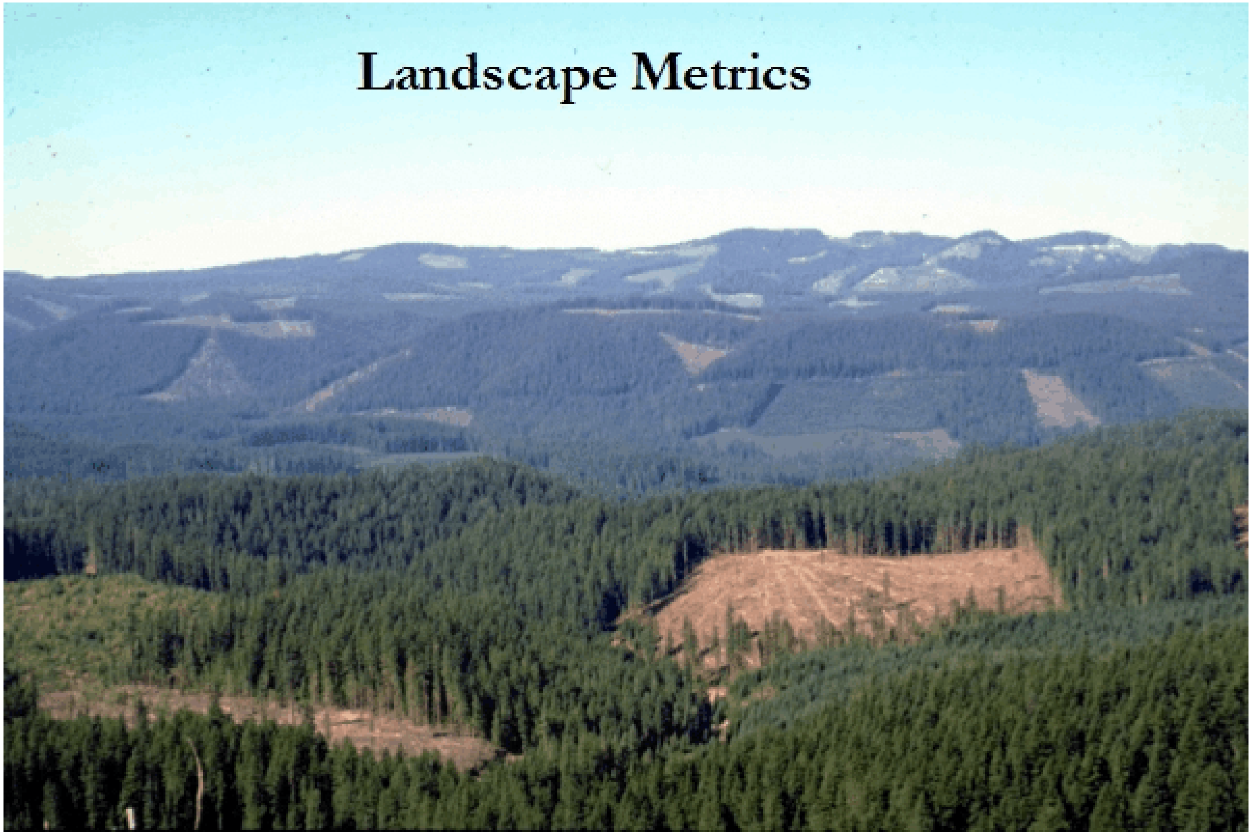


Landscape Metrics for Categorical Map Patterns

Instructor: K. McGarigal

Assigned Reading: Turner et al. 2001 (Chapter 5); McGarigal (Lecture notes)

Objective: Provide an overview of common landscape metrics and insights into their use and interpretation. Highlight importance of selecting the “right” metric for the “right” problem.

Topics covered:
1. Overview of landscape metrics
2. Area/density/edge metrics
3. Shape metrics
4. Core area metrics
5. Contrast metrics
6. Contagion/interspersion metrics
7. Isolation/proximity metrics
8. Connectivity metrics
9. Diversity metrics
10. Insights on the use of landscape metrics

1. Introduction and Overview

FRAGSTATS computes several statistics for each patch and class (patch type) in the landscape and for the landscape as a whole. At the class and landscape level, some of the metrics quantify landscape composition, while others quantify landscape configuration. Landscape composition and configuration can affect ecological processes independently and interactively (see FRAGSTATS Foundation). Thus, it is especially important to understand for each metric what aspect of landscape pattern is being quantified. In addition, many of the metrics are partially or completely redundant; that is, they quantify a similar or identical aspect of landscape pattern. In most cases, redundant metrics will be very highly or even perfectly correlated. For example, at the landscape level, *patch density* (PD) and *mean patch size* (MPS) will be perfectly correlated because they represent the same information. These redundant metrics are alternative ways of representing the same information; they are included in FRAGSTATS because the preferred form of representing a particular aspect of landscape pattern will differ among applications and users. It behooves the user to understand these redundancies, because in most applications only 1 of each set of redundant metrics should be employed. It is important to note that in a particular application, some metrics may be empirically redundant as well; not because they measure the same aspect of landscape pattern, but because for the particular landscapes under investigation, different aspects of landscape pattern are statistically correlated. The distinction between this form of redundancy and the former is important, because little can be learned by interpreting metrics that are inherently redundant, but much can be learned about landscapes by interpreting metrics that are empirically redundant.

Many of the patch metrics have counterparts at the class and landscape levels. For example, many of the class metrics (e.g., mean shape index) represent the same basic information as the corresponding patch metrics (e.g., patch shape index), but instead of considering a single patch, they consider all patches of a particular type simultaneously. Likewise, many of the landscape metrics are derived from patch or class characteristics. Consequently, many of the class and landscape metrics are computed from patch and class statistics by summing or averaging over all patches or classes. Even though many of the class and landscape metrics represent the same fundamental information, naturally the algorithms differ slightly. Class metrics represent the spatial distribution and pattern within a landscape of a single patch type; whereas, landscape metrics represent the spatial pattern of the entire landscape mosaic, considering all patch types simultaneously. Thus, even though many of the metrics have counterparts at the class and landscape levels, their interpretations may be somewhat different. Most of the class metrics can be interpreted as fragmentation indices because they measure the configuration of a particular patch type; whereas, most of the landscape metrics can be interpreted more broadly as landscape heterogeneity indices because they measure the overall landscape pattern. Hence, it is important to interpret each metric in a manner appropriate to its scale (patch, class, or landscape).

In the sections that follow, each metric computed in FRAGSTATS is described in detail. Metrics are grouped loosely according to the aspect of landscape pattern measured – but note that these groupings are done for mostly for convenience as these are not independent aspects of landscape pattern and most metrics can fall into more than one group – as follows:

- Area/density/edge metrics
- Shape metrics
- Core area metrics
- Contrast metrics
- Contagion/interspersion metrics
- Isolation/proximity metrics
- Connectivity metrics
- Diversity metrics

Within each of these groups, metrics are further grouped into patch, class, and landscape metrics, as follows:

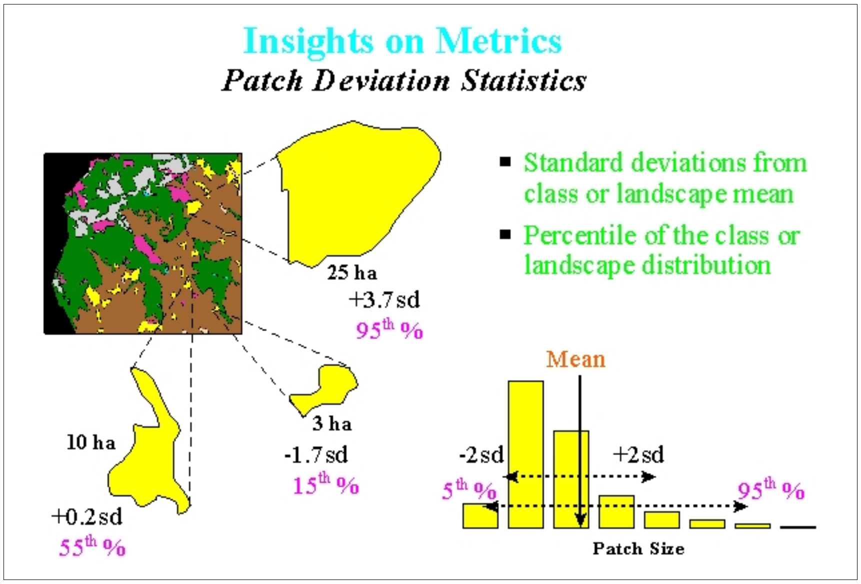
1.1. Patch Metrics

Patch metrics are computed for every patch in the landscape; the resulting patch output file contains a row (observation vector) for every patch, where the columns (fields) represent the individual metrics. The first three columns include header information about the patch:

> **(P1) Landscape ID**.--The first field in the patch output file is landscape ID (LID). Landscape ID is set to the name of the input image obtained from the input file (see Run Parameters).
>
> **(P2) Patch ID**.--The second field in the patch output file is patch ID (PID). If a Patch ID image is specified that contains unique ID's for each patch, FRAGSTATS reads the patch ID from the designated image. If an image is not specified, FRAGSTATS creates unique ID's for each patch and optionally produces an image that contains patch ID's that correspond to the FRAGSTATS output.
>
> **(P3) Patch Type**.--The third field in the patch output file is patch type (TYPE). FRAGSTATS contains an option to name an ASCII file (class properties file) that contains character descriptors for each patch type. If the class properties option is not used, FRAGSTATS will write the numeric patch type codes to TYPE.

There are two basic types of metrics at the patch level: (1) indices of the spatial character and context of individual patches, and (2) measures of the deviation from class and landscape norms; that is, how much the computed value of each metric for a patch deviates from the class and landscape means. The deviation statistics are useful in identifying patches with extreme values on each metric. Because the deviation statistics are computed similarly for all patch metrics, they are described in common below:

__Patch Deviation Statistics__.--In addition to the standard patch metrics, FRAGSTATS computes several deviation statistics for each patch that measures how much it deviates from the class or landscape norm (i.e., how extreme an observation it is) for each metric. Specifically, for each patch and each patch metric, FRAGSTATS computes the following four measures of deviation: (1) standard deviations from the class mean, (2) percentile of the class distribution, (3) standard deviations from the landscape mean, and (4) percentile of the landscape distribution.



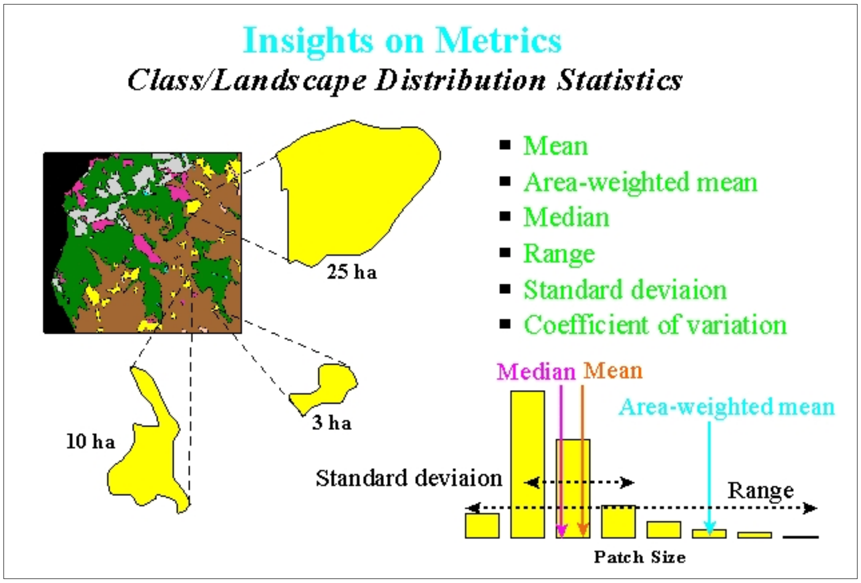
1.2. Class Metrics

Class metrics are computed for every patch type or class in the landscape; the resulting class output file contains a row (observation vector) for every class, where the columns (fields) represent the individual metrics. The first two columns include header information about the class:

> **(C1) Landscape ID**.--The first field in the class output file is landscape ID (LID). Landscape ID is set to the name of the input image obtained from the input file (see Run Parameters).
>
> **(C2) Patch Type**.--The second field in the class output file is patch type (TYPE). FRAGSTATS contains an option to name an ASCII file (class properties file) that contains character descriptors for each patch type. If the class descriptor option is not used, FRAGSTATS will write the numeric patch type codes to TYPE.

There are two basic types of metrics at the class level: (1) indices of the amount and spatial configuration of the class, and (2) distribution statistics that provide first- and second-order statistical summaries of the patch metrics for the focal class. The latter are used to summarize the mean, area-weighted mean, median, range, standard deviation, and coefficient of variation in the patch attributes across all patches in the focal class. Because the distribution statistics are computed similarly for all class metrics, they are described in common below:

__Class Distribution Statistics__.--Class metrics measure the aggregate properties of the patches belonging to a single class or patch type. Some class metrics go about this by characterizing the aggregate properties without distinction among the separate patches that comprise the class. These metrics are defined elsewhere. Another way to quantify the configuration of patches at the class level is to summarize the aggregate distribution of the patch metrics for all patches of the corresponding patch type. In other words, since the class represents an aggregation of patches of the same type, we can characterize the class by summarizing the patch metrics for the patches that comprise each class. There are many possible first- and second-order statistics that can be used to summarize the patch distribution. FRAGSTATS computes the following: (1) mean (MN), (2) area-weighted mean (AM), (3) median (MD), (4) range (RA), (5) standard deviation (SD), and (6) coefficient of variation (CV). FRAGSTATS computes these distribution statistics for all patch metrics at the class level. In the class output file, these metrics are labeled by concatenating the metric acronym with an underscore and the distribution statistic acronym. For example, patch area (AREA) is summarized at the class level by each of the distribution statistics and reported in the class output file as follows: mean patch area (AREA_MN), area-weighted mean patch area (AREA_AM), median patch area (AREA_MD), range in patch area (AREA_RA), standard deviation in patch area (AREA_SD), and coefficient of variation in patch area (AREA_CV).



1.3. Landscape Metrics

Landscape metrics are computed for entire patch mosaic; the resulting landscape output file contains a single row (observation vector) for the landscape, where the columns (fields) represent the individual metrics. The first column includes header information about the landscape:

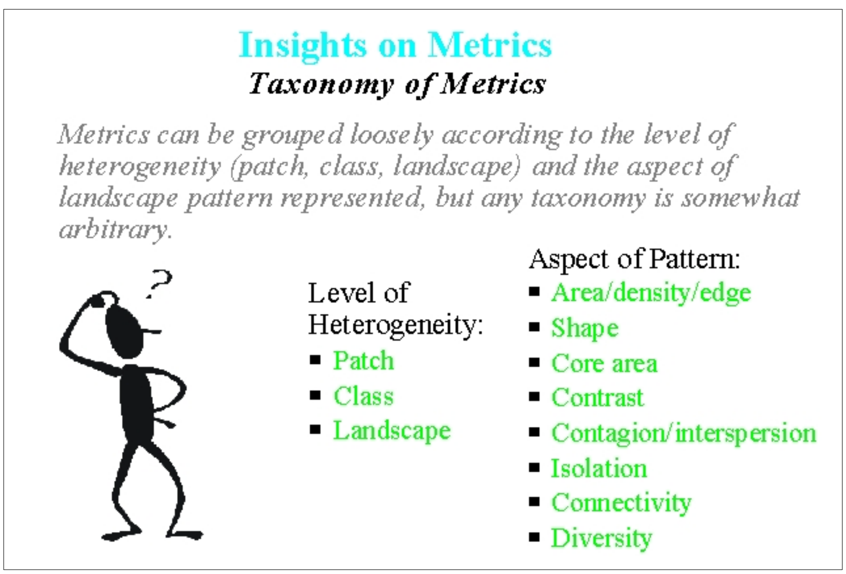
> **(L1) Landscape ID**.--The first field in the landscape output file is landscape ID (LID). Landscape ID is set to the name of the input image obtained from the input file (see Run Parameters).

Like class metrics, there are two basic types of metrics at the landscape level: (1) indices of the composition and spatial configuration of the landscape, and (2) distribution statistics that provide first- and second-order statistical summaries of the patch metrics for the entire landscape. The latter are used to summarize the mean, area-weighted mean, median, range, standard deviation, and coefficient of variation in the patch attributes across all patches in the landscape. Because the distribution statistics are computed similarly for all landscape metrics, they are described in common below:

Landscape Distribution Statistics.--Landscape metrics measure the aggregate properties of the entire patch mosaic. Some landscape metrics go about this by characterizing the aggregate properties without distinction among the separate patches that comprise the mosaic. These metrics are defined elsewhere. Another way to quantify the configuration of patches at the landscape level is to summarize the aggregate distribution of the patch metrics for all patches in the landscape. In other words, since the landscape represents an aggregation of patches, we can characterize the landscape by summarizing the patch metrics. There are many possible first- and second-order statistics that can be used to summarize the patch distribution. FRAGSTATS computes the following: (1) mean (MN), (2) area-weighted mean (AM), (3) median (MD), (4) range (RA), (5) standard deviation (SD), and (6) coefficient of variation (CV). FRAGSTATS computes these distribution statistics for all patch metrics at the landscape level. In the landscape output file, these metrics are labeled by concatenating the metric acronym with an underscore and the distribution statistic acronym. For example, patch area (AREA) is summarized at the class level by each of the distribution statistics and reported in the class output file as follows: mean patch area (AREA_MN), area-weighted mean patch area (AREA_AM), median patch area (AREA_MD), range in patch area (AREA_RA), standard deviation in patch area (AREA_SD), and coefficient of variation in patch area (AREA_CV). Note, the acronyms for the distribution statistics are the same at the class and landscape levels, so they can only be distinguished by the output file they belong to (i.e., ".basename".class or "basename".land).

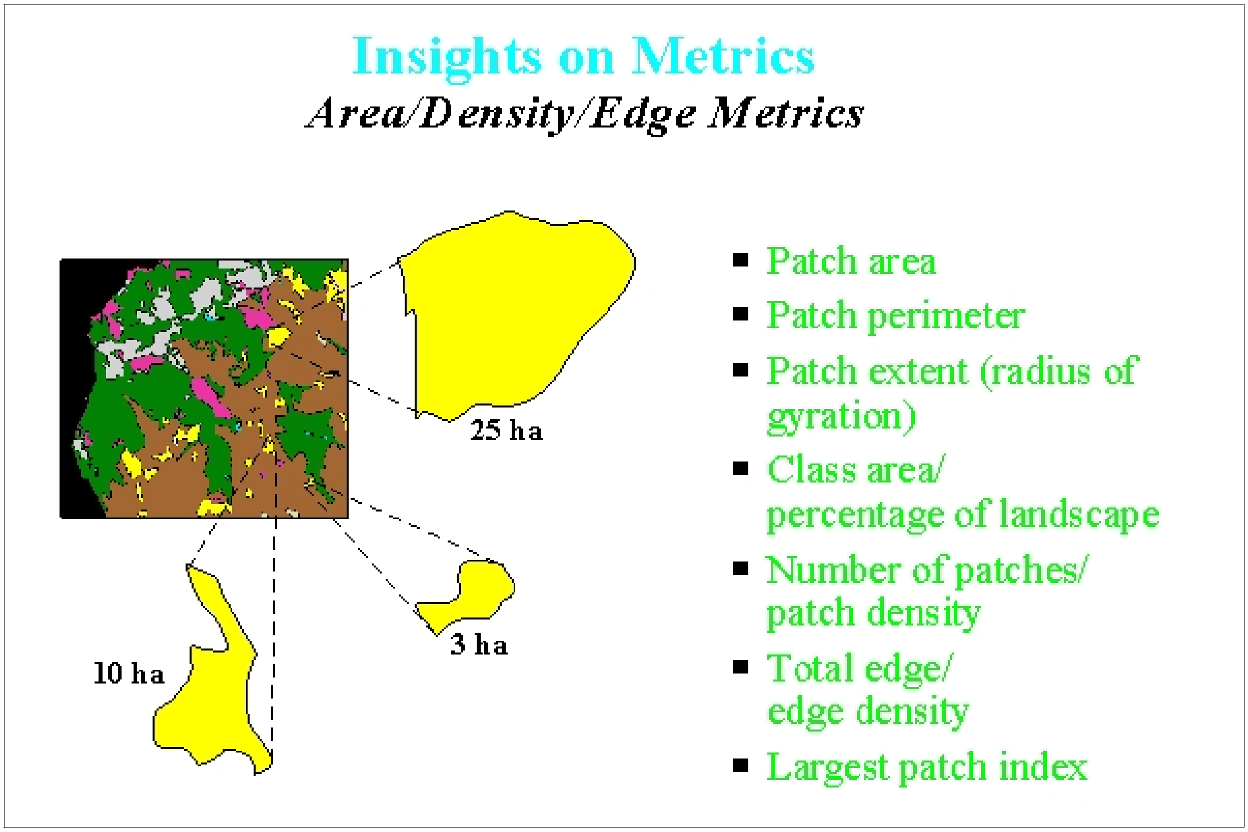
1.4. General Comments

Not all groups of metrics (see previous list) have metrics at all levels. For example, diversity metrics only exist at the landscape level. Also note that the organizational hierarchy used here is opposite of that used in the FRAGSTATS graphical user interface (GUI). In the GUI, metrics are first grouped by level (patch, class, and landscape) and then further grouped by the aspect of landscape pattern measured. The GUI organization strives to be consistent with the way most users conduct a FRAGSTATS analysis. Often times, for example, users are only interested in class level metrics. Here, however, the discussion of the metrics is facilitated by reversing the hierarchy and first grouping them according the aspect of



pattern measured, then by the level of organization (patch, class, and landscape). In this manner, issues common to all metrics that relate to the same aspect of landscape pattern can be discussed once.

Following this convention, each metrics section begins with a brief introduction to the metrics in the group, followed by an overview of the various metrics computed by FRAGSTATS and a discussion of important limitations in their use and interpretation. Following this overview, each metric is defined, including a mathematical definition, measurement units, theoretical range in values, and any special considerations or limitations in the use of the metric. For each metric, the mathematical formula is described in narrative terms to facilitate interpretation of the formula. The acronym for the metric given on the left-hand side of the equation is the field name used in the ASCII output files. To facilitate interpretation of the algorithm, we intentionally separate from each equation any constants used to rescale the metric. For example, in many cases the right-hand side of the equation is multiplied by 100 to convert a proportion to a percentage, or multiplied or divided by 10,000 to convert m^2 to hectares. These conversion factors are separated out by parentheses even though they may be factored into the equation differently in the computational form of the algorithm.



2. Area/Density/Edge Metrics

Background.--This group of metrics represents a loose collection of metrics that deal with the number and size of patches and the amount of edge created by these patches. Although these metrics could easily be subdivided into separate groups or assigned to other already recognized groups, there is enough similarity in the basic patterns assessed by these metrics to include them under one umbrella.

The area of each patch comprising a landscape mosaic is perhaps the single most important and useful piece of information contained in the landscape. Not only is this information the basis for many of the patch, class, and landscape indices, but patch area has a great deal of ecological utility in its own right. For example, there is considerable evidence that bird species richness and the occurrence and abundance of some species are strongly correlated with patch size (e.g., Robbins et al. 1989). Most species have minimum area requirements: the minimum area needed to meet all life history requirements. Some of these species require that their minimum area requirements be fulfilled in contiguous habitat patches; in other words, the individual habitat patch must be larger than the species minimum area requirement for them to occupy the patch. These species are sometimes referred to as “area-sensitive” species. Thus, patch size information alone could be used to model species richness, patch occupancy, and species distribution patterns in a landscape given the appropriate empirical relationships derived from field studies.

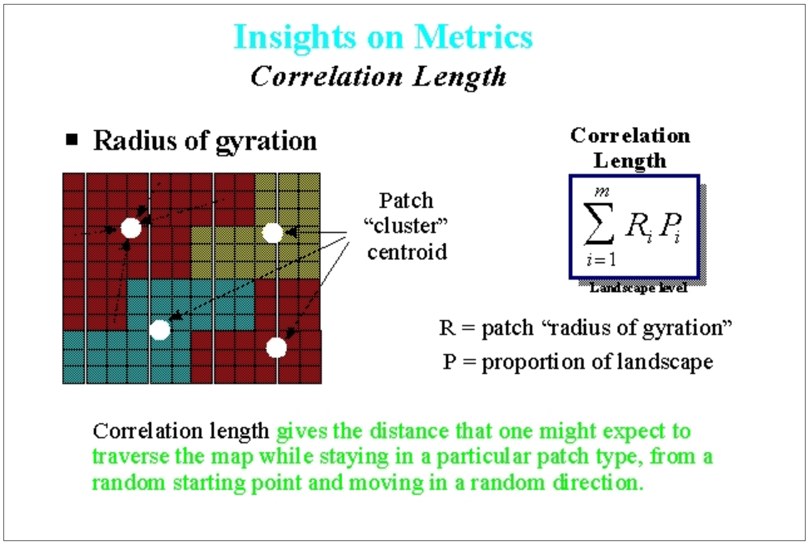
Similarly, the size and number of patches comprising a class or the entire landscape mosaic is perhaps the most basic aspect of landscape pattern that can affect myriad processes. For example, although there are myriad effects of habitat fragmentation on individual behavior, habitat use patterns, and intra- and inter-specific interactions, many of these effects are caused by: (1) a reduction in habitat area (area effects), and (2) an increase in the proportion of edge-influenced habitat (edge effects). Briefly, as a species' habitat is lost from the landscape (without being fragmented), at some point there will be insufficient area of habitat to support a viable population, and with continued loss eventually there will be insufficient area of habitat to support even a single individual and the species will be extirpated from the landscape. This area relationship is expected to vary among species depending on their minimum area requirements. Moreover, the area threshold for occupancy may occur when total habitat area is still much greater than the individual's minimum area requirement. For example, an individual may not occupy available habitat unless there are other individuals of the same species occupying the same or nearby patches of habitat, or an individual's occupancy may be influenced by what other species are occupying the patch. Similarly, as habitat is lost and simultaneously fragmented into smaller and more isolated patches, at some point there will be insufficient area of suitable habitat within a home range size area to support an individual. In either case, the effect of habitat area on the occurrence and abundance of a species (or species) is referred to as the "area effect." This is the ultimate consequence of habitat loss and fragmentation–insufficient habitat quantity and quality to support individuals and viable populations.

Total amount of edge in a landscape is important to many ecological phenomena. In particular, a great deal of attention has been given to wildlife-edge relationships (Thomas et al. 1978 and 1979, Strelke and Dickson 1980, Morgan and Gates 1982, Logan et al. 1985). In landscape ecological investigations, much of the presumed importance of spatial pattern is related to edge effects. The forest edge effect, for example, results primarily from differences in wind and light intensity and quality reaching a forest patch that alter microclimate and disturbance rates (e.g., Gratkowski 1956, Ranney et al. 1981, Chen and Franklin 1990). These changes, in combination with changes in seed dispersal and herbivory, can influence vegetation composition and structure (Ranney et al. 1981). The proportion of a forest patch that is affected in this manner is dependent, therefore, upon patch shape and orientation, and by adjacent land cover. A large but convoluted patch, for example, could be entirely edge habitat. It is now widely accepted that edge effects must be viewed from an organism-centered perspective because edge effects influence organisms differently; some species have an affinity for edges, some are unaffected, and others are adversely affected.

