said to belong to the same "group".

Figure 3 contains one example of a simulated ecotone surface from each of the 25 groups simulated. Figure 4 contains the classified maps derived from the same surfaces. Although each ecotone is just one example of the patterns created by the simulations, there are observable differences between types. Changes in the degree of abruptness are most noticeable among the lower levels of abruptness; abruptness levels 4 and 5 are not as separable. It appears that differences in the degree of patchiness are easier to distinguish at lower levels abruptness.

Table 2 contains descriptive statistics and Moran's I spatial autocorrelation coefficients for the simulated ecotones, summarized by ecotone group. As planned, the mean range and surface mean values were similar between groups and the group surface means were very close to zero. The group mean surface standard deviation was similar within abruptness groups and variable between abruptness groups. It was variable within patchiness groups. Adjusting the

Simulated Ecotone Surfaces

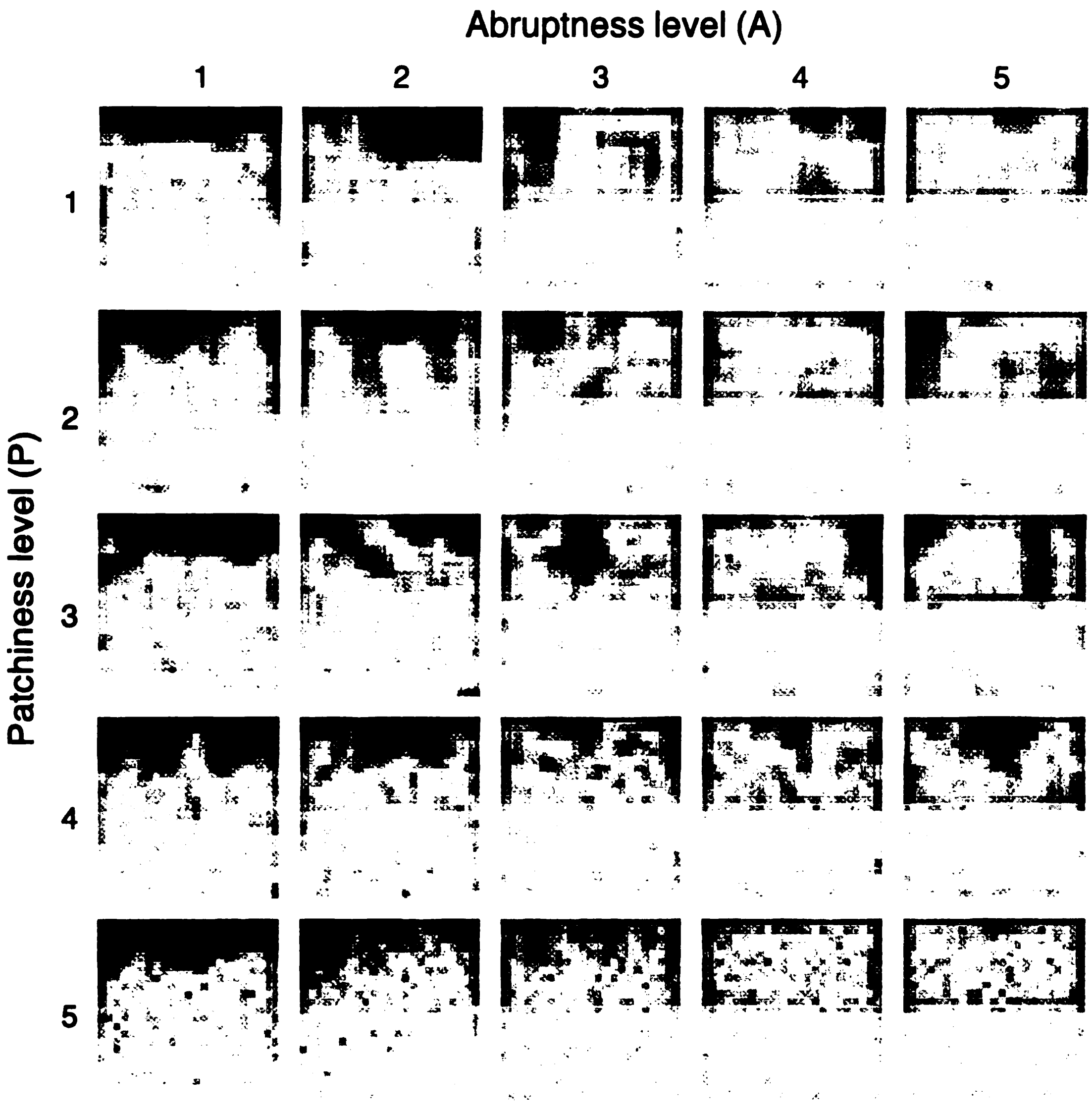


Figure 3. An example of the simulated ecotone surfaces from each of the 25 groups. Each surface is the result of adding a perturbation surface of a given patchiness level to a deterministic surface of a given abruptness level. The brightness of the surface shading represents the strength of tree presence.

Cla

Patchiness level (P)

Black

Note:

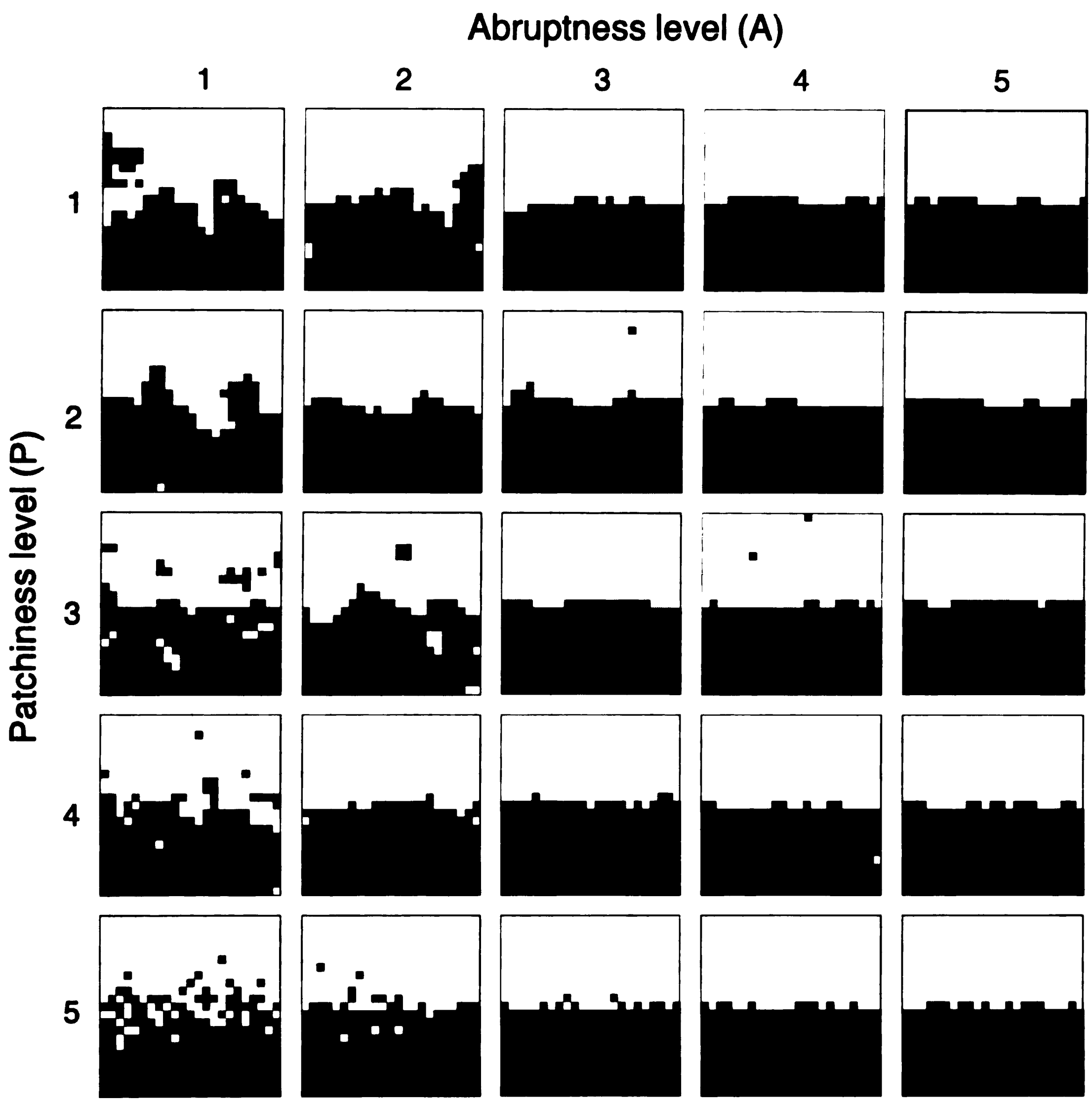
Figure

classified

represen

rock, and

Classified Simulated Ecotone Surfaces



Black = Tree presence White = tree absence

Note: The ecotone transition was simulated in the north-south direction.

Figure 4. An example of the simulated ecotone surfaces that have been classified into tree presence/absence from each of the 25 groups. Black represents tree presence, white represents tree absence (i.e., tundra species, rock, and bare soil).

Table 2. Descriptive statistics and Moran's I spatial autocorrelation coefficient for the simulated ecotones, summarized by ecotone group

		Range	Mean	Stdv	Moran's I
A_1	P_1	1.828	0.009	0.369	0.916
	P_2	1.777	0.001	0.369	0.916
	P_3	1.859	0.003	0.373	0.892
	P_4	1.816	0.000	0.365	0.877
	P_5	1.687	-0.001	0.361	0.811
A_2	P_1	1.848	0.002	0.419	0.942
	P_2	1.746	-0.004	0.408	0.938
	P_3	1.838	0.000	0.414	0.922
	P_4	1.774	0.001	0.406	0.907
	P_5	1.678	0.000	0.403	0.858
A_3	P_1	1.797	0.003	0.457	0.953
	P_2	1.787	0.000	0.449	0.949
	P_3	1.862	0.000	0.456	0.934
	P_4	1.781	-0.001	0.447	0.923
	P_5	1.713	0.001	0.444	0.881
A_4	P_1	1.886	-0.006	0.496	0.953
	P_2	1.827	-0.009	0.496	0.953
	P_3	1.929	-0.001	0.499	0.941
	P_4	1.848	0.000	0.493	0.933
	P_5	1.759	-0.003	0.490	0.898
A_5	P_1	1.851	0.004	0.518	0.956
	P_2	1.840	-0.002	0.516	0.955
	P_3	1.935	0.003	0.519	0.942
	P_4	1.878	0.003	0.511	0.935
	P_5	1.779	0.001	0.508	0.902

standard deviations of the perturbation surfaces during the simulation effectively minimized the difference in surface standard deviation between patchiness levels in the same abruptness group. However, the difference in surface standard deviation between abruptness groups was unavoidable. In order to create different degrees of abruptness for the same value range, the deterministic surfaces had to have variable standard deviations. As a result, the combination of deterministic surfaces with variable surface standard deviations with the perturbation surface with similar surface standard deviations produced ecotones whose surface standard deviation increases slightly with abruptness level. The simulation produced surfaces that were sufficiently similar in terms of the numerical distribution of surface values that any observable differences among surfaces from different groups should be attributable solely to the spatial pattern of surface values.

The Moran's I spatial autocorrelation coefficient was used as a preliminary measure of spatial pattern to make sure the groups displayed differences in spatial pattern before testing the metrics on them. Moran's I was first thought of as a baseline index of surface patchiness but it also seemed to be affected by differences in abruptness. Figure 5 graphically illustrates the relationship of Moran's I with patchiness and abruptness. As was expected, Moran's I decreased with increasing patchiness. Moran's I also decreased with increasing abruptness. At each level of abruptness, differences in Moran's I between patchiness levels 1 and 2 were small as were differences between abruptness levels 4 and 5 at each level of patchiness. The variability in Moran's I reveals that

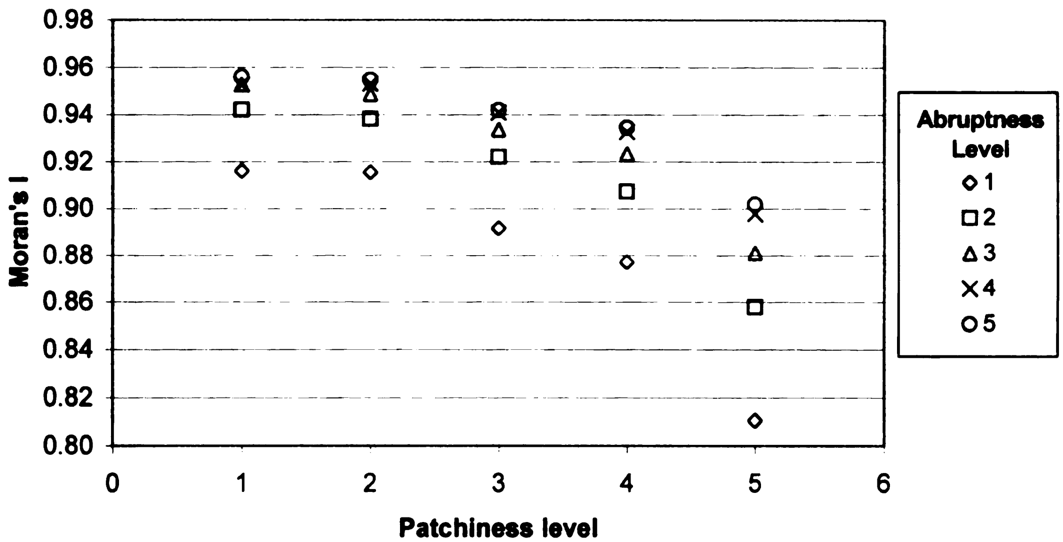


Figure 5. Mean Moran's I spatial autocorrelation coefficient for each group of simulated ecotone surfaces. The variation in spatial autocorrelation between groups was used as evidence that the simulation produced ecotone surfaces that were different with regard to spatial pattern.

there were differences in the spatial pattern among groups. However, the differences did not appear to be linear across all levels of patchiness or across all levels of abruptness (i.e., differences between level 1 and 2 were not the same as differences between levels 4 and 5). In fact, differences between patchiness levels increased with patchiness level while differences between abruptness levels decreased with abruptness level. This phenomenon is also apparent in the examples shown in Figures 3 and 4. Non-linearity in the simulated differences between patchiness and abruptness levels requires a careful interpretation of metric sensitivity. Since the differences between abruptness levels 4 and 5 are small, metrics capable of detecting the differences might be considered more sensitive to abruptness than metrics that could only distinguish differences between levels 3 and 4. The same applies to metric sensitivity to patchiness since the differences between patchiness levels 1 and 2 appear to be minute. The non-linearity in the simulation provides an additional test for the metrics. Metrics truly measuring patchiness or abruptness should produce difference magnitudes that are smallest between patchiness levels 1 and 2 and abruptness levels 4 and 5.

Calculating patch-based metrics

FRAGSTATS (McGariagal and Marks, 1993) was used to calculate the patch-based metrics used in the analysis. The program calculates metrics at the landscape, class, and patch levels of aggregation. Landscape level metrics quantify characteristics of the entire area of interest, class level metrics quantify characteristics of each class in the landscape, and patch metrics are generated for every patch of each class. Each of the classified ecotone maps was submitted to FRAGSTATS and all possible landscape, class, and patch metrics were calculated. Later, the patch and class level metrics were excluded and metrics for final analysis were chosen from the landscape level only.

Table 3 contains a list and brief description of the patch-based metrics evaluated. This particular set of metrics was selected because each was thought to have some utility for measuring either patchiness or abruptness. As a patch-based approach, all metrics calculated by FRAGSTATS relate to some degree to the patchiness or, as the name implies, fragmentation of the landscape. It might

Table 3. Patch-based metrics and hypothesized function. Adapted from McGariagal and Marks (1993).

Metric	Description	Hypothesized function
Area-weighted mean patch fractal dimension (AWMPFD)	Average fractal dimension over all patches weighted by area. Fractal dimension is a measure of the degree of complexity of planar shapes. A shape with a high fractal dimension is more plane filling than a shape with a low fractal dimension.	Patchiness and abruptness metric
Area-weighted mean shape index (AWMSI)	Average perimeter to area ratio for all patches weighted by area.	Patchiness and abruptness metric
Contagion (CONTAG)	Measures both patch interspersion (the intermixing of different patch types) and patch dispersion (the spatial distribution of a patch type). Low values of CONTAG are equated with a high degree of patch interspersion and/or dispersion.	Patchiness and Abruptness metric
Largest patch index (LPI)	Percentage of landscape area comprised by the largest patch.	Patchiness metric
Patch size coefficient of variation (PSCV)	Measures the relative variability of patch size about the mean patch size; variability as a percentage of the mean.	Patchiness metric
Mean patch size (MPS)	Average area of all patches in the ecotone.	Patchiness metric
Number of patches (NP)	A count of all patches in the ecotone.	Patchiness metric
Total Edge (TE)	Absolute measure of total edge between all patches.	Patchiness and Abruptness metric

be difficult to find patch-based metrics that exclusively measure patchiness or abruptness. Unfortunately, the suite of available patch-based metrics lacks a metric specifically designed to measure abruptness but surrogates may exist. Four of the metrics chosen for use, LPI, MPS, NP and PSCV, were designated as the primary patchiness metrics and were thought to have little utility for measuring abruptness. These metrics were suspected to be the best indicators of patchiness because they rely on the relationship between the number of patches determined by classification and the fixed size of the ecotone landscape. As patchiness increases, the number of patches (NP) should increase and mean patch size (MPS) along with the largest patch index (LPI) should decrease. PSCV should increase with patchiness as the chance for patches of a variety of sizes should also increase with the number of patches.

The remaining patch-based metrics, the area weighted shape metrics (AWMPFD and AWMSI), contagion (CONTAG) and total edge (TE), were expected to be equally useful for measuring patchiness and abruptness. Values of AWMPFD and AWMSI should decrease with abruptness. Patches in gradual ecotones should form more complex shapes because they are not confined by a steep gradient and are able to spread out on the landscape. As abruptness increases the complexity of patch shape should decrease as patches are confined to smaller areas of transition. As ecotone patchiness increases, the potential for patches to form convoluted shapes increases. Therefore, values of AWMPFD and AWMSI were expected to increase with increasing patchiness. Since CONTAG is supposed to measure the degree to which patches of different classes are intermixed, or patch interspersion, it should be sensitive to patchiness. Patch interspersion increases as patchiness increases especially when only two classes are present. CONTAG also measures patch dispersion, in other words, the degree to which patches of the same class are separated. Patch dispersion would be low for an abrupt ecotone because the zone of transition is short causing patches to be clumped together. Low values of CONTAG were expected as patchiness increased, while high values were expected as abruptness increased. Total Edge (TE) measures the length of the boundaries between all patches of different classes. TE was expected to increase with increasing patchiness and decrease with increasing abruptness. As patchiness increases, the number of patches increases and patch size will decrease leading to an increase in the amount of edge between patches. This is akin to the surface area of fine grain material being greater than that of a coarse grain material. TE was expected to decrease with increases in abruptness. An abrupt transition should form patches without complex shapes and therefore generally less edge.

Calculating surface-based metrics

Lattice delineation and the collection of subgraph statistics were performed using the capabilities of ARC/INFO geographic information system and two supplemental programs written in C. The work of Fortin (1994) and the alpha version of the program GEM: Geographic Boundary Analysis Software (Jacquez and Maruca, 1998), were used as a template for the ARC/INFO and C routines in this study. Although GEM is fully functional and adaptable to the file structure of the simulated ecotones, it was not used due to the lack of an efficient method for batch processing. To accommodate processing in ARC/INFO the methods used here differ slightly from those used in GEM and by others (Barbujani et al., 1989; Fortin, 1994).

Lattice delineation of each ecotone required that a rate-of-change surface be computed for all variables under investigation. Only one variable was investigated so only one rate-of-change surface was generated for each ecotone. A rate-of-change (ROC) or slope surface is a vector surface (as opposed to a scalar surface) consisting of two components: gradient and aspect (Chrisman, 1997). Gradient defines the magnitude of change while aspect equals the direction of change. Each of these components was used in the lattice delineation. All locations on the ROC surface with gradient values greater than a given threshold were selected (discussed in detail below). These locations, termed boundary elements, became candidates to form subgraphs, contiguous areas of high ROC. Subgraphs are formed through the application of a threshold on the aspect component of the boundary elements. The boundary elements whose aspects differed less than the threshold were connected to form subgraphs. This rule was imposed in order to prevent areas of rapid, unrelated variation from being classified as boundaries (Jacquez et al., 1999).

Choosing threshold values

When performing lattice delineation, threshold value selection is subjective. However, conventional values have been used. The rules most commonly used in lattice delineation result in the selection of the top 5 or 10% of gradient values as boundary elements (Barbujani et al., 1989; Fortin 1994; Fortin and Drapeau, 1995) and use 30 degrees as the aspect threshold for boundary element connection (Barbujani et al., 1989; Jacquez et al., 1998). Under these rules, the number of boundary elements selected is roughly equal to the threshold percentage (i.e., 5%) of the total number of ROC locations. The 30-degree aspect threshold was used here but a different approach to selecting boundary elements was chosen. Instead of selecting locations of high rate-of-change until an area threshold is met, each ROC surface was divided into 20 equal intervals based on the range of ROC values. Each interval could contain a different number of ROC locations, but the value of each ROC location was within the same range of ROC values. After forming the intervals, the ROC locations in each interval were combined to form "slices". A slice was produced by selecting all ROC locations whose value is greater than or equal to the lower limit of a specific interval. For example, the first slice would contain all locations whose ROC values were greater than or equal to the maximum ROC minus the range of ROC values divided by 20 (e.g., gradient $\text{threshold}_{\text{slice number}} = ROC_{max} - [\text{slice number} * (ROC_{range} * .05)]$). Subgraphs were formed for each of the 20 slices. This approach was taken in order to develop the cumulative boundary elements metric (discussed below) and to explore a less arbitrary approach to selecting a gradient threshold at which to calculate subgraph statistics.

Avoiding the use of an arbitrary gradient threshold level was accomplished by selecting the ROC slice that provided the most information content among all of the subgraph statistics. Information content was judged by the variation present within the subgraph statistics at each of the slice levels; a large variation indicated a potentially large amount of information. Here it was assumed that variability was the result of the unique response of each subgraph statistic to the simulated differences among ecotone types and not experimental error. The coefficient of variation (CV = standard deviation * 100 / mean) was used as relative measure of variation within the subgraph statistics. The CV of each subgraph statistic was calculated over the 1250 realizations that make up each ROC slice. Then the mean CV of the 8 subgraph statistics was computed for each ROC slice. The ROC slice that produced the maximum mean CV was chosen for use in the calculation of subgraph statistics.

Subgraph statistics and hypothesized function

Statistics were generated for each subgraph formed during lattice delineation. The number of subgraphs and singletons, descriptive statistics on subgraph length and a subgraph dispersion metric were calculated for each ecotone. The length of a subgraph is equal to the number of boundary elements it contains. The dispersion metric summarized the mean distance of each boundary element from the geographic center of all boundary elements. A list and description of the subgraph statistics is provided in Table 4.

