FRACTAL CHARACTERIZATION OF MULTITEMPORAL SCALED REMOTE SENSING DATA

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Scale, Scaling, and Multiscaled Remote Sensing Data

Scale is an "innate" concept in geographic information systems. It is recognized as something that is intrinsic to the ingestion, storage, manipulation, analysis, modeling, and output of space and time data within a GIS purview, yet the relative meaning and ramifications of scaling spatial and temporal data from this perspective remain enigmatic. As GISs become more sophisticated as a product of more robust software and more powerful computer systems, there is an urgent need to examine the issue of scale, and its relationship to the whole body of spatiotemporal data, as imparted in GISs. Scale is fundamental to the characterization of geo-spatial data as represented in GISs, but we have relatively little insight on the effects of, or how to measure the effects of, scale in representing multiscaled data; i.e., data that are acquired in different formats (e.g., map, digital) and exist in varying spatial, temporal, and in the case of remote sensing data, radiometric, configurations. This is particularly true in the emerging era of Integrated GISs (IGIS), wherein spatial data in a variety of formats (e.g., raster, vector) are combined with multiscaled remote sensing data, capable of performing highly sophisticated space-time data analyses and modeling. Moreover, the complexities associated with the integration of multiscaled data sets in a multitude of formats are exacerbated by the confusion of what the term "scale" is from a multidisciplinary perspective; i.e., "scale" takes on significantly different meanings depending upon one's disciplinary background and spatial perspective which can lead to substantive confusion in the input, manipulation, analyses, and output of IGISs (Quattrochi, 1993). Hence, we must begin to look at the universality of scale and begin to develop the theory, methods, and techniques necessary to advance knowledge on the "Science of Scale" across a wide number of spatial disciplines that use GISs.

To adequately address the complexities of scale within an IGIS framework, we must not only have a better understanding of what scale *is*, and what its dynamics *are*, but we must also develop innovative and robust methods or "tools" to adequately manipulate, analyze and convey the very nature of multiscaled data (in both space and time). This is particularly true with the advent of remote sensing platforms, such as the NASA (Earth Observing System) EOS suite of sensors tentatively set to be launched in 1998 (see MTPE EOS, 1995), where large quantities of remote sensing data will become available at many different space, time, and radiometric resolutions. Although we may envision that these data will be used in highly complex space-time models to observe, analyze, and measure a host of land surface process and biophysical interrelationships (see Asrar and Dozier, 1994), there are a number of vexing questions that must be addressed on how we approach using such multiscaled data in an IGIS format. Outside of the mechanical difficulties that need to be overcome in manipulating multiscaled data, of paramount concern is how to analyze such complex data sets. What tools do we use to robustly maximize the information content within and amongst different remote sensing data sets and assess highly complex interrelationships between these data sets using an IGIS approach?

Geostatistics and Fractal Analysis

Although still somewhat nascent, the application of geostatistics to remote sensing appears to offer great potential for analyzing multiscaled data collected at different space, time and radiometric resolutions. In its "purest" sense, *geostatistics* relate to statistical techniques that emphasize location within areal distributions (Cressie, 1993). For analysis of remote sensing data, however, geostatistics can be perceived in a more universal role where the focus of concern is with statistical theory and applications for processes with continuous spatial index; i.e., where the data represent spatiotemporal processes continuously across or throughout a domain or region. From this purview, geostatistics may be particularly useful for *characterizing* and visualizing the state, distribution, pattern, and arrangement of landscape attributes and processes as manifested in multiscale remote sensing data. Questions of scale in remote sensing and spatial statistics combine both the issues of level of aggregation of the observation (i.e., the "volume" of space that a remote sensing observation represents) and the extent of the observation (the "footprint" of the data and the times of data collection). These are not unrelated, particularly if the data behave in a self-similar way across a number of scales; that is, processes or patterns estimated or measured from remote sensing data at one space and time scale are relevant to the inference of these processes at different scales. Self-similarity is the foundation for fractal analysis (Mandelbrot, 1977 and 1983), which is why there has been a great deal of recent interest in this geostatistical technique to model naturally occurring phenomenon (Goodchild and Mark, 1987; De Cola, 1989; Lam, 1990; Lam and De Cola, 1993; Barton and La Pointe, 1995; Quattrochi and Goodchild, 1997).

