THE EFFECT OF SPATIAL RESOLUTION ON LANDSCAPE MEASUREMENTS OF POST DISTURBANCE VEGETATION

Michael J. Gluck and Robert S. Rempel

Centre for Northern Forest Ecosystem Research, Ontario Ministry of Natural Resources, c/o Lakehead University, 955 Oliver Road, Thunder Bay, Ontario, P7B 5E1 Canada.

ABSTRACT

Interpretation of landscape structure from remote sensing is, in part, dependent on the spatial resolution of the data. A challenge facing ecologists is to consider how landscape structure measured at one resolution relates to measurements made at another. Our work examines the correlation of pixel size with patch size, shape, and interspersion measurements of post-wildfire and clearcut landcover. We have measured landscape structure using remotely sensed data at spatial resolutions of 1, 2, 4 and 25 m pixel sizes at the stand level (ca. 100 ha) to determine which landscape metrics are scale dependent and which are scale invariant. Our results show that patch size measurements are strongly correlated with pixel size, that shape measurements are moderately correlated with both pixel size, and that interspersion is invariant of pixel size. We recommend use of interspersion and area weighted mean shape index as a robust metric for describing landscape structure across spatial scales.

INTRODUCTION

Forest ecosystem managers are investigating ways to design land use practices that use natural disturbance patterns as a guide to maintaining a more natural landscape mosaic (Hansen et al. 1991, Franklin 1993). Understanding natural disturbance patterns and how they differ from those caused by humans requires their measurement and remotely sensed data and Geographic Information Systems (GIS) provide the ability to measure and compare landscape patterns (Franklin and Forman 1987, Gluck and Rempel 1996). However, the interpretation of these measurements is, in part, dependent upon the spatial resolution of the data (e.g., Kotliar and Wiens 1990, Leduc et al. 1994, Simmons et al. 1992). Some structural measurements are constrained by the grain and extent of the data from which they are calculated (McGarigal and Marks 1993). A challenge facing ecologists is to determine how to compare structure of landscapes measured at different spatial scales.

Although much attention has been focused on the effects of spatial resolution of space-borne sensors on measurements of landscape structure (Benson and MacKenzie 1995, White and Running 1994, Nellis and Briggs 1989, Mosbech and Hansen 1994), many of these efforts address landscape structure in the range of 3,000 to 15,000 ha in extent. Yet to investigate and use natural disturbance patterns there is also a need to understand landcover characteristics at the stand-level (10-100 ha). Aerial photography is a useful tool for addressing

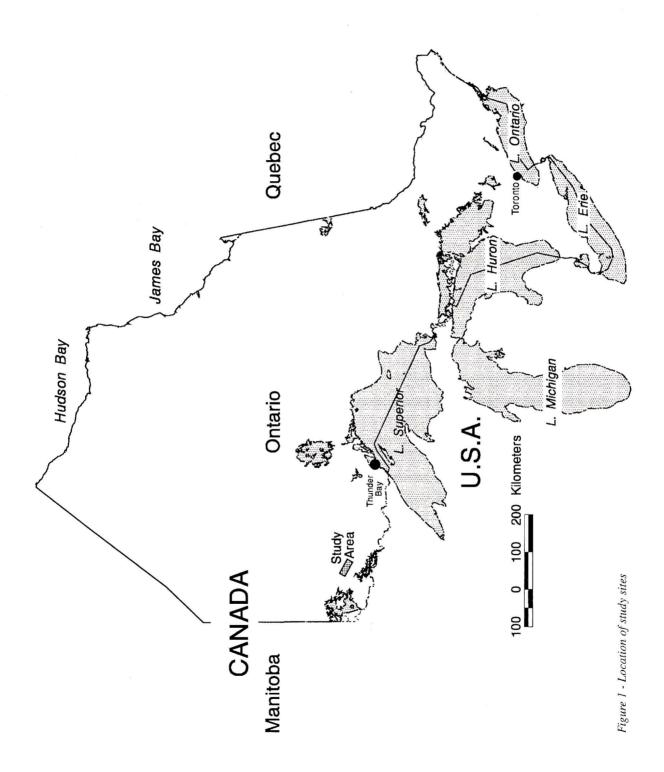
questions concerning stand-level structure because of its fine spatial resolution, opportunity to measure height and canopy layers using stereo pairs, and because forest managers are familiar with its use. Alternatively, coarser resolution, satellite-based remote sensing can provide comprehensive information for entire regions at less than the cost of aerial photography, but with a loss of spectral resolution. Interpretations of landscape structure will differ as pixel size changes. For example, large pixel size remote sensing may mask the heterogeneity of a landscape and make it appear more homogeneous than it actually is.

