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Use of fourier transforms to define landscape scales of analysis for disturbances: a case study of thinned and unthinned forest stands

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Abstract

Various disturbances such as disease and management practices cause canopy gaps that change patterns of forest stand structure. This study examined the usefulness of digital image analysis using aerial photos, Fourier Tranforms, and cluster analysis to investigate how different spatial statistics are affected by spatial scale. The specific aims were to: 1) evaluate how a Fourier filter could be used to classify canopy gap sizes objectively, 2) determine which statistics might be useful for detecting and measuring disturbance impacts, and 3) examine the potential for this method to determine spatial domains in a pair of ponderosa pine (*Pinus ponderosa*) stands in the Black Hills of South Dakota, USA. The eventual goal is to develop an operational method of assessing the impacts of natural disturbances such as disease. Results indicated that several spatial metrics discriminated between harvested and unharvested stands. We hypothesize that these metrics will be useful as spatial measures of disease impact if the analyses are performed on specific size classes of forest gaps.

Introduction

Disturbances within forest landscapes are major causes of spatial heterogeneity that impact many of the resources managed by forest managers. Some consider these disturbances to be resources themselves and that they should be conserved and studied for their management utility (Baker 1992). Silviculturists try to control stand structure and composition by mimicking natural small-scale disturbances (Smith 1986). To manage, manipulate, or mimic disturbances effectively, managers must be able to adequately measure their impacts on the ecosystem.

Forest managers have traditionally addressed impact assessments from a timber production point of view. Methods used to assess disturbances have been based on timber metrics such as volume or board feet of standing growing stock of saw-timber (Stark 1987). These metrics have been useful for making timber production decisions, but they may be less useful for making decisions about such non-timber resources as wildlife habitat, recreation, wilderness, and aesthetic values. An alternative to impact assessments based on timber production metrics is an assessment based on spatial metrics that describe how conditions vary in space.

Tree diseases, insect pests, strong winds, lightning strikes, and other kinds of disturbances influence forest landscape structure by killing trees. Canopy gaps that result from tree mortality vary in size, shape, and frequency. Specific disturbance agents generate canopy gaps that often have distinctive characteristics (Lundquist 1995). For example, gaps caused by root diseases are commonly composed of trees in various stages of dying and degradation, whereas groups of trees in approximately the same state of degradation often make up gaps caused by bark beetles. Commonly, trees stressed by root diseases attract bark beetles resulting in gaps with characteristics of both diseases and insects, making impact alone difficult to assess. Basic research is needed to identify which metrics are most appropriate for measuring disturbance impact. In particular, the variation of metrics with spatial scale may provide a useful method of classifying different landscapes.

Characterization of spatial scale has long been a central theme of landscape ecology (Levin 1992). Various studies have examined how scale affects spatial statistics (Turner et al. 1991; Cullinan and Thomas 1992; Lundquist 1995; Qi and Wu 1996; Meisel and Turner 1998; Hargis et al. 1997). Wiens (1989) defines spatial domain as "regions of the spectrum over which … patterns either do not change or change monotonically with changes in scale." Several authors describe how scale affects the spatial domain by observing trends in the variance of various statistics with increasing scale (O'Neill et al. 1986; Carlile et al. 1989; Woodcock and Strahler 1987; Horne and Schneider 1995). Most of these discussions have been theoretical and/or based on artificial landscapes; little has been done with actual field data. One of the aims of this paper is to perform a preliminary evaluation of an objective method of classifying spatial scales of real landscapes.

One method of discriminating features at different spatial scales uses low pass Fourier Transforms. This procedure removes unwanted detail from images based on size; viz., features smaller than a given size are removed by filtering. In effect, this procedure helps to focus on features of interest by reducing noise caused by these unwanted features (Sommerfeld et al. 1998). Technically, the Fourier Transform splits a signal into a set of sine and cosine functions of different scales. In our case, the signal consists of the brightness levels of pixels of grayscale aerial photos. The analysis results in a two-dimensional plot of signal amplitudes at different scales. A low pass filter is implemented by zeroing the coefficients of the sine and cosine functions for separations smaller than some cutoff scale. By performing this analysis at different cutoffs a series of images can be developed that emphasize progressively larger spatial scales. In the study described below, we examine images of landscapes based on patterns of distribution of increasingly larger canopy gap sizes.

The long-term goal of this research is to improve methods for assessing disease impacts on forests. In this case study, we compared plots in an unharvested stand of ponderosa pine (*Pinus ponderosa*) to plots in a managed stand that had been thinned using the assumption that tree harvesting is comparable to extreme disease conditions. The analysis took two highly contrasting canopy conditions with the aim of assessing whether the Fourier Transform had potential for measuring more subtle differences in landscape patterns more commonly associated with diseases and other small-scale disturbances. More specifically, we investigated how different spatial metrics were affected as the spatial scale varied to 1) determine which metrics might be useful for measuring disease impacts, and 2) examine the potential for this method to determine spatial domains in forest stands.

