[FC-05-021] Resolution

Abstract

Resolution in the spatial domain refers to the size of the smallest measurement unit observed or recorded for an object, such as pixels in a remote sensing image or line segments used to record a curve. Resolution, also called the measurement scale, is considered one of the four major dimensions of scale, along with the operational scale, observational scale, and cartographic scale. Like the broader concept of scale, resolution is a fundamental consideration in GIScience because it affects the reliability of a study and contributes to the uncertainties of the findings and conclusions. While resolution effects may never be eliminated, techniques such as fractals could be used to reveal the multi-resolution property of a phenomenon and help guide the selection of resolution level for a study.

Keywords: environmental assessment and monitoring, environmental health, fractals, generalization, neighborhood effects, operational scale, scale, spatial context, Uncertainty

Author & citation

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Explanation

1. Introduction

The term “resolution” means different things in different disciplines and settings. In the spatial domain, “resolution” is the size of the smallest distinguishable parts of an object (Tobler, 1988), such as pixels in a remote sensing image or sampling intervals in an ecological study (Lam, 2004). The smaller the distinguishable part, the higher or the finer is the resolution of the object. Like “scale”, “resolution” is foundational and central to the study of geography and GIScience, as well as disciplines employing spatial data and spatial analysis such as ecology and environmental health sciences. Scale and resolution are two inseparable concepts; they are often used interchangeably in the literature.

Deciding what level of resolution a study should base on is critical because it affects the accuracy of the study and is a main source of uncertainties. The effects of resolution have been observed and documented long ago as part of the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984). As early as in 1950, Robinson showed that as resolution increased from census region, to state, and to individual study scales, correlations between IQ and race decreased from 0.94 to 0.73, and finally to 0.20 (Robinson 1950). Many studies have shown similar effects, such as the example in Figure 1 where an image becomes unrecognizable as resolution becomes coarser.

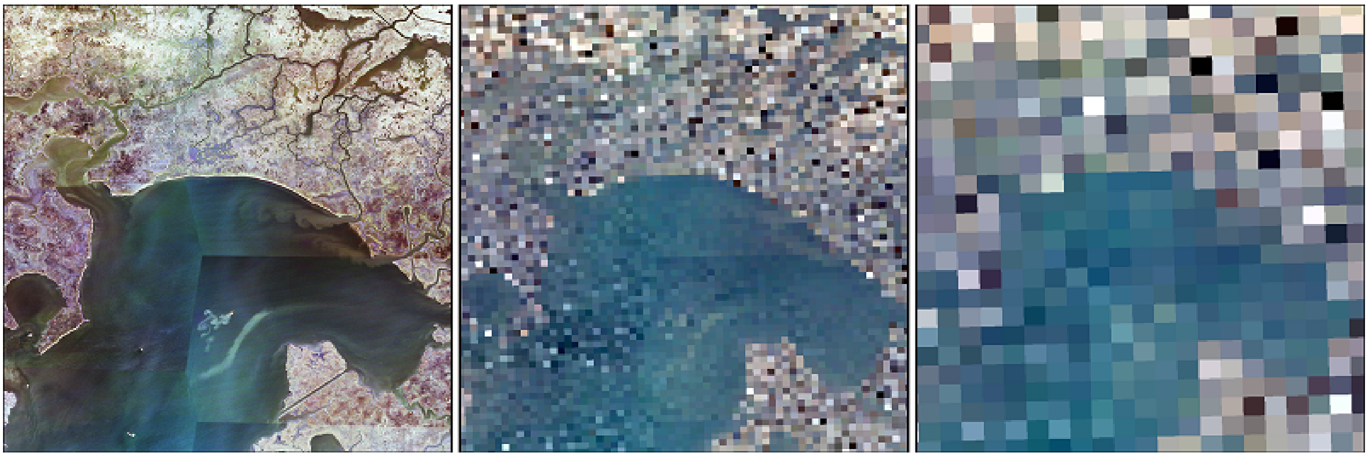

Figure 1. An image of Bay Batiste, Louisiana (Quarter Quad ID: F2908934NWS) defined in three pixel resolutions from left to right: one-meter, 100-meter, and 300-meter. Source: author. Image downloaded from the Louisiana State University Atlas website and created by V. Mihunov, May 2019.

This article aims to clarify the concepts of resolution and introduce some of the GIScience methods that can be used to identify and mitigate the resolution effects. In what follows, this article first explains the main concepts related to resolution. Then, the effects of resolution on research findings are demonstrated using application examples in environmental monitoring and environmental health. The final section describes the fractal technique that can be used to understand and mitigate the resolution effects.

