# Novel Models for Multi-Scale Spatial and Temporal Analyses

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## Abstract

Multi-scale analysis for spatio-temporal data forms a fundamental challenge for many analytic systems. In geographic information systems, analysis and modeling at pre-defined spatial and temporal scales may miss critical relationships in other scales. Previous studies have investigated the uses of the triangle model as a multi-scale framework in analyzing temporal data. This article demonstrates the utilities of the triangle model and pyramid model for multi-scale spatial analysis through real-world analytical tasks and discusses the potential of developing a unified modeling framework that integrates the two models.

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## 1 Introduction

Currently, the increasing diversity of geospatial data collected at different resolutions (e.g. satellite, UAV, field sampling, and census data) poses serious challenges for data integration and analyses. The choice of analytic scale to a large extent determines the insights that can be gained, due to the nature of geospatial information and due to its sensitivity to spatial and temporal resolution. The importance of scale has been epitomized in the well-known Modifiable Areal Unit Problem (MAUP). Ideally, geospatial data should be analyzed at multiple scales to reveal the nested interactions at different scales and decisions should be made at the level where the spatial and temporal relationships are maximized. However, the scale of analysis that is best suited for a given problem is not always immediately evident, which raises a compelling justification for exploring data solutions supporting multiple-scale analyses.


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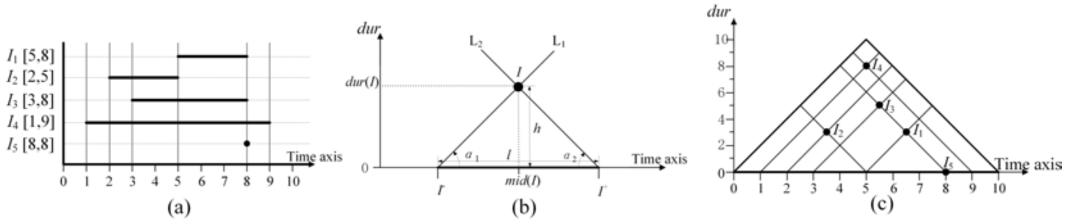
Multi-scale analysis for spatio-temporal data forms a longstanding challenge for analytic systems in different disciplines. In GIS, spatial data are represented as flat layers and temporal data are represented as linear sequences at pre-determined resolution, with spatial analysis tools operating usually at a single scale. For instance, kernel density can display clusters of features only at a single spatial scale. To discover clusters concealed in other scales, the analysis needs to adjust the bandwidth using an inefficient "trial-and-error" approach that repeats the density calculation at one or more alternative scales. Similar issues exist in image classification and land cover change modeling, which usually are based on pixel-centered single-scale methodologies that can ignore or obscure the impact of scale and hierarchy in landscape processes that drive pattern creation. To fully understand the complexity of coupled natural and human systems, the interactions and competitions among different systems need to be analyzed and modeled at multiple scales.

To address the issue of multi-scale temporal analysis, Qiang et al. [4][5] proposed a Triangle Model (TM) that projects linear temporal data onto a 2D space and demonstrated how variation of data across multiple temporal scales can be represented in a continuous 2D space [3]. The TM was later applied in analyzing movement data [7]. This paper demonstrates the utility of the triangle model in evaluating surface-adjusted distance measurements in digital elevation models and the utility of its extension (the pyramid model) in analyzing land fragmentation. Finally, we will discuss the potential of building a unified framework for integrating the triangle and pyramid model for multi-scale spatio-temporal analyses.

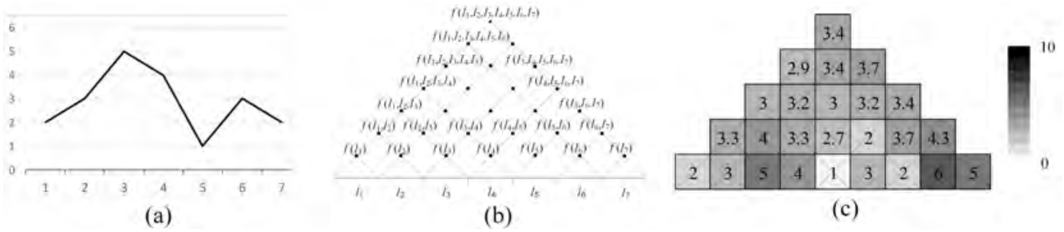
## 2 Triangle Model

Time intervals are conventionally represented as linear segments in a one-dimensional space (Figure 1(a)). Alternatively, a 2D representation of intervals was originally introduced by Kulpa [2] as a diagrammatic tool for mathematical reasoning. Later, Qiang et al. [4][5][3] extended the model for spatio-temporal analysis, and implemented it into a GIS. In Qiang et al's approach, a time interval (starting at $I^-$ and ending at $I^+$ can be mapped to a point at $((I^+ + I^-)/2, (I^+ - I^-)/2)$ in a 2D Cartesian coordinate system (Figure 1(b)). The position of the point in the horizontal axis $((I^+ + I^-)/2)$ indicates the midpoint of the interval, while the vertical position $((I^+ - I^-)/2)$ is proportional to the length of the interval. Using this approach, which is termed the Triangle Model (TM), all time intervals can be represented as unique points in a 2D coordinate space. Figure 1(c) demonstrates a TM depiction of the five intervals shown in Figure 1(a), illustrating its facility for representing temporal properties (e.g. start, end, midpoint and duration) in a compact view. One of the advantages of the TM is that by converting temporal relations into a spatial representation, the TM permits temporal analysis to be conducted seamlessly across multiple scales using simple GIS operations.