The surface-based metrics were generally thought to be more capable of measuring abruptness than patchiness. However, certain surface-based metrics were expected to be at least somewhat sensitive to ecotone patchiness. The extent to which these surface-based metrics are capable of measuring ecotone patchiness depends in part on how many boundary elements were included in the calculation of the subgraph statistics. Subgraph statistics calculated on too few boundary elements may not adequately represent the patchiness characteristics of the entire ecotone landscape but rather just the patchiness of the local edges the boundary elements represent. The number of singletons (NS) and the standard deviation of subgraph length (L_{stdv}) were hypothesized as patchiness metrics among the surface-based set. NS was expected to increase as patchiness increased because patchiness would tend to promote locations of rapid, unrelated change that would not be connected during lattice delineation. L_{stdv} was expected to decrease as patchiness increased. As patchiness increases, the probability of forming long subgraphs decreases and short subgraphs of similar lengths should form.

The number of boundary elements (BEs), the number of subgraphs (N) and the boundary element dispersion metric were hypothesized primarily as abruptness metrics. As an ecotone becomes more abrupt, the area of transition decreases, which means the number of high ROC locations also decreases. For this reason, the number of boundary elements (BEs) along with the number of

Table 4. Subgraph statistics and hypothesized function.

Subgraph statistic	**Description**	**Hypothesized function**
Number of Boundary Elements (BEs)	Count of boundary elements (ROC locations) selected during lattice delineation	Abruptness metric
Number of subgraphs (N)	Count of subgraphs, two or more connected boundary elements	Abruptness metric
Number of singletons (NS)	Count of boundary elements not connected to any other boundary elements	Patchiness metric
Minimum length (L_{min})	Minimum number of boundary elements in any one subgraph	Patchiness and abruptness metric
Maximum length (L_{max})	Maximum number of boundary elements in any one subgraph	Patchiness and abruptness metric
Mean length (L_{mean})	Average number of boundary elements per subgraph	Patchiness and abruptness metric
Standard deviation of length (L_{stdv})	Standard deviation of subgraph length	Patchiness metric
Subgraph dispersion (Disp)	The average distance of each BE from the centroid of all BEs combined. The distance used is the y distance from the centroid of all BEs to the centroid of each BE.	Abruptness metric

subgraphs (N) was expected to decrease as abruptness increased. Subgraphs form by connecting boundary elements of similar aspects. Abrupt ecotones should have distinct transition areas that result in boundary elements with similar aspects. Therefore, boundary elements of abrupt ecotones should have a higher connectivity, which translates into fewer subgraphs (N) per ecotone. The boundary element dispersion metric (Disp) was developed to measure the degree of boundary element clumping in the direction of the ecotone transition. The more contiguous boundaries produced by abrupt ecotones were expected to form boundary element patterns that were clumped together resulting in a low Disp value. Gradual ecotones were hypothesized to have higher values of Disp since boundary elements would tend to be more dispersed throughout the ecotone.

The remaining subgraph statistics, L_{max}, L_{mean} and L_{min} were proposed to be useful for measuring both patchiness and abruptness. As patchiness increases, L_{max}, L_{mean} and L_{min} are expected to decrease because of the negative effect patchiness has on the connection of boundary elements into long subgraphs. L_{max}, L_{mean} and L_{min} are expected to increase as abruptness increases because abrupt transitions should have similar aspect values and thus be more connectable.

Cumulative boundary elements

Cumulative boundary elements, an alternative surface-based metric, was developed and calculated for each ecotone surface. Cumulative boundary elements uses data from each of the 20 slice levels avoiding the need to choose one specific gradient threshold at which to conduct the analysis. This metric was called cumulative boundary elements (CBE) because it was calculated as the total sum of boundary elements over all threshold levels. CBE roughly approximates the integral of the response curve produced by plotting the number of BEs verses ROC slice level. It was thought that ecotones with different abruptness characteristics would produce noticeably different response curves and that the integral of these curves would provide a numerical means to differentiate them.

It is easier to conceptualize the differences in response curves for progressively more abrupt ecotones than for progressively patchy ecotones. The area under the response curve for an abrupt ecotone should be less than the area under the curve depicting a more gradual ecotone. When the transition is confined to a small geographic range, as is the case with an abrupt ecotone, the rate-of-change values are very high within the area of transition. When the rate-of-change surface for an abrupt ecotone is sliced into equal intervals, each successive slice will contain a few more boundary elements until all of the area of transition is sliced through. The transition of a more gradual ecotone occurs over a broader geographic range and produces a rate-of-change surface with a lower, more equally distributed, range of values. When a gradual rate-of-change surface is sliced into equal intervals, each successive slice contains proportionately more boundary elements than would each successive slice of an abrupt rate-of-change surface. It is in this way that the response curves for gradual and abrupt ecotones differ. CBE was the metric used to quantify the differences in response curves and was hypothesized to be a prime metric of abruptness.

Figure 6 shows the boundary elements of a gradual (i.e., less abrupt) and an abrupt ecotone for each of 20 ROC slice levels. Also shown is the boundary element response curve for both ecotones. Notice that the area under the abrupt ecotone's response curve is noticeably smaller than the area under the less abrupt ecotone's response curve. The less abrupt ecotone had a CBE value of 3049 verses a CBE of 1835 for the abrupt ecotone.

Data summary

The calculation of the patch- and surface-based metrics produced a substantial amount of data. The entire set of data can be summarized using the idea of a data cube. The dimensions of the patch-based data cube were: 8 patch-based metrics x 25 ecotone groups x 50 replicates per group. The data for the surface-based metrics includes those for the 8 subgraph statistics calculated at a particular ROC slice and those for the cumulative boundary elements metric The subgraph statistics form a cube with the dimensions: 8 surface-based metrics x 25 ecotone groups x 50 replicates per group. The CBE data were collected for each of the 50 replicates of the 25 ecotone groups.

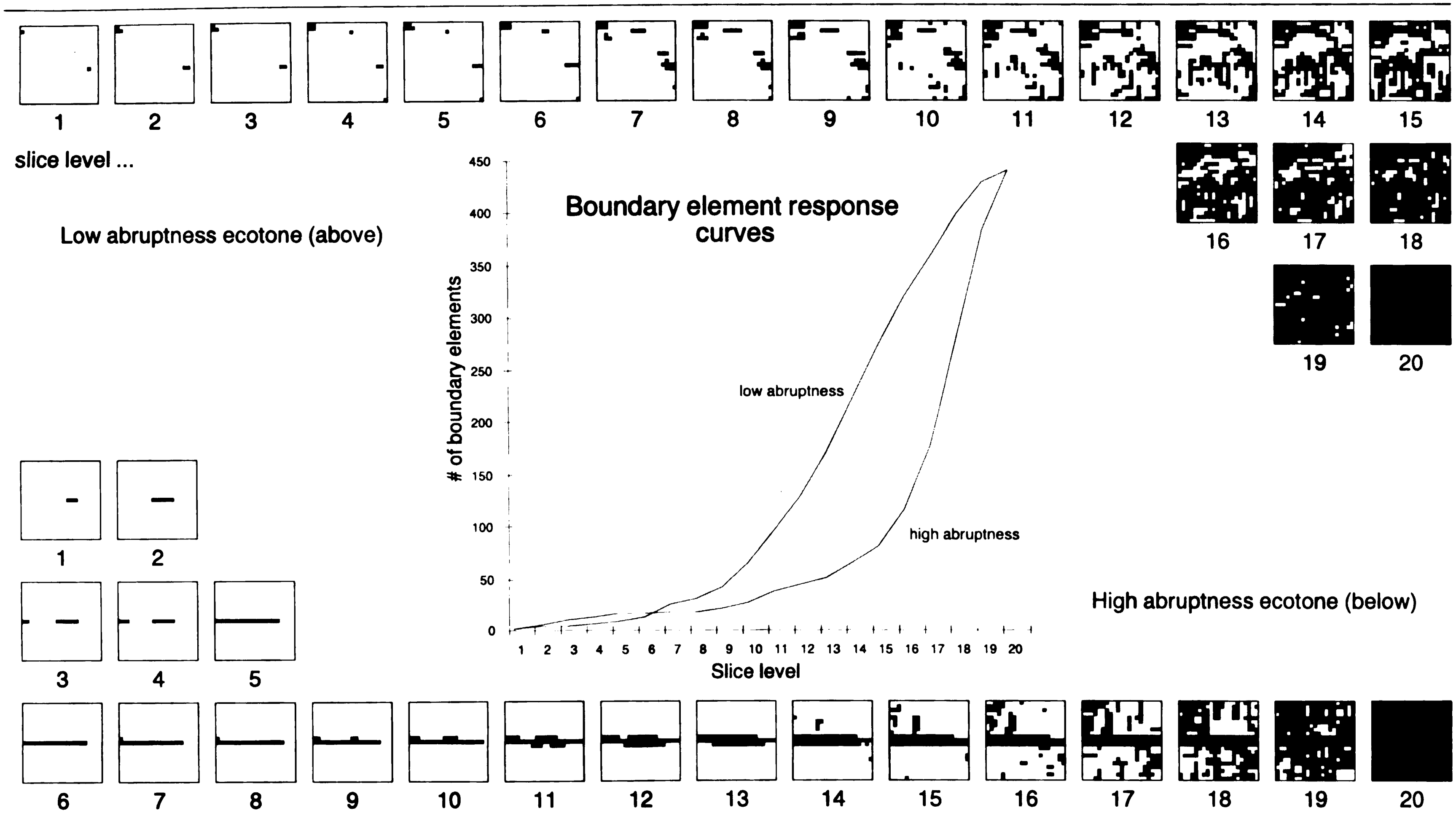


Figure 6. Depiction of the cumulative boundary elements metric for an ecotone of low abruptness vs. an ecotone of high abruptness. The chart in the center illustrates the difference in the boundary element response curves of the two ecotones. Maps of the boundary elements for each ecotone at 20 ROC slice levels are shown above and below the chart. Boundary elements are shown in black.

Analysis of Variance

The metric data were organized to facilitate a pair of two-way factorial ANOVA experiments (see Bhattacharyya and Johnson, 1977); one for the patch-based approach and another for the surface-based approach. The two-way ANOVA design was chosen because it simultaneously considers the effects of two factors (independent variables), including the effects due to their interaction, on a dependent variable. The ecotone characteristics, patchiness and abruptness, were considered as factors, while each of the patch- and surface-based metrics were treated as dependent variables.

Since a simulation was used to produce definite differences between the ecotone groups, the ANOVA results reflect the degree to which each metric was capable of detecting the simulated differences. In other words, the ANOVA statistically determined whether the metrics were sensitive to differences resulting from simulated combinations of unique patchiness and abruptness levels. The unique combinations of patchiness and abruptness are called treatments and the quantitative differences in patchiness and abruptness themselves are known as treatment effects. Since all of the metrics were subjected to the same simulated differences in patchiness and abruptness, those that produced the largest treatment effects were said to be the most sensitive.

The ANOVA determines the presence and magnitude of treatment effects through the comparison of two independent estimates of population variance. One estimate is obtained from the variance between subjects given the same treatments; it is called the within group variance. The other estimate, known as the between group variance, is obtained from the variance measured among subjects that were treated differently. Since it is calculated on subjects that were treated alike, the within groups variance is attributed to unsystematic errors beyond the control of the experimenter. The variation between groups on the other hand, is the result of unsystematic error along with an added component due to treatment effects (Sokal and Rohlf, 1995). The ratio of the two estimates (between group variance / within group variance), referred to as the F-ratio, is used to test whether the treatment effects are larger than what would be expected by chance alone.

Keppel (1991) summarizes the three important pieces of information that can be gleaned from a factorial ANOVA regarding treatment effects:

> First, we have the simple effects, which refer to the results of the component single-factor experiments making up the factorial design. These effects reflect treatment effects associated with one of the independent variables, with the other one held constant. Second, we have interaction effects, which reflect a comparison of the simple effects. Interaction is present when the component single-factor experiments produce different results; interaction is absent when the results are the same. Finally, we have the main effects, which essentially transform the factorial design into two single-factor experiments. Main effects are of primary interest in the absence of interaction, when it is safe to combine the data from the component experiments. (p. 191-192)

Main effects

The main effects of the factorial design were examined first to determine whether the metrics were sensitive to one or both of the factors. The main effects tested the null hypothesis that the mean metric values observed at each level of one factor are equal when the effects of the second factor are disregarded. Rejection of the null hypothesis based on the F-ratio provided by the ANOVA indicated that the mean metric value under study was significantly different for at least two of the factor levels. For each metric being tested there was a null hypothesis for each main effect:

> H_o: there are no differences between the mean values of the metric at each level of patchiness.
>
> H_o: there are no differences between the mean values of the metric at each level of abruptness.

Failure to reject the null hypothesis indicated that the metric being analyzed was not sensitive to the treatments effects produced by that factor. When the null hypothesis was rejected, the metric was determined capable of detecting differences in either patchiness or abruptness.

Interaction Effects

Interaction occurs when the affect of one factor on the dependent variable changes at different levels of the other independent variable (Keppel, 1991). The factorial ANOVA provided an F-ratio to test for significance of interaction. The null hypothesis is:

> H_o: interaction is not present; the mean value observed at each level of one factor does not depend on the level of the other factor

Rejection of the null indicated significant interaction. The presence of interaction did not allow for an easy interpretation of the main effects. Significant interaction meant that the metric being tested did not perform consistently across all levels of one or both of the independent variables. For example, a metric may have been more sensitive to abruptness at lower levels of patchiness than at higher patchiness levels. Information elucidating such patterns was not available in the main effects. However, examination of the simple effects (discussed below) provided a means to uncover the patterns of interaction.

In the two-way factorial ANOVAs used here there were four component sources of variance contributing to the experiment. They were: the variance due to patchiness treatments (σ^2_p), abruptness treatments (σ^2_a), the interaction of patchiness and abruptness ($\sigma^2_{p \times a}$) and experimental error (σ^2_{error}). Estimates of the four component variances were calculated using the average variance estimates from the ANOVA and were used to compute a relative index of treatment magnitude for each component. The index used is called Omega Squared and was chosen because it provided a way to standardize the measures of treatment effects so they could be compared within and between experiments (Keppel, 1991). For example, the treatment effect observed for a patch-based metric could be compared with the treatment effect observed for a surface-based metric. Omega squared was calculated as the ratio of the treatment effect variance estimate to the combined variance estimates of all sources. For example, the Omega squared calculation for the patchiness main effects was:

$$\omega^2_p = \sigma^2_p / (\sigma^2_p + \sigma^2_a + \sigma^2_{p \times a} + \sigma^2_{error})$$

Omega squared ranges from 0 to 1 with higher values representing larger treatment effects (Keppel, 1991). Metrics that produced high Omega squared values were interpreted as being more sensitive to differences produced by the simulation than those with lower Omega squared values.

Simple effects

If one of the metrics produced significant interaction effects in the factorial ANOVA, the simple effects of the metric were analyzed. This was accomplished by decomposing the factorial ANOVA into 10 single-factor ANOVA experiments. Each single-factor ANOVA was equivalent to holding the level of one factor constant while studying the effects of the other factor. The simple effects of patchiness were evaluated at each level of abruptness as well as the simple effects of abruptness at each level of patchiness. In the single factor ANOVAs there were only two variance components, variance due to the independent variable (i.e., either patchiness or abruptness) and variance due to experimental error. Therefore, the Omega squared for the single factor ANOVAs is equal to the treatment effect variance estimate divided by the treatment effect variance estimate plus the error variance estimate (Keppel, 1991). For an ANOVA set up to examine patchiness simple effects the Omega squared calculation was:

$$\omega^2_p = \sigma^2_p / (\sigma^2_p + \sigma^2_{error})$$

Again, metrics exhibiting higher Omega squared values were considered more sensitive to the differences in the factor being examined.

For each of the single factor ANOVAs, pairwise multiple comparisons between factor levels were conducted using the Bonferroni method. The Bonferroni comparisons determine when the mean metric value between two levels of the same factor is significantly different. There were 10 pairwise comparisons for each of the simple effects, equal to the number of unique pairs that can be taken from 5 levels of one factor. The calculation of pairwise comparisons provided the magnitude and sign of the mean difference between each pair of factor levels. The sign of the difference provided evidence of whether the metric was performing the way it was suspected to perform. For example, the number of patches metric (NP) was expected to increase with patchiness level which means the subtraction of NP at patchiness level 5 from NP at patchiness level 4, $P_4 - P_5$, would be negative. A magnitude difference between a comparison made at one factor level and the same comparison made at a different factor level also indicates the presence of interaction. The magnitude differences were interpreted to determine at which levels of one factor was the metric most capable of detecting differences in the other factor. This information was examined at each level of patchiness and abruptness to resolve the patterns of interaction.

The Bonferroni comparisons were also used to evaluate whether the metrics were behaving consistently with the known differences in patchiness and abruptness. Two different aspects of consistency were considered. The first, termed external consistency, summarized the degree to which the hypothesized response (sign of the mean difference) of the metric changed as factor level changed. The hypothesized response of a metric with a high external consistency changed little with factor level. A low external consistency indicated that the interaction was such that the response (sign) of the metric changed as factor level varied. External consistency was calculated as the ratio of the number of significant comparisons that produced the hypothesized sign (which indicated the metric was responding as expected) to the total number of significant comparisons. This ratio was referred to as the external consistency index.

The second aspect of consistency, termed internal consistency, summarized the degree to which significant comparisons were observed in a logical sequence. For example, a metric is said to be highly sensitive to patchiness if one observes high Omega squared values for the patchiness simple effects. Assume that further examination determines that the metric is capable of detecting the difference between patchiness levels 1 and 2 but not between patchiness levels 1 and 5. If a metric is internally consistent and it detected a small difference in patchiness, it should also detect a larger difference in patchiness. Of course, the fact that a metric detects large differences in an ecotone characteristic does not guarantee it will detect small ones. Internal consistency was calculated as the ratio between the number of significant comparisons and the number of significant comparisons that would have been detected if the metric was responding in a 100 percent logical manner. This ratio was referred to as the internal consistency index.

Metric suitability ranking

Four properties were used to rank the patch- and surface-based metrics according to their ability to quantify patchiness and abruptness. The properties were: 1.) main effect sensitivity (S_{ME}); 2.) simple effect sensitivity (S_{SE}); 3.) external consistency (C_E); and 4.) internal consistency (C_I). Each metric received a standardized score for each property and the sum of the four scores was used for the final ranking. The score for main effect sensitivity was calculated as:

$$S_{ME} = \omega^2 / \omega^2_{max}$$

where ω^2_{max} was the Omega squared value of the metric with the highest main effect sensitivity and ω^2 was the Omega squared value for the metric for which the score was being calculated. The score for simple effect sensitivity was calculated as:

$$S_{SE} = \frac{\sum_{i=1}^{n} (\omega^2{}_i \, / \, \omega^2{}_{i\,max})}{n}$$

where n equals the number of simple effects (5) and $\omega^2{}_i$ and $\omega^2{}_{i\,max}$ were the Omega squared value for a particular metric and the maximum Omega squared value for each simple effect, respectively. The external consistency score was calculated as:

$$C_E = \text{external consistency / maximum external consistency}$$

and the internal consistency score was calculated as:

$$C_I = \text{internal consistency / maximum internal consistency}$$

The scores for each property ranged from 0 to 1 with 1 representing the highest performance for a property. Accordingly, the metrics' total scores ranged from 0 to 4 with 4 representing the best overall suitability. This method was used to produce a ranking for each set of metrics as well as a ranking for the two sets combined.

RESULTS

Patch-based metric ANOVA results

The factorial ANOVAs for the patch-based metrics are summarized in Table 5. The F-ratios, Omega squared values, and p-values at the 0.01 significance level are given for each metric for the patchiness and abruptness main effects and the interaction effect. It is immediately apparent that each patch-based metric was at least somewhat sensitive to the simulated differences in patchiness and abruptness. Also, as expected, certain metrics were more sensitive to the simulated differences than others. However, significant main effects in Table 5 are not entirely conclusive of metric behavior because interaction effects were significant for each metric. The simple effects of each metric were evaluated to provide a better description of metric sensitivity at different factor levels. The Omega squared values for each of the component single-factor ANOVAs (i.e., simple effects) are summarized in Table 6. The Bonferroni comparisons for each of the single factor ANOVAs are provided in Appendix P.

AWMPFD and AWMSI

Not surprisingly, the two patch shape metrics produced very similar results. Both AWMPFD and AWMSI were proposed as useful metrics for patchiness or abruptness but each performed better as an abruptness metric. In fact, they were the top two metrics most sensitive to abruptness (Table 5). Their sensitivity to patchiness was among the worst of all the patch-based metrics.

Table 5. Main and interaction effects for factorial ANOVA on patch-based metrics.

Source	Metric	F	ω^2	P
Patchiness	LPI	84.023	0.170	0.000
	NP	378.237	0.128	0.000
	PSCV	114.323	0.067	0.000
	TE	202.863	0.063	0.000
	CONTAG	197.974	0.061	0.000
	AWMPFD	112.687	0.046	0.000
	AWMSI	114.468	0.045	0.000
	MPS	47.757	0.037	0.000
Abruptness	AWMPFD	1983.536	0.815	0.000
	AWMSI	2023.419	0.806	0.000
	CONTAG	2537.143	0.790	0.000
	TE	2427.515	0.758	0.000
	MPS	846.495	0.671	0.000
	PSCV	1099.728	0.647	0.000
	NP	1443.752	0.490	0.000
	LPI	9.504	0.017	0.000
Interaction	NP	203.467	0.275	0.000
	LPI	22.047	0.172	0.000
	PSCV	44.151	0.102	0.000
	TE	65.916	0.081	0.000
	CONTAG	41.778	0.051	0.000
	MPS	14.684	0.043	0.000
	AWMSI	16.505	0.025	0.000
	AWMPFD	7.604	0.011	0.000

Table 6. Simple effects results for ANOVA on patch-based metrics. Maximum Omega squared values are in bold, minimum are underlined. An "ns" indicates an ANOVA that was not significant.

Patchiness simple effects

	AWMPFD	AWMSI	CONTAG	LPI	MPS	NP	PSCV	TE
A_1	**0.110**	**0.126**	**0.277**	**0.114**	**0.141**	**0.536**	**0.399**	**0.298**
A_2	0.047	0.048	0.093	0.082	0.106	0.182	0.139	0.087
A_3	0.072	0.077	0.073	0.043	0.027	0.030	0.026	0.070
A_4	0.069	0.086	0.045	0.002ns	0.004ns	0.005ns	0.004ns	0.044
A_5	0.088	0.122	0.076	0.026	0.008	0.009	0.007ns	0.072

Abruptness simple effects

	AWMPFD	AWMSI	CONTAG	LPI	MPS	NP	PSCV	TE
P_1	0.397	0.366	0.387	0.022	0.201	0.217	0.211	0.363
P_2	0.489	0.479	0.493	0.031	0.250	0.251	0.254	0.475
P_3	0.565	0.577	0.592	0.004ns	0.314	0.318	0.317	0.575
P_4	0.640	0.636	0.707	0.034	0.440	0.541	0.482	0.688
P_5	**0.711**	**0.736**	**0.821**	**0.474**	**0.597**	**0.722**	**0.705**	**0.800**

The interaction effects for AWMPFD and AWMSI were the weakest. AWMPFD and AWMSI also exhibited the same interaction patterns. Table 6 indicates that the patchiness sensitivity of AWMPFD and AWMSI was highest at abruptness level 1, reached a low at abruptness level 2 then increased with subsequent patchiness levels. The abruptness sensitivity of AWMPFD and AWMSI steadily increased with patchiness.