Methods and materials

Study site

This study was conducted in the Black Hills National Forest in southwestern South Dakota, USA. Two sites composed mostly of mature ponderosa pine were used. The first was 5.2 ha of the 110 ha Upper Pine Creek Research Natural Area (UPC), a first order watershed of the Upper Pine Creek. The other site was 16.3 ha of the 28 ha Cameron Creek Timber Sale (CAM), an area that had been thinned from a basal area of 10.2 m^2 to 7.5 m^2 in 1989.

Aerial photographs

Aerial photos (1:14800) of the study areas were digitized using a Sony color video camera to images of 399 × 399 pixels, well above the 110-pixel limit for stable results specified by Hargis et al. (1997). Scales were determined by measuring points of known separation on the images. The 5.2 ha Upper Pine Creek subarea had a scale of .33 m^2 per pixel and the 16.3 ha Cameron subarea had a scale of 1.02 m^2 per pixel. Image acquisition and processing were performed using Image Pro (Media Cybernetics 1995). Rock outcrops were masked out of the image since these features were irrelevant to this study.

Fourier transform

The Fourier Tranform is a curve fitting technique, which for two dimensions, uses a series of the form,

$$f(x, y) = \frac{1}{2}a_0 + \Sigma a_{ni\ \ nj} \cos\sqrt{(n_i x)^2 - (n_j y)^2} + \Sigma b_{ni\ \ nj} \sin\sqrt{(n_i x)^2 + (n_j y)^2} \qquad (1)$$

to fit the function *f(x,y)*, where *x* and *y* are the pixel dimension in the x and y directions and ni and n_j are integers each spanning the range from 1 to 399. The coefficients, $a_{ni\ nj}$ and $b_{ni\ nj}$ are determined by solving the set of simultaneous equations where *f(x,y)* is the brightness of the pixel at each location. If *f(x,y)* contains elements which repeat over a set spacing, the Fourier Tranform identifies these with large coefficients *a* and *b* for those spacings. For example clearcutting might occur in regularly spaced blocks of 30 m^2. In that case the coefficient for $n_i x$ = 30 m and $n_j y$ = 30 m would be large. Generally, however, the transform merely provides a convenient curve fitting technique which produces an alternative representation of the data. Some manipulations of the data are more convenient using this alternative representation. For our application, the Fourier Tranform provides a convenient method of implementing a low pass spatial filter which eliminates the finer detail and emphasizes the coarser features. The low pass filtering is accomplished by setting the coefficients $a_{ni\ nj}$ and $b_{ni\ nj}$ to zero for spacings $n_i x$ and $n_j y$ smaller than the desired cutoff spacing since the finer detail is represented by coefficients of smaller *n*. *f(x,y)* is then recalculated using the remaining coefficients and can be presented as a blurred image. The amount of blurring depends on the number of coefficients which are zeroed. Currently available software makes the calculation of the two-dimensional Fourier Tranform and its inverse (*f(x,y)*) for all combinations of $n_i x$ and $n_j y$ practical and indeed almost effortless. We use ImagePro Plus (Media Cybernetics 1995).

The Fourier Tranform used as a low pass filter gives information equivalent to a moving window analysis with the cutoff spacing closely related to the window size. We used the Fourier Transform because the software available to us provided a wider choice of cutoff window sizes than did the available moving window analysis. The Fourier Transform produces gray scale images smoothed by the low pass filtering. Application of a threshold level converts the resultant images to black and white Boolean images. Canopy gaps are a lighter gray than the trees so that the white spaces correspond to the gaps in the thresholded image. Pixels with brightness values above the threshold value are forced to white and those with values below to black.

Images produced by the low pass Fourier filtering are gray scale images with the lighter regions (gaps) grading into the darker regions. Therefore, the resultant gap size in the thresholded black and white Boolean image is a function of the threshold level. A higher threshold level moves the boundaries toward the lighter regions decreasing the gap size, while a lower level moves the boundaries toward the darker regions increasing the gap size. For consistent results, it is necessary to use a consistent criterion for choosing a threshold level. A uniform distribution of gap sizes has a 1 to 1 correspondence between gap size and window size. The threshold levels in each case in this study were chosen as a close approximation to the following:

$$A_{gap} = (spacing/2)^2 + K, \qquad (2)$$

where A_{gap} is the mean gap area. The expression $(spacing/2)^2$ represents the effective area of the bright half (gap) of the filtered image (Sommerfeld et al. 1994). Spacing is termed lag in that publication. K is a constant related to the minimum gap area. Deviations from a straight line indicate a non-uniform distribution. For example, if a size category is missing, the moving window will find the next larger category, creating a step in the curve. Linear regressions of the mean gap area versus window area determined K and were used to aid in judging the best threshold level for each image for this study. Because the distributions were not necessarily uniform some judgment was involved.