The objective of our work is to examine the correlation of pixel size with important metrics of landscape structure, i.e., patch size, shape, and interspersion. To determine which landscape measurements are scale dependent and which are scale invariant we use GIS to quantify landscape structure of post-disturbance landscapes from remotely sensed data at spatial resolutions of 1, 2, 4 and 25 m.

METHODS

Study Area

The study area is located 300 km west of Thunder Bay, Ontario, Canada (Figure 1) centred at 49.0° N, 93.0° W and within the Quetico section of the boreal forest region of Canada (Rowe 1972). Two recently burned and 3 clear-cut areas, ca. 100 ha each, were selected along overlapping transects of multiple scales of colour infrared



(CIR) aerial photography. The burned sites are part of a 1981 summer fire that burned over 18,000 ha of mature jack pine (*Pinus banksiana* Lamb.) dominated forest in 4 days. The other sites were clear-cut between 1981 and 1986.

All of the sites are shallow mineral soils and are naturally regenerating to aspen (*Populus tremuloides* Michx.) and jack pine stands ranging in size from 10 to 200 ha and can be considered typical of recently disturbed forests in this forest region. Forest fire and timber management the two major agents responsible for altering the landscape structure of the boreal forest in northwestern Ontario, Canada (Ward and Tithecott 1993).

Landcover mapping

Three scales of CIR aerial photography, 1:5,000, 1:10,000, and 1:20,000 were converted to a raster data matrix and classified to create landcover maps. Aerial photographs were scanned in colour to produce a single channel raster with a colour look-up table. The raster for the 1:5,000 scale photos had 1 m, the 1:10,000 2 m, and 1:20,000 4 m pixel size. Grey level thresholds for each land class were determined using ground reference data, and pixels were assigned to exposed bedrock, sparse vegetation, shrub cover, young trees or residual forest land classes using IDRISI GIS®. (Figure 2).

Bands 2, 3 and 4 from a Landsat TM image, recorded in August 1991, were used to create landcover maps because they approximated the same spectral range as the CIR aerial photography. The image was geocoded to a UTM projection using 63 ground control points to satisfy an RMS error of less than 25 metres. Disturbance boundaries, wetlands and water waterbodies were masked from the classification using on-screen digitizing. Training sites were chosen based on ground reference, and a maximum likelihood classifier in IDRISI GIS® was applied to the 3-channel image to assign pixels to exposed bedrock, sparse vegetation, shrub cover, young trees or residual forest.

Mapping accuracy was assessed by selecting 3 points per land class on the original imagery and 3 points on the classified landcover maps for 5 study areas (i.e., 3 image points + 3 landcover map points x 4 data layers x 5 land classes x 5 study areas = 600 points) and comparing the points to the mapped and field interpreted land classes respectively. Each point was located independent of the photo interpreter and was at least two pixels from the edge of a land class patch.

Accuracy was expressed as KHAT, the estimate of Kappa (Congalton 1991).

