

Scale in Remote Sensing and GIS

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Cover: Color composite image of processed Landsat Thematic Mapper image recorded September 14, 1989 over the central Amazon River approximately 50 km upstream from the town of Óbidos and 650 km downstream from the town of Manaus. The record flood of 1989 has receded approximately 2 m, the floodplain is draining, and flow is from left to right (west to east) in the main channel which is 4 to 6 km wide. The color of the main channel (red) indicates relatively high suspended-sediment concentrations in the water. The dark blue color indicates relatively clear water, and blue-green indicates tropical forest. Image processing completed by A. K. Mertes, Department of Geography, University of California, Santa Barbara. Raw image provided by R. Almeida Filho of INPE, Brazil.

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Multiresolution Covariation Among Landsat and AVHRR Vegetation Indices

Lee De Cola

INTRODUCTION

The treatment of data at multiple scales is well-established in the spatial analytical literature (Bian and Walsh, 1993; Franklin, 1994; Frank et al., 1994; Lambin et al., 1995) and is becoming increasingly common in broader discussions of biophysical and landscape processes (Meentemeyer and Box, 1987; Turner and Gardner, 1992). Quattrochi (1993) provides a "lexicon of scale" that presents the fundamental dimensions of the problem. I would rearrange his discussion by prioritizing the issues:

- Space: absolute and relative
- Measurement: resolution and extent
- Analysis: scaling and measures of spatial complexity (Stoms, 1994)
- Objects and processes: resolution element (fine level) and characteristic size (coarse level) (Cullinan and Thomas, 1992)

This organization begins with abstract space, which forms a framework for measurement that produces data to be analyzed at multiple resolutions for the characterization of processes and the identification of objects. In this chapter the first and last issues are not explored as the data are already given; the focus is more on technique than on characterization either of the landscape in general or of vegetation in particular.

The typical approach to scale issues argues that each phenomenon requires a specific scale of data for its characterization (Jensen, 1986). This book demonstrates how information from a range of scales is critical to the understanding of spatial processes. In keeping with Quattrochi's system, all data may be considered as

existing in a space of four conceptual dimensions, each with its unique characteristics:

- Space — continuous and unbounded (Getis and Franklin, 1987)
- Time — continuous and bounded in one direction (the future) (Peuquet, 1993)
- Feature — discontinuous and unbounded (Buttenfield, 1994)
- Scale — continuous and bounded in one direction (the finest available resolution) (Basseville et al., 1992)

This scheme augments the usual notion of features in space and time by highlighting the nature of scale itself as a hierarchical framework within which phenomena may be studied. Each of the first three dimensions presents us with (usually strongly related) scale issues. Moreover, time and scale have directionality. Time moves from past through present to future, and we have more confidence in historical data based on prior states of a system than in future projections. Scale moves from coarse to fine, and we become less certain of lower-level (finer) representations based on interpolations of spatial data than on higher-level generalizations. Finally, spatial scale itself is a continuum that reveals useful information about phenomena only when we look at multiple scales.

Nevertheless, the word “scale” will be avoided here because it has strict cartographic and loose physical meanings that are opposite in intent, and because the term is better constrained to references to some continuum (small to big) than applied to specific levels within the range. As this chapter is concerned with satellite data, the term “resolution” is used instead. The next sections formalize these ideas, introduce data to illustrate them, and then analyze the data. The chapter concludes with a broader view of this research.

MULTIRESOLUTION ANALYSIS

Let $l = 0, \dots, L$ be a resolution level, where larger values of l denote larger (coarser) physical resolutions of observation or analysis. Let a given dataset A_0 consist of measurements made at some resolution considered to be level-0 for the available data (for example, for the Landsat thematic mapper (TM) level-0 is based on 30-m instantaneous field of view (Richards, 1986)). The integer index l will correspond to the relative physical size of the units of observation, in this case grid cells. The exploration of scaling in data is sometimes based on multiple levels of observations but usually depends upon the analysis of original data at multiple resolutions created by some kind of a generalization operator $g(\)$ that should not introduce artifacts into the data. Consider the production of $A_1 = g(A_0)$ where A_1 is some generalized version of A_0 . This process can be repeatedly applied

$$g^2(A) = A_{l+2} = g(A_{l+1}) = g(g(A_l)) \quad (1)$$

to produce a recursively constructed data pyramid

$$\{A\} = \{A_l; l = 0, \dots, L\} \quad (2)$$

based on level-0 (Samet, 1989). There are many ways to generalize data, such as sampling, filtering, and averaging, which are appropriate for various kinds of objects and fields (Buttenfield and McMaster, 1991). In the present case the generalization is done by averaging 2×2 non-overlapping windows (De Cola, 1994).

