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CORT WILLMOTT is Chair of the Department of Geography and Professor of Geography and Marine Studies at the University of Delaware. He also is a member of the University's Center for Climatic Research. His research interests include the relationships between land-surface processes and climate, and the statistical analysis of large-scale climate fields.

JOHANNES FEDDEMA is Assistant Professor of Geography at the University of California, Los Angeles. He was formerly a Ph.D. student at the University of Delaware. His research interests include water balance climatology and climate/teleconnection processes.

On the Issues of Scale, Resolution, and Fractal Analysis in the Mapping Sciences*

Nina Siu-Ngan Lam
Louisiana State University

Dale A. Quattrochi
NASA Science and Technology Laboratory, Stennis Space Center

Scale and resolution have long been key issues in geography. The rapid development of analytical cartography, GIS, and remote sensing (the mapping sciences) in the last decade has forced the issues of scale and resolution to be treated formally and better defined. This paper addresses the problem of scale and resolution in geographical studies, with special reference to the mapping sciences. The fractal concept is introduced, and its use in identifying the scale and resolution problem is discussed. The implications of the scale and resolution problem on studies of global change and modeling are also explored. **Key words: scale, resolution, fractals, mapping sciences.**

Scale, Resolution, and Geography

The concept of scale is central to geography (Harvey 1969; Meentemeyer 1989; Watson 1978; Woodcock and Strahler 1987). It is one of the main characteristics that portrays geographic data and provides a unique perception of spatial attributes as they relate to form, process, and dimension. Geographers often deal with spatial phenomena of various scales. For example, geomorphology encompasses studies ranging from patterns of river networks, river basins, and coastline changes to potholes, cave, and gully formation based on international, national, regional, or local scales. Climatologists study upper air circulation around the globe as well as effects of local climate on agricultural production and health. Urban geography includes studies ranging from analyzing the urban systems in an international, national, or regional context to assessing the impact of facility location on local areas. Some geographers rely on data obtained from satellites, yet others depend on data regarding pollen counts and soil particles obtained through electronic microscopes. Diversity within the discipline results in the need to address spatial problems from multiple scales and resolutions.

This variation in scales can be regarded both as a strength and weakness of the discipline. Analyzing geographical phenomena using a range of scales offers a special view and methodology that other disciplines seldom employ, enhancing geography's strength. To the contrary, the massive amount of data needed for analysis of spatial phenomena at various scales, coupled with the possibility of applying an inappropriate methodology, often leads to a meaningless study. This invites criticism and confusion from within the discipline and from other related disciplines.

This paper does not attempt to solve issues of scale and resolution, but rather brings to-

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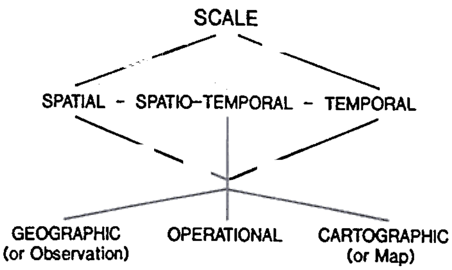

Figure 1: *Meanings of scale.*

gether important points regarding scale and resolution in light of recent developments, and proposes the use of fractals for analyzing spatial phenomena encompassing various scales. With appropriate methodology and sufficient attention to the problem of scale, we believe that the geographical perspective derived from analysis using differing scales can contribute in many ways to an understanding of various spatial phenomena. This is particularly important in relating earth processes or other spatial and environmental phenomena within the context of global dynamics (e.g., the International Geosphere/Biosphere Program).

Controversies over the exact definition and measurement of scale and resolution exist (Woodcock and Strahler 1987). Some clarification of terminology, therefore, is necessary. The term scale may include all aspects—spatial, temporal, or spatio-temporal (Fig. 1). In this paper we focus on spatial scale. There are at least three meanings of scale. First, the term scale may be used to denote the spatial extent of a study (i.e., geographic scale or scale of observation). For example, a spatial analysis of land use across the entire United States is considered a large-scale study, as compared to a land use plan for a city. This definition of scale is quite different from the second use called cartographic scale, where a large-scale map covers smaller area but generally with more detail, and a small-scale map covers larger area with less detail. The third usage of scale refers to the spatial extent at which a particular phenomenon operates (i.e., operational scale). For example, mountain-building processes operate at a much larger scale than that of river pothole formation. These three meanings of scale, however, are often mixed and used vaguely in the literature.