Two artifacts are generated by the low pass Fourier filtering that influence the way various metrics change with scale. First, shapes are simplified as the cutoff frequency is reduced (i.e., effective window size increased) (Hargis et al. 1997). Compare Figure 1A with Figure 1B. An example of the consequences of this artifact is the decreasing trend of the mean fractal dimension with increasing window size in Sommerfeld et al. (1998). Areas that were emphasized in that study became visually closer to simple circular shapes. This artifact may be removed by ANDing the thresholded Fourier filtered image with the non-filtered thresholded image.

The logical AND as applied to the Boolean images consists of a pixel-by-pixel comparison of two images. The result is white where both pixels are white. A black pixel in either (or both) images produces a black pixel in the result. The main result for our images is that the irregular edges of the unfiltered image are added back into the filtered image. Careful comparison of Figure 1A and 1D illustrates the result of this technique. This technique emphasizes either larger gaps or clumps of gaps where the gap or clump

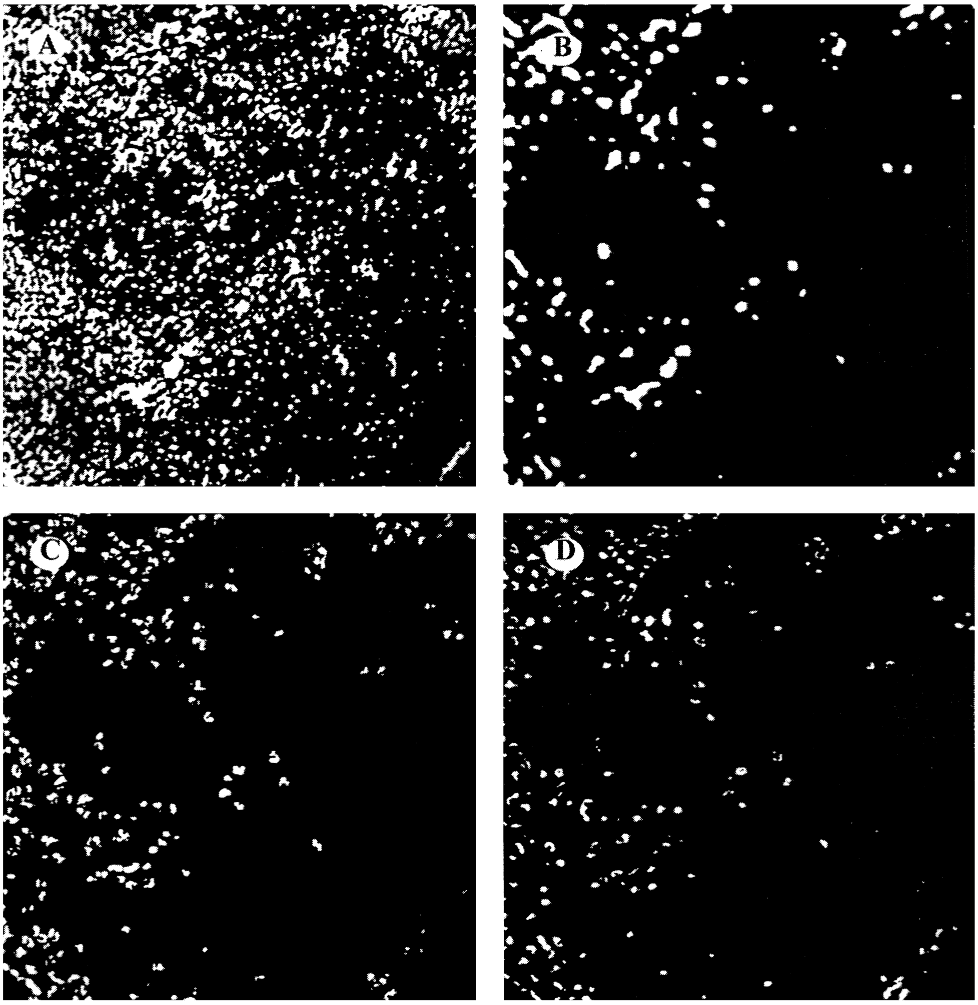

Figure 1. Original monochrome image thresholded at a level selected according to Equation (2). (A) Low pass Fourier image filtered at 12 × 12 pixels and thresholded as above. (B) Fourier filtered at 14 × 14 pixels subtracted from the 12 × 12 filtered image. (C) Final result of 12 × 12 pixel low pass Fourier filter, thresholding, subtraction of the 14 × 14 filtered image ANDed with the unfiltered image (D).

size is related to the Fourier window size. In other words, the Fourier filtering selects for larger features and the ANDing procedure adds the finer details back into these larger features.