One of the most dramatic and well-studied consequences of habitat fragmentation is an increase in the proportional abundance of edge-influenced habitat. Early wildlife management efforts were focused on maximizing edge habitat because it was believed that most species favored habitat conditions created by edges and that the juxtaposition of different habitats would increase species diversity (Leopold 1933). Indeed this concept of edge as a positive influence guided land management practices for most of the twentieth century. Recent studies, however, have suggested that changes in microclimate, vegetation, invertebrate populations, predation, brood parasitism, and competition along forest edges (i.e., edge effects) has resulted in the population declines of several vertebrate species dependent upon forest interior conditions (e.g., Strelke and

Dickson 1980, Whitcomb et al. 1981, Kroodsma 1982, Brittingham and Temple 1983, Wilcove 1985, Temple 1986, Noss 1988, Yahner and Scott 1988, Robbins et al. 1989). In fact, many of the adverse effects of forest fragmentation on organisms seem to be directly or indirectly related to these so-called edge effects. Forest interior species, therefore, may be sensitive to patch shape because for a given patch size, the more complex the shape, the larger the edge-to-interior ratio. Total class edge in a landscape, therefore, often is the most critical piece of information in the study of fragmentation, and many of the class indices directly or indirectly reflect the amount of class edge. Similarly, the total amount of edge in a landscape is directly related to the degree of spatial heterogeneity in that landscape.

<u>FRAGSTATS Metrics</u>.--FRAGSTATS computes several simple statistics representing area and perimeter (or edge) at the patch, class, and landscape levels. Area metrics quantify landscape composition, not landscape configuration. As noted above, the *area* (AREA) of each patch comprising a landscape mosaic is perhaps the single most important and useful piece of information contained in the landscape. However, the size of a patch may not be as important as the extensiveness of the patch for some organisms and processes. *Radius of gyration* (GYRATE) is a measure of patch extent; that is, how far across the landscape a patch extends its reach. All other things equal, the larger the patch, the larger the radius of gyration. Similarly, holding area constant, the more extensive the patch (i.e., elongated and less compact), the greater the radius of gyration. The radius of gyration can be considered a measure of the average distance an organism can move within a patch before encountering the patch boundary from a random starting point. When aggregated at the class or landscape level, radius of gyration provides a measure of landscape connectivity (known as *correlation length*) that represents the average traversability of the landscape for an organism that is confined to remain within a single patch.



Class area (CA) and *percentage of landscape* (PLAND) are measures of landscape composition; specifically, how much of the landscape is comprised of a particular patch type. This is an important characteristic in a number of ecological applications. For example, an important by-product of habitat fragmentation is habitat loss. In the study of forest fragmentation, therefore, it is important to know how much of the target patch type (habitat) exists within the landscape. In addition, although many vertebrate species that specialize on a particular habitat have minimum area requirements (e.g., Robbins et al. 1989), not all species require that suitable habitat to be present in a single contiguous patch. For example, northern spotted owls have minimum area requirements for late-seral forest that varies geographically;

yet, individual spotted owls use late-seral forest that may be distributed among many patches (Forsman et al. 1984). For this species, late-seral forest area might be a good index of habitat suitability within landscapes the size of spotted owl home ranges (Lehmkuhl and Raphael 1993). In addition to its direct interpretive value, class area (in absolute or relative terms) is used in the computations for many of the class and landscape metrics.

FRAGSTATS computes several simple statistics representing the number or density of patches, the average size or radius of gyration of patches, and the variation in patch size or radius of gyration at the class and landscape levels. These metrics usually are best considered as representing landscape configuration, even though they are not spatially explicit measures. *Number of patches* (NP) or *patch density* (PD) of a particular habitat type may affect a variety of ecological processes, depending on the landscape context. For example, the number or density of patches may determine the number of subpopulations in a spatially-dispersed population, or metapopulation, for species exclusively associated with that habitat type. The number of subpopulations could influence the dynamics and persistence of the metapopulation (Gilpin and Hanski 1991). The number or density of patches also can alter the stability of species interactions and opportunities for coexistence in both predator-prey and competitive systems (Kareiva 1990). The number or density of patches in a landscape mosaic (pooled across patch types) can have the same ecological applicability, but more often serves as a general index of spatial heterogeneity of the entire landscape mosaic. A landscape with a greater number or density of patches has a finer grain; that is, the spatial heterogeneity occurs at a finer resolution. Although the number or density of patches in a class or in the landscape may be fundamentally important to a number of ecological processes, often it does not have any interpretive value by itself because it conveys no information about the area or distribution of patches. Number or density of patches is probably most valuable, however, as the basis for computing other, more interpretable, metrics.

In addition to these primary metrics, FRAGSTATS also summarizes the distribution of patch area and extent (radius of gyration) across all patches at the class and landscape levels. For example, the distribution of patch area (AREA) is summarized by its mean and variability. These summary measures provide a way to characterize the distribution of area among patches at the class or landscape level. For example, progressive reduction in the size of habitat fragments is a key component of habitat fragmentation. Thus, a landscape with a smaller mean patch size for the target patch type than another landscape might be considered more fragmented. Similarly, within a single landscape, a patch type with a smaller mean patch size than another patch type might be considered more fragmented. Thus, mean patch size can serve as a habitat fragmentation index, although the limitations discussed below may reduce its utility in this respect.

Mean patch size at the class level is a function of the number of patches in the class and total class area. In contrast, patch density is a function of total landscape area. Therefore, at the class level, these two indices represent slightly different aspects of class structure. For example, two landscapes could have the same number and size distribution of patches for a given class and thus have the same mean patch size; yet, if total landscape area differed, patch density could be very different between landscapes. Alternatively, two landscapes could have the same number of patches and total landscape area and thus have the same patch density; yet, if class area differed, mean patch size could be very different between landscapes. These differences should be kept in mind when selecting class metrics for a particular application. In addition, although mean patch size is derived from the number of patches, it does not convey any information about how many patches are present. A mean patch size of 10 ha could represent 1 or 100 patches and the difference could have profound ecological implications. Furthermore, mean patch size represents the average condition. Variation in patch size may convey more useful information. For example, a mean patch size of 10 ha could represent a class with 5 10-ha patches or a class with 2-, 3-, 5-, 10-, and 30-ha patches, and this difference could be important ecologically. For these reasons, mean patch size is probably best interpreted in conjunction with total class area, patch density (or number of patches), and patch size variability. At the landscape level, mean patch size and patch density are both a function of number of patches and total landscape area. In contrast to the class level, these indices are completely redundant (assuming there is no internal background). Although both indices may be useful for "describing" 1 or more landscapes, they would never be used simultaneously in a statistical analysis of landscape structure.

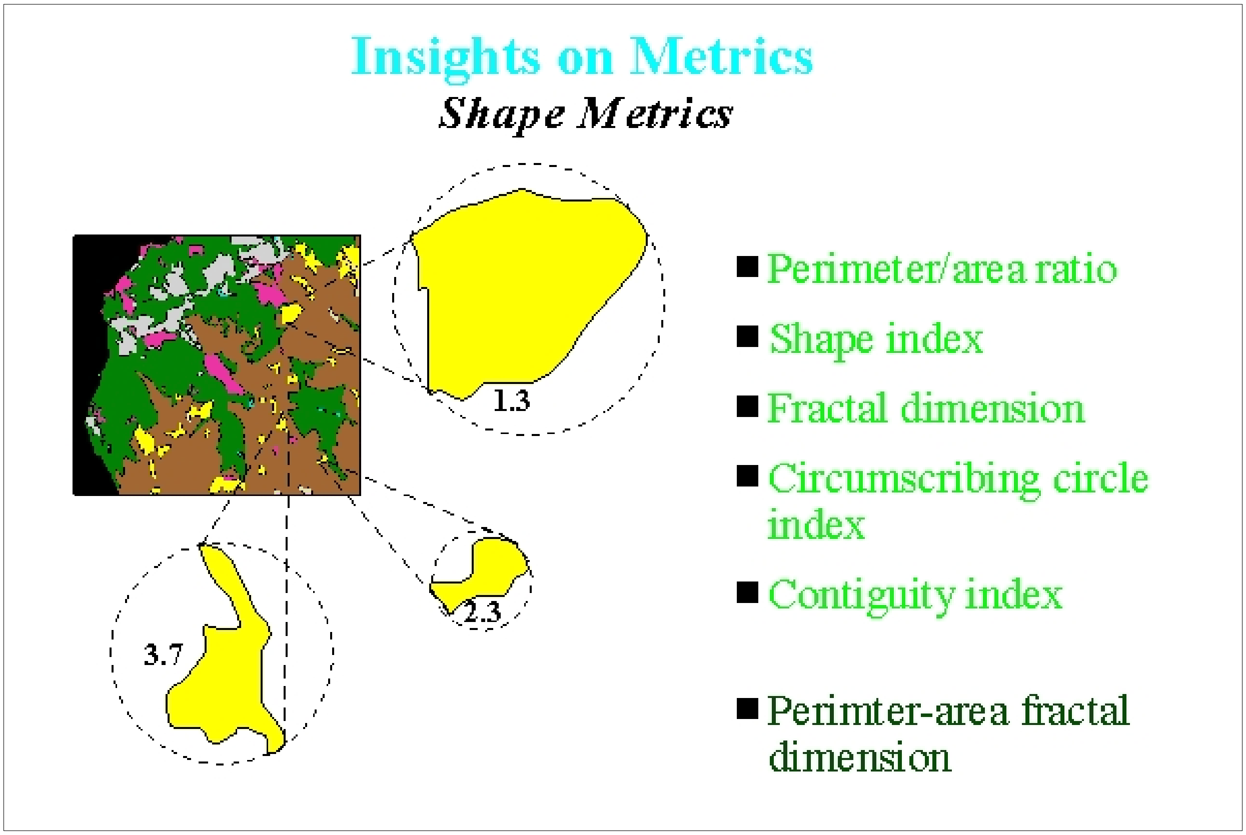
In many ecological applications, second-order statistics, such as the variation in patch size, may convey more useful information than first-order statistics, such as mean patch size. Variability in patch size measures a key aspect of landscape heterogeneity that is not captured by mean patch size and other first-order statistics. For example, consider 2 landscapes with the same patch density and mean patch size, but with very different levels of variation in patch size. Greater variability indicates less uniformity in pattern either at the class level or landscape level and may reflect differences in underlying processes affecting the landscapes. Variability is a difficult thing to summarize in a single metric. FRAGSTATS computes three of the simplest measures of variability–range, standard deviation, and coefficient of variation.

Patch size standard deviation (AREA_SD) is a measure of absolute variation; it is a function of the mean patch size and the difference in patch size among patches. Thus, although patch size standard deviation conveys information about patch size variability, it is a difficult parameter to interpret without doing so in conjunction with mean patch size because the absolute variation is dependent on mean patch size. For example, two landscapes may have the same patch size standard deviation, e.g., 10 ha; yet one landscape may have a mean patch size of 10 ha, while the other may have a mean patch size of 100 ha. In this case, the interpretations of landscape pattern would be very different, even though absolute variation is the same. Specifically, the former landscape has greatly varying and smaller patch sizes, while the latter has more uniformly-sized and larger patches. For this reason, *patch size coefficient of variation* (AREA_CV) is generally preferable to standard deviation for comparing variability among landscapes. Patch size coefficient of variation measures relative variability about the mean (i.e., variability as a percentage of the mean), not absolute variability. Thus, it is not necessary to know mean patch size to interpret the coefficient of variation. Nevertheless, patch size coefficient of variation also can be misleading with regards to landscape structure in the absence of information on the number of patches or patch density and other structural characteristics. For example, two landscapes may have the same patch size coefficient of variation, e.g., 100%; yet one landscape may have 100 patches with a mean patch size of 10 ha, while the other may have 10 patches with a mean patch size of 100 ha. In this case, the interpretations of landscape structure could be very different, even though the coefficient of variation is the same. Ultimately, the choice of standard deviation or coefficient of variation will depend on whether absolute or relative variation is more meaningful in a particular application. Because these measures are not wholly redundant, it may be meaningful to interpret both measures in some applications.

It is important to keep in mind that both standard deviation and coefficient of variation assume a normal distribution about the mean. In a real landscape, the distribution of patch sizes may be highly irregular. It may be more informative to inspect the actual distribution itself, rather than relying on summary statistics such as these that make assumptions about the distribution and therefore can be misleading. Also, note that patch size standard deviation and coefficient of variation can equal 0 under 2 different conditions: (1) when there is only 1 patch in the landscape; and (2) when there is more than 1 patch, but they are all the same size. In both cases, there is no variability in patch size, yet the ecological interpretations could be different.

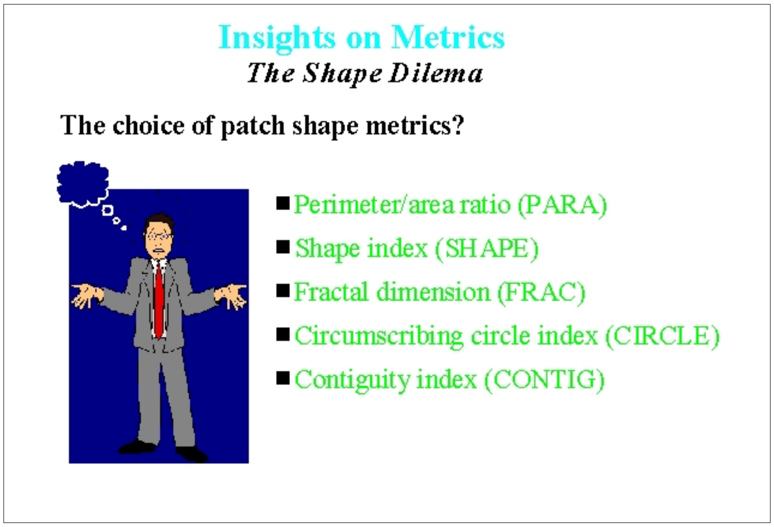
FRAGSTATS computes several statistics representing the amount of perimeter (or edge) at the patch, class, and landscape levels. Edge metrics usually are best considered as representing landscape configuration, even though they are not spatially explicit at all. At the patch level, edge is a function of patch *perimeter* (PERIM). At the class and landscape levels, edge can be quantified in other ways. *Total edge* (TE) is an absolute measure of total edge length of a particular patch type (class level) or of all patch types (landscape level). In applications that involve comparing landscapes of varying size, this index may not be useful. *Edge density* (ED) standardizes edge to a per unit area basis that facilitates comparisons among landscapes of varying size. However, when comparing landscapes of identical size, total edge and edge density are completely redundant. Alternatively, the amount of edge present in a landscape can be compared to that expected for a landscape of the same size but with a simple geometric shape (square) and no internal edge. *Landscape shape index* (LSI) does this. This index measures the perimeter-to-area ratio for the landscape as a whole. This index is identical to the habitat diversity index proposed by Patton (1975), except that we apply the index at the class level as well. Landscape shape index is identical to the shape index at the patch level (SHAPE), except that it treats the entire landscape as if it were one patch and any patch edges (or class edges) as though they belong to the perimeter. The landscape boundary must be included as edge in the calculation in order to use a square standard for comparison. Unfortunately, this may not be meaningful in cases where the landscape boundary does not represent true edge and/or the actual shape of the landscape is of no particular interest. In this case, the total amount of true edge, or some other index based on edge, would probably be more meaningful. If the landscape boundary represents true edge or the shape of the landscape is particularly important, then the landscape shape index can be a useful index, especially when comparing among landscapes of varying sizes.

Limitations.--Area metrics have limitations imposed by the scale of investigation. Minimum patch size and landscape extent set the lower and upper limits of these area metrics, respectively. These are critical limits to recognize because they establish the lower and upper limits of resolution for the analysis of landscape composition and configuration. Otherwise, area metrics have few limitations. All edge indices are affected by the resolution of the image. Generally, the finer the resolution (i.e., the greater the detail with which edges are delineated), the greater the edge length. At coarse resolutions, edges may appear as relatively straight lines; whereas, at finer resolutions, edges may appear as highly convoluted lines. Thus, values calculated for edge metrics should not be compared among images with different resolutions. In addition, patch perimeter and the length of edges will be biased upward in raster images because of the stair-step patch outline, and this will affect all edge indices. The magnitude of this bias will vary in relation to the grain or resolution of the image, and the consequences of this bias with regards to the use and interpretation of these indices must be weighed relative to the phenomenon under investigation.

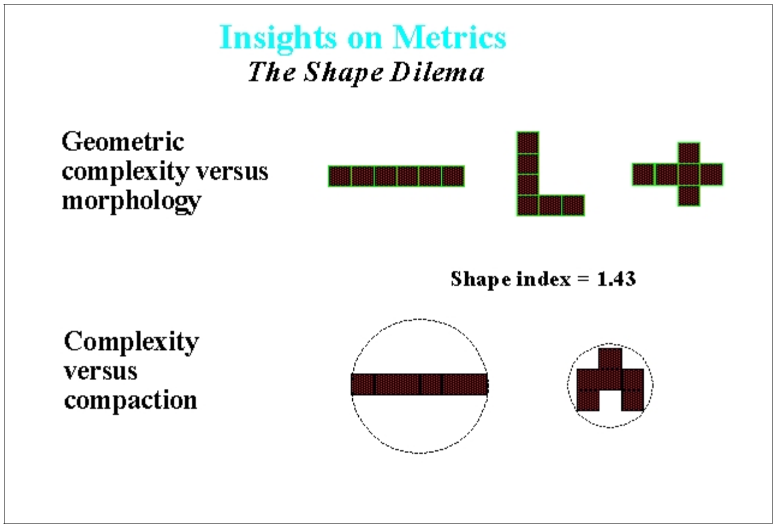


3. Shape Metrics

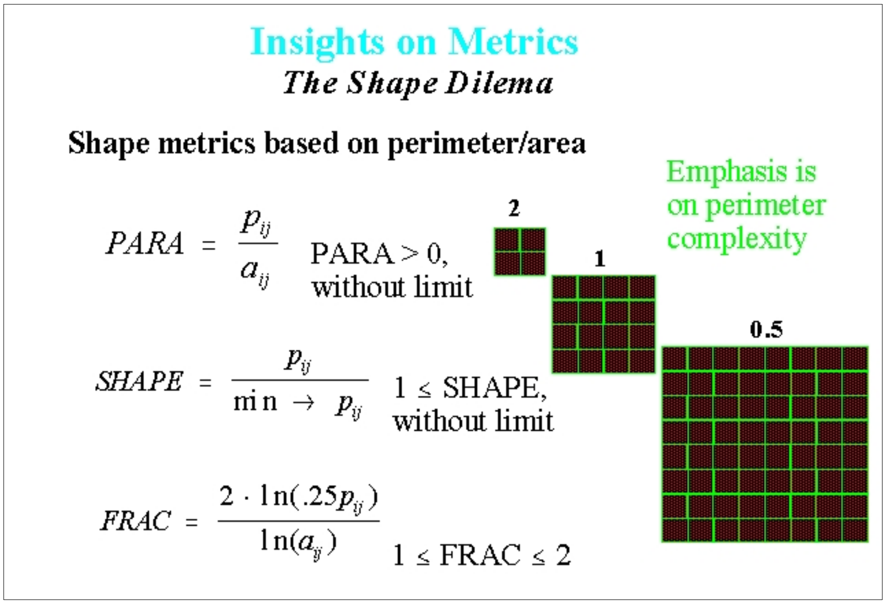
Background.--The interaction of patch shape and size can influence a number of important ecological processes. Patch shape has been shown to influence inter-patch processes such as small mammal migration (Buechner 1989) and woody plant colonization (Hardt and Forman 1989), and may influence animal foraging strategies (Forman and Godron 1986). However, the primary significance of shape in determining the nature of patches in a landscape seems to be related to the 'edge effect' (see discussion of edge effects for Area/Density/Edge Metrics). Shape is a difficult parameter to quantify concisely in a metric for the reasons discussed below.



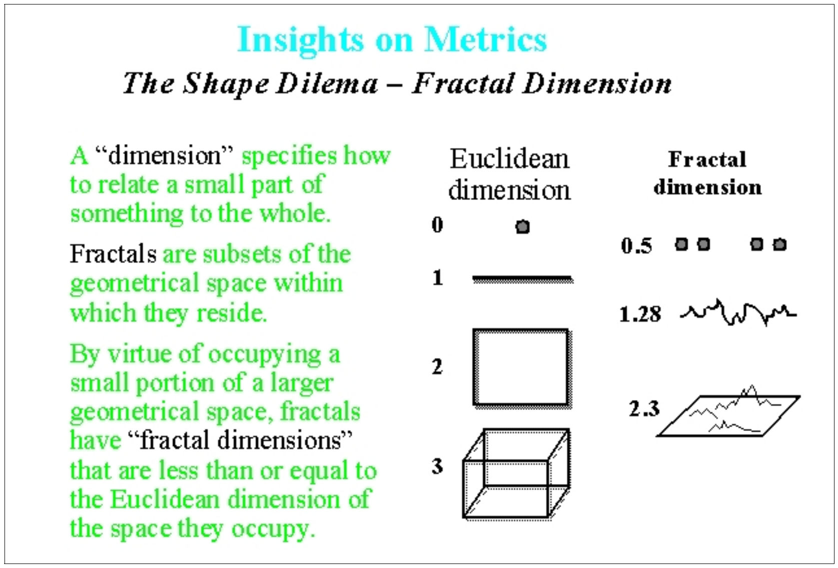
FRAGSTATS Metrics.--FRAGSTATS computes several metrics that quantify landscape configuration in terms of the complexity of patch shape at the patch, class, and landscape levels. Most of these shape metrics are based on perimeter-area relationships. Perhaps the simplest shape index is a straightforward perimeter-area ratio (PARA). A problem with this metric as a shape index is that it varies with the size of the patch. For example, holding shape constant, an increase in patch size will cause a decrease in the perimeter-area ratio. Patton (1975) proposed a diversity index based on shape for quantifying habitat edge for wildlife species and as a means for comparing alternative habitat improvement efforts (e.g., wildlife clearings). This *shape index* (SHAPE) measures the complexity of patch shape compared to a standard shape (square) of the same size, and therefore alleviates the size dependency problem of PARA. This shape index is widely applicable in landscape ecological research (Forman and Godron 1986).



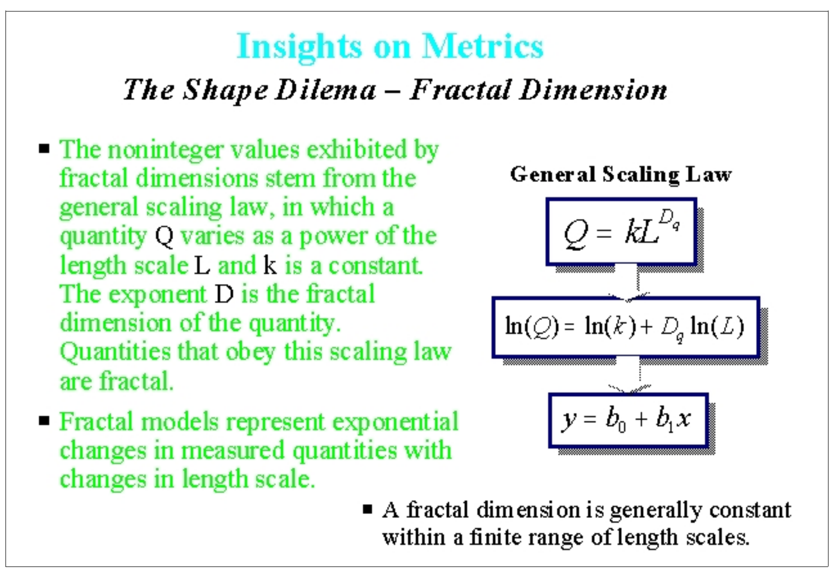
Another other basic type of shape index based on perimeter-area relationships is the fractal dimension index. In landscape ecological research, patch shapes are frequently characterized via the *fractal dimension* (Krummel et al. 1987, Milne 1988, Turner and Ruscher 1988, Iverson 1989, Ripple et al. 1991). The appeal of fractal analysis is that it can be applied to spatial features over a wide variety of scales. Mandelbrot (1977, 1982) introduced the concept of fractal, a geometric form that exhibits structure at all spatial scales, and proposed a perimeter-area method to calculate the fractal dimension of natural planar shapes. The perimeter-area method quantifies the degree of complexity of the planar shapes. The degree of complexity of a polygon is characterized by the fractal dimension (D), such that the perimeter (P) of a patch is related to the area (A) of the same patch by $P \approx \sqrt{A}^D$ (i.e., log P ≈ ½D



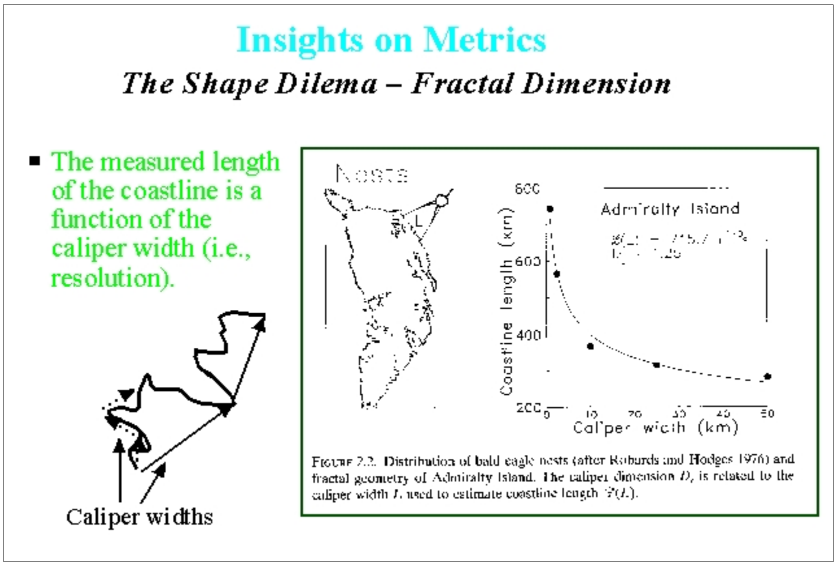
log A). For simple Euclidean shapes (e.g., circles and rectangles), $P \approx \sqrt{A}$ and D = 1 (the dimension of a line). As the polygons become more complex, the perimeter becomes increasingly plane-filling and $P \approx A$ with $D \rightarrow 2$. Although fractal analysis typically has not been used to characterize individual patches in landscape ecological research, we use this relationship to calculate the fractal dimension of each patch separately. Note that the value of the fractal dimension calculated in this manner is dependent upon patch size and/or the units used (Rogers 1993). Thus, varying the cell size of the input image will affect the patch fractal dimension. Therefore, caution should be exercised when using this fractal dimension index as a measure of patch shape complexity.

