Multiscale Effects of Grain Size on Landscape Pattern Analysis

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Abstract
We used multiple resolutions of remotely sensed data to explore the relationship between grain size and landscape pattern. Holding extent constant, we aggregated fine grained and coarse grained data to provide a continuum of grain sizes ranging from 5 m to 30 m on a side. Landscape metrics were calculated for each image and varied widely between grain sizes. Finer grained images appeared to be more fragmented and complex than coarser grained images for the same landscape. Most metrics varied smoothly as a function of grain size and were fitted to nonlinear models. Results showed that the models failed to accurately predict the metrics for the second landscape, although the metrics did display similar scaling patterns as in the first image. Further research using additional images of landscapes and a greater range of grain sizes is necessary to determine whether general scaling laws can be determined.

I. INTRODUCTION

A central goal of landscape ecology is to understand the relationship between pattern and scale and how that relationship affects ecological processes [1], [2], [3]. In order to link patterns to ecological processes we must first recognize that a landscape contains multiple scales of heterogeneity [4], [5]. A landscape is considered to be a large, heterogeneous area containing a mosaic of interacting ecosystems or patches [6], [7]. A patch is defined as a homogeneous unit within that landscape which differs from its surroundings [8]. Each patch exists within a mosaic of other patches or within a homogeneous matrix which together make up the landscape pattern [6]. These patterns occur as the result of complex interactions between climate, terrain, soil, water availability, and biota which create a dynamic patchwork of ecosystems across the landscape [9], [6]. These patterns form a feedback loop with ecological processes by affecting the exchange of energy and materials at multiple scales, both within and between patches [10]. At a fine scale, within a forest stand, a patch might consist of a different species or a wind throw. At a coarser scale, the stand could be considered a patch set among a mosaic of different aged stands or other vegetation types. Thus scale is inherent in the delineation of patches in the landscape and the characterization of landscape pattern depends on both the resolution (grain size) and the extent of the data [8].

The identification of scales of landscape patterns and examination of the effects of changing scales on pattern analysis (which are intrinsically related) are but two aspects of the pattern-scale problem in ecology [3]. The dependence of pattern on scale adds a level of complexity to the study of landscapes that is poorly understood. Scale usually refers to the resolution at which a pattern is measured [11]. Resolution is most commonly used to refer to the grain or pixel size of the data. However, it must be remembered that the spatial and temporal extent of the study can also affect the patterns perceived.

Ecologists have long been aware of the need for multiple scale analyses because many characteristics of landscapes vary with scale, such as vegetation [12], animal density [13], patch geometry [14], and resource availability [15]. Indeed multiple scale patterns have been described in a number of different in plant communities, including a semiarid grassland in New Mexico, a series of calcareous openings in a deciduous forest in Tennessee, a shrub-steppe system in Washington, and a juniper woodland in eastern Oregon [16], [17]. In addition, scale effects have been shown to be important in disturbance regimes [18], forest dynamics [19], biodiversity [20], and global change [21].

A number of studies have been carried out on detection and characterization of spatial patterns [22], [23], [24], [25], [26], [27] and, as a rsult, numerous metrics have been developed. However, many of the metrics and indices used to describe spatial pattern are scale dependent. For example, individual patches reveal scaling behavior in patch shape, patch boundary, and fractal dimension [14]. Mosaics of patches also reveal

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fractal scaling in total patch boundaries, patch centers of mass, and patch area distribution [28]. Diversity, dominance, contagion, and autocorrelation indices have been shown to be sensitive to changes in spatial scale across a landscape [3], [29], [30]. Despite these dependencies, few studies have specifically addressed the question of how changing scale affects the results of spatial analysis [3], [29]. Most ecological studies occur at a fine scale and small extent. Nonetheless, ecologists are being challenged to scale up to broader extents and scales. Particularly, in order to understand the complex interactions between land and the atmosphere, ecologists must convey information about fine-scale ecological patterns and processes to broad-scale applications [31]. Although problematic, the issue of scaling can be addressed through purposeful manipulation of the scale of observation or renormalization to discover how phenomena change steadily, and predictably, with scale [11].

Remotely sensed data are available at a number spatial and temporal resolutions, and as such, are appropriate for studying scale effects, with changing resolution. Also, remotely sensed data are synoptic, allowing us to observe large areas at a time and obtain consistent measurements [8]. Cullinan et al. [17] found remotely measured scales of pattern to be highly correlated with those detected in field-based measurements. Thus, satellite imagery can be a useful tool for detecting ecological change associated with changes in scales of vegetative patterns provided it is spatially explicit enough to detect those changes [17]. However, this leads to another question: what is the appropriate grain size to look at ecological processes? As grain size decreases, the volume of data increases geometrically and can lead to limitations in storage and computer processing. Thus, the use of very high resolution remotely sensed data may be limited to small regional studies [8].