The second artifact generated by Fourier filtering (and a moving window analysis) arises because it selects for regions that are the same size *or larger* than the effective window area. This also leads to difficulties in interpreting the data. Note the large clearing in the lower left of Figures 1A and 1B. It is larger than the 12 × 12 pixel size of the filter of Figure 1B. It is possible to subtract the Fourier filtered and thresholded image of the next larger window image from the size of interest. This, in turn, generates a different artifact. The regions selected are not monochromatic in the spatial domain. In other words, a collection of gaps of a certain size is not represented by a sharp peak in the Fourier analysis, but by a broad peak. Thus, the next larger window image often contains smaller residuals of the regions that were enhanced by the smaller window. The result is that many of the regions remaining after subtraction are in the form of rims delineating the edges of the desired gaps, as shown in Figure 1C. A method of resolving this problem is to dilate the white rims until they form continuous regions with the mean gap area again closely approximating the window area. This procedure tends to narrow the size distribution of the regions enhanced in the image. Then ANDing with the unfiltered thresholded image adds the fine detail back in

Table 1. Various spatial statistics generated from analyses of digitized and transformed images of an unharvested forest landscape (Upper Pine Creek Research Natural Area) and a harvested landscape (Cameron). Statistics were calculated using window sizes of 185 and 1085 m^2. Spatial statistics were calculated using FRAGSTATS (McGarigal and Marks 1995).

Variable Description	Variable Name	Window size 185 m^2			Window size 1085 m^2		
		UPC	Cameron	Difference (%)	UPC	Cameron	Difference (%)
Index of landscape shape	LNDSHAPE	4.87	7.56	55	2.21	2.96	33
Mean gap fractal	MEAN_D	1.14	1.08	−5.2	1.16	1.11	−4
Percent of landscape in gaps	CLASS%	3.46	3.69	6.54	1.39	1.83	31
Total number of gaps	NOPATCH	277	827	198	59	117	99
Mean shape index	AVESHAPE	1.29	1.22	−5.11	1.41	1.42	0.82
Contagion in percent	CONTAG	83	80	−3.27	92	89.84	−2.3
Mean area-weighted shape index	WTSHAPE	1.44	1.33	−7.6	1.96	1.76	−10
Standard deviation of gap area (ha)	SIZE_CV	82	75	−8.19	145	114	−21
Edge density in meters/hectare	EDGEDENS	322	203	−36	101	60	−40
Area-wted mean fractal dimension	WT_D	1.18	1.11	−5.85	1.25	1.17	−6.58
Gap area standard deviation (ha)	SIZE_SD	0.002	0.005	163	0.008	0.03	276
Total gap edge length (m)	TOTEDGE	7424	33939	357	2329	10166	336
Total within-gap core area	TOTCORE	0.18	6.16	3288	0.10	3.06	2741
Total area in gaps (ha)	CLASSAREA	0.79	6.16	674	0.32	3.06	855
Mean gap area (ha)	AVESIZE	0.003	0.007	142	0.005	0.02	434
Double fractal dimension	DOUB_D	1.30	1.32	1.35	1.35	1.31	−3.13
Mean nearest neighbor distance (m)	MEAN_NN	5.48	11.39	107	3.63	12.87	253
CVof the nearest neighbor distance	NN_CV	136	97	−28	129	201	56
SD of the nearest neighbor distance	NN_SD	7.48	11.09	48	4.70	26.23	457
Mean proximity index	MEANPROX	6.18	2.54	−58	27	14.19	−47

only to those regions that are enhanced. This procedure emphasizes gaps or clumps of gaps whose size corresponds to the Fourier window size. The final result is shown in Figure 1D.

Metrics using the smallest and the largest window sizes may also generate artifacts. The smallest window size is equivalent to the pixel size. The spatial metrics may be affected by the square shape of the pixels. The largest window size (2100 m^2) may not contain enough data for accurate calculation of the metrics.

Two-dimensional Fourier Tranforms were applied and adjusted to successively reject finer spatial information from about 3 to 2100 m^2 window sizes. The images were thresholded at a level that produced a close correspondence between the window size and the gap size. The next larger window image was subtracted and the resulting image was dilated until mean canopy gap size equaled the window size. AND was used with the smallest window image to recover the spatial details of the gap edges.

Transformed images were entered into a GIS and spatial statistics were calculated (Table 1) with the spatial analysis program FRAGSTAT (McGarigal and Marks 1995). Spatial metrics were compared visually by standardizing their values in terms of the number of standard deviations from each metric's combined mean.