Closely related to scale is the concept of resolution. Resolution refers to the smallest distinguishable parts in an object or a sequence (Tobler 1988), and is often determined by the capability of the instrument or the sampling interval used in a study. A map containing data by county is considered of finer spatial resolution than a map by state. In reference to the three meanings of scale, small-scale studies usually employ data of finer spatial resolution than large-scale studies. Small-scale maps, on the contrary, often contain lower or coarser resolution data than large-scale maps. Finally, phenomena operating at a smaller scale, such as potholes and caves, require data of finer resolution. Because large-scale studies (geographic or observation scale) involving fine resolution are rather uncommon, scale and resolution are often blended together and loosely referred to as "scale," although it is recognized that a large-scale study does not necessarily mean that it has a coarser resolution, and vice versa. In this paper the notion of the resolution is generally implied whenever the term scale is used.

Methodological Issues Related to Scale and Resolution

Several methodological dilemmas surrounding the scale and resolution issue can be summarized here. First, different spatial processes operate at different scales, and thus interpretations based on data of one scale may not apply to another scale (Harvey 1968, 1969; Stone 1972). The noted "ecological fallacy" in spatial analysis, making inferences about phenomena observed at differing scales or implying finer resolution from coarser resolution data, attests to this problem. A simple example by Robinson (1950) shows that correlations between two variables, measured IQ and race, decreased from 0.94 to 0.73, and finally to 0.20, as resolution increased from census region, to state, and to individual study scales (Openshaw 1984).

Because spatial patterns are usually scale specific, inferring spatial process from spatial pattern is perplexing; this is illustrated by the well-known dilemma of different processes leading to the same spatial pattern (Harvey 1969; Turner et al. 1989b). Moreover, a spatial pattern may look clustered at one scale but random at another. For example, the mortality pattern of leukemia cancer in China appears randomly distributed if based on county-level data; if the data are aggregated and reported by province, a clustered geographical pattern results (Lam et al. 1989). Depending upon the scale of observation, therefore, processes that appear homogeneous at a small scale may become heterogeneous at a larger scale. This may be exemplified by patterns of coniferous forests infested with pine bark beetle blight. At a small spatial scale, the patterns of infected individual trees or groups of trees within the forest are not evident, because the pattern of insect damage becomes integrated as part of the spatially homogeneous coniferous forest. At a large geographic scale, however, groups of trees infected with pine bark beetle blight appear as patches of dead trees and can be easily distinguished from other trees. Thus, the pattern of insect infestation becomes heterogeneous at larger scales. How do we know what scale and resolution we should use? And how do we know when the results are meaningful and valid given the scale and resolution of the data?

Rapid development in the mapping sciences, particularly GIS and remote sensing, in the last decade has to a great extent "formalized" the scale and resolution problem. An immediate question in designing a GIS and remote sensing system is: what scale and resolution should we use for a specific application? For example, shall we use a 1:24,000 or 1:250,000 scale map? Will Landsat TM imagery (with a pixel size of 30m) be more appropriate than Landsat MSS imagery (80m pixel)? Shall we sample or update the data every five or 10 years? The concern here is both theoretical and practical. Increased resolution will increase data storage and processing time, whereas decreased resolution leads to inaccuracy that compounds quickly when several types of data are overlaid and analyzed. What is the optimum resolution or does an optimum really exist? Ultimately, the "best" resolution depends upon the study objectives, the type of environment, and the kind of information desired. Hence, much more work is required to understand the effects of scale in interpreting variability in earth processes and landscape patterns, and to utilize fully remote sensing and GIS.

In an integrated GIS and remote sensing system, data of various types, scales, and resolutions are used. How will the analytical methods and results be affected by different scales and resolutions? What is the relationship between scale and accuracy? The selection of an appropriate scale is also influenced by the techniques used to extract information from remote sensing data. The factors of scale and resolution, therefore, have become a major research direction in GIS and remote sensing.