Fractal analysis offers significant potential for improvement in the measurement and analysis of spatially, temporally, and spectrally complex remote sensing data within an IGIS format (Lam and Quattrochi, 1992; de Jong and Burrough, 1995; Pecknold et al., 1997). Because of self-similarity, fractal analysis of multiscale remote sensing data can potentially yield quantitative insight on the spatial complexity and information content contained within these data. Hence, remote sensing data acquired from different sensors and at differing spatial, temporal, and spectral resolutions could be compared and evaluated based on fractal measurements. This is especially true when one considers that remote sensing is the main source of data that we can use for analyzing the space and time dependence of surface and atmospheric phenomena at relatively large scales and over large areas (Lovejoy and Schertzer, 1988,1990; Davis et al., 1991).

Fractal dimensions derived from multiscale remote sensing data could also be compared with other geostatistical measures (see Cressie, 1993) to better understand the significance of the spatial and temporal interrelationships present within multiple representations of image data. Thus, an integrated software package that contains a robust set of fractal measurement algorithms embedded in a GIS-type architecture would be a useful tool for characterizing multiscaled remote sensing and associated spatial data within an IGIS perspective. Software of this type would permit studying biophysical, ecological, and environmental phenomena using data obtained from different remote sensing systems. A tool such as this would also enable the modeling of how these phenomena change through space and time. Additionally, a geostatistical package of this type would permit an easier and more robust testing of the suitability, reliability, and accuracy of fractals for the characterization and spatial and temporal modeling of multiscaled landscape phenomena as measured from remote sensing data.

Fractal Analysis Using the Image Characterization and Modeling System (ICAMS)

We have developed a GIS module called the Image Characterization and Modeling System (ICAMS) to measure, characterize, and model multiscale remotely sensed data (Quattrochi, et al., 1997; Lam, et al., 1998). ICAMS contains a number of spatial measurement methods that are not conveniently available in one software package to the general research community:

- fractal measurement
- spatial autocorrelation
- land/water and vegetated/nonvegetated boundary delineation
- textural measures
- spatial aggregation routines

as well as other descriptive measures and specialized functions, along with image input and output routines. ICAMS currently runs on the ArcInfo and Intergraph MGE platforms. Ongoing work will make ICAMS more broadly available as a non-specific workstation package that will be able to be implemented as hardware-generic software. ICAMS has four subsystems: 1) *Image Input*, which includes basic image processing functions, such as format transformation, georeferencing and co-registration, noise removal, and filtering functions; 2) *Image Characterization*, which provides users with an array of non-spatial, as well as spatial measures, for characterizing image data. The non-spatial measures include mean, mode, median, variance, and histogram. The spatial measures include fractal analysis, variogram analysis, spatial autocorrelation statistics, and textural measures; 3) *Specialized Functions*, for calculation of the Normalized Difference Vegetation Index (NDVI) and provides the capability for delineation of land/water and vegetated/non-vegetated boundaries. This subsystem also provides aggregation routines for aggregating pixels to simulate multiscaled data for scale effect analyses; and 4) *Image Display and Output*, for the display and output of images in two-dimensional or three dimensional form, output of analytical results and statistics, and creates digital output of intermediate or derived images. A more complete description of ICAMS and its operation is given in Quattrochi et al., 1997.

Fractal measurement in ICAMS focuses on three methods for calculating the fractal dimension: isarithm, variogram, and triangular prism. These three methods were implemented and tested previously in a comparative analysis as applied to remote sensing data with both interesting and differing results (Jaggi et al., 1993). Given their earlier use, they were ported to ICAMS to permit more widespread and more robust testing by the broader spatial analysis community.