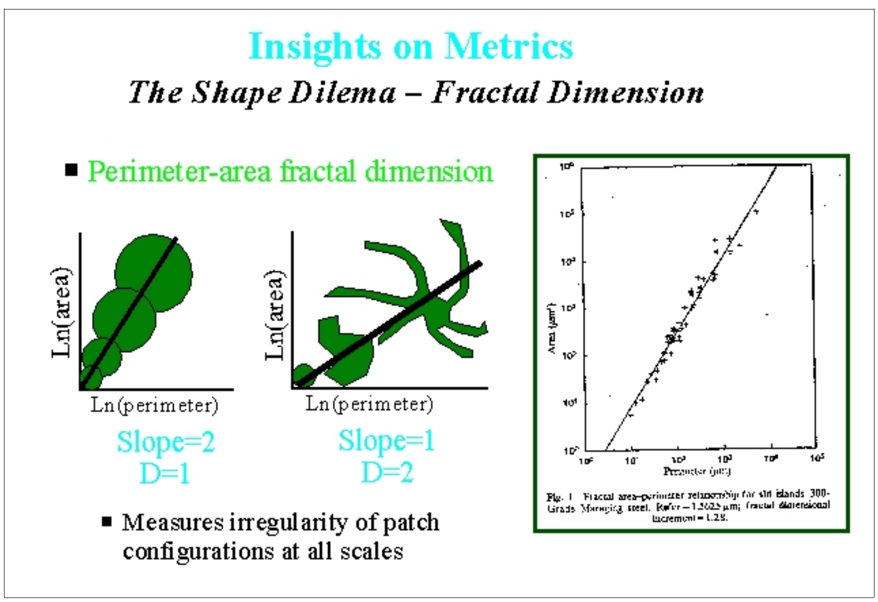


Fractal analysis usually is applied to the entire landscape mosaic using the perimeter-area relationship $A = k\,P^{2/D}$, where k is a constant (Burrough 1986). If sufficient data are available, the slope of the line obtained by regressing log(P) on log(A) is equal to 2/D (Burrough 1986). Note, fractal dimension computed in this manner is equal to 2 divided by the slope; D is not equal to the slope (Krummel et al. 1987) nor is it equal to 2 times the slope (e.g., O'Neill et al. 1988, Gustafson and Parker 1992). We refer to this index as the *perimeter-area fractal dimension* (PAFRAC) in FRAGSTATS. Because this index employs regression analysis, it is subject to spurious results when sample sizes are small. In landscapes with only a few patches, it is not unusual to get values that greatly exceed the theoretical limits of this index. Thus, this index is probably only useful if sample sizes are large (e.g., n > 20; although PAFRAC is computed in FRAGSTATS if $n \geq 10$). If insufficient data are available, an alternative to the regression approach is to



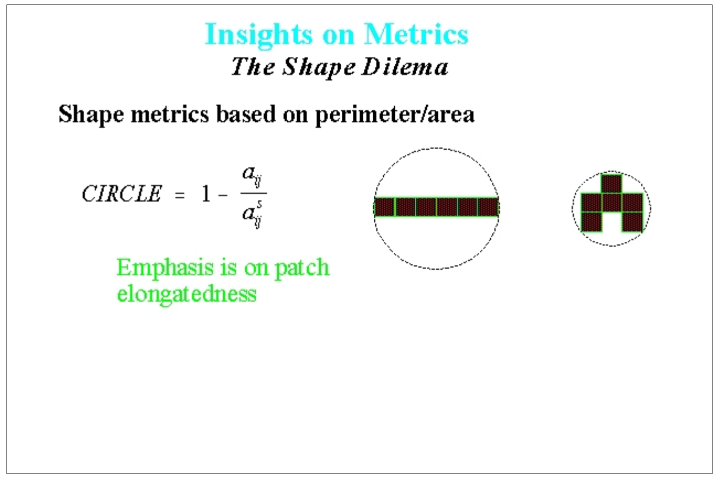
calculate the *mean patch fractal dimension* (FRAC_MN) based on the fractal dimension of each patch, or the *area-weighted mean patch fractal dimension* (FRAC_AM) at the class and landscape levels by weighting patches according to their size, although these metrics do not have the same interpretation or utility as PAFRAC. In contrast to the fractal dimension of a single patch, which provides an index of shape complexity for that patch, the perimeter-area fractal dimension of a patch mosaic provides an index of patch shape complexity across a wide range of spatial scales (i.e., patch sizes). Specifically, it describes the power relationship between patch area and perimeter, and thus describes how patch perimeter increases per unit increase in patch area. If, for example, small and large patches alike have simple geometric shapes, then PAFRAC will be relatively low, indicating that patch perimeter increases relatively slowly as patch area increases. Conversely, if small and large patches have complex shapes, then PAFRAC will be much higher, indicating that patch perimeter increases more rapidly as patch area increases–reflecting a consistency of complex patch shapes across spatial scales. The fractal dimension of patch shapes, therefore, is suggestive of a common ecological process or anthropogenic influence affecting patches across a wide range of scales, and differences between landscapes can suggest differences in the underlying pattern-generating process (e.g., Krummel 1987).





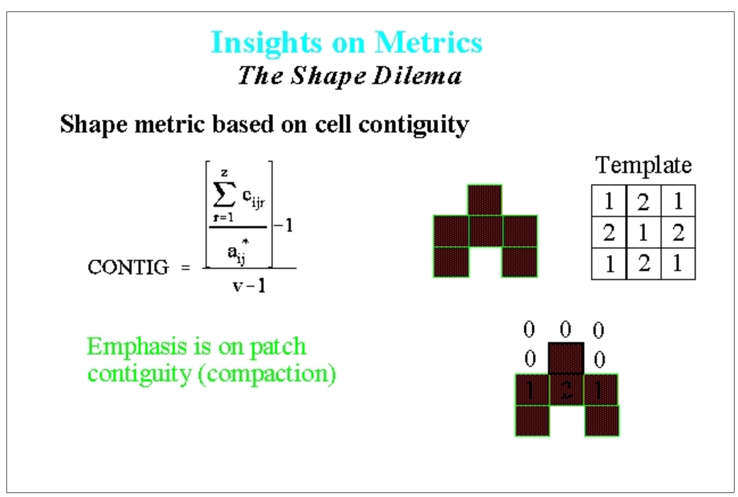
An alternative method of assessing shape is based is based on the medial axis transformation (MAT) of the patch (Gustafson and Parker 1992). The MAT skeleton is derived from a depth map of the patch, where each pixel value represents the distance (in pixels) to the nearest edge.

The MAT skeleton is then produced by removing all pixels from the depth map except local maxima (pixels with no neighbors having greater values). The *linearity index* (LINEAR) is based on the fact that elongated patches of a given area have MAT skeletons closer to their edges than square patches of the same area. This index reflects linear features of the patch which may not necessarily be the overall elongation of the patch. Dendritic patterns result in higher values of LINEAR due to the elongated appendages of the patch. Inflated values may also result from patches with even small interior openings since these represent edge, and the MAT skeleton will surround the openings, resulting in lower MAT values than if the openings were not present.



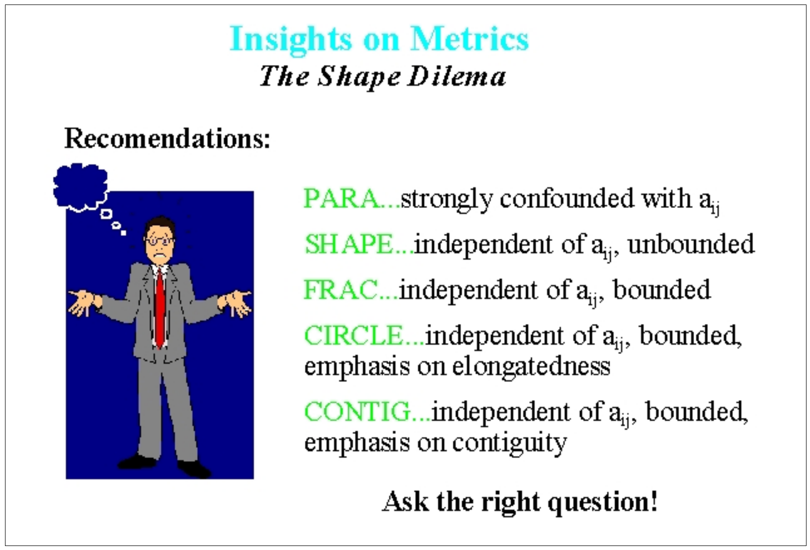
Another method of assessing shape is based on ratio of patch area to the area of the smallest circumscribing square. *Related circumscribing circle* (CIRCLE) (Baker and Cai 1992). In contrast to the linearity index, related circumscribing square provides a measure of overall patch elongation. A highly convoluted but narrow patch can have a high linearity index if the medial axial skeleton is close to the patch edge, but have a low related circumscribing square index due to the relative compactness of the patch. Conversely, a narrow and elongated patch can have a high linearity index as well as a high related circumscribing square index. This index may be particularly useful for distinguishing patches that are both linear (narrow) and elongated.

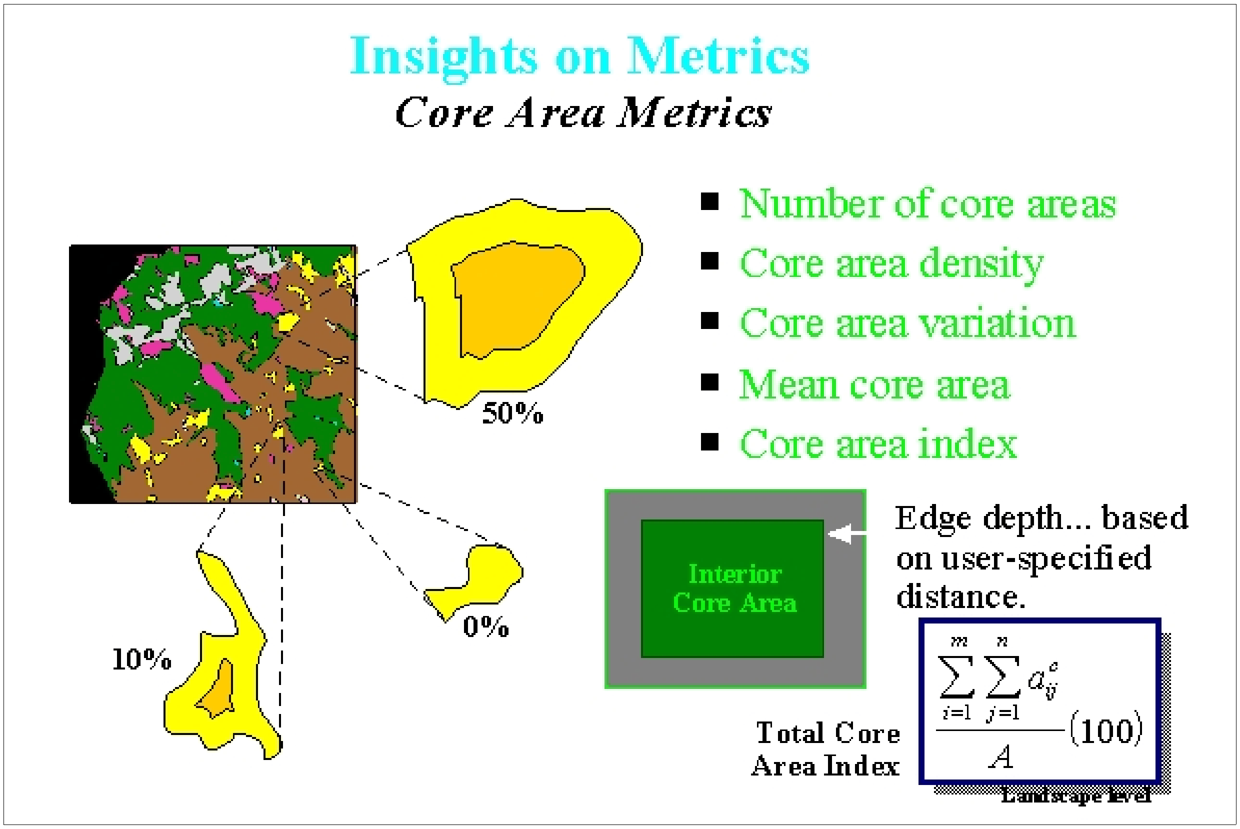
A final method of assessing patch shape is based on the spatial connectedness, or contiguity, of cells within a grid-cell patch to provide an index on patch boundary configuration and thus patch shape (LaGro 1991). *Contiguity index* (CONTIG) is quantified by convolving a 3x3 pixel template with a binary digital image in which the pixels within the patch of interest are assigned a value of 1 and the background pixels (all other patch types) are given a value of zero. A template value of 2 is assigned to quantify horizontal and vertical pixel relationships within the image and a value of 1 is assigned to quantify diagonal relationships. This combination of integer values weights orthogonally contiguous pixels more heavily than diagonally contiguous pixels, yet keeps computations relatively simple. The



center pixel in the template is assigned a value of 1 to ensure that a single-pixel patch in the output image has a value of 1, rather than 0. The value of each pixel in the output image, computed when at the center of the moving template, is a function of the number and location of pixels, of the same class, within the nine cell image neighborhood. Specifically, the contiguity value for a pixel in the output image is the sum of the products, of each template value and the corresponding input image pixel value, within the nine cell neighborhood. Thus, large contiguous patches result in larger contiguity index values.

Limitations.--All shape indices based on perimeter-area relationships have important limitations. First, perimeter lengths are biased upward in raster images because of the stair-stepping pattern of line segments, and the magnitude of this bias varies in relation to the grain or resolution of the image. Thus, the computed perimeter-area ratio will be somewhat higher than it actually is in the real-world. Second, as an index of "shape", the perimeter-to-area ratio method is relatively insensitive to differences in patch morphology. Thus, although patches may possess very different shapes, they may have identical areas and perimeters. For this reason, shape indices based on perimeter-area ratios are not useful as measures of patch morphology; they are best considered as measures of overall shape complexity. Alternative indices of shape that are not based on perimeter-area rations are less troubled by these limitations. But these too, generally do not distinguish patch morphology, but instead emphasize one or more aspects of shape complexity (e.g., elongation).



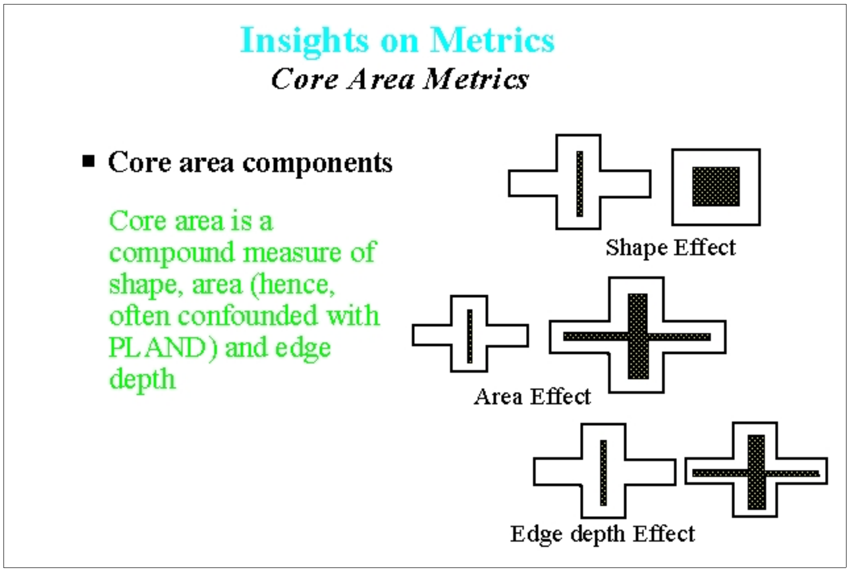


4. Core Area Metrics

<u>Background</u>.– Core area is defined as the area within a patch beyond some specified depth-of-edge influence (i.e., edge distance) or buffer width. Like patch shape, the primary significance of core area in determining the character and function of patches in a landscape appears to be related to the 'edge effect.' As discussed elsewhere (see Area/Density/Edge Metrics), edge effects result from a combination of biotic and abiotic factors that alter environmental conditions along patch edges compared to patch interiors. The nature of the edge effect differs among organisms and ecological processes (Hansen and di Castri 1992). For example, some bird species are adversely affected by predation, competition, brood parasitism, and perhaps other factors along forest edges. Core area has been found to be a much better predictor of habitat quality than patch area for these forest interior specialists (Temple 1986). Unlike patch area, core area is affected by patch shape. Thus, while a patch may be large enough to support a given species, it still may not contain enough suitable core area to support the species. In some cases, it seems likely that edge effects would vary in relation to the type and nature of the edge (e.g., the degree of floristic and structural contrast and orientation). Thus, FRAGSTATS allows the user to specified an edge depth file that contains edge influence distances for every pairwise combination of patch types. In the absence of such information, the user can specify a single edge depth for all edge types.

In raster images, there are different ways to determine core area. FRAGSTATS employs a method involving the use of a variably-sized masked placed on cells on the perimeter of a patch, where the mask size varies depending the specified edge depth associated with the corresponding combination of patch types. Actually, the mask is placed over cells just outside the patch perimeter; referred to here as 'bounding' cells. Briefly, a mask is placed over each bounding cell. The mask itself is near circular in shape (as circular as you can get in the raster world) and sized according to the specified edge depth. Note, the resolution of the mask is constrained by cell size; thus, the mask is rounded up or down to the nearest cell given the specified edge depth. For example, given a 30 m cell size and a specified edge depth of 50 m, the mask will be rounded up to 2 cells (60 m) wide in the orthogonal directions. The non-orthogonal directions will be rounded similarly, producing a near circular mask. Cells within the mask are eliminated from the 'core' of the patch. After all bounding cells are treated in this manner, the remaining cells not masked constitute the 'core' of the patch.

<u>FRAGSTATS Metics</u>.--FRAGSTATS computes several metrics based on core area at the patch, class, and landscape levels. Most of the indices dealing with number or density of patches, size of patches, and variability in patch size have corresponding core area indices computed in the same manner after eliminating the specified edge from all patches. For example, patch area, class area, total landscape area, and the percentage of landscape in each patch type all have counterparts computed after eliminating edge area defined by the specified edge depth; these are *core area* (CORE) at the patch level, *total core area* (TCA) at the class and landscape levels, and *core area percent of landscape* (CPLAND) at the class level. The latter index quantifies the core area in each patch type as a percentage of total landscape area. For organisms strongly associated with patch interiors, this index may provide a better measure of habitat availability than its counterpart, *percentage of landscape* (PLAND). In contrast to their counterparts, these core area indices integrate into a single measure the affects of patch area, patch shape, and edge effect distance. Therefore, although they quantify landscape composition, they are affected by landscape configuration. For this reason, these metrics at the class level may be useful in the study of habitat loss and fragmentation.



From an organism-centered perspective, a single patch may actually contain several disjunct patches of suitable interior habitat, and it may be more appropriate to consider disjunct core areas as separate patches. For this reason, FRAGSTATS computes the *number of core areas*

(NCORE) in each patch, as well as the number in each class and the landscape as a whole (NDCA). If core area is deemed more important than total area, then these indices may be more applicable than their counterparts, but they are subject to the same limitations as their counterparts (number of patches) because they are not standardized with respect to area. For this reason, number of core areas can be reported on a per unit area basis (*disjunct core area density*, DCAD) that has the same ecological applicability as its counterpart (patch density), except that all edge area is eliminated from consideration. Conversely, this information can be represented as mean core area (CORE_MN). Like their counterparts, note the difference between core area density and mean core area at the class level. Specifically, core area density is based on total landscape area; whereas, mean core area is based on total core area for the class. In contrast, at the landscape level, they are both based on total landscape area and are therefore completely redundant (at least if the landscape contains no background). Furthermore, mean core area can be defined in 2 ways. First, mean core area can be defined as the *mean core area per patch* (CORE_MN). Thus, patches with no core area are included in the average, and the total core area in a patch is considered together as 1 observation, regardless of whether the core area is contiguous or divided into 2 or more disjunct areas within the patch. Alternatively, mean core area can be defined as the *mean area per disjunct core* (DCORE_MN). The distinction between these 2 ways of defining mean core area should be noted.

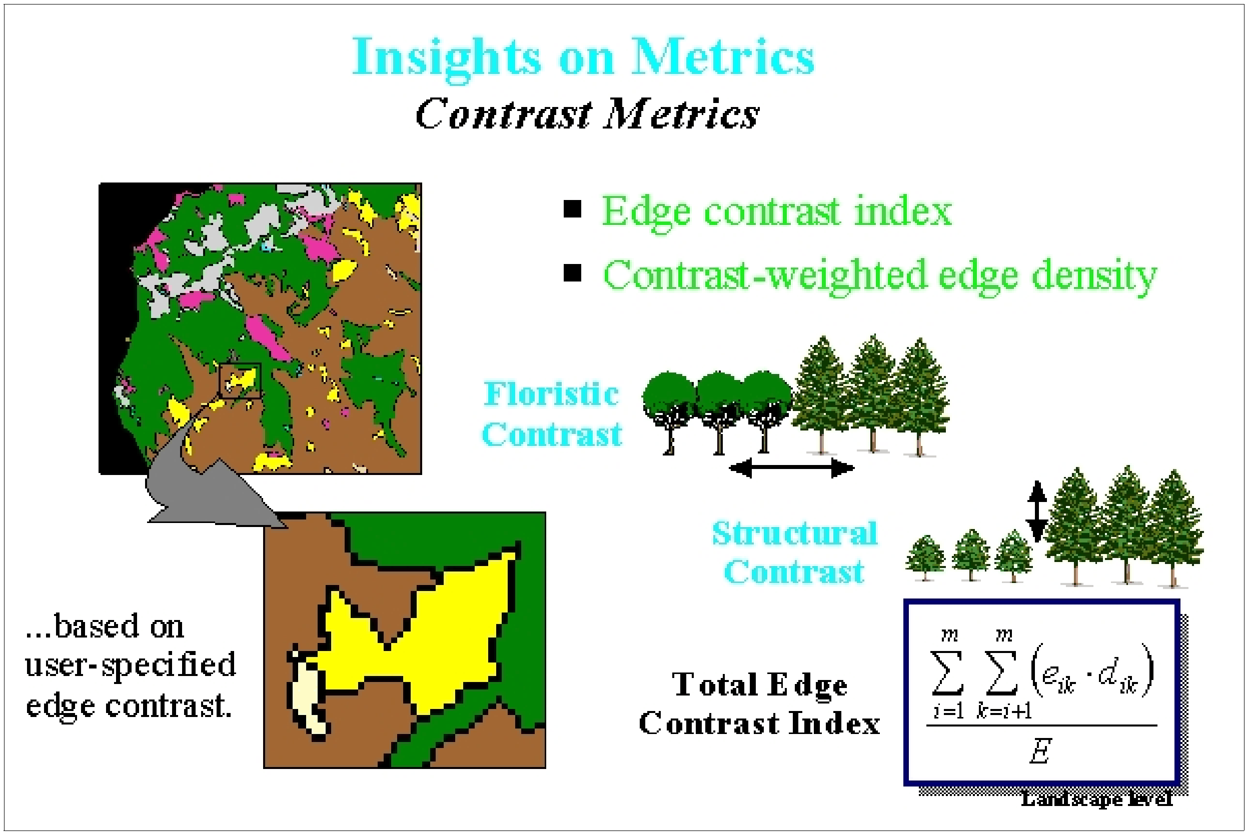
FRAGSTATS also computes an index that quantifies core area as a percentage of total area. The *core area index* (CAI) at the patch level quantifies the percentage of the patch that is comprised of core area. Similarly, at the class and landscape levels *core area index area-weighted mean* (CAI_AM) quantifies core area for the entire class or landscape as a percentage of total class or landscape area, respectively. Note, that this is equivalent to the *total core area index* reported in FRAGSTATS 2.0. The core area index is basically an edge-to-interior ratio like many of the shape indices (see Shape Metrics), the main difference being that the core area index treats edge as an area of varying width and not as a line (perimeter) around each patch. In addition, the core area index is a relative measure; it does not reflect patch size, class area, or total landscape area; it merely quantifies the percentage of available area, regardless of whether it is 10 ha or 1,000 ha, comprised of core. This index does not confound area and configuration like the previous core area indices; rather, it isolates the configuration effect. For this reason, the core area index is probably best interpreted in conjunction with total area at the corresponding scale. For example, in conjunction with total class area, this index could serve as an effective fragmentation index for a particular class.

An alternative method of assessing core area is based is based on the medial axis transformation (MAT) of the patch (Gustafson and Parker 1992). The MAT skeleton is derived from a depth map of the patch, where each pixel value represents the distance (in pixels) to the nearest edge. The MAT skeleton is then produced by removing all pixels from the depth map except local maxima (pixels with no neighbors having greater values). The resulting MAT skeleton gives the depth to the extreme core of the patch. As such, it provides explicit information on how far the 'core' of the patch is from the nearest edge. The *average depth index* (ADEPTH) and *maximum depth index* (MDEPTH) provide two different ways to summarize the depth of the MAT skeleton. Like most other core area metrics, indices based on the MAT skeleton integrate the effects of patch area and shape. Holding area constant, more convoluted shapes will tend to have

MAT skeletons closer to the perimeter. Similarly, holding shape constant, larger patches will have MAT skeletons farther from the perimeter. However, in contrast to all other core area metrics, metrics based on the MAT skeleton do not depend on user-specified edge depths. Thus, the ecological interpretation of these metrics is done after-the-fact based on the ecological phenomena under consideration; whereas the functional relevance of edge effects is explictly incorporated into the edge depths used in all other core area metrics.

Limitations.--All core area indices are affected by the interaction of patch size, patch shape, and the specified edge depths, except for those based on the MAT skeleton as noted above. In particular, increasing edge depths or shape complexity, or decreasing patch size will decrease core area, and vice versa. On the one hand, this may be desirable as an integrative measure that has explicit functional relevance to the organism or process under consideration. On the other hand, there are potential pitfalls associated with integrative measures like core area. In particular, the confounding of patch area and configuration effects can complicate interpretation. For example, if the core area is small, it indicates that very little core area is available, but it does not discriminate between a small patch (area effect) and a large patch with a complex shape (configuration effect). In addition, core area is meaningful only if the specified depth-of-edge distance is meaningful to the phenomenon under investigation. Unfortunately, in many cases there is no empirical basis for specifying any particular depth-of-edge effect and so it must be chosen somewhat arbitrarily. The usefulness of core area as a metric is directly related to the arbitrariness in the specified edge depths, and this should be clearly understood when using these metrics.

Ultimately, the utility of core area metrics compared to their patch area counterparts depends on the resolution, minimum patch dimensions, and edge influence distance(s) employed. For example, given a landscape with a resolution of 1 m^2 and minimum patch dimensions of 100 x 100 m, if an edge influence distance of 1 m is specified, then core area and patch area will be nearly identical and core area will be relatively insensitive to differences in patch size and shape. In this case, core area offers little over its patch area counterpart.