Measurement of landscape structure

Landcover maps were analyzed using FRAGSTATS (McGarigal and Marks 1991) to measure patch density, mean patch size, edge density, area-weighted mean shape index, area-weighted mean patch fractal dimension, and patch interspersion. Patch density expresses the number of patches on a per unit area basis that facilitates comparisons among landscapes of varying sizes and mean patch size is the average area comprised by each land class patch. density is the amount of edge between a class and all other land classes standardized to a per unit area, and area weighted mean shape index expresses the complexity of all patches belonging to a particular class using an area to perimeter ratio. dimension quantifies the complexity of a patch by relating the perimeter to area. A square patch has a fractal dimension of 1 and can increase to 2 as patch shape becomes more complex. The fractal dimension of landscapes under changing pixel sizes quantifies the scale dependency of an object's structure. As measurements of pattern complexity increase, so too does fractal dimension (Milne 1990). interspersion index measures the distribution of the types of adjacencies between different patch types. Higher values characterize landscapes in which the adjacencies are well interspersed (i.e., equally adjacent to one another), whereas lower values reflect landscapes with unequal distribution of patches.

Analysis of Landscape Structure

Linear regression of log-transformed structural measurements versus log_e pixel size were calculated for each landcover class to determine which landscape measurements were scale dependent and which were scale invariant. The residual forest land class did not occur in sites 2 and 5 and subsequently was omitted from the regression for that class. We constructed a simple model of the expected structural measurements of single pixels at different sizes (Table 1). We then compared these expected results to those measured from the landcover maps.

Landcover Mapping

Overall mapping accuracy was expressed as KAPPA estimates and percent agreement for each scale of data (Table 2). Highest thematic accuracy was 0.87 KHAT (or 90% agreement) for 1:5,000 scale CIR whereas Landsat TM based mapping provided 0.53

Table 1. Expected relationships between structural measurements and pixel size for random landscape with no adjacent classes.

PIXEL SIZE (m)			LOG STRUCTURAL MEASUREMENTS	AL MEASURE	MENTS ¹	
	SIZE	(r)		SHAPE		INTERSPERSION
	MPS	PD	ED	AWMSI	AWMPFD	III
	(ha)	(#/100 ha)	(m/ha)			
1	0.0001	1,000,000	40,000	10,000	1	high ²
2	0.0004	250,000	20,000	5,000	П	high
4	0.0016	62,500	10,000	2,500	1	high
25	0.0625	1,600	1,600	400	1	high

1. MPS = mean patch size, ED = edge density, AWMSI = area weighted mean shape index, AWMPFD = area weighted mean patch fractal dimension, IJI = interspersion/juxtaposition index

2. assuming equal distribution of adjacencies

Table 2. Results of accuracy assessment.

DATA SOURCE	KHAT ¹	PERCENT AGREEMENT.
1:5,000	78.	06
1:10,000	.80	85
1:20,000	89.	76
Landsat TM	.54	65
1VIIAT - 241		

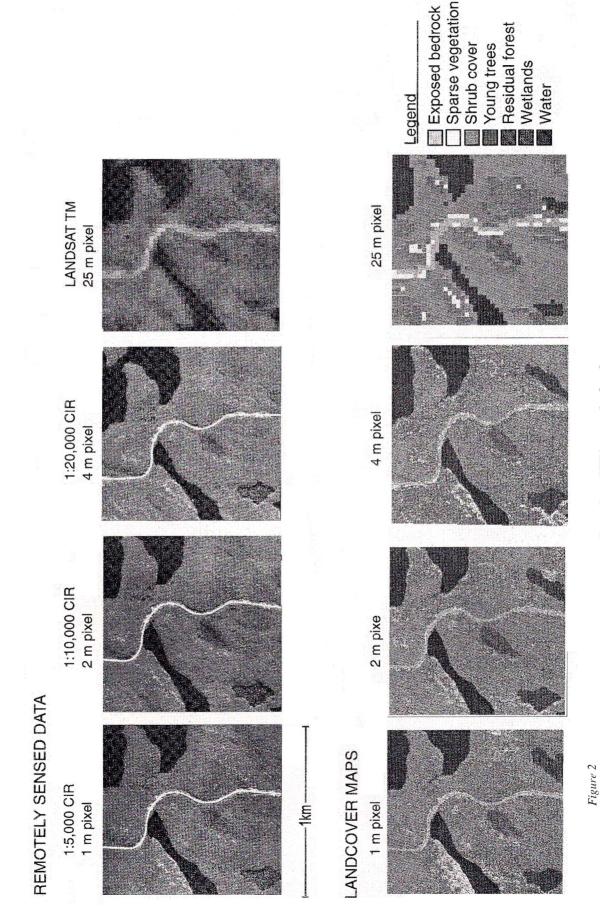
¹KHAT = estimate of Kappa, Congalton 1991