In addition, as resolution increases so does variability lending complexity to analysis of the data [8], [30]. For example, at very large pixel size, only broad vegetation classes can be distinguished. As resolution increases, each pixel represents a smaller area on the ground. At a grain size equal to or below the size of a tree canopy, individuals can be detected. At even smaller grain sizes, each pixel can be a mixture of individual leaves and gaps within a single canopy. Waring and Running [8] suggest that choosing the largest grain size possible is the best answer to this problem. However, doing this can lead to missing finer scale patterns. What are needed are the tools necessary to scale from one grain size to another. Ecological studies addressing this problem are limited although it has been addressed more strongly in the geologic literature (for an example see Openshaw and Taylor [32]). One approach to this problem is to aggregate data systematically and examine changes in pattern as scale changes. As demonstrated by Jelinski and Wu [30] aggregating real data does not change the mean but decreases the variance. Aggregation has a smoothing effect resulting in the loss of spatial heterogeneity representing fine scale patchiness. We would thus expect that as resolution decreases there will be a reduction in the number of patches while their sizes increase. If landscape metrics change solely as a function of grain size they should change smoothly as grain size increases . Turner at al. [29], however, demonstrated the existence of thresholds in spatial patterns in keeping with the predictions of hierarchy theory. Hierarchy theory postulates that ecological processes occur at distinct scales due to the nonlinear interactions between biotic and abiotic components of the system that result in distinct scales of spatial patterning [31], [34]. This suggests that as grain size changes, there will be discrete changes in spatial patterns reflecting similar changes in ecological processes. Thus, landscape metrics should exhibit a stair step pattern as grain size changes reflecting a hierarchical pattern.

From the above, we can arrive at two opposing hypotheses: landscape metrics will vary smoothly with changing grain size as pixels are aggregated reflecting a decrease in variability. Or, landscape metrics will show discrete changes as grain changes reflecting a hierarchy of ecological processes. We addressed these two hypotheses by investigating changes in landscape metrics as a function of the grain size of remotely sensed data. Additionally, we wanted to determine if these changes could be modeled and, if so, could these models predict scale change effects on landscape metrics at either finer or coarser scales.

II. METHODS

Study Area

The research area is located north of Flagstaff, Arizona on the leeward side of San Francisco Mountains. The region is semiarid with a bimodal precipitation pattern. Two separate study sites were chosen based on the availability of remotely sensed data (Figure. 1). The first site is located along Deadman's Wash and represents a gentle topographic gradient. This study area was the source of data for model development. The second, more topographically diverse site is located to the north and was used for model verification. Both sites have a variety of vegetation types ranging from Great Basin desert scrub in the lower elevations, through pinyon-juniper woodlands, ponderosa pine forests and spruce-fir

Figure 1. False color infrared Landsat thematic mapper image of the study area overlaid by the two NS001 images used. Site A was used to develop the models and site B to test the models for predictive capability. Site B is more topographically diverse than site A, including a number of cinder cones.

forests at the higher elevations.

Remote Sensing

In July of 1995 a NS001, a thematic mapper simulator, was flown over the study area in a C-130 airplane. The NS001 records radiance in eight wavelength bands, seven of which are analogous to the Landsat thematic mapper bands and an additional band in the mid infrared. The pixel size of NS001 data in this study was approximately 5 m on a side. In addition, we used a summer, 1996, Landsat thematic mapper scene of the study area with pixel size of 30 m (Figure. 1).

Each image was georectified to within 1.4 pixels using differentially corrected GPS control points and atmospherically corrected using a dark-object subtraction technique developed by Chavez [33]. Image processing was done in ER Mapper version 5.5. We extracted equal area plots from the two NS001 images and used those to clip the same areas from the TM image. Bands 3 and 4 (red and near infrared) were exported as ASCII files from ER Mapper. A Unix script file was used to convert the ASCII files from space to comma delimited to export them as tables to ArcView. ArcView was used to convert the files to ARC/Info shape files, that were converted to grid files. The net result was two grid files (bands 3 and 4) for each of the TM and the NS001 images.

The NS001 grids were resampled to pixel sizes of 10 m, 15 m, 20 m, and 25 m on a side using bilinear interpolation. Bilinear interpolation resamples the grid by distance weighted averaging of the nearest four neighboring pixels of each pixel in the grid. We felt this method best approximated the smoothing that would occur if a sensor with a larger instantaneous field of view had recorded the data.

The resulting grids were recombined into normalized difference vegetation index (NDVI) images. NDVI is a commonly used vegetation index which is based on the differential reflectance of vegetation to red and near infrared light (e.g. [36], [37], [38], [39]). The ratio of these two bands is indicative of the amount of chlorophyll present. NDVI is calculated as: (NIR - R)/(NIR+R) and is high when vegetation is dense and low over sparse vegetation.