With the advent of ICAMS, we have performed further analyses with these three fractal measurement routines as applied to remote sensing data (Lam et al., 1997, 1998; Quattrochi et al., 1997). Recent work with ICAMS has focused on testing how fractal dimension varies between two dates of Landsat Thematic Mapper (TM) data sets and the aggregation of these data over an urban area in southwestern Louisiana, U.S.A. (Lam et al., 1998). We present an overview of the results obtained from this study and compare them with an analysis of the fractal measurement of satellite data collected at different time periods over a portion of the Great Basin Desert region in eastern Nevada, U.S.A. to represent a "natural" landscape. This comparison provides a good test of the application of fractal analysis for characterizing landscape spatiotemporal dynamics, and also illustrates the utility of ICAMS for facilitating the more efficient and in-depth use of geostatistics for analysis of remote sensing data.

Fractal Analysis of Landsat TM Data for Lake Charles, Louisiana, U.S.A.

Landsat TM images acquired at two different dates for the city of Lake Charles, Louisiana have been used to analyze variability in fractal dimension for multitemporal data via ICAMS. Lake Charles is located in the southwestern portion of Louisiana (Figure 1). The first image was acquired on November 30, 1984, and the second on February 8, 1993, a difference of approximately 9 years. Subsets of a 5 km by 5 km area with a pixel resolution of 25 m by 25 m were created, with each subset containing 201 by 201 pixels. The subsets cover part of the city of Lake Charles, which had a population of about 75,000 in 1980 and decreased in size to 71,000 in 1992. The 1984 subset has been used as a representative urban landscape in a previous study that examined the fractal properties of remote sensing images (Lam, 1990). The selection of the same study area for the present investigation is based on the availability of data in two dates, so that analysis of temporal changes can be made. At the same time, we realize that the study area covers a medium-size urban area with little urban growth, and significant changes in terms of land cover are not expected in this region between these two dates.

Figure 2 displays the two Landsat TM images for Lake Charles. While large changes in land cover were not expected, a visual comparison between the two images shows that the 1993 image has slightly more roads and buildings, as evidenced in the southeast corner and along the highway (Highway 210) in the southern part of the image. Table 1 lists the summary statistics of all seven bands for the two images, as well as the fractal dimension values computed for the two images (discussed below). With the exception of the thermal band (band 6), the 1993 image generally has smaller ranges of spectral reflectance values; lower maximum values; and smaller coefficients of variation (standard deviation/mean). These two Landsat images have not been normalized to minimize sensor calibration offsets and differences in atmospheric effects, but we believe this will not seriously impact the use of these two data sets to illustrate how fractals in general, can be applied to characterize temporal differences in remote sensing data.

ICAMS Fractal Analysis of Multidate Lake Charles TM Data

The fractal analysis module in ICAMS was applied to the two images to examine their spatial and temporal characteristics. The overarching question for this analysis is how fractal dimensions change with spectral band, pixel resolution, and date of the image. The answer to this question, if tested with more images in the future, can be used to determine whether fractal analysis is an effective means for assessing and monitoring environmental conditions or landscape characteristics from remote sensing data.

The measurement of the fractal dimension D of a spatial phenomenon is the first step towards developing an understanding of spatial complexity. The higher the D, the more spatial complexity present. The fractal dimension of a point pattern can be any value between 0 and 1, a curve, between 1 and 2, and a surface, between 2 and 3. For example, coastlines have dimension values typically around 1.2-1.3, and topographic surfaces around 2.2-2.3 (Mandelbrot, 1983). For spectral reflectance surfaces, such as those reflected by Landsat-TM, the fractal dimensions are much higher, around 2.7-2.9 (Lam, 1990; Jaggi et al., 1993).

There are many methods to define and measure the fractal dimensions of curves and surfaces. The following provides a brief description of how fractal dimension is calculated in ICAMS to assist interpretation of the results computed below. More detailed descriptions of the major algorithms for geoscience applications can be found in Klinkenberg and Goodchild (1992), Lam and De Cola (1993), Olsen et al. (1993), and Klinkenberg (1994).