5. Contrast Metrics

Background.--Contrast refers to the magnitude of difference between adjacent patch types with respect to one or more ecological attributes at a given scale that are relevant to the organism or process under consideration. The contrast between a patch and its neighborhood can influence a number of important ecological processes (Forman and Godron 1986). The 'edge effects' described elsewhere (see Area/Density/Edge Metrics), for example, are influenced by the degree of contrast between patches. Microclimatic changes (e.g., wind, light intensity and quality, etc.) are likely to extend farther into a patch along an edge with high structural contrast than along an edge with low structural contrast (Ranney et al. 1981). Similarly, the adverse affects of brown-headed cowbird nest parasitism on some forest-dwelling neotropical migratory bird species are likely to be greatest along high-contrast forest edges (e.g., between mature forest patches and grassland), because cowbirds prefer to forage in early-seral habitats and parasitize nests in late-seral habitats (Brittingham and Temple 1983). In addition, patch isolation may be a function of the contrast between a patch and its ecological neighborhood. In particular, the degree of contrast between a habitat patch and the surrounding landscape may influence dispersal patterns and survival, and thus indirectly affect the degree of patch isolation. Similarly, an organism's ability to use the resources in adjacent patches, as in the process of landscape supplementation (Dunning et al. 1992), may depend on the nature of the boundary between the patches. The boundary between patches can function as a barrier to movement, a differentially-permeable membrane that facilitates some ecological flows but impedes others, or as a semipermeable membrane that partially impairs flows (Wiens et al. 1985, Hansen and di Castri 1992). The contrast along an edge may influence its function in this regard. For example, high-contrast edges may prohibit or inhibit some organisms from seeking supplementary resources in surrounding patches. Conversely, some species (e.g., great horned owl, *Bubo virginianus*) seem to prefer the juxtaposition of patch types with high contrast, as in the process of landscape complementation (Dunning et al. 1992).

Insights on Metrics

Establishing Contrast Weights

For example, each patch type is assigned a score (1-10) for each of four factors (vegetation structure, floristics, wetness, and hydrology), where appropriate.

Community contrast key:

value	Structure	Floristics	Wetness	Hydrology	value
	(short)	**(deciduous)**	**(dry)**	**(still)**	
1	unvegetated	pure deciduous	xeric	stagnant	1
2	lichen or moss			still	2
3	herbaceous		mesic		3
4				slow flow	4
5	shrub	mixed	temporarily saturated		5
6					6
7	tree: open canopy		temporarily flooded	moderate flow	7
8					8
9			permanently flooded		9
10	tree: closed canopy	pure coniferous	deepwater	fast flow	10
	(tall)	**(coniferous)**	**(wet)**	**(fast)**	

Clearly, edge contrast can assume a variety of meanings for different ecological processes. Therefore, contrast can be defined in a variety of ways, but it always reflects the magnitude of difference between patches with respect to one or more ecological attributes at a given scale that are important to the phenomenon under investigation (Kotliar and Wiens 1990, Wiens et al. 1985). Similar to Romme (1982), FRAGSTATS employs weights to represent the magnitude of edge contrast between adjacent patch types; weights must range between 0 (no contrast) and 1 (maximum contrast). Under most circumstances, it is probably not valid to assume that all edges function similarly. Often there will not be a strong empirical basis for establishing a weighting scheme, but a reasoned guess based on a theoretical understanding of the phenomenon is probably better than assuming all edges are alike. For example, from an avian habitat use standpoint, we might weight edges somewhat subjectively according to the degree of structural and floristic contrast between adjacent patches,

Insights on Metrics

Establishing Contrast Weights

Next, each patch type is assigned a score (1-10) for each of four factors (vegetation structure, floristics, wetness, and hydrology), where appropriate.

Code	Natural Community		Structure	Floristics	Wetness	Hydro.
		Weight:	4	1	3	1
100	**FORESTS**		8	*	2	*
110 111	**Deciduous forest**		8	2	2	*
120 121	**Mixed forest**		8	5	2	*
130 131	**Coniferous forest**		9	8	2	*
190 191	**Forested wetland**		7	*	7	1
200	**NONFORESTED UPLANDS**		3	*	1	*
210	**Shrubland**		5	5	1	*
211	Powerline shrubland		4	*	*	*
212	Old field		5	*	*	*
220 221	**Grasslands** Cultural grassland		3	*	2	*
230 231	**Cliffs & steep slopes**		2	*	1	*

because a number of studies have shown these features to be important to many bird species (Thomas et al. 1978 and 1979, Logan et al. 1985).

Insights on Metrics

Establishing Contrast Weights

Finally, the contrast between each pair of patch types is computed empirically based on the weighted Euclidean distance among the vegetation and hydrography factors.

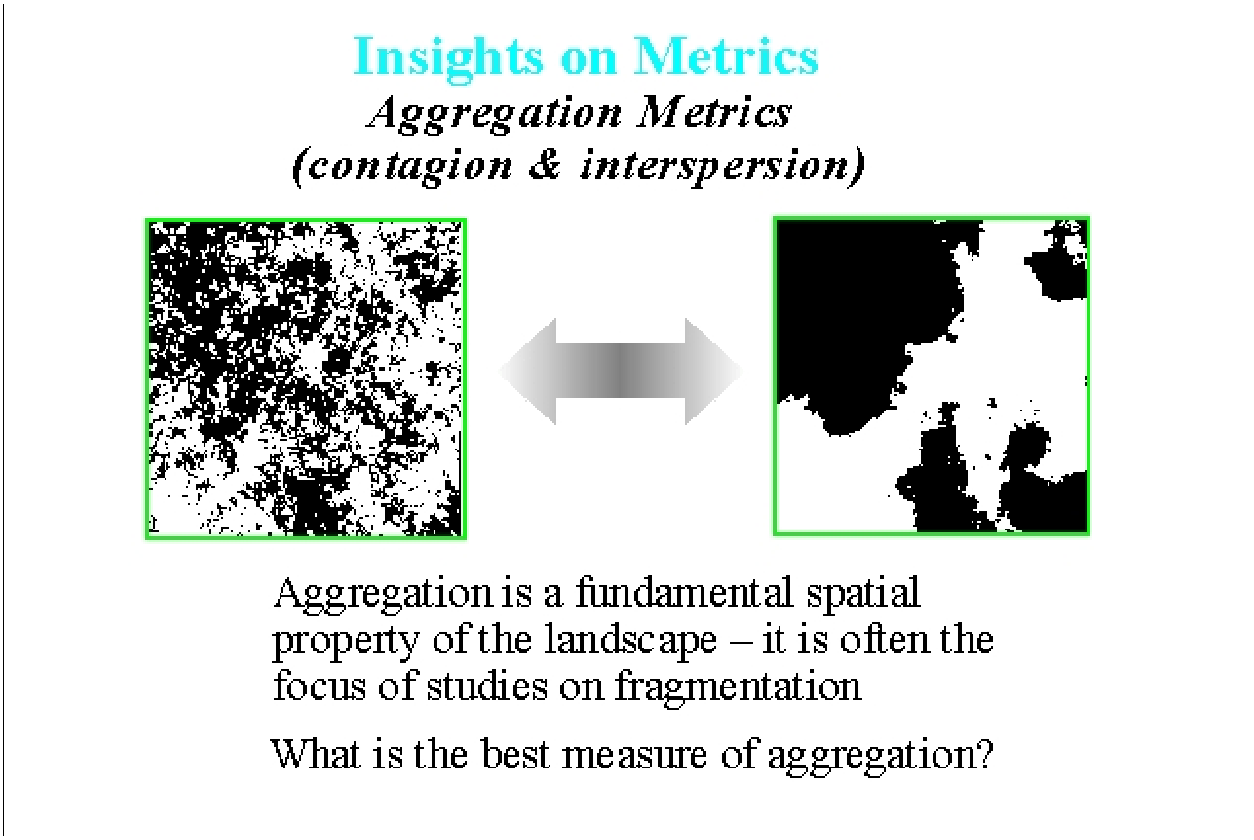
	High-intens	Low-intens	High-densit	Low-densit	Agriculture	Dam (large	Dam (medi	Dam (smal	Dam (non-j	Expresswa
Deciduous forest	0.62	0.62	0.62	0.09	0.44	0.62	0.62	0.62	0.62	0.62
Mixed forest	0.62	0.62	0.62	0.09	0.44	0.62	0.62	0.62	0.62	0.62
Coniferous forest	0.71	0.71	0.71	0.18	0.53	0.71	0.71	0.71	0.71	0.71
Forested wetland	0.66	0.63	0.63	0.33	0.48	0.66	0.66	0.66	0.66	0.66
Powerline shrubland	0.38	0.38	0.38	0.38	0.13	0.38	0.38	0.38	0.38	0.38
Old field	0.50	0.50	0.50	0.25	0.25	0.50	0.50	0.50	0.50	0.50
Cultural grassland	0.19	0.18	0.18	0.35	0.00	0.19	0.19	0.19	0.19	0.19
Cliff and steep slope	0.09	0.11	0.11	0.45	0.11	0.09	0.09	0.09	0.09	0.09
Shrub swamp	0.58	0.53	0.53	0.44	0.44	0.58	0.58	0.58	0.58	0.58
Emergent marsh	0.56	0.50	0.50	0.58	0.46	0.56	0.56	0.56	0.56	0.56
Pond	0.60	0.53	0.53	0.75	0.56	0.60	0.60	0.60	0.60	0.60
Vernal pool	0.62	0.62	0.62	0.09	0.44	0.62	0.62	0.62	0.62	0.62
Lake	0.60	0.53	0.53	0.75	0.56	0.60	0.60	0.60	0.60	0.60
First order flatwater	0.75	0.66	0.66	0.66	0.66	0.75	0.75	0.75	0.75	0.75
First order pool-riffle	0.75	0.66	0.66	0.66	0.66	0.75	0.75	0.75	0.75	0.75
First order plane-bed	0.75	0.66	0.66	0.66	0.66	0.75	0.75	0.75	0.75	0.75
First order step-pool	0.75	0.66	0.66	0.66	0.66	0.75	0.75	0.75	0.75	0.75
First order cascade	0.75	0.66	0.66	0.66	0.66	0.75	0.75	0.75	0.75	0.75

FRAGSTATS Metrics.–FRAGSTATS computes several indices based on edge contrast at the patch, class, and landscape levels. At the patch level, the *edge contrast index* (ECON) measures the degree of contrast between a patch and its immediate neighborhood. Each segment of the patch perimeter is weighted by the degree of contrast with the adjacent patch. Total patch perimeter is reduced proportionate to the degree of contrast in the perimeter and reported as a percentage of the total perimeter. Thus, a patch with a 10% edge contrast index has very little contrast with its neighborhood; it has the equivalent of 10% of its perimeter in maximum-contrast edge. Conversely, a patch with a 90% edge contrast index has high contrast with its neighborhood. Note that this index is a relative measure. Given any amount of edge, it measures the degree of contrast in that edge. In other words, high values of ECON mean that the edge present, regardless of whether it is 10 m or 1,000 m, is of high contrast, and vice versa. At the class and landscape levels, FRAGSTATS computes a *total edge contrast index* (TECI). Like its patch-level counterpart, this index quantifies edge contrast as a percentage of maximum possible. However, this index ignores patch distinctions; it quantifies edge contrast for the landscape as a whole. FRAGSTATS also computes distribution statistics for the edge contrast index at the class and landscape levels. The *mean edge contrast index* (ECON_MN), for example, quantifies the average edge contrast for patches of a particular patch type (class level) or for all patches in the landscape.

These edge contrast indices are relative measures. Given any amount or density of edge, they measure the degree of contrast in that edge. High values of these indices mean that the edge present, regardless of whether it is 10 m or 1,000 m, is of high contrast, and vice versa. For this reason, these indices are probably best interpreted in conjunction with total edge or edge density. Because of this, FRAGSTATS also computes an index that incorporates both edge density and edge contrast in a single index. *Contrast-weighted edge density* (CWED) standardizes edge to a per unit area basis that facilitates comparison among landscapes of varying size. Unlike edge density, however, this index reduces the length of each edge segment proportionate to the degree of contrast. Thus, 100 m/ha of maximum-contrast edge (i.e., weight = 1) is unaffected; but 100 m/ha of edge with a contrast weight of 0.2 is reduced by 80% to 20 m/ha of contrast-weighted edge. This index measures the equivalent maximum-contrast edge density. For example, an edge density of 100 means that there are 100 meters of edge per hectare in the landscape. A contrast-weighted edge density of 80 for the same landscape means that there are an equivalent of 80 meters of maximum-contrast edge per hectare in the landscape. A landscape with 100 m/ha of edge and an average contrast weight of 0.8 would have twice the contrast-weighted edge density (80 m/ha) as a landscape with only 50 m/ha of edge but with the same average contrast weight (40 m/ha). Thus, both edge density and edge contrast are reflected in this index. For many ecological phenomena, edge types function differently. Consequently, comparing total edge density among landscapes may be misleading because of differences in edge types. This contrast-weighted edge density index attempts to quantify edge from the perspective of its functional significance. Thus, landscapes with the same contrast-weighted edge density are presumed to have the same total magnitude of edge effects from a functional perspective.

All edge contrast indices consider landscape boundary and background segments even if they have an edge contrast weight of zero. In the absence of a landscape border, the landscape boundary is assigned as background edge and treated according to the background contrast weight specified in the contrast weight file. In the presence of a landscape border, all landscape boundary edges are made explicit by the information present in the border and are assigned the appropriate contrast weight given in the contrast weight file. Regardless of whether a border is present or not, all background edges, both internal (positively valued) and external (negatively valued), are assigned the background contrast weight specified in the contrast weight file. Assigning a meaningful contrast weight to the boundary and background presents a special challenge because, in practice, background (and the boundary, in the absence of a border) often represents area for which nothing is known. Thus, it can be difficult to assign a single contrast weight that applies equally well to all background/boundary edges. A landscape border is often included to avoid this problem, because all boundary edges are made explicit; however, even a border doesn't eliminate the problem of assigning a weight to background if it exists. The potential severity of the boundary/background problem depends on the size and heterogeneity of the landscape and the extent of background edge. Larger and more heterogeneous landscapes without little or no background will have proportionately less total edge located along the boundary and/or background.

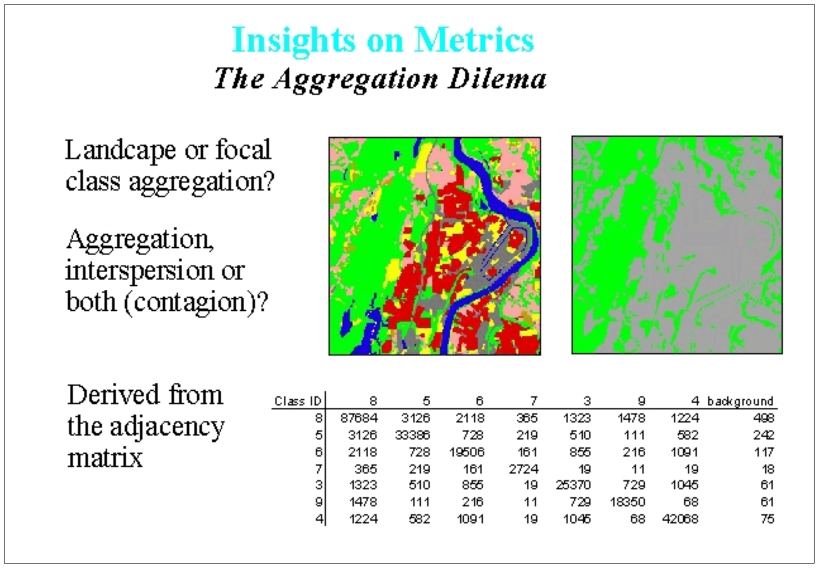
Limitations.–Edge contrast indices are limited by the considerations discussed elsewhere for metrics based on total edge length (see Area/Density/Edge Metrics). These indices are only calculated if an edge contrast weight file is specified. The usefulness of these indices is directly related to the meaningfulness of the weighting scheme used to quantify edge contrast. Careful consideration should be given to devising weights that reflect any empirical and theoretical knowledge and understanding of the phenomenon under consideration. If the weighting scheme does not accurately represent the phenomenon under investigation, then the results will be spurious.



6. Contagion & Interspersion Metrics

Background.–Contagion refers to the tendency of patch types to be spatially aggregated; that is, to occur in large, aggregated or "contagious" distributions. Contagion ignores patches *per se* and refers to the extent to which cells (pixels) of the same class are aggregated together into clumped distributions. Interspersion, on the other hand, refers to the intermixing of patches of different types and is based solely on patch (as opposed to cell) adjacencies. Contagion and interspersion are both aspects of landscape texture; they both reflect the adjacency of patch types, but do so in a different manner. Contagion reflects both the dispersion (i.e., the spatial distribution) and intermixing of patch types, whereas interspersion reflects only the latter. Thus, as a measure of landscape texture, contagion subsumes interspersion.

Contagion is also closely allied to the concept of subdivision. In its narrowest sense, contagion ignores patches *per se* and measures the extent to which cells of similar class are aggregated. In other words, contagion reflects the overall clumpiness of the landscape without explicit reference to the patches. Subdivision, on the other hand, refers explicitly to the degree to which patch types are broken up (i.e., subdivided) into separate patches (i.e., fragments), *not* the shape, relative location, or spatial arrangement of those patches. These differences are subtle, but important–at least computationally, if not conceptually. Contagion (at the landscape level) deals with both the dispersion and interspersion of patch types, while subdivision deals only with the dispersion of patch types, not interspersion. This distinction is relatively straightforward. The confusion between contagion and subdivision lies in how they handle dispersion. Contagion deals specifically with the ‘aggregation’ of patch types; it is affected only by the clumpiness of cells of the same class. Computationally, contagion is computed from the proportion of cell adjacencies that involve the same class (i.e., like-adjacencies); it doesn’t matter what patch a cell belongs to or how many patches there are, only how many of the cell sides are like-adjacencies. Large, compact patches have a high proportion of like-adjacencies and therefore produce high contagion. Conversely, large, but highly convoluted (e.g., linear) patches have a low proportion of like-adjacencies and therefore produce low contagion–despite the similarity in patch sizes. Accordingly, the number and size of disjunct patches–that is, the subdivision of the landscape–affects contagion only indirectly by affecting the proportion of like adjacencies. Thus, contagion reflects the ‘compactness’ of patches, not the number and size of patches *per se*–although in real landscapes compactness and size are often highly correlated. Subdivision, on the other hand, deals with the aggregation of patch types, like contagion, but deals explicitly with the number and size of patches as well. Indeed, the subdivision metrics computed by FRAGSTATS (described below) are based on the cumulative patch size distribution, not cell adjacencies. Large, contiguous patches, even if they are highly elongated or convoluted, are undivided and therefore produce low subdivision. Despite the theoretical and conceptual differences between contagion and subdivision, in practice these two aspects of landscape texture are often highly confounded.

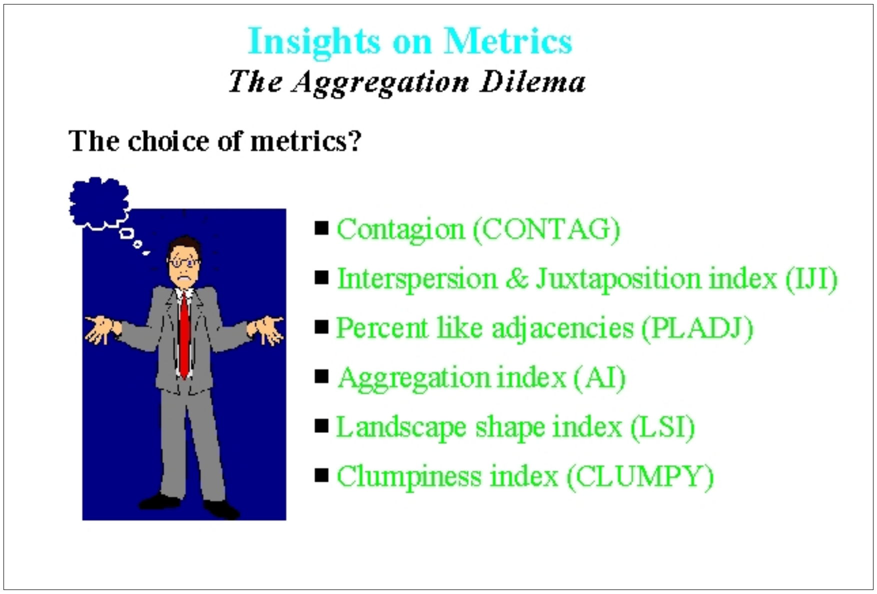


Class ID	8	5	6	7	3	9	4	background
8	87684	3126	2118	365	1323	1478	1224	498
5	3126	33386	728	219	510	111	582	242
6	2118	728	19506	161	855	216	1091	117
7	365	219	161	2724	19	11	19	18
3	1323	510	855	19	25370	729	1045	61
9	1478	111	216	11	729	18350	68	61
4	1224	582	1091	19	1045	68	42068	75

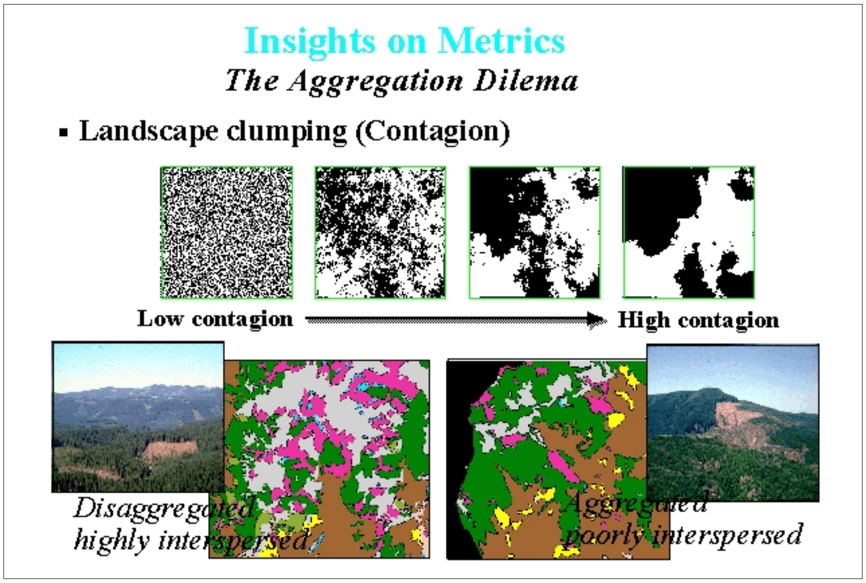
Contagion and interspersion broadly refer to the overall texture of the entire landscape mosaic, as described above. However, contagion and interspersion can be applied at the class level as well, although their meaning changes somewhat. At the class level, interspersion has basically the same interpretation; it refers to the intermixing of the focal patch type with the other patch types. The distinction here is the focus on a single patch type and its adjacencies to other patch types, as opposed to the intermixing of all patches. Similarly, contagion at the class level refers to the tendency of a single focal patch type to be spatially aggregated; that is, to occur in large, aggregated or “contagious” distributions. Here, the distinction between class and landscape levels is important. Recall that at the landscape level, contagion refers to both the dispersion and interspersion of patch types. At the class level, however, contagion refers to the spatial aggregation of the focal patch type without reference to its interspersion. Consequently, measures of class-level contagion are quite different computationally from measures of contagion computed at the landscape level. At the class level, contagion is more closely akin to the concept of subdivision because it deals exclusively with the aggregation or disaggregation (i.e., fragmentation) of the focal class–although the subtle distinction between contagion and subdivision regarding dispersion described above still applies.

The texture of a landscape is a fundamental aspect of landscape pattern and is important in many ecological processes. The subdivision of a patch type of course plays a crucial role in the process of habitat fragmentation. Specifically, habitat fragmentation involves the disaggregation and subdivision of contiguous habitat into disaggregated and/or disjunct patches. As habitat fragmentation proceeds, habitat contagion decreases, habitat subdivision increases, and eventually ecological function is impaired (Saunders et al.1991). Specifically, the subdivision and isolation of populations caused by this fragmentation can lead to reduced dispersal success and patch colonization rates which may result in a decline in the persistence of individual populations and an enhanced probability of regional extinction for entire populations across the landscape (e.g., Lande 1987; With and King 1999a,b; With 1999). In addition, the subdivision and interspersion of patch types may affect the propagation of disturbances across a landscape (Franklin and Forman 1987). Specifically, a patch type that is highly disaggregated and/or subdivided may be more resistant to the propagation of some disturbances (e.g., disease, fire, etc.), and thus more likely to persist in a landscape than a patch type that is highly aggregated and/or contiguous. Conversely, highly disaggregated and/or subdivided patch types may suffer higher rates of disturbance for some disturbance types (e.g. windthrow) than more aggregated and /or contiguous distributions. Similarly, interspersion is presumed to affect the quality of habitat for many species that require different patch types to meet different life history requisites, as in the process of landscape complementation (Dunning et al. 1992). Indeed, the notion of habitat interspersion has had a preeminent role in wildlife management during the past century. Wildlife management efforts are often focused on maximizing habitat interspersion because it is believed that the juxtaposition of different habitats will increase species diversity (Leopold 1933).

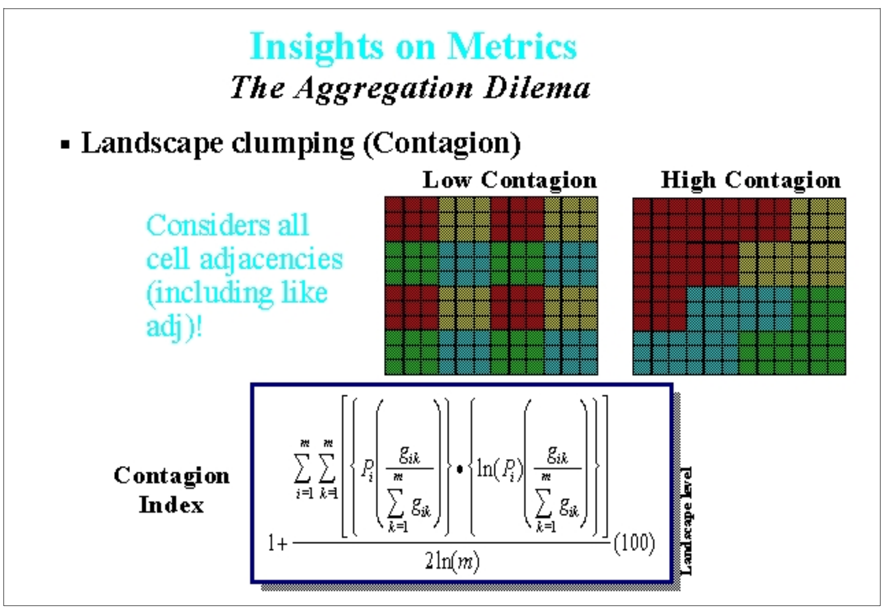
FRAGSTATS Metrics.–There are several different approaches for measuring contagion and interspersion. One popular index that subsumes both dispersion and interspersion is the *contagion index* (CONTAG) based on the probability of finding a cell of type i next to a cell of type j. This index was proposed first by O'Neill et al. (1988) and subsequently it has been widely used (Turner and



Ruscher 1988, Turner 1989, Turner et al. 1989, Turner 1990a and b, Graham et al. 1991, Gustafson and Parker 1992). Li and Reynolds (1993) showed that the original formula was incorrect; they introduced 2 forms of an alternative contagion index that corrects this error and has improved performance. FRAGSTATS computes one of the contagion indices proposed by Li and Reynolds (1993). This contagion index is based on raster "cell" adjacencies, not "patch" adjacencies, and consists of the sum, over patch types, of the product of 2 probabilities: (1) the probability that a randomly chosen cell belongs to patch type i (estimated by the proportional abundance of patch type i), and (2) the conditional probability that given a cell is of patch type i, one of its neighboring cells belongs to patch type j (estimated by the proportional abundance of patch type i adjacencies involving patch type j). The product of these probabilities equals the probability that 2 randomly chosen adjacent cells belong to patch type i and j. This contagion index is appealing because of the straightforward and intuitive interpretation of this probability.