NDVI of images collected at different times have been shown to vary seasonally and annually [38]. However, NDVI is a less subjective measure of vegetation patterns than classification schemes that depend on the interpretation of the user. We classified the NDVI values into three classes based on dividing the histograms of the images in thirds to minimize differences in NDVI between the NS001 images and the TM images which could be due to inter annual variation. The three classes represent low, medium, and high vegetation coverage on each image which also served to reduce noise from soil reflectance. The resulting classified NDVI images with resolutions of 5 m, 10 m, 15 m, 20 m, 25 m, and 30 m, were exported from ARC/INFO as ASCII rasters.

It should be noted that the range of scales, from 5 m to 30 m, is limited. Initially we planned to include AVHRR data with 1 km pixels. However we chose a study area that covered approximately 550 by 2200 pixels in the finest resolution NS001. This was the most that we could analyze using the available computers. Although this data set consisted of 1,210,000 pixels it only corresponded to an area of 30 km^2 on the ground. Hence an AVHRR scene of the same size wold only consist of 30 pixels, not enough for this analysis. We chose, therefore, to limit the range of resolutions we would look at to those defined by NS001 and Landsat thermatic mapper sensors recognizing that we might miss some ecologically important scales by doing so.

Spatial Analysis

We used FRAGSTATS software to analyze each vegetation map and to quantify landscape structure with a number of metrics [40]. We investigated the scale dependency of a subset of the available metrics, especially how patch and edge indices change with spatial scale. This analysis concentrated on metrics

Table1. Landscape analysis of NS0001 image and the corresponding area clipped from a thematic mapper image.

	NS001	TM	% Change
Total Area (ha)	11685.855	11898.407	1.8
Largest Patch Index (%)	14.436	49.312	70.7
Number of Patches	118191	1600	-7286.9
Patch Density (3/100 ha)	1011.402	13.447	-7421.4
Mean Patch Size (ha)	0.099	7.437	98.7
Patch Size Coeff. Of Variation	8218.227	2072.610	-296.5
Total Edge (m)	8806446	972705	-805.4
Edge Density (m/ha)	753.599	81.751	-821.8
Landscape Shape Index	220.072	23.625	-831.5
Mean Shape Index	1.266	1.323	4.3
Mean Patch Fractal Dim.	1.063	1.043	-1.9
Area-weighted Mean Fractal Dim.	1.470	1.284	14.5
Shannon's Diversity Index	0.907	0.975	7.0
Simpson's Diversity Index	0.536	0.585	8.4
Modified Simpson's Diversity Index	0.767	0.878	12.6
Patch Richness Density (#/100 ha)	0.026	0.025	-4.0
Shannon's Eveness Index	0.826	0.888	7.0
Simpson's Eveness Index	0.803	0.877	8.4
Modified Simpson's Eveness Index	0.698	0.799	12.6
Interspersion/Juxtaposition Index (%)	88.653	87.750	-1.0
Contagion (%)	30.564	36.642	16.6