As noted earlier, the key concept underlying fractals is *self-similarity*. Many curves and surfaces are self-similar either strictly or statistically, meaning that the curve or surface is made up of copies of itself in a reduced scale. The number of copies (*m*) and the scale reduction factor (*r*) can be used to determine the dimensionality of the curve or surface, where $D = -log(m)/log(r)$ (Falconer, 1990). Practically, the D value of a curve is estimated by measuring the length of the curve using various step sizes, a procedure commonly called the walking-divider method. The more irregular the curve, the greater increase in length as step size decreases. Such an inverse relationship between total line length and step size can be captured by a linear regression:

$$Log(L) = C + B\ log(S)$$

where L is the line length, S is the step size, B is the slope of the regression, and C is the constant. D can then be calculated by:

$$D = 1\text{-}B.$$

In addition to computing R^2 for the regression, the scatterplot illustrating the relationship between step size and line length, known as the fractal plot, is often used as a visual aid to determine whether the linear fit is good for all step sizes . Many studies have shown that fractal plots of empirical curves are seldom linear, with many of them demonstrating an obvious break (Mark and Aronson, 1984). This indicates that real-world phenomena are seldom pure fractals and self-similarity rarely exists at all scales. In such cases, specific fractal dimensions are defined only for specific *scale ranges* at which the regression behaves linearly.

We have implemented fractal surface measurement methods in ICAMS, including the isarithm, variogram, and triangular prism methods. The isarithm method was used to compute the fractal dimensions of the images in this study. Previous work has shown that the isarithm method produces stable results for surfaces with known fractal dimensions, as opposed to the triangular prism and variogram methods (Lam et al., 1997). The isarithm method follows the walking-divider logic by measuring the dimensions of individual isarithms derived from the remote sensing surface (i.e., the iso-spectral reflectance lines). The D value is calculated using:

$$D = 2\text{-}B.$$

The final D of the surface is the average of the isarithms that have R^2 greater than 0.9. (This algorithm is slightly different from the one presented in Lam's 1990 study, as the latter averages all isarithms regardless of the R^2 values). In ICAMS, the user has a choice of whether the calculation is based only along rows, columns, or both directions. Other user input includes the isarithm interval and number of walks.

Table 1 and the corresponding Figure 3 compare the results of the two images. The number of walks were set to 6 (i.e., 1, 2, 4, 8, 16, 32 pixel intervals), using the row/column option, and the isarithm interval set to 2 for all calculations.

A comparison between the coefficients of variation and the fractal dimension values (Table 1) for the 1984 and 1993 Lake Charles images show a moderate correlation between these two sets of numbers, with r's computed as 0.67 and 0.73 for the 1984 and 1993 images, respectively. For example, in the 1984 image, band 1 has the lowest coefficient of variation (except band 6) with a value of 0.18 but the highest fractal dimension with a value of 2.95. This demonstrates the utility of spatial indices: the coefficient of variation is a non-spatial index summarizing the variations of the pixel values regardless of their locations, and the fractal dimension, a spatial index, describes the spatial complexity of the pixel values. When the two indices are used together, a broad but basic impression of an image can be formed, even without viewing the image. As such, these indices could be used as part of the metadata for the image. For example, when an image has a high coefficient of variation but relatively low fractal dimension, such as band 5 of the 1984 image, the surface would mostly likely exhibit a more spatially homogeneous pattern, or sometimes with a detectable trend. On the contrary, if an image has a low coefficient of variation but high fractal dimension, such as band 1, the surface is much more fragmented and spatially varying. This result confirms the need to utilize spatial indices, in addition to the traditional non-spatial statistics, in visualizing and detecting environmental patterns. The fractal indices used here have provided added information and have served as a quick tool in understanding the spatial and temporal dimensionality of the images compared for the Lake Charles study area.

Fractal Analysis of Landsat TM Data for Eastern Nevada, U.S.A.