The relationships of AWMPFD and AWMSI to patchiness and abruptness were externally consistent with hypotheses. Each was directly related to patchiness and inversely related to abruptness. Also, AWMPFD and AWMSI appear to be internally consistent. The Bonferroni comparisons (Appendix P) indicate AWMPFD and AWMSI were not significantly different when patchiness was one level apart. At intermediate abruptness levels, AWMPFD and AWMSI did not differentiate high levels of patchiness. AWMPFD and AWMSI were not sensitive to differences between intermediate and high levels of abruptness at low levels of patchiness but this problem improved at higher levels of patchiness.

CONTAG and TE

CONTAG and TE also produced comparable results. Like AWMPFD and AWMSI, CONTAG and TE were proposed as potential patchiness and abruptness metrics and each was sensitive to changes in both characteristics. CONTAG performed better as an abruptness metric while TE performed equally well as a metric of both characteristics. CONTAG ranked third and TE ranked fourth among the patch-based metrics in terms of abruptness main effects sensitivity. TE was the fourth most sensitive metric to patchiness main effects and CONTAG the fifth.

The interaction effects for CONTAG and TE were moderate and both exhibited the same pattern of changing patchiness and abruptness sensitivity over factor levels. Their patchiness sensitivity decreased as abruptness level increased while abruptness sensitivity increased as patchiness increased.

As hypothesized, CONTAG was inversely related to patchiness and directly related to abruptness. TE's response was also consistent with hypotheses as it was directly related to patchiness and inversely related to abruptness. CONTAG and TE were internally consistent as patchiness metrics except at abruptness level 3. CONTAG was not internally consistent because it was unable to detect differences between patchiness levels 2 and 4, and between patchiness levels 3 and 5, when it successfully found differences between levels 2 and 3 or 3 and 4. TE failed to detect patchiness differences 2 levels apart when it was successful at detecting patchiness levels 1 level apart. The response of both metrics to abruptness was internally consistent at all levels of patchiness. CONTAG and TE did not distinguish small and intermediate differences in patchiness as abruptness increased. CONTAG did not detect differences between intermediate and high levels of abruptness at low levels of patchiness but did improve at higher levels of patchiness. TE did not detect differences among intermediate and high level abruptness at all patchiness levels except for patchiness level 3.

LPI, NP and PSCV

LPI, NP, and PSCV were hypothesized to perform best as patchiness metrics. They were the top three metrics in regard to patchiness main effects sensitivity but were also the patch-based metrics with the strongest interaction effects.

The effects of interaction on LPI, NP and PSCV were very obvious; they were highly sensitive to patchiness at low abruptness levels but sensitivity decreased as abruptness increased. In fact, patchiness sensitivity decreases so dramatically that LPI, NP and PSCV were not significantly related to patchiness levels at abruptness level 4 and were nearly so at abruptness level 5 (Table 6). These metrics perform very well as patchiness metrics but only on ecotones with a low degree of abruptness.

LPI, NP and PSCV responded as hypothesized to changes in patchiness. LPI decreased as patchiness increased while NP and PSCV increased as patchiness increased. LPI responded internally consistently to differences in patchiness at all levels of abruptness. LPI failed to detect one and two level patchiness differences at both low and high levels of abruptness. NP behaved internally consistently to patchiness at abruptness levels 1, 2 and 5 but not at level 3. PSCV behaved internally consistently to patchiness at abruptness levels 1 and 2 but not at level 3. At abruptness level 3, both NP and PSCV were not internally consistent because they were not sensitive to differences between patchiness levels 1 and 4, 2 and 4 or 4 and 5. However, they were sensitive to differences between patchiness levels 1 and 3, 2 and 3 and 3 and 4. PSCV and

NP were capable of detecting 1, 2, 3 and 4 level patchiness differences at low levels of abruptness but failed to do so as abruptness increased.

MPS

MPS, although similar in many respects to LPI, NP, and PSCV, performed poorly as a patchiness metric but had weaker interaction effects than LPI, NP and PSCV. MPS was sensitive to differences in both patchiness and abruptness. It was the least sensitive to the patchiness main effects and was moderately sensitive to the abruptness main effects (Table 5). The poor performance of MPS as a patchiness metric was surprising, especially since the other patch size metrics (LPI and PSCV) performed well (at least at low abruptness levels). The poor performance of MPS as a patchiness metric could be attributed to the vagueness of information provided by a mean. The mean patch size is a good representative of ecotone characteristics only if patch sizes are normally distributed. Otherwise, outliers, extremely large or small patch sizes, may bias the value of MPS. A bias of this type may prevent MPS from distinguishing patchiness differences.

MPS had the third weakest interaction effect. AWMSI and AWMPFD were the only patch-based metrics with weaker interaction effects. The interaction was such that the patchiness sensitivity of MPS decreased as abruptness increased (Table 6). At abruptness level 4, MPS did not detect patchiness differences. This is the same pattern exhibited by LPI, NP and PSCV but the difference in patchiness sensitivities between abruptness levels is smaller for MPS.

As hypothesized, MPS decreased as patchiness increased. MPS responded sensibly to patchiness differences at abruptness levels 1, 2 and 5 but not at abruptness level 3. Just like NP and PSCV, MPS failed to find differences between patchiness levels 1 and 4, 2 and 4 and 3 and 5 when differences between 1 and 3, 2 and 3 and 3 and 4 were significantly different. MPS was able to differentiate patchiness 1, 2, 3 and 4 levels apart at low abruptness levels but failed to do so as abruptness increased.

Patch-based metrics ranked by simple effects

Table 7 shows the patch-based metrics ranked by Omega squared for each of the patchiness and abruptness simple effects. The ranking clearly indicates that relative metric performance was highly dependent on factor level. For example, NP was the superior patchiness metric at low levels of abruptness but it was outperformed at intermediate and high levels of abruptness. The same is true for PSCV. Oppositely, performance of AWMPFD and AWMSI as patchiness metrics improved as abruptness level increased. CONTAG, AWMSI, AWMPFD, and TE are the superior abruptness metrics across all levels of patchiness. MPS and LPI consistently perform as poor abruptness metrics regardless of patchiness level.

There were larger differences in the metric rank order for the patchiness simple effects than for the abruptness simple effects. This suggests that the

Table 7. Patch-based metrics ranked by single-factor Omega Squared values.

Patchiness simple effects

A_1		A_2		A_3		A_4		A_5	
Metric	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2
NP	0.536	NP	0.182	AWMSI	0.077	AWMSI	0.086	AWMSI	0.122
PSCV	0.399	PSCV	0.139	CONTAG	0.073	AWMPFD	0.069	AWMPFD	0.088
TE	0.298	MPS	0.106	AWMPFD	0.072	CONTAG	0.045	CONTAG	0.076
CONTAG	0.277	CONTAG	0.093	TE	0.070	TE	0.044	TE	0.072
MPS	0.141	TE	0.087	LPI	0.043	NP	0.005	LPI	0.026
AWMSI	0.126	LPI	0.082	NP	0.030	PSCV	0.004	NP	0.009
LPI	0.114	AWMSI	0.048	MPS	0.027	MPS	0.004	MPS	0.008
AWMPFD	0.110	AWMPFD	0.047	PSCV	0.026	LPI	0.002	PSCV	0.007

Abruptness simple effects

P_1		P_2		P_3		P_4		P_5	
Metric	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2
AWMPFD	0.397	CONTAG	0.493	CONTAG	0.592	CONTAG	0.707	CONTAG	0.821
CONTAG	0.387	AWMPFD	0.489	AWMSI	0.577	TE	0.688	TE	0.800
AWMSI	0.366	AWMSI	0.479	TE	0.575	AWMPFD	0.640	AWMSI	0.736
TE	0.363	TE	0.475	AWMPFD	0.565	AWMSI	0.636	NP	0.722
NP	0.217	PSCV	0.254	NP	0.318	NP	0.541	AWMPFD	0.711
PSCV	0.211	NP	0.251	PSCV	0.317	PSCV	0.482	PSCV	0.705
MPS	0.201	MPS	0.250	MPS	0.314	MPS	0.440	MPS	0.597
LPI	0.022	LPI	0.031	LPI	0.004	LPI	0.034	LPI	0.474

decision to use a particular metric to measure patchiness at a given abruptness level is more consequential than the decision to use a particular metric for abruptness at a given patchiness level.

Patch-based metric suitability ranking

Table 8 contains the scores used to calculate the metric suitability ranking for the patch-based metrics. Standardized scores for main effects sensitivity, simple effects sensitivity, external and internal consistency were totaled and provided the basis to judge the metrics' overall suitability as patchiness and/or abruptness metrics. The size of a score is relative to the highest score recorded for the property that was measured. A metric that performed the best for each of the properties would receive a score of 4. A score of less than 4 indicated that at least one property of the metric was inferior to the others.

The patch-based metrics in order of their suitability as patchiness metrics were: LPI, NP, AWMSI, CONTAG, TE, AWMPFD, PSCV and MPS. Of the metrics that were predicted to be most useful as patchiness metrics, only LPI and TE were in the top half of the suitability ranking. PSCV and MPS received scores that placed them in the bottom half of the ranking. MPS had the lowest score for each of the four properties contributing to the final score. PSCV, while not the least sensitive to patchiness, ranked low because of its low consistency scores. The suitability scores of CONTAG, TE and AWMPFD were very close and they ranked as mediocre patchiness metrics. It should be noted that only three of the

Table 8. Patch-based metrics ranked by patchiness and abruptness suitability scores.

Patchiness suitability scores

Metric	Main effects sensitivity	Simple effects sensitivity	External Consistency	Internal Consistency	Total
LPI	1.00	0.29	1.00	1.00	3.29
NP	0.75	0.51	0.91	0.85	3.01
AWMSI	0.27	0.68	1.00	1.00	2.94
CONTAG	0.36	0.63	0.97	0.94	2.90
TE	0.37	0.61	0.97	0.94	2.89
AWMPFD	0.27	0.61	1.00	1.00	2.88
PSCV	0.39	0.39	0.95	0.84	2.58
MPS	0.22	0.26	0.90	0.84	2.23

Abruptness suitability scores

Metric	Main effects sensitivity	Simple effects sensitivity	External Consistency	Internal Consistency	Total
CONTAG	0.97	0.99	1.00	1.00	3.96
AWMPFD	1.00	0.94	1.00	1.00	3.94
AWMSI	0.99	0.93	1.00	0.98	3.90
TE	0.93	0.96	1.00	1.00	3.89
PSCV	0.79	0.62	1.00	1.00	3.42
MPS	0.82	0.58	1.00	1.00	3.40
NP	0.60	0.65	1.00	1.00	3.25
LPI	0.02	0.15	0.43	0.95	1.55

patch-based metrics, LPI, AWMSI, and AWMPFD had perfect external and internal consistency scores.

The patch-based metrics in order of their suitability as abruptness metrics were: CONTAG, AWMPFD, AWMSI, TE, PSCV, MPS, NP and LPI. This order was convincing because the metrics that were hypothesized as poor abruptness metrics (LPI, MPS, NP and PSCV) ranked lower in terms of their abruptness metric suitability. The patch-based metrics were far more consistent as abruptness metrics than as patchiness metrics. LPI was an exception due to its very low external consistency.

Surface-based metrics ANOVA results

Subgraph statistics

The results from two ANOVA experiments, one that used the subgraph statistics produced at slice level 1 and another that used subgraph statistics from slice level 9, were evaluated. The decision to use slice level 1 came from the interpretation of the mean metric coefficient of variation at each of the 20 slice levels (Figure 7). Slice 1 had the highest mean metric coefficient of variation and was chosen because it was thought have produced the most information to distinguish differences among ecotone groups. The decision to use slice 9 was based on the traditional method of selecting boundary elements discussed previously. Slice level 9 was chosen because the mean number of boundary elements (43.5) for the 1250 ecotones was the closest of all the slices to 10

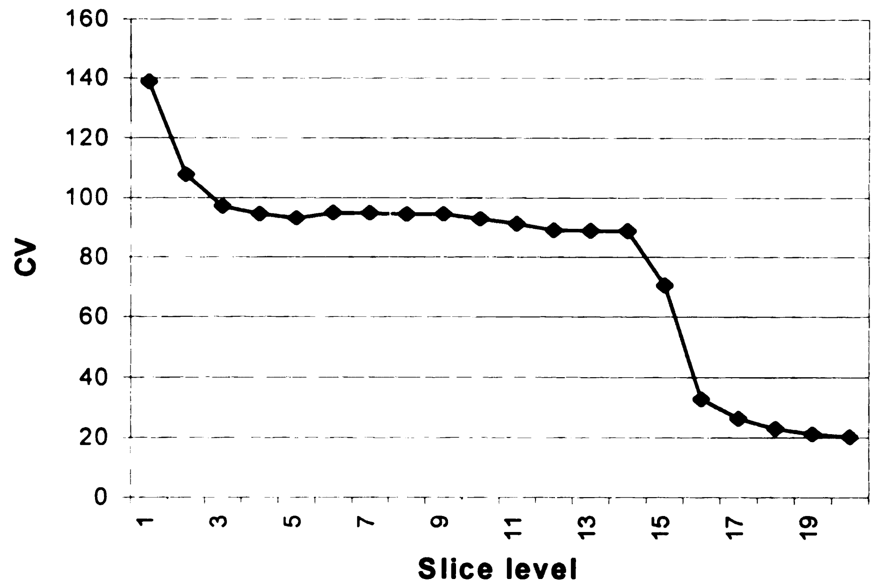


Figure 7. Mean coefficient of variation of the 8 subgraph statistics by ROC slice level. The coefficient of variation summarized the potential amount of information available that could be used to distinguish differences among the 1250 ecotones.

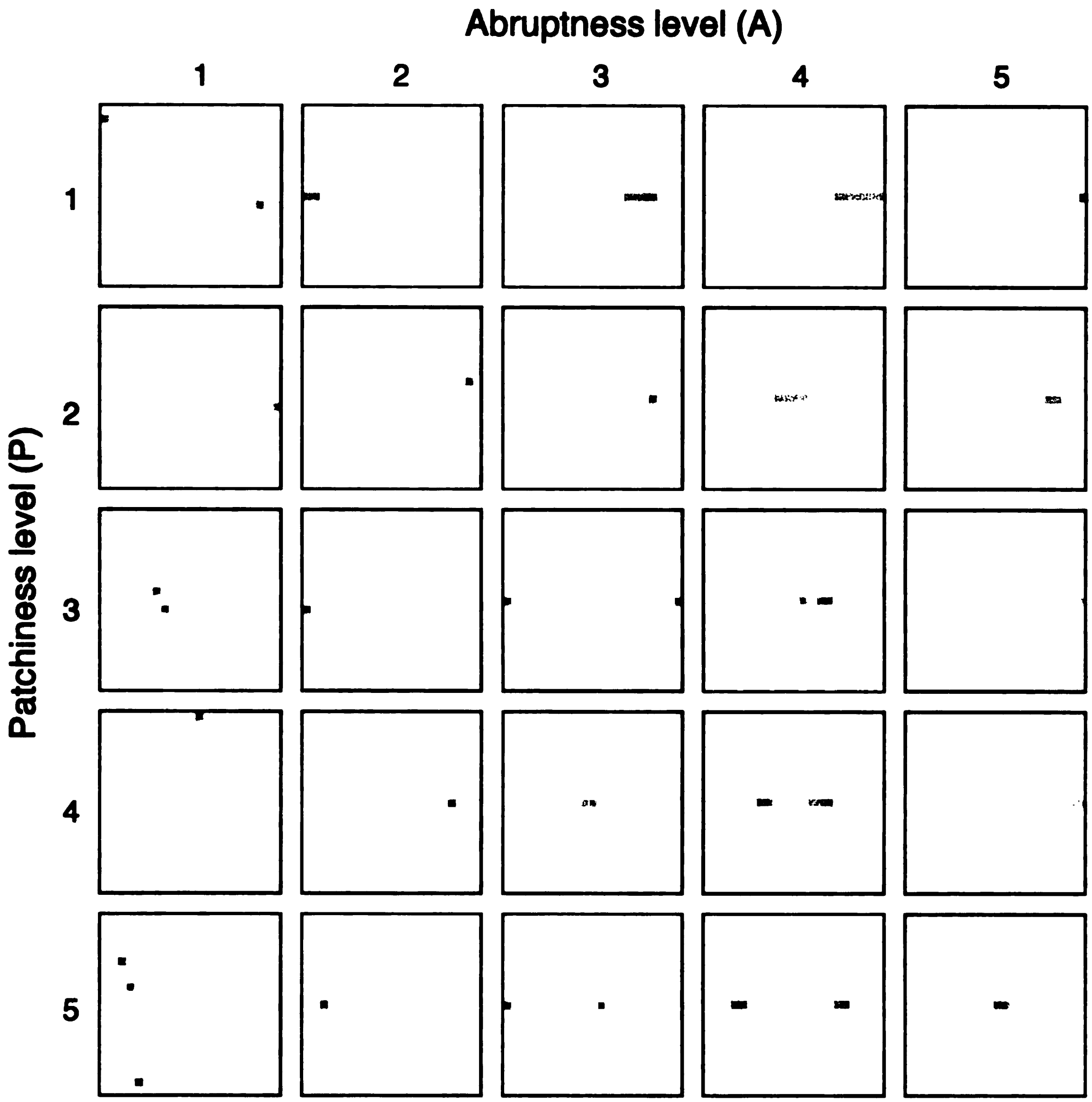
percent of the total ecotone area. The 10 percent value is a typical value used during lattice delineation.

Figure 8 shows a subgraph map from each of the 25 simulated ecotone groups when slice level 1 was used for lattice delineation. Figure 9 shows a subgraph map from each of the 25 simulated ecotone groups when slice level 9 was used for lattice delineation.

SLICE LEVEL 1

The main effects of the slice level 1 subgraph statistics are summarized in Table 9. The most noticeable property of the subgraph statistics produced by

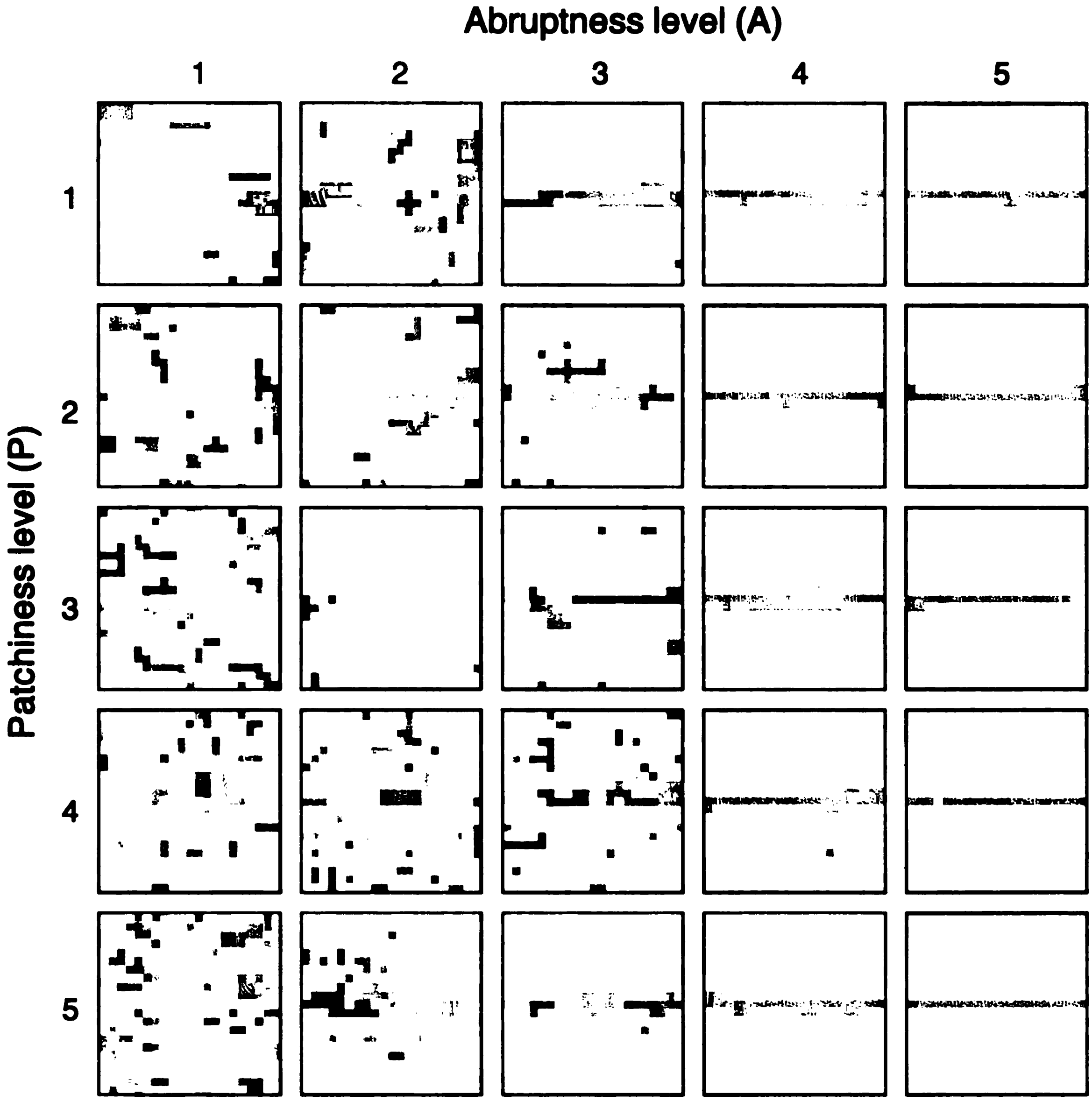
Slice 1 Subgraph maps



Note: The ecotone transition was simulated in the north-south direction.

Figure 8. An example from each of the 25 groups of the subgraph maps created from the lattice delineation that used slice level 1 as the gradient threshold. Areas of homogeneous color represent individual subgraphs or singletons.

Slice 9 Subgraph Maps



Note: The ecotone transition was simulated in the north-south direction.

Figure 9. An example from each of the 25 groups of the subgraph maps created from the lattice delineation that used slice level 9 as the gradient threshold. Areas of homogeneous color represent individual subgraphs or singletons.

Table 9. Main and interaction effects results for ANOVA on level 1 subgraph statistics. Significance is for α = 0.01. A "ns" indicates that the variation in the source was not significant different.