The contagion index has been widely used in landscape ecology because it seems to be an effective summary of overall clumpiness on categorical maps (Turner 1989). In addition, in many landscapes, it is highly correlated with indices of patch type diversity and dominance (Ritters et al. 1995) and thus may be an effective surrogate for those important components of pattern (O'Neill et al. 1996). Contagion measures both patch type interspersion (i.e., the intermixing of units of different patch types) as well as patch dispersion (i.e., the spatial distribution of a patch

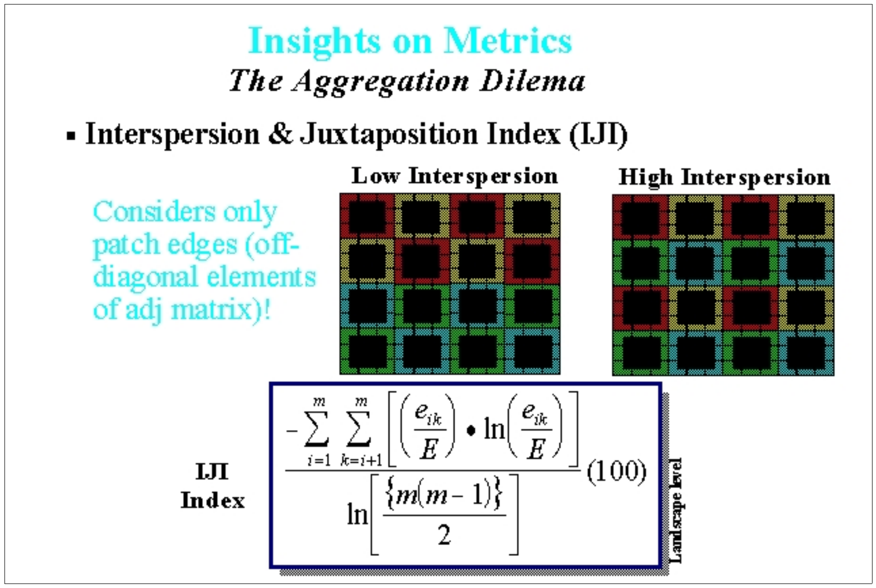


$$1+\frac{\sum_{i=1}^{m}\sum_{k=1}^{m}\left[\left\{P_i\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right\}\bullet\left\{\ln(P_i)\left(\frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}}\right)\right\}\right]}{2\ln(m)}(100)$$

type) at the landscape level. All other things being equal, a landscape in which the patch types are well interspersed will have lower contagion than a landscape in which patch types are poorly interspersed. Contagion measures the extent to which patch types are aggregated or clumped; higher values of contagion may result from landscapes with a few large, contiguous patches, whereas lower values generally characterize landscapes with many small and dispersed patches. Thus, holding interspersion constant, a landscape in which the patch types are aggregated into larger, contiguous patches will have greater contagion than a landscape in which the patch types are fragmented into many small patches. Contagion measures dispersion in addition to patch type interspersion because cells, not patches, are evaluated for adjacency. Landscapes consisting of large, contiguous patches have a majority of internal cells with like adjacencies. In this case, contagion is high because the proportion of total cell adjacencies comprised of like adjacencies is very large and the distribution of adjacencies among edge types is very uneven.

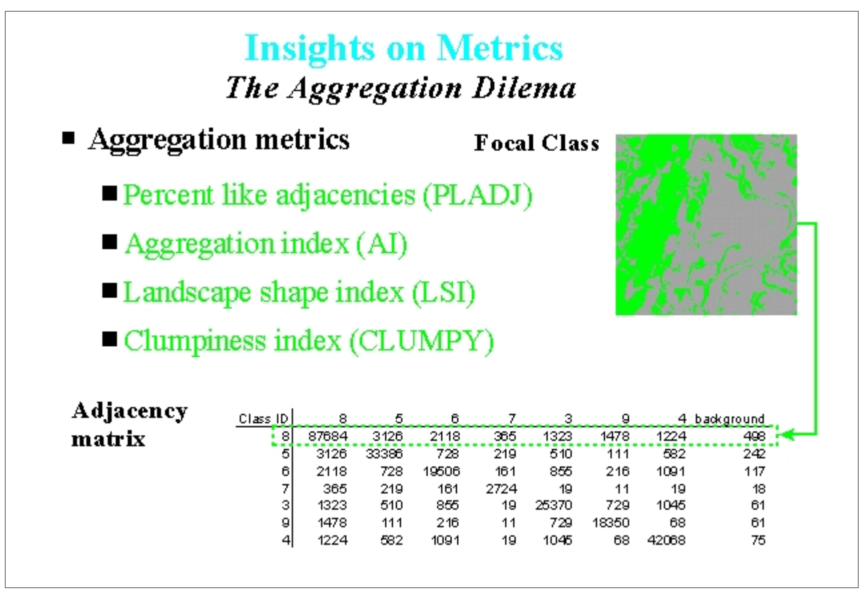
Unfortunately, as alluded to above, there are alternative procedures for computing contagion, and this has contributed to some confusion over the interpretation of published contagion values (see Ritters et al. 1996 for a discussion). Briefly, to calculate contagion, the adjacency of patch types is first summarized in an *adjacency* or *co-occurrence* matrix, which shows the frequency with which different pairs of patch types (including like adjacencies between the same patch type) appear side-by-side on the map (note, FRAGSTATS includes only the 4 orthogonal neighbors, not diagonal neighbors, regardless of the choice of neighbor rules for defining patches). Although this would seem to be a simple task, it is the source of differences among procedures for calculating contagion. The difference arises out of the option to count each immediately-adjacent pixel pair once or twice. In the *single-count* method, each pixel adjacency is counted once and the order of pixels is not preserved; whereas, in the *double-count* method, each pixel adjacency is counted twice and the order of pixels is preserved. Ritters et al. (1996) discuss the merits of both approaches. FRAGSTATS adopts the *double-count* method in which pixel order is preserved, with two exceptions. If a landscape border is present, the adjacencies along the landscape boundary (i.e., those between cells *inside* the landscape and those in the border) are only counted once, and they are tallied for the cells inside the landscape. For example, an adjacency on the landscape boundary between class 2 (inside the landscape) and class -3 (in the landscape border) is recorded as a 2-3 adjacency in the adjacency matrix, not a 3-2. Thus, if a landscape border is present, the adjacency matrix includes double-counts for all internal cell adjacencies and single-counts for all adjacencies on the landscape boundary not involving background. In effect, this gives double the weight to the internal adjacencies than those on the boundary, although the effect will be trivial in most landscapes because the boundary edges will represent a relative minor proportion of the total adjacencies. Similarly, all adjacencies involving background (both internal, i.e., inside the landscape, and external, i.e., on the landscape boundary) are counted only once, and they are tallied for the non-background cells. Essentially, each non-background cell inside the landscape is visited and the four cell sides are evaluated and tallied in the adjacency matrix. Since background cells and all cells in the landscape border, if present, are not visited per se, the edges involving these cells only get tallied once in association with the non-background cell inside the landscape.

McGarigal and Marks (1995) introduced a complementary *interspersion and juxtaposition index* (IJI) that increases in value as patches tend to be more evenly interspersed in a "salt and pepper"



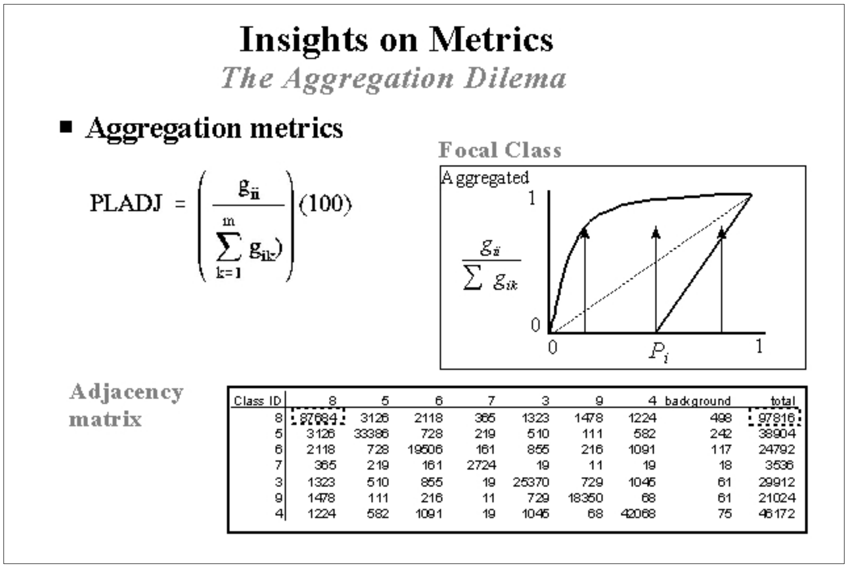
$$\frac{-\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right)\bullet\ln\left(\frac{e_{ik}}{E}\right)\right]}{\ln\left[\frac{\{m(m-1)\}}{2}\right]}(100)$$

mixture. Unlike the earlier contagion indices that are based on raster *cell* adjacencies, this index is based on *patch* adjacencies; only the patch perimeters are considered in determining the total length of each unique edge type. Each patch is evaluated for adjacency with all other patch types; like adjacencies are not possible because a patch can never be adjacent to a patch of the same type. Because this index is a measure of *patch* adjacency and not *cell* adjacency, the interpretation is somewhat different than the contagion index. The interspersion index measures the extent to which patch types are interspersed (not necessarily dispersed); higher values result from landscapes in which the patch types are well interspersed (i.e., equally adjacent to each other), whereas lower values characterize landscapes in which the patch types are poorly interspersed (i.e., disproportionate distribution of patch type adjacencies). The interspersion index is not directly affected by the number, size, contiguity, or dispersion of patches per se, as is the contagion index. Consequently, a landscape containing 4 large patches, each a different patch type, and a landscape of the same extent containing 100 small patches of 4 patch types will have the same index value if the patch types are equally interspersed (or adjacent to each other based on the proportion of total edge length in each edge type); whereas, the value of contagion would be quite different. Like the contagion index, the interspersion index is a relative index that represents the observed level of interspersion as a percentage of the maximum possible given the total number of patch types.



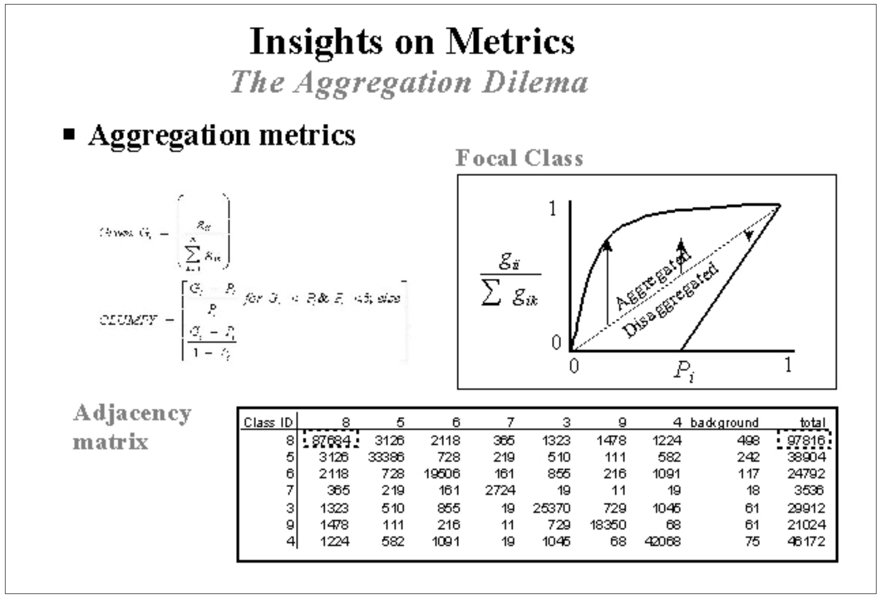
Class ID	8	5	6	7	3	9	4	background
8	87684	3126	2118	365	1323	1478	1224	498
5	3126	33386	728	219	510	111	582	242
6	2118	728	19506	161	855	216	1091	117
7	365	219	161	2724	19	11	19	18
3	1323	510	855	19	25370	729	1045	61
9	1478	111	216	11	729	18350	68	61
4	1224	582	1091	19	1045	68	42068	75

It is important to note the differences between the contagion index and the interspersion and juxtaposition index. Contagion is affected by both interspersion and dispersion. The interspersion and juxtaposition index, in contrast, is affected only by patch type interspersion and not necessarily by the size, contiguity, or dispersion of patches. Thus, although often indirectly affected by dispersion, the interspersion and juxtaposition index directly measures patch type interspersion, whereas contagion measures a combination of both patch type interspersion and dispersion. In addition, contagion and interspersion are typically inversely related to each other. Higher contagion generally corresponds to lower interspersion and vice versa. Finally, in contrast to the interspersion and juxtaposition index, the contagion index is strongly affected by the grain size or resolution of the image. Given a particular patch mosaic, a smaller grain size will result in greater contagion because of the proportional increase in like adjacencies from internal cells. The interspersion and juxtaposition index is not affected in this manner because it considers only patch edges. This scale effect should be carefully considered when attempting to compare results from different studies.

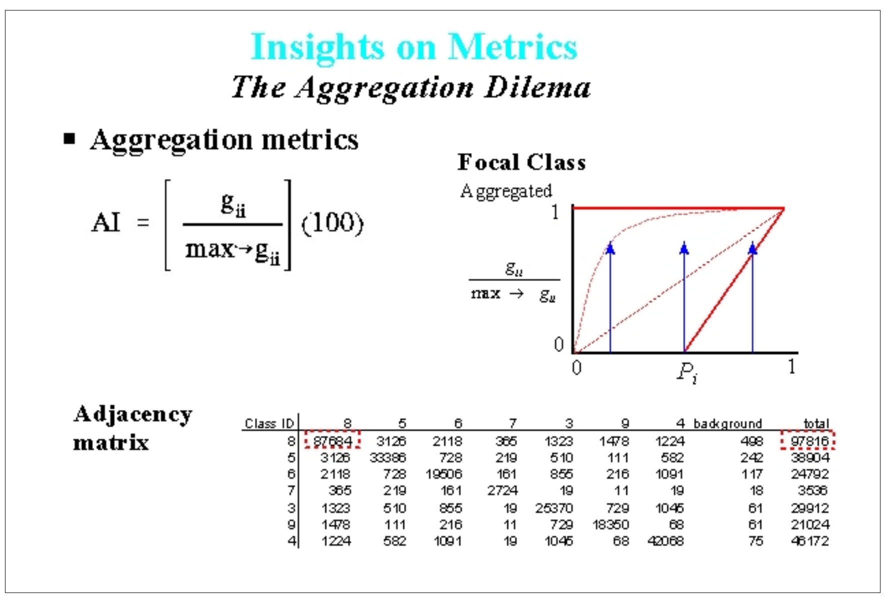


Class ID	8	5	6	7	3	9	4	background	total
8	87684	3126	2118	365	1323	1478	1224	498	97816
5	3126	33386	728	219	510	111	582	242	38904
6	2118	728	19506	161	855	216	1091	117	24792
7	365	219	161	2724	19	11	19	18	3536
3	1323	510	855	19	25370	729	1046	61	29912
9	1478	111	216	11	729	18350	68	61	21024
4	1224	582	1091	19	1046	68	42068	75	46172

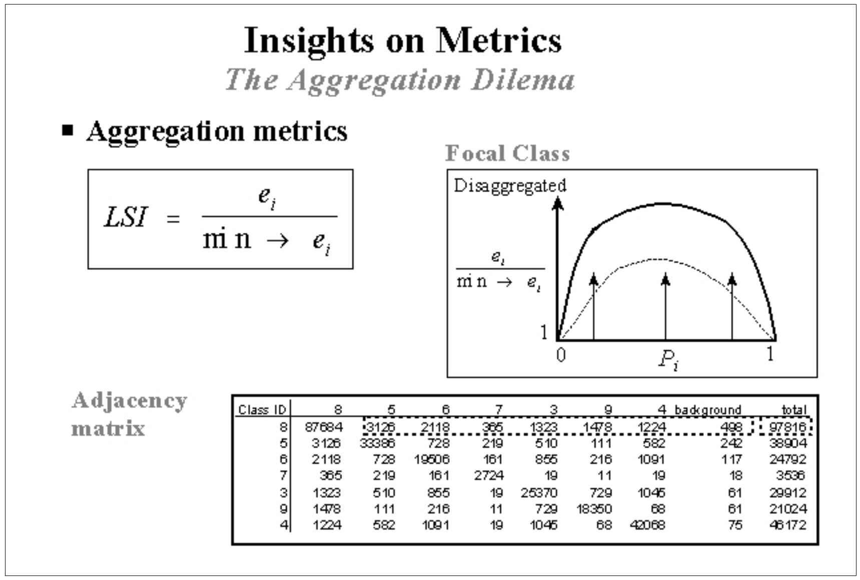
Other contagion-like metrics can be generated from the matrix of pairwise adjacencies between patch types. FRAGSTATS computes the *percentage of like adjacencies* (PLADJ), which is computed as the sum of the diagonal elements (i.e., like adjacencies) of the adjacency matrix divided by the total number of adjacencies. A landscape containing greater aggregation of patch types (e.g., larger patches with compact shapes) will contain a higher proportion of like adjacencies than a landscape containing disaggregated patch types (e.g., smaller patches and more complex shapes). In contrast to the contagion index, this metric measures only patch type dispersion, not interspersion, and is unaffected by the method used to summarize adjacencies. At the class level, this metric is computed as the percentage of like adjacencies of the focal class. A highly contagious (aggregated) patch type will contain a higher percentage of like adjacencies. Conversely, a highly fragmented (disaggregated) patch type will contain proportionately fewer like adjacencies. As such, this index provides an effective measure of class-specific contagion that isolates the dispersion (as opposed to interspersion) component of configuration. However, this index requires careful interpretation because it varies in relation to the proportion of the landscape comprised of the focal class (P_i). It has been shown that PLADJ for class i will equal P_i for a completely random map (Gardner and O'Neill 1991). If the focal class is more dispersed than is expected of a random distribution (i.e., overdispersed), then PLADJ < P_i. If the focal class is more contagiously distributed, then PLADJ > P_i. Thus, although PLADJ provides an absolute measure of aggregation of the focal class, it is difficult to interpret as a measure of contagion without adjusting for P_i.

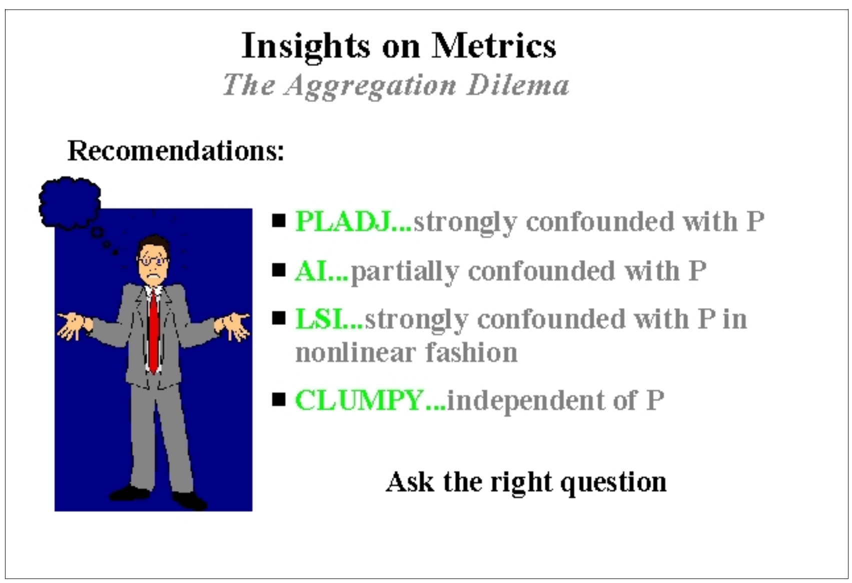


FRAGSTATS computes two class-specific indices based on PLADJ that adjust for P_i in different ways. The *clumpiness index* (CLUMPY) introduced here is computed such that it ranges from -1 when the patch type is maximally disaggregated to 1 when the patch type is maximally clumped. It returns a value of zero for a random distribution, regardless of P_i. Values less than zero indicate greater dispersion (or disaggregation) than expected under a spatially random distribution, and values greater than zero indicate greater contagion. Hence, this index provides a measure of class-specific contagion that effectively isolates the configuration component from the area component and, as such, provides an effective index of fragmentation of the focal class that is not confounded by changes in class area. The *aggregation index* (AI) is computed as a percentage based on the ratio of the observed number of like adjacencies ($e_{i,i}$), based on the *single-count* method, to the maximum possible number of like adjacencies (max_$e_{i,i}$) given P_i (He et al. 2000). Note, the single-count method of tallying adjacencies is employed to be consistent with the published algorithm. The maximum number of like adjacencies is achieved when the class is clumped into a single compact patch, which does not have to be a square. The trick here is in determining the maximum value of $e_{i,i}$ for any $P_{i,}$. He et al. (2000) provide the formula for computing max_$e_{i,i}$. The index ranges from 0 when there is no like adjacencies (i.e., when the class is maximally dissagregated) to 1 when $e_{i,i}$ reaches the maximum (i.e., when the class is maximally aggregated).



The *landscape shape index* (LSI) described in the section on Area/Edge/Density Metrics is closely allied to the former aggregation metrics and can be considered as an alternative aggregation metric. The former metrics relate the percentage of like adjacencies to that expected for a maximally compact distribution. LSI functions similarly, but instead of considering the ratio of internal (like) adjacencies, it is based on the ratio of external (or perimeter) cell adjacencies. Because a maximally compact patch of any size has a known perimeter (i.e., the perimeter of a square or maximally square-like shape), the number of internal like adjacencies is also known. Consequently, these metrics are computationally closely related. The differences between these metrics lies in how the boundary of the landscape is taken into account. In the landscape shape index, the landscape boundary is always considered as edge (or perimeter) regardless of whether a border is provided. In the aggregation index (AI), the landscape boundary is never considered regardless of whether a border is provided. In the clumpiness index (CLUMPY), the landscape boundary is treated according to the information present, i.e., it takes into account the border if present. The net result of these differences depends on the ratio of boundary to internal edge but can lead to a different types of confounding with P (percentage of the landscape comprised of the focal class).

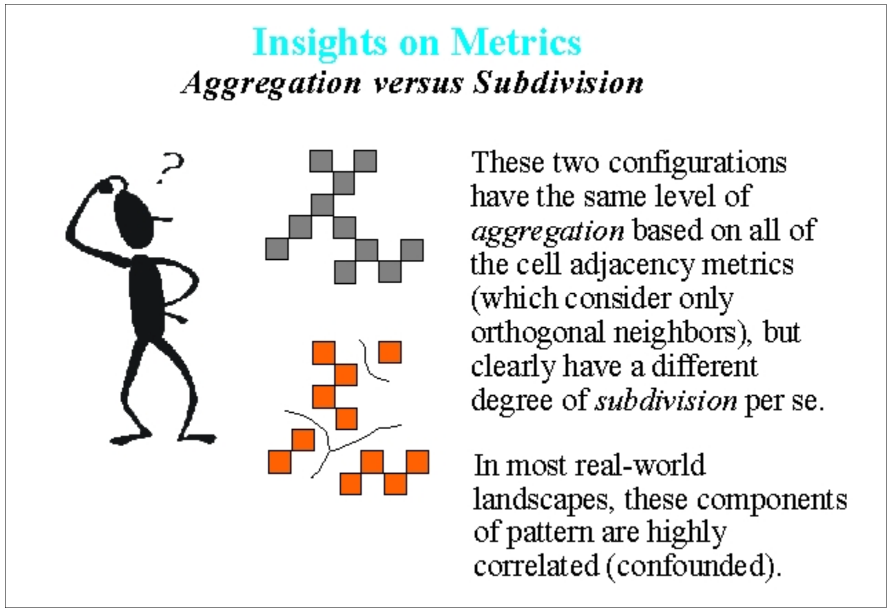




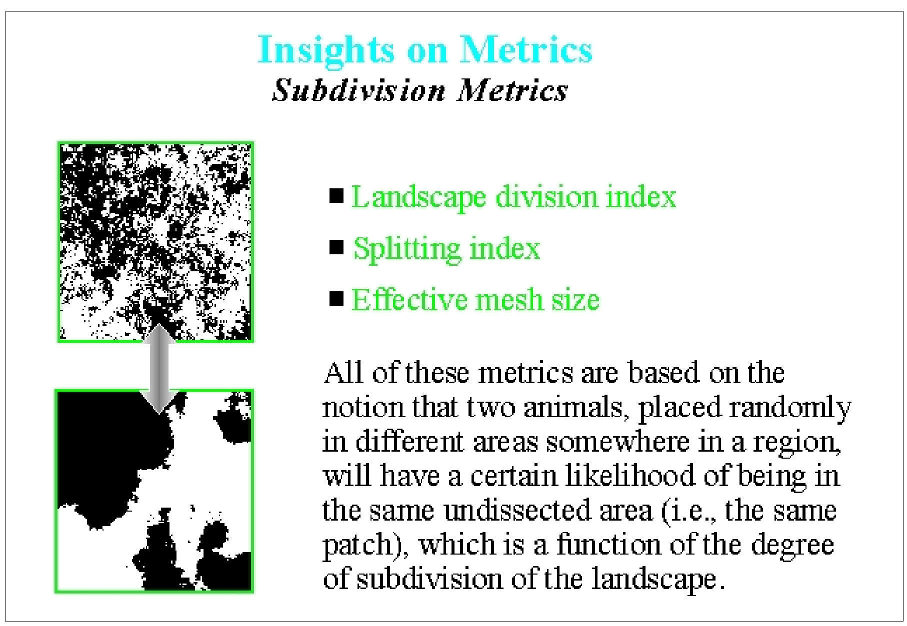
There are alternative methods for calculating class-specific contagion using fractal geometry (Gardner and O'Neill 1991). FRAGSTATS computes the *mass fractal dimension* (MFRAC) for each class, which is based on the scaling relationship between box mass (i.e., the number of pixels of a focal class within a window) and the size of the box defining the window (r). Specifically, a range of box sizes is used to delineate windows, from 3 pixels on a side (r=3) to a maximum of approximately ⅓ of the landscape. For each box size, the mean number of pixels of the focal class is determined by centering the box on every pixel of that class and counting the number of pixels of that class in the box sample. Mass fractal dimension is equal to the slope derived from regressing the log of the mean number of pixels for each box size on the log of the box lengths (Voss 1988, Milne 1991). Mass fractal dimension decreases as the percentage of the landscape comprised of the focal class decreases. After accounting for this relationship, higher values of mass fractal dimension are associated with higher contagion.