The examination of fractal dimensions for Landsat TM data obtained at two different dates over Lake Charles, Louisiana represents analysis of a highly modified landscape -- that of an urban area – albeit, a medium-to-small city in both spatial extent and population by U.S. standards. For a comparative assessment of how fractal dimension changes as a function of land cover, terrain, and time characteristics, ICAMS has been used to derive fractal values from two dates of Landsat TM data for an area located in the

Great Basin Desert region of eastern Nevada, USA (Figure 4). The study area encompasses the Ruby Mountains and the East Humboldt Range near Elko, Nevada. The two Landsat TM scenes used for analysis were obtained in May and August, 1993, respectively. These dates have been selected to coincide with seasonal vegetation "green-up" and "die-back" in the eastern Nevada study area; the Landsat TM data sets are shown in Figures 5 and 6. The study area is entirely rural with only limited agricultural cultivation present; the predominant land use is grazing for cattle. The major topographic feature within the study area is a mountain range with elevations greater than 2,600 m. This area of the Great Basin contains several parallel ranges of roughly 2,800 m mountains separated by broad valleys at about 1800 m above sea level. The mountain ranges in this region have very little vegetation, with much of the existing vegetation occurring in desert valleys or on alluvial fans adjacent to the mountains. Valleys are dominated by shrub vegetation with understory forbs and grasses. The most prevalent shrubs are big sagebrush (*Artemsia tridentata wyomingensis*), black greasewood (*Sarcobatus vermiculatus*), and shadscale (*Atriplex convertifolia*). Other minor shrubs, forbs, and grasses include Gardner's saltbush (*Atriplex gerdneri*), gray molly (*Elymus elymoides*), Indian rice grass (*Oryzopsis hymenoides*), and cheat grass (*Bromus tectorum*). Sagebrush is common on the higher elevations of the well-drained alluvial fans, and it eventually gives way to grasses, forbs and small perennials at lower elevations (Laymon, et al., 1998).

As with the Lake Charles TM data sets, the eastern Nevada data have not been normalized to minimize sensor calibration offsets or differences in atmospheric effects. Again, we believe this will not be a predominant impact on our comparative analysis of temporal fractal dimensions between the May and August 1993 data sets. A 201x201 pixel area of the same geographic location from each date of satellite data was a focus for our comparative fractal assessment (Figures 5 and 6). *D* was calculated in the row, column, and row/column directions using the isarithm method in ICAMS for both dates of data. Table 2 gives the basic image statistics and *D* values computed for the May vs. August 1993 Nevada data sets by TM band. A graph of the *D* values for the row, column, and row/column directions is given in Figure 7.

An observation of the plots given in Figure 7 provides insight into how both different and similar the *D* values are for the two dates of data across all 7 TM bands. The plots of isarithm values for May vs. August for channels 1-4 for row, column, and row/column have similar forms, but obviously different fractal dimensions. The fractal values vary for TM channels 1-4, but are similar for TM channels 5-7. Discounting any anisotropic effects caused by running the isarithm algorithm in row, or column directions across the data for both acquisition dates, it is interesting to see from both Table 2 and Figure 7 that the lowest fractal dimension values occur for the May column isarithm values across all TM Channels, except channel 7, while the highest fractal dimensions occur for the August row/column values. There is also a grouping trend apparent in Figure 7, where fractal dimensions for the August data are generally in the 2.8-2.9 range for channels 1-3, while *D* values for the May data are grouped in the 2.6-2.7 range for these same channels. Although more research is needed, this grouping trend could indicate that fractals can be used to characterize temporal changes in landscape properties from the Landsat TM visible channels 1-3.