A Brief Description of Fractals

Fractals are now widely used for measuring, as well as simulating, forms and processes and are attractive as a spatial analytical tool in the mapping sciences. Since Mandelbrot coined the term in 1975 (Mandelbrot 1977), the concept has been further developed and expanded across virtually every major discipline. Works by Mandelbrot (1977, 1983), Peitgen and Saupe (1988), Feder (1988), and more recently Falconer (1990) articulate some of the thought-provoking issues related to fractal analysis. An overview of the use of fractals in geography has been presented by Goodchild and Mark (1987) and recently by Lam and De Cola (forthcoming).

Fractals were derived mainly because of the difficulty in analyzing spatial forms and processes by classical geometry. In classical geometry (i.e., Euclidean geometry), the dimension of a curve is defined as 1, a plane as 2, and a cube as 3. This is called topological dimension (D_t). In fractal geometry, the fractal dimension D of a curve can be any value between 1 and 2, and a surface between 2 and 3, according to the complexity of the curve and surface. Coastlines have fractal dimension values typically around 1.2, and relief dimensions around 2.2. Fractal dimensions of 1.5 and 2.5 for lines and surfaces, respectively, are too large (i.e., irregular) for modeling earth features (Mandelbrot 1983, 260 and 264–65).

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

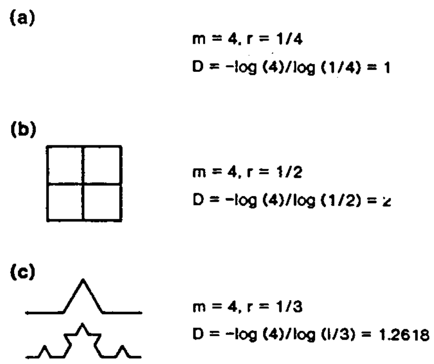

Figure 2: *Relationships between fractal dimension (D), number of copies (m), and scale factor (r).*

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). For example, in Figure 2a, a line segment is made up of four copies of itself, scaled by a factor ¼ (i.e., one-fourth of the line length), and the dimension D = −log4/log(¼) = 1. A square (Fig. 2b) is made up of four copies of itself and scaled by a factor ½ (i.e., half of the side length), thus yielding D = −log4/log(½) = 2. Similarly, a von Koch curve is made up of four copies of itself with a scaled factor ⅓ and having dimension D = −log4/log(⅓) = 1.262 (Fig. 2c).

Practically, the D value of a curve (e.g., coastline) is estimated by measuring the length of the curve using various step sizes. The more irregular the curve, the greater increase in length as step size decreases; D can also be calculated for a curve by the regression equation logL = C + BlogG and D = 1 − B, where L is the length of the curve, G is the step size, B is the slope of the regression, and C is a constant. The D value of a surface can be estimated in a similar fashion and several algorithms for measuring surface dimension have already been developed (e.g., Shelberg et al. 1983). A scatterplot illustrating the relationship between step size and line length in logarithmic form (i.e., fractal plot) becomes the source of the derivation of fractal dimension. An example of a fractal plot using the Louisiana coastline and its corresponding map

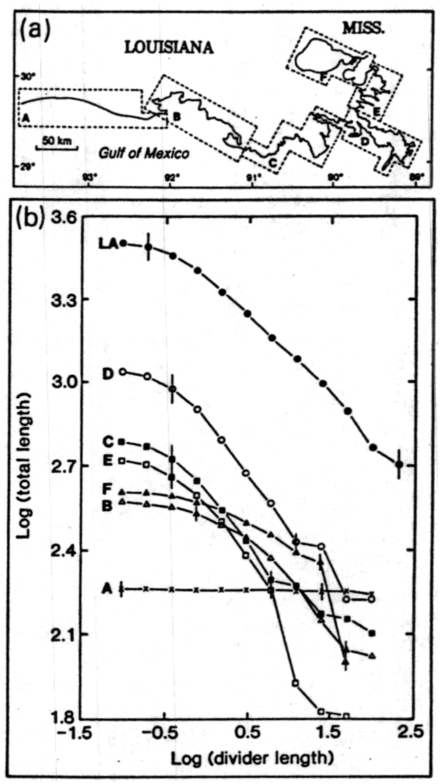

Figure 3: *(a) Louisiana coastline and its subdivisions; coasts A to F are: Chenier plain, Sale-Cypremort subdelta, Teche and Lafourche subdeltas, Plaquemines and Balize subdeltas, St. Bernard subdelta, and Lake Ponchartrain and Lake Borgne; (b) corresponding fractal plot; the bars on each curve show the range of points (i.e., steps) used in the regression and thus define the self-similarity range; the number of steps used for coasts A to F and the overall coastline (LA) are 9,7,5,6,5,6, and 11, respectively. (Adapted from Qiu 1988 and Lam and Qiu, forthcoming).*

is shown in Figure 3 (Lam and Qiu, forthcoming; Qiu 1988). Previous studies have demonstrated that fractal plots of empirical curves and surfaces are seldom linear, with many of them demonstrating an obvious break (Buttenfield 1989; Goodchild 1980; Mark and Aronson 1984). This indicates that true fractals with self-similarity at all scales are uncommon.