Table 3. Summary of linear regression coefficients (r^2) between log pixel size and structural measurements stratified by land class

LAND CLASS			TOG	LOG STRUCTURAL MEASUREMENTS ¹	ASUREMENTS!	
		SIZE		SHAPE	PE	INTERSPERSION
	MPS	PD	ED	AWMSI	AWMPFD	IJI
exposed bedrock	.79ª	.94a	.578	.19	.49 ^b	.10
sparse vegetation	.86ª	.96ª	.72°		.75ª	.05
shrub	.79ª	.92ª	.86	.51ª	.86ª	.28
young tree	.76ª	.94ª	.94ª		.87ª	.39
residual forest ²	.75ª	.82ª	.42 ^b		.70ª	.40

1. MPS = mean patch size, ED = edge density, AWMSI = area weighted mean shape index, AWMPFD = area weighted mean patch fractal dimension, IJI = interspersion/juxtaposition index. Probability $r^2 = 0$ is 0.001 for (a), and 0.01 for (b).

2. sites 1, 3, and 4 only



See plate XIV at end of volume

KHAT (or 60% agreement). We accepted these results as suitable for landcover analysis in this study, but realized that structural measurements made from Landsat TM based maps were less accurate than those from CIR aerial photography.

Analysis of Landscape Structure

Landscape structure was characterized from landcover maps at spatial resolutions of 1, 2, 4 and 25 m. The uneven distribution of pixel sizes resulted in an intentional "gap" between the 1:20,000 CIR photography and Landsat TM imagery. Landscape managers in northwestern Ontario must choose between aerial photography and satellite imagery to characterize landscape structure. Often this means using large-scale aerial photography (1:5000 and greater), 1:20,000 scale photography or Landsat TM-based landcover maps.

As measured by correlation coefficients, structural measurements of all land classes exhibited strong scale dependency for size, moderate dependency for shape, but no dependency for interspersion measurements (Table 3). Size measurements (mean patch size and patch density) showed the strongest correlation with pixel size, with all r^2 values > 0.75 (P = 0.001). Mean patch size increased and patch density decreased with increasing pixel size. These results are expected since pixel size is a lower limit of patch size.

For shape measurements, edge density $(r^2 > 0.42, P <$ 0.01) and fractal dimension $(r^2 > 49, P < 0.01)$ were moderately to strongly correlated with pixel size for most land classes, yet area-weighted mean patch shape index was only moderately ($r^2 = 0.61$, P <0.001) or not at all correlated ($r^2 = 0.19$) with pixel size. As expected, edge density decreased with pixel size because edges appeared as convoluted lines at fine resolutions whereas they appeared straight as larger pixel sizes. However, this "smoothing" was not evenly distributed across patches, and the "smoothing" effect varied between complex and simple patches. This resulted in varied correlations between area-weighted mean shape index and increasing pixel size. Although both edge density and area-weighted mean shape index generally describe the merging of patches into larger, more complex shapes as pixel size increases, weak correlations of the latter with pixel size probably resulted from the range in variability expressed by the mean shape index metric.

In contrast, area weighted mean patch fractal dimension generally showed strong correlation (r^2 >

42, P < 0.001) with pixel size over all of the vegetated land classes, indicating that patch complexity decreased as pixel size increased. The range of variability which masked correlations of mean shape index and pixel size is not an issue in this case because fractal dimension is calculated based on the natural logarithms of area perimeter measurements.

Although we expected fractal dimension to be invariant of scale, our results support those of Leduc *et al.* (1994) that fractal dimension is scale-dependent. Therefore we caution the use of fractal dimensions as a scale-invariant characterization of landscapes.

