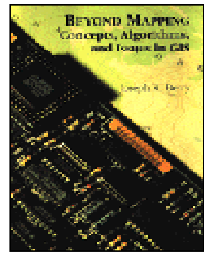
Beyond Mapping I



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Topic 5 – *Assessing Variability, Shape, and Pattern of Map Features*

Note: The processing and figures discussed in this topic were derived using MapCalc[TM] software. See www.innovativegis.com to download a free MapCalc Learner version with tutorial materials for classroom and self-learning map analysis concepts and procedures.

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Need to Ask the Right Questions Takes You Beyond Mapping

(GIS World, August 1991)

...where up so floating, many bells down... (T.S. Eliot)

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Is some of this "Beyond Mapping" discussion a bit dense? Like a T.S. Eliot poem— full of significance (?), but somewhat confusing for the uninitiated. I am sure many of you have been left musing, "So what... this GIS processing just sounds like a bunch of gibberish to me." You're right. You are a decision-maker, not a technician. The specifics of processing are not beyond you and your familiar map; it's just that such details are best left to the technologist... or are they?

The earlier topics addressed this concern. They established GIS as, above all else, a communication device facilitating the discussion and evaluation of different perspectives of our actions on the landscape. The hardest part of GIS is not digitizing, database creation, or even communicating with the 'blasted' system. Those are technical considerations which have technical solutions outlined in the manual. The hardest part of GIS is asking the right questions. Those involve conceptual considerations requiring you to think spatially. That's why you, the GIS user, need to go beyond mapping. So you can formulate your complex questions about geographic space in a manner that the technology can use. GIS can do a lot of things— but it doesn't know what to do without your help. A prerequisite to this partnership is your responsibility to develop an understanding of what GIS can, and can't do.

With this flourish in mind, let's complete our techy discussion of neighborhood operators (GIS World issues June-December, 1990). Recall that these techniques involve summarizing the information found in the general vicinity of each map location. These summaries can characterize the surface configuration (e.g., slope and aspect) or generate a statistic (e.g., total and average values). The neighborhood definition, or 'roving window,' can have a simple geometric shape (e.g., all locations within a quarter of a mile) or a complex shape (all locations within a ten minute drive). Window shape and summary technique are what define the wealth of neighborhood operators, from simple statistics to spatial derivative and interpolation. OK, so much for review; now onto the new stuff.

An interesting group of these operators are referred to as 'filters'. Most are simple binary or weighted windows as discussed in previous issues. But one has captivated my imagination since Dennis Murphy of the EROS Data Center introduced me to it late 1970's. He identified a technique for estimating neighborhood variability of nominal scale data using a Binary Comparison Matrix (BCM). That's mouthful of nomenclature, but it's fairly simple, and extremely useful concept. As we are becoming more aware, variability within a landscape plays a significant role in how we (and our other biotic friends) perceive an area. But, how can we assess such an elusive concept in decision terms?

Neighborhood variability can be described two ways— the complexity of an entire neighborhood and the comparison of conditions within the neighborhood. These concepts can be outlined as follows.

