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Fractal Analysis of a Classified Landsat Scene

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ABSTRACT: Remotely sensed images tend to be spatially very complicated, revealing regions of homogeneously classified pixels with quite convoluted perimeters. Fractal analysis, the study of complicated phenomena manifesting self-similarity at many scales, is suited to the description of the form and sizes of these regions. I apply fractal analysis to the patterns created by eight land-cover classes from a Landsat TM image of northwest Vermont. The results suggest that forests manifest high fractal dimension and large regions, agricultural activities have large regions with fractal dimension inversely related to the intensity of cultivation, and urban land cover yields small regions with relatively high fractal dimension. Analysis of the individual urban regions provides a data structure in the form of a raster-based GIS which can be used to investigate the location and description of individual regions and to diagnose the reliability of the classification and labeling processes.

INTRODUCTION

THE OBJECTIVE OF THIS PAPER is to demonstrate the applicability of fractal concepts to the spatial analysis of classified digital imagery. The paper is organized as follows. In the next section I use an example of an ideal fractal process to illustrate the theory underlying the analytical technique to be developed. Next, I introduce an algorithmic approach to three analytical steps: the segmentation of a classified image into homogeneous regions, the estimation for each class of the fractal dimension of regional perimeters, and the determination of a parameter describing regional sizes. Section four presents the empirical analysis of the eight land-cover classes from a Landsat Thematic Mapper image of northwest Vermont. This discussion provides fractal parameters which can be related to the classes, as well as a database containing locations and descriptions of the individual regions (clusters of pixels) from each class. I conclude by outlining a complete image segmentation/fractal analysis/GIS scheme that could profit from such advanced computing techniques as parallel processing.

FRACTALS AND REMOTE SENSING

REGIONS IN THE SPATIAL ANALYSIS OF DIGITAL DATA

The processing of digital image sensed data relies heavily on the analysis of energy spectra in order to classify pixels and to make judgments about the appropriateness of class labels. A great deal of attention in the literature is therefore given to quite sophisticated multidimensional techniques for the examination of patterns in the *spectral* space spanned by the various sensor bands (Richards, 1986). The pattern recognition literature, however, concentrates more on the investigation of the *spatial* patterns made by the classes themselves in the Euclidean space (\mathcal{R}^2 or the real plane) in which the image lies (NASA, 1988, chapter 7). This distinction is not meant to deny the existence in remote sensing analysis of such approaches as filtering and Fourier techniques, which examine both neighborhood patterns at the small scale as well as texture and orientation characteristics at the large (Whalley and Orford, 1982). But it must be admitted that comparatively little use is made of much of the rich information that can be extracted from the spatial as opposed to the spectral characteristics of a scene.

An important reason for the relatively restricted extent of explicitly spatial techniques is the daunting complexity and apparent noisiness of images. Figure 1, for example, shows the patterns made by each of the eight classes of 256^2 pixels centered around St Albans, Vermont (these images are subscenes from the full study area discussed below). The human eye has little trouble distinguishing among the various textures, shapes, and

forms in these pictures; yet it is at present a major challenge to bestow even rudimentary visual sophistication upon machines (Hillis, 1985). The first characteristic to appreciate about such patterns, however, is that they are formed of a collection of distinct regions of different sizes and circumscribed by complicated perimeters of various lengths. Let us focus, therefore, on the numbers, sizes, and perimeters of regions formed by clusters of homogeneous pixels in the digital (or map) space $I \times I = \mathcal{P}$ (a subset of \mathcal{R}^2).

THE FRACTAL DIMENSION OF REGIONAL PERIMETERS

A fractal has been defined recently by Benoit Mandelbrot as a pattern "made of parts similar to the whole in some way" (quoted in Feder (1988), p. 11). Phenomena displaying apparent self-similarity are abundant in the real world. Observation reveals that large waves are made up of smaller waves and ripples, clouds can be decomposed into smaller clouds and wisps, trees are made up of hierarchical systems of trunks-branches-twigs-leaves-veins, and so forth. Current fractal research in the spatial sciences makes use of the fact that complicatedness is a direct consequence of the operation of many different spatial processes at a wide range of scales. Mark and Aronson (1984), for example, use fractal dimension to describe terrains; Arlinghaus (1985) demonstrates the fractal nature of central place systems; and Plotnick (1986) points out the fractal characteristics of sedimentation.