Source	Metric	F	ω^2	P
Patchiness	L_{mean}	12.242	0.067	0.000
	L_{max}	11.837	0.065	0.000
	L_{min}	11.291	0.062	0.000
	NS	23.704	0.062	0.000
	N	20.832	0.051	0.000
	BEs	17.107	0.046	0.000
	Disp	0.522	-0.001	0.719 ns
	L_{stdv}	0.794	-0.001	0.530 ns
Abruptness	N	66.582	0.165	0.000
	Disp	62.110	0.164	0.000
	NS	40.766	0.106	0.000
	BEs	32.382	0.087	0.000
	L_{max}	2.876	0.011	0.022 ns
	L_{mean}	2.224	0.007	0.065 ns
	L_{stdv}	1.531	0.003	0.191 ns
	L_{min}	1.438	0.003	0.220 ns
Interaction	Disp	1.129	0.001	0.322 ns
	BEs	1.112	0.001	0.338 ns
	NS	0.988	0.000	0.467 ns
	N	0.971	0.000	0.487 ns
	L_{min}	0.944	-0.001	0.518 ns
	L_{stdv}	0.934	-0.002	0.530 ns
	L_{mean}	0.810	-0.004	0.675 ns
	L_{max}	0.698	-0.007	0.797 ns

slice level 1 is the lack of significant interaction effects. The response of each slice 1 metric in regard to one factor was not dependent on the level of the other factor. This is important because it means that the metric response to ecotone characteristics, patchiness or abruptness, was consistent over all degrees of each characteristic. The lack of interaction also allows for a less extensive investigation of the metrics; the simple effects do not have to be evaluated to uncover patterns of interaction. Instead, the main effects are wholly representative of the component ANOVAs that make up the simple effects. available for detecting differences between the 1250 simulated ecotone surfaces in each slice level.

Disp and L_{stdv} did not produce significantly different values among patchiness groups while L_{max}, L_{mean}, L_{stdv}, and L_{min} were not significantly different among abruptness groups. Insignificant differences in the Disp metric within the patchiness main effects was consistent with hypotheses because it was not designed to measure patchiness, however insignificance in L_{stdv} was surprising. The insignificance of L_{min} within the abruptness main effects was predictable because every set of subgraphs produced by slice 1 had a minimum subgraph length (L_{min}) of 2. Therefore the mean differences between the ecotone groups would be zero and insignificant. L_{max} and L_{mean}, were not hypothesized to be insignificant within the abruptness main effects. It is possible that the surprising insignificance of L_{stdv} in the patchiness main effects and L_{max} and Lmean in the abruptness main effects was tied to the fact that slice level 1 produced metric values that were based on a very small proportion of the ecotone area. The average number of BEs for slice level 1 was 2.32 or 0.5% of the total ecotone area. The small area used by slice level 1 did not allow the metrics to differ enough to produce significant differences in the ANOVA when in fact the ecotones were different in terms of their characteristics. It was for this reason that metrics from slice level 9 were chosen and further evaluation of slice level 1 was abandoned.

SLICE LEVEL 9

There are four notable differences between the subgraph statistics produced using slice 1 and those produced using slice 9. First, the average percentage of ecotone area selected as boundary elements is much greater for slice 9: 9.9 vs. 0.5 for slice 1. Second, all of the slice 9 metrics showed significant differences in the patchiness and abruptness main effects (Table 10). Third, the slice 9 metrics were much more sensitive (higher omega squared values) to abruptness differences than were the metrics from slice 1. Note however that patchiness sensitivity of the two slices was quite similar. The fourth difference is that each slice 9 metric had significant interaction effects whereas the slice 1 metrics did not. The first three differences were advantages of using slice 9; using a larger area should make the metrics more accountable for the simulated differences and finding the metrics with a high sensitivity was a primary goal. Unfortunately, the significant interaction effects with slice 9 are a disadvantage since another goal was to find patchiness and abruptness metrics that operate consistently across factor levels. Despite the presence of interaction, the slice 9 metrics were chosen over the metrics calculated at slice level 1 for comparison against the patch-based metrics.

The factorial ANOVAs for the slice 9 subgraph statistics indicate that all of the metrics were at least somewhat sensitive to both patchiness and abruptness. Table 10 shows the F-ratios, Omega squared values, and p-values of the factorial ANOVA for each metric and each factor. While the sensitivity of the metrics was variable among patchiness and abruptness main effects, sensitivity to patchiness was more variable than sensitivity to abruptness. Interaction of factors was significant for each of the subgraph statistics, requiring interpretation of the simple effects to reveal specific patterns of metric behavior at different factor levels. Table 11 contains the results of the surface-based simple effects. NS exhibited the strongest interaction, the interaction effects of L_{stdv} and L_{max} were the next strongest while L_{min}, L_{mean}, Disp, BEs, and N exhibited weaker interaction. Appendix S contains the results of the Bonferroni comparisons that were used to further examine the interaction effects.

NS and L_{stdv}

NS and L_{stdv} were introduced as patchiness metrics. NS was the metric most sensitive among the surface-based metrics to the patchiness main effects, L_{stdv} was the fourth most sensitive (Table 10). Both metrics were also sensitive to abruptness but ranked among the lower half of the metrics in that regard. L_{stdv} was the least sensitive of all the surface-based metrics to abruptness. The interaction effects for NS and L_{stdv} were very strong and the

Table 10. Main and interaction effects results for ANOVA on level 9 subgraph statistics. Significance is for $\alpha = 0.01$. A "ns" indicates that the variation in the source was not significant different.

Source	Metric	F	ω^2	P
Patchiness	NS	166.576	0.103	0.000
	L_{max}	70.049	0.101	0.000
	L_{mean}	37.256	0.035	0.000
	L_{stdv}	11.159	0.024	0.000
	L_{min}	19.344	0.022	0.000
	N	15.503	0.013	0.000
	BEs	7.867	0.010	0.000
	Disp	28.801	0.009	0.000
Abruptness	Disp	2772.977	0.880	0.000
	N	826.595	0.710	0.000
	L_{mean}	708.935	0.661	0.000
	L_{min}	522.168	0.602	0.000
	NS	891.857	0.544	0.000
	BEs	380.321	0.538	0.000
	L_{max}	293.554	0.420	0.000
	L_{stdv}	73.251	0.170	0.000
Interaction	NS	66.955	0.161	0.000
	L_{stdv}	8.644	0.072	0.000
	L_{max}	6.069	0.029	0.000
	L_{min}	4.216	0.015	0.000
	L_{mean}	4.239	0.012	0.000
	Disp	10.096	0.012	0.000
	BEs	2.712	0.010	0.000
	N	3.642	0.009	0.000

Table 11. Omega Squared values for each single-factor ANOVA for each subgraph statistic. Maximum Omega squared values are in bold, minimum are underlined. An "ns" indicates an ANOVA that was not significant.

Patchiness simple effects

	BEs	Disp	L_{max}	L_{mean}	L_{min}	NS	N	L_{stdv}
A_1	0.003 ns	0.003 ns	**0.144**	**0.214**	0.006 ns	**0.307**	0.006 ns	**0.154**
A_2	**0.017**	0.050	0.116	0.113	0.003 ns	0.123	0.020	0.094
A_3	0.006 ns	**0.061**	0.040	0.050	0.019	0.098	**0.053**	0.022
A_4	0.001 ns	0.008 ns	0.017	0.025	**0.025**	0.027	0.027	0.010
A_5	-0.002 ns	0.005 ns	0.003 ns	0.008	0.011	0.002 ns	0.025	0.014

Abruptness simple effects

	BEs	Disp	L_{max}	L_{mean}	L_{min}	NS	N	L_{stdv}
P_1	0.209	0.629	0.062	0.308	0.299	0.301	0.364	**0.098**
P_2	0.207	0.552	0.094	**0.345**	**0.332**	0.305	**0.370**	0.090
P_3	**0.210**	0.623	0.199	0.329	0.234	0.328	**0.370**	0.024
P_4	0.161	0.670	0.236	0.260	0.148	0.381	0.314	0.021
P_5	0.194	**0.772**	**0.309**	0.331	0.254	**0.513**	0.338	0.046

interaction effects of NS were twice as strong as the interaction effects of L_{stdv}.

As abruptness increased, the patchiness sensitivity of NS and L_{stdv} decreased (Table 11). Interaction was so strong that NS failed to detect differences in patchiness at abruptness level 5 even though it was the most sensitive to patchiness at abruptness levels 1, 2 and 3 and the second most sensitive at abruptness level 4. L_{stdv} found significant differences in patchiness at all levels of abruptness.

NS was hypothesized to increase as patchiness increased. This relationship was confirmed by examining the Bonferroni comparisons for NS (Appendix B). The difference was negative when the mean NS of a higher patchiness level was subtracted from the mean NS of a lower patchiness level. There were three comparisons where this did not occur. The comparisons between patchiness levels 3 and 5 and 4 and 5 at abruptness level 3 were positive when 5 was subtracted from 3 and 4 respectively. This indicates that NS was lower at patchiness level 5 when it was expected to be higher. Since this did not occur at every level of abruptness, it must be attributed either to an interaction effect or an unusual error. Also, other comparisons between patchiness level 5 and lower patchiness levels were not significant at higher levels of abruptness. In other words, this metric cannot make distinctions at higher levels of abruptness. NS was externally consistent with regard to patchiness differences at abruptness levels 1 and 2 but not at abruptness levels 3, 4 and 5. NS detected differences between patchiness levels 1, 2, 3 and 4 levels apart at abruptness levels 1 and 2 but not at 4 and 5. At abruptness level

3, NS differentiated patchiness differences of 1, 2 and 3 levels but did not differentiate a 4 level difference in patchiness.

The response of L_{stdv} exhibited interaction. L_{stdv} was hypothesized to decrease as patchiness increased. L_{stdv} met hypotheses at low levels of abruptness but at high levels of abruptness L_{stdv} increased with patchiness. Also, L_{stdv} responded internally consistently to patchiness at low levels of abruptness but not at high abruptness levels. L_{stdv} detected 1, 2, 3 and 4 level differences in patchiness at abruptness levels 1 and 2 but not at abruptness levels 3, 4 and 5.

BEs, Disp and N

BEs, Disp and N were hypothesized to be most useful as abruptness metrics. Each was sensitive to abruptness as well as patchiness, but they excelled as abruptness metrics. Disp and N ranked as the top two subgraph statistics in terms of sensitivity to the abruptness main effects while BEs ranked sixth (Table 10). N, BEs and Disp were the worst of the subgraph statistics in terms of patchiness sensitivity. The interaction effects for BEs, N and Disp were the weakest.

For BEs and N, the presence of interaction produced similar patterns of abruptness sensitivity within the abruptness simple effects (Table 11). Abruptness sensitivity for both BEs and N was fairly constant at patchiness levels 1, 2 and 3, dropped to a minimum at patchiness level 4, then increased slightly at patchiness level 5. Abruptness sensitivity of Disp was the opposite, exhibiting a trend of increasing abruptness sensitivity as patchiness increased. Disp had maximum abruptness sensitivity at patchiness level 5.

BEs, N and Disp each responded to abruptness differences in a predictable and internally consistent manner (Appendix B). As hypothesized, BEs, N and Disp decreased as abruptness increased. Disp was significantly different for comparisons between all abruptness levels except the comparisons between abruptness levels 4 and 5. Similarly, BEs and N did not detect a difference between abruptness levels 4 and 5. N and BEs did not distinguish the difference between intermediate and high levels of abruptness at certain patchiness levels. In addition, both N and BEs failed to detect a difference between abruptness levels 1 and 2 at patchiness level 3. The difference between 1 and 2 should have been easily distinguished since the surface with abruptness level 1 was planar while the surface with abruptness level 2 was curvilinear. The fact that N and BEs did not detect this difference was curious.

L_{max}, L_{mean} and L_{min}

L_{max}, L_{mean} and L_{min} were hypothesized as functional patchiness and abruptness metrics. Each metric had significant patchiness and abruptness main effects as well as significant interaction effects (Table 10). With regard to the patchiness main effects, L_{max} ranked second, L_{mean} ranked third and L_{min} ranked fifth. As abruptness metrics, L_{mean} ranked third, L_{min} fourth and L_{max} seventh. L_{mean} had the weakest interaction effects of the three followed by L_{min} then L_{max}.

The interaction effects on L_{max} were nearly twice as strong as the interaction effects on L_{mean} and L_{min}.

For L_{max} and L_{mean}, the presence of interaction resulted in a decrease in patchiness sensitivity as abruptness increased (Table 11). In fact, L_{max} did not distinguish any difference in patchiness at abruptness level 5. L_{mean} found significant differences at all levels of abruptness. L_{min} was unable to detect patchiness differences at abruptness levels 1 and 2 but its patchiness sensitivity increased as abruptness increased.

The interaction effect for L_{max} was such that abruptness sensitivity increased steadily as patchiness increased (Table 11). L_{mean} and L_{min} exhibited patterns of interaction more similar to N and L_{stdv} than L_{max}. Maximum abruptness sensitivity for L_{mean} and L_{min} occurred at patchiness level 2 while the minimum occurred at patchiness level 4 and it fluctuated at the remaining patchiness levels.

L_{max}, L_{mean} and L_{min} were less predictable and responded with less internal consistency as patchiness metrics than they did as abruptness metrics (Appendix B). L_{max} was the only metric to respond as hypothesized for every patchiness comparison; L_{max} decreased as patchiness increased. L_{mean} and L_{min} also had this relationship with patchiness except in comparisons involving patchiness level 5. The same pattern was observed for NS and L_{stdv}; both deviated from expected responses in comparisons involving patchiness level 5. L_{max} did not respond to patchiness in an internally consistent manner at abruptness levels 3 and 4. For example, L_{max} found the comparison between patchiness levels 2 and 4 significantly different but not the comparison between level 2 and 5. L_{mean} and L_{min} had similar problems at abruptness levels 3, 4 and 5.

As abruptness metrics, L_{max}, L_{mean} and L_{min} performed as hypothesized for every abruptness comparison made (Appendix B). Values of L_{max}, L_{mean} and L_{min} increased as abruptness increased. L_{mean} and L_{min} responded internally consistently to abruptness differences at each patchiness level while L_{max} had an internally inconsistent comparison at patchiness level 1 and 2. None of the three metrics distinguished a difference between abruptness levels 4 and 5 and 1 and 2 but did distinguish large and small degree differences in abruptness.

Cumulative boundary elements

The factorial ANOVA results for CBE are found in Table 12. CBE was sensitive to both the patchiness and abruptness main effects. Its Omega squared value for the patchiness main effects (0.018) ranked CBE as the sixth most sensitive metric of all the surface-based metrics. With an Omega squared value of 0.806, CBE ranked as the second most sensitive metric to abruptness. Although it was hoped the response of CBE would avoid significant interaction effects, interaction was significant but very low ($\omega^2 = 0.006$).

The single factor ANOVA results for CBE are found in Table 13. CBE detected significant differences in patchiness at every level of abruptness except abruptness level 1. CBE also detected significant differences in abruptness at every level of patchiness. CBE interaction effects exhibited a pattern of increased CBE patchiness sensitivity as abruptness increased. Abruptness sensitivity decreased with successive patchiness level until patchiness level 5 where it greatly increased.

Table 12. Main and interaction effects for ANOVA on the cumulative boundary elements metric. An "ns" indicates that the variation in the source was not significant different.

Source	F	ω^2	P
Patchiness	33.260	0.018	0.000
Abruptness	1478.364	0.806	0.000
Interaction	3.880	0.006	0.000

Table 13. Simple effects results for ANOVA on the cumulative boundary elements metric. The maximum Omega squared value is in bold; the minimum is underlined. An "ns" indicates an ANOVA that was not significant.

Patchiness simple effects **Abruptness simple effects**

	CBE		CBE
A_1	<u>0.003</u> ns	P_1	0.501
A_2	0.018	P_2	0.479
A_3	0.036	P_3	0.458
A_4	0.070	P_4	<u>0.424</u>
A_5	**0.122**	P_5	**0.571**

The Bonferroni comparisons of each single factor ANOVA computed for CBE are included in Appendix C. The comparisons among the patchiness simple effects are not externally consistent, the sign of the mean differences between patchiness levels changes depending on the comparison being made. Also, at abruptness levels 3 and 4, the significant comparisons of CBE did not form an internally consistent pattern. No hypotheses were made as to how CBE would respond to patchiness differences, but the sign changes and inconsistent behavior suggest CBE is not a very good patchiness metric. On the other hand, the comparisons among the abruptness simple effects were externally and internally consistent. CBE, hypothesized to be inversely related to abruptness, did decrease as abruptness increased at every comparison made. CBE did not detect a difference between abruptness levels 4 and 5 at any patchiness level nor between abruptness level 1 and 2 at patchiness levels 3 and 4. CBE found significant differences for all other comparisons. CBE's pattern of significantly different comparisons among abruptness is nearly identical to the pattern exhibited by N.

Surface-based metrics ranked by simple effects

The surface-based metrics ranked in order of simple effects patchiness and abruptness sensitivity are found in Table 14. Across the 5 abruptness levels, NS and L_{mean} consistently ranked as high patchiness detectors, while BEs and L_{max} consistently ranked low. The CBE, N and L_{min} metrics improved in rank as abruptness increased. L_{stdv} ranked low as a patchiness metric at abruptness levels 3 and 4 but was among the best at abruptness levels 1, 2, and 5. At abruptness level 3, Disp was the second ranked patchiness metric but was less impressive at all other abruptness levels. Disp, CBE and N consistently ranked as superior abruptness metrics, while L_{stdv}, L_{max}, and BEs repeatedly ranked among the lower half. At lower levels of patchiness, L_{min} and NS were mediocre abruptness metrics. L_{min} decreased in rank as patchiness increased but NS improved to be the second ranked abruptness metric at patchiness levels 4 and 5. L_{mean} was an average abruptness metric at all patchiness levels.

Table 14. Surface-based metrics ranked by single-factor Omega Squared values.

Patchiness simple effects

A_1		A_2		A_3		A_4		A_5	
Metric	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2
NS	0.307	NS	0.123	NS	0.098	CBE	0.070	CBE	0.122
L_{mean}	0.214	L_{max}	0.116	Disp	0.061	N	0.027	N	0.025
L_{stdv}	0.154	L_{mean}	0.113	N	0.053	NS	0.027	L_{stdv}	0.014
L_{max}	0.144	L_{stdv}	0.094	L_{mean}	0.050	L_{min}	0.025	L_{min}	0.011
N	0.006	Disp	0.050	L_{max}	0.040	L_{mean}	0.025	L_{mean}	0.008
L_{min}	0.006	N	0.020	CBE	0.036	L_{max}	0.017	Disp	0.005
CBE	0.003	CBE	0.018	L_{stdv}	0.022	L_{stdv}	0.010	L_{max}	0.003
BEs	0.003	BEs	0.017	L_{min}	0.019	Disp	0.008	NS	0.002
Disp	0.003	L_{min}	0.003	BEs	0.006	BEs	0.001	BEs	-0.002

Abruptness simple effects

P_1		P_2		P_3		P_4		P_5	
Metric	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2	**Metric**	ω^2
Disp	0.629	Disp	0.552	Disp	0.623	Disp	0.670	Disp	0.772
CBE	0.501	CBE	0.479	CBE	0.458	CBE	0.424	CBE	0.571
N	0.364	N	0.370	N	0.370	NS	0.381	NS	0.513
L_{mean}	0.308	L_{mean}	0.345	L_{mean}	0.329	N	0.314	N	0.338
NS	0.301	L_{min}	0.332	NS	0.328	L_{mean}	0.260	L_{mean}	0.331
L_{min}	0.299	NS	0.305	L_{min}	0.234	L_{max}	0.236	L_{max}	0.309
BEs	0.209	BEs	0.207	BEs	0.210	BEs	0.161	L_{min}	0.254
L_{stdv}	0.098	L_{max}	0.094	L_{max}	0.199	L_{min}	0.148	BEs	0.194
L_{max}	0.062	L_{stdv}	0.090	L_{stdv}	0.024	L_{stdv}	0.021	L_{stdv}	0.046

Surface-based suitability ranking

The suitability scores for each of the eight subgraph statistics and CBE are presented in Table 15. In descending order, the most suitable surface-based metrics for quantifying patchiness were: NS, L_{max}, L_{mean}, L_{min}, N, Disp, CBE and BEs. The two surface-based metrics thought to be exclusively patchiness metrics, NS and L_{stdv}, did rank among the best. Not surprisingly, the hypothesized abruptness metrics, BE, CBE, Disp and N, performed poorly as patchiness metrics. L_{max} was a better patchiness metric than an abruptness metric while L_{min} did not perform particularly well as either. L_{max} was the only surface-based metric that was completely externally consistent with regard to patchiness. BEs was the only surface-based metric that was completely internally consistent with regard to patchiness.

In descending order, the most suitable surface-based metrics for quantifying abruptness were: Disp, CBE, N, L_{mean}, NS, L_{min}, BEs, L_{max}, L_{stdv}. This order conforms to the expected function of the metrics. CBE and Disp were designed specifically to measure abruptness and ranked as the most suitable abruptness metrics. L_{mean} was the only metric to rank in the top half as both a patchiness metric and abruptness metric. All of the surface-based metrics, except for L_{max} and L_{stdv}, were completely externally and internally consistent with regard to abruptness.

Table 15. Surface-based metrics ranked by patchiness and abruptness suitability scores.

Patchiness suitability scores

Metric	Main effects sensitivity	Simple effects sensitivity	External Consistency	Internal Consistency	Total
NS	1.00	0.68	0.88	0.86	3.41
L_{max}	0.98	0.42	1.00	0.87	3.27
L_{mean}	0.33	0.51	0.86	0.81	2.52
L_{stdv}	0.24	0.35	0.95	0.87	2.41
L_{min}	0.21	0.14	0.75	0.62	1.71
N	0.12	0.26	0.69	0.59	1.67
Disp	0.09	0.24	0.42	0.86	1.60
CBE	0.17	0.50	0.00	0.75	1.43
BEs	0.10	0.04	0.00	1.00	1.14

Abruptness suitability scores

Metric	Main effects sensitivity	Simple effects sensitivity	External Consistency	Internal Consistency	Total
Disp	1.00	1.00	1.00	1.00	4.00
CBE	0.92	0.75	1.00	1.00	3.67
N	0.81	0.55	1.00	1.00	3.36
L_{mean}	0.75	0.49	1.00	1.00	3.24
NS	0.62	0.56	1.00	1.00	3.18
L_{min}	0.68	0.40	1.00	1.00	3.08
BEs	0.61	0.31	1.00	1.00	2.92
L_{max}	0.48	0.27	1.00	0.95	2.69
L_{stdv}	0.19	0.09	0.58	0.68	1.54

Patch-based suitability vs. Surface-based suitability

The primary goal of this research has been to determine which approach, the patch- or surface-based, would be most suitable for quantifying ecotone patchiness and abruptness. Both approaches were sensitive to patchiness and abruptness, but the patch-based metrics were on average more sensitive to both characteristics than the surface-based metrics. On average, the surface-based metrics had weaker interaction effects. Both sets of metrics were more externally and internally consistent as abruptness metrics than as patchiness metrics. In order to determine which metrics performed the best relative to one another, they were ranked according to their patchiness and abruptness suitability. The patchiness suitability ranking is shown in Table 16 while the abruptness suitability ranking is shown in Table 17. Mean suitability scores for each set of metrics are also provided.