Table 1 describes a power-2 grid pyramid of size $L = 10$ ($2^L = 2^{10} = 1024$) based on 31.25-m data. The columns of the table show level l , which indexes the layers of the pyramid, the number of cells in each row (= number of cells in each column), and the size of each cell. Three types of data are also shown for reference, from 1000-m advanced very high resolution radiometer (AVHRR) cells, through 30-m Landsat TM, to 1-m digital orthophoto quad imagery. In this chapter the word grid is used to refer to imagery or raster data to convey the idea that these operations could be performed on any kind of rectangular array.

19
21,229 Km
earth
Table 1 Description of Pyramids Used in this Chapter and Comparisons with Other Grid Data

Level	Cells in each row	Cell size (m)	Grid data examples	Typical regions
13	0.125	256,000		Chesapeake Bay
12	0.25	128,000		1 degree
11	0.5	64,000		
10	1	32,000		
9	2	16,000		1:24,000 USGS quad
8	4	8000		
7	8	4000		
6	16	2000		
5	32	1000	AVHRR	
4	64	500		
3	128	250		
2	256	125		
1	512	62.5		
0	1024	31.25	Landsat TM	
-1	2048	15.62		
-2	4096	7.81		
-3	8192	3.91		
-4	16384	1.95		
-5	32768	0.98	DOQ	

It should be noted that in $E = 2$ -dimensional space, Vol , the volume of data (or number of cells, for example in bytes; see Light, 1986) of a pyramid is only $1/3$ greater than that of its lowest level. This advantage is even greater for 3-dimensional pyramids, for which the additional size is only $1/7$. In fact, for any physical space of E dimensions, the ratio of the size of a pyramid and that of its lowest level is

$$Vol(\{A\})/Vol(\{A_0\}) = 2^E/(2^E - 1) \quad (3)$$

and this ratio $\rightarrow 1$ as $E \rightarrow \infty$, so the savings realized by generalization become quite dramatic for high-dimensional data structures (for a practical example of data reduction by resolution manipulation see Nozette et al. (1994)).

The highest level L represents how far the generalization operation $g(\)$ can proceed until there is one object (point location or grid cell mean) corresponding to the "scope" or maximum extent of the data (Schneider, 1994), which may also be the highest level of interest. L should also be larger than the "characteristic scale" of the phenomenon; if we are trying to understand grizzly bear habitats, for example, the physical extent of our data should span a region at least as large as that occupied by the animals during a yearly breeding cycle. But again this relates more to Quattrochi's 4th process-level problem, which this technical chapter will not address.

Multiresolution Variance

The visualization of data pyramids is quite common; indeed, all grids can in some sense be regarded as generalizations of the real-world data on which they are based, and most practical visualizations are further generalized (for display, transmission, or analysis) from some lowest-level dataset. There are also many ways to characterize such pyramids quantitatively. The mean values of the $\{A_l\}$ for each l can serve as a check on the generalization (this series should be unchanging to within a given level of tolerance). The variance $\sigma^2(A_l)$ of the pyramid levels is sensitive to spatial structure (Arbia, 1990). In the case of a random field, $\sigma^2(A_{l+1}) \approx \sigma^2(A_l)/2^E$, where E is the dimension of the physical space in which the data lie.

The scaling characteristics of the variance can be determined from

$$\sigma^2(A_l) = a(2^l)^b \quad (4)$$

where a is predicted variance at level-0 and b is an (inverse) index of spatial autocorrelation that varies between $b = 2$ for random data and $b = 0$ for extremely simple data such as a polygon (De Cola, 1994). This scheme implies that any particular dataset lies at a point in the scale dimension, and the techniques presented here allow us to explore this dimension; but only in one direction, for although we can aggregate data from level $l = 0$ to higher (coarser) levels, we cannot move in the other direction ($l < 0$) with any certainty. (Table 1, therefore, only suggests the existence of lower-level data for this study; although such data exist, they cannot be created with perfect accuracy from higher levels.) This does not deny that there is a wide range of tools, such as interpolation and kriging, for moving down the scale continuum (Cressie, 1991), but such approaches correspond to forecasting in the time dimension, which is speculation, not history.