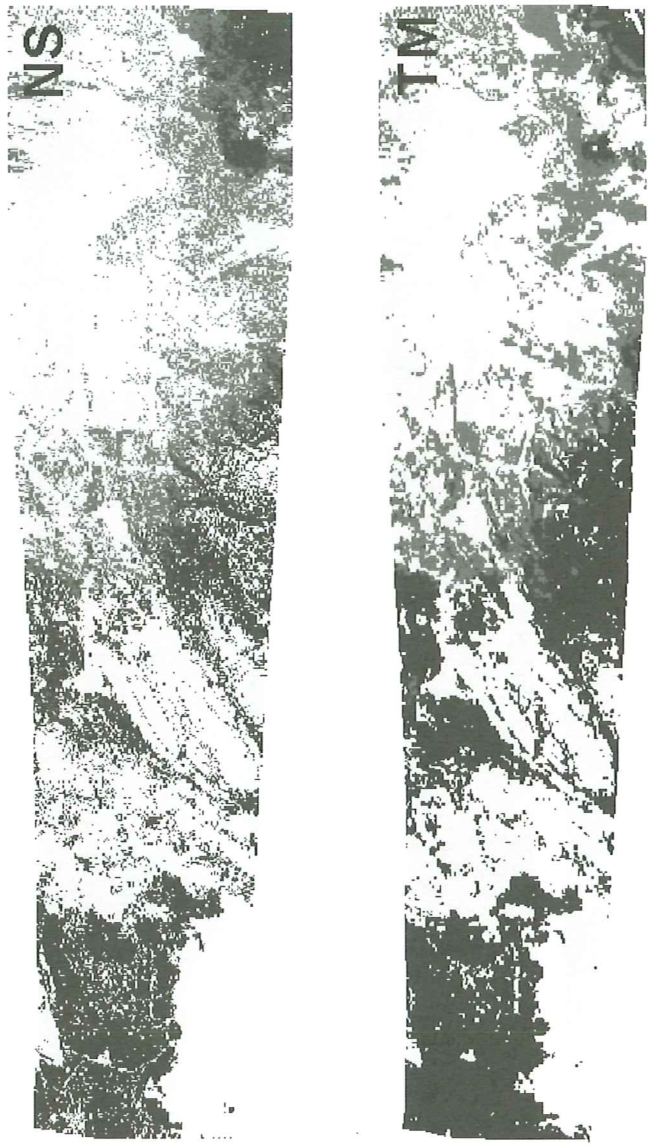

Figure 2. The classified NS001 (NS) and thematic mapper (TM) images. Light gray represents areas with low NDVI's, medium gray with medium NDVI's and dark gray with high NDVI's.

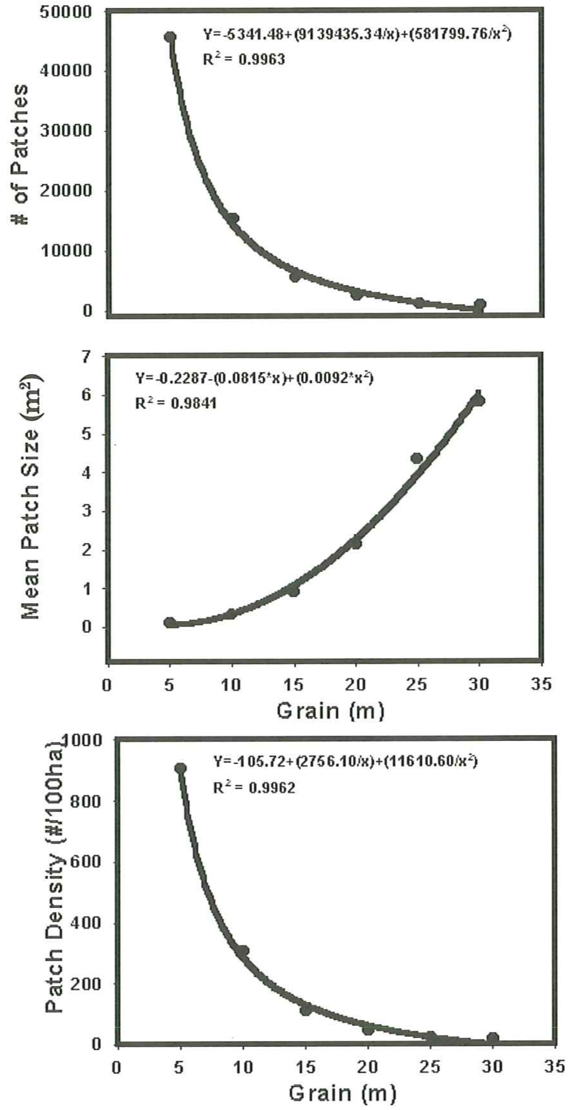

Figure 3. Regression analysis of patch indices as a function of grain size. The dots indicate actual data and the lines indicate the values predicted by the non-linear regression. The R^2 values are adjusted for the degrees of freedom.

such as the amount and distribution of patch types and of corresponding edges. This emphasis was designed to determine how level of resolution affects the perception of landscape structure and habitat fragmentation. The results of the metric calculations were regressed against the grain of the image using nonlinear curve fitting routines (Sigmaplot version 4.0). The regression equations were used to model changes in landscape metrics as a function of grain size. We then applied these models to a different, independent landscape to determine if they were generally applicable.

III. RESULTS

Images

Figure 2 shows the classified NS001 and thematic mapper images with a classification scheme of low, medium and high NDVI's. This classification scheme, although not directly determined by analysis of the spectral signature of the vegetation, does roughly represent the location of different vegetation types. Thus, the low NDVI values occur in areas consisting of grass and shrublands, the middle NDVI values occur in pinyon-juniper woodlands and the high values in ponderosa pine and mixed conifer forests.