According to the patchiness suitability ranking of all the metrics (Table 16), the patch-based set performed better as patchiness metrics than the surface-based set. The patch-based mean patchiness suitability score (2.81) was greater than the surface-based mean patchiness suitability score (1.92). On average, the patch-based metrics received higher scores for main effects sensitivity, simple effects sensitivity, external and internal consistency than the surface-based metrics. Patch-based metrics occupied the 5 highest ranks for patchiness detection.

Table 16. Patch- and surface-based metrics ranked according to patchiness suitability scores. Patch-based metrics are underlined.

Patchiness suitability scores

Metric	Main effects sensitivity	Simple effects sensitivity	External Consistency	Internal Consistency	Total
LPI	1.00	0.27	1.00	1.00	3.27
NP	0.75	0.49	0.91	0.85	3.00
AWMSI	0.27	0.66	1.00	1.00	2.92
CONTAG	0.36	0.59	0.97	0.94	2.86
TE	0.37	0.57	0.97	0.94	2.86
NS	0.61	0.52	0.88	0.86	2.86
AWMPFD	0.27	0.55	1.00	1.00	2.82
L_{max}	0.60	0.31	1.00	0.87	2.77
PSCV	0.39	0.38	0.95	0.84	2.56
L_{mean}	0.20	0.38	0.86	0.81	2.26
L_{stdv}	0.14	0.25	0.95	0.87	2.22
MPS	0.22	0.25	0.90	0.84	2.21
L_{min}	0.13	0.12	0.75	0.62	1.61
N	0.07	0.24	0.69	0.59	1.59
Disp	0.05	0.21	0.42	0.86	1.53
CBE	0.11	0.46	0.00	0.75	1.31
BEs	0.06	0.03	0.00	1.00	1.09
Patch-based mean	0.45	0.47	0.96	0.93	2.81
Surface-based mean	0.22	0.28	0.62	0.80	1.92

Table 17. Patch- and surface-based metrics ranked according to abruptness suitability scores. Patch-based metrics are underlined.

Abruptness suitability scores

Metric	Main effects sensitivity	Simple effects sensitivity	External Consistency	Internal Consistency	Total
Disp	1.00	0.98	1.00	1.00	3.98
CONTAG	0.90	0.89	1.00	1.00	3.79
AWMPFD	0.93	0.84	1.00	1.00	3.77
AWMSI	0.92	0.83	1.00	0.98	3.73
TE	0.86	0.86	1.00	1.00	3.72
CBE	0.92	0.74	1.00	1.00	3.65
N	0.81	0.54	1.00	1.00	3.35
PSCV	0.74	0.57	1.00	1.00	3.30
MPS	0.76	0.53	1.00	1.00	3.29
L_{mean}	0.75	0.48	1.00	1.00	3.23
NS	0.62	0.54	1.00	1.00	3.16
NP	0.56	0.59	1.00	1.00	3.15
L_{min}	0.68	0.39	1.00	1.00	3.08
BEs	0.61	0.30	1.00	1.00	2.91
L_{max}	0.48	0.26	1.00	0.95	2.68
LPI	0.02	0.14	0.43	0.95	1.55
L_{stdv}	0.19	0.09	0.58	0.68	1.54
Patch-based mean	0.71	0.66	0.93	0.99	3.29
Surface-based mean	0.67	0.48	0.95	0.96	3.07

The abruptness suitability ranking (Table 17) indicated that the patch-based set also performed better than the surface-based set as abruptness metrics. The patch-based set had a mean suitability score of 3.29 verses a mean suitability score of 3.07 for the surface-based set. The patch-based metrics had, on average, higher main effects sensitivity, simple effects sensitivity, and internal consistency scores. The surface-based metrics had, on average, slightly better external consistency. Disp, the most suitable surface-based abruptness metric, outperformed the most suitable patch-based abruptness metric CONTAG. Disp had a nearly perfect suitability score (3.98) that was much higher than the second ranked CONTAG (3.79).

It was surprising for the patch-based metrics to outperform most of the surface-based metrics as both patchiness and abruptness metrics. The surface-based approach was hypothesized as the superior approach for quantifying abruptness but the suitability scores suggest otherwise. However, when applying one approach or another to quantify patchiness or abruptness an entire set of metrics need not be used. Only the metrics that were the most suitable for quantifying the characteristic should be selected. In that case the patch-based approach remains the superior approach for quantifying patchiness, and since Disp ranked as the most suitable abruptness metric, the surface-based approach might be the more attractive method for quantifying abruptness.

DISCUSSION AND CONCLUSIONS

Eight patch-based metrics and nine surface-based metrics were evaluated to determine which were the most suitable for quantifying ecotone patchiness and abruptness. Suitability was based on a ranking of scores totaled from 4 categories. The score for each category was based on the metrics' response to simulated patchiness and abruptness differences captured in a factorial analysis of variance. As a whole, the patch-based set of metrics was more suitable than the surface-based set as both patchiness and abruptness metrics. However, individual surface-based metrics were modestly suitable as patchiness metrics and highly suitable as abruptness metrics.

Research Questions Revisited

Do patch-based metrics only measure patchiness or are they capable of measuring abruptness? Which of the patch-based metrics are most suitable as patchiness metrics and which are most suitable as abruptness metrics?

All of patch-based metrics measured differences in both patchiness and abruptness. LPI, NP, and AWMSI ranked as the most suitable patchiness metrics while CONTAG, AWMPFD, and AWMSI ranked as the most suitable abruptness metrics.

The fact that AWMSI excelled at measuring both characteristics could be problematic. When AWMSI is applied to an ecotone of unknown patchiness and abruptness characteristics it would be difficult to determine whether the metric is measuring patchiness or abruptness. For instance, consider two ecotones A and B; ecotone A has an AWMSI of 1.0 and ecotone B has an AWMSI of 1.5. Based on the results of this study, the smaller AWMSI of ecotone A suggests that it is more abrupt than ecotone B. However, the smaller AWMSI also suggests that it is less patchy than ecotone B. If it is assumed that patchiness and abruptness are independent of one another, AWMSI is difficult to interpret; its value could either represent a degree of patchiness or a degree of abruptness. This interpretation problem is avoided by using a metric that was only effective at measuring one characteristic; in other words, one that had a high polarity between patchiness suitability and abruptness suitability. Under this criterion, LPI and NP stand out as a superior patchiness metrics. However, none of the patch-based metrics that were highly suitable abruptness metrics were particularly poor patchiness quantifiers. AWMPFD ranked low as a patchiness metric but its perfect consistency scores suggest it was a fairly good patchiness metric. CONTAG, although it showed high sensitivity to patchiness was not as consistent as the other patch-based metrics. For this reason, CONTAG was considered a poor patchiness metric and was considered most useful as an abruptness metric.

Are the surface-based metrics able to measure patchiness? Do the surface-based metrics measure abruptness? Which of the surface-based metrics are most suitable as patchiness metrics and which are most suitable as abruptness metrics?

The surface-based metrics also measured both patchiness and abruptness. NS, L_{max} and L_{mean} ranked as the most suitable surface-based patchiness metrics and Disp, CBE, and N ranked as the most suitable surface-based abruptness metrics. However, none of the surface-based metrics were completely consistent with regard to patchiness. This is a big concern if they are to be applied as patchiness metrics.

Of the most suitable surface-based patchiness metrics only L_{max} had a high polarity between patchiness suitability and abruptness suitability. L_{max} was the only surface-based patchiness metric unlikely to confuse patchiness and abruptness. NS and L_{mean} both showed relatively high suitability as abruptness metrics which could lead to interpretation problems. On the other hand, the most suitable surface-based abruptness metrics (Disp, CBE, and N) had a very high polarity between their abruptness suitability and patchiness suitability. The risk of interpretation problems between patchiness and abruptness when using Disp, CBE, and N as abruptness quantifiers should be minimal.

The CBE metric was a very impressive abruptness metric. Several properties make this metric the superior choice for quantifying abruptness. First, the metric ranked as a highly suitable abruptness quantifier with a high polarity to patchiness suitability. Second, the response of CBE exhibited a very weak interaction effect. It had a completely consistent response, both externally and internally, to abruptness. Lastly, unlike the subgraph statistics, the method by which CBE is calculated avoids the use of an arbitrary ROC threshold.

Future research should be directed at improving the CBE metric. The weak interaction effects it displayed might be further minimized or eliminated by investigating the effect of the kernel size of the moving window used to compute the ROC surface. CBE's already weak interaction effects may prove to be reduced further if a larger kernel size is used. A larger kernel size may continue to capture the variation in the ecotone surface due to the transition present without being as affected by the finer-grain variation due to patchiness.

How does the degree of one ecotone characteristic affect the measurement of another? Is it possible to measure the degree of patchiness at multiple degrees of abruptness and visa versa. Is metric performance dependent on the level of patchiness or abruptness? For instance, does a patchiness metric lose its ability to measure patchiness as abruptness increases.

Each metric exhibited at least a weak interaction effect. Significant interaction effects indicated that the metrics' ability to measure one ecotone characteristic was dependent on the strength of the other characteristic. In some cases the interaction effect was so strong that the metric failed to detect characteristic differences at one level when it was successful at detecting differences at another. In some cases, interaction was such that metric response was inconsistent. In other cases, the presence of interaction did not always result in an inconsistent response.

The interaction effects of the patch-based metrics were stronger than the interaction effects of surface-based metrics. On average the patch-based set exhibited an interaction effect that was more than twice as strong as the interaction effect of the surface-based set. The mean Omega squared for the interaction effects on the patch-based metrics was 0.095 as compared to 0.036 for the surface-based metrics. The patch-based metric with the weakest interaction effect, AWMPFD ($\omega^2 = 0.109$), had an interaction effect that was much stronger (18x) than the interaction effect of the surface-based metric with the weakest interaction effect, CBE ($\omega^2 = 0.006$). Despite the large difference in interaction effects, the two sets of metrics were comparable in terms of external and internal consistency, especially with regard to consistency as abruptness metrics. This indicates that the presence of interaction did not always translate into adverse consistency effects. Even so, interaction should still be considered a poor property of these metrics.

The presence of interaction could lead to misinterpretation of metric values. Interaction indicated that the response of a metric to a difference in one factor changes with the degree of another factor. For example, the mean difference between NP of patchiness level 1 and NP of patchiness level 5 was 16.680, 5.240 and 0.860 at abruptness levels 1, 2 and 3 respectively. At abruptness levels 4 and 5 the difference was not significant. Although the way in which the difference between patchiness levels 1 and 5 was simulated did not change over abruptness levels, the value of the NP metric did. The difference in NP between abruptness levels was attributed to the interaction of patchiness and abruptness. Therefore, when interaction was present, an NP difference of a particular magnitude at a low level of abruptness did not represent the same difference in patchiness as the same magnitude difference in NP at a higher abruptness level. Interpretation of a metric in the presence of interaction must take into account the way in which the combination of factors contributes to the metric's response. Without a priori knowledge of the patchiness and abruptness characteristics of the ecotones being quantified (i.e., using real world data) interpretation of the metric interaction effects would be difficult, if not impossible.

When the use of the metric suitability ranking was first considered, a score based on the interaction Omega squared was included in the total score used for the ranking. After further consideration, it was decided that the inclusion of this score would overly weight interaction effects in the suitability total since the simple effect sensitivity and the external and internal consistency scores provided evidence of the effects of interaction. Inclusion of the interaction score to the suitability rankings did change the results of ranking. With the interaction score included, AWMPFD and AWMSI rank as both the best patch-based patchiness and abruptness metrics. L_{max}, NS, and L_{mean} are the top ranked surface-based patchiness metrics and CBE, Disp, and N remain the top ranked surface-based abruptness metrics when the interaction score is included. When interaction is included in the suitability ranking of both sets combined, AWMPFD, LPI, and AWMSI rank as the top patchiness metrics and CBE, Disp, and AWMPFD rank as the top abruptness metrics.

Considerations

The simulated ecotones used to evaluate the metrics were oriented so that the transition of the ecotone was parallel to the vertical dimensions of the surface cells. When these methods are used on real world data, the transition will most likely not be oriented in that manner (i.e., the transition as viewed by the satellite image will not always be aligned with the grid). This orientation might affect how the subgraphs are calculated and how the surface-based statistics are interpreted. Calculation of the Disp metric is the most affected by the orientation of the transition. Disp was designed to calculate the dispersion of subgraphs in the direction perpendicular to the transition. This calculation is easily made when the transition is parallel to the surface cells. When the transition is oriented otherwise, the way in which Disp is calculated would have to account for the difference between the orientation of the transition and the orientation of the surface cells.

The surface data can be transformed so that the transition is parallel to the vertical dimensions of the surface cells through a process called resampling. However, resampling could result in two problems. First, how do you determine the orientation of the transition? For alpine treeline ecotones, the orientation of the transition is typically similar to the slope aspect of the terrain the ecotone is situated on, but not always. Where terrain, disturbance regime or ecological processes are especially complex, the transition may not be aligned with the slope aspect. In that case, the orientation would have to be determined another way. One way would be to compute an aspect surface for the ecological variable surface (i.e., LAI or NDVI) and then determine the majority aspect value (the aspect value that occurs the most frequently). The majority aspect value of the variable surface should provide an acceptable estimate of the transition orientation. The transition orientation may end up being a compromise between the terrain aspect and the ecological aspect.

The other problem is the effect the resampling might have on the raw data values. If the method of resampling is weighted, like that of bilinear interpolation or cubic convolution, the data values prior to resampling are changed. Bilinear interpolation is an interpolation method where the value of a location is obtained by linear interpolation on two axes using four neighbors (Chrisman, 1997). Cubic convolution is an interpolation method where the value is obtained by fitting a third-order equation to the 16 neighbors surrounding the desired location (Chrisman, 1997). The changes resulting from the resampling may be large enough so that the integrity of the original data is sacrificed. For this reason, it would be wise to employ the nearest neighbor method of resampling if resampling is necessary. The nearest neighbor method uses the value of the location nearest to the desired location as the interpolated value.

Summary

The goal of this research was to determine which approach was better suited to measure the patchiness and abruptness patterns of alpine treeline ecotones. The suitability scores indicated that the patch-based approach was superior to the surface-based approach. However, the patch-based metrics as abruptness quantifiers were thought to be easily misinterpreted as patchiness quantifiers due to their low degree of polarity between patchiness and abruptness suitability. Conversely, the surface-based metrics were considered good abruptness quantifiers because they had a high patchiness/abruptness suitability polarity. Therefore, this research suggests that the patch-based metrics were optimal for quantifying patchiness while the surface-based metrics were optimal for quantifying abruptness.

In application, it would be most efficient to use only one of the approaches. It would be burdensome in terms of both time and effort to use one approach for patchiness and one approach for abruptness. Each approach could be used to quantify both patterns but the limitations of the approach being used need to be recognized. Use of the patch-based approach runs the risk of misinterpreting abruptness metrics for patchiness. Use of the surface-based approach must consider that the surface-based metrics were not very consistent patchiness quantifiers.

APPENDICES

APPENDIX A

Bonferroni Comparisons for patch-based metrics

The following tables contain the results of the Bonferroni pairwise multiple comparisons that were calculated from the single-factor ANOVA for each metric. The leftmost column indicates the factor level that was held constant in the single-factor ANOVA. The second column from the left and the second row index each of the comparisons made. The number in a cell in the table is the mean difference in metric value for the comparison being made (column minus row). Cells containing a "." indicate that the comparison was not significantly different at the 0.01 significance level.

Bonferonni comparisons for patchiness simple effects

		AWMPFD					AWMSI				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
	P_1	.	.	0.017	0.020	0.035	.	.	0.183	0.221	0.410
	P_2	.	.	0.013	0.016	0.031	.	.	0.156	0.195	0.384
A_1	P_3	-0.017	-0.013	.	.	0.018	-0.183	-0.156	.	.	0.227
	P_4	-0.020	-0.016	.	.	0.015	-0.221	-0.195	.	.	0.189
	P_5	-0.035	-0.031	-0.018	-0.015	.	-0.410	-0.384	-0.227	-0.189	.
	P_1	.	.	0.012	0.011	0.018	.	.	0.102	0.097	0.150
	P_2	.	.	0.012	0.012	0.019	.	.	0.106	0.102	0.155
A_2	P_3	-0.012	-0.012	.	.	.	-0.102	-0.106	.	.	.
	P_4	-0.011	-0.012	.	.	.	-0.097	-0.102	.	.	.
	P_5	-0.018	-0.019	.	.	.	-0.150	-0.155	.	.	.
	P_1	.	.	0.012	0.009	0.013	.	.	0.088	0.059	0.104
	P_2	.	.	0.011	0.007	0.011	.	.	0.071	0.041	0.086
A_3	P_3	-0.012	-0.011	.	.	.	-0.088	-0.071	.	.	.
	P_4	-0.009	-0.007	.	.	.	-0.059	-0.041	.	.	0.045
	P_5	-0.013	-0.011	.	.	.	-0.104	-0.086	.	-0.045	.
	P_1	.	.	.	0.005	0.012	.	.	.	0.035	0.082
	P_2	.	.	.	0.005	0.012	.	.	.	0.033	0.080
A_4	P_3	.	.	.	.	0.009	.	.	.	.	0.060
	P_4	-0.005	-0.005	.	.	0.007	-0.035	-0.033	.	.	0.048
	P_5	-0.012	-0.012	-0.009	-0.007	.	-0.082	-0.080	-0.060	-0.048	.
	P_1	.	.	0.004	0.008	0.012	.	.	0.029	0.054	0.088
	P_2	.	.	.	0.006	0.010	.	.	.	0.039	0.073
A_5	P_3	-0.004	.	.	.	0.008	-0.029	.	.	0.025	0.059
	P_4	-0.008	-0.006	.	.	0.004	-0.054	-0.039	-0.025	.	0.034
	P_5	-0.012	-0.010	-0.008	-0.004	.	-0.088	-0.073	-0.059	-0.034	.

Cont...

Bonferonni comparisons for patchiness simple effects

		CONTAG					LPI				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
A_1	P_1	.	.	-3.662	-5.096	-10.945	.	.	.	-2.925	-4.956
	P_2	.	.	-3.418	-4.852	-10.702	.	.	.	-2.534	-4.565
	P_3	3.662	3.418	.	.	-7.283	.	.	.	.	-3.514
	P_4	5.096	4.852	.	.	-5.849	2.925	2.534	.	.	-2.031
	P_5	10.945	10.702	7.283	5.849	.	4.956	4.565	3.514	2.031	.
A_2	P_1	.	.	-2.435	-2.572	-4.606	.	.	-1.251	-1.786	-2.435
	P_2	.	.	-2.433	-2.570	-4.604	.	.	.	-1.369	-2.018
	P_3	2.435	2.433	.	.	-2.171	1.251	.	.	.	-1.184
	P_4	2.572	2.570	.	.	-2.033	1.786	1.369	.	.	.
	P_5	4.606	4.604	2.171	2.033	.	2.435	2.018	1.184	.	.
A_3	P_1	.	.	-2.132	-1.080	-2.141	.	.	-0.663	-0.608	-0.912
	P_2	.	.	-1.708	.	-1.716	.	.	-0.527	-0.472	-0.776
	P_3	2.132	1.708	.	1.053	.	0.663	0.527	.	.	.
	P_4	1.080	.	-1.053	.	-1.061	0.608	0.472	.	.	.
	P_5	2.141	1.716	.	1.061	.	0.912	0.776	.	.	.
A_4	P_1	.	.	.	.	-1.229	.	.	.	.	.
	P_2	.	.	.	.	-1.311	.	.	.	.	.
	P_3	.	.	.	.	-0.910	.	.	.	.	.
	P_4	.	.	.	.	-0.781	.	.	.	.	.
	P_5	1.229	1.311	0.910	0.781	.	.	.	.	.	.
A_5	P_1	.	.	-0.666	-0.934	-1.467	.	.	-0.386	-0.418	-0.441
	P_2	.	.	.	-0.648	-1.181	.	.	.	.	.
	P_3	0.666	.	.	.	-0.801	0.386	.	.	.	.
	P_4	0.934	0.648	.	.	-0.533	0.418	.	.	.	.
	P_5	1.467	1.181	0.801	0.533	.	0.441	.	.	.	.

Cont...

Bonferonni comparisons for patchiness simple effects

		MPS					NP				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
A_1	P_1	.	.	-2.438	-3.964	-6.027	.	.	1.860	4.560	16.680
	P_2	.	.	-2.228	-3.753	-5.816	.	.	2.060	4.760	16.880
	P_3	2.438	2.228	.	.	-3.589	-1.860	-2.060	.	2.700	14.820
	P_4	3.964	3.753	.	.	-2.063	-4.560	-4.760	-2.700	.	12.120
	P_5	6.027	5.816	3.589	2.063	.	-16.680	-16.880	-14.820	-12.120	.
A_2	P_1	.	.	-4.359	-4.532	-8.348	.	.	1.480	1.860	5.240
	P_2	.	.	-3.564	-3.738	-7.554	.	.	1.360	1.740	5.120
	P_3	4.359	3.564	.	.	-3.990	-1.480	-1.360	.	.	3.760
	P_4	4.532	3.738	.	.	-3.816	-1.860	-1.740	.	.	3.380
	P_5	8.348	7.554	3.990	3.816	.	-5.240	-5.120	-3.760	-3.380	.
A_3	P_1	.	.	-4.450	.	-3.471	.	.	1.040	.	0.860
	P_2	.	.	-3.326	.	.	.	.	0.800	.	.
	P_3	4.450	3.326	.	3.181	.	-1.040	-0.800	.	-0.800	.
	P_4	.	.	-3.181	.	.	.	.	0.800	.	.
	P_5	3.471	.	.	.	.	-0.860	.	.	.	.
A_4	P_1	.	.	.	.	.	.	.	.	.	.
	P_2	.	.	.	.	.	.	.	.	.	.
	P_3	.	.	.	.	.	.	.	.	.	.
	P_4	.	.	.	.	.	.	.	.	.	.
	P_5	.	.	.	.	.	.	.	.	.	.
A_5	P_1	.	.	.	.	.	.	.	.	.	.
	P_2	.	.	.	.	.	.	.	.	.	.
	P_3	.	.	.	.	1.587	.	.	.	.	-0.280
	P_4	.	.	.	.	.	.	.	.	.	.
	P_5	.	.	-1.587	.	.	.	.	0.280	.	.