NEIGHBORHOOD VARIABILITY

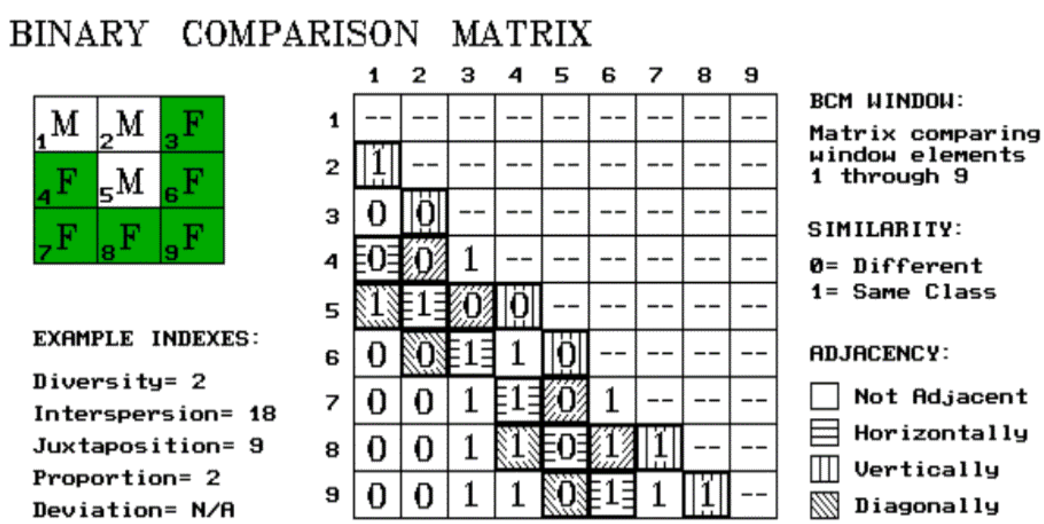
- ✓ **COMPLEXITY** (Entire Neighborhood)
- o **DIVERSITY**— number of different classes

- o **INTERSPERSION**— frequency of class occurrence
- o **JUXTAPOSION**— spatial arrangement of classes

- ✓ **COMPARISON** (Individual Versus Neighbors)
- o **PROPORTION**— number of neighbors having the same class as the window center
- o **DEVIATION**— difference between the window center and the average of its neighbors

Consider the 3x3 window in figure 1. Assume "M" is one class of vegetation (or soil, or land use) and "F" is another. The simplest summary of neighborhood variability is to say there are two classes. If there was only one class in the window, you would say there is no variability. If there were nine classes, you would say there is a lot more variability. The count of the number of different classes is called diversity, the broadest measure of neighborhood variability. If there were only one cell of "M" and eight of "F", you would probably say, "sure the diversity is still two, but there is less variability than the three of "M" versus six of "F" condition in our example.

The measure of the frequency of occurrence of each class, termed interspersion, is a refinement on the simple diversity count. But doesn't the positioning of the different classes contribute to window variability? It sure does. If our example's three "M's" were more spread out like a checkerboard, you would probably say there was more variability. The relative positioning of the classes is termed juxtapositioning.



The Binary Comparison Matrix summarizes neighborhood variablity. Window element with the same class are assigned 1 and those with different classes are assigned 0. Summing various groups of matrix pairings results in several neighborhood variability indexes.

Figure 1. Binary Comparison Matrix summarizes neighborhood variability.

We're not done yet. There is another whole dimension to neighborhood variability. The measures of diversity, interspersion and juxtapositioning summarize an entire neighborhood's complexity. Another way to view variability is to compare one neighborhood element to its surrounding elements. These measures focus on how different (often termed anomaly detection) a specific cell is to its surroundings. For our example, we could calculate the number of neighbors having the same classification as the center element. This technique, termed proportion, is appropriate for nominal, discontinuous mapped data like a vegetation map. For gradient data, like elevation, deviation can be computed by subtracting the average of the neighbors from the center element. The greater the difference, the more unusual the center is. The sign of the difference tells you the nature of the anomaly— unusually bigger (+) or smaller (-).

Whew! That's a lot of detail. And, like TS's poems, it may seem like a lot of gibberish. You just look at landscape and intuitively sense the degree of variability. Yep, you're smart— but the computer is dumb. It has to quantify the concept of variability. So how does it do it? …using a Binary Comparison Matrix of course. First, "Binary" means we will only work with 0's and 1's. "Comparison" says we will compare each element in the window with every other element. If they are the same assign a 1. If different, assign a 0. The term "Matrix" tells us how the data will be organized.

Now let's put it all together. In the figure, the window elements are numbered from one through nine. Is the class for element 1 the same as for element 2? Yes (both are "M"), so assign a 1 at the top of column one in the table. How about elements 1 and 3? Nope, so assign a 0 in the second position of column one. How about 1 and 4? Nope, then assign another 0. Etc., etc., etc, until all of the columns in the matrix contain a "0" or a "1". But you are bored already. That's the beauty of the computer. It enjoys completing the table. And yet another table for next position as the window moves to the right. And the next ...and the next ...for thousands of times, as the roving the window moves throughout a map.