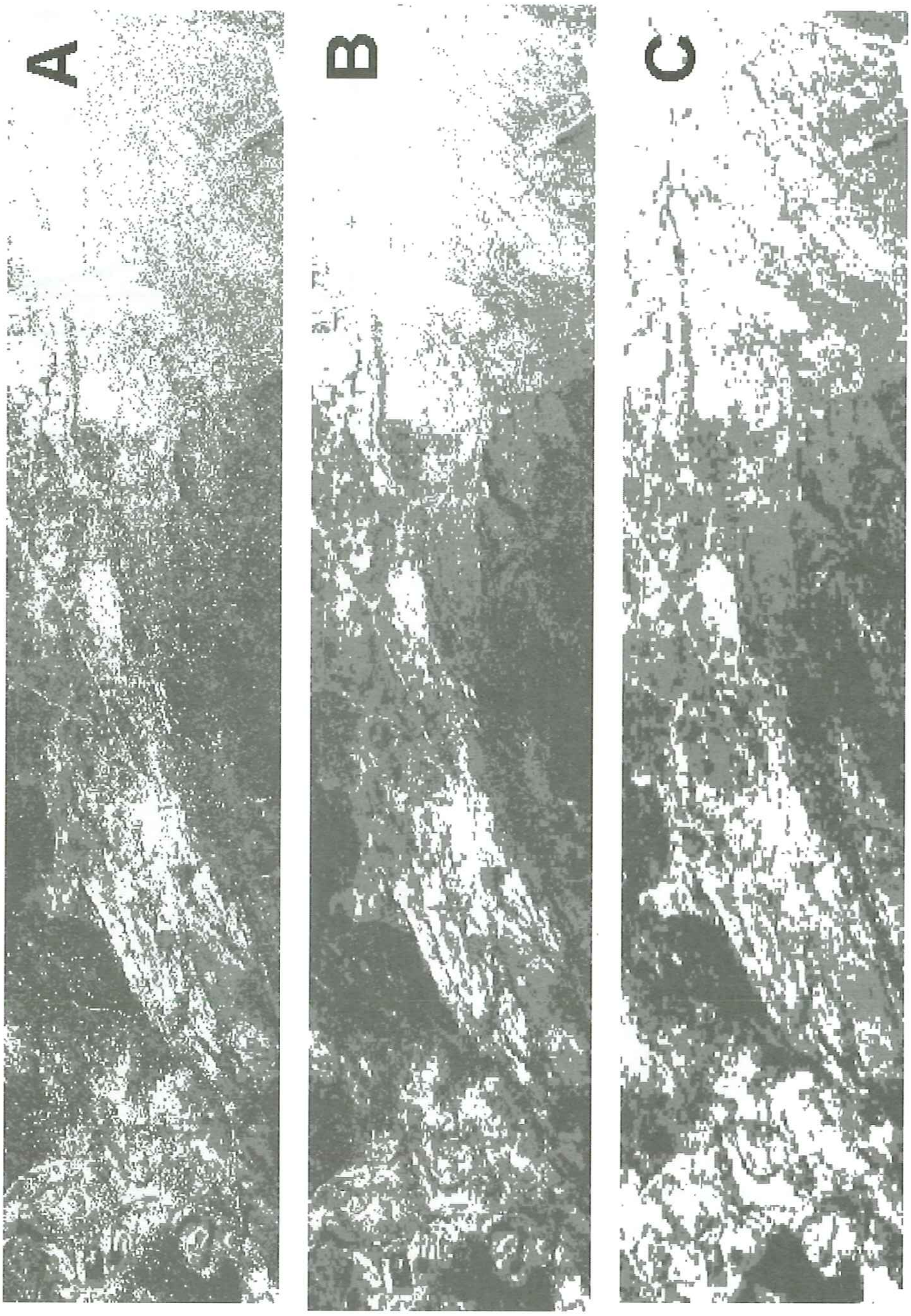

Figure 4. Three grain sizes of the clipped NS001 image. The top image (A) is the original NS001 image with a grain size of 5 m. The middle (B) and bottom (C) images show the NS001 resampled to a grain size of 10 m and 20 m respectively.

Visual analysis of these two images confirms that although grain size changes from 25 m^2 to 900 m^2, the spatial distribution of the classes across the landscape is consistent. Different total areas were calculated for these two images because of the irregular shape of the images, making precise clipping of the TM difficult and that imprecision was compounded by the different pixel sizes. The images were clipped to rectangular shapes for the rest of the analysis to minimize the problem. Three grain sizes of the clipped NS001 image are shown in Figure 4. Resampling the data results in a smoothing effect as detail is lost but the general landscape pattern remains the same.

Landscape Metrics

An analysis of the two landscapes resulted in significantly different landscape metrics (Table 1). The

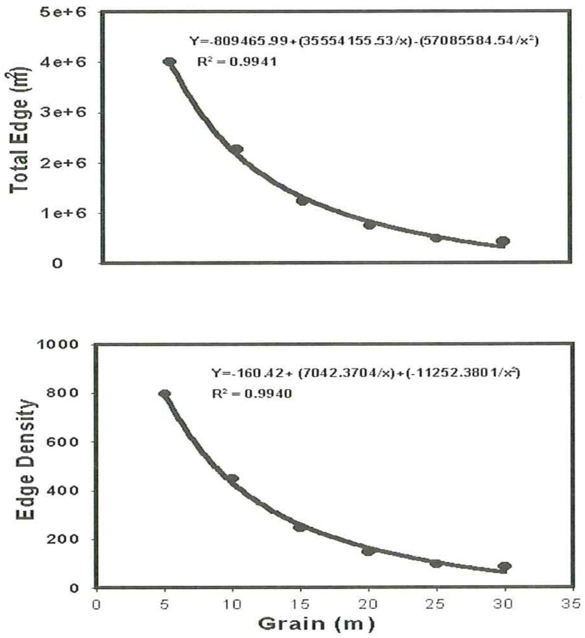

Figure 5. Regression analysis of edge metrics as a function of grain size. Actual data is depicted as dots and predicted values as a line. The R^2 values are adjusted for the degrees of freedom.