2. Concepts of Resolution

Resolution is considered one of the four major dimensions of scale (Lam & Quattrochi, 1992; Lam, 2004; Lam et al., 2005). The other three dimensions are operational, observational, and cartographic scales (Figure 2). These four dimensions are interrelated, meaning that changes in one dimension would affect the use of the other dimensions. Thus, it is necessary to elaborate these four dimensions when discussing resolution. In addition, resolution, as a dimension of scale, can be considered in spatial, spatiotemporal, or temporal domain. Similar issues in the spatiotemporal domain have been documented and coined as the Modifiable Temporal Unit Problem (MTUP) (Cheng & Adepeju, 2014). As mentioned above, this article focuses on examples in the spatial domain.

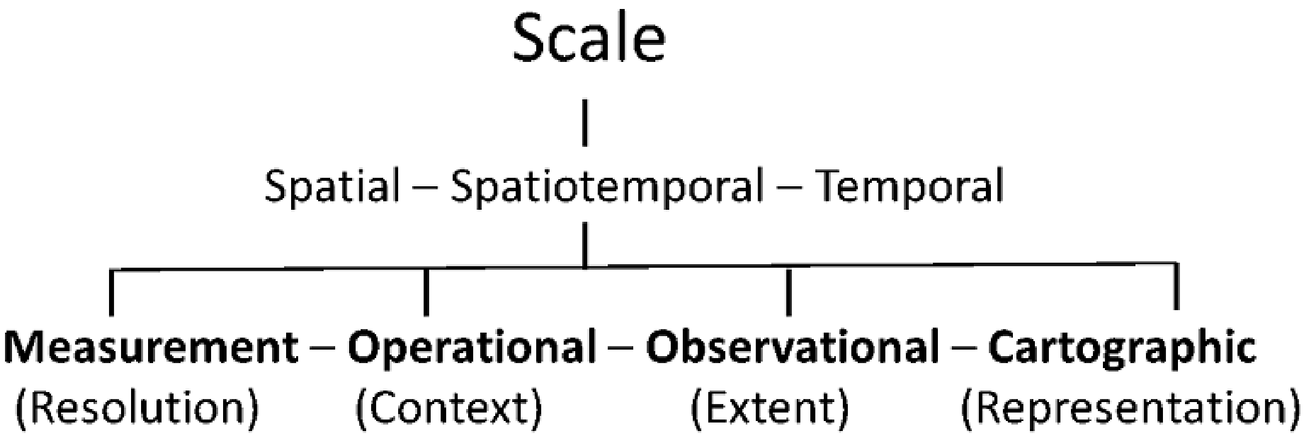

Figure 2. The four dimensions of scale (modified from Lam, 1992).

Resolution is the first dimension of scale, and is also referred as the “measurement scale.” Although there is difference between scale and resolution, the effect of resolution is often used interchangeably as the scale effect in the literature. Resolution refers to the size of the smallest unit of measurement observed or recorded for an object, such as pixels in a remote sensing image or line segments used to record a curve such as coastline. Remote sensing images have a range of spatial resolutions. For example, Landsat-TM imagery is made up of pixels with a spatial resolution of 30 meters, whereas LiDAR imagery has a much finer spatial resolution with pixel sizes about 4 meters or less. In the ecological literature, resolution is also termed as “grain”. Smaller grain size used in a study means finer resolution and vice versa. Studies with finer resolution are considered to be more accurate and thus preferable. However, as elaborated below, such relationship is not necessarily true for all resolution levels (Lam & Quattrochi, 1992; Lam et al., 2018). Finally, it is important to clarify that once the spatial data such as remote sensing image or map is digitized or recorded using a specific level of resolution, the accuracy of the image or map is fixed at that level. Zooming in during display in a graphic device can only increase its cartographic scale but not the accuracy of the map, which is governed by the resolution.