Cont…

Bonferonni comparisons for patchiness simple effects

		PSCV					TE				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
A_1	P_1	.	.	31.8	66.5	166.9	.	.	520.8	741.6	1840.8
	P_2	.	.	31.8	66.4	166.9	.	.	523.2	744.0	1843.2
	P_3	-31.8	-31.8	.	34.6	135.1	-520.8	-523.2	.	.	1320.0
	P_4	-66.5	-66.4	-34.6	.	100.5	-741.6	-744.0	.	.	1099.2
	P_5	-166.9	-166.9	-135.1	-100.5	.	-1840.8	-1843.2	-1320.0	-1099.2	.
A_2	P_1	.	.	44.3	48.2	107.0	.	.	286.2	301.8	565.8
	P_2	.	.	36.9	40.8	99.6	.	.	292.8	308.4	572.4
	P_3	-44.3	-36.9	.	.	62.7	-286.2	-292.8	.	.	279.6
	P_4	-48.2	-40.8	.	.	58.8	-301.8	-308.4	.	.	264.0
	P_5	-107.0	-99.6	-62.7	-58.8	.	-565.8	-572.4	-279.6	-264.0	.
A_3	P_1	.	.	44.2	.	34.1	.	.	234.0	112.2	229.8
	P_2	.	.	33.5	.	.	.	.	189.0	.	184.8
	P_3	-44.2	-33.5	.	-31.8	.	-234.0	-189.0	.	-121.8	.
	P_4	.	.	31.8	.	.	-112.2	.	121.8	.	117.6
	P_5	-34.1	.	.	.	.	-229.8	-184.8	.	-117.6	.
A_4	P_1	.	.	.	.	.	.	.	.	.	125.4
	P_2	.	.	.	.	.	.	.	.	.	135.6
	P_3	.	.	.	.	.	.	.	.	.	94.8
	P_4	.	.	.	.	.	.	.	.	.	82.2
	P_5	.	.	.	.	.	-125.4	-135.6	-94.8	-82.2	.
A_5	P_1	.	.	.	.	.	.	.	67.2	93.6	150.0
	P_2	.	.	.	.	.	.	.	.	66.0	122.4
	P_3	.	.	.	.	.	-67.2	.	.	.	82.8
	P_4	.	.	.	.	.	-93.6	-66.0	.	.	56.4
	P_5	.	.	.	.	.	-150.0	-122.4	-82.8	-56.4	.

Bonferroni comparisons for abruptness simple effects

		AWMPFD					AWMSI				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	-0.035	-0.056	-0.062	-0.063	.	-0.328	-0.498	-0.537	-0.543
	A_2	0.035	.	-0.022	-0.028	-0.028	0.328	.	-0.170	-0.209	-0.215
	A_3	0.056	0.022	.	.	.	0.498	0.170	.	.	.
	A_4	0.062	0.028	.	.	.	0.537	0.209	.	.	.
	A_5	0.063	0.028	.	.	.	0.543	0.215	.	.	.
P_2	A_1	.	-0.040	-0.059	-0.066	-0.065	.	-0.358	-0.507	-0.561	-0.554
	A_2	0.040	.	-0.019	-0.027	-0.026	0.358	.	-0.148	-0.202	-0.196
	A_3	0.059	0.019	.	.	.	0.507	0.148	.	.	.
	A_4	0.066	0.027	.	.	.	0.561	0.202	.	.	.
	A_5	0.065	0.026	.	.	.	0.554	0.196	.	.	.
P_3	A_1	.	-0.041	-0.061	-0.077	-0.076	.	-0.408	-0.592	-0.697	-0.697
	A_2	0.041	.	-0.021	-0.036	-0.036	0.408	.	-0.184	-0.288	-0.288
	A_3	0.061	0.021	.	-0.015	-0.015	0.592	0.184	.	-0.104	-0.104
	A_4	0.077	0.036	0.015	.	.	0.697	0.288	0.104	.	.
	A_5	0.076	0.036	0.015	.	.	0.697	0.288	0.104	.	.
P_4	A_1	.	-0.044	-0.068	-0.077	-0.075	.	-0.452	-0.661	-0.723	-0.710
	A_2	0.044	.	-0.024	-0.033	-0.031	0.452	.	-0.209	-0.272	-0.259
	A_3	0.068	0.024	.	-0.009	-0.007	0.661	0.209	.	-0.063	.
	A_4	0.077	0.033	0.009	.	.	0.723	0.272	0.063	.	.
	A_5	0.075	0.031	0.007	.	.	0.710	0.259	.	.	.
P_5	A_1	.	-0.052	-0.079	-0.086	-0.086	.	-0.587	-0.804	-0.864	-0.865
	A_2	0.052	.	-0.027	-0.033	-0.034	0.587	.	-0.217	-0.277	-0.277
	A_3	0.079	0.027	.	-0.007	-0.007	0.804	0.217	.	-0.060	-0.061
	A_4	0.086	0.033	0.007	.	.	0.864	0.277	0.060	.	.
	A_5	0.086	0.034	0.007	.	.	0.865	0.277	0.061	.	.

Cont...

Bonferroni comparisons for abruptness simple effects

		CONTAG					LPI				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	6.51	9.73	10.40	10.68	.	.	.	-1.492	-1.542
	A_2	-6.51	.	3.22	3.89	4.17	.	.	.	-1.360	-1.410
	A_3	-9.73	-3.22	.	.	.	.	.	.	.	.
	A_4	-10.40	-3.89	.	.	.	1.492	1.360	.	.	.
	A_5	-10.68	-4.17	.	.	.	1.542	1.410	.	.	.
P_2	A_1	.	6.76	9.55	10.73	10.64	.	.	-0.906	-1.142	-1.319
	A_2	-6.76	.	2.80	3.97	3.88	.	.	.	-0.984	-1.161
	A_3	-9.55	-2.80	.	.	.	0.906	.	.	.	.
	A_4	-10.73	-3.97	.	.	.	1.142	0.984	.	.	.
	A_5	-10.64	-3.88	.	.	.	1.319	1.161	.	.	.
P_3	A_1	.	7.74	11.26	13.75	13.68	.	.	.	.	.
	A_2	-7.74	.	3.52	6.01	5.94	.	.	.	.	.
	A_3	-11.26	-3.52	.	2.48	2.42	.	.	.	.	.
	A_4	-13.75	-6.01	-2.48	.	.	.	.	.	.	.
	A_5	-13.68	-5.94	-2.42	.	.	.	.	.	.	.
P_4	A_1	.	9.04	13.75	15.05	14.84	.	1.007	1.156	1.210	0.965
	A_2	-9.04	.	4.71	6.01	5.81	-1.007	.	.	.	.
	A_3	-13.75	-4.71	.	1.30	1.10	-1.156	.	.	.	.
	A_4	-15.05	-6.01	-1.30	.	.	-1.210	.	.	.	.
	A_5	-14.84	-5.81	-1.10	.	.	-0.965	.	.	.	.
P_5	A_1	.	12.85	18.54	20.12	20.16	.	2.389	2.883	3.341	2.973
	A_2	-12.85	.	5.68	7.27	7.31	-2.389	.	0.494	0.952	0.584
	A_3	-18.54	-5.68	.	1.58	1.62	-2.883	-0.494	.	0.458	.
	A_4	-20.12	-7.27	-1.58	.	.	-3.341	-0.952	-0.458	.	.
	A_5	-20.16	-7.31	-1.62	.	.	-2.973	-0.584	.	.	.

Cont…

Bonferroni comparisons for abruptness simple effects

		MPS					NP				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	5.85	9.64	10.00	11.49	.	-2.86	-3.76	-3.76	-4.06
	A_2	-5.85	.	3.79	4.15	5.65	2.86	.	-0.90	-0.90	-1.20
	A_3	-9.64	-3.79	.	.	.	3.76	0.90	.	.	.
	A_4	-10.00	-4.15	.	.	.	3.76	0.90	.	.	.
	A_5	-11.49	-5.65	.	.	.	4.06	1.20	.	.	.
P_2	A_1	.	5.26	8.73	11.31	11.50	.	-2.54	-3.32	-3.80	-3.82
	A_2	-5.26	.	3.46	6.04	6.24	2.54	.	-0.78	-1.26	-1.28
	A_3	-8.73	-3.46	.	2.58	2.78	3.32	0.78	.	.	.
	A_4	-11.31	-6.04	-2.58	.	.	3.80	1.26	.	.	.
	A_5	-11.50	-6.24	-2.78	.	.	3.82	1.28	.	.	.
P_3	A_1	.	3.93	7.63	12.67	12.61	.	-3.24	-4.58	-5.72	-5.68
	A_2	-3.93	.	3.70	8.75	8.68	3.24	.	-1.34	-2.48	-2.44
	A_3	-7.63	-3.70	.	5.05	4.98	4.58	1.34	.	-1.14	-1.10
	A_4	-12.67	-8.75	-5.05	.	.	5.72	2.48	1.14	.	.
	A_5	-12.61	-8.68	-4.98	.	.	5.68	2.44	1.10	.	.
P_4	A_1	.	5.28	12.34	14.99	15.19	.	-5.56	-8.08	-8.54	-8.58
	A_2	-5.28	.	7.06	9.71	9.91	5.56	.	-2.52	-2.98	-3.02
	A_3	-12.34	-7.06	.	2.66	2.86	8.08	2.52	.	.	.
	A_4	-14.99	-9.71	-2.66	.	.	8.54	2.98	.	.	.
	A_5	-15.19	-9.91	-2.86	.	.	8.58	3.02	.	.	.
P_5	A_1	.	3.53	12.20	17.45	17.78	.	-14.30	-19.58	-20.72	-20.78
	A_2	-3.53	.	8.67	13.93	14.26	14.30	.	-5.28	-6.42	-6.48
	A_3	-12.20	-8.67	.	5.26	5.59	19.58	5.28	.	.	.
	A_4	-17.45	-13.93	-5.26	.	.	20.72	6.42	.	.	.
	A_5	-17.78	-14.26	-5.59	.	.	20.78	6.48	.	.	.

Cont...

Bonferroni comparisons for abruptness simple effects

		PSCV					TE				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
	A_1	.	-64.6	-103.0	-107.4	-122.4	.	-904.2	-1284.0	-1354.8	-1384.8
	A_2	64.6	.	-38.4	-42.8	-57.8	904.2	.	-379.8	-450.6	-480.6
P_1	A_3	103.0	38.4	.	.	.	1284.0	379.8	.	.	.
	A_4	107.4	42.8	.	.	.	1354.8	450.6	.	.	.
	A_5	122.4	57.8	.	.	.	1384.8	480.6	.	.	.
	A_1	.	-57.3	-92.4	-118.3	-120.9	.	-908.4	-1236.6	-1362.6	-1354.8
	A_2	57.3	.	-35.1	-61.0	-63.6	908.4	.	-328.2	-454.2	-446.4
P_2	A_3	92.4	35.1	.	-26.0	-28.5	1236.6	328.2	.	.	.
	A_4	118.3	61.0	26.0	.	.	1362.6	454.2	.	.	.
	A_5	120.9	63.6	28.5	.	.	1354.8	446.4	.	.	.
	A_1	.	-52.1	-90.6	-141.5	-141.5	.	-1138.8	-1570.8	-1845.0	-1838.4
	A_2	52.1	.	-38.5	-89.3	-89.4	1138.8	.	-432.0	-706.2	-699.6
P_3	A_3	90.6	38.5	.	-50.8	-50.9	1570.8	432.0	.	-274.2	-267.6
	A_4	141.5	89.3	50.8	.	.	1845.0	706.2	274.2	.	.
	A_5	141.5	89.4	50.9	.	.	1838.4	699.6	267.6	.	.
	A_1	.	-82.9	-157.1	-184.5	-186.9	.	-1344.0	-1913.4	-2053.2	-2032.8
	A_2	82.9	.	-74.2	-101.6	-103.9	1344.0	.	-569.4	-709.2	-688.8
P_4	A_3	157.1	74.2	.	-27.4	-29.8	1913.4	569.4	.	.	.
	A_4	184.5	101.6	27.4	.	.	2053.2	709.2	.	.	.
	A_5	186.9	103.9	29.8	.	.	2032.8	688.8	.	.	.
	A_1	.	-124.6	-235.8	-288.9	-292.9	.	-2179.2	-2895.0	-3070.2	-3075.6
	A_2	124.6	.	-111.3	-164.4	-168.3	2179.2	.	-715.8	-891.0	-896.4
P_5	A_3	235.8	111.3	.	-53.1	-57.1	2895.0	715.8	.	-175.2	-180.6
	A_4	288.9	164.4	53.1	.	.	3070.2	891.0	175.2	.	.
	A_5	292.9	168.3	57.1	.	.	3075.6	896.4	180.6	.	.

APPENDIX B

Bonferroni comparisons for surface-based metrics

The following tables contain the results of the Bonferroni pairwise multiple comparisons that were calculated from the single-factor ANOVA for each metric. The leftmost column indicates the factor level that was held constant in the single-factor ANOVA. The second column from the left and the second row index each of the comparisons made. The number in a cell in the table is the mean difference in metric value for the comparison being made (column minus row). Cells containing a "." indicate that the comparison was not significantly different at the 0.01 significance level.

Bonferroni comparisons for patchiness simple effects

		BEs					Disp				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
A_1	P_1	0.00	.	.	.	.	0.00	.	.	.	.
	P_2	.	0.00	.	.	.	.	0.00	.	.	.
	P_3	.	.	0.00	.	.	.	.	0.00	.	.
	P_4	.	.	.	0.00	.	.	.	.	0.00	.
	P_5	.	.	.	.	0.00	.	.	.	.	0.00
A_2	P_1	0.00	.	.	.	.	0.00	.	8.99	.	.
	P_2	.	0.00	.	.	.	.	0.00	7.55	.	.
	P_3	.	.	0.00	.	-38.02	-8.99	-7.55	0.00	.	-12.80
	P_4	.	.	.	0.00	.	.	.	.	0.00	-9.71
	P_5	.	.	38.02	.	0.00	.	.	12.80	9.71	0.00
A_3	P_1	0.00	.	27.87.	.	-23.16	0.00	.	15.48	16.11	-13.35
	P_2	.	0.00	26.98	.	-24.05.	.	0.00	14.80	15.44	-14.03
	P_3	-27.87.	-26.98	0.00	.	-51.04	-15.48	-14.80	0.00	.	-28.83
	P_4	.	.	.	0.00	-42.90	-16.11	-15.44	.	0.00	-29.47
	P_5	23.16	24.05.	51.04	42.90	0.00	13.35	14.03	28.83	29.47	0.00
A_4	P_1	0.00	.	17.86	14.36	-11.48	0.00	.	24.34	23.56	-21.85
	P_2	.	0.00	15.54	12.04	-13.80	.	0.00	23.43	22.65	-22.75
	P_3	-17.86	-15.54	0.00	.	-29.34	-24.34	-23.43	0.00	.	-46.19
	P_4	-14.36	-12.04	.	0.00	-25.84	-23.56	-22.65	.	0.00	-45.41
	P_5	11.48	13.80	29.34	25.84	0.00	21.85	22.75	46.19	45.41	0.00
A_5	P_1	0.00	.	14.82	13.60	.	0.00	.	30.56	31.17	.
	P_2	.	0.00	13.54	12.32	.	.	0.00	26.82	27.43	-15.07
	P_3	-14.82	-13.54	0.00	.	-19.87.	-30.56	-26.82	0.00	.	-41.89
	P_4	-13.60	-12.32	.	0.00	-18.66	-31.17	-27.43	.	0.00	-42.50
	P_5	.	.	19.87.	18.66	0.00	.	15.07	41.89	42.50	0.00

Cont...

Bonferroni comparisons for patchiness simple effects

		L_{max}					L_{mean}				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
A_1	P_1	.	.	-12.96	-24.16	-24.50	.	.	-1.48	-3.66	-3.99
	P_2	.	.	-9.04	-20.24	-20.58	.	.	-1.10	-3.29	-3.62
	P_3	12.96	9.04	.	-11.20	-11.54	1.48	1.10	.	-2.19	-2.51
	P_4	24.16	20.24	11.20	.	.	3.66	3.29	2.19	.	.
	P_5	24.50	20.58	11.54	.	.	3.99	3.62	2.51	.	.
A_2	P_1	.	.	-14.22	-26.44	-26.05.	.	-0.71	-1.79	-4.00	-4.21
	P_2	.	.	.	-19.98	-19.60	0.71	.	-1.07	-3.29	-3.50
	P_3	14.22	.	.	-12.22	-11.84	1.79	1.07	.	-2.21	-2.42
	P_4	26.44	19.98	12.22	.	.	4.00	3.29	2.21	.	.
	P_5	26.05.	19.60	11.84	.	.	4.21	3.50	2.42	.	.
A_3	P_1	.	.	-14.32	-21.42	-14.72	.	.	-1.62	-3.19	-1.94
	P_2	.	.	.	-13.12	.	.	.	-1.06	-2.64	-1.38
	P_3	14.32	.	.	.	.	1.62	1.06	.	-1.57	.
	P_4	21.42	13.12	.	.	.	3.19	2.64	1.57	.	1.25
	P_5	14.72	.	.	.	.	1.94	1.38	.	-1.25	.
A_4	P_1	.	.	.	-9.02	.	.	.	-6.44	-7.33	15.78
	P_2	.	.	.	-8.38	.	.	.	-6.15	-7.04	16.06
	P_3	.	.	.	-4.82	.	6.44	6.15	.	.	22.21
	P_4	9.02	8.38	4.82	.	7.06	7.33	7.04	.	.	23.11
	P_5	.	.	.	-7.06	.	-15.78	-16.06	-22.21	-23.11	.
A_5	P_1	.	.	.	-5.70	.	.	.	-18.63	-18.40	16.35
	P_2	.	.	.	-5.28	.	.	.	-11.14	-10.91	23.84
	P_3	.	.	.	.	.	18.63	11.14	.	.	34.98
	P_4	5.70	5.28	.	.	3.74	18.40	10.91	.	.	34.75
	P_5	.	.	.	-3.74	.	-16.35	-23.84	-34.98	-34.75	.

Cont...

Bonferroni comparisons for patchiness simple effects

		L_{min}					NS				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
A_1	P_1	.	.	.	.	.	.	.	.	20.40	30.2.9
	P_2	.	.	.	.	.	.	.	.	19.48	29.37.
	P_3	.	.	.	.	.	.	.	.	17.26	27.16
	P_4	.	.	.	.	.	-20.40	-19.48	-17.26	.	9.90
	P_5	.	.	.	.	.	-30.2.9	-29.37.	-27.16	-9.90	.
A_2	P_1	.	.	.	.	.	.	.	5.50	22.40	29.92
	P_2	.	.	.	.	.	.	.	.	20.44	27.95.
	P_3	.	.	.	.	.	-5.50	.	.	16.90	24.42
	P_4	.	.	.	.	.	-22.40	-20.44	-16.90	.	7.52
	P_5	.	.	.	.	.	-29.92	-27.95.	-24.42	-7.52	.
A_3	P_1	.	.	.	.	.	.	.	.	17.52	16.04
	P_2	.	.	.	.	.	.	.	.	16.84	15.36
	P_3	.	.	.	.	.	.	.	.	13.92	12.44
	P_4	.	.	.	.	.	-17.52	-16.84	-13.92	.	.
	P_5	.	.	.	.	.	-16.04	-15.36	-12.44	.	.
A_4	P_1	.	.	.	.	11.92	.	.	4.78	11.42	3.22
	P_2	.	.	.	.	10.74	.	.	3.82	10.46	.
	P_3	.	.	.	.	13.06	-4.78	-3.82	.	6.64	.
	P_4	.	.	.	.	13.08	-11.42	-10.46	-6.64	.	-8.20
	P_5	-11.92	-10.74	-13.06	-13.08	.	-3.22	.	.	8.20	.
A_5	P_1	.	.	-13.94	-14.94	22.7.9	.	.	3.62	8.94	.
	P_2	.	.	.	.	32.18	.	.	3.10	8.42	.
	P_3	13.94	.	.	.	36.74	-3.62	-3.10	.	5.32	-2.48
	P_4	14.94	.	.	.	37.74	-8.94	-8.42	-5.32	.	-7.80
	P_5	-22.7.9	-32.18	-36.74	-37.74	.	.	.	2.48	7.80	.

Cont...

Bonferroni comparisons for patchiness simple effects

		L_{stdv}					N				
		P_1	P_2	P_3	P_4	P_5	P_1	P_2	P_3	P_4	P_5
	P_1	.	.	-3.24	-5.86	-6.04	.	.	4.84	15.54	18.36
	P_2	.	.	-2.38	-4.99	-5.18	.	.	4.48	15.18	18.00
A_1	P_3	3.24	2.38	.	-2.61	-2.79	-4.84	-4.48	.	10.70	13.52
	P_4	5.86	4.99	2.61	.	.	-15.54	-15.18	-10.70	.	.
	P_5	6.04	5.18	2.79	.	.	-18.36	-18.00	-13.52	.	.
	P_1	.	-1.69	-4.14	-6.85	-6.50	.	.	8.06	15.16	11.78
	P_2	1.69	.	-2.45	-5.16	-4.81	.	.	5.94	13.04	9.66
A_2	P_3	4.14	2.45	.	-2.71	-2.35	-8.06	-5.94	.	7.10	.
	P_4	6.85	5.16	2.71	.	.	-15.16	-13.04	-7.10	.	.
	P_5	6.50	4.81	2.35	.	.	-11.78	-9.66	.	.	.
	P_1	.	.	-5.21	-6.98	-3.09	.	.	7.10	10.04	.
	P_2	.	.	-3.02	-4.79	.	.	.	6.36	9.30	.
A_3	P_3	5.21	3.02	.	.	.	-7.10	-6.36	.	.	-8.24
	P_4	6.98	4.79	.	.	3.89	-10.04	-9.30	.	.	-11.18
	P_5	3.09	.	.	-3.89	.	.	.	8.24	11.18	.
	P_1	.	.	-7.29	-8.65	.	.	.	4.54	4.56	-3.48
	P_2	.	.	.	-6.65	.	.	.	3.98	4.00	-4.04
A_4	P_3	7.29	.	.	.	8.50	-4.54	-3.98	.	.	-8.02
	P_4	8.65	6.65	.	.	9.86	-4.56	-4.00	.	.	-8.04
	P_5	.	.	-8.50	-9.86	.	3.48	4.04	8.02	8.04	.
	P_1	.	.	.	.	-12.03	.	.	4.40	3.78	.
	P_2	.	.	.	.	-16.15	.	.	3.92	3.30	-2.00
A_5	P_3	.	.	.	.	-9.16	-4.40	-3.92	.	.	-5.92
	P_4	.	.	.	.	-10.48	-3.78	-3.30	.	.	-5.30
	P_5	12.03	16.15	9.16	10.48	.	.	2.00	5.92	5.30	.