So why put your silicon subordinate through all this work. Surely its electrons get enough exercise just reading your electronic mail. The work is worth it because the BCM contains the necessary data to quantify variability. It is how your computer 'sees' landscape variability from its digital world. As the computer compares the window elements it keeps track of the number of different classes it encounters— diversity= 2. Within the table there are 36 possible comparisons. In our example, we find that eighteen of these are similar by summing the entire matrix— interspersion= 18. The relative positioning of classes in the window can be summarized in several ways. Orthogonal adjacency (side-by-side and top-bottom) is frequently used and is computed by summing the vertical/horizontal cross-hatched elements in the table— juxtaposition= 9. Diagonally adjacent and non-adjacent variability indexes sum different sets of window elements. Comparison of the center to its neighbors computes the sum for all pairs involving element 5— proportion= 2.

The techy reader is, by now, bursting with ideas of other ways to summarize the table. The rest of you are back to asking, "So what. Why should I care?" You can easily ignore the mechanics of the computations and still be a good decision-maker. But can you ignore the indexes? Sure, if you are willing to visit every hectare of your management area. Or visually assess every square millimeter of your map. And convince me, your clients and the judge of your exceptional mental capacity for detail. Or you could learn, on your terms, to interpret the computer's packaging of variability.

Does the spotted owl prefer higher or lower juxtapositioning values? What about the pine martin? Or Dan Martin, my neighbor? Extracting meaning from T.S. Eliot is a lot work. Same goes for the unfamiliar analytical capabilities, such as the BCM. It's not beyond you. You just need a good reason to take the plunge.

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In advance, I apologize to all quantitative geographers and pattern recognition professionals for the 'poetic license' I have invoked in this terse treatise of a technical subject. At the other extreme, those interested in going farther in "topological space" some classic texts are: Abler, R.J., J.S. Adams and P. Gould. 1971. Spatial Organization- The Geographer's View of the World, Prentice-Hall; and Munkres, J.R. 1975. Topology: A First Course, Prentice-Hall.

You Can't See the Forest for the Trees

...but on the other hand, you can't see the trees for the forest

(GIS World, September 1991)

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The previous section described how the computer sees landscape variability by computing indices of neighborhood "Complexity and Comparison." This may have incited your spirited reaction, "That's interesting. But, so what, I can see the variability of landscapes at a glance." That's the point. You *see* it as an image; the computer must *calculate* it from mapped data. You and your sickly, gray-toned companion live in different worlds— inked lines, colors and planimeters for you and numbers, algorithms and map-ematics for your computer. Can such a marriage last? It's like hippo and hummingbird romance— bound to go flat.

In the image world of your map, your eye jumps around at what futurist Walter Doherty calls "human viewing speed" …very fast random access of information (holistic). The computer, on the other hand, is much more methodical. It plods through thousands of serial summaries developed by focusing on each piece of the landscape puzzle (atomistic). In short, you see the forest; it sees the trees. You couldn't be further apart. Right?

No, it's just the opposite. The match couldn't be better. Both the strategic and the tactical perspectives are needed for a complete understanding of maps. Our cognitive analyses have been fine tuned through years of experience. It's just that they are hard to summarize and fold into on-the-ground decisions. In the past, our numerical analyses have been as overly simplifying, as they have been tedious. There is just too much information for human serial processing at the "tree" level of detail. That's where the computer's indices of spatial patterns come in. They provide an entirely new view of your landscape. One that requires a planner's and manager's understanding and interpretation before it can be effectively used in decision-making.