In what follows I shall explore the application of fractal concepts to regions, which may be defined as connected sets of points, e.g., pixel locations, for which area is an appropriate measure. A natural way to describe and compare regions is by measuring area, which in the case of a digital image would be a count of the number of pixels in the region multiplied by the area of each pixel. Another regional characteristic is shape, which may be defined as the degree of similarity between the region and some simple geometric figure. Indices of shape have a venerable geographic history (Haggett *et al.*, 1977, section 9.6), but shape is by no means a simple concept. For digital spatial data the concept of shape requires a measurement of regional perimeter, which may be defined as the number of line segments bounding the region.

A common example of the investigation of regions is the fractal analysis of islands and continents, which are bounded by coastlines having a fractal dimension D , defined below (Mandelbrot, 1982, chapter 5). In fact, a coastline is simply one kind of perimeter — in this case an isoline at sea level — having fractal dimension ranging from $D = 1$ (a straight line) to $D = 2$ (an infinitely complicated and therefore plane-filling curve) (Goodchild and Dubuc, 1987; Burrough, 1986). When the scale of analysis is increased, coastlines reveal three important and

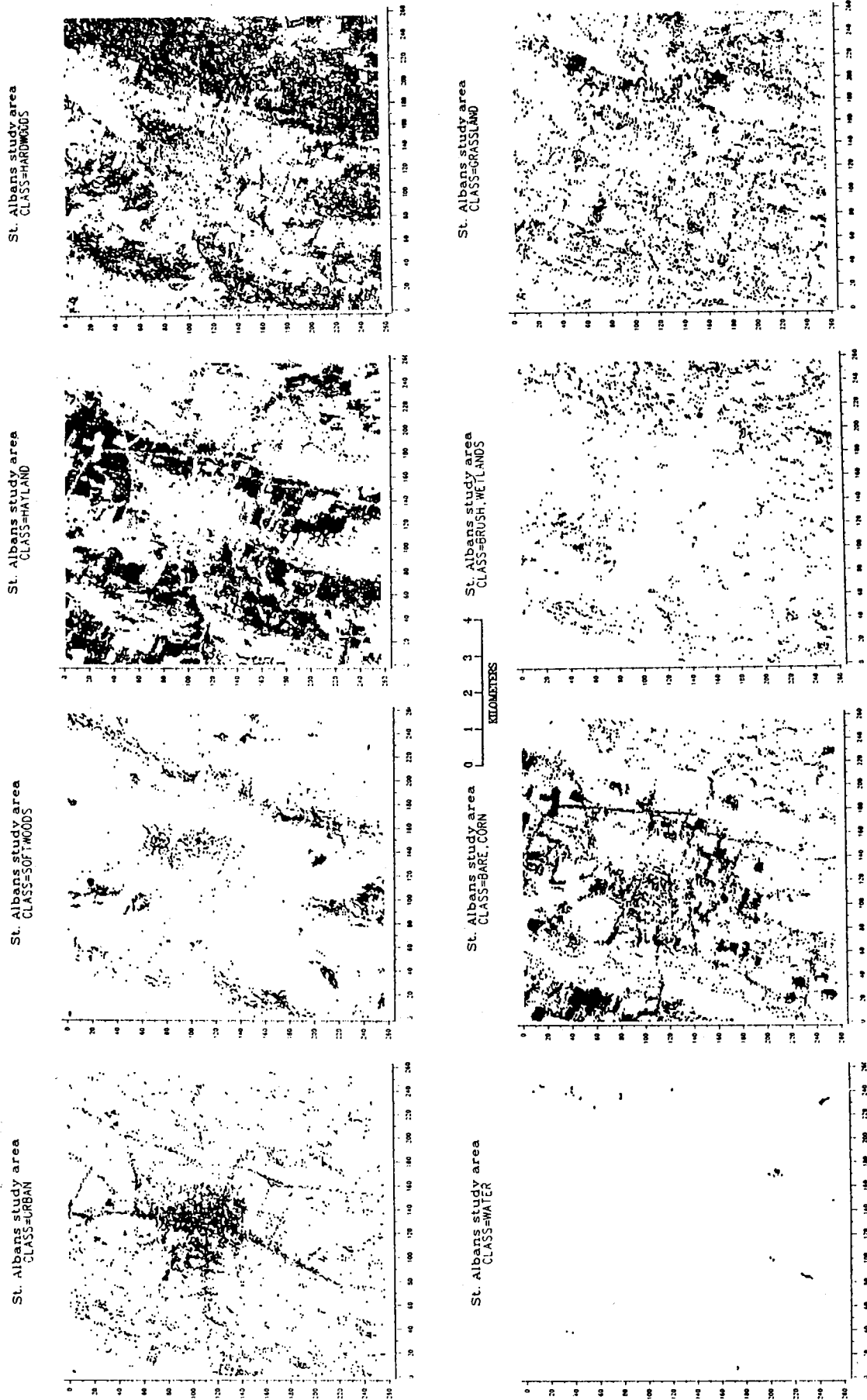


FIG. 1. Regions generated by eight land-cover classes in a 256- by 256-pixel window around St Albans, Vermont, from the full study area.

related characteristics. First, as Mandelbrot observes above, these curves are self-similar: large scale patterns look very much like small scale patterns. Second, these curves are quite complicated, so that lengths measured at large scales are greater than lengths measured at small scales. Third, these regions tend to have no characteristic size. I shall discuss this third characteristic below.

