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Using Landscape Metrics to Create an Index of Forest Fragmentation for the State of Maryland

by

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THESIS APPROVAL PAGE

This is to certify that the thesis prepared by Jennifer L. Pfister, entitled Using Landscape Metrics to Create an Index of Forest Fragmentation for the State of Maryland, has been approved by this committee as satisfactory completion of the requirement for the degree of Master of Arts in Geography in the Department of Geography and Environmental Planning.

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ABSTRACT

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Jennifer L. Pfister

Human population growth is fragmenting forests and impacting biological diversity worldwide. A variety of software packages and fragmentation indices measure the degree of forest fragmentation, but the relationship between indices and their utility for ecosystem assessments has yet to be systematically investigated. I analyzed Maryland land cover data with a spatial pattern analysis program, calculating 81 indices of forest fragmentation for a random sample of 60 circular, 5000 ha landscapes. I examined the matrix of Pearson correlation coefficients among indices, eliminating 38 indices that were redundant ($|r| > 0.90$). Based on a principal components analysis of the remaining indices, I selected eight indices that best captured the variation in forest fragmentation among landscapes. Five of these indices could be placed on an ordinal scale of human impact. I included these five indices in a weighted sums equation to measure the overall forest fragmentation across Maryland.

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Introduction

Rapid and broad-scale changes to our environment fueled the need for environmental assessment at the landscape level (Turner et al. 2001). This is particularly true for forestlands of the northeastern United States where forests were historically the dominant land cover type and suburban sprawl (i.e. the construction of housing complexes, roads, strip-malls, and other development) has resulted in large losses and fragmentation of remaining forestland (Matlack 1997). The forest fragmentation process involves changes in landscape composition, structure, and function over a range of scales (McGarigal and Cushman 2002) including habitat loss and fragmentation, and isolation of remaining forest patches (McGarigal and McComb 1999).

Forest loss and fragmentation have a number of ecological effects on forest associated species and communities (Harrison and Bruna 1999; Fahrig 2003). As patches of suitable habitat become smaller and more isolated, survival and reproduction rates of many organisms decrease; ultimately, patches may be too small to sustain viable wildlife populations on their own, and movements between patches may be hindered or impossible due to isolation of patches by the surrounding matrix of human land uses (McGarigal and McComb 1999). In contrast, increased amounts of forest edge may favor edge thriving generalist species (e.g. raccoons, crows, cats) while interior species (e.g. neotropical migrant birds) are confined to core habitat areas sometimes orders of magnitude smaller than the patch itself (Kremsater and Bunnel 1999). Often associated with increases in generalist species abundances are increased predation rates, reductions in forest interior species, and in the case of interior forest birds, increased brood parasitism by cowbirds (Kremsater and Bunnell 1999; Marzluff and Restani 1999). Furthermore, edges may subject forested habitats to extreme microclimatic conditions (i.*e*. light, wind, humidity, and temperature) affecting both flora and fauna (Kremsater and Bunnell 1999; Debinsky and Holt 2000). Therefore, forest fragmentation undermines the biological integrity of forest ecosystems.

Landscape metrics can assist in quantifying the fragmentation process, and in assessing the biological integrity of the remaining forest. However, with literally hundreds of metrics available, it is imperative to address several questions when using landscape metrics in assessment efforts: (1) What are the objectives of the study (i.e. are the selected metrics related to the ecological processes being examined)? (2) What is the behavior of the metrics over a range of landscape configurations? (3) What are the effects of scale on the metrics? And (4) are the metrics correlated or redundant (Turner et al. 2001).

The use of landscape metrics for analyzing spatial patterns has become quite popular. However, the use of landscape metrics specifically for monitoring forest habitat has been more limited. Some effort has been made to examine the behavior and limitations of landscape metrics for forested landscapes (Gustafson and Parker 1992; Baskent and Jordan 1995; Haines-Young and Chopping 1996; Gustafson 1998; Hargis et. al. 1998). Many of these studies examined artificial landscapes representing fragmented forests (Gustafson and Parker 1992; Hargis et. al. 1998). Other research efforts have concentrated on correlating forest landscape structure with ecological community structure or function (Robinson et. al. 1995; McGarigal and McComb 1995; Tischendorf 2001). In addition, more recent efforts have modeled forest landscape pattern or spatial configuration (Cumming and Vernier 2002). Here I use a set of real landscapes to synthesize independent metrics into an overall measurement of forest ecosystem integrity.

In this paper I investigate the effects of scale on a number of forest class metrics and the correlation among metrics using a forest cover map for Maryland developed from Landsat imagery. Our overall objectives were (a) to identify a subset of metrics that capture the majority of variation in forest fragmentation in Maryland, and (b) incorporate this subset of metrics into an overall measure of forest landscape integrity. Specifically, I ask: (1) At what spatial scale do estimates of the metrics stabilize; and (2) What is the relationship among individual metrics? In order to determine the proper scale of analysis, I sampled regions of varying sizes within the state and computed class-level landscape metrics for each region. To identify a subset of independent landscape metrics I computed 81 landscape metrics for 60 regions within the State of Maryland and used Pearson correlation coefficient and Principal Components Analysis (PCA) to eliminated redundant metrics. Five of these metrics were combined to create a forest ecosystem integrity index for the complete State of Maryland.

Methods

Study Area and Landcover Data Set

The State of Maryland plays a vital role in the health and sustainability of the resources within the Chesapeake Bay. Current trends in population growth, development patterns, and agricultural practices have significantly impacted the Bay's ecosystem. Maryland's population has grown from 4,781,468 million in 1990 to 5,296,486 million in 2000 (United States Census 2000). Much of this growth has occurred in the formerly agricultural counties surrounding Washington, D.C. and Baltimore. This suburbanization fragments the regions' forests. The State of Maryland is currently making efforts to control rural population growth, but it is likely that further fragmentation of the state's forests will occur. Mapping the location and status of Maryland's forests is critical to protect forest re-growth and minimize further forest fragmentation, while still supporting human population growth.