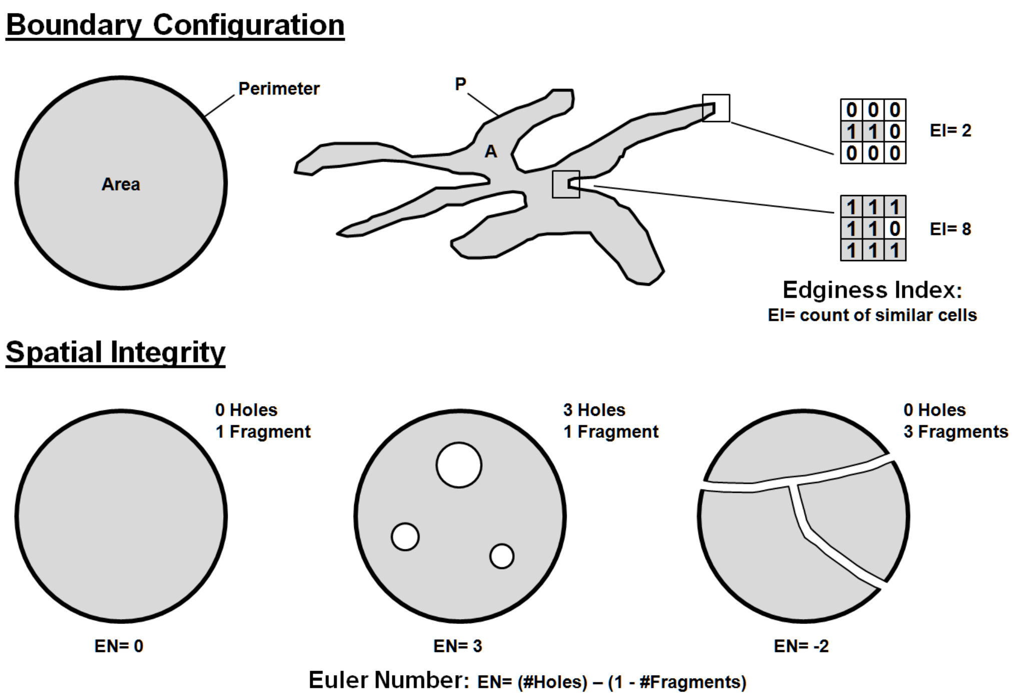

Figure 1. Characterizing boundary configuration and spatial integrity.

In addition to landscape variability discussed in the previous section, the size and shape of individual features affects your impression of spatial patterns. For example, suppose you are a wildlife manager assessing ruffed grouse habitat and population dynamics. Obviously the total acreage of suitable habitat is the major determinant of population size. That's a task for the "electronic planimeter" of the GIS toolbox— cell counts in raster systems, and table summaries in most vector systems. But is that enough? Likely not, if you want fat and happy birds.

The shape of each habitat unit plays a part. Within a broad context, shape involves two characteristics— Boundary Configuration and Spatial Integrity. Consider the top portion of the figure 1. Both habitat units are thirty acres in size. Therefore, they should support the same grouse grouping. Right? But research has shown that the bird prefers lots of forest/opening edge. That's the case on the right; it's boring and regular on the left. You can easily see it in the example. But what happens if your map has hundreds, or even thousands individual parcels. Your mind is quickly lost in the "tree" level detail of the "forest."

That's where the computer comes in. The boundary configuration, or "outward contour," of each feature is easily calculated as a ratio of the perimeter to the area. In planimetric space, the circle has the least amount of perimeter per unit area. Any other shape has more perimeter, and, as a result, a different "convexity index." In the few GIS's having this capability, the index uses a 'fudge factor (k)' to produce a range of values from 1 to 100. A theoretical zero indicates an infinitely large perimeter around an infinitesimally small area. At the other end, an index of a hundred is interpreted as being 100% similar to a perfect circle. Values in between define a continuum of boundary regularity. As a GIS user, your challenge is to translate this index into decision terms... "Oh, so the ruffed grouse likes it rough. Then the parcels with convexity indices less than fifty are particularly good, provided they are more than ten acres, of course." Now you're beyond mapping and actually GIS'ing.