A hierarchical cluster analysis using Euclidean distances with single linkage was performed on standardized data and all 20 metrics for each window size for both sites. The assumption was made that window sizes that clustered together represented members of the same spatial domain and by observing the cluster behavior the number and bounds of various spatial domains could be determined.

Profiles composed of values for all of the spatial statistics between sites were compared to define how stand manipulation altered the range of spatial domains and spatial heterogeneity and to determine which metrics were most sensitive to these changes. Values for UPC wre used as reference. Values for each variable of the middle window size of each cluster (spatial domain) in UPC were used for comparison with the same window size in CAM. The assumptions were made that UPC was similar to CAM if the latter had not been disturbed and that sensitive variables would be useful candidate variables for impacts caused by diseases and other disturbances that are normally less intrusive than the silvicultural manipulations used at CAM. The intent was to use these metrics in a later more robust study comparing diseased and non-diseased forest stands and using a wider range of landscape conditions.

Results

Spatial analysis

The shapes of these trend curves varied among metrics as their values changed with increasing Fourier Transform window size (Figure 2). Metrics were classified according to similarity in curve shape between the two sites. Three categories were defined as follows:

1. Metrics that show little difference between UPC and CAM. These included: Landscape Shape (A); Class (C); Number of Patches (D); Average Shape (E); and Contagion (F). Because these metrics were apparently not responsive to disturbance, they were not useful in assessing disturbance impact and were not considered further in this study.
2. Metrics with relatively simple curves that were similar in shape but showed distinct differences in values over a significant range of scales. UPC had higher values than CAM for Weighted Shape (G), Size Coefficient of variation (H), Edge Density (I), and Weighted Fractal Dimension (J), and lower values for Mean Gap Fractal (B), Size Standard Deviation (K), Total Edge (L), Class Area (M), and Average Size (N).
3. Metrics with complex shapes showing distinct differences between UPC and CAM. These included: Double Log Fractal Dimension (O); Total Core (P); Mean Nearest Neighbor (Q); Nearest Neighbor Coefficient of Variation (R); Nearest Neighbor Standard Deviation (S); and Mean Proximity (T). Trend curves (Figure 2) showed relatively abrupt changes in shape at various window sizes for these metrics. For UPC, these changes occurred at 10 (Figure 2O, 2P), 314 (Figure 2S, 2T), 530 (Figure 2Q, 2R, 2S), 829 (Figure 2O, 2R, 2S, 2T), 1983 (Figure 2O, 2R), and 1475 m^2 (Figure 2R). For CAM, trend changes occurred at 40 (Figure 2 O, P, Q), 95 (Figure 2Q), 380 (Figure 2T), 517 (Figure 2Q, 2T), 655 (Figure 2Q, 2R, 2S), and 1164 m^2 (Figure 2R). In general, most trend changes occurred in the mid size ranges and the frequency of changes in trend shape was less in CAM than UPC.

Cluster analysis

Figure 3 represents the results of the cluster analysis using all window sizes. At a distance of 0.8, the largest and smallest window sizes for both UPC and CAM fail to cluster with any other window sizes. All other window sizes form four clusters at a distance of 0.5. For UPC, the first cluster is composed of window sizes that range from 20 to 530 m^2 and the second cluster ranges from 830 to 1475 m^2. For CAM, these ranges are 40 to 520 m^2 and 655 to 1165 m^2, respectively.

Comparisons based on selected single window sizes

Metric values calculated at scales of 185 m^2 and 1085 m^2 gave distinct differences for most metrics. These were used to contrast harvested and unharvested plots. The percent difference varies from −58% to 3288%, depending on the metric and the window size used for assessment (Table 1). Most variables had different values at different scales. These differences were usually either both positive or both negative. Some variables showed a positive difference at one scale and a negative difference at another.

Discussion

In this study, timber harvesting was used to identify the sensitivity of spatial metrics to disturbance. Harvesting is a broad scale disturbance and arguably represents an epidemic condition similar in some ways to disease-caused epidemics because both cause gaps. Based on the assumption that the Upper Pine Creek Research Natural Area adequately represents CAM before it was harvested, the following observations could be made. At CAM, harvesting: 1) increased the total number of gaps in the stand, 2) increased or decreased the average gap size depending on scale, 3) increased the total length and density of gap edges, 4) decreased the variation in size among gaps, 5) increased the total within gap core area, 6) increased the mean nearest neighbor distance and the variation in distance among gaps, 7) decreased the mean proxim-