The land cover data used in this study were produced by Jay Morgan and the Center for Geographic Information Science (CGIS) (Morgan et al, 2001). They are available online from http://chesapeake.towson.edu/. CGIS created the data from radiometrically corrected, georeferenced Landsat 7 Enhanced Thematic Mapper imagery. Image dates and locations are listed in Table 1. Once delivered, the data were further georeferenced using Maryland State Highway Administration vector data, and projected into Maryland State Plane coordinates. Each scene had a minimum of 50 coordinate pairs, and was resampled using a 6^{th} order polynomial to a final raster size of 25 m x 25 m. Final RMS error was less than 0.5 pixels.

Nine land cover classes were identified in the imagery using a maximum likelihood algorithm. For the purposes of this study, the nine classes were collapsed into five: forest (coniferous and deciduous), agriculture (e.g. row crops and golf courses, fertilized lawns and grassy parks), urban (e.g. housing developments, paved roads, parking lots, and buildings), bare ground, and water. 'Training' sites used to classify the imagery were derived from 1:12,000 orthophoto quarter quads, National Wetland Inventory wetlands, and MRLC land cover data. The imagery classification was conducted one county at a time, in order to improve the classification accuracy. The final 'Maryland Impervious Surface Map' was stored as a 118 Mb GeoTIFF file.

The final land cover data were assessed for accuracy using an innovative partnership between the Center for Geographic Information Sciences, the Maryland Virtual High School, and Raytheon Systems (Morgan et al, 2001). Eighty-five teachers were trained in the research protocol and the use of Global Positioning System receivers during two, one-day workshops. Seventy-five Garmin GPS III+ receivers were given to teachers from Maryland. The teachers used the GPS receivers with their classes to collect over 1,350 ground-truthing points in a series of lesson plans developed by the Center. These data indicate an accuracy of 91.8 percent during classification. The reclassified data used in this study should have a lower misclassification error, due to the reduced number of classes.

Determining the Appropriate Scale

The second step in mapping forest ecosystem integrity was determining the appropriate scale of analysis for this study. Class-level fragmentation indices are calculated on sample regions. The size of the sample region will affect the result. Below an “ideal” size the analysis will be overwhelmed by the edge effects created by the boundaries of each of the many small regions. The value of these ‘too small’ sample regions will correlate with the area of the region. However, regions that are too large will lower the resolution of the analysis.

To determine the most appropriate size for our regions I first created a random sample of 10 points within Maryland that were separated from each other by a minimum of 12,000 m and from the Maryland border by 6000 m. At each point, I sampled the landcover data with six different sizes of circular sample region (300 ha, 1200 ha, 2800 ha, 5000 ha, 7900 ha, 11300 ha). I calculated a total of 20 metrics on each of the 60 sample regions using FRAGSTATS 3.3. The values of the metrics were plotted against the size of the sample regions to ascertain at what average area the majority of curves would become asymptotic. It was evident that the values for nearly all metrics leveled out between 4000-6000 ha, therefore, I chose 5000 ha as the appropriate size for our sample regions (Figure 1).

Relationship Among Metrics

Once I identified the proper scale for our sample regions, I then determined the metrics that best measured the arrangement of Maryland’s forest habitat. To do this, I measured 81 class metrics with FRAGSTATS on a sample of 64 randomly selected, 5000 ha landscape grids. Class metrics in FRAGSTATS are computed for every patch type or landcover class in the landscape. There are two basic types of metrics at the class level: (1) indices of the amount and spatial configuration of the class, which I refer to as primary metrics, and (2) distributional statistics that provide central tendency (e.g. mean and area weighted mean) and variance (standard deviation and coefficient of variation) statistical summaries of the patch metrics for the focal class (McGarigal and Marks 1995). By first examining the matrix of Pearson correlation coefficients, I used these criteria to determine which of the highly correlated ($|r| > 0.90$) metrics to retain. Those metrics representing primary metrics or central tendency metrics were chosen first because I considered them more oriented to good or bad forest habitat conditions.

I then determined which of the remaining metrics were most highly correlated by running a principal components analysis (PCA). The PCA was used to identify the main axes of variation. I then used varimax rotation to facilitate the interpretation of each axis (Table 3) and chose a metric to represent each axis. Primary and first order metrics were again chosen over second order metrics.

Mapping Forest Fragmentation

To create maps of habitat fragmentation for the State of Maryland I calculated selected metrics for 580 hexagonal regions of 5000 ha covering the State of Maryland. I chose to use hexagons (instead of our previously run circular landscapes) because hexagons are the closest regular shape to a circle that will tile a plane with no overlap along the edges. Therefore, I would not have to overlap circles or leave some regions uncalculated.

After creating the 580 hexagonal regions, I then reran the FRAGSTATS program using the eight metrics and our 580 hexagonal regions. After examining the results, I elected to eliminate three of the metrics from the analysis due to ambiguity in interpretation. For each of the hexagonal regions I standardized the values of the remaining five metrics and weighted each by their eigenvalues. Finally, I combined the standardized weighted metrics to create a final index of forest ecosystem integrity.

Results

Using the matrix of Pearson correlation coefficients ($|r| > 0.90$), I eliminated 37 of the original 81 metrics. Of the 37 eliminated metrics 32% were primary metrics, 35 % were central tendency metrics (i.e. mean or area weighted mean), and 32% were variance metrics (i.e. standard deviation or coefficient of variation). Of the 44 retained metrics, 30% were primary metrics, 32% were central tendency metrics, and 39% were variance metrics.