Lacunarity is another method borrowed from fractal geometry by which class-specific contagion can be characterized across a range of spatial scales (Plotnick et al. 1993 and 1996, Dale 2000). Consider a binary ("on/off") raster map of dimension m. The technique involves using a moving window and is concerned with the frequency with which one encounters the focal class in a window of different sizes, similar to the mass fractal dimension. To do this, a gliding box is constructed of dimension r, and a frequency distribution of tallies of S=1,2, ..., r^2 "on" cells is constructed. In this gliding, the box is moved over one cell at a time, so that the boxes overlap during the sliding. Define n(S,r) as the number of boxes that tally S "on" cells for a box of size r. There are $N(r)=(m-r+1)^2$ boxes of size r, and the probability associated with n(S,r) is Q(S,r)=n(S,r)/N(r). The first and second moments of Q are used to define lacunarity L (lambda) for this box size as a variance to mean-square ratio. This is repeated for a range of box sizes r. A log-log plot of lacunarity against window size expresses the contagion of the map, or its tendency to aggregate into discrete patches, across a range of spatial scales. Note that as r increases, the tally n(S,r) converges on the mean and its variance converges on 0. Thus, for very large boxes L=1 and ln(L)=0. At the smallest box size (r=1), L(1) = 1/p, where p is the proportion of the map occupied ("on"). Thus, for the finest resolution of a map, L depends solely on p. At intermediate scales, lacunarity expresses the contagion of the map, or its tendency to clump into discrete patches. So the lacunarity plot summarizes the contagion of the map across all scales.

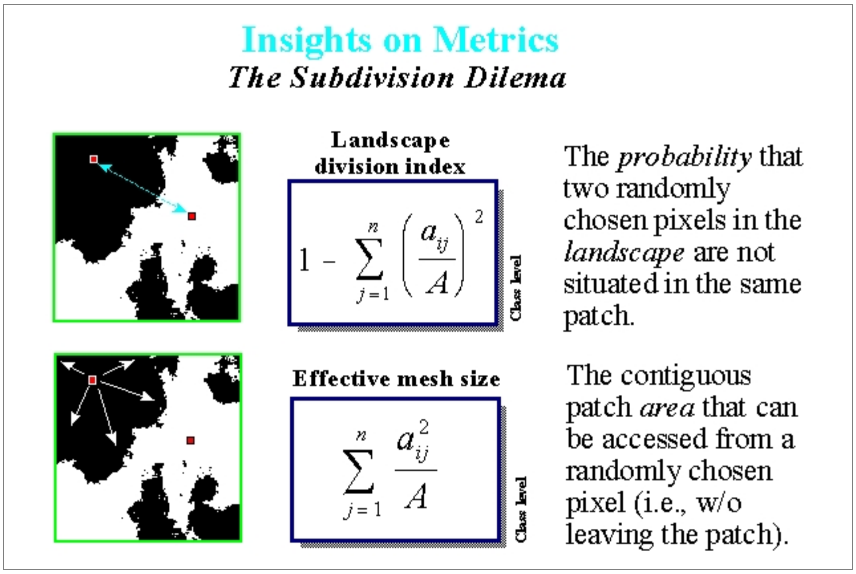
As noted in the background discussion, contagion and subdivision are closely related concepts. Both refer to the aggregation of patch types, but subdivision deals explicitly with the degree to which patch types are broken up (i.e., subdivided) into separate patches (i.e., fragments). Subdivision can be evaluated using a wide variety of metrics already described; for example, the number, density, and average size of patches and the degree of contagion all indirectly relate to subdivision. However, these metrics have been criticized for their insensitivity and inconsistent behavior across a wide range of subdivision patterns. Jaeger (2000) discussed the limitations of these metrics for evaluating habitat fragmentation and concluded that most of these metrics do not behave in a consistent and logical manner across all phases of the fragmentation process. He introduced a suite of metrics derived from the cumulative distribution of patch sizes that provide alternative and more explicit measures of subdivision. When applied at the class level, these metrics can be used to measure the degree of fragmentation of the focal patch type. Applied at the landscape level, these metrics measure the graininess of the landscape; i.e., the tendency of the landscape to exhibit a fine- versus coarse-grain texture. A fine-grain landscape is characterized by many small patches (highly subdivided); whereas, a coarse-grain landscape is characterized by fewer large patches.

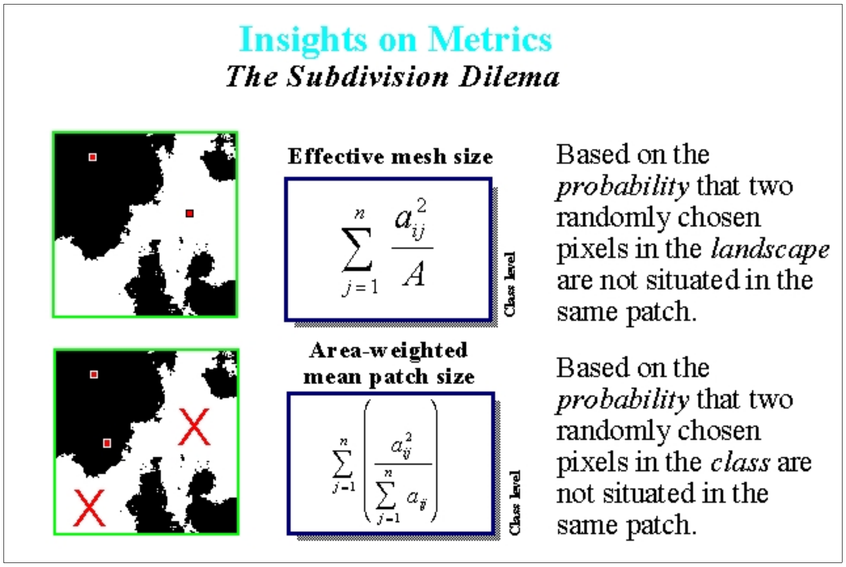


FRAGSTATS computes three of the subdivision metrics proposed by Jaeger (2000). All of these metrics are based on the notion that two animals, placed randomly in different areas somewhere in a region, will have a certain likelihood of being in the same undissected area (i.e., the same patch), which is a function of the degree of subdivision of the landscape. The *landscape division index* (DIVISION) is based on the degree of coherence (C), which is defined as the probability that two animals placed in different areas somewhere in the region of investigation might find each other. Degree of coherence is based on the cumulative patch area distribution and is represented graphically as the area above the cumulative area distribution curve. Degree of coherence represents the probability that two animals, which have been able to move throughout the whole region before the landscape was subdivided, will be found in the same patch after the subdivision is in place. The degree of landscape division is simply the complement of coherence and is defined as the probability that two randomly chosen places in the landscape are not situated in the same undissected patch. Graphically, the degree of landscape division is equal to the area below the cumulative area distribution curve.

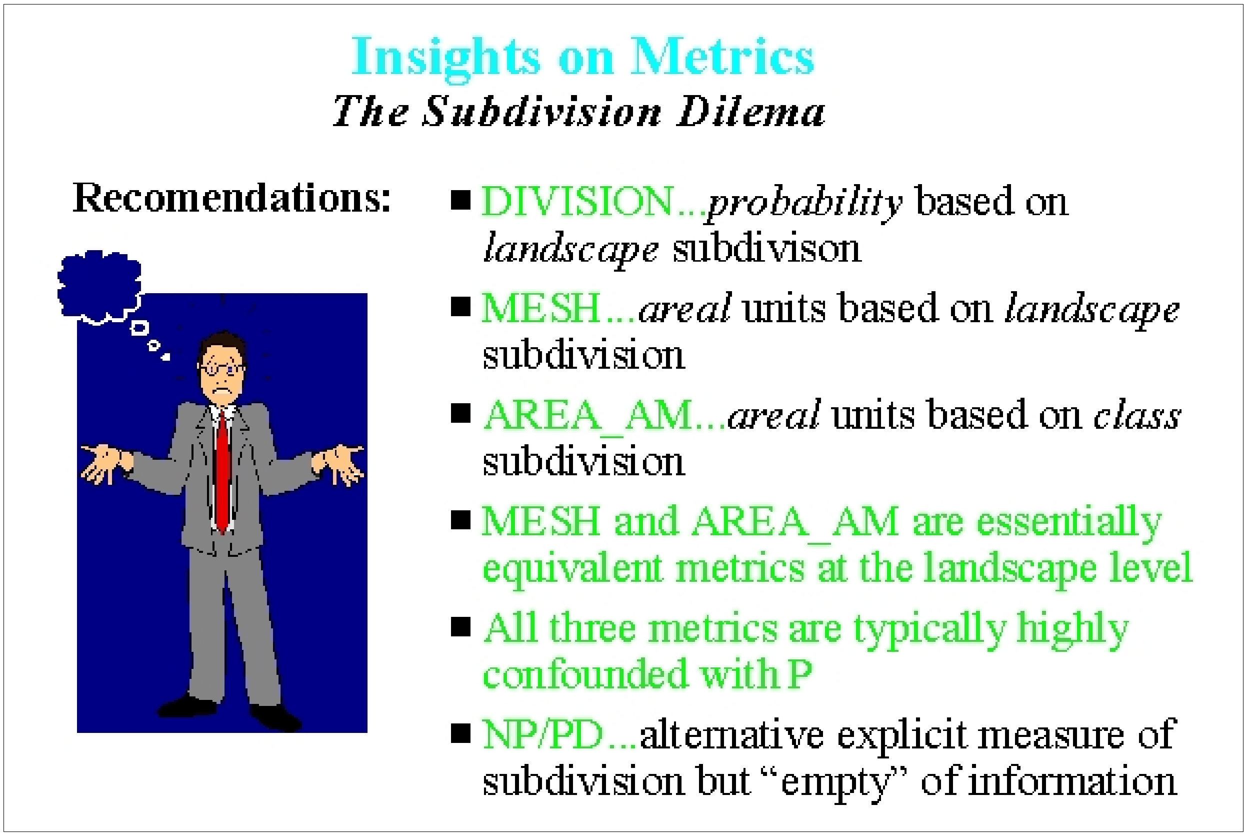


The *splitting index* (SPLIT) is defined as the number of patches one gets when dividing the total landscape into patches of equal size in such a way that this new configuration leads to the same degree of landscape division as obtained for the observed cumulative area distribution. The splitting index can be interpreted to be the "effective mesh number" of a patch mosaic with a constant patch size dividing the landscape into S patches, where S is the splitting index. The *effective mesh size* (MESH) simply denotes the size of the patches when the landscape is divided into S areas (each of the same size) with the same degree of landscape division as obtained for the observed cumulative area distribution. Thus, all three subdivision metrics are easily computed from the cumulative patch area distribution. These measures have the particular advantage over other conventional measures of subdivision (e.g., mean patch size, patch density) in that they are insensitive to the omission or addition of very small patches. In practice, this makes the results more reproducible as investigators do not always use the same lower limit of patch size. Jaeger (2000) argues that the most important and advantageous feature of these new measures is that effective mesh size is 'area-proportionately additive'; that is, it characterizes the subdivision of a landscape independently of its size. In fact, these three measures are closely related to the area-weighted mean patch size (AREA_AM) discussed previously, and under certain circumstances are perfectly redundant. The distinctions are discussed below for each metric.





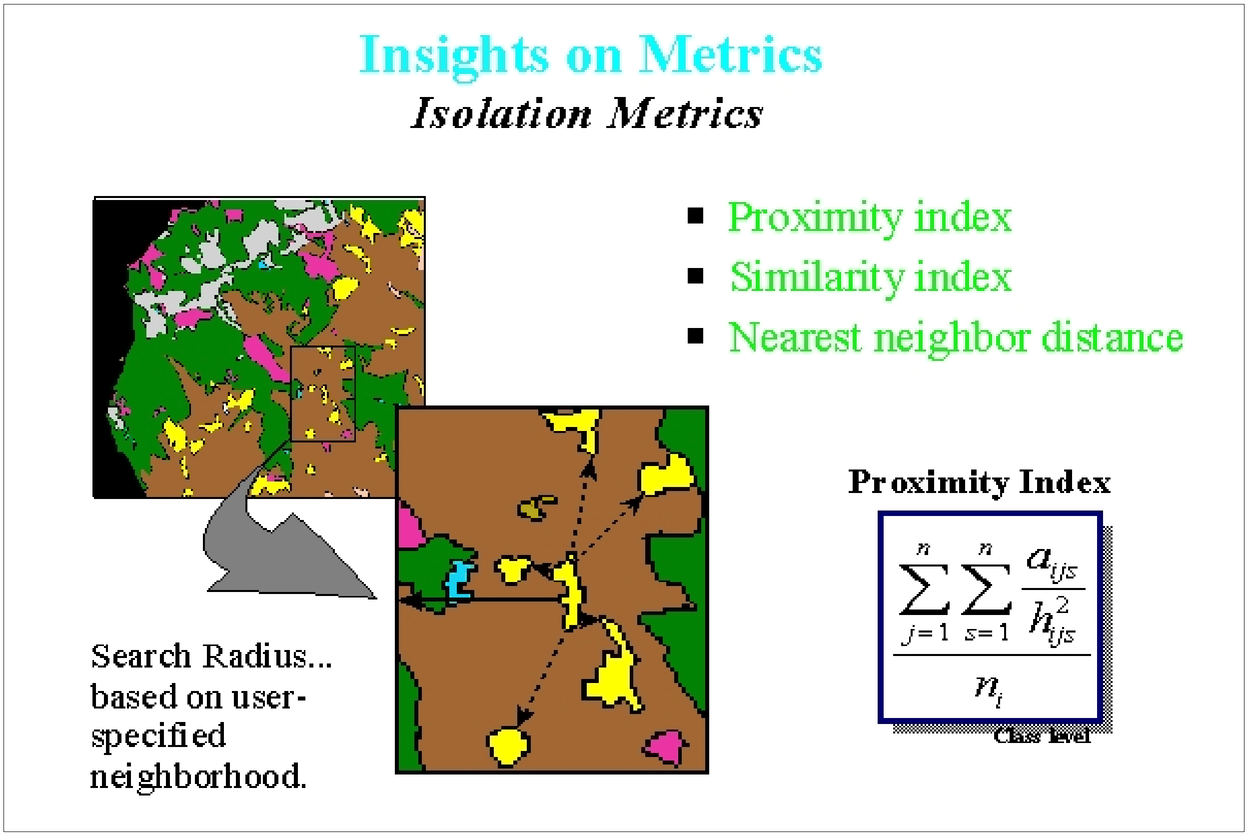
Limitations.–All measures based on the adjacency matrix (i.e., the number of adjacencies between each pair of patch types) that include like-adjacencies (i.e., percentage of like



adjacencies, clumpiness index, aggregation index, and contagion) are strongly affected by the grain size or resolution of the image. Given a particular patch mosaic, a smaller grain size will result in a proportional increase in like adjacencies. Given this scale dependency, these metrics are best used if the scale is held constant. Note, interspersion is not affected by resolution directly because only patch edges are considered. In addition, there are alternative ways to consider cell adjacencies. Adjacencies may include only the 4 cells sharing a side with the focal cell, or they may include the diagonal neighbors as well. FRAGSTATS uses the *4-neighbor* approach for the purpose of calculating these metrics. Further, there are at least two basic approaches for counting cell adjacencies, referred to as the single count and double count methods. As noted above, FRAGSTATS adopts the *double count* method in which pixel order is preserved. In this method, all non-background cells inside the landscape (i.e., positively-valued cells) are visited and the four sides of each cell are tallied in the adjacency matrix. As a result, all cell sides involving non-background classes inside the landscape are tallied twice (hence the term double count), but all cell sides involving background or landscape border (i.e., negatively-valued cells) are only counted once, as those cells are not themselves visited. Finally, mass fractal dimension and lacunarity involve the use of moving windows of many sizes; these can be computationally demanding and for large landscapes may take a very long time to compute.

Metrics based on fractal geometry such as mass fractal dimension are subject to several limitations (as discussed by Hargis et al. 1998). First, the simplifications of landscape pattern produced during the mapping process yield images that are not truly fractal, and the application of fractal measures in the strictest sense is therefore questionable. Fractal geometry assumes that the quantity being measured and the ruler length of measurement have a linear relationship when both are logarithmically transformed (Voss 1988). If this condition is not met, the object (in this case, the landscape) may not be fractal. Any smoothing or renormalization of landscape patterns during the mapping process may cause this relationship to deviate from linearity, and the use of fractal dimension may be questionable. Second, landscape extent and grain affect the ability to derive an accurate scaling relationship between box size and mass. A large ratio of extent to grain is needed to produce a reasonable range of box sizes for generating an accurate slope. Finally, the relationship between grain and average patch size can affect the accuracy and meaningfulness of the derived fractal dimension. If map resolution allows only two or three box sizes before the sample box exceeds the size of the average patch, the slope derived from these points is questionable. In this case, when larger box sizes are added to the regression line, any interesting differences are lost in the averaging process.

The subdivision metrics based on the cumulative patch size distribution are essentially free of any known limitations. Perhaps the greatest limitation is that they have not yet been used extensively by landscape ecologists, so their behavior under various conditions has not been fully explored.



7. Isolation/Proximity Metrics

<u>Background</u>.--Isolation deals explicitly with the spatial and temporal *context* of habitat patches, rather than the spatial character of the patches themselves. Isolation of habitat patches is a critical factor in the dynamics of spatially structured populations. For example, there has been a proliferation of mathematical models on population dynamics and species interactions in spatially subdivided populations (Kareiva 1990), and results suggest that the dynamics of local plant and animal populations in a patch are influenced by their proximity to other subpopulations of the same or competing species. Patch isolation plays a critical role in island biogeographic theory (MacArthur and Wilson 1967) and metapopulation theory (Levins 1970, Gilpin and Hanski 1991). The role of patch isolation (e.g., as measured by interpatch distance) in metapopulations has had a preeminent role in conservation efforts for endangered species (e.g., Lamberson et al. 1992, McKelvey et al. 1992).

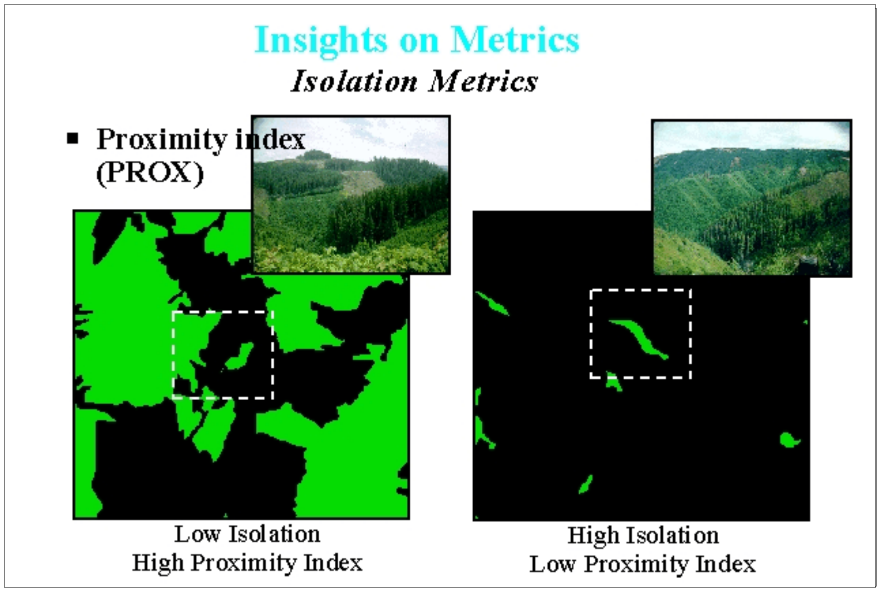
Isolation is particularly important in the context of habitat fragmentation. Several authors have claimed, for example, that patch isolation explains why fragmented habitats often contain fewer bird species than contiguous habitats (Moore and Hooper 1975, Forman et al. 1976, Helliwell 1976, Whitcomb et al. 1981, Hayden et al. 1985, Dickman 1987). Specifically, as habitat is lost and fragmented, residual habitat patches become more isolated from each other in space and time. One of the more immediate consequence of this is the disruption of movement patterns and the resulting isolation of individuals and local populations. This has important metapopulation consequences. As habitat is fragmented, it is broken up into remnants that are isolated to varying degrees. Because remnant habitat patches are relatively small and therefore support fewer individuals, there will be fewer local (within patch) opportunities for intra-specific interactions. This may not present a problem for individuals (and the persistence of the population) if movement among patches is largely unimpeded by intervening habitats in the matrix and connectivity across the landscape can be maintained. However, if movement among habitat patches is significantly impeded or prevented, then individuals (and local populations) in remnant habitat patches may become functionally isolated. The degree of isolation for any fragmented habitat distribution will vary among species depending on how they perceive and interact with landscape patterns (Dale et al. 1994, With and Crist 1995, Pearson et al. 1996, With et al. 1997, With 1999); less vagile species with very restrictive habitat requirements and limited gap-crossing ability will likely be most sensitive to isolation effects.

Habitat patches can become functionally isolated in several ways. First, the patch edge may act as a filter or barrier that impedes or prevents movement, thereby disrupting emigration and dispersal from the patch (Wiens et al. 1985). Some evidence for this exists for small mammals (e.g., Wegner and Merriam 1979, Chasko and Gates 1982, Bendell and Gates 1987, Yahner 1986), but the data are scarce for other vertebrates. Whether edges themselves can limit movement presumably depends on what species are trying to cross the edge and on the structure of the edge habitat (Kremsater and Bunnell 1999). Second, the distance from remnant habitat patches to other neighboring habitat patches may influence the likelihood of successful movement of individuals among habitat patches. Again, the distance at which movement rates significantly decline will vary among species depending on how they scale the environment. In general, larger organisms can travel longer distances. Therefore, a 100 m-wide agricultural field may be a complete barrier to dispersal for small organisms such as invertebrates (e.g., Mader 1984), yet be quite permeable for larger and more vagile organisms such as birds. Lastly, the composition and structure of the intervening landscape mosaic may determine the permeability of the landscape to movements. Note that under an island biogeographic perspective, habitat patches exist in a uniform sea that is hostile to both survival and dispersal. In this case, the matrix is presumed to contain no meaningful structure and isolation is influenced largely by the distance among favorable habitat patches. However, under a landscape mosaic perspective, habitat patches are bounded by other patches that may be more or less similar (as opposed to highly contrasting and hostile) and connectivity is assessed by the extent to which movement is facilitated or impeded through different habitat types across the landscape. Each habitat may differ in its “viscosity” or resistance to movement, facilitating movement through certain elements of the landscape and impeding it in others. Again, the degree to which a given landscape structure facilitates or impedes movement will vary among organisms. Regardless of how habitat patches become isolated, whether it be due to properties of the edges themselves, the distance between patches, or properties of the intervening matrix, the end result is the same–fewer individual movements among habitat patches.

Unfortunately, because of the many factors that influence the functional isolation of a patch, it is a difficult thing to capture in a single measure. In the context of fragmentation, isolation can be measured as the time since the habitat was physically subdivided, but this is fraught with practical difficulties. For example, rarely do we have accurate historical data from which to determine when each patch was isolated. Moreover, given that fragmentation is an ongoing process, it can be difficult to objectively determine at what point the habitat becomes subdivided, since this is largely a function of scale. Isolation can be measured in the spatial dimension in several ways, depending on how one views the concept of isolation. The simplest measures are based on Euclidean distance between nearest neighbors (McGarigal and Marks 1995) or the cumulative area of neighboring habitat patches (weighted by nearest neighbor distance) within some ecological neighborhood (Gustafson and Parker 1992). These measures adopt an island biogeographic perspective, as they treat the landscape as a binary mosaic consisting of habitat patches and uniform matrix. Thus, the context of a patch is defined by the proximity and area of neighboring habitat patches; the role of the matrix is ignored. However, these measures can be modified to take into account other habitat types in the so-called matrix and their affects on the insularity of the focal habitat. For example, simple Euclidean distance can be modified to account for functional differences among organisms. The functional distance between patches clearly depends on how each organism scales and interacts with landscape patterns (With 1999); in other words, the same gap between patches may not be perceived as a relevant disconnection for some organisms, but may be an impassable barrier for others. Similarly, the matrix can be treated as a mosaic of patch types that contribute differentially to the isolation of the focal habitat. For example, isolation can be measured by the degree of contrast (i.e., the magnitude of differences in one or more attributes between adjacent patch types) between the focal habitat and neighboring patches.

FRAGSTATS Metrics.--FRAGSTATS computes several isolation metrics based on nearest-neighbor distance at the patch, class, and landscape levels. Nearest-neighbor distance is defined as the distance from a patch to a neighboring patch of the same or different class, based on the nearest cell center-to-cell center. That is, the distance between the two closest cells from the respective patches, based on the distance between their cell centers. Note, this is a change from version 2.0 which based nearest neighbor distance on cell edge-to-edge distance. These metrics are all fundamentally patch-level metrics (i.e., measured for each patch) that can be summarized at the class or landscape levels.

FRAGSTATS computes two metrics that adopt an island biogeographic perspective on patch isolation: (1) Euclidean nearest neighbor distance and (2) proximity index. *Euclidean nearest neighbor distance* (ENN) is perhaps the simplest measure of patch context and has been used extensively to quantify patch isolation. Here, nearest neighbor distance is defined using simple Euclidean geometry as the shortest straight-line distance between the focal patch and its nearest neighbor of the same class. Even though nearest neighbor distance is often used to evaluate patch isolation, it is important to recognize that the single nearest patch may not fully represent the ecological neighborhood of the focal patch. For example, a neighboring patch 100 m away that is 1 ha is size may not be as important to the effective isolation of the focal patch as a neighboring patch 200 m away, but 1000 ha in size. To overcome this limitation, the *proximity index* (PROX) was developed by Gustafson and Parker (1992)[see also Gustafson and Parker 1994, Gustafson et al. 1994, Whitcomb et al. 1981]. This index considers the size and proximity of all patches whose edges are within a specified search radius of the focal patch. The index is computed as the sum, over all patches of the corresponding patch type whose edges are within the search radius of the focal patch, of each patch size divided by the square of its distance from the focal patch. Note that FRAGSTATS uses the distance between the focal patch and each of the other patches within the search radius, similar to the isolation index of Whitcomb et al. (1981), rather than the nearest-neighbor distance of each patch within the search radius (which could be to a patch other than the focal patch), as in Gustafson and Parker (1992). The proximity index quantifies the spatial context of a (habitat) patch in relation to its neighbors of the same class; specifically, the index distinguishes sparse distributions of small habitat patches from configurations where the habitat forms a complex cluster of larger patches. All other things being equal, a patch located in a neighborhood (defined by the search radius) containing more of the corresponding patch type than another patch will have a larger index value. Similarly, all other things being equal, a patch located in a neighborhood in which the corresponding patch type is distributed in larger, more contiguous, and/or closer patches than another patch will have a larger index value. Thus, the proximity index measures both the degree of patch isolation and the degree of fragmentation of the corresponding patch type within the specified neighborhood of the focal patch.