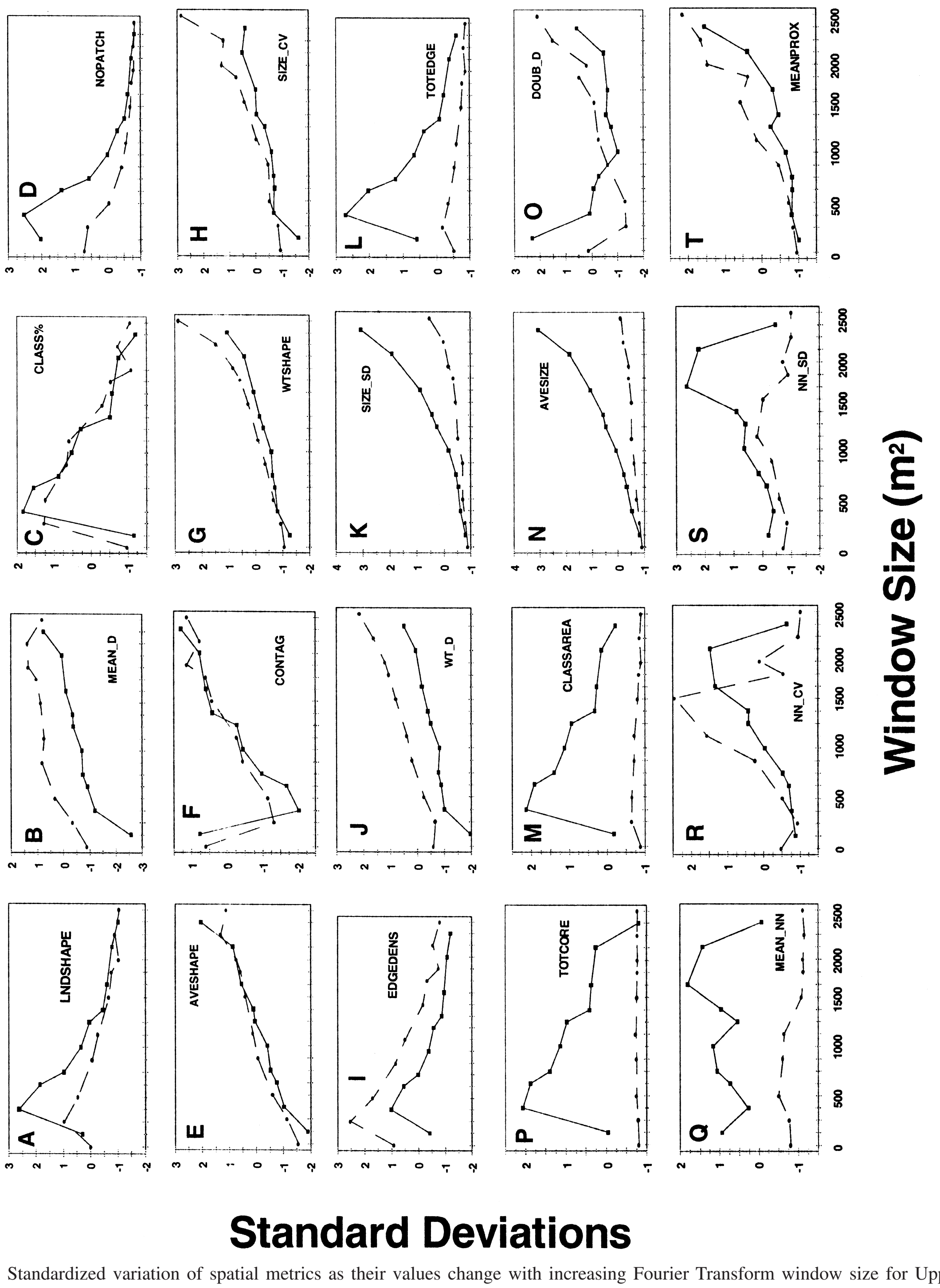

Figure 2. Standardized variation of spatial metrics as their values change with increasing Fourier Transform window size for Upper Pine Creek Research Natural Area, which was an unharvested site (solid lines), and for Cameron Creek Timber Sale, which was a previously harvested site (dotted lines). The statistics used were: A) Index of landscape shape (LNDSHAPE), B) Mean gap fractal (MEAN_D), C) Percent of landscape in gaps (CLASS%), D) Total number of gaps (NOPATCH), E) Mean shape index (AVESHAPE), F) Contagion in percent (CONTAG), G) Mean area-weighted shape index (WTSHAPE), H) Standard deviation of gap area (SIZE_CV), I) Edge density in meters/hectare (EDGEDENS), J) Area-weighted mean fractal dimension (WT_D), K) Gap area standard deviation (SIZE_SD), L) Total gap edge length (TOTEDGE), M) Total area in gaps (CLASSAREA), N) Mean gap area (AVESIZE), O) Double fractal dimension (DOUB_D), P) Total within-gap core area (TOTCORE), Q) Mean nearest neighbor distance (MEAN_NN), R) CV of the nearest neighbor distance (NN_CV); S) SD of the nearest neighbor distance (NN_SD); T) Mean proximity index (MEANPROX).