In addition to time intervals, the TM can be used to represent sequential time series data [3]. A time series (e.g. daily temperature) consists of a sequence of intervals (e.g. days) associated with an attribute (e.g. average temperature of the day) (Figure 2(a)). Daily intervals, which are the finest granularity, can be represented as points at the lowest level in a TM. Intervals of every two days can be represented as points at 2nd level and intervals of every three days can be represented as points at the 3rd level. The point on the top represents the interval of the entire time series (Figure 2(b)). Each point in the TM is associated with an aggregated value (e.g., the mean or standard deviation) of attributes of the intervals it represents. Figure 2(c) shows the values of each day shown in Figure 2(a) along its lowest level; and a nested average for each interval is easily computed in the TM. Interpolation of




■ **Figure 1** The transformation from the linear model to the triangle model. (a) Time intervals in the linear model. (b) Projecting a time interval into a point in the triangle model. (c) Time intervals in (a) shown in the triangle model.




■ **Figure 2** Representation of time series in the TM: (a) a time series represented in a conventional line chart; (b) representing time intervals in the time series in (a) as points in the TM; (c) a rasterized TM showing nested means for the time series.

the nested values within the TM can form a continuous field representing all intervals in the time series, providing an explicit view of the hierarchy and nested relations of patterns across different scales. Using conventional spatial analysis methods, (e.g. classification, overlay, and Map Algebra), multiple time series can be compared to support multi-criteria decision-making at different temporal scales.

## 3 Surface-Adjusted Distance in the Triangle Model

In GIScience, distance is the most fundamental spatial metric that anchors proximity analysis, spatial pattern detection, and spatial interpolation, and, indeed, underlies detection of nearly every type of geospatial pattern. Similar to time series data, distance measurement is a linear process based on aggregating distances in small intervals. Current distance measurement on terrain assumes that Digital Elevation Model (DEM) pixels are rigid and flat, as tiny facets of ceramic tile approximating a continuous terrain surface. It is still unclear how the measurement errors using different approaches propagate over scales in all types of terrain. As the measured distance increases, the errors introduced by the assumption of rigid pixels can propagate dramatically and increase overall error [1], or cancel each other out and result in coarse-scale accuracy.

Distance measurements of four surface-adjustment approaches, including weighted average (WeiAve), and three polynomial approaches (i.e. Bilinear, Biquadratic and Bicubic) are compared in this section. Please refer to [1] for the details of these surface-adjusted approaches. The distance of a transect is measured using the four surface-adjustment approaches on DEMs at different resolutions (10, 30, 100 and 1000m). Then, the measured distances are compared with the benchmark distance measured on a 3m LiDAR DEM to evaluate their accuracies. Using traditional visualization methods, accuracies of the surface-adjustment distance measurements can only be examined at a single scale. For instance, Figure 3 shows

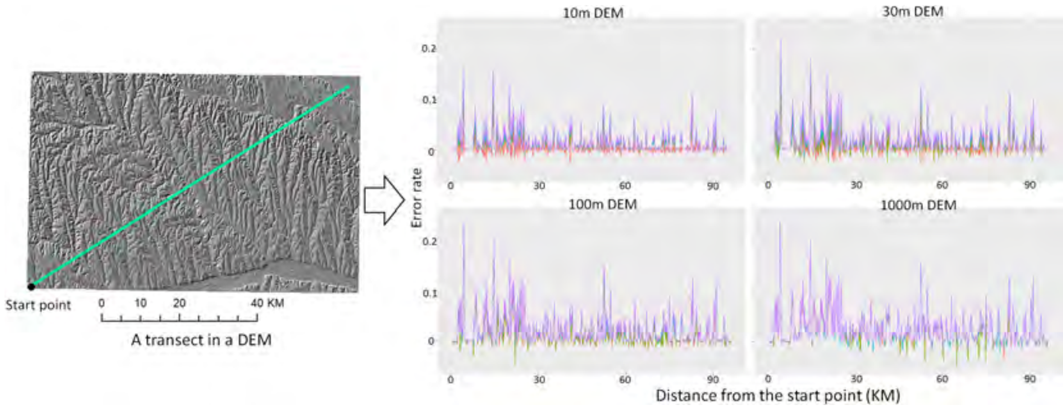



**Figure 3** A transect in a DEM (left) and error rates of distance measurement in 100m intervals along the transect (right). The colors of the lines indicate different surface-adjusted methods.