The PCA then identified 8 main axes of variation in the remaining 44 metrics. Results of the PCA indicated the first eight factors (eigenvalues > 1.0) explained 87.9 % of the variation. I chose metrics to represent the eight factors based on criteria similar to that of the Pearson correlation matrix: 1) the metric should be loaded highly on only one or very few axes 2) primary or central tendency metrics were preferred, and 3) easy to interpret metrics were preferred. I interpreted the eight factors based on factor loadings for each of the axes of the PCA (Table 3). Factor loadings on the first axis of the PCA suggested a relationship to the amount of total forest area within each landscape, and therefore, I chose mean patch area to represent this axis. Factor loadings on the second

PCA axis suggested a relationship to the shape of forest patches. I chose FRAC_MN, or mean patch fractal dimension to represent this axis. Factor loadings on the third through the eighth axes suggested, respectively, a relationship to adjacency among patches, variation in adjacency among patches, adjacency of forest patches, core area, variation in shape or size, quality of adjacent patches, and shape of the larger patches within the landscape. I chose CLUMPY, or clumpy index, PAFRAC or perimeter area fractal dimension, CAI_MN, or mean core area index, PARA_SD standard deviation of perimeter area ratio, IJI, or class area interspersion and juxtaposition index, and (8) SHAPE_AM or area-weighted mean shape index to represent these axes, respectively.

Upon examining results for each metric, I chose to eliminate the fourth, sixth and, seventh factors. In the case of the fourth factor, the metric perimeter area fractal dimension (PAFRAC) loaded highest on the PCA axes. I elected to eliminate PAFRAC because landscapes containing less than 10 patches of forest could not be calculated. Choosing another metric to represent this factor resulted in problems similar to problems faced with the sixth factor. This problem being, that measures of variation such as PARA_SD, which I chose to represent factor six, were not useful in describing forest integrity. Regions with similar values for these metrics had very different configurations (Figure 2, A and B). In some cases, forest is the matrix (i.e. most abundant land cover type) with at least one large patch of forest with a few patches of human land use within the large forest patch, and in other cases, human land use was the matrix with a few patches of forest located within this matrix. In either case, the metric values were the same, leaving interpretation of the metric rather ambiguous. In the case of the seventh factor, IJI, this index is based on *patch* adjacencies and is greatest when the focal patch type (in our case the forest) is equally adjacent to all other patch types (i.e., maximally interspersed and juxtaposed to other patch types) (McGarigal and Marks 1995). It was difficult to discern if high or low values indicated areas of high forest fragmentation, therefore, I elected to not use this index. Each of the remaining five factors, explaining 64.4% of the variation, was then mapped for each hexagonal landscape covering the state (Figures 3-7).

To create the final index representing forest ecosystem integrity for the State of Maryland, I first standardized the values of each metric, and the final fragmentation index (*Frag*) was the sum of the five fragmentation indices weighted by their eigenvalue (Equation 1):

$$Frag_i = e_1 AREA\_MN_i - e_2 FRAC\_MN_i + e_3 CLUMPY_i + e_5 CAI\_MN_i - e_8 SHAPE\_AM_i \quad \text{Equation 1}$$

where:

$Frag_i$ is the value of the fragmentation index for the i^{th} landscape
e_j is the eigenvalue for the j^{th} fragmentation index
$AREA\_MN_i$ is the standardized Mean Patch Area for the i^{th} landscape
$FRAC\_MN_i$ is the standardized Mean Patch Fractal Dimension for the i^{th} landscape
$CLUMPY_i$ is the standardized Clumpy index for the i^{th} landscape
CAI_MN_i is the standardized Mean Core Area Index for the i^{th} landscape
$SHAPE\_AM_i$ is the standardized Area Weighted Mean Shape Index for the i^{th} landscape

I then produced a final map representing an index of forest ecosystem integrity (Figure 8). Regions that are highly urban are also highly fragmented, and regions that contain large areas of publicly owned lands such as parks and reserves are much less fragmented. The highly fragmented areas include the Baltimore and Washington D.C. areas as well as the smaller urbanized regions of Frederick, Salisbury, and Hagerstown. Areas that are fragmented, but less fragmented than the large urban regions, include smaller cities (*e.g.*, Cumberland, Westminster), and regions where urban sprawl is occurring (*e.g.*, Carroll, Howard, Frederick, and Anne Arundel counties) or areas with large amounts of agriculture (*e.g.*, much of southern and eastern Maryland, and the Northern portions of Carroll County, and much of Harford County).

Regions that are least fragmented coincide with publicly owned lands and reserves, and with regions that are less populated, or where agriculture is declining and forests are recovering. Publicly owned lands that are least fragmented include much of the western portions of the state, such as Catoctin Mountain region, and the Green Ridge State Forest in Allegheny County. In addition, much of Garrett County in western Maryland is mountainous terrain and includes many state parks. Much of Southeastern Maryland contains numerous Wildlife Management Areas, wildlife refuges, and includes the Pocomoke River State Forest and Park areas. Eastern portions of the state, on the other hand, were formerly agricultural but now are less cultivated, and less developed, therefore, forests are beginning to return.

Discussion

Up to this point, an ideal method of how to measure patterns of fragmentation has yet to be determined. It has been suggested that factors involved in fragmentation are often so complex that the use of one single measure is not adequate (Davidson, 1998). Bissonette and Storch (2002) have also suggested that agreement on appropriate measures of fragmentation is a necessary step in order to draw conclusions from experiments or observations. I was able to determine a suite of five metrics from an initial 81 metrics that best represent patterns of forest integrity which could certainly be used in future research. Correlation analyses coupled with principal components analysis has been shown as an effective practice for eliminating redundant metrics (O'Neill et al 1988, Riiters et al. 1995, Cain et al. 1997, Hargis et al. 1998, Griffith et al. 2000, Cumming and Vernier 2002). The use of this technique, coupled with a scale analyses to appropriately delineate a region, and by weighting the metrics according to their percentage of the variance, represent a viable method for determining forest fragmentation patterns and for creating an overall regional index.