The “operational scale” refers to the spatial extent at which certain processes operate in the environment, which may take from several to hundreds of pixels. For example, mountain-building processes operate at a much larger scale than that of river pothole formation. Some researchers refer the operational scale as the ‘scale of action”, that is, the scale at which the pattern manifests the maximum variability, and methods have been suggested to find the scale of action (Lam & Quattrochi, 1992). Knowing the operational scale of a phenomenon in a study is important, because it can inform how large the spatial extent (the observational scale) and how fine the resolution (the measurement scale) of a study should be in order to capture the major variability or characteristics of the pattern, which would ultimately affect the ability of the study in revealing the underlying processes. Researchers have suggested that the operational scale of a phenomenon can be detected through fractal analysis and neighborhood analysis (Lam, 2004; Lam et al., 2018). Recently, Kwan (2012) highlights the importance of “context” and uncertainty in spatial research and called the problem as the Uncertain Geographic Context Problem, which is a concept similar to the neighborhood influence or the operational scale. As already documented in the literature, the success of methods for detecting the operational scale is also dependent on the resolution of the study (e.g., Chen et al., 2014; Lam et al., 2018).

The other two dimensions of scale will also influence the resolution level used in a study. The “observational” scale is the geographical extent of the study, and it ranges from global, regional, to local scale. Under this usage, a large-scale study covers a large study area such as a country, whereas a small-scale study involves a local study area such as a city. A large-scale study is likely associated with coarse resolution because of the large data volume needed to cover the large study area. On the contrary, a small-scale study is more likely to be able to afford using fine-resolution data due to the small area coverage and data availability.

The “cartographic” or representation scale refers to the ratio between the measurement on a map and the actual measurement on the ground, which is expressed by either the representative fraction (1:24,000 or 1/24,000) or shown as a scale bar on a map. A large-scale map under this usage implies a map with a small study area, and the map generally has more detailed information (of higher resolution) such as a city map. On the other hand, a small-scale map generally covers a large area but with less details, such as world maps. According to the U.S. Geological Survey (2018), small-scale maps are maps with scale of 1:250,000 (approximately 1 inch represents 4 miles or 1 centimeter for 2.5 kilometers) and smaller. The scale used for most United States topographic maps is 1:24,000 (also called 7.5-minute quadrangle maps), and they are considered large-scale maps.

3. Resolution Effects in Environmental Monitoring Studies

Below are examples of resolution effects in two application domains, environmental monitoring and environmental health risk assessment. These two application domains have a major difference, which is data availability. Fine-resolution data for environmental health and associated socioeconomic data are limited due to confidentiality concerns, whereas fine-resolution data are more likely to be found for environmental monitoring studies.

A major application of remote sensing and GIS in environmental monitoring is to assess changes in landscape parameters or land-use land-cover. The effects of pixel resolution in these types of application using remote sensing imagery have been well documented. For example, Bian and Walsh (1993) found that R2 values of a regression between two variables, biomass index and elevation, increased from 0.46, 0.68, to 0.71 in Montana when the pixel resolution decreased from 1, 33, to 75 pixels, respectively. The implication of this study is that the fundamental biophysical relationship changes with pixel resolution, making it difficult to infer the results to larger spatial extent where pixel resolution is generally coarser.

Another study by Benson and Mackenzie (1995) shows that landscape parameters computed from a series of images aggregated from a 30-meter Landsat-TM image changed drastically. As pixel size increased, the values of some parameters increased, such as percentage of water and number of lakes, whereas other parameters decreased, such as mean lake area. Their findings reflect the complex effects of resolution; not only that the values of landscape parameters change with resolution, they also change in different directions and rates. Thus, the unpredictable nature of resolution effects is a major source of uncertainty that is difficult to quantify and generalize.

More recently, Lam et al. (2018) studied the effects of landscape fragmentation on land loss in Mississippi River Delta. The hypothesis was that the higher the degree of fragmentation, the greater the amount of land loss in the next time period. The study used Landsat-TM images with a pixel resolution of 30 meters in 1996 and 2010. Spatial autocorrelation statistics and fractal dimension indices were calculated to represent the degree of fragmentation. Like most landscape indices, these two indices require a neighborhood box to calculate the indices. Four neighborhood box sizes, each with 100 samples, were tested. The four box sizes were 101x101, 71x71, 51x51, and 31x31. To isolate the effects of fragmentation from other effects, only samples with a 50% water-land ratio were used. Regression results between land loss in the next time period and fragmentation indices in the present period show that R2 values for box sizes of 71x71, 51x51, and 31x31 pixels were statistically significant (0.20, 0.45, and 0.35, respectively), with box size of 51x51 yielding the highest R2 value. Box size of 101x101 was found to be not significant.