Consider for the moment the two sets of regions shown in Figure 2: squares and so-called Koch quadratic figure (Mandelbrot, 1982, chapter 12; Feder, 1988, chapter 12). These "regions" may be measured in terms of AREA and PERIMETER. On the one hand, note that for squares -- regions with smooth perimeters -- it is the case that PERIMETER $\propto \sqrt{\text{AREA}}$. This relationship holds for all regions of fractal dimension $D = 1$, and for squares in particular it is the case that PERIMETER = $4\sqrt{\text{AREA}}$.

Now consider, on the other hand, the Koch quadratic regions, which have been constructed to have the same AREAs as the squares -- 16 and 256, respectively -- but with significantly more convoluted perimeters, so that PERIMETER $\propto \sqrt{\text{AREA}}^{3/2}$. Consequently, large Koch regions reveal more detail than do small regions, even though the former are constructed from the latter. In other words, if we think of the larger figures as "growing" out of the smaller figures (perhaps as a specific type of land cover spreads), then for the Koch model perimeter grows faster than it does in the case of growing squares. In fact, these Koch regions have been constructed with PERIMETER = $4\sqrt{\text{AREA}}^{3/2}$.

To make this argument more formal, for any region let $s = \text{AREA}$ (or, more generally, "size") and $p = \text{PERIMETER}$. If a given region is bounded by a smooth perimeter of fractal dimension $D = 1$, then it is the case that

$$p = c\sqrt{s} \tag{1}$$

where $c = 4$ for a square, $c = 2\sqrt{\pi}$ for a disk, and so forth. In such cases -- where we assume that any imaging system of however small a resolution would continue to show a smooth perimeter -- c is an index of shape.

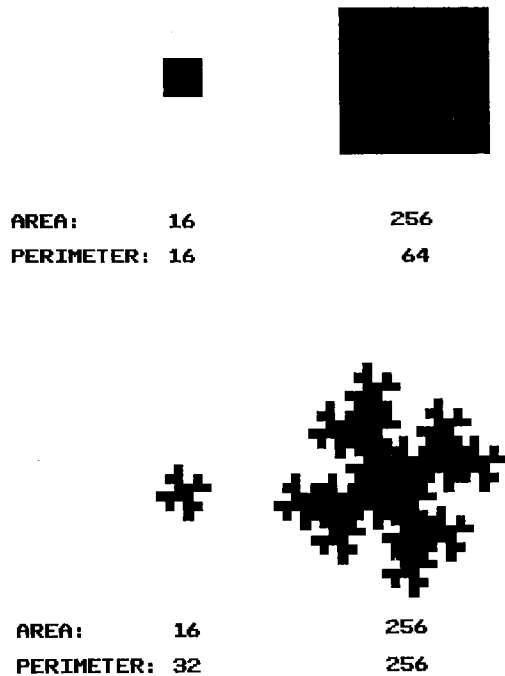


Fig. 2. Comparisons of measurements of squares ($D = 1$) and Koch regions ($D = 3/2$).