But what about the character of the edge as we move along the boundary of habitat parcels? Are some places better than others? Try an "Edginess Index." It's similar to the Binary Comparison Matrix (BCM) discussed in the previous section. A 3x3 analysis window is moved about the edge of a map feature. A "1" is assigned to cells with the same classification as the edge cell; a "0" to those that are different. Two extreme results are shown in the figure. A count of "two" indicates an edge location that's really hanging out there. An "eight count" is an edge, but it is barely exposed to the outside. Which condition does the grouse prefer? Or an elk? Or the members of the Elks Lodge, for that matter? Maybe the factors of your decision-making don't care. At least it's comforting to know that such spatial variability can be quantified in a way the computer can 'see' it, and spatial modelers can use it.

That brings us to our final consideration— spatial integrity. It involves a count of "holes" and "fragments" associated with map features. If a parcel is just one glob, without holes poked in it, it is said to be intact, or "spatially balanced." If holes begin to violate its interior, or it is broken into pieces, the parcel's character obviously changes. Your eye easily assesses that. It is said that the spotted owl's eyes easily assess that, with the bird preferring large uninterrupted old growth forest canopies. But how about a computer's eye?

In its digital way, the computer counts the number of holes and fragments for the map features you specify. In a raster system, the algorithms performing the task are fairly involved. In a vector system, the topological structure of the data plays a big part in the processing. That's the concern of the programmer. For the rest of us, our concern is in understanding what it all means and how we might use it.

The simple counts of the number of holes and fragments are useful data. But these data taken alone can be as misleading as total acreage calculations. The interplay provides additional information, summarized by the "Euler Number" depicted in the figure. This index tracks the balance between the two elements of spatial integrity by computing their difference. If EN= 0, the feature is balanced. As you poke more holes in a feature, the index becomes positively unbalanced (large positive values). If you break it into a bunch of pieces, its index becomes negatively unbalanced (large negative values). If you poke it with the same number of holes as you break it into pieces, a feature becomes spatially balanced.

"What? That's gibberish." No, it's actually good information. It can tell you such enduring questions as "Does a Zebra have white strips on a black background; or black strips on a white background?" Or, "Is a region best characterized as containing urban pockets surrounded by a natural landscape; or natural areas surrounded by urban sprawl?" Or, "As we continue clear-cutting the forest, when do we change the fabric of the landscape from a forest with cut patches, to islands of trees within a clear-cut backdrop?" It's more than simple area calculations of the GIS.

Shape analysis is more than a simple impression you get as you look at a map. It's more than simple tabular descriptions in a map's legend. It's both the "forest" and the "trees"— an informational interplay between your reasoning and the computer's calculations.

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As with all Beyond Mapping articles, allow me to apologize in advance for the "poetic license" invoked in this terse treatment of a technical subject. Those interested in further readings having a resource application orientation should consult "Indices of landscape pattern," by O'Niell, et. al., in Landscape Ecology, 1(3):153-162, 1988, or any of the recent papers by Monica Turner, Environmental Sciences Division, Oak Ridge National Laboratory.

Discovering Feature Patterns *...everything has its place; everything in its place (Granny)*

(GIS World, October 1991)

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Granny was as insightful as she was practical. Her prodding to get the socks picked up and placed in the drawer is actually a lesson in the basic elements of ecology. The results of the dynamic interactions within a complex web of physical and biological factors put "everything in its place." The obvious outcome of this process is the unique arrangement of land cover features that seem to be tossed across a landscape. Mother Nature nurtures such a seemingly disorganized arrangement. Good thing her housekeeping never met up with Granny.

The last two sections have dealt with quantifying spatial arrangements into landscape *variability* and individual feature *shape*. This article is concerned with another characteristic your eye senses as you view a landscape— the *pattern* formed by the collection of individual features. We use such terms as 'dispersed' or 'diffused' and 'bunched' or 'clumped' to describe the patterns formed on the landscape. However, these terms are useless to our 'senseless' computer. It doesn't see the landscape as an image, nor has it had the years of practical experience required for such judgment. Terms describing patterns reside in your visceral. You just know these things. Stupid computer, it hasn't a clue. Or does it?

As previously established, the computer 'sees' the landscape in an entirely different way— digitally. Its view isn't a continuum of colors and shadings that form features, but an overwhelming pile of numbers. The real difference is that you use 'grey matter' and it uses 'computation' to sort through the spatial information.