Much of landscape structure and pattern analysis is based upon research that has focused at the landscape scale (O'Neill et al. 1988, Ritters et al.1995, Haines-Young and Chopping 1996, Cain et al. 1997, Griffith et al. 2000). Studies examining both class and landscape level metrics in relation to forest patterns, and other class level patterns, have highlighted the importance of using class level indices (Gustafson 1998, Tinker et al. 1998, Griffith et al. 2000, Tischendorf 2001, Heilman et al. 2002). Forest fragmentation is a class-level process, and only McGarigal and McComb (1995), and Cumming and Vernier (2002) focused specifically on using class-level metrics and attempted to systematically determine an appropriate suite of indices.

Despite the confusing array of research on habitat fragmentation, researchers have consistently identified key metrics despite differences in scale, region, and overall method. At the landscape scale, the factors of greatest importance appear to be measures of landscape diversity and texture first, with measures of shape and size being of lesser importance (Cain et al. 1997, Griffith et al. 2000). At the class-level, measures of patch area, core area, patch shape, and patch isolation appeared rather consistently (Cumming and Vernier 2002, Tinker et al. 1998, Griffith et al. 2000). Specifically, Cumming and Vernier (2002), examined four classes of forest habitat and found in each case the first principal component, accounting for 50-67% of the variation was positively related to measures of patch shape, core area, and patch isolation and in general the second and third principal components describe additional aspects of patch shape, and mean distances between similar patches. Tinker et al. (1998), examined forest landscape patterns among 12 watersheds and also found mean patch area, core area, and edge density (i.e. shape) measures to appear rather consistently as key factors among watersheds highly fragmented by clearcuts and roads.

My findings are consistent with the literature. Measures of area and shape represent the first two factors in our PCA. Core area measures did not account for a large percent of the total variation, but represent a fairly unique measure that loaded highly on the fifth axis. Other studies found patch isolation to be important (Cumming and Vernier 2002, Tinker et al. 1998, Griffith et al. 2000); these measures had high negative weights on my ‘aggregation’ axis (axis 3). The ideal method for delineating large landscapes into sub-regions or land units for pattern analysis with landscape metrics has yet to be determined. Various methods have been explored, including the use of features (i.e. roads) to create boundaries between ecological regions (Heilman et. al. 2002), using watershed boundaries, and using simple Landsat image boundaries (Cain et al. 1997, Tinker et al. 1998). The US Environmental Protection Agency’s Environmental Monitoring and Assessment Program monitors landscapes and ecosystems using hexagonal sampling units (White et al. 1992, Hunsaker et al. 1994) of an arbitrary size (Griffith et al. 2000).

In our case, each of these methods created potential problems and did not fit our objectives. I wanted an overall index that was biologically meaningful, however I was not focusing on correlating fragmentation effects with a specific ecological community structure. It has been argued that watershed boundaries make more biological sense as a means of delineating a region, but as Heilman et al. (2002) discuss, the use of watershed boundaries for delineation of forests may artificially dissect intact forest patches, and organisms can freely travel between watershed boundaries. Therefore, a more logical means of delineating a landscape is to dissect by features such as roads, which represent more of a natural barrier to a majority of organisms (Heilman et al. 2002). However, in either case, it is difficult to make comparisons of class-level metric values for watersheds, or for barrier delineated sub-regions, because the regions have different spatial resolutions. Choosing regularly shaped sub-units of equal size was therefore the most logical means of comparing metric values, and to ultimately create an index for the State of Maryland. However, the issue again, becomes what is the appropriate size of this regularly shaped sub-unit that will also be biologically meaningful (i.e. does not create boundary effects). Some have chosen to use an arbitrary size unit (Cain et al. 1997, Griffith et al. 2000) but I chose to determine the most appropriate size to limit boundary effects based on a scale analysis (Figure 1).

Upon choosing our five metrics and running them for each of our 580 hexagonal sub-regions, I standardized the values, and then chose to weight each according to the percentage of the variance each factor represented in our PCA. The percentage of the variance is an indication of each factor’s importance, therefore, weighting according to this percentage is a logical method for representing metric importance when creating an index.

This systematic approach of creating a fragmentation index is not only a useful method that can be replicated in other regions, but the information provided can also be of use to ecologists, natural resource managers, and planners. Forest fragmentation results in many negative and often irreversible effects such as loss of rare or critical habitat, loss of biodiversity, changes in hydrologic and climatic cycles, which in turn can lead to reduced water quality and increased flooding (Paul and Meyer, 2001). This decreased ecological integrity is of key importance to ecologists, planners, and natural resource managers. Effectively and efficiently, measuring and monitoring of forest fragmentation can lead to sound recommendations for future planning and conservation efforts. Studies such as this, coupled with remote sensing techniques, make it possible to monitor changes and to keep track of current conditions. Development of maps that identify areas highly fragmented can be useful tools in prioritizing land parcels for purchase by planners and natural resource managers. Growth due to urbanization can be directed toward regions highly fragmented (i.e. have little chance of reforestation) and steered away from regions of low fragmentation. Measuring the geographic extent and the patterns of forest fragmentation within regions is a key step of understanding the impacts and making wise planning decisions.

Conclusion

Many indices of fragmentation vary according to the scale of analysis. This variation can lead to measurement errors and spurious results (i.e. repeated measurements of the same location, but at different scales will result in different answers). This study has shown that it is possible to identify the appropriate scale of analysis by sampling various sizes of landscapes within the larger focus region.

Despite the numerous metrics available to quantify patterns of forest integrity in the State of Maryland, it is possible to objectively narrow these metrics to a small set of metrics which capture patterns of forest integrity over a region. Specific indices may vary from region to region, but studies of different scales, methods, and objectives have consistently identified similar types of indices.

Finally, by choosing a small set of metrics that are representative of forest patterns within a landscape, standardizing, weighting, and finally combining these metrics it is possible to create an index of forest fragmentation for entire region that can be mapped. This study used mean patch area, mean patch fractal dimension, clumpy index, core area index, and the area-weighted mean shape index. Combined these indices in an equation, creating a final map representing forest fragmentation in the State Maryland.