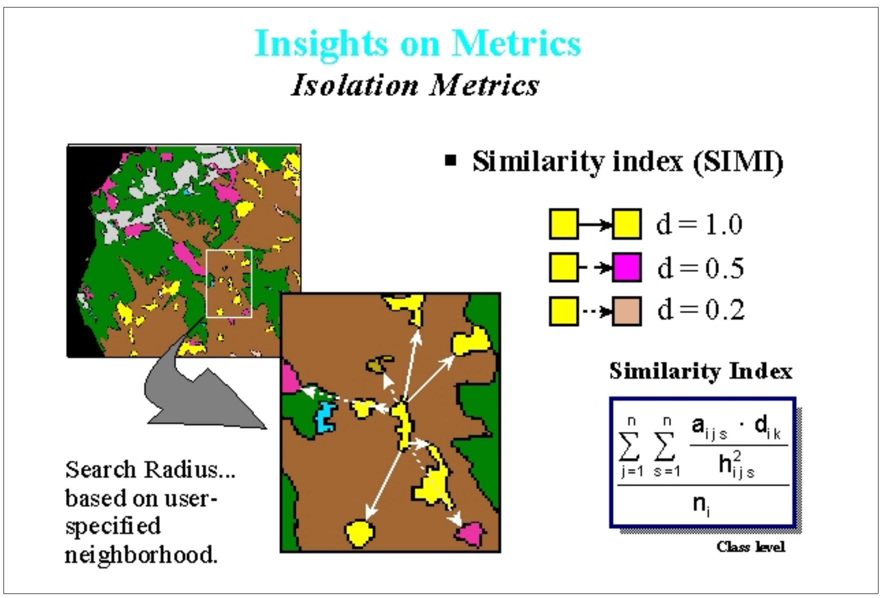


At the class and landscape levels, FRAGSTATS computes several distribution statistics associated with the Euclidean nearest neighbor distance and proximity index. At the class level, the mean proximity index measures the degree of isolation and fragmentation of the corresponding patch type and the performance of the index under various scenarios is described in detail by Gustafson and Parker (1994). FRAGSTATS also summarizes the proximity index at the landscape level by aggregating across all patches in the landscape, although the performance of this index as a measure of overall landscape pattern has not been evaluated quantitatively. Similarly, at the class and landscape levels, FRAGSTATS computes the mean and variability in Euclidean nearest neighbor distance. At the class level, mean nearest-neighbor distance can only be computed if there are at least 2 patches of the corresponding type. At the landscape level, mean nearest-neighbor distance considers only patches that have neighbors. Thus, there could be 10 patches in the landscape, but 8 of them might belong to separate patch types and therefore have no neighbor within the landscape. In this case, mean nearest-neighbor distance would be based on the distance between the 2 patches of the same type. These 2 patches could be close together or far apart. In either case, the mean nearest-neighbor distance for this landscape may not characterize the entire landscape very well. For this reason, these metrics should be interpreted carefully when landscapes contain rare patch types.

In addition to these first-order statistics, the variability in nearest-neighbor distance measures a key aspect of landscape heterogeneity. Specifically, the *standard deviation* (SD)in Euclidean nearest neighbor distance (ENN_SD) is a measure of patch dispersion; a small SD relative to the mean implies a fairly uniform or regular distribution of patches across landscapes, whereas a large SD relative to the mean implies a more irregular or uneven distribution of patches. The distribution of patches may reflect underlying natural processes or human-caused disturbance patterns. In absolute terms, the magnitude of nearest-neighbor SD is a function of the mean nearest-neighbor distance and variation in nearest-neighbor distance among patches. Thus, while SD does convey information about nearest neighbor variability, it is a difficult parameter to interpret without doing so in conjunction with the mean nearest-neighbor distance. For example, 2 landscapes may have the same nearest-neighbor SD, e.g., 100 m; yet 1 landscape may have a mean nearest-neighbor distance of 100 m, while the other may have a mean nearest-neighbor distance of 1,000 m. In this case, the interpretations of landscape pattern would be very different, even though the absolute variation is the same. Specifically, the former landscape has a more irregular but concentrated pattern of patches, while the latter has a more regular but dispersed pattern of patches. For these reasons, *coefficient of variation* (CV) often is preferable to SD for comparing variability among landscapes. Coefficient of variation measures relative variability about the mean (i.e., variability as a percentage of the mean), not absolute variability, and is akin to the familiar indices of dispersion in point patterns based on the variance to mean ratio in nearest neighbor distance (e.g., Clark and Evans 1954). Thus, it is not necessary to know the mean nearest-neighbor distance to interpret this metric. Even so, nearest-neighbor CV can be misleading with regards to landscape structure without also knowing the number of patches or patch density and other structural characteristics. For example, 2 landscapes may have the same nearest-neighbor CV, e.g., 100%; yet 1 landscape may have 100 patches with a mean nearest-neighbor distance of 100 m, while the other may have 10 patches with a mean nearest-neighbor distance of 1,000 m. In this case, the interpretations of overall landscape pattern could be very different, even though nearest-neighbor CV is the same; although the identical CV's indicate that both landscapes have the same regularity or uniformity in patch distribution. Finally, both SD and CV assume a normal distribution about the mean. In a real landscape, nearest-neighbor distribution may be highly irregular. In this case, it may be more informative to inspect the actual distribution itself (e.g., plot a histogram of the nearest neighbor distances for the corresponding patches), rather than relying on summary statistics such as SD and CV that make assumptions about the distribution and therefore can be misleading.

FRAGSTATS computes two isolation metrics that adopt a landscape mosaic perspective on patch isolation: (1) functional nearest neighbor distance and (2) similarity index. *Similarity index* (SIMI) is a modification of the proximity index, the difference being that similarity considers the size and proximity of all patches, regardless of class, whose edges are within a specified search radius of the focal patch. The similarity index quantifies the spatial context of a (habitat) patch in relation to its neighbors of the same or similar class; specifically, the index distinguishes sparse distributions of small and insular habitat patches from configurations where the habitat forms a complex cluster of larger, hospitable (i.e., similar) patches. All other things being equal, a patch located in a neighborhood (defined by the search radius) deemed more similar (i.e., containing greater area in patches with high similarity) than another patch will have a larger index value. Similarly, all other things being equal, a patch located in a neighborhood in which the similar patches are distributed in larger, more contiguous, and/or closer patches than another patch will have a larger index value. Essentially, the similarity index performs much the same way as the proximity index, but instead of focusing on only a single patch type (i.e., island biogeographic perspective), it considers all patch types in the mosaic (i.e., landscape mosaic perspective). Thus, the similarity index is a more comprehensive measure of patch isolation than the proximity index for organisms and processes that perceive and respond to patch types differentially.

Similarly, *functional nearest-neighbor distance* (FNN) accounts for one of the major shortcomings of using Euclidean distance to assess ecological relationships; namely, that the shortest geographic distance may not be the shortest ecological distance as perceived by an organism or process. The character of the intervening landscape can significantly alter the rate of flow of the organism or process of interest. Therefore, it may be more meaningful to assess distance using a least cost path approach. Here, in effect, the distance across a cell is weighted by the degree of resistance it offers to the ecological flow of interest. Thus, the functional distance between two patches is increased proportionate the degree of resistance in the intervening landscape.



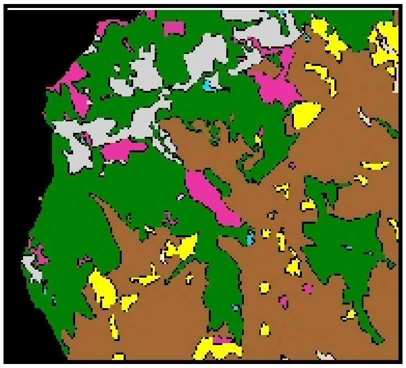
Limitations.--There are significant limitations associated with the use of isolation metrics that must be understood before they are used. The most important limitation of these particular metrics is that nearest-neighbor distances are computed solely from patches contained within the landscape boundary. If the landscape extent is small relative to the scale of the organism or ecological processes under consideration and the landscape is an "open" system relative to that organism or process, then nearest-neighbor results can be misleading. For example, consider a small subpopulation of a bird species occupying a patch near the boundary of a somewhat arbitrarily defined (from a bird's perspective) landscape. The nearest neighbor within the landscape boundary might be quite far away, yet in reality the closest patch might be very close, but just outside the designated landscape boundary. The magnitude of this problem is a function of scale. Increasing the size of the landscape relative to the scale at which the organism under investigation perceives and responds to the environment will decrease the severity of this problem.

Similarly, the proximity and similarity indices involve a search window around the focal patch. Thus, these metrics may be biased low for patches located within the search radius distance from the landscape boundary because a portion of the search area will be outside the area under consideration. The magnitude is of this problem is also a function of scale. Increasing the size of the landscape relative to the average patch size and/or decreasing the search radius will decrease the severity of this problem at the class and landscape levels. However, at the patch level, regardless of scale, individual patches located within the search radius of the boundary will have biased indices. In addition, these indices evaluate the landscape context of patches at a specific scale of analysis defined by the size of the search radius. Therefore, these indices are only meaningful if the specified search radius has some ecological relevance to the phenomenon under consideration. Otherwise, the results will be arbitrary and therefore meaningless.

Lastly, functional nearest-neighbor distance and the similarity index are functional metrics in that they require additional parameterization, in this case, resistance coefficients that are unique to the ecological phenomenon under consideration. Consequently, as with any functional metric, their relevance depends entirely on the meaningfulness of the resistance coefficients applied. If these are arbitrary assignments or based on weak observational data, results will be arbitrary and therefore meaningless.

Insights on Metrics

Connectivity Metrics



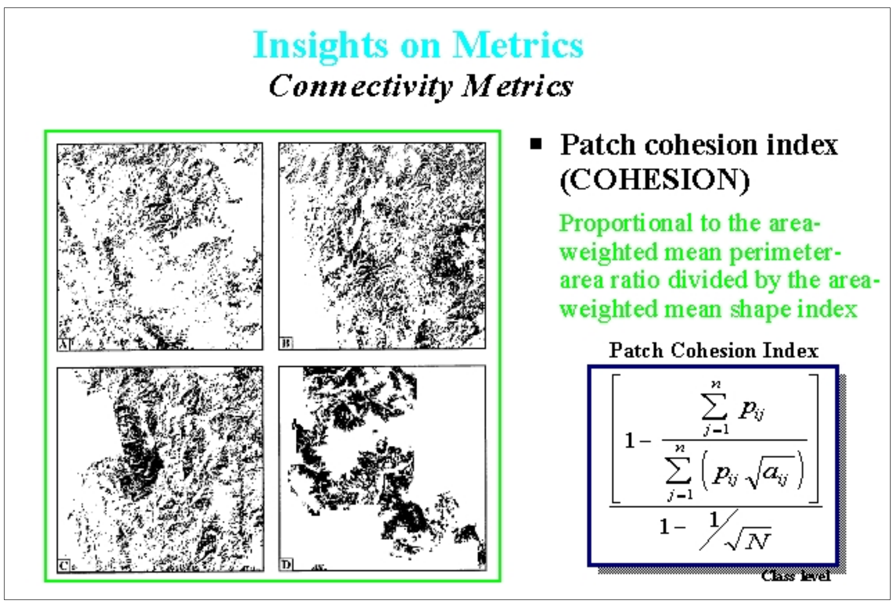
- Connectance index
- Patch cohesion index

"What ultimately influences the connectivity of the landscape from the organism's perspective is the scale and pattern of movement (scale at which the organism perceives the landscape) relative to the scale and pattern of patchiness."

8. Connectivity Metrics

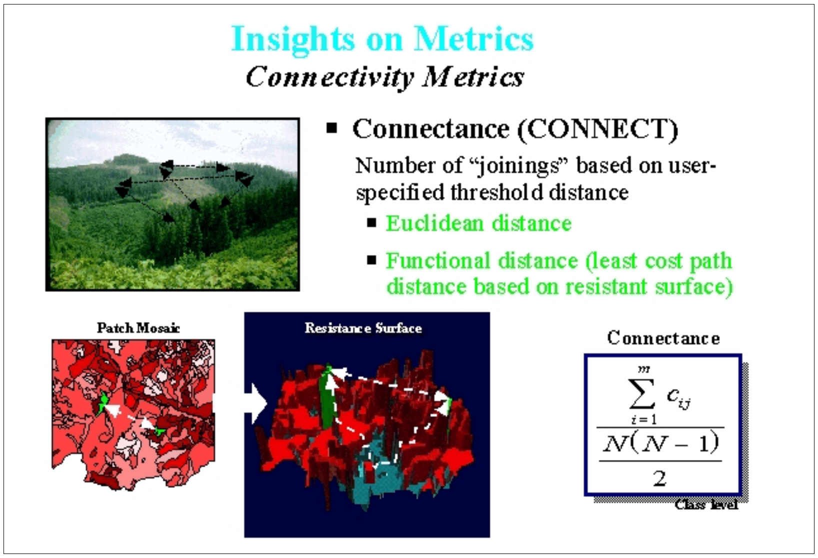
<u>Background</u>.–Connectivity refers to the degree to which a landscape facilitates or impedes ecological flows (e.g., the movement of organisms among habitat patches and therefore the rate of movement among local populations in a metapopulation). An abrupt change in the connectivity of the landscape, for example, as might be caused by habitat loss and fragmentation, may interfere with dispersal success, such that formerly widespread populations may suddenly become fragmented into small, isolated populations. This may in turn lead to an abrupt decline in patch occupancy (metapopulation dynamics) and ultimately extinction of the population across the landscape (extinction thresholds).

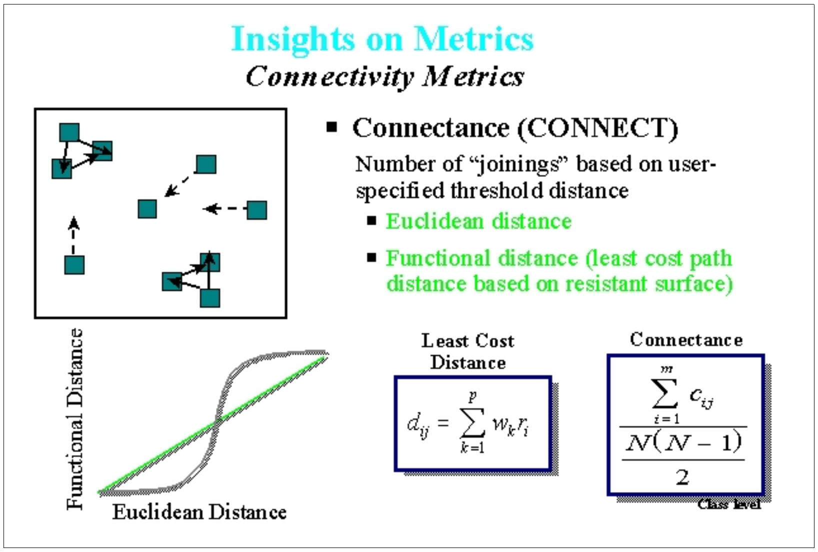
Although connectivity is considered a "vital element of landscape structure" (Taylor et al., 1993), it has eluded precise definition and has been difficult to quantify and implement in practice. In part, this is due to differences between the "structural connectedness" of patch types (or habitat) and the "functional connectedness" of the landscape as perceived by an organism or ecological process. Structural connectedness refers to the physical continuity of a patch type (or a habitat) across the landscape. Contiguous habitat is physically connected, but once subdivided, for example, as a result of habitat fragmentation, it becomes physically disconnected. Structural connectedness can be evaluated by a combination of measures of habitat extent, subdivision, and contagion. The notion of structural connectedness adopts an island biogeographic perspective because the focus is on the physical continuity of a single patch type. What constitutes "functional connectedness" between patches, on the other hand, clearly depends on the organism or process of interest; patches that are connected for bird dispersal might not be connected for salamanders, seed dispersal, fire spread, or hydrologic flow. As With (1999) notes, “what ultimately influences the connectivity of the landscape from the organism’s perspective is the scale and pattern of movement (scale at which the organism perceives the landscape) relative to the scale and pattern of patchiness (structure of the landscape); ...i.e., a species’ gap-crossing or dispersal ability relative to the gap-size distribution on the landscape”(Dale et al. 1994, With and Crist 1995, Pearson et al. 1996, With et al. 1997). Functional connectedness, therefore, relates to the interaction of ecological flows (including organisms) with landscape pattern. Functional connections might be based on: (1) strict adjacency (touching) or some threshold distance (a maximum dispersal distance); (2) some decreasing function of distance that reflects the probability of connection at a given distance; or (3) a resistance-weighted distance function, e.g., where the distance between two patches is computed as the least cost distance on a resistance surface, where each intervening location between habitat patches is assigned a resistance value based on its permeability to movement by the focal organism. Then various indices of overall connectedness can be derived based on the pairwise connections between patches.



FRAGSTATS Metrics.–Although connectivity can be evaluated using a wide variety of FRAGSTATS metrics that indirectly say something about either the structural or functional connectedness of the landscape, FRAGSTATS computes a few metrics whose sole purpose is to measure connectivity. *Patch cohesion* (COHESION) was proposed by Schumaker (1996) to quantify the connectivity of habitat as perceived by organisms dispersing in binary landscapes. Patch cohesion is computed from the information contained in patch area and perimeter. Briefly, it is proportional to the area-weighted mean perimeter-area ratio divided by the area-weighted mean patch shape index (i.e., standardized perimeter-area ratio). It is well known that, on random binary maps, patches gradually coalesce as the proportion of habitat cells increases, forming a large, highly connected patch (termed a percolating cluster) that spans that lattice at a critical proportion (p_c) that varies with the neighbor rule used to delineate patches (Staufer 1985, Gardner et al. 1987). Patch cohesion has the interesting property of increasing monotonically until an asymptote is reached near the critical proportion. Another index, *connectance*

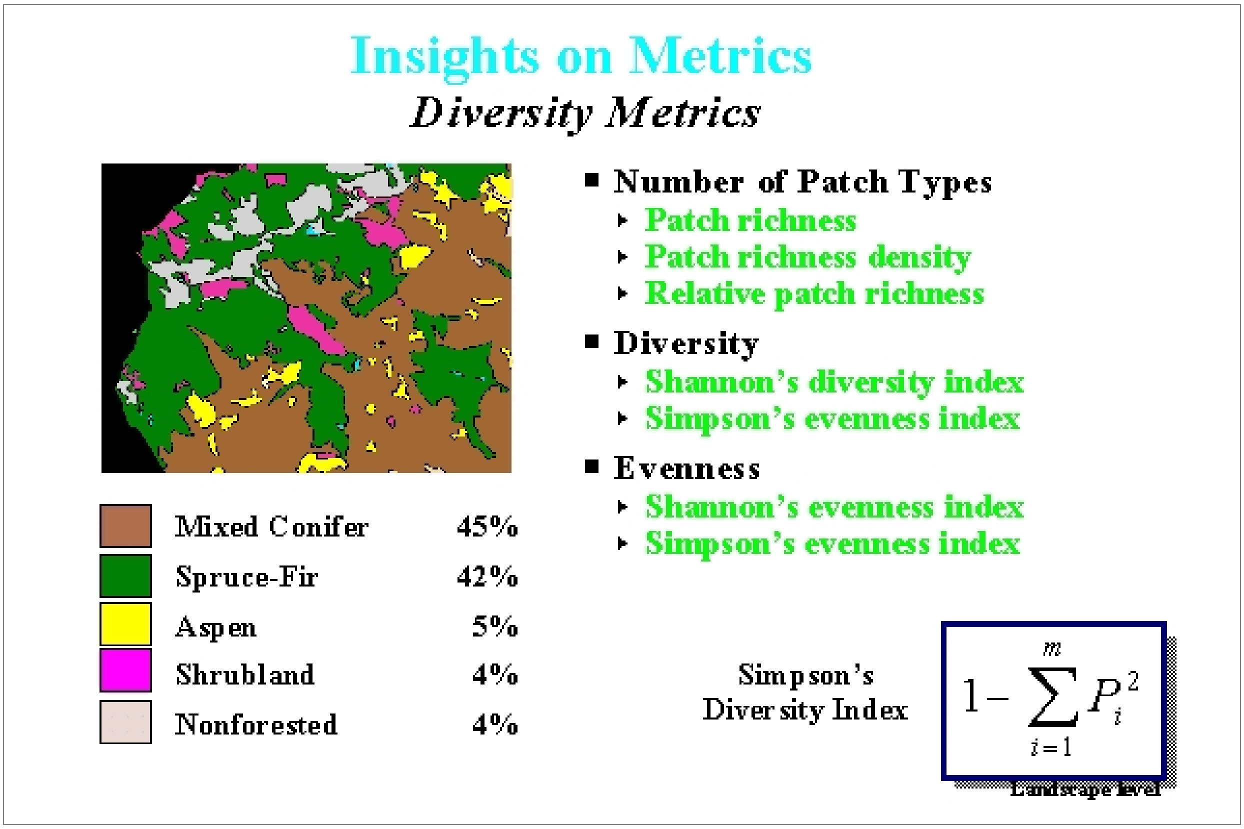
(CONNECT), can be defined on the number of functional joinings, where each pair of patches is either connected or not based on some criterion. FRAGSTATS computes connectance using a threshold distance specified by the user and reports it as a percentage of the maximum possible connectance given the number of patches. The threshold distance can be based on either Euclidean distance or functional distance, as described elsewhere (see Isolation/Proximity Metrics). Connectedness can also be defined in terms of *correlation length* for a raster map comprised of patches defined as clusters of connected cells. Correlation length is based on the average extensiveness of connected cells, and is computed as the area-weighted mean radius of gyration across all patches in the class or landscape. Correlation length is not included with the connectivity metrics in the FRAGSTATS graphical user interface because it is already included as a distribution metric for patch radius of gyration (GYRATE_AM) under the Area/Density/Edge metrics. A map's correlation length is interpreted as the average distance one might traverse the map, on average, from a random starting point and moving in a random direction, i.e., it is the expected traversability of the map (Keitt et al. 1997).





Finally, FRAGSTATS also computes a *traversability index* (TRAVERSE) based on the idea of ecological resistance. A hypothetical organism in a highly traversable neighborhood cell can reach a large area with minimal crossing of "hostile" cells. This metric uses a resistance-weighted spread algorithm to determine the area that can be reached from each cell in a focal patch. The focal cell gets an organism-specific "bank account," which represents, say, an energy budget available to the organism for dispersal from the focal cell. The size of the account is selected to reflect the organism's dispersal or movement ability, and translates into ecological neighborhood size around a focal cell. Each patch type (including the focal patch type) is assigned a cost, based on a user-specified resistance matrix. Specifically, relative to a each focal patch type, each patch type is assigned a resistance coefficient in the form of weights ranging from 1 (minimum resistance, usually associated with focal patch type) to any higher number that reflects the relative increase in resistance associated with each patch type. The index is computed at the individual cell level as follows. The metric is computed by simulating movement away from the focal cell in all directions, where there is a cost to move through every cell. Even a cell of the same patch type will have a cost, usually set to 1, so that under the best circumstances (i.e., minimum resistance), there will exist a maximum dispersal area based on the specified account or energy budget. Note that assigning a (small) cost for traveling through the focal community (typically a cost of 1) results in a linearly decaying function. Moving through more resistant cells costs more and drains the account faster. Thus, depending on the resistance of the actual landscape in the vicinity of the focal cell, there will be a certain area that a dispersing organism can access. This area represents the least-cost hull around the focal cell, or the maximum distance that can be moved from the cell in all directions until the "bank account" is depleted. This dispersal area, given as a percentage of the maximum dispersal area under conditions of minimum resistance, provides a measure of the traversability of the landscape in the vicinity of the focal cell. Averaging this index across cells at the patch, class, or landscape level provides an index of traversability.

Limitations.–These metrics are limited in a variety of ways. First, patch cohesion is based on perimeter and area calculations and is therefore subject to the same limitations discussed elsewhere (see Area/Density/Edge Metrics) for edge calculations. Moreover, despite its appealing performance under certain conditions (e.g., Schumaker 1996), this index is plagued by the lack of a straightforward and intuitive interpretation. As a result, it remains largely untested in other ecological applications. Like all distance-based metrics, connectance suffers from the same limitations as nearest-neighbor distance (see Isolation/Proximity Metrics). Specifically, only patches within the landscape are considered when determining if a patch is connected or not, despite the fact that a patches' nearest neighbor may be just outside the landscape boundary. Finally, like all functional metrics, the traversability index requires substantial knowledge of the organism or process under consideration in order to specify meaningful resistance coefficients. If the weighting scheme does not accurately represent the phenomenon under investigation, then the results will be spurious.



9. Diversity Metrics

Background.–Diversity measures have been used extensively in a variety of ecological applications. They originally gained popularity as measures of plant and animal species diversity. There has been a proliferation of diversity indices and we will make no attempt to review them here. FRAGSTATS computes 3 diversity indices. These diversity measures are influenced by 2 components--richness and evenness. Richness refers to the number of patch types present; evenness refers to the distribution of area among different types. Richness and evenness are generally referred to as the compositional and structural components of diversity, respectively. Some indices (e.g., Shannon's diversity index) are more sensitive to richness than evenness. Thus, rare patch types have a disproportionately large influence on the magnitude of the index. Other indices (e.g., Simpson's diversity index) are relatively less sensitive to richness and thus place more weight on the common patch types. These diversity indices have been applied by landscape ecologists to measure one aspect of landscape structure--landscape composition (e.g., Romme 1982, O'Neill et al. 1988, Turner 1990a).

FRAGSTATS Metrics.–FRAGSTATS computes several statistics that quantify diversity at the landscape level. These metrics quantify landscape composition at the landscape level; they are not affected by the spatial configuration of patches. The most popular diversity index is *Shannon's diversity index* (SHDI) based on information theory (Shannon and Weaver 1949). The value of this index represents the amount of "information" per individual (or patch, in this case). Information is a somewhat abstract mathematical concept that we will not attempt to define. The absolute magnitude of Shannon's diversity index is not particularly meaningful; therefore, it is used as a relative index for comparing different landscapes or the same landscape at different times. *Simpson's diversity index* (SIDI) is another popular diversity measure that is not based on information theory (Simpson 1949). Simpson's index is less sensitive to the presence of rare types and has an interpretation that is much more intuitive than Shannon's index. Specifically, the value of Simpson's index represents the probability that any two cells selected at random would be different patch types. Thus, the higher the value the greater the likelihood that any 2 randomly drawn cells would be different patch types. Because Simpson's index is a probability, it can be interpreted in both absolute and relative terms. FRAGSTATS also computes a *modified Simpson's diversity index* (MSIDI) based on Pielou's (1975) modification of Simpson's diversity index; this index was used by Romme (1982). The modification eliminates the intuitive interpretation of Simpson's index as a probability, but transforms the index into one that belongs to a general class of diversity indices to which Shannon's diversity index belongs (Pielou 1975). Thus, the modified Simpson's and Shannon's diversity indices are similar in many respects and have the same applicability.

Patch richness (PR) measures the number of patch types present; it is not affected by the relative abundance of each patch type or the spatial arrangement of patches. Therefore, two landscapes may have very different structure yet have the same richness. For example, one landscape may be comprised of 96% patch type A and 1% each of patch types B-E, whereas another landscape may be comprised of 20% each of patch types A-E. Although patch richness would be the same, the functioning of these landscapes and the structure of the animal and plant communities would likely be greatly different. Because richness does not account for the relative abundance of each patch type, rare patch types and common patch types contribute equally to richness. Nevertheless, patch richness is a key element of landscape structure because the variety of landscape elements present in a landscape can have an important influence on a variety of ecological processes. Because many organisms are associated with a single patch type, patch richness often correlates well with species richness.