The fact that self-similarity exists only over a limited range of scales could be utilized positively, however, to summarize scale changes. Thus, fractals are potentially useful tools for investigating the issues of scale and resolution.

Based on the self-similarity concept, curves and surfaces of various dimensionalities can be generated, and it is the simulation capability of fractals that makes this technique a favorable tool for spatial analysis. Moreover, various objects and structures, such as planets, clouds, ocean floors, trees, particle growth, and urban morphology can be simulated using fractals (Peitgen and Richter 1986; Peitgen and Saupe 1988). Several methods have been developed to simulate fractal curves and surfaces, including the shear displacement method, the modified Markov method, the inverse Fourier transform method, and the recursive subdivision method (e.g., Carpenter 1981; Dutton 1981; Fournier et al. 1982). Figure 4 shows some sample surfaces with different D values generated using a shear displacement algorithm (Goodchild 1980; Lam 1990).

The foregoing description of fractals is rather elementary and intentionally made simple. There are many other ways of defining fractal dimensions and hence, the applications of fractals vary extensively. Recent additions in the fractal literature, such as the concepts of self-affinity, random fractals, and multifractals, have expanded fractal applications to many phenomena where true fractals with strict self-similarity do not exist. At the same time, fractals have generated criticisms from researchers in various disciplines, and indeed there are limitations in effectively applying fractals.

Fractals in the Mapping Sciences

There is a relative paucity of research that employs fractals in the mapping sciences. Goodchild (1980) in a pioneer article demonstrated that the fractal dimension can be used to predict the effects of cartographic generalization and spatial sampling, a result that may help in determining the appropriate resolution of pixels and polygons used in studies related to GIS and remote sensing. Muller (1986) proposed the use of fractal dimension as a guiding principle for future implementation of generalization algorithms in automated cartography. Fractal surfaces have been used as test data sets to examine the performance of various spatial interpolation methods (Lam 1982,

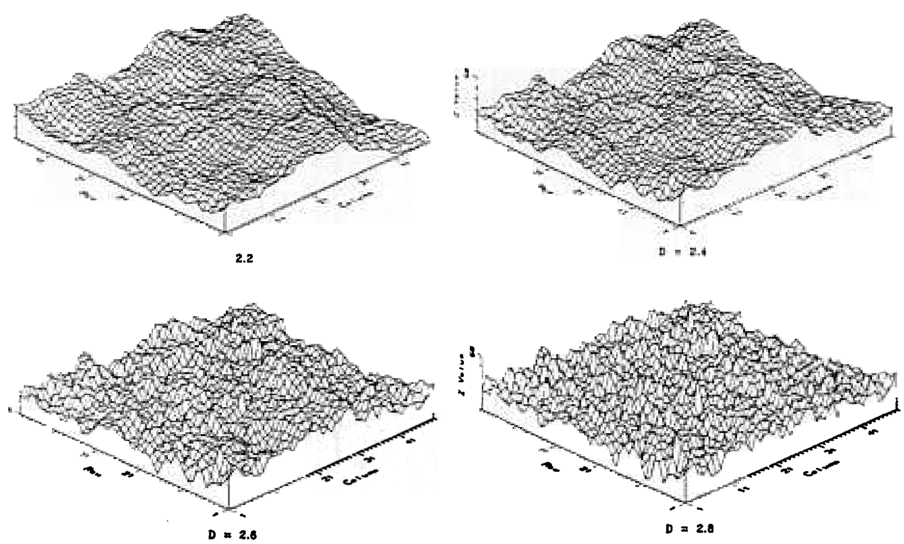

Figure 4: *Examples of fractal surfaces generated using a shear displacement algorithm. Source: Lam 1990*

1983) and to assess the efficiency of a quadtree data structure (Mark and Lauzon 1985). Fractal curve generation, on the other hand, has been used as an interpolation method and as the inverse of curve generalization by adding more details to the generalized curve (Carpenter 1981; Dutton 1981; Jiang 1984).