Table 1. List of Landsat 7 images used in analysis.

Row	Path	Date
33	17	3/6/2000
33	16	3/31/2000
33	15	3/24/2000
33	14	10/25/1999

Table 2. List of class level metrics used in the investigation. For full description of metrics see McGarigal and Marks, 1995.

Metric	Abbreviation	Name
AREA/EDGE/DENSITY		
	CA[3,5]	Total Class Area
	PLAND[4,5]	Percentage of Landscape
	NP[4,5]	Number of Patches
	PD[4,5]	Patch Density
	LPI[4,5]	Largest Patch Index
	TE[4,5]	Total Edge
	ED[4,5]	Edge Density
	LSI[3,5]	Landscape Shape Index
	AREA_MN[1,3,5]	Mean Patch Area
	AREA_AM[4,5]	Area Weighted Mean Patch Area
	AREA_SD[3,5]	Standard Deviation of Mean Patch Area
	AREA_CV[3,5]	Coefficient of Variation of Mean Patch Area
	GYRATE_MN[3]	Mean Radius of Gyration Distribution
	GYRATE_AM[3]	Area Weighted Mean of Radius of Gyration Distribution
	GYRATE_SD[3]	Standard Deviation of Radius of Gyration Distribution
	GYRATE_CV[3]	Coefficient of Variation of Radius of Gyration Distribution
	nLSI[3]	Normalized Landscape Shape Index
SHAPE		
	SHAPE_MN[3,5]	Mean Shape Index
	SHAPE_AM[1,3]	Area Weighted Mean Shape Index
	SHAPE_SD[4]	Standard Deviation of Mean Shape Index
	SHAPE_CV[3]	Coeffiecient of Variation of Mean Shape Index
	FRAC_MN[1,3,5]	Mean Fractal Dimension Index
	FRAC_AM[4]	Area Weighted Mean Fractal Dimension Index
	FRAC_SD[4]	Standard Deviation of Mean Fractal Dimension Index

FRAC_CV [3,4]	Coefficient of Variation of Mean Fractal Dimension Index
PARA_MN [3,5]	Mean Perimeter Area Ratio
PARA_AM [4]	Area Weighted Mean Perimeter Area Ratio
PARA_SD [2,3]	Standard Deviation of Mean Perimeter Area Ratio
PARA_CV [4]	Coefficient of Variation of Mean Perimeter Area Ratio
CIRCLE_MN [3]	Mean Related Circumscribing Circle
CIRCLE_AM [4]	Area Weighted Mean Related Circumscribing Circle
CIRCLE_SD [3]	Standard Deviation of Mean Related Circumscribing Circle
CIRCLE_CV [3]	Coefficient of Variation of Mean Related Circumscribing Circle
CONTIG_MN [3,5]	Mean Contiguity Index
CONTIG_AM [3]	Area Weighted Mean Contiguity Index
CONTIG_SD [3]	Standard Deviation of Contiguity Index
CONTIG_CV [3]	Coefficient of Variation of Contiguity Index
PAFRAC [2,3,5]	Perimeter Area Fractal Dimension

CORE AREA

TCA [4*]	Total Core Area
CPLAND [4*]	Core Percentage of Landscape
NDCA [4*]	Number of Disjunct Core Areas
DCAD [3*]	Disjunct Core Area Density
CORE_MN [4*]	Mean Core Area
CORE_AM [4*]	Area Weighted Mean Core Area
CORE_SD [4*]	Standard Deviation of Core Area
CORE_CV [4*]	Coefficient of Variation of Core Area
DCORE_MN [4*]	Mean Disjunct Core Area Distribution
DCORE_AM [4*]	Area Weighted Mean Disjunct Core Area Distribution
DCORE_SD [4*]	Standard Deviation of Disjunct Core Area Distribution
DCORE_CV [3*]	Coefficient of Variation of Disjunct Core Area Distribution
CAI_MN [1,3*]	Mean Core Area Index
CAI_AM [3*]	Area Weighted Mean Core Area Index
CAI_SD [4*]	Standard Deviation of Core Area Index
CAI_CV [3*]	Coefficient of Variation of Core Area Index

PROXIMITY/ ISOLATION

PROX_MN [3**]	Mean Proximity Index
PROX_AM [3**]	Area Weighted Mean Proximity Index
PROX_SD [4**]	Standard Deviation of Proximity Index
PROX_CV [3**]	Coefficient of Variation of Proximity Index
SIMI_MN [4***]	Mean Similarity Index
SIMI_AM [4***]	Area Weighted Mean Similarity Index
SIMI_SD [4***]	Standard Deviation of Similarity Index

	SIMI_CV [4 ***]	Coefficient of Variation of Similarity Index
	ENN_MN [3 5]	Mean Euclidian Nearest Neighbor Index
	ENN_AM [3 5]	Area Weighted Mean Euclidian Nearest Neighbor Index
	ENN_SD [4 5]	Standard Deviation of Euclidian Nearest Neighbor Index
	ENN_CV [3 5]	Coefficient of Variation of Euclidian Nearest Neighbor Index
CONTRAST		
	CWED [4 ****]	Contrast Weighted Edge Density
	TECI [4 ****]	Total Edge Contrast Index
	ECON_MN [4 ****]	Mean Edge Contrast Index
	ECON_AM [4 ****]	Area Wieghted Mean Edge Contrast Index
	ECON_SD [3 ****]	Standard Deviation of Edge Contrast Index
	ECON_CV [3 ****]	Coefficient of Variation of Edge Contrast Index
CONTAGION/ INTERSPERSION		
	CLUMPY [1 3]	Clumpy Index
	PLADJ [3]	Percentage of Like Adjacencies
	IJI [2 3 5]	Interspersion Juxtaposition Index
	DIVISION [4]	Landscape Division Index
	MESH [4]	Effective Mesh Size
	SPLIT [3]	Splitting Index
	AI [4]	Aggregation Index
CONNECTIVITY		
	CONNECT [3]	Connectance Index
	COHESION [5]	Patch Cohesion Index

[1] Metric was used in our final weighted index.