This treatment of scale as a line segment that spans a range from the finest available resolution of the data to a single summary statistic, rather than as a single point or as a number of discrete points, highlights the pyramid as a nested set in which the variance of each resolution level consists of the variances of the levels above plus some new information (signal or noise), so that the so-called scaled variance

$$\Delta\sigma_i^2 = \sigma^2(A_i) - \sigma^2(A_{i+1}) \quad (5)$$

is of interest (Justice, Townshend, and Kalb, 1991). This approach is based on the idea of nested variation in which movement down the resolution scale (from coarse to fine) may reveal structure at some level (Moellering and Tobler, 1972). This may happen when the spatial organization of the source data lies around the middle of the random-to-simple continuum (De Cola, 1991). As the analysis increases resolution, there is the expectation that variance $0 \leq \Delta\sigma_i^2 \leq 4$. When little additional variance is found a relatively spatially coherent feature may be detected; when considerable additional variance is found there is probably noise at that level. This argument obviously requires variable resolution data rather than data from a few distinct resolutions. It should be noted that a richer resolution-based characterization of the spatial complexity is afforded by scaling various dimensions, but this treatment would require a digression into multifractality, pursued elsewhere in this book (see Chapter 16).

Composition of Aggregation with Other Operators

An important research issue is the problem of the composition of aggregation and other operations on grids. Consider for example some operator $f(\)$ that transforms grids. It is possible to examine $f(A_i)$ as well as $g(f(A_i))$, its generalization. The question is whether

$$f(g(A_i)) = g(f(A_i))? \quad (6)$$

We need to know if these operations are commutative for at least three reasons. First, it is theoretically interesting to know if Eq. 6 holds or nearly does. Second, the scaling behavior of the operator $f(\)$ may tell us something useful about the phenomenon (for example, that the slope of elevation data is not self-similar). Third, it may be much faster to generalize and then transform the data, producing $f(g(A_0))$, than to transform the low-level data and then generalize the result, producing $g(f(A_0))$. This will particularly be true if f is computationally intensive and therefore faster to perform on generalized data. If the difference is small for some purpose then we can store (or generate) $\{A\}$ (defined in Eq. 2) and perform various operations on it without having to perform each of them on the finest level data. Tobler (1979) discusses the composition, as well as inversion, of operations in a different context.

This is a relatively unexplored issue, and yet it is important for the management and analysis of large datasets. For example, is there an important difference between computing an index (say NDVI) from two or more level-0 (30-m) TM bands and then aggregating the results to some coarser level, vs. aggregating the bands and then computing the index? If any operator is substituted for the normalized difference vegetation index (NDVI) computation, this question becomes general and is relevant to issues of data storage and computational speed, as well as interpretation of

processes and features. And of course beyond questions of computational efficiency, it is also useful to know just how such transformations scale.

Multiresolution Covariation

When we have characterized the scaling of one set of measurements, interest turns to one or more other datasets $\{B\}$ and their comparisons with $\{A\}$. Again, the sequence of steps is as above: visualization, analysis of variation, and other operations. As with any analysis of covariation we are concerned with statistical criteria of difference. Another approach is to examine the scaled variances $\Delta\sigma_7^2$ (Equation 5) to determine if $\{B\}$ is sensitive to the same scale breaks as $\{A\}$. Finally, we can examine scatter diagrams and correlation coefficients to compare the grids. Large correlation values are necessary but not sufficient conditions for strong process linkages between A and B .

Another obvious way to compare data is to examine multiresolution covariation $Cov(A, B)$. The most general statement of this situation is the modifiable area unit problem (Fotheringham and Wong, 1991). This series tells us not only about similarities between A and B but also about the scale structure of their association (Arbia, 1990). This issue will be explored in detail below.

The multiresolution analysis of data uses a *Mathematica* package of seven major modules, each of which has several related functions (Wolfram, 1991). (NOTE: Any use of trade, product, or firm names in this chapter is for descriptive purposes only and does not imply endorsement by the U.S. Government.) Table 2 outlines the functions in the package, and is shown to highlight the basic tools that are necessary for multiresolution grid analysis. The package requires statistical and visualization functions as well as tools that provide information about data or perform normalization (Abramowitz and Stegun, 1965). Data input/output and the NDVI transformation are included next, and then basic statistical operations. Visualization is handled by programs that display data in 2-D, 3-D, or arrayed by resolution. The scale operations themselves make pyramids and either expand (replicate) or interpolate grid data. Finally, a number of multiscale tools analyze the data at multiple levels.

STUDY AREA AND DATA SOURCES

Techniques are driven both by theory and practical needs. The USGS distributes and regularly uses three major grid data series: 1-m digital orthophotoquads (DOQ), 30-m Landsat TM (Lillesand and Kiefer, 1987), and 1000-m AVHRR, whose resolutions are compared in Table 1. An important challenge in the management and use of these data is the characterization of the land not only at multiple resolutions (in this case 3) but at a continuous range of resolutions spanning three orders of magnitude or 10 powers of 2.