The use of fractals in remote sensing is relatively new and seems to have great potential. De Cola (1989) applies fractal analysis to land cover patterns derived from Landsat Thematic Mapper (TM) data and concludes that self-similarity, fractal dimension, and Pareto size parameter are useful measures for analyzing digital images. His results also show that urban land cover gives rise to more complicated spatial patterns than does intensive agriculture. In a study comparing urban, rural, and coastal areas using Landsat TM imagery, Lam (1990) has demonstrated that different land cover types have different fractal dimensions in different bands. Urban land cover was found to have the highest dimension, followed closely by coastal and rural land cover types.

In addition to the two types of applications mentioned above, fractal surfaces have been suggested as a null-hypothesis terrain or norm whereby further simulation of various geomorphic processes can be made (Goodchild and Mark 1987). Similarly, Loehle (1983), in a paper examining the applications of fractal concepts in ecology, suggested using the fractal dimension as a parameter summarizing the effect of a certain process up to a particular scale. He also proposed the use of the self-similarity property as a null hypothesis. In other work by Burrough (1981), it was shown that many environmental variables are fractals with varying fractal dimensions, and that the examination of D values would be useful for separating scales of variation that might be the result of natural processes.

Furthermore, fractals can help formulate hypotheses concerning the spatial scale of process-pattern interactions (Krummel et al. 1987). It was also concluded that fractal techniques should be particularly applicable to analysis of remotely sensed data, since it provides D as a simple measure that indicates the scale at which processes are occurring (i.e., operational scale). Changes in D computed from remote sensing data, therefore, have primary implications for changes in environmental conditions over extensive areas of the earth. O'Neill et al. (1988) showed that the fractal dimension has a highly significant correlation with the degree of human manipulation of the landscape. Landscapes dominated by agriculture tend to have simple polygons and low fractal dimensions (negative correlation), and landscapes dominated by forest tend to have complex shapes and high fractal dimensions (positive correlation). Thus, the application of fractals allows not only a different and convenient way of describing spatial patterns, but also the generation of hypotheses about the causes of the patterns. The above suggestions open new directions for the potential application of fractals.

Fractals, Scale, and Resolution

It is apparent that the fractal model is a useful tool for simulation and modeling. Fractal analysis of spatial forms and processes, however, can be limited by problems at both the theoretical and technical levels (Lam 1990). The first and foremost problem relates directly to scale and resolution. The self-similarity property underlying the original fractal model assumes that the form or pattern of the spatial phenomenon remains unchanged throughout all scales, implying that one cannot, through fractal analysis, determine the scale of the spatial phenomenon from its form or pattern. This kind of strict self-similarity is considered unacceptable in principle, and hence, has generated criticism about the spatial application of fractals. Empirical studies have shown that most real-world curves and surfaces are not pure fractals with a constant D at all scales. Instead, D varies across a range of scales (Goodchild 1980; Mark and Aronson 1984). These findings, however, can be interpreted positively. Rather than using D in the strict sense as defined by Mandelbrot (1983), it is possible to use the D parameter to summarize the scale changes of the spatial phenomenon. This latter use of fractals is supported by the results from Burrough's (1981) work, where it is suggested that Mandelbrot's D value can be used as an indicator over many scales for natural phenomena. Through interpretation of D values, therefore, it may be possible to relate or separate scales of variation that might be the result of particular natural processes.

The second problem of applying fractals relates to the technical aspect of fractal measurement. The fact that self-similarity exists only within certain ranges of scales makes it difficult to determine a breaking point for self-similarity; i.e., a point at which self-similarity ends for a curve or surface (Fig. 3b). This affects the final D value, which is then used to characterize the curve or surface (Buttenfield 1989). Furthermore, there is some question as to whether maps or map products provide sufficient detail to accurately measure the fractal dimension (Carstensen 1989). The calculation of the fractal dimension for surfaces presents an added technical problem. Roy et al. (1987) have shown that for the same surface, different D values could result from using different algorithms, with a range as low as 2.01 to a high of 2.33. Finally, all the existing methods have so far been applied only to regular grid data, such as digital terrain model data or Landsat TM data. Fractal measurement of many other socio-economic phenomena, such as population and disease distributions, or environmental process-response phenomena, presents another challenge. For example, identification of the patterns of pine bark beetle infestation within a forest may reveal insight into possible causes-responses of forest landscape dynamics as affected by insect infestation. These data are typically reported in an aggregate polygonal form, with irregular boundaries and possibly holes (in the forms of lakes or islands) or missing data. The existing algorithms used to delineate such features will have to be modified and extra steps will have to be taken before actual measurement takes place (Krummel et al. 1987).