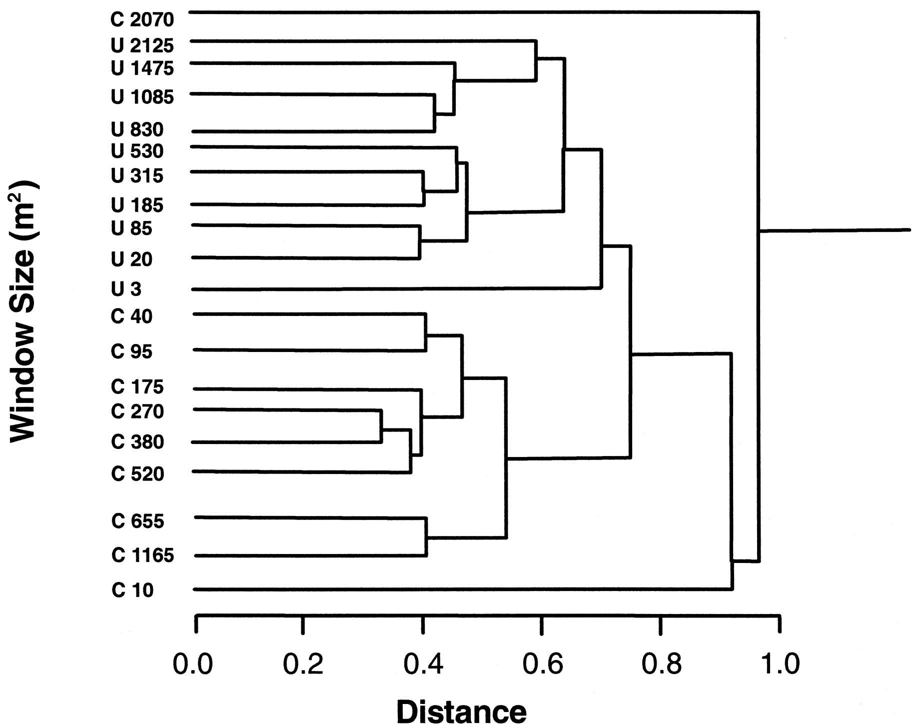

Figure 3. Cluster analysis of standardized profiles of 20 spatial metrics for differing window size for both harvested and unharvested stands examined in this study. Values correspond to window size and preceding letters are C for Cameron (harvested) and U for Upper Pine Creek (unharvested).

ity index, and 8) reduced the complexity of gap shapes.

Results showed that the interpretation of impact of a disturbance is largely dependent on the spatial scale at which the affected landscape is measured. Disturbances have different kinds and magnitudes of impact at different scales. In order to adequately characterize and measure impact, a suitable scale must be determined. In this regard, Wiens (1989) describes a useful analogy, "acts in what Hutchinson (1965) has called the 'ecological theatre' are played out on various scales of space and time. To understand the drama, we must view it on the appropriate scale." What is a 'suitable scale' of analysis largely depends on the resource or issue of concern. In this study, differences of impact of the disturbance on the spatial metrics varied from −58% to 3288%, depending on the metric and the spatial scale (Table 1). Traditionally, impact assessments have been based on a single spatial scale. Operationally, defining a significant scale helps limit the number of observations needed to contrast disturbed and undisturbed sites and thus simplifies the analysis. Category 2 variables seemed more useful for quantifying impact since magnitude rather than curve shape changed with disturbance.

Remote sensing techniques coupled with digital transformations offer useful avenues for assessing canopy structure and quantifying its spatial patterns. This study uses digital imagery of aerial photos, the Fourier Tranform, and a cluster analysis to contrast a naturally diverse canopy structure with one that had been made uniform by thinning. The results indicate that aerial photos and the two-dimensional Fourier filter can be used to classify gap sizes. The technique is less labor intensive and more objective than field surveys. Results also suggest that several spatial metrics will shift values when landscape patterns change. These shifts can be interpreted in terms of changes in the existence and characteristics of landscape domains. Wiens (1989) and others (e.g., Dayton and Tegner (1984) and Maurer (1985), Morris (1987)) believe that there exist inherent scales in nature. Not all have agreed. Allen and Starr (1982), for example, describe scale as, "not an inherent attribute of the process, but an artifact of the levels of resolution used to measure the process." The method we describe here might be a useful tool for addressing this debate.