As another general observation of the trends exhibited in fractal dimensions in Figure 7, it is interesting to see that as TM spectral band wavelength increases, D values become more similar; i.e., in TM channels 4-7, D values both for the May and August data, and run in the row, column, and row/column directions, become highly correlated. This suggests that in the near infrared, middle infrared, and thermal infrared bands of the Landsat TM, the radiometric influence of each of these channels becomes increasingly less of a defining factor in affecting D values – at least for the data used here – as opposed to the potential influence of differences exhibited in landscape features between these multitemporal data. In observation of Table 2 and Figure 7, we see where fractal dimensions for the two dates of data are between 2.65 and 2.7 for TM near infrared channel 4 (0.76-0.90 μm). D values are similarly in close approximation between 2.69-2.73 for both of the TM middle infrared channels 5 (1.55-1.75 μm) and 7 (2.08-2.35 μm). Again, this indicates for the two dates of satellite data examined here, that at the near and middle infrared wavelengths of the TM data that radiometric characteristics (e.g., chlorophyll and water content spectral response of vegetation) have a more pronounced effect on D values than do landscape type, pattern or temporal variability characteristics. It must be noted, however, that these images cover a landscape that is predominated by semi-desert vegetation where the background spectral signature of soil may have a pronounced influence on the overall spectral signatures expressed in the near and middle infrared portions of the electromagnetic spectrum (Laymon et al., 1998). TM band 6 is the thermal infrared channel (10.42-12.50 μm) and is anomalous from the other six TM bands because of its different spectral wavelength, and because it has a spatial resolution of 120 m, as opposed to 30 m. It is suspected that the dramatic drop in fractal dimension, and hence, image complexity, exhibited for both the May and August TM data (Figure 7) is a function of the decreased spatial resolution in TM band 6 (120 m as opposed 30 m in the other TM bands).

As a more detailed analysis of the differences in fractal dimension between the two dates of data used in this investigation, it is useful to compare on an individual basis, the plots of *D* values run via the isarithm method at the row, column, and row/column directions. Figures 8, 9, and 10 show plots of May vs. August *D* values as computed in the row, column, and row/column directions, respectively. Although as noted above, *D* values in TM channels 4-7 are very similar, there are in some cases, striking differences in fractal dimensions for TM channels 1-3 between the two dates of data. In all three cases (Figures 8-10), the widest range of comparative *D* values occurs for TM channel 1 located in the visible portion of the electromagnetic spectrum (0.45-0.52 μm). Additionally, in all three graphs, the highest *D* values for the TM visible channels occur for the August 19, 1993 date. For the May vs. August row directions, channel 1 fractal dimensions are 2.69 and 2.83, respectively, while comparative *D* values for TM bands 2 and 3 are 2.73 vs. 2.79, and 2.79 vs. 2.71, respectively, for May and August. Differences in *D* values for the May vs. August column isarithm runs (Figure 9) for TM channels 1-3 are larger than those shown for those computed for rows given in Figure 8. For channel 1, comparative *D* column values are 2.89 for August and 2.6 for May, channel 2 values are 2.86 and 2.65 for August and May, respectively, and channel 3 values are 2.85 (August) and 2.63 (May). Excluding anisotropic effects, reasons for why the August TM visible band data have higher fractal dimensions than those exhibited by the May visible bands can only be speculated. Most likely, image complexity is greater within the TM visible bands for

August because of the heterogeneous influence of the high spectral response of desert soils interspersed with semi-arid vegetation that is either senescing or has senesced, which becomes a predominating effect on the visible channel data. Image complexity in the August TM visible data may also be enhanced by the vegetation extant on the mountains as opposed to the snow evident in the May TM scene (Figure 5). Moreover, other factors, such as water vapor in the atmosphere, may have a damping effect on image signal in the visible bandwidths for the May data, thereby effectively reducing or mitigating overall image complexity, as reflected in the *D* values for May. These similar trends of having higher fractal dimensions for visible band TM data and more closely related *D* values for TM near, middle, and thermal infrared band data are also evident in the plot of fractal dimensions for the Lake Charles, Louisiana data investigated in this study (Figure 3). Obviously, this trend needs to be examined further using other remote sensing data sets to see if this is a general reflection of how fractal dimension behaves in the visible versus near, middle, and thermal infrared portions of the electromagnetic spectrum, and if so, what the causal factors are behind this phenomenon. These differences, however, may potentially indicate that fractals are useful for characterizing temporal differences in landscape attributes using the visible channels in Landsat TM, and possibly other, remotely sensed data.