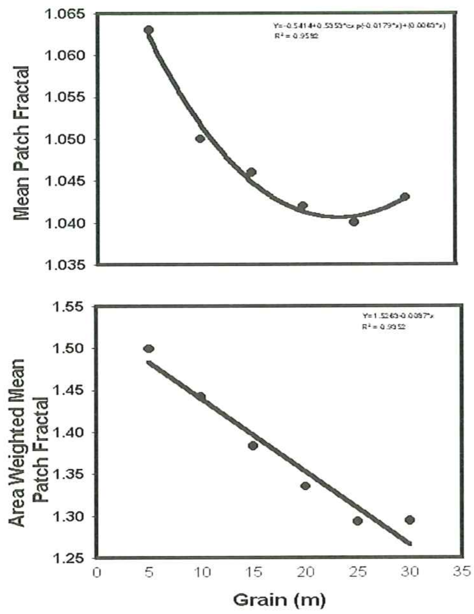

Figure 6. Regression analysis of patch fractal metrics. The dots indicate actual data and the lines indicate the values predicted by the nonlinear regression. The R^2 values are adjusted for the degrees of freedom.

number of patches and edge metrics changed in a dramatically nonlinear fashion while others, such as the diversity indices, remained somewhat robust. The results of the analyses of patch metrics are shown in Figure 3. All of the patch metrics fitted a smooth curve. Both the number of patches and patch density display inverse quadratic behavior as a function of grain. The similarity of results is not surprising, as these two metrics are directly correlated. However, the quadratic behavior is not entirely expected. We expected that the number of patches would be determined by the square of the resolution because as pixels are aggregated the size of the pixel increases as a square function. Thus, the smoothing of the data would also be expected to be a square function. Mean patch size also increased with resolution again as a quadratic function, the inverse of number of patches.

Edge metrics are depicted in Figure 5. Both total edge and edge density display inverse quadratic behavior as a function of grain size. Thus, perceived edge and edge habitat decrease smoothly with increasing grain size. Mean patch fractal, on the other hand, is a negative exponential function of grain size (Figure. 6). This result is interesting because the fractal dimension is indicative of the degree of complexity of the edge of the patch. These results show that as grain size increases, patch shape seems to become exponentially less complex. Thus as individual patches (i.e., trees in this analysis) are aggregated into larger patches (indicative of stands) the overall fractal dimension of the landscape becomes smaller. For this reason, the area weighted mean patch fractal which displays a nearly linear behavior with regards to grain size (Figure. 6) may be a better indicator of the changes taking place with aggregation. Area weighted mean patch fractal is the fractal dimension of individual patches weighted by their size and averaged over the landscape. This metric takes into account the increasing size of the patches relative to the complexity of their edges and is indicative of the smoothing effect associated with aggregating pixels.

The mean shape index (Figure. 7) measures the complexity of patch shape relative to a square for raster data and increases as patches become less square [40]. This metric does not behave as a smooth curve as a function of grain size (Figure. 7). Rather, it shows discrete jumps between grain sizes of 10 m and 15 m and between 25 m and 30 m. This stair step pattern is expected if the metric is following a hierarchical pattern. However, more data points are necessary to determine that this is a discontinuous curve. On the other hand, landscape shape index, which measure the perimeter to area ratio for the entire landscape [40], behaves as expected. As pixels are aggregated, patches become larger patches with fewer edges thus the landscape shape index decreases with increasing grain. The final metric examined was mean nearest neighbor (Figure. 7). This metric