These results have at least three implications related to resolution and scale. First, the results demonstrate that resolution effects are complex and difficult to predict; they do not increase or increase monotonically. There is a need to conduct multi-resolution analysis to help unveil the underlying process, i.e., the scale of action. Second, the results imply that pixel resolution and neighborhood scale (box size) are interrelated and they both affect the results. It is expected that if a larger pixel size is used, then a smaller neighborhood size might be sufficient to maintain the same land loss-fragmentation relationship. However, whether this expectation is true will need to be tested in each case. Third, the study demonstrates that landscape fragmentation effects are significant and are better observed at certain scales. The study shows clearly that spatial resolution and context matter. The spatial context in this case can be interpreted as the operational scale of the land fragmentation phenomenon in the study area.

4. Resolution Effects in Environmental Health Studies

In environmental health applications, at least four types of analysis are affected by resolution. Ranging from simple to complex, these four types of analysis are measurement, visualization, cluster detection, and exposure modeling (Lam, 2012).

First, in a study of the 1973-1975 cancer mortality patterns in China, Lam (1986) compared the spatial patterns of major cancer types mapped using county-level data versus those mapped using provincial-level data. The county-level maps were created and documented in The Atlas of Cancer Mortality in the People’s Republic of China (Lam, 1986), whereas the provincial-level maps were generated by the author based on the provincial-level mortality data listed in the Atlas. In the case of esophagus cancer, which was the second most common cancer mortality type in China during the time period, the county-level map for male shows distinct clustering in the central part of China. Clusters of high rates were also observed in remote counties located in northern and northwestern parts of China. However, when the mortality rates were mapped at the provincial level, the spatial pattern becomes more generalized and the clusters in the remote counties disappear. These remote, less-developed counties could be important clues for studying the etiology of the disease, and hypotheses could be generated to further the investigation. However, because of mapping using data defined at different resolutions, some of the patterns could not be revealed. The loss of insights generated at the visualization stage is critical, as disease mapping, when mapped appropriately, is an effective tool to visualize the pattern and generate meaningful hypotheses.

Second, cluster detection of disease occurrence is commonly used to identify clusters that are significant and merit further investigation. This type of analysis is highly sensitive to resolution effects. Figure 3 is a simplified example showing how resolution, together with the aggregation method (boundary delineation), can impact cluster detection (Lam, 2012). Consider a hypothetical study area, the dots in the figure represent individual disease occurrence. At an individual level, one can observe a cluster in the lower middle part of the figure. But when the study area is aggregated into nine grids, the number in each grid will be equal to three for all the grids, and the cluster will not be detected at the grid level. In the cancer cluster detection literature, it is well known that disease clusters could be made to appear or disappear, and resolution effect is one of the many problems that is difficult to tackle.

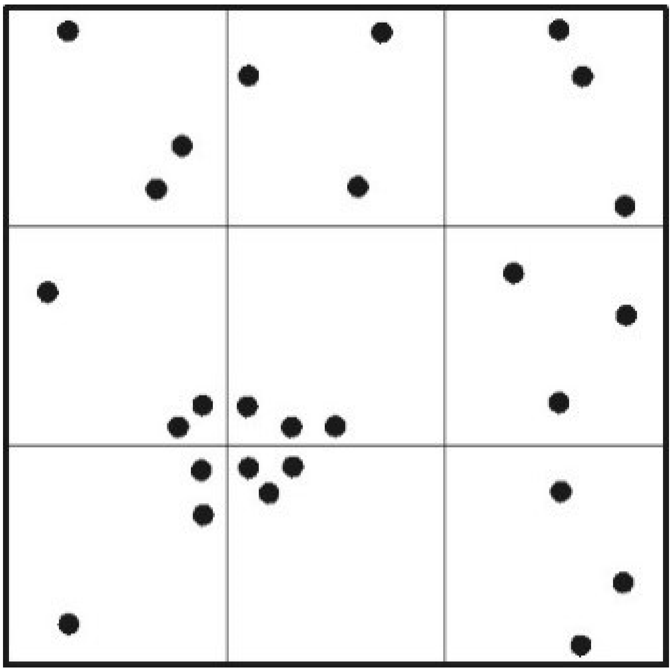

Figure 3. A hypothetical example showing how a cluster can be detected at individual level but not at aggregated grid level as each grid will have equal number of occurrences (modified from Lam, 2012).