Summary and Conclusions

An analysis of two different sets of multidate TM imagery for Lake Charles, Louisiana and for eastern Nevada, has demonstrated that computation of the fractal dimension by spectral channel for remote sensing data yields interesting results on how image complexity varies for two dates of satellite data for the same geographic area. In using the ICAMS software to calculate D values via the isarithm method, we have shown that fractal dimension values for the multidate satellite data examined here tend to become similar (i.e., closely related in value) in the near infrared, middle infrared, and thermal infrared TM bands. Fractal values for the TM visible bands (i.e., channels 1, 2, and 3) are different and suggest there may be more image complexity evident in the visible portion of the electromagnetic spectrum than for the infrared bands. Additionally, from observation of Figures 8-10, it appears that discounting any anisotropic effects, there are relatively little differences in D values when the isarithm method is applied in the row, column, or row/column method – at least for the eastern Nevada data used in this analysis – in respect to the form of the fractal dimension plots for May and August.

Finally, when the two sets of multidate images are compared, the Lake Charles images (representing a human-modified landscape) have smaller changes in the fractal dimension values between the two dates than that of the Nevada multidate images (representing a natural landscape). The seasonal changes in the Nevada natural landscape, especially in the visible spectrum, have been adequately reflected by the fractal dimension values computed for the images.

Although this study does not provide conclusive evidence on how fractal dimension can be used to define or quantitatively describe temporal landscape differences between two dates of TM imagery obtained for the same area, it does show that D values can potentially be useful for developing a better understanding of remote sensing data characteristics, particularly in regard to examining how spectral response affects fractal dimension over time. The use of fractal dimension, therefore, when combined with "traditional" non-spatial statistics, such as coefficient of variation, could be important metadata information that can be used as a guide for relating spectral band information with image content as a function of spectral wavelength. This information is going to be immensely useful for analysis of the voluminous amounts of satellite remote sensing data obtained from the NASA EOS suite of sensors. Here fractal dimension values of individual bands could be used as a pre-analysis tool for selecting individual channels or combinations of bands for assessment of specific landscape processes or phenomena. Such application will be especially useful for the analysis of hyperspectral image data.

Moreover, this study annunciates the need for more research on what the differences in fractal dimension *quantitatively mean* for different landscape characteristics as manifested in remote sensing data. For example, comparison of the plots of fractal dimension for the Lake Charles and eastern Nevada TM data (e.g., Figures 3 and 7) show there are differences in both the D values and their overall form across TM bands for these two landscapes. An understanding of what the subtleties of these differences mean in respect to landscape composition and spectral response needs to be developed to make fractal analysis a truly useful geostatistical analytical tool. Concomitant with this need to define what fractals values mean, is the need for more research in applying fractal analysis to multitemporal and multiscaled remote sensing data to better understand what changes in D values describe or define as represented in these data. Again, the plots of D values for the Lake Charles and eastern Nevada data illustrate there are both temporal and intrannual differences in fractal dimension derived from multitemporal TM data for the study areas examined in this investigation. These differences or changes in fractal dimension must be quantitatively associated with specific landscape attributes and spectral band characteristics, to realize what these changes in fractal dimension through time mean;

(e.g., is a fractal dimension of 2.6 vs. 2.7 significant in terms of relating changes in landscape characteristics as identified from remote sensing data?). Lastly, although this study has intimated that spectral response has a very profound influence on fractal dimension, more research is required to understand how fractal dimension is related to, or affected by, differences in spectral resolutions of remote sensing data. This ultimately, may be a key aspect in determining how useful fractals are for providing new, and heretofore unrealized, quantitative data on which spectral bandwidths are most important for discriminating or spectrally separating landscape features or land surface processes.

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