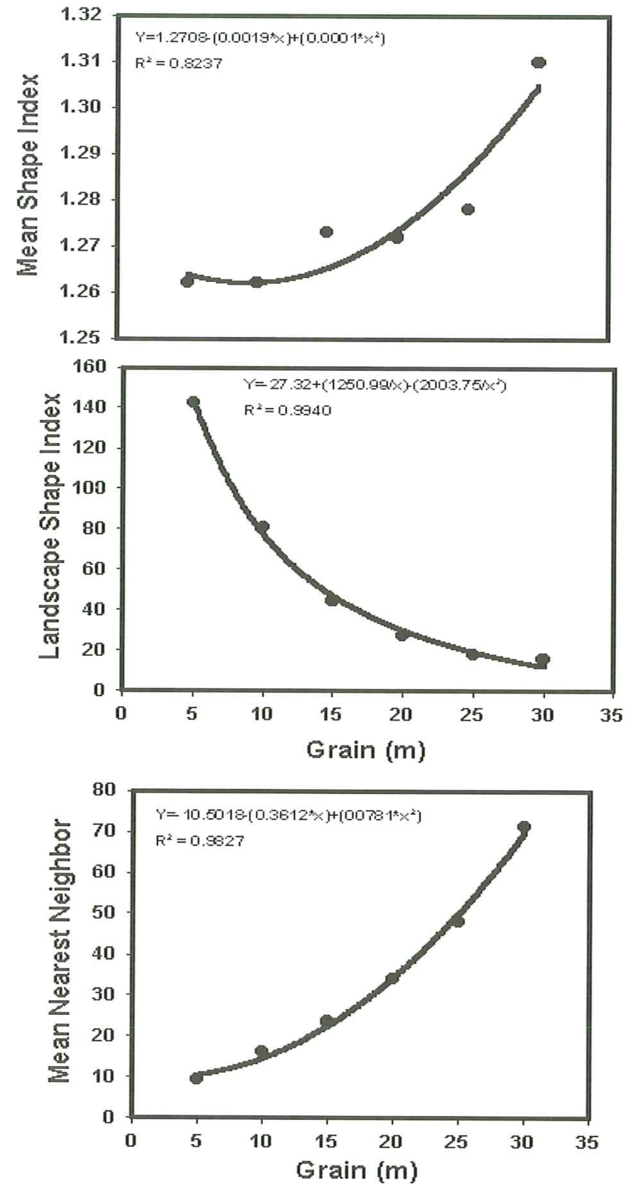

Figure 7. Regression analysis of shape indices and mean nearest neighbor. The dots indicate actual data and the lines indicate the values predicted by the non-linear regression. The R^2 values are adjusted for the degrees of freedom

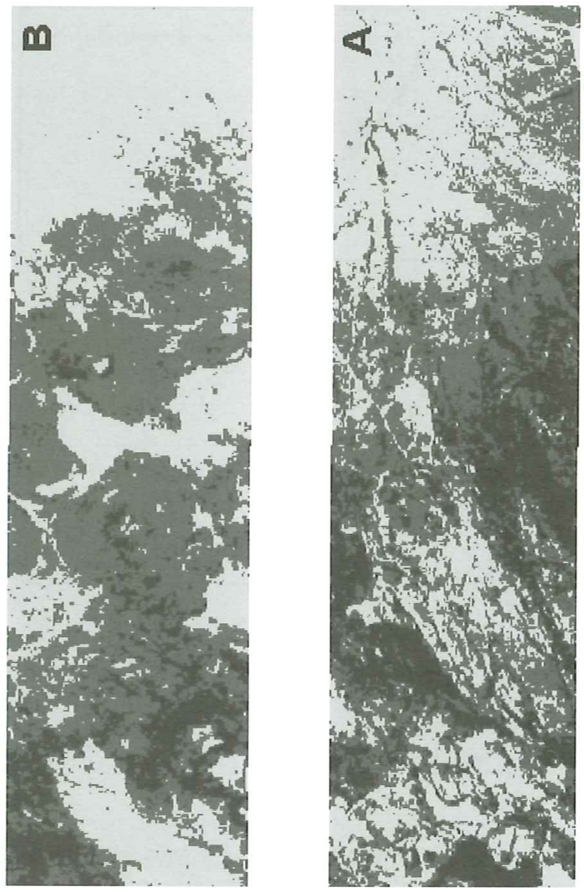

Figure 8. The classified NS001 images of the two study sites. Site B is north of site A and includes two cinder cones located near the center of the image. Light gray indicates low NDVI, medium gray medium NDVI, and dark gray high NDVI.

measures the edge to edge difference between patches of the same type. This distance increases smoothly as grain size increases reflecting the aggregation of different patches such that patches become large and the distance between patches centers also becomes greater.

Model Predictions

All of the metrics tested, with the exception of the mean shape index, varied smoothly as a function of grain size and were modeled to test whether or not these models were applicable to another landscape. A second study site was chosen north of the first that represented a very different landscape (Figure. 8). Study site A, used to develop the models, represents an elevational gradient with generally higher elevations on the left side of the image. The vegetation reflects this gradient such that higher NDVI values occur in the higher elevations in both site A and site B. However, site B is more topographically diverse incorporating rapid changes in elevation. For example, two cinder cones occur side by side near the center of the image and each has patches of high NDVI near their apexes. As a result of this topographic heterogeneity the different classes tend to occur in discrete patches throughout the landscape as opposed to the progressive change from one class to another seen in landscape A.