So how does it analyze a pattern formed by the collection of map features? It follows, that the computer's view of landscape patterns must be some sort of a mathematical summary of numbers. Over the years, a wealth of indices has been suggested. Most of the measures can be divided into two broad approaches— those summarizing individual feature characteristics and those summarizing spacing among features.

Feature characteristics, such as abundance, size and shape can be summarized for an entire landscape. These landscape statistics provide a glimpse of the overall pattern of features. Imagine a large, forested area pocketed with clear-cut patches. A simple count of the number of clear-cuts gives you a 'first cut' measure of forest fragmentation. An area with hundreds of cuts is likely more fragmented than an equal-sized area with only a few. But it also depends on the size of each cut. And, as discussed in last section, the shape of each cut.

Putting size and shape together over an entire area is the basis of fractal geometry. In mathematical terms, the fractal dimension, D, is used to quantify the complexity of the shape of features using a perimeter-area relation. Specifically,

$$P \sim A^{**}(D/2)$$

where P is the patch perimeter and A is the patch area. The fractal dimension for an entire area is estimated by regressing the logarithm of patch area on its corresponding log-transformed perimeter. Whew! Imposing mathematical mechanics, but a fairly simple concept— more edge for a given area of patches means things are more complex. To the user, it is sufficient to know that the fractal dimension is simply a useful index. As it gets larger, it indicates an increasing 'departure from Euclidean geometry.' Or, in more humane terms, a large index indicates a more fragmented forest, and, quite possibly, more irritable beasts and birds.

Feature spacing addresses another aspect of landscape pattern. With a ruler, you can measure the distances from the center of each clear-cut patch to the center of its nearest neighboring patch. The average of all the nearest-neighbor distances characterizes feature spacing for an entire landscape. This is theoretically simple, but both too tedious to implement and too generalized to be very useful. It works great on scattering of marbles. But, as patch size and density increase and shapes become more irregular, this measure of feature spacing becomes ineffective. The merging of both area-perimeter characterization and nearest-neighbor spacing into an index provides much better estimates.

For example, a frequently used measure, termed 'dispersion,' developed in 1950's uses the equation

$$R = 2((p^{**}1/2) * r)$$

where R is dispersion, r is the average nearest-neighbor distance and p is the average patch density (computed as the number of patches per unit area). When R equals 1, a completely random patch arrangement is indicated. A dispersion value less than 1 indicates increasing aggregation; a value more than 1 indicates a more regular dispersed pattern.

All of the equations, however, are based in scalar mathematics and simply use GIS to calculate equation parameters. This isn't a step beyond mapping, but an automation of current practice. Consider figure 1 for a couple of new approaches. The center two plots depict two radically different patterns of 'globs'— a systematic arrangement (Pattern A) on the top and an aggregated one on the bottom (Pattern B).