Hargis et al. (1997) investigated the trends of various spatial statistics by varying the proportion of gapped area (5% to 95%) in simulations of small landscapes. They found the following: edge density and contagion are inversely correlated; mean nearest neighbor was a useful measure of a changing landscape when less than 20% of the landscape was in the measured class; mean proximity index could be used as a measure of gap isolation best at low percentages of the measured class area; and fractal dimension did not indicate differences among gaps with small differences in shape. Although our study covers a much more limited range than that used by Hargis et al. (1997), our results are in good agreement with theirs after artifacts generated by Fourier Transforms are corrected (Figure 2). At lower proportions, the edge density increases with proportion of the measured class (Figure 9.5 in Hargis et al. (1997)) with a slope lower for the clear cut as opposed to the random patches. Edge densities calculated in our study show a similar pattern with the values for the managed stand lower for each map proportion than for the unmanaged stand. Contagion shows a similar agreement, although differences between the two types of landscapes are not as large as for edge density. Mean proximity distance in our study showed distinct differences between the two stand types, but the differences are not apparent in Hargis et al. (1997) and may be due to differences in graph scale.

We used cluster analysis to define spatial domains. Theoretically, spatial domains should also be detectable by examining changes in trends as the proportion of gap area increases (Qi and Wu 1996). In this research, nearest neighbor statistics were most sensitive to these changes and might be useful for determining domains as defined by Wiens (1989) and for assessing the impacts that diseases and other disturbances have on landscape structure. The coefficient of variation of the nearest neighbor distance shows low values at 20 m^2, 725 m^2, and between 1474 m^2 and 2123 m^2. These values parallel the bounds of the two spatial domains identified by cluster analysis. Low CV values apparently indicate transitions between scales. Gradual slopes presumably are associated with irregular landscape patterns and plateaus or ‘stair steps’ are associated with regular repeating patterns. Since the graphs in Figure 2 show both, the landscape appears to be a mixture of irregular and regular patterns. The lower domain corresponds to diameters of roughly 1.81 m to 23 m and the upper domain corresponds to 28.8 to 38.4 m. The former is probably associated with spaces between individual trees and the latter to canopy gaps.

Several disturbance agents have been identified as causing tree mortality resulting in canopy gaps in the Upper Pine Creek, including: diseases, wildfire, heavy winds, bark beetles, tree suppression, competition, snow/ice buildup, shrub competition, site quality, and lightning (Lundquist 1995). Pattern irregularities within the upper spatial domain might have been caused by disturbance agents that individually operate at different scales within a domain, or agents that overlap in time and space (Carlile et al. 1989). Furthermore, interacting agents may synergistically create conditions that single agents cannot create alone. For example, Armillaria root disease can create a limited gap that spreads relatively slowly, but this gap can act as a focal point for the subsequent development of bark beetles that greatly and rapidly expand the disturbed area (Rykiel et al. 1988).

Canopy patterns can be immensely complex because they are commonly determined by disturbance and recovery processes continuously interacting, evolving, and adjusting in time and space. Impacts of disturbances are reflected in the changing spatial structure of the forest canopy. Because of the direct and indirect interactions associated with these systems, it is difficult to determine which disturbance components are important and what is the relative significance of each. This is especially important with diseases that are often well integrated with other ecological processes that effect canopy structure. One of the major challenges in disturbance ecology is to describe and understand the nature of these interactions. Dividing the landscape into spatial domains is a useful way of partitioning a complex environment into the processes that sculpture structure. One way of partitioning the environment is to determine significant spatial ranges over groups of disturbances occur.

We suggest that the concept of disturbance regime and mortality patterns can be used as a basis of measuring the severity and impact of forest diseases, and other disturbances acting within the same spatial domain. Few studies have used spatial metrics to characterize these types of disturbances, but there is little doubt that spatially referenced assessments will become more prominent as the use of GIS becomes more prevalent among forest managers. According to Levin (1992), “understanding patterns in terms of the processes that produce them is the essence of science, and is the key to the development of principles for management”.

Disturbances of a similar spatial and temporal scale have a certain ecological equivalency that at a first approximation offers a logical place to compare and contrast and examine the interactive nature of co-occurring disturbances. Grouping disturbances on the basis of scale may be a useful way of classifying them into functional groups of disturbances or groups that have similar structural or process features that can influence the forest ecosystem (Korner 1993). This presents a potential method of comparing across different types of disturbances.

The method we presented above is relatively new to landscape ecology. Its usefulness depends largely on its reliability and sensitivity, which we did not investigate here. Our focus was to explore the potential of this method using extreme differences in landscape conditions. Showing associations between spatial patterns of canopy and causes and predicting effects of different causes requires an understanding of the ranges of values and trends of these values as landscape patterns change (Hargis et al. 1997). More analyses need to be done of this method to establish these values before a more general recommendation could be made. In particular, a more rigorous test using a wider range of conditions would be needed to determine its use in assessing impacts of disturbances that cause more subtle changes in spatial structure, like forest tree diseases.

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