For a fractal phenomenon, however, it is the case that

$$p = c\sqrt{s}^D \tag{2}$$

where $1 \leq D \leq 2$. For smooth shapes such as circles and squares (which might be called "degenerate" fractals) $D = 1$, as in Equation 1, while $D = 3/2$ for the Koch model, and $D = 2$ in the case of infinitely complicated feature whose perimeter fills the plane. Mandelbrot (1982, chapter 12) uses the term "fractal dimension" to characterize the parameter D .

It should be emphasized that two spatial indices are therefore being distinguished here: c , a measure of overall regional shape (which, because $c = 4$ in both cases, obviously does not distinguish between the square and the Koch regions!) and fractal dimension D , an index of what I call regional form or perimeter complicatedness. The Koch model illustrates the essential self-similarity of ideal fractals: each increase in map scale (in this case by a linear factor of 4) reveals a longer perimeter (here by a factor of $(4)^{3/2} = 8$) in the case of complicated figures than in the case of simple figures. In other words, fractal phenomena for which $D > 1$ have the cartographically commonplace characteristic of revealing more detail at a larger scale. Moreover, at a given scale, larger features manifest significantly longer perimeters (by the exponent D) than do smaller. It is these inter-feature comparisons of area and perimeter that I shall use below to estimate regional fractal dimension D according to Equation 2.

TECHNIQUE

IMAGE SEGMENTATION AND THE CREATION OF REGIONS

Perhaps the clearest empirical example of the kind of argument to be used here is Lovejoy's (1982) fractal analysis of cloud images. Clouds tend to be quite complicated, self-similar phenomena. Lovejoy studied digital Geostationary Operational Environmental Satellite (GOES) and radar images of clouds and rain areas using the perimeter/area relationship of Equation 2 and determined that the fractal dimension of the perimeter of these cloud/regions was $D = 1.73$ over a range of cloud sizes from less than 1 km² to over 10⁶ km². Lovejoy's technique is formalized in this section and applied below to the analysis of land-cover classes from a Thematic Mapper image.

Let a digital space be $P^2 = I \times I$, where I is the set of integers, and let $W \subset P^2$ be a square image or "window" composed of N^2 pixels $x \in W$. Next, associate with each of these pixels an integer-valued index $i \in [0, m] \subset I$ representing one of m land cover classes (class 0 can be regarded as residual or unclassified). In the simplest case $m = 1$ so that the image is a black-and-white scene such as the 6 by 6 image shown in Figure 3; class 0 is colored white and class 1 colored black.

Each class i , therefore, imposes a regionalization on the image corresponding to the $m + 1$ -valued function $f: x \rightarrow [0, m]$. For any i a subset of this regionalization is the set $F_i = \{x: f(x) = i\}$, the set of all pixels to which the class i is ascribed. The first step in image description is usually the examination of the set $\{N_{ij}\}$, the histogram of the image given by the number of pixels in each class i , and the corresponding fraction of such pixels $\{f_i\}$, where $f_i = N_i/N^2$. For the simple scene, $f_1 = 9/36$.

Labeling may be thought of as the association of some spatial/spectral pattern with class i , but for the moment assume that the pixels are merely assigned to distinct categories: spectral, functional, or otherwise. Let us therefore focus on a single land-cover class and, for convenience, drop references to the index i . We shall return later to inter-class comparisons, once class i has been spatially characterized.

The following image segmentation algorithm partitions the regionalization F (referred to as F_i above) into n distinct and disjoint regions E_j such that $\cup E_j = F$, where $j = 1, \dots, n$. Each