[2] Metric was chosen to represent one of the eight axes but was removed from the final weighted index.

[3] Metric was used in PCA.

[4] Metric was removed based on Pearson Correlation Matrix (|r| > 0.9).

[5] Metric was used in scale Analysis.

[*] Calculated using edge depths of 25 m if forest patch is located adjacent to water; 50 m if forest patch is located adjacent to agriculture; 100 m if forest patch is located adjacent to urban areas.

[**] Calculated using search radius of 100 m.

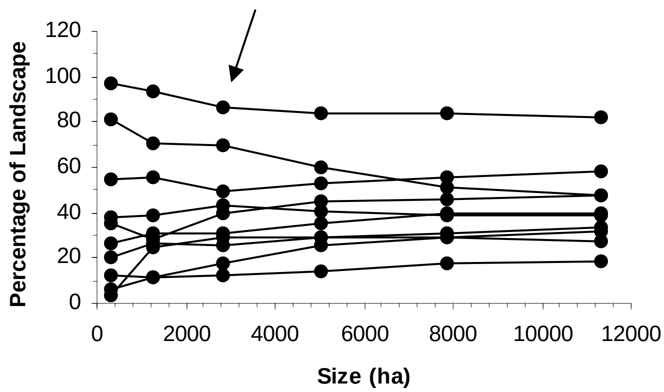
[***] Calculated using similarity weighting of 1.0 for forest patches located in 100 m proximity to other forest patches; 0.8 for forest patches in 100 m proximity of water; 0.6 for forest patches located within 100 m of agriculture; and 0.1 for forest patches within 100 m of urban areas.

[****] Calculated using edge contrast weighting of 0 for forest patches adjacent to other forest patches; 0.3 for forest patches located adjacent to water; 0.6 for forest patches adjacent to agriculture; and 0.9 for forest patches adjacent to urban areas.

Table 3. PCA results after Varimax rotation; underlining indicates metrics chosen to represent each factor.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
PD	-0.7414							
LSI	-0.72314			0.52169				
DCAD	-0.69187			0.52759				
PROX_CV	-0.58805							-0.48052
TECI	-0.42817				-0.71822			
CAI_AM	0.52793		0.71334					
SHAPE_CV	0.57948			0.43651				0.54489
GYRATE_MN	0.69273	0.53668						
LPI	0.73811							0.40688
PROX_MN	0.75791							
GYRATE_SD	0.88179							
AREA_SD	0.92022							
AREA_MN	**0.92533**							
CONNECT	0.93043							
PARA_MN		-0.90075						
CONTIG_CV		-0.84835						
DCORE_CV		-0.5146	0.54665					
AREA_CV		-0.48673	0.42625					
GYRATE_CV		-0.47014	0.47965					0.48584
SHAPE_MN		0.72043				0.43321		
CIRCLE_MN		0.78617						
FRAC_MN		**0.89542**						
NLSI			-0.93259					
SPLIT			-0.78185					
ENN_AM			-0.63642	-0.56501				
ENN_MN			-0.48962	-0.68149				
PLADJ			0.86335					
CLUMPY			**0.88956**					
ENN_CV				-0.73427				
FRAC_CV				0.53512		0.55992		
ED				0.6511				0.42411
PAFRAC				**0.82002**				
CAI_CV					-0.77029			
PROX_AM					-0.46186			
ECON_CV					0.59049		0.59059	
CIRCLE_CV					0.62638	0.48112		-0.42579
CIRCLE_SD					0.67822			-0.40757
CAI_MN					**0.7062**			
CONTIG_SD						0.86231		
PARA_SD						**0.93834**		
ECON_SD							0.8048	
IJI							**0.83898**	
SHAPE_AM								**0.75332**
% of variance	20.1	15.1	13.2	10.4	10.1	7.23	5.91	5.85
Cum.variance	20.1	35.2	48.4	58.8	68.9	76.1	82.0	87.9

A.



B.

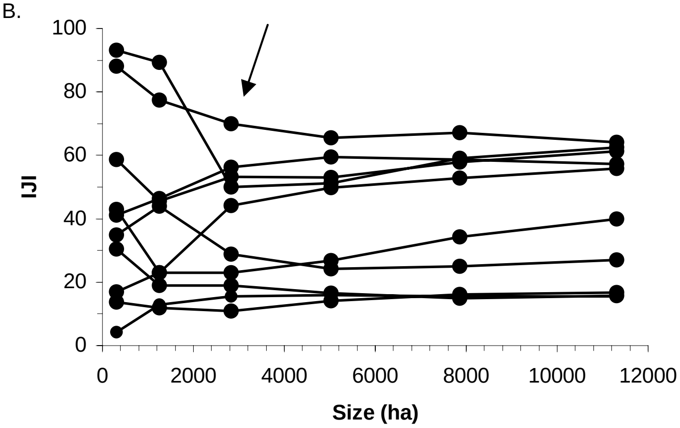


Figure 1. Metric Values plotted against area of 10 sampled grids: (A.) Percentage of Landscape (PLAND), (B.) Interspersion juxtaposition Index (IJI).