Interspersion was not correlated ($r^2 < 0.40$) with pixel size for any land class. We expected interspersion to be relatively invariant of pixel size since it considers only the adjacency of patches to one another. Benson and MacKenzie (1995) found a similar measurement, the contrast index, to also be relatively invariant over changes in satellite-based pixel size. Nellis and Briggs (1989) also found contrast measures to be useful for comparing satellite imagery at different pixel sizes. For these reasons we also suggest interspersion as a scale invariant metric for comparing landscape structure from data derived from different mapping technologies.

CONCLUSION

The results of this work show that post-disturbance landcover patch size and shape measurements, fractal dimension, are strongly including moderately correlated with pixel size. However, interspersion is invariant of pixel size and we suggest it as an appropriate metric for comparing landscape structure derived from different mapping technologies. Even minor adjustments in pixel size, e.g., increasing pixel size from 2 to 4 m (1:5,000 to 1:10,000 scale photography), has a significant impact on measurements of patch size and shape of landcover, but not on patch interspersion.

REFERENCES

Benson, B.J. and M.D. MacKenzie, 1995. Effects of sensor resolution on landscape structure parameters. Landscape Ecology 10:113-120.

Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens. Env. 37:35-46.

Franklin, J.E. and R.T.T. Forman, 1987. Creating landscape patterns by forest cutting: ecological consequences and principles. Landscape Ecology 1:5-18.

Franklin, J.F., 1993. Preserving biodiversity: species, ecosystems, or landscapes. Ecological Applications 3:202-205.

Gluck, M.J. and R.S. Rempel, 1996. Structural characteristics of post-wildfire and clearcut landscapes. Environmental Monitoring and Assessment 39:435-340.

Hansen, A.J., T.A. Spies, F.J. Swanson and J.L. Ohmann, 1991. Conserving biodiversity in managed forests. Bioscience 41:382-392.

Kotliar, N.B. and J.A. Wiens, 1990. Multiple scales of patchiness and patch structure: a hierarchical framework for the study of heterogeneity. Oikos 59:253-260.

Leduc, A., Y.T. Prairie and Y. Bergeron, 1994. Fractal dimension estimates of a fragmented landscape: sources of variability. Landscape Ecology 9:279-286.

McGarigal, K. and B.J. Marks, 1991. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure, Unpublished manuscript, Dept. Forest Science, Oregon State University, Corvallis, Oregon. 62 pp.

Milne, B.T., 1990. Lessons from Applying Fractal Models to Landscape Patterns, pp. 199-235 in Turner, M.G. and R.H. Gardner (eds.), 1990. Quantitative

Methods in Landscape Ecology. Springer-Verlag, New York, USA. 536 pp.

Mosbech, A. and B.U. Hansen, 1994. Comparison of satellite imagery and infrared aerial photography as vegetation mapping methods in an arctic study area: Jameson Land, East Greenland. Polar Research 13:139-152.

Nellis, M.D. and J.M. Briggs, 1989. The effect of spatial scale on Konza landscape classification using textural analysis. Landscape Ecology 2:93-100.

Rowe, J.S., 1972. Forest Regions of Canada. Publ. No. 1300, Dep. Environ., Can. Forest Service, Ottawa, Ontario, Canada. 172 pp.

Simmons, M.A., V.I. Cullinan and J.M. Thomas, 1992. Satellite imagery as a tool to evaluate ecological scale. Landscape Ecology 7:77-85.

Sokal, R.R. and N.L. Oden, 1978. Spatial autocorrelation in biology, 1. methodology. Biological Journal of the Limnological Society 10:199-228.

Ward, P.C. and A.G. Tithecott, 1993. The impact of fire management on the boreal landscape of Ontario. Ontario Ministry of Natural Resources, Aviation, Flood and Fire Management Branch Publication No. 305. 12 pp.

White, J.D. and S.W. Running, 1994. Testing scale dependent assumptions in regional ecosystem simulations. Journal of Vegetation Science 5:687-702.