A Research Agenda

As mentioned previously, the basic question surrounding the issues of scale and resolution is: can a study predicated on or founded at one scale be used to make inferences to the same phenomena under observation at different scales? To answer this question, several interrelated steps are involved (Turner et al. 1989a). First, the spatial and temporal scale of the process must be identified. Second, the importance or changes in importance of the variables influencing the process at different scales must be understood. Third, the appropriate methods for translating the results from one scale to another must be developed. Finally, the methods and results must be tested across scales.

Several methods have been employed to examine issues related to the scale and resolution problem, including for example, spectral analysis (Moellering and Tobler 1972), moving standard deviation measures (Woodcock and Strahler 1987), and variance and spatial correlation measures (Carlile et al. 1989). With consideration of the conceptual and technical uncertainties associated with their use, fractals could contribute to all four steps noted above. Fractals could be used to identify the spatial and temporal scale of the process. The fractal plot of step size against line length or area measurement can be used to determine the dimension values and their corresponding self-similarity ranges. These values can be utilized to help identify the underlying processes creating the patterns. Since most natural curves are not strictly self-similar, the derivations of the fractal dimension and associated self-similarity range are often based only on the range of points showing linearity (Fig. 3b).

For example, a study of the Louisiana coastline by Qiu (1988) has demonstrated that coasts of different origins and development stages are distinguishable by their fractal dimension values and associated self-similarity ranges (Lam and Qiu, forthcoming). Coasts dominated by deltaic processes generally have higher fractal dimensions (about 1.3) with a narrower scale range of 0.4–12.8 km, while coasts dominated by marine processes have lower dimensions (about 1.1) and a wider self-similarity range of 0.2–51.2 km (Fig. 3a and b).

In analyzing China's cancer mortality patterns using data by commune for the Taihu Region, Lam and Qiu (1990) have demonstrated that distinct self-similarity ranges exist in the three leading cancer mortality patterns in China (stomach, esophagus, and liver). Fractal dimensions and self-similar ranges for these cancer surfaces were computed by the variogram method (Mark and Aronson 1984). Figure 5 is the variogram plot in logarithmic form illustrating the relationship between dis-

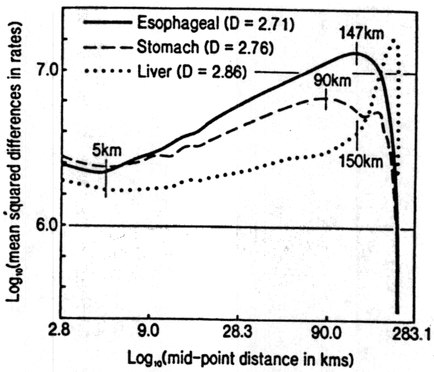

Figure 5: *The variogram plot of the three major cancer patterns (esophageal, stomach, liver) for the Taihu Region, China. The bars on each curve indicate the scale ranges over which fractal dimensions were calculated.*

tance and variance (or squared difference) for all three cancer patterns. Fractal dimensions of these patterns can be determined by the equation $D = 3 - (B/2)$, where B is the slope of the individual regression line through the respective points in the variogram. In this study the mortality pattern of liver cancer was found to have the highest dimension ($D = 2.86$), followed by stomach ($D = 2.76$) and esophageal ($D = 2.71$). The linearity exhibited on the variogram plot for all three patterns indicates that self-similarity exists within certain scale ranges. The patterns behave differently, however, when reaching a certain scale or in this case, a distance range (i.e., the break point in the variogram plot). Esophageal and liver cancers have similar distance limits of about 5–150 km, while the limit is approximately 5–90 km for stomach cancer. This suggests that if the communes are aggregated to a distance range as large as the limit, the patterns would look very different and would result in a different interpretation of the processes underlying the patterns as defined by that level of scale and resolution. Furthermore, it is suspected that whatever the underlying controlling factors (e.g., climate, topography, pollution), they are likely to operate in scale ranges similar to those of the cancer mortalities.