The USGS is currently conducting research that uses vector and raster data to develop new ways of mapping the land in space and time (Kirtland et al., 1994). A current research project, for example, focuses on human-induced land transforma-

Table 2 The *Mathematica* PYRAMID System

```
(* INITIALIZATION *)
Needs["Statistics`DescriptiveStatistics`"]
Needs["Graphics`Graphics`"]
Needs["Statistics`LinearRegression`"]
Install["/home/nmd/idecola/math/binary"]
```

```
(* A FEW BASIC TOOLS *)
showmem.m
vartable.m
ndvi.m
```

```
(* DATA INPUT & OUTPUT *)
readdata.m
writepyr.m
window.m
```

```
(* STATISTICS *)
range.m
normalize.m
var.m
invnorm.m
standardize.m
report.m
plotcdf.m
```

```
(* VISUALIZATION *)
plotdensity.m
pyrarray.m
drape.m
```

```
(* AGGREGATION, REPLICATION, INTERPOLATION *)
makepyr.m
expand.m
interp.m
```

```
(* PYRAMID ANALYSIS *)
multvar.m
msscatter.m
corr.m
mscorr.m
```

tions both in central California and in the upper Chesapeake Bay. Urbanization in the latter region focuses on the Baltimore/Washington metropolis (Acevedo, Foreman, and Buchanan, 1996), which is shown in Plate 1* as a perspective rendering with AVHRR NDVI data draped on digital elevation data for level 9 (16-km) and level 5 (1-km). This figure illustrates one of the uses of multiresolution techniques. The example on the top is based on mapping the NDVI values on a brown-to-green hue spectrum and required less than 1 second of processing time on an IBM RISC/6000 model 590 with 128 MB of memory running at approximately 93 Mflops. The view on the bottom required 3 minutes.

We are interested not only in the synoptic characteristics of a region, but also in gaining more detailed information about the Baltimore area and specifically four

* Color plates follow numbered page 168.

cells from the level-9 data shown in the top frame of Plate 1. Plate 2* shows the location of the data for both the 256²-pixel AVHRR grid and the 1024²-pixel TM grid. The figure illustrates how the AVHRR dataset gives a synoptic view of the region and the TM data provides more detailed information about the city of Baltimore. This visualization also suggests the way that data sources span the scale space mentioned above. The fact that these two sensors span a resolution range of over five levels ($\text{Log}_2(1000/30) = 5.06$) makes comparisons between them difficult.

Table 3 outlines the steps that were taken to conflate the two datasets. The AVHRR Baltimore scene was extracted from a 1990 CD-ROM that contained biweekly data for the U.S. at 1000-m resolution. This established the base projection and level-5 resolution standard for the study. The other dataset is a Landsat TM grid that was created as follows. A 2048²-pixel 7-band, 30-m grid was first georectified using 1:100,000 scale USGS maps, resampled to 31.25 m, and then reprojected to Lambert Equal Area. A 1024²-pixel window was extracted, resulting in an error of no more than 100 m between the two grids. Note that square power-2 grids are used throughout to facilitate aggregation.

Table 3 Steps in Conflating the Two Datasets

	Landsat TM		AVHRR	
	→		←	
Date	1998/07/06		1990/06/22-07/05	
Data	7 bands	NDVI	NDVI	7 bands
Location	Chesapeake	Baltimore	Baltimore	U.S.
Coverage	32,000 km ²	1,024 km ²	1,024 km ²	13 M km ²
Projection	SOM ^a	Lambert	Lambert	Lambert
Resolution	30 m	31.25 m	1000 m	1000 m
Level	-0.133 ^b	0	5	5
Data volume	40 MB	1024 ² bytes	32 ² bytes	13 MB

^a Space Oblique Mercator.

^b Shown for reference only; level is typically an integer.

There are obvious difficulties with the conflation used here (as opposed to the use of two sensors with identical spectral response imaging the same region at the same time). At the finest spatial resolution near level-0 the data are subjected to varying degrees of modification in the process of resampling and reprojecting. Temporally, the data were collected at different points in time. And spectrally, the sensors have different wavelength sensitivities. It is therefore difficult to determine exactly what the effects of these inherent and pre-processing differences are; yet, as we shall see, these differences significantly diminish at coarser resolutions.

ANALYSIS

The two color plates illustrate that the simplest yet often most powerful form of analysis is the visualization of data directly at multiple resolutions and from multiple

* Color plates follow numbered page 168.