A third example is related to exposure modeling. In studying whether cancer incidence is significantly higher for residents living near a Superfund hazardous waste site, a common analysis step is to delineate a neighborhood of influence such as using a one-mile radius and then compare the cancer incidence rate within the radius with the rate of a comparable region. Lam (2012) used this method to assess the health risk surrounding a Superfund hazardous waste site in central Louisiana. The incidence rates for a number of cancer types within a one-mile and a two-mile radii were computed by using the data of the census block groups intersecting the buffer boundaries. These rates were then compared with the state rates. The results show that for the one-mile buffer zone, the cancer incidence rate for male non-Hodgkin’s lymphoma was significantly higher than the state rate. However, for the two-mile buffer zone, none of the cancer incidence rates were significantly elevated. This example highlights the uncertainty surrounding resolution (whether census blocks or block groups should be used), neighborhood size, and the associated GIS methods used in the analysis.

5. Mitigating the Effects of Resolution Using Fractals

Unfortunately, there is no easy way to eliminate the errors and uncertainties resulted from the resolution issue. Two questions we often ask: how do we know what resolution we should use? And how do we know when the results are valid given the resolution of the data? In studying a phenomenon, it is common that we see different patterns at different resolutions, and all observations may be valid (Odum & Barrett, 1971). Thus in principle, we should obtain data at the highest resolution possible to allow aggregating them into a range of resolutions to observe the changing patterns. However, fine-resolution data are often not available. Also, increased resolution also increases data storage and processing time. Thus, in real-world applications, the optimal resolution will depend on the study objectives and the expected outcomes from the study. There are some tools that can be used to help reveal the multi-resolution properties of a phenomenon and thus can be used to guide the selection of a resolution level. This article introduces the fractal technique as follows.

The fractal technique has been used to characterize the scale changes of many phenomena and help identify their underlying processes at specific ranges of resolution. Fractal geometry was derived by Mandelbrot (1983) to describe complex curves and landscapes because classical geometry is inefficient in describing and analyzing them. In classical geometry, a point has a topological dimension of zero, a line has a dimension value of one, and an area has a value of two. In fractal geometry, the fractal dimension (D) is a non-integer value, where a point pattern can have a dimension from zero to one, a line from one to two, and an area from two to three. The more complex the geometry of an object, the higher is its fractal dimension. Coastlines typically have fractal dimensions around 1.2, and topographic surfaces around 2.2. Remote sensing images generally have higher dimensions than topographic surfaces, with values around 2.5 (Lam, 1990).

To estimate the fractal dimension of an object, we use a fractal plot, which shows the regression relationship between the resolution of an object (e.g., step size used to measure a curve) and the measured object size (e.g., total line length) in a double logarithm form. The fractal dimension D is estimated by:

$$\text{Log } L = K + B \text{ Log } S$$

$$D = 1 - B$$

where L is the length of the curve, S is the step size, B is the slope of the regression, and K is a constant. Since it is expected that the smaller the step size, the longer the line length (a key concept that fractal is based on), B is often a negative value (negative slope). From the above equations, D is a function of the slope. The steeper the negative slope, the larger is the value of D, or in other words, the higher the fractal dimension.

A main concept of fractal geometry is the self-similarity property, which assumes that the form or pattern of a spatial phenomenon will not change throughout all scales, i.e., the regression line is a straight line on the fractal plot. This strict self-similarity property was soon replaced with the concept of statistical self-similarity, as fractal plots of many empirical curves and surfaces have shown that self-similarity only exist within a range of measurement scales (resolution). These changes in scale ranges can be used as a tool to understand the scale of action of the phenomenon as well as determine the range of resolutions used in studying the phenomenon (Lam & Quattrochi, 1992).