This difference in landscape structure may partially explain the lack of fit of the models to the data from study area B (Figure. 9). However, the data do fit the

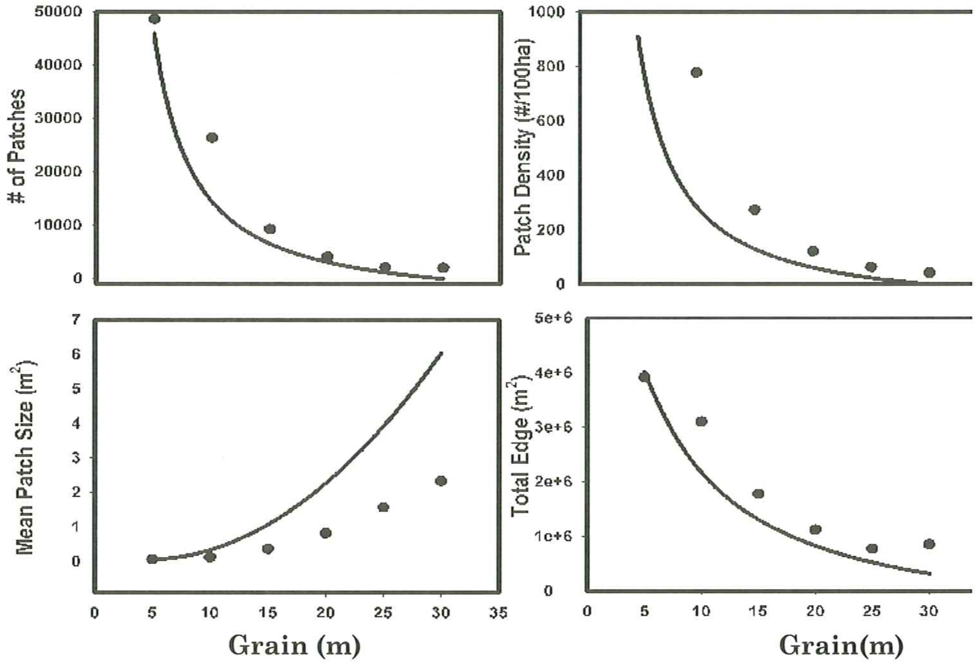

Figure 9. Patch Metrics for study site B compared to predictions made from models developed for study site A. The dots represent actual data from study site B and the lines predicted values.

same general trend of that predicted by the models. For example, number of patches and patch density still fit an inverse quadratic curve although they are shifted to the right. The model underestimates the number of patches and patch density while simultaneously overestimates mean patch size. This general pattern fit all of the metrics tested although only a few are shown.

IV. DISCUSSION

We analyzed the behavior of a variety of commonly used landscape metrics as a function of grain size while holding extent constant. All of the metrics investigated displayed a strong scale dependence. Aggregating pixels to ever increasing grain size resulted in a loss of spatial heterogeneity in the data. The landscape appears less patchy at coarser grains with fewer but larger patches. In other words, the landscape appears more fragmented at finer scales. Total edge and edge density also decreased with increasing grain size due to the aggregation of individual patches into larger patches. Edge effects are important to many ecological studies since edges represent an area of rapidly changing conditions such as light intensity, moisture availability and wind intensity. The physical conditions along such edges support specialized associations of species [41]. In addition, edges may act as amplifiers or filters for the transfer of energy, matter, organisms, and disturbance between adjacent patches [10], [7]. Thus perception of the amount of edge habitat available in a landscape may have important ramifications in conservation biology and in the design of refuges. The mean patch fractal dimension is related to the amount of edge in the landscape as it is a function of relationship between the perimeter and area of each patch. So it is not surprising that the mean patch fractal dimension also decreases with increasing grain size. Fractal dimension, however, is an indicator of the complexity of the landscape so a landscape examined at a coarse grain appears to be less complex than the same landscape examined at a finer grain. Interestingly, the mean shape index, which is based on the average perimeter-to-area ratio for all patches in the landscape, showed just the opposite behavior and was the only metric to display hierarchical behavior. Mean shape index increases with increasing grain size suggesting that the shape of patches becomes more complex as grain size increases. This is exactly the opposite effect expected from smoothing the data but is similar to that found by Strand et al. [43].

All of the metrics except the mean shape index varied smoothly as a function of grain size. This is what we had expected due to the smoothing effect of pixel aggregation. However, given the small range of scales examined, we cannot discount the possibility of hierarchical patterns at either smaller or larger scales. Due to the smooth behavior, however, we were able to fit the data to nonlinear models. This suggests that it is possible to scale up or down within a landscape, at least within the limits of the range we examined. Our attempt to apply these models to an independent landscape were unsuccessful. The data from the second landscape did, however, follow the same general pattern as that of the first landscape. This result suggests that general scaling rules might be developed by further investigation using a wider range of scales and a greater number of data sets.

In conclusion landscape metrics are extremely dependent upon the grain size of the data. A fine grain size affords more detail but results in the landscape appearing to be more highly fragmented and complex than the same landscape examined with a coarser grain. In view of this, extreme caution must be exercised in comparing landscapes at different scales and in choosing the resolution of the data that best describes the process under study.

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