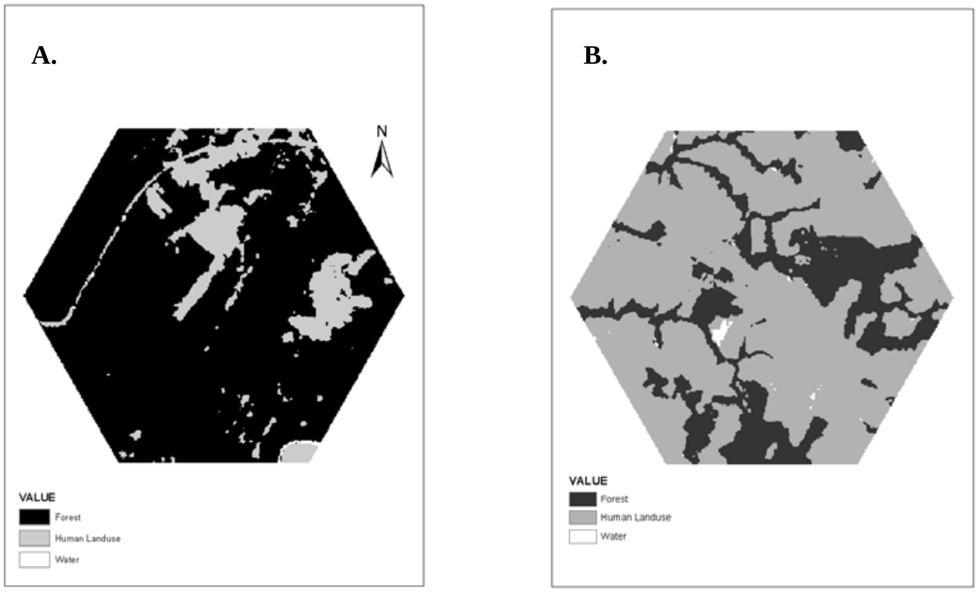


Figure 2. Example of two landscapes that produce similar values in measures of variation. (A.) Forest is matrix (i.e. most abundant landcover type) with smaller patches of human landuse located within the forest matrix; (B.) Human land use matrix with patches of forest within the matrix.

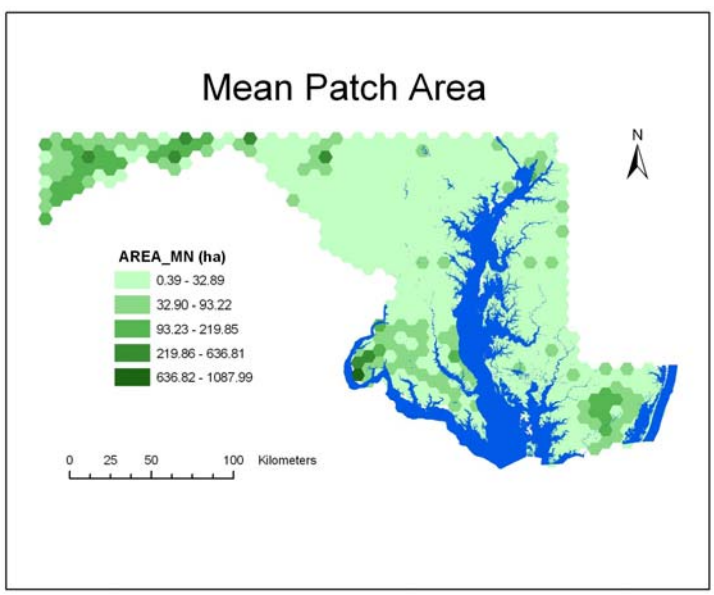


Figure 3. Map of Mean Patch Area metric (AREA_MN).

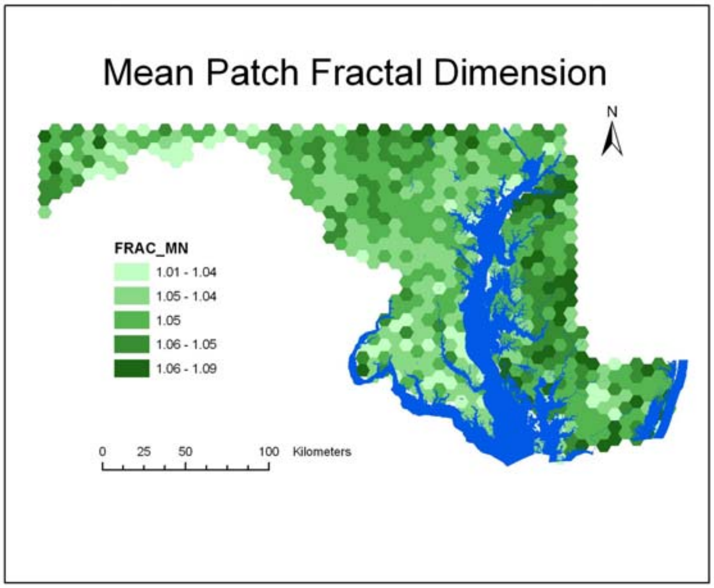


Figure 4. Map of Mean Patch Fractal Dimension Index (FRAC_MN).

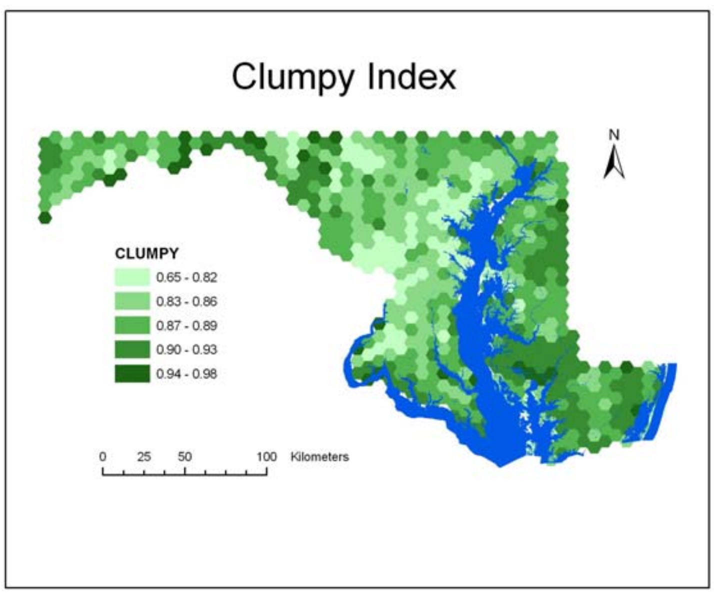


Figure 5. Map of Clumpy Index (CLUMPY).