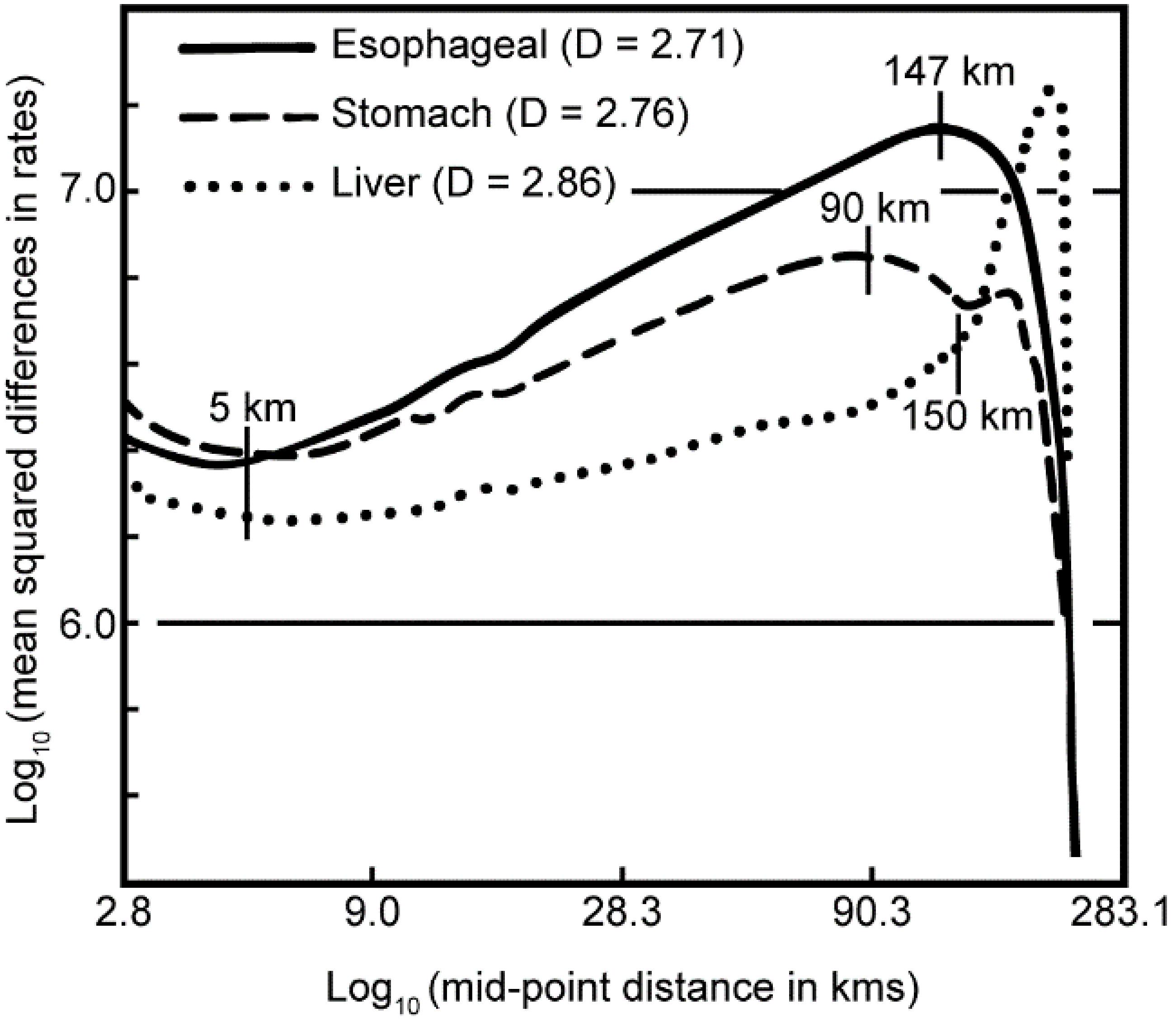

Figure 4. Variogram plot of the three leading cancer mortality types (stomach, esophageal, liver) for the Taihu Region, China. The bars on each curve indicate the scale ranges that show linearity, which were then used to calculate the fractal dimensions. Source: author, modified from Lam & Quattrochi ,1992.

For example, Lam et al. (1993) analyzed China’s cancer mortality patterns using data by commune for the Taihu Region. The study created fractal plots (in the form of variograms) for the three leading cancer mortality types (stomach, esophagus, and liver) (Figure 4), which demonstrate the relationship between distance and variance in a double-logarithmic form. The linearity exhibited on the variogram plot for all three patterns indicates that self-similarity exists only within those scale ranges. Esophageal and liver cancers had similar scale (distance) limits of about 5-150 km, while the scale range for stomach cancer was approximately 5-90 km. These results suggest that if the communes are aggregated to a distance range as large as the distance limit (i.e., decreasing resolution), the patterns would look very different and would result in a different interpretation of the processes underlying the patterns. Furthermore, it is suspected that whatever the underlying controlling factors are (e.g., climate, topography, pollution), they are likely to operate in scale ranges similar to those of the cancer mortalities.

6. Conclusion

This article explains the concept of resolution and identifies it as one of the four dimensions of Scale. Resolution, like the other three dimensions of scale, is a main source of uncertainties and reliability in any spatial or temporal studies. Example applications in environmental change detection and environment health risk assessment have been shown to be easily affected by the choice of resolution level. Recognizing that resolution effects cannot be eliminated, mitigation methods such as the fractal technique would help unveil the scaling property of a phenomenon and guide the selection of a resolution level. An important future research goal is to develop effective spatial techniques for quantifying the resolution effects in these studies.

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