Bonferroni comparisons for abruptness simple effects

		BEs					Disp				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	-26.94	-111.32	-173.10	-185.50	.	-21.87	-49.74	-93.73	-118.02
	A_2	26.94	.	-84.38	-146.16	-158.56	21.87	.	-27.87	-71.87	-96.15
	A_3	111.32	84.38	.	-61.78	-74.18	49.74	27.87	.	-44.00	-68.28
	A_4	173.10	146.16	61.78	.	.	93.73	71.87	44.00	.	-24.28
	A_5	185.50	158.56	74.18	.	.	118.02	96.15	68.28	24.28	.
P_2	A_1	.	-21.14	-105.24	-165.60	-179.04	.	-17.39	-46.02	-89.79	-111.24
	A_2	21.14	.	-84.10	-144.46	-157.90	17.39	.	-28.63	-72.40	-93.85
	A_3	105.24	84.10	.	-60.36	-73.80	46.02	28.63	.	-43.77	-65.22
	A_4	165.60	144.46	60.36	.	.	89.79	72.40	43.77	.	-21.45
	A_5	179.04	157.90	73.80	.	.	111.24	93.85	65.22	21.45	.
P_3	A_1	.	.	-77.02	-148.82	-164.26	.	.	-31.62	-66.75	-84.82
	A_2	.	.	-73.74	-145.54	-160.98	.	.	-21.38	-56.51	-74.58
	A_3	77.02	73.74	.	-71.80	-87.24	31.62	21.38	.	-35.13	-53.20
	A_4	148.82	145.54	71.80	.	.	66.75	56.51	35.13	.	-18.06
	A_5	164.26	160.98	87.24	.	.	84.82	74.58	53.20	18.06	.
P_4	A_1	.	.	-76.24	-143.40	-156.56	.	-13.68	-31.34	-67.89	-84.57
	A_2	.	.	-59.70	-126.86	-140.02	13.68	.	-17.66	-54.21	-70.89
	A_3	76.24	59.70	.	-67.16	-80.32	31.34	17.66	.	-36.55	-53.23
	A_4	143.40	126.86	67.16	.	.	67.89	54.21	36.55	.	-16.68
	A_5	156.56	140.02	80.32	.	.	84.57	70.89	53.23	16.68	.
P_5	A_1	.	-38.58	-125.34	-175.44	-181.42	.	-23.41	-60.83	-113.32	-127.09
	A_2	38.58	.	-86.76	-136.86	-142.84	23.41	.	-37.41	-89.90	-103.68
	A_3	125.34	86.76	.	-50.10	-56.08	60.83	37.41	.	-52.49	-66.26
	A_4	175.44	136.86	50.10	.	.	113.32	89.90	52.49	.	-13.77
	A_5	181.42	142.84	56.08	.	.	127.09	103.68	66.26	13.77	.

Cont...

Bonferroni comparisons for abruptness simple effects

		L_{max}					L_{mean}				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	10.12	18.76	18.46	18.50	.	.	.	7.69	23.15
	A_2	-10.12	.	.	.	.	.	.	.	7.15	22.62
	A_3	-18.76	.	.	.	.	.	.	.	7.41	22.88
	A_4	-18.46	.	.	.	.	-7.69	-7.15	-7.41	.	15.47
	A_5	-18.50	.	.	.	.	-23.15	-22.62	-22.88	-15.47	.
P_2	A_1	.	7.58	14.38	21.74	22.00	.	.	.	7.78	16.04
	A_2	-7.58	.	.	14.16	14.42	.	.	.	7.58	15.84
	A_3	-14.38	.	.	7.36	7.62	.	.	.	7.69	15.95
	A_4	-21.74	-14.16	-7.36	.	.	-7.78	-7.58	-7.69	.	8.26
	A_5	-22.00	-14.42	-7.62	.	.	-16.04	-15.84	-15.95	-8.26	.
P_3	A_1	.	8.86	17.40	27.22	28.38	.	.	.	2.73	6.00
	A_2	-8.86	.	8.54	18.36	19.52	.	.	.	2.51	5.78
	A_3	-17.40	-8.54	.	9.82	10.98	.	.	.	2.60	5.87
	A_4	-27.22	-18.36	-9.82	.	.	-2.73	-2.51	-2.60	.	3.28
	A_5	-28.38	-19.52	-10.98	.	.	-6.00	-5.78	-5.87	-3.28	.
P_4	A_1	.	7.84	21.50	33.60	36.96	.	.	.	4.02	8.41
	A_2	-7.84	.	13.66	25.76	29.12	.	.	.	3.83	8.22
	A_3	-21.50	-13.66	.	12.10	15.46	.	.	.	3.28	7.67
	A_4	-33.60	-25.76	-12.10	.	.	-4.02	-3.83	-3.28	.	4.39
	A_5	-36.96	-29.12	-15.46	.	.	-8.41	-8.22	-7.67	-4.39	.
P_5	A_1	.	8.56	28.54	41.00	41.04	.	.	.	27.46	43.49
	A_2	-8.56	.	19.98	32.44	32.48	.	.	.	27.14	43.18
	A_3	-28.54	-19.98	.	12.46	12.50	.	.	.	25.13	41.17
	A_4	-41.00	-32.44	-12.46	.	.	-27.46	-27.14	-25.13	.	16.04
	A_5	-41.04	-32.48	-12.50	.	.	-43.49	-43.18	-41.17	-16.04	.

Cont...

Bonferroni comparisons for abruptness simple effects

		L_{min}					NS				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	.	.	.	14.98	.	-2.68	-5.04	-11.06	-12.98
	A_2	.	.	.	.	14.96	2.68	.	.	-8.38	-10.30
	A_3	.	.	.	.	14.98	5.04	.	.	-6.02	-7.94
	A_4	.	.	.	.	13.82	11.06	8.38	6.02	.	.
	A_5	-14.98	-14.96	-14.98	-13.82	.	12.98	10.30	7.94	.	.
P_2	A_1	.	.	.	.	.	.	.	-5.28	-11.02	-13.38
	A_2	.	.	.	.	.	.	.	-3.64	-9.38	-11.74
	A_3	.	.	.	.	.	5.28	3.64	.	-5.74	-8.10
	A_4	.	.	.	.	.	11.02	9.38	5.74	.	.
	A_5	.	.	.	.	.	13.38	11.74	8.10	.	.
P_3	A_1	.	.	.	.	.	.	.	-4.58	-9.42	-12.50
	A_2	.	.	.	.	.	.	.	-4.26	-9.10	-12.18
	A_3	.	.	.	.	.	4.58	4.26	.	-4.84	-7.92
	A_4	.	.	.	.	.	9.42	9.10	4.84	.	-3.08
	A_5	.	.	.	.	.	12.50	12.18	7.92	3.08	.
P_4	A_1	.	.	.	.	.	.	.	-7.92	-20.04	-24.44
	A_2	.	.	.	.	.	.	.	-7.24	-19.36	-23.76
	A_3	.	.	.	.	.	7.92	7.24	.	-12.12	-16.52
	A_4	.	.	.	.	.	20.04	19.36	12.12	.	.
	A_5	.	.	.	.	.	24.44	23.76	16.52	.	.
P_5	A_1	.	.	.	13.08	37.78	.	.	-19.30	-38.14	-42.14
	A_2	.	.	.	13.08	37.78	.	.	-16.24	-35.08	-39.08
	A_3	.	.	.	13.08	37.78	19.30	16.24	.	-18.84	-22.84
	A_4	-13.08	-13.08	-13.08	.	24.70	38.14	35.08	18.84	.	.
	A_5	-37.78	-37.78	-37.78	-24.70	.	42.14	39.08	22.84	.	.

Cont...

Bonferroni comparisons for abruptness simple effects

		L_{stdv}					N				
		A_1	A_2	A_3	A_4	A_5	A_1	A_2	A_3	A_4	A_5
	A_1	.	.	5.68	15.31	14.26	.	-4.92	-13.60	-24.06	-26.98
	A_2	.	.	.	13.12	12.07	4.92	.	-8.68	-19.14	-22.06
P_1	A_3	-5.68	.	.	9.63	8.58	13.60	8.68	.	-10.46	-13.38
	A_4	-15.31	-13.12	-9.63	.	.	24.06	19.14	10.46	.	-2.92
	A_5	-14.26	-12.07	-8.58	.	.	26.98	22.06	13.38	2.92	.
	A_1	.	.	4.35	14.17	19.25	.	-3.16	-13.22	-23.86	-26.86
	A_2	.	.	.	12.81	17.89	3.16	.	-10.06	-20.70	-23.70
P_2	A_3	-4.35	.	.	9.82	14.89	13.22	10.06	.	-10.64	-13.64
	A_4	-14.17	-12.81	-9.82	.	5.07	23.86	20.70	10.64	.	-3.00
	A_5	-19.25	-17.89	-14.89	-5.07	.	26.86	23.70	13.64	3.00	.
	A_1	.	.	3.71	11.26	14.64	.	.	-11.34	-24.36	-27.42
	A_2	.	.	.	9.97	13.35	.	.	-9.64	-22.66	-25.72
P_3	A_3	-3.71	.	.	7.55	10.93	11.34	9.64	.	-13.02	-16.08
	A_4	-11.26	-9.97	-7.55	.	3.38	24.36	22.66	13.02	.	.
	A_5	-14.64	-13.35	-10.93	-3.38	.	27.42	25.72	16.08	.	.
	A_1	.	.	4.55	12.52	18.57	.	-5.30	-19.10	-35.04	-38.74
	A_2	.	.	3.36	11.32	17.38	5.30	.	-13.80	-29.74	-33.44
P_4	A_3	-4.55	-3.36	.	7.96	14.02	19.10	13.80	.	-15.94	-19.64
	A_4	-12.52	-11.32	-7.96	.	6.05	35.04	29.74	15.94	.	.
	A_5	-18.57	-17.38	-14.02	-6.05	.	38.74	33.44	19.64	.	.
	A_1	.	.	8.63	22.56	8.27	.	-11.50	-33.10	-45.90	-46.86
	A_2	.	.	.	20.83	.	11.50	.	-21.60	-34.40	-35.36
P_5	A_3	-8.63	.	.	13.93	.	33.10	21.60	.	-12.80	-13.76
	A_4	-22.56	-20.83	-13.93	.	-14.28	45.90	34.40	12.80	.	.
	A_5	-8.27	.	.	14.28	.	46.86	35.36	13.76	.	.

APPENDIX C

Bonferroni Comparisons for the CBE metric

The following tables contain the results of the Bonferroni pairwise multiple comparisons that were calculated from the single-factor ANOVA for the CBE metric. The leftmost column indicates the factor level that was held constant in the single-factor ANOVA. The second column from the left and the second row index each of the comparisons made. The number in a cell in the table is the mean difference in metric value for the comparison being made (column minus row). Cells containing a "." indicate that the comparison was not significantly different at the 0.01 significance level.

Bonferroni comparisons for patchiness simple effects

		CBE				
		P_1	P_2	P_3	P_4	P_5
A_1	P_1	.	.	.	.	.
	P_2	.	.	.	.	.
	P_3	.	.	.	.	.
	P_4	.	.	.	.	.
	P_5	.	.	.	.	.
A_2	P_1	.	.	.	.	.
	P_2	.	.	.	.	.
	P_3	.	.	.	.	-319.76
	P_4	.	.	.	.	.
	P_5	.	.	319.76	.	.
A_3	P_1	.	.	170.36	.	.
	P_2	.	.	178.90	.	.
	P_3	-170.36	-178.90	.	.	-336.94
	P_4	.	.	.	.	-266.30
	P_5	.	.	336.94	266.30	.
A_4	P_1	.	.	151.68	.	-128.92
	P_2	.	.	131.16	.	-149.44
	P_3	-151.68	-131.16	.	.	-280.60
	P_4	.	.	.	.	-222.06
	P_5	128.92	149.44	280.60	222.06	.
A_5	P_1	.	.	183.54	161.54	-96.22
	P_2	.	.	157.64	135.64	-122.12
	P_3	-183.54	-157.64	.	.	-279.76
	P_4	-161.54	-135.64	.	.	-257.76
	P_5	96.22	122.12	279.76	257.76	.

Cont…

Bonferroni comparisons for abruptness simple effects

		CBE				
		A_1	A_2	A_3	A_4	A_5
P_1	A_1	.	-216.06	-834.42	-1298.90	-1467.84
	A_2	216.06	.	-618.36	-1082.84	-1251.78
	A_3	834.42	618.36	.	-464.48	-633.42
	A_4	1298.90	1082.84	464.48	.	.
	A_5	1467.84	1251.78	633.42	.	.
P_2	A_1	.	-173.24	-803.12	-1238.54	-1402.10
	A_2	173.24	.	-629.88	-1065.30	-1228.86
	A_3	803.12	629.88	.	-435.42	-598.98
	A_4	1238.54	1065.30	435.42	.	.
	A_5	1402.10	1228.86	598.98	.	.
P_3	A_1	.	.	-598.36	-1081.52	-1218.60
	A_2	.	.	-579.78	-1062.94	-1200.02
	A_3	598.36	579.78	.	-483.16	-620.24
	A_4	1081.52	1062.94	483.16	.	.
	A_5	1218.60	1200.02	620.24	.	.
P_4	A_1	.	.	-570.04	-1041.10	-1141.64
	A_2	.	.	-439.82	-910.88	-1011.42
	A_3	570.04	439.82	.	-471.06	-571.60
	A_4	1041.10	910.88	471.06	.	.
	A_5	1141.64	1011.42	571.60	.	.
P_5	A_1	.	-302.14	-899.10	-1325.92	-1462.16
	A_2	302.14	.	-596.96	-1023.78	-1160.02
	A_3	899.10	596.96	.	-426.82	-563.06
	A_4	1325.92	1023.78	426.82	.	.
	A_5	1462.16	1160.02	563.06	.	.

APPENDIX D

Source Code

This appendix contains the AML and C programs used to for the simulation and the calculation of the surface-based metrics. The first several lines of each program provide a brief explanation of the program's purpose.

Simdeterm.c

```
/*simdeterm.c was used to generate the five deterministic surfaces. The
deterministic surfaces where based on the equation y = sign(x)(abs(x^1/n)). The
(n) term controls the abruptness of the surface.*/

#include <stdio.h>
#include <stdlib.h>
#include <math.h>
char ascii[20];
double x, y, lower, upper, increment, sum, mean;
double r = 1;
int i;
int n,a,q,c;
int nrows = 23;
int ncols = 23;
int count;
double column[50];
double grid[50][50];
long xllcorner = 307630;
long yllcorner = 5395930;
long xllcorner0 = 307630;
long yllcorner0 = 5395930;
int cellsize = 30;
FILE *fp;
FILE *fs;

int main()
{
	if ((fs = fopen("simstats.txt", "a")) == NULL)
	  {
	  fprintf(stderr, " error opening stats file.\n\n");
	  exit(1);
	  }
```

```
	fprintf(fs, "surface r sum mean lower upper\n");

for(n=1; n < 101; n++)
{
	sum = 0;
	mean = 0;

	if(n < 10)
		sprintf(ascii, "det0%d.asc", n);
	else
		sprintf(ascii, "det%d.asc", n);


	if ((fp = fopen(ascii, "a")) == NULL)
	{
	fprintf(stderr, "error opening input file.\n\n");
	exit(1);
	}
	fprintf(fp,"ncols %d\n", ncols);
	fprintf(fp,"nrows %d\n", nrows);
	fprintf(fp,"xllcorner %ld\n", xllcorner);
	fprintf(fp,"yllcorner %ld\n", yllcorner);
	fprintf(fp,"cellsize %d\n", cellsize);
	fprintf(fp,"NODATA_value -9999\n");

	x = -1.1;

	for(a=0; a < nrows; a++)
	{
	if(x < 0)
	{
	column[a] = (-1*(pow(fabs(x),1/r)) * .5);
	}

	else
	{
	column[a] = (pow(x,1/r) * .5);
	}
	x = x + .1;

	if(a == 1)
	lower = column[a];

	if(a == 21)
	upper = column[a];
```

```
        if(3 <= a <= 23)
        sum = sum + column[a];

}
mean = sum / 21;
for(q = 0; q < nrows; q++)
{
        for(c = 0; c < ncols; c++)
        {
        grid[q][c] = column[q];
        fprintf(fp,"%f ", grid[q][c]);
}
        }
        fclose(fp);
        fprintf(fs, "%s %f %f %f %f\n", ascii, r, sum, mean, lower, upper);
        xllcorner = xllcorner + 840;
        if(n == 10)
        {
        yllcorner = yllcorner - 840;
        xllcorner = xllcorner0;
        }
        if(n == 20)
        {
        yllcorner = yllcorner - 840;
        xllcorner = xllcorner0;
        }
        if(n == 30)
        {
        yllcorner = yllcorner - 840;
        xllcorner = xllcorner0;
        }

        if(n == 40)
        {
        yllcorner = yllcorner - 840;
        xllcorner = xllcorner0;
        }

        column[0] = '\0';
        grid[0][0] = '\0';
        r = r+.25;
}

fclose(fs);

}/*end of main*/
```

Matrix.aml

/* matrix.aml was used to combine the deterministic surfaces created by simdeterm.c with /*the perturbation surfaces to create the simulated ecotone surfaces. The surfaces are /*perturbed according to their row and column in the matrix. Patchiness increases with /*row number, abruptness increases with column number. Matrix.aml performs the /*simulation 50 times for each simulate ecotone type (25), so 1250 surfaces are created.

```
/* open file to hold stats
&s fileunit := [open stats4matrix.txt openstat -w]
&if %openstat% ne 0 &then
  &return &inform Could not open stats ouput file.

&s writestat := [write %fileunit% 'group, filename, normal mean, normal std,
normSM l, normSM mean, normSM std, surface l, surface min, surface max,
surface mean, surface std']

&sv i = 1
&do i = 1 &to 50

/*  loop for rows in matrix
&sv row = 1
&do row = 1 &to 5

&if %row% eq 1 &then
&do
&sv smooth = 5
&sv stdev = .8
&end

&if %row% eq 2 &then
&do
&sv smooth = 4
&sv stdev = .6
&end

&if %row% eq 3 &then
&do
&sv smooth = 3
&sv stdev = .49
&end

&if %row% eq 4 &then
&do
```

```
&sv smooth = 2
&sv stdev = .29
&end

&if %row% eq 5 &then
&do
&sv smooth = 1
&sv stdev = .14
&end

/*loop for columns in matrix
&sv col = 1
&do col = 1 &to 5

&if %col% eq 1 &then
&do
&sv r = 01
&sv base = aee
&end

&if %col% eq 2 &then
&do
&sv r = 05
&sv base = bee
&end

&if %col% eq 3 &then
&do
&sv r = 13
&sv base = cee
&end

&if %col% eq 4 &then
&do
&sv r = 61
&sv base = dee
&end

&if %col% eq 5 &then
&do
&sv r = l5
&sv base = eee
&end

/* create zone grids for zonalstats
setcell det%r%
```

```
setwindow det%r%
mask%r% = 1

/* describe deterministic function surface to collect stdv
describe det%r%

 /*create perturb surface and smooth accordingly
norm%col%%row% = normal() * %stdev%
smooth%col%%row% = focalmean(norm%col%%row%, rectangle, %smooth%,
%smooth%)
%base%%row%-%i% = smooth%col%%row% + det%r%

/*classify surface into trees not trees
junk = int(%base%%row%-%i% * 10000000)
junkstat = zonalstats(mask%r%, junk, median)
kill junk all
cursor cur declare junkstat INFO ro
cursor cur open
cursor cur 1
&listvar :cur.median
&sv med = %:cur.median% / 10000000
cursor cur remove
q
tables
kill junkstat
q stop
grid
setcell det%r%
setwindow det%r%
if (%base%%row%-%i% > %med%)
if (%base%%row%-%i% > 0)
%base%%row%cl-%i% = 1
endif

/* setup normal() surface for stat export
describe norm%col%%row%
&sv normalstd = %grd$stdv%
&sv normalm = %grd$mean%

/* setup smoothed normal for stat export
describe smooth%col%%row%
&sv normSMstd = %grd$stdv%
&sv normSMm = %grd$mean%
moran smooth%col%%row%
&sv normSMI = %.moran_out%
```

```
/* setup final surface for stat export
describe %base%%row%-%i%
&sv quadstd = %grd$stdv%
&sv quadmean = %grd$mean%
&sv quadmin = %grd$zmin%
&sv quadmax = %grd$zmax%
moran %base%%row%-%i%
&sv quadI = %.moran_out%
&sv filename = %base%%row%-%i%

/* write to stats file
&s writestat := [write %fileunit% [quote
%base%%row%,%filename%,%normalm%,%normalstd%,%normSMI%,%normS
Mm%,%normSMstd%,%quadI%,%quadmin%,%quadmax%,%quadmean%,%qua
dstd%]]

kill norm%col%%row% all
kill smooth%col%%row% all
kill mask%r% all
/*kill %base%%row%-%i% all
/*kill %base%%row%cl-%i% all

&end /*end of column loop
&end /* end of row loop
&end /* end of 50 times

&s closestat := [close %fileunit%]
&return
```