Different processes operate at different scales and so does the importance of controlling factors. Cancer mortality studies can again provide an example in this context (Lam et al. 1989). It is possible that, as a first step, the broad environmental context for certain cancer types can be determined by the typical GIS-overlaying methodology using large scale, coarse resolution data (e.g., climate, relief). This is then followed by a small scale, finer resolution study investigating local factors (e.g., industrial locations, water supply). Another example that requires data of various scales is in veterinary medicine and parasitology. Coarse resolution satellite data, such as those obtained from the AVHRR (Advanced Very High Resolution Radiometer) with an average pixel resolution of 1 km, could be used to monitor and identify broad areas of large animal parasite habitats (e.g., snails, mosquitos). The broad areas of habitat could then be refined using finer resolution remote sensing data, such as airborne scanner data with pixel resolution of five meters or less. Fractals, along with other statistical measures, can be used to determine the complexity and spatial clustering of these patterns, thus providing clues on the existence of certain factors related to the distribution of parasite habitats.

The capability of fractal models in simulation, or rather, interpolation or extrapolation, provides another method for translating results across scales. If the phenomenon of interest displays a self-similarity property with a relatively stable dimensionality, one can invert the process and re-generate the pattern based on the fractal dimension value. The issue of line generalization and line generation, which has been a subject of intense research in analytical cartography, is basically an issue of translating results across scales. Fractals, although with relatively less success, have played an important role in this realm of analysis (e.g., Dutton 1981; Jiang 1984; Muller 1986). More studies in this area, however, are needed.

Finally, fractal analysis can be used as a means to test the results across multiple scales. In addition to the cancer studies mentioned earlier, research is now underway in which digital remote sensing images of different resolutions are being tested and examined by means of fractals (Quattrochi and Lam 1991).

The results will provide insights with regard to scale, resolution, accuracy, and landscape representation. Fractals may offer a useful perspective on predicting spatial, environmental, and ecological system dynamics by revealing the self-similarity of phenomena at different scales, in turn, providing better models in a hierarchical framework for the analysis of scale (O'Neill et al. 1989).

The issues of scale and resolution are now emerging as important aspects of the mapping sciences that will have a significant place in global change and global modeling studies (NASA 1988; Wickland 1989). It is recognized that more than a single scale of observation may exist, thereby necessitating measurement at several levels of resolution. One of the major analytical challenges in studying global processes is to develop measurement sampling techniques that will elucidate how these processes range over broad spatial and temporal scales. Fractal analysis may become a major tool for measuring, and ultimately predicting, how landscape patterns and distributions, as important contributors to land-atmosphere global processes, change through a hierarchy of scales. Fractals may also be useful in identifying the break points in a pattern or distribution at a particular scale where the processes contributing to these patterns become unstable (i.e., a homogeneous pattern becomes heterogeneous and vice versa). This is important to the isolation of selected interactive variables, such as the relationship of precipitation distribution with other meteorological and hydrological variables at a local or regional scale for development of more reliable hydrometeorlogical models at the global scale. Moreover, it may not be economically or logistically feasible to measure the phenomenon at the most appropriate scale, especially in the case of socio-economic data that are already collected by pre-defined areal units (e.g., census tracts). Knowledge of the appropriate scale for a particular phenomenon or a process will, therefore, lead to efficient sampling that yields the most information about the phenomena. Without a clear understanding of the effects of scale and resolution on various models, and how the results are translated to other scales, interpretations based on the results and predictions could be invalid. ■

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NINA SIU-NGAN LAM is Associate Professor of Geography at Louisiana State University, Baton Rouge, LA 70803. Her current research interests

are fractals, scale, and error issues in the mapping sciences and spatial modeling in medical geography.

DALE A. QUATTROCHI is a Geographer with the National Aeronautics and Space Administration, Science and Technology Laboratory, located at the John C. Stennis Space Center, MS 39529-6000. His research interests focus on the integration of multiple scaled remote sensing data with GIS, spatial analysis in landscape ecology, and thermal remote sensing.