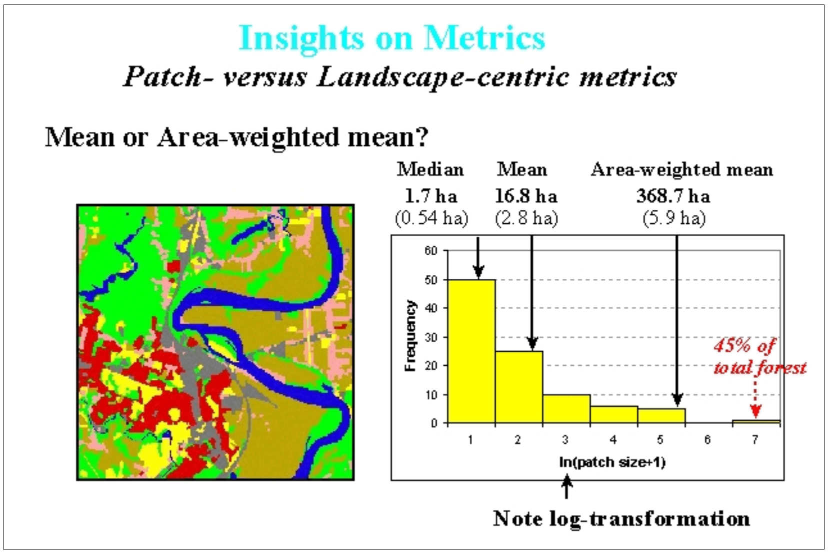
Richness is partially a function of scale. Larger areas are generally richer because there is generally greater heterogeneity over larger areas than over comparable smaller areas. This contributes to the species-area relationship predicted by island biogeographic theory (MacArthur and Wilson 1967). Therefore, comparing richness among landscapes that vary in size can be problematic. *Patch richness density* (PRD) standardizes richness to a per area basis that facilitates comparison among landscapes, although it does not correct for this interaction with scale. FRAGSTATS also computes a relative richness index. *Relative patch richness* (RPR) is similar to patch richness, but it represents richness as a percentage of the maximum potential richness as specified by the user (Romme 1982). This form may have more interpretive value than absolute richness or richness density in some applications. Note that relative patch richness and patch richness are completely redundant and would not be used simultaneously in any subsequent statistical analysis.

Evenness measures the other aspect of landscape diversity--the distribution of area among patch types. There are numerous ways to quantify evenness and most diversity indices have a corresponding evenness index derived from them. In addition, evenness can be expressed as its compliment--dominance (i.e., evenness = 1 - dominance). Indeed, dominance has often been the chosen form in landscape ecological investigations (e.g., O'Neill et al. 1988, Turner et al. 1989, Turner 1990a), although we prefer evenness because larger values imply greater landscape diversity. FRAGSTATS computes 3 evenness indices (*Shannon's evenness index*, SHEI; *Simpson's evenness index*, SIEI; *modified Simpson's evenness index*, MSIEI), corresponding to the 3 diversity indices. Each evenness index isolates the evenness component of diversity by controlling for the contribution of richness to the diversity index. Evenness is expressed as the observed level of diversity divided by the maximum possible diversity for a given patch richness. Maximum diversity for any level of richness is achieved when there is an equal distribution of area among patch types. Therefore, the observed diversity divided by the maximum diversity (i.e., equal distribution) for a given number of patch types represents the proportional reduction in the diversity index attributed to lack of perfect evenness. As the evenness index approaches 1, the observed diversity approaches perfect evenness. Because evenness is represented as a proportion of maximum evenness, Shannon's evenness index does not suffer from the limitation of Shannon's diversity index with respect to interpretability.

Limitations.–The use of diversity measures in community ecology has been heavily criticized because diversity conveys no information on the actual species composition of a community. Species diversity is a community summary measure that does not take into account the uniqueness or potential ecological, social, or economical importance of individual species. A community may have high species diversity yet be comprised largely of common or undesirable species. Conversely, a community may have low species diversity yet be comprised of especially unique, rare, or highly desired species. Although these criticisms have not been discussed explicitly with regards to the landscape ecological application of diversity measures, these criticisms are equally valid when diversity measures are applied to patch types instead of species. In addition, diversity indices like Shannon’s index and Simpson’s index combine richness and evenness components into a single measure, even though it is usually more informative to evaluate richness and evenness independently.

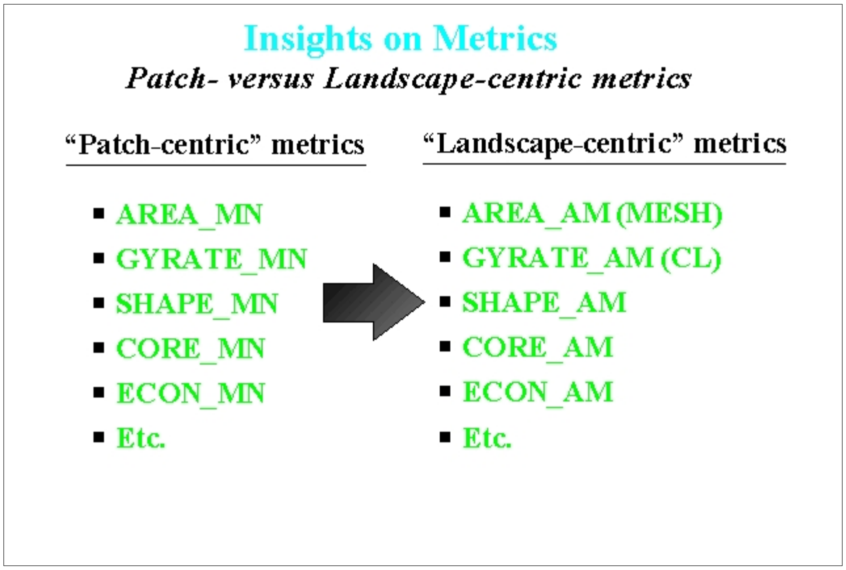
10. Insights on the Use of Landscape Metrics

All landscape metrics suffer from limitations that restrict their use and/or interpretation in different contexts. Unfortunately, a comprehensive theoretical understanding of metric behavior under varying conditions does not exist. Moreover, given the varied landscape contexts in which metrics are applied in real-world landscapes, a comprehensive empirical understanding of metric behavior under the full range of conditions in which they may be applied is not possible. Consequently, the choice and interpretation of metrics in any particular application is often quite challenging. In addition to the many specific considerations and limitations of particular metrics or groups of metrics discussed above, a few additional insights regarding the overall use of metrics are warranted.

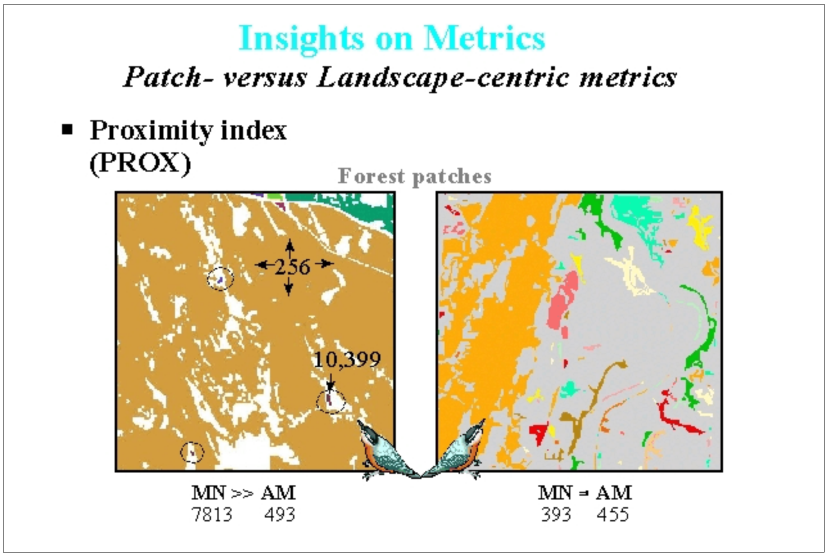


(1). *Patch- versus landscape-based perspective*.–Metrics applied to categorical patch mosaics (under the "landscape mosaic model" of landscape structure) fundamentally represent the structure of the landscape as defined by its *patch* structure. Clearly, patches are the basic building blocks of categorical patch mosaics and, as such, most metrics derive from the spatial character and distribution of the patches themselves. However, most patch-based metrics can be summarized at the class and landscape levels to reflect the character and distribution of individual patches over a broad extent. Indeed, in most applications, the objective involves characterizing the patch structure for a single focal class or for the entire patch mosaic across the full extent of the landscape, rather than focusing on individual patches. Despite the common objective of characterizing the class or landscape structure, metrics differ in whether they offer a "patch-based" or "landscape-based" perspective of landscape structure. This is perhaps best illustrated by the difference between class and/or landscape distribution metrics based on the simple arithmetic mean or the area-weighted mean.

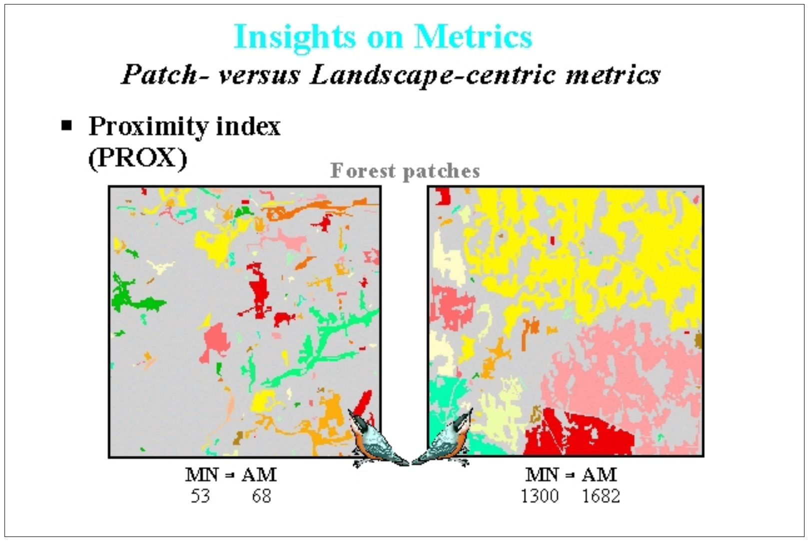
Metrics based on the *mean* patch characteristic, such as mean patch size (AREA_MN) or mean patch shape index (SHAPE_MN), provide a measure of central tendency in the corresponding patch characteristic across the entire landscape, but nevertheless describe the patch structure of the landscape as that of the average patch characteristic. Thus, each patch regardless of its size is considered equally (i.e., given equal weight) in describing the landscape structure. Consequently, metrics based on the mean patch characteristic offer a fundamentally patch-based perspective of the landscape structure. They do not describe the conditions, for example, that an animal dropped at random on the landscape would experience, because that depends on the probability of landing in a particular patch, which is dependent on patch size.



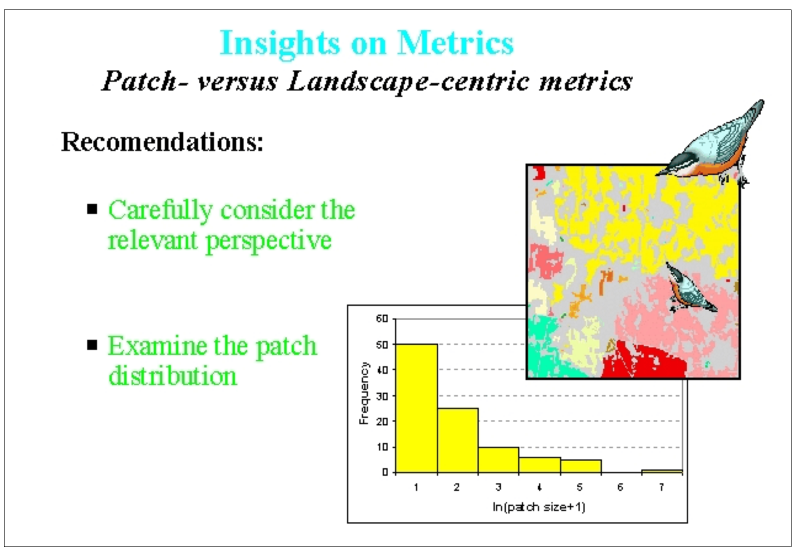
Conversely, metrics based on the *area-weighted mean* patch characteristic, such as the area-weighted mean patch size (AREA_AM) and area-weighted mean patch shape index (SHAPE_AM), while still derived from patch characteristics, provide a landscape-based perspective of landscape structure because they reflect the average conditions of a pixel chosen at random or the conditions that an animal dropped at random on the landscape would experience. This is in fact the basis for the subdivision metrics of Jaeger (2000) described previously. There are some special cases involving the isolation metrics (proximity index, similarity index, and nearest neighbor distance), however, where the area-weighted mean patch characteristic can provide misleading results. The isolation metrics describe the spatial context of individual patches, and they can be summarized at the class or landscape level to characterize the entire landscape. Consider the proximity index (PROX). The proximity index operates at the patch level. For each patch, the size and distance to all neighboring patches of the same type (within some specified search distance) are enumerated to provide an index of patch isolation. A patch with lots of other large patches in close proximity will have a large index value (i.e., low isolation). Both the mean and area-weighted mean proximity index can be calculated at the class and landscape levels. A potential problem in interpretation lies in cases involving widely varying patch sizes. Consider the special case involving 10 patches of the focal class, in



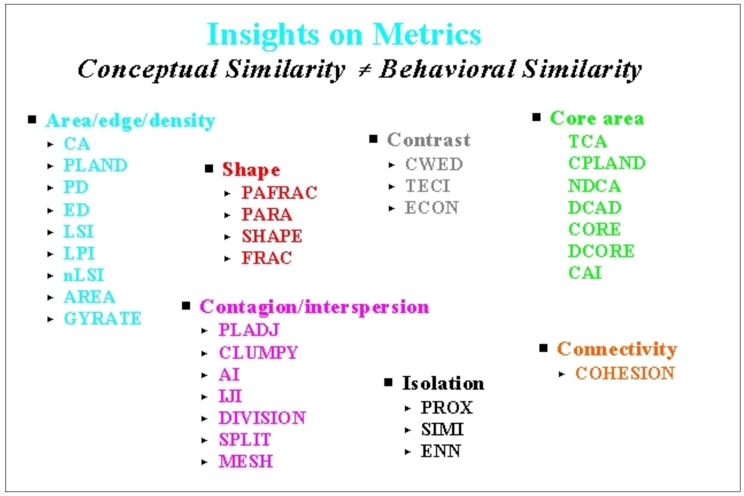
which 9 of the 10 patches are equal in size and quite small (say 1 ha each). The ninth patch, however, is quite large (say 1,000 ha). Let's assume that all the small patches are close to the large patch (within the search distance). The proximity index for each of the 9 small patches will be quite large, because the single large patch will be enumerated in the index. The proximity index for the single large patch will be quite small, because the only neighboring patches are quite small (1 ha each). Consequently, the mean proximity index will be much larger than the area-weighted mean proximity index, connoting very different levels of patch isolation. Which is correct? It is difficult to say. From a purely patch-based perspective, the mean would appear to capture the structure best, since the average "patch" is not very isolated. However, the average "organism" would be found in the single large patch, since it represents >99% of the focal habitat area, so it seems logical that the area-weighted mean would provide a better measure. In this case, the area-weighted mean proximity index will be quite small, connoting high isolation, when in fact the single large patch represent the matrix of the landscape. In this case, it is not clear whether either the mean or area-weighted mean proximity index provides a useful measure of isolation. The important point here is that for some metrics, namely the isolation metrics, under some conditions, namely extreme patch size distributions, the mean and area-weighted mean can provide different and potentially misleading results.

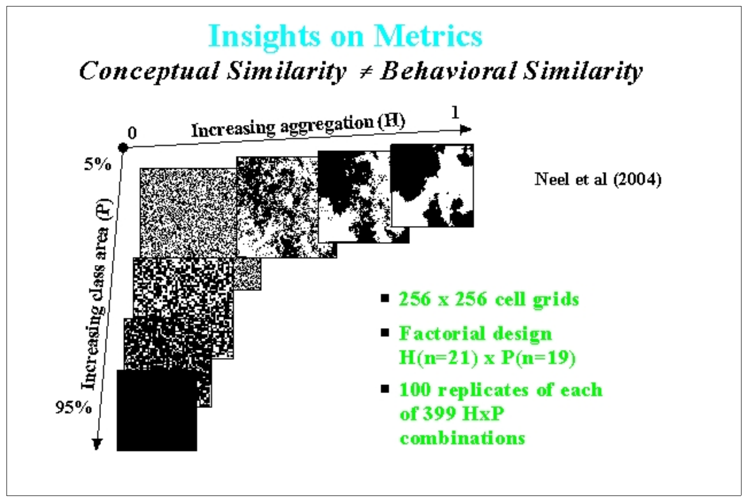


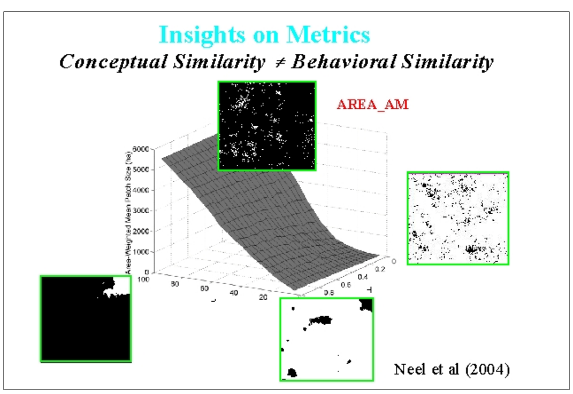
Given these important differences between the mean and area-weighted mean, careful consideration should be given to the choice of metrics in any particular application. Despite the preponderance of use of the mean in practice, in most applications, it is likely that the area-weighted mean provides a more meaningful perspective on landscape structure, although for the isolation metrics one needs to take great care to ensure that the interpretation is meaningful given the landscape structure.

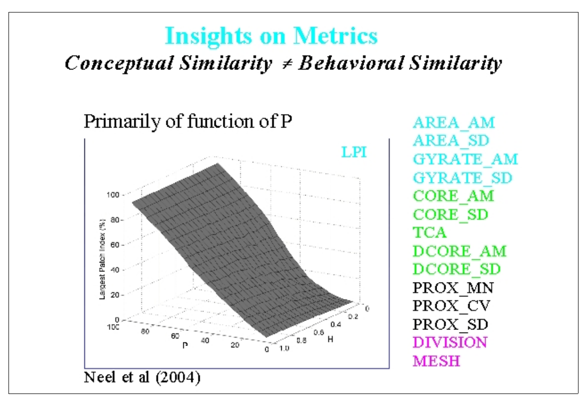


(2). _Conceptual similarity does not equal behavioral similarity_.–As noted in the introduction, landscape structure metrics have traditionally been organized conceptually according to the aspect of landscape composition or configuration they supposedly measure (as in the previous sections). It is common for practitioners to choose metrics from each of the conceptual classes in order to describe different aspects of a landscape (Ripple et al. 1991). Neel et al (2004) demonstrate that it is also important to consider behavioral groupings because a number of conceptually different metrics have similar behavior and thus are redundant. Similarly, metrics from the same conceptual group often exhibit widely varying behaviors indicating differences in how they respond to attributes of landscape pattern. Unfortunately, given the range of conditions in real-world landscapes, it is not possible to assign metrics to behavioral groups that are guaranteed to be stable across the full range of real-world landscapes. The important point here is that conceptual similarity does not always equal behavioral similarity. Thus, in choosing a parsimonious suite of metrics for a particular application, don’t simply used conceptual groups as the basis for metric choice.





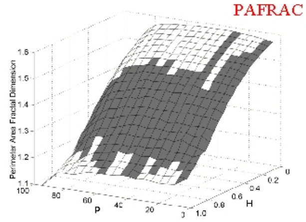




Insights on Metrics

Conceptual Similarity ≠ Behavioral Similarity

Primarily of function of H



PAFRAC

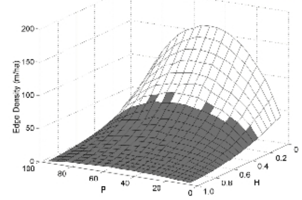
nLSI
PARA_SD
FRAC_CV
FRAC_SD
CAI_SD
CLUMPY

Neel et al (2004)

Insights on Metrics

Conceptual Similarity ≠ Behavioral Similarity

Interaction of P and H
(parabolic response along P)



ED

LSI
PD
GYRATE_CV
FRAC_AM
SHAPE_AM
SHAPE_CV
SHAPE_SD
PROX_AM
DCORE_CV
DCAD

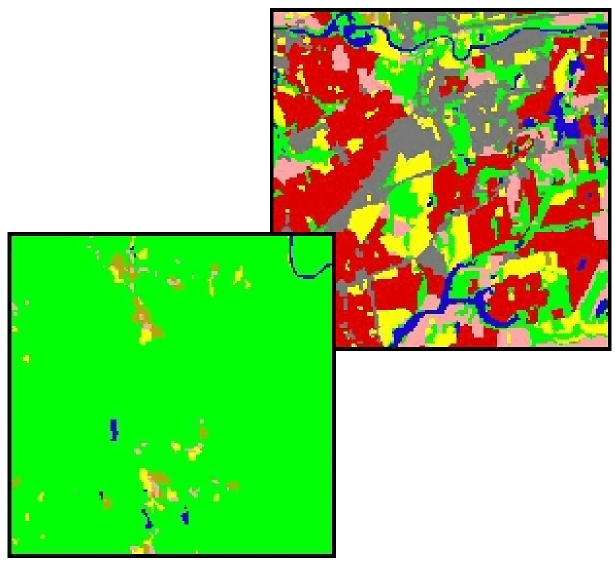
Neel et al (2004)

Insights on Metrics

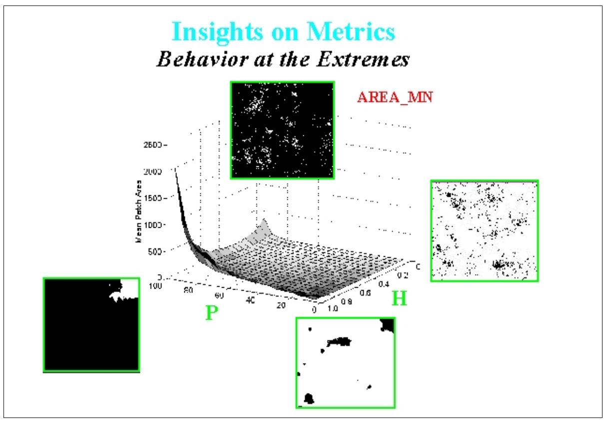
Conceptual Similarity ≠ Behavioral Similarity

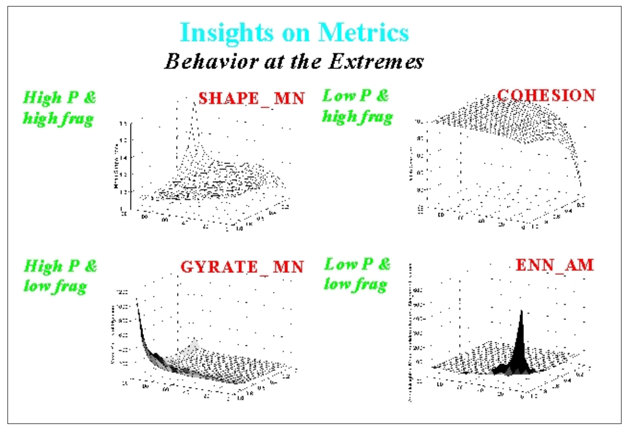
Recomendations:

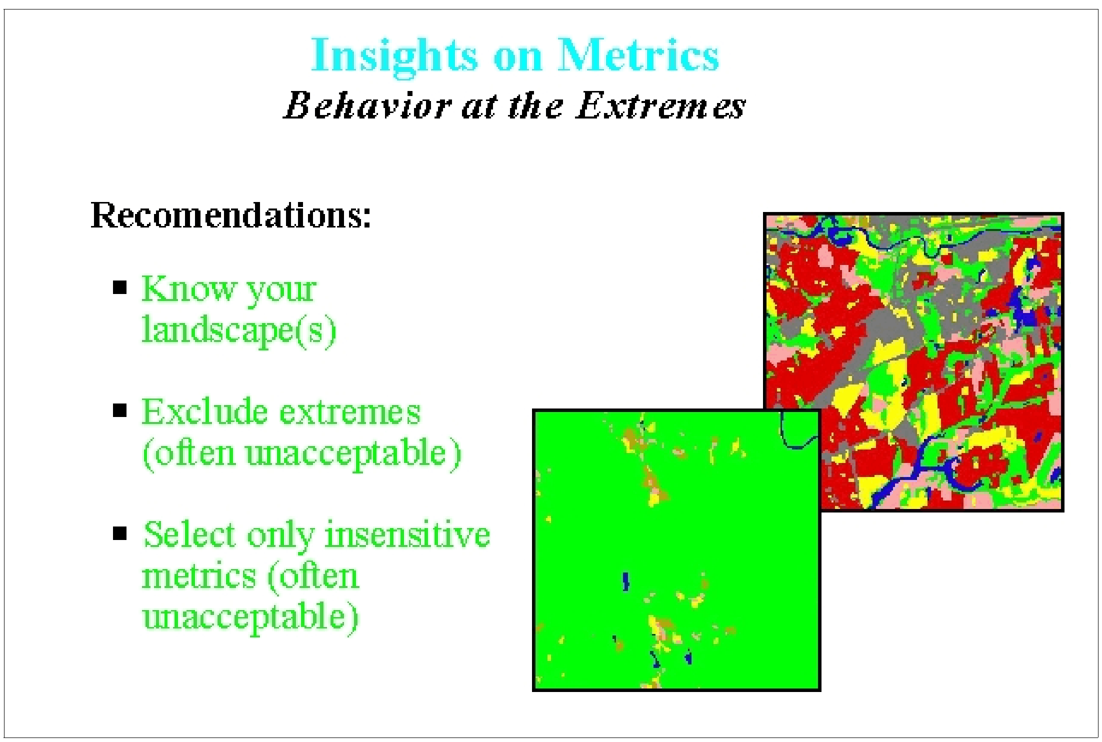
- Know your metrics
- Select metrics based on hypothesized relationships
- Conduct redundancy analysis, if practical



(3). ***Behavior at the extremes***.–Finally, a number metrics exhibit erratic and/or unstable behavior at extreme conditions and demonstrate that landscape structure is difficult to characterize at the class level when the focal class is either dominant or extremely rare and at the landscape level when a single class is dominant (Neel et al. 2004). Fortunately, quantifying configuration may not be that relevant or interesting in such landscapes anyway. This instability is not necessarily a problem with the metrics per se, but rather accentuates the need to understand what the metrics are describing and to apply them intelligently. For example, when the focal class dominates the landscape and forms a matrix, it is not meaningful to measure landscape structure with patch-based metrics. Similarly, when the focal class is extremely rare, patch-based metrics do a poor job of distinguishing among levels of configuration.







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