Gemit.aml

```
/* gemit.aml was used to do the lattice delineation and calculate the surface-
/*based metrics. Gemit.aml was modeled after the capabilities of the GEM
/*Boundary Analysis software from Biomedware. The #be's, subgraph,
/*singletons, minlength, maxlength, meanlength, stdvlength, and dispersion
/*metrics are calculated. These metrics are calculated for a user specified
/*number of ROC thresholds by using the slice command in GRID.
/* The C programs from connect2.c and dispersion.c are called from this aml.

/* prompt user for parameters
&sv basename = [response 'Enter basename (i.e., aee* or bee*)' aee*]
&sv numintervals = [response 'Slice ROC surface into how many intervals' 20]
&sv aspectthreshold = [response 'Enter aspect threshold for BE connection' 30]
&s count := [filelist %basename% outfile -file]
&if %count% <= 0 &then
```

```
        &return Error generating outfile file
&s unit := [open outfile ok -read]

/* open output file for statistics dump
&s fileunit := [open gemstatsa.txt openstat -a]
&if %openstat% ne 0 &then
  &return &error Error opening gemstats.txt file

&s writestat := [write %fileunit%
'group,filename,i,#be's,subgraph,singletons,minlength,maxlength,meanlength,std
vlength,disp1,disp2,disp3,disp4']

/* open temporary file
&s tempunit := [open temp.txt openstat -a]
&if %openstat% ne 0 &then
  &return &error Error opening tempory file

/* write aspect threshold value to temp file for connect2.c to read
&s writestat := [write %tempunit% [quote %aspectthreshold%]]
&s ok := [close %tempunit%]

/* Process each file in outfile list
&do j := 1 &to %count%
&s ezero := [read %unit% ok]
&s cover = [before %ezero% .]

/*import ezerozero file
import grid %ezero% %cover%
grid

/*calculate slope and aspect
&ty Deriving slope and aspect for %cover%.
slope1 = slope(%cover%)
aspect1 = aspect(%cover%)

/*gridclip to study area, the surfaces were made with a one cell border to
/*eliminate edge effects when calculating the slope and aspect
&ty Removing outer edge of slope and aspect grids.
describe slope1
&sv imin = %grd$xmin% + %grd$dx%
&sv jmin = %grd$ymin% + %grd$dy%
&sv imax = %grd$xmax% - %grd$dx%
&sv jmax = %grd$ymax% - %grd$dy%
gridclip slope1 slope BOX %imin% %jmin% %imax% %jmax%
gridclip aspect1 aspect BOX %imin% %jmin% %imax% %jmax%
kill slope1 all
```

```
kill aspect1 all

/* slice the slope grid into x number of intervals
&ty Slicing rate of change surface into %numintervals% intervals.
sliced = slice(slope, eqinterval, %numintervals%)

/* process interval by interval
&sv i = 1
&do &until %numintervals% lt 1
&ty Processing interval %i% for %cover%.
%cover%m_%i% = select(sliced, "value >= %numintervals%")

if (%cover%m_%i% > 0) then
%cover%m2_%i% = 0
endif

%cover%asp%i% = %cover%m2_%i% + aspect
besasp.asc = gridascii(%cover%asp%i%)
kill %cover%asp%i% all
kill %cover%m_%i% all

/*run connect2.c to connect be's based on aspect threshold
&ty Calling C program "connectum".
&sys ./connectum
%cover%bes%i% = asciigrid(beconnect.asc)
&sys rm besasp.asc

/*quit to arc, additem to separate sings and subs for stats
q
additem %cover%bes%i%.vat %cover%bes%i%.vat subgraph 4 4 b
grid

/* calculate subgraph item
reselect %cover%bes%i%.vat INFO count gt 1
calculate %cover%bes%i%.vat INFO subgraph = 1

/*collect #boundary elements, min, mean, and max length
&ty Collecting subboundary statistics.

/*first, subgraph records
statistics %cover%bes%i%.vat INFO
min count
max count
mean count
standarddeviation count
end
```

```
&sv minlength = [show statistic 1 1]
&sv maxlength = [show statistic 2 1]
&sv meanlength = [show statistic 3 1]
&sv stdvlength = [show statistic 4 1]

/*select singleton records
aselect %cover%bes%i%.vat INFO
reselect %cover%bes%i%.vat INFO subgraph eq 0
statistics %cover%bes%i%.vat INFO
sum count
end
&sv singleton = [show statistic 1 1]

 /*select all
aselect %cover%bes%i%.vat INFO
statistics %cover%bes%i%.vat INFO
sum count
sum subgraph
end
&sv numbes = [show statistic 1 1]
&sv subgraph = [show statistic 2 1]

/* find centroids and call dispersion.c to calc distances from "mean treeline"
&ty Calculating centroids
meancent = zonalcentroid(%cover%m2_%i%)
meancent.asc = gridascii(meancent)
kill meancent all
becents.asc = gridascii(%cover%m2_%i%)
kill %cover%m2_%i% all
cents = zonalcentroid(%cover%bes%i%)
cents.asc = gridascii(cents)
kill cents all
&sys ./dispersum
&sys rm becents.asc
&sys rm cents.asc
&sys rm meancent.asc

/* open output from dispersion.c and read into variables
&s dispunit := [open dispersion.txt openstats -r]
&if %openstats% ne 0 &then
  &return &error Error opening dispersion.txt file
&do d := 1 &to 4
&s disp%d% := [read %dispunit% ok]
&end
&s ok := [close %dispunit%]
```

```
/* Prepare output, write output.
&ty Writing output to gemstats.txt.
&sv group = [substr %cover% 1 4]
&s writestat := [write %fileunit% [quote
%group%,%cover%,%i%,%numbes%,%subgraph%,%singleton%,%minlength%,
%maxlength%,%meanlength%,%stdvlength%,%disp1%,%disp2%,%disp3%,%di
sp4%]]

/* clean out grids and ascii files, increment counter
q
export grid %cover%bes%i% %cover%bes%i%.e00
grid
&sys mv %cover%bes%i%.e00 subgraphs
kill %cover%bes%i% all
&s ok := [delete beconnect.asc -file]
&s ok := [delete dispersion.txt -file]
&sv i = %i% + 1
&sv numintervals = %numintervals% - 1

&end /*belongs to process interval by interval
kill %cover% all
kill slope all
kill aspect all
kill sliced all
q
&end /*process next surface
&s closestat := [close %fileunit%]
&s ok := [close %unit%]
&s ok := [delete outfile -file]
&s ok := [delete temp.txt -file]
&return
```

Connect2.c

```
/* connect2.c was designed to be called from gemit.aml. connect2.c was used to
connect boundary elements that were within the aspect difference threshold.*/

#include <stdio.h>
#include <stdlib.h>
#include <math.h>

int ncols, nrows, rowextent, colextent, cellsize, i, j, x, y, beid, l, d, max, opal;
long xllcorner, yllcorner;
float grid[100][100]; /*holds aspect values read from gridascii*/
int connect[100][100];
```

```
int where[100][100];
float n, ne, e, se, s, sw, w, nw;
float threshold = 30;
FILE *fp;
FILE *fpg;
FILE *ft;

int main()
{
printf("\n Successful call to connect2.c\n");

/* open temp.txt to get the aspect threshold entered at start of gemit.aml */

if ((ft = fopen("temp.txt", "r")) == NULL)
        {
                fprintf(stderr, "error opening temp.txt file.\n");
                exit(1);
        }
        fscanf(ft, "%f", &threshold);

fclose(ft);


printf("\n Connecting all boundary elements within %f degree aspect threshold\n",
threshold);

if ((fp = fopen("besasp.asc", "r")) == NULL)
        {
                fprintf(stderr, "error opening besasp.asc file.\n");
                exit(1);
        }

        fscanf(fp, "%*s %d\n%*s %d\n%*s %ld\n%*s %ld\n%*s %d\n%*s %*s\n",
           &ncols, &nrows, &xllcorner, &yllcorner, &cellsize);
           rowextent = nrows + 5;
        colextent = ncols + 5;

        /*fill matrix full of values that are not within the thresh of each other*/
        opal = -10000 - threshold;

        for (j=0; j < rowextent; j++)
        {
                for (i=0; i < colextent; i++)
                {
                        grid[i][j] = opal;
```

```
				opal = opal - threshold - 1;
			}
		}

		for (j=1; j <= nrows; j++)
		{
			for (i=1; i <= ncols; i++)
			{
				fscanf(fp, "%f", &grid[i][j]);
				if(grid[i][j] != -9999)
				{
					/*convert to radians*/
					grid[i][j] = grid[i][j] * .01745329252;
				}
			}
		}
	fclose(fp);

	/*convert to radians*/
	threshold = cos(threshold * .01745329252);
	/*connect*/
	for(j=1; j <= nrows; j++)
	{
		for(i=1; i <= ncols; i++)
		{
			/*first check to see if current cell is connected*/
			if(connect[i][j] > 0)
			{
				beid = connect[i][j];

				if(grid[i][j-1] != -9999)
				n = cos(grid[i][j] - grid[i][j-1]);
				else
				n = 0;

				if(grid[i+1][j-1] != -9999)
				ne = cos(grid[i][j] - grid[i+1][j-1]);
				else
				ne = 0;

				if(grid[i+1][j] != -9999)
				e = cos(grid[i][j] - grid[i+1][j]);
				else
				e = 0;

				if(grid[i+1][j+1] != -9999)
```

```
se = cos(grid[i][j] - grid[i+1][j+1]);
else
se = 0;

if(grid[i][j+1] != -9999)
s = cos(grid[i][j] - grid[i][j+1]);
else
s = 0;

if(grid[i-1][j+1] != -9999)
sw = cos(grid[i][j] - grid[i-1][j+1]);
else
sw = 0;

if(grid[i-1][j] != -9999)
w = cos(grid[i][j] - grid[i-1][j]);
else
w = 0;

if(grid[i-1][j-1] != -9999)
nw = cos(grid[i][j] - grid[i-1][j-1]);
else
nw = 0;

if(n > threshold)
{
        connect[i][j-1] = beid;
        connect[i][j] = beid;
}
if(ne > threshold)
{
        connect[i+1][j-1] = beid;
        connect[i][j] = beid;
}
if(e > threshold)
{
        connect[i+1][j] = beid;
        connect[i][j] = beid;
}
if(se > threshold)
{
        connect[i+1][j+1] = beid;
        connect[i][j] = beid;
}
if(s > threshold)
{
```

```
                    connect[i][j+1] = beid;
                    connect[i][j] = beid;
            }
            if(sw > threshold)
            {
                    connect[i-1][j+1] = beid;
                    connect[i][j] = beid;
            }
            if(w > threshold)
            {
                    connect[i-1][j] = beid;
                    connect[i][j] = beid;
            }
            if(nw > threshold)
            {
                    connect[i-1][j-1] = beid;
                    connect[i][j] = beid;
            }

/*end of if*/    }
        else /*else #1 if current cell is not connected*/
        {

            if(grid[i][j] == -9999) /*deal with nodata*/
            {
            connect[i][j] = -9999;
            }
            else /*if not connected and not nodata*/
            {

             /* calcuate the subgraph id by finding the highest value
                in connect grid and add one */

                    max = connect[1][1];

                    for (d=1; d <= nrows; d++)
                    {
                            for (l=1; l <= ncols; l++)
                            {
                                    if(connect[l][d] > max)
                                    max = connect[l][d];
                            }
                    }

            beid = max + 1;
```

```
if(grid[i][j-1] != -9999)
n = cos(grid[i][j] - grid[i][j-1]);
else
n = 0;

if(grid[i+1][j-1] != -9999)
ne = cos(grid[i][j] - grid[i+1][j-1]);
else
ne = 0;

if(grid[i+1][j] != -9999)
e = cos(grid[i][j] - grid[i+1][j]);
else
e = 0;

if(grid[i+1][j+1] != -9999)
se = cos(grid[i][j] - grid[i+1][j+1]);
else
se = 0;

if(grid[i][j+1] != -9999)
s = cos(grid[i][j] - grid[i][j+1]);
else
s = 0;

if(grid[i-1][j+1] != -9999)
sw = cos(grid[i][j] - grid[i-1][j+1]);
else
sw = 0;

if(grid[i-1][j] != -9999)
w = cos(grid[i][j] - grid[i-1][j]);
else
w = 0;

if(grid[i-1][j-1] != -9999)
nw = cos(grid[i][j] - grid[i-1][j-1]);
else
nw = 0;

if(n > threshold)
{
        connect[i][j-1] = beid;
        connect[i][j] = beid;
}
if(ne > threshold)
```

```
                {
                        connect[i+1][j-1] = beid;
                        connect[i][j] = beid;
                }
                if(e > threshold)
                {
                        connect[i+1][j] = beid;
                        connect[i][j] = beid;
                }
                if(se > threshold)
                {
                        connect[i+1][j+1] = beid;
                        connect[i][j] = beid;
                }
                if(s > threshold)
                {
                        connect[i][j+1] = beid;
                        connect[i][j] = beid;
                }
                if(sw > threshold)
                {
                        connect[i-1][j+1] = beid;
                        connect[i][j] = beid;
                }
                if(w > threshold)
                {
                        connect[i-1][j] = beid;
                        connect[i][j] = beid;
                }
                if(nw > threshold)
                {
                        connect[i-1][j-1] = beid;
                        connect[i][j] = beid;
                }

                /*deal with singletons, if no connections just assign
                value to current connect cell*/

                if(connect[i][j] == 0)
                {
                        connect[i][j] = beid;
                }

                }/*end of inner else*/
        }/*end of else #1*/
}/*end of i for*/
```

```
}/*end of j for*/

/*open the output file */

        if ((fpg = fopen("beconnect.asc", "w")) == NULL)
        {
                fprintf(stderr, "error opening connect.asc file.");
                exit(1);
        }

        fprintf(fpg,"ncols %d\n", ncols);
        fprintf(fpg,"nrows %d\n", nrows);
        fprintf(fpg,"xllcorner %ld\n", xllcorner);
        fprintf(fpg,"yllcorner %ld\n", yllcorner);
        fprintf(fpg,"cellsize %d\n", cellsize);
        fprintf(fpg,"NODATA_value -9999\n");


        for (j=1; j <= nrows; j++)
        {
                for (i=1; i <= ncols; i++)
                {
                        fprintf(fpg, "%d ", connect[i][j]);
                }
        fprintf(fpg, "\n");
        }
fclose(fpg);    /*close sub grid output file*/
}/*end of main*/
```

Dispersion.c

```
/* dispersion.c was used to calculate the subgraph dispersion metric (Disp). Disp
was calculated as the mean distance from the centroid of all boundary elements
to each individual boundary element. Dispersion.c was designed to be called
from gemit.aml and uses gridascii ouput created by gemit.aml. */

#include <stdio.h>
#include <stdlib.h>
#include <math.h>

int ncols, nrows, cellsize, i, j, n, m;
long xllcorner, yllcorner;
float cents[100][100];
float meancent[100][100];
```

```
float becents[100][100];
float dist, meandist, dist2, meandist2, bedist, bedist2, bemeandist, bemeandist2,
subscent, subscent2, x, y, xcent, ycent, xcent2, ycent2;
FILE *fm;
FILE *fcs;
FILE *fbcs;
FILE *fo;

int main()
{
printf("\n Successful call to dispersion.c \n");

if ((fcs = fopen("cents.asc", "r")) == NULL)
	{
		fprintf(stderr, "error opening centroid file.\n");
		exit(1);
	}

	fscanf(fcs, "%*s %d\n%*s %d\n%*s %ld\n%*s %ld\n%*s %d\n%*s %*d\n",
	&ncols, &nrows, &xllcorner, &yllcorner, &cellsize);

	for (j=0; j < nrows; j++)
	{
		for (i=0; i < ncols; i++)
		{
			fscanf(fcs, "%f", &cents[i][j]);
		}
	}

	fclose(fcs);

if ((fm = fopen("meancent.asc", "r")) == NULL)
	{
		fprintf(stderr, "error opening centroid file.\n");
		exit(1);
	}

	fscanf(fm, "%*s %d\n%*s %d\n%*s %ld\n%*s %ld\n%*s %d\n%*s %*d\n",
	&ncols, &nrows, &xllcorner, &yllcorner, &cellsize);

	for (j=0; j < nrows; j++)
	{
		for (i=0; i < ncols; i++)
		{
			fscanf(fm, "%f", &meancent[i][j]);
		}
```

```
	}

	fclose(fm);

if ((fbcs = fopen("becents.asc", "r")) == NULL)
	{
		fprintf(stderr, "error opening centroid file.\n");
		exit(1);
	}

	fscanf(fbcs, "%*s %d\n%*s %d\n%*s %ld\n%*s %ld\n%*s %d\n%*s
	%*d\n", &ncols, &nrows, &xllcorner, &yllcorner, &cellsize);

	for (j=0; j < nrows; j++)
	{
		for (i=0; i < ncols; i++)
		{
			fscanf(fbcs, "%f", &becents[i][j]);
		}
	}

	fclose(fbcs);

/*find what row the centroid of all bes combined is*/

	for (j=0; j < nrows; j++)
	{
		for (i=0; i < ncols; i++)
		{
			if(meancent[i][j] != -9999)
			{
			subscent = j;
			xcent = i;
			ycent = j;
			}
		}
	}

/*find distance between centroid of each subgraph and the row of the centroid of
all subgraphs */

n=0;
dist=0;
dist2=0;

for (j=0; j < nrows; j++)
```

```
	{
		for (i=0; i < ncols; i++)
		{
			if(cents[i][j] != -9999)
			{
			x = i;
			y = j;
			dist = dist + abs(subscent - j);
			dist2 = dist2 + pow(pow(x - xcent, 2) + pow(y - ycent,2), .5);
			n++;
			}
		}
	}

/*average distance in meters*/

meandist = (dist / n) * cellsize;
meandist2 = (dist2 / n) * cellsize;

m=0;
bedist=0;
bedist2=0;

for (j=0; j < nrows; j++)
	{
		for (i=0; i < ncols; i++)
		{
			if(becents[i][j] != -9999)
			{
			x = i;
			y = j;
			bedist = bedist + abs(subscent - j);
			bedist2 = bedist2 + pow(pow(x - xcent, 2) + pow(y - ycent,2),
			.5);
			m++;
			}
		}
	}

/*average distance in meters*/

bemeandist = (bedist / m) * cellsize;
bemeandist2 = (bedist2 / m) * cellsize;


/*write output*/
```

```
if ((fo = fopen("dispersion.txt", "w")) == NULL)
        {
                fprintf(stderr, "error opening ouput file.\n");
                exit(1);
        }

fprintf(fo, "%f\n%f\n%f\n%f\n", bemeandist, bemeandist2, meandist, meandist2);
fclose(fo);
printf("\n dispersion.c finished. \n");

}/*end of main*/
```

BIBLIOGRAPHY

BIBLIOGRAPHY

Allen, T.R., and S.J. Walsh, 1996. Spatial and compositional pattern of alpine treeline, Glacier National Park, Montana, *Photogrammetric Engineering & Remote Sensing*, 62(11):1261-1268.

Armand, A.D., 1992. Sharp and gradual mountain timberlines as result of species interaction, *Landscape Boundaries: Consequences for Biotic Diversity and Ecological Flows*, (A.J. Hansen and F. di Castri, editors), Springer-Verlag, New York, pp. 361-378.

Armand, A.D., 1985. The change of vegetation near the timber-line. *Inter-Nord*, 17:59-62

Baker, W.L. and Y. Cai, 1992. The r. le programs for multiscale analysis of landscape structure using the GRASS geographical information system, *Landscape Ecology*, 7:291-302.

Baker, W.L., and P.J. Weisberg, 1995. Landscape analysis of the forest-tundra ecotone in Rocky Mountain National Park, Colorado, *Professional Geographer*, 47(4):361-375.

Barbujani, G., N.L. Oden, and R.R. Sokal, 1989. Detecting regions of abrupt change in maps of biological variables, *Sytematic Zoology,* 38(4):376-389.

Bhattacharyya, G.K., and R.A. Johnson, 1977. *Statistical concepts and methods*, John Wiley & Sons, New York.

Brown, D.G. 1998. Classification and boundary vagueness in mapping presettlement forest types. *International Journal of Geographical Information Science*, 12(2):105-129.

Chrisman, N., 1997. *Exploring Geographic Information Systems*, John Wiley & Sons, New York.

Churkina, G., and Y. Svirezhev, 1995. Dynamics and forms of ecotone of under the impact of climatic change: mathematical approach, *Journal of Biogeography*, 22:565-569.

Fortin, M.J., 1994. Edge detection algorithms for two-dimensional ecological data, *Ecology*, 75(4):956-965.

Fortin, M.J., and P. Drapeau, 1995. Delineation of ecological boundaries: comparison of approaches and significance tests, *Oikos*, 72:323-332.

Forman, R.T.T., and M. Godron, 1986. *Landscape Ecology*, John Wiley & Sons, New York.

Gustafson, E.J., 1998. Quantifying landscape spatial pattern: what is the state of the art?, *Ecosystems*, 1:143-156.

Haines-Young, R., and M. Chopping, 1996. Quantifying landscape structure: a review of landscape indices and their application to forested landscapes, *Progress in Physical Geography*, 20(4):418:445.

Holland, M.M., 1988. SCOPE/MAB Technical consultations on landscape boundaries: report of a SCOPE/MAB workshop on ecotones, *Biology International, Special Issue*, 17:47-106.

Jacquez, G.M., and S.L. Maruca, 1998. Geographic boundary detection, *Proceedings of the 8th International Symposium on Spatial Data Handling* (T.K. Poiker and N. Chrisman, editors), International Geographical Union, pp. 496-509.

Jacquez, G.M., S.L. Maruca, and M.J. Fortin, 1999. From fields to objects: a review of geographic boundary analysis. *Journal of Geographic Systems*, in press.

Johnston, C.A., and J. Bonde, 1989. Quantitative analysis of ecotones using a geographic information system, *Photogrammetric Engineering and Remote Sensing*, 55(11):1643-1647.

Johnston, C.A., J. Pastor, and G. Pinay, 1992. Quantitative methods for studying landscape boundaries. *Landscape Boundaries: Consequences for Biotic Diversity and Ecological Flows*, (A.J. Hansen and F. di Castri, editors), Springer-Verlag, New York, pp. 107-125.

Keppel, G., 1991. *Design and Analysis: A researcher's handbook*, Prentice Hall, Englewood Cliffs, New Jersey.

Kent, M., W.J. Gill, R.E. Weaver, and R.P. Armitage, 1997. Landscape and plant community boundaries in biogeography, *Progress in Physical Geography*, 21(3):315-353.

Krummel, J.R., R.H. Gardner, G. Sugihara, R.V. O'Neill, and P.R. Coleman, 1987. Landscape patterns in a disturbed environment, *Oikos*, 48(3):321-324.

Legendre, P., and M.J. Fortin, 1989. Spatial pattern and ecological analysis, *Vegetatio*, 80:107-138.

Ludwig, J.A., and J.M. Cornelius, 1987. Locating discontinuities along ecological gradients, *Ecology*, 68(2):448-450.

Malanson, G.P., 1997. Effects of feedbacks and seed rain on ecotone patterns, *Landscape Ecology*, 12(1):27-38.

Malanson, G.P., and D.G. Brown, 1996. Collaborative research on process and pattern at alpine treeline, Project Proposal funded by National Science Foundation (#97-14347).

Malanson, G.P., and D.R. Butler, 1994. Tree-tundra competitive hierarchies, soil fertility gradients, and the elevation of treeline in Glacier National Park, Montana, *Physical Geography*, 15:166-180.

McGarigal, K., and B.J. Marks, 1993. *FRAGSTATS: Spatial Pattern Analysis for Quantifying Landscape Structure, Version 1.0*, Forest Science Department, Oregon State University, pp. 1-62 (software manual).

Oden, N.L., R.R. Sokal, M. J. Fortin, and H. Goebl, 1993. Categorical wombling: detecting regions of significant change in spatially located categorical variables, *Geographical Analysis*, 25:315-336.

Orloci, L., and M. Orloci, 1990. Edge detection in vegetation: Jornada revisited, *Journal of Vegetation Science*, 1:311-324.

Risser, P.G., 1995. The status of the science examing ecotones, *BioScience*, 45(5):318-326.

Sokal, R.R., and F.J. Rohlf, 1995. *Biometry: The principles and practice of statistics in biological research*, W.H. Freeman and Company, New York.

Stevens, G.C., and J.F. Fox, 1991. The causes of Treeline, *Annual Review of Ecological Systems*, 22:177-91.

Timoney, K.P., G.H. LaRoi, and M.R.T. Dale, 1993. Subarctic forest-tundra vegetation gradients: The sigmoid wave hypothesis, *Journal of Vegetation Science*, 4:387-394.

Turner, M.G., 1989. Landscape ecology: the effect of pattern on process. *Annual Review of Ecology and Systematics*, 20:171-197.

Turner, M.G., 1990. Spatial and temporal analysis of landscape patterns, *Landscape Ecology*, 4:21-30.

Wiens, J.A., Crawford, C.S., and J.R. Gosz, 1985. Boundary dynamics: a conceptual framework for studying landscape ecosystems, *Oikos*, 45:421-427.

Womble, W.H., 1951. Differential Systematics, *Science*, 114:315-322.

Wood, T.F., and Foody, G.M., 1989. Analysis and representation of vegetation continua from Landsat Thematic Mapper data for lowland heaths, *International Journal of Remote Sensing*, 10(1):181-191.

Wilson, J.B., and A.D.Q. Agnew, 1992. Positive-feedback switches in plant communities, *Advances in Ecological Research*, 23:263-336.