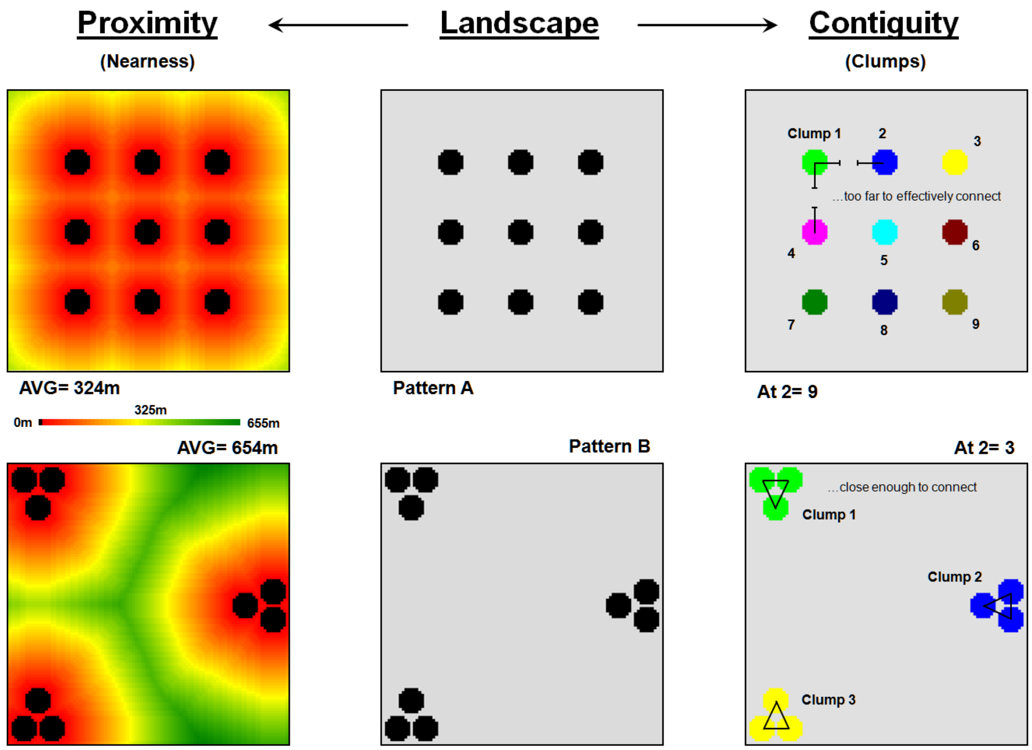

Figure 1. Characterizing map feature spacing and pattern.

The Proximity measure on the left side forms a continuous surface of 'buffers' around each glob. The result is a proximity surface indicating the distance from each map location to its nearest glob. For the systematic pattern, A, the average proximity is only 324 meters with a maximum distance of 933m and a standard deviation of +213m. The aggregated pattern, B, has a much larger average of 654m, with a maximum distance of 1515m and a much larger standard deviation of +387m. Heck, where the green-tones start it is more than 3250m to the nearest glob— more than the farthest distance in the systematic pattern. Your eye senses this 'void'; the computer recognizes it as having large proximity values.

The Contiguity measure on the right side of the figure takes a different perspective. It looks at how the globs are grouped. It asks the question, "If each glob is allowed to reach out a bit, which ones are so close that they will effectively touch? If the 'reach at' factor is only one (1 'step' of 30m), none of the nine individual clumps will be grouped in either pattern A or B. However, if the factor is two, grouping occurs in Pattern B and the total number of 'extended' clumps is reduced to three. As shown in the figure, an 'at' factor of two results in just three extended clumps for the clumped pattern. The systematic pattern is still left with the original nine. Your eye senses the 'nearness' of globs; the computer recognizes this same thing as the number of effective clumps.

See, both you and your computer can 'see' the differences in the patterns. But, the computer sees it in a quantitative fashion, with a lot more detail in its summaries. But there is more. Remember those articles describing 'effective distance' (GIS WORLD September, 1989 through February, 1990)? Not all things align themselves in straight lines 'as-the-crow-flies." Suppose some patches are separated by streams your beast of interest can't cross. Or areas, such as high human activity, which they could cross, but prefer not to cross unless they have to. Now, what is the real feature spacing? You don't have a clue. But the proximity and contiguity distributions will tell you what it is really like to move among the features.

Without the computer, you must assume your animal moves in the straight line of a ruler and the real-world complexity of landscape patterns can be reduced to a single value. Bold assumptions, that asks little of GIS. To go beyond mapping, GIS asks a great deal of you— to rethink your assumptions and methodology in light of its new tools.

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As with all Beyond Mapping articles, allow me to apologize in advance for the "poetic license" invoked in this terse treatment of a technical subject. A good reference on fractal geometry is "Measuring the Fractal Geometry of Landscapes," by Bruce T. Milne, in Applied Mathematics and Computation, 27:67-79 (1988). An excellent practical application of forest fragmentation analysis is "Measuring Forest Landscape Patterns in the Cascade Range of Oregon," by William J. Ripple, et. al., in Biological Conservation, 57:73-88 (1991).

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