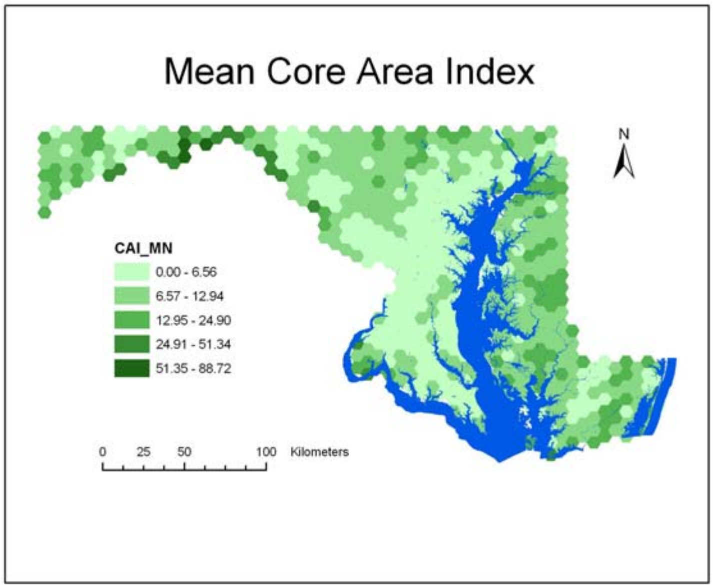


Figure 6. Map of Mean Core Area Index (CAI_MN).

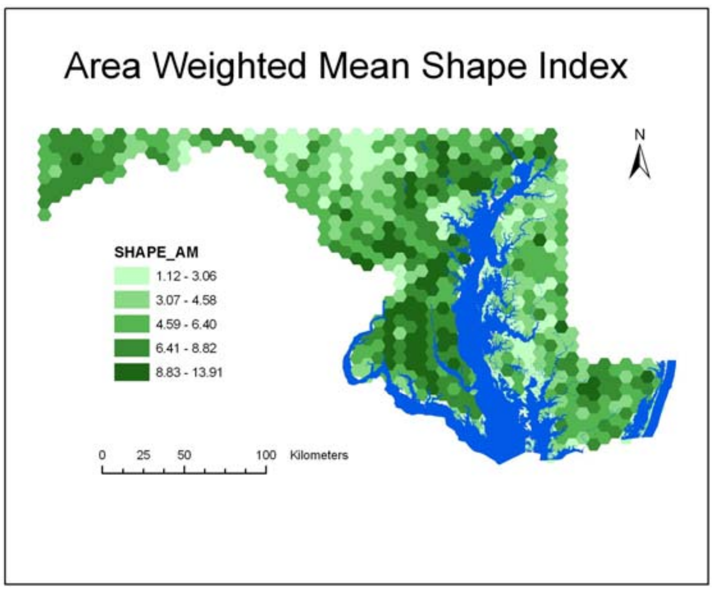


Figure 7. Map of Area Weighted Mean Shape Index (SHAPE_AM).

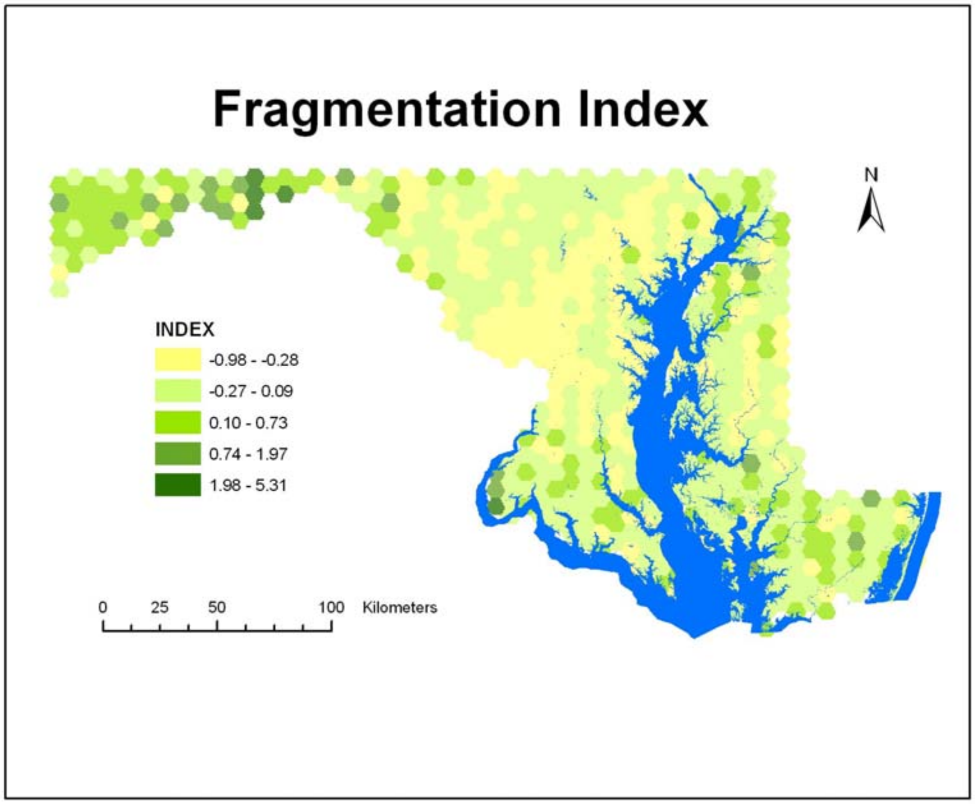


Figure 8. Final weighted index of forest fragmentation for Maryland. Forest landcover (dark green) and urban landcover are overlayed indicating correlation with the index values. High values indicate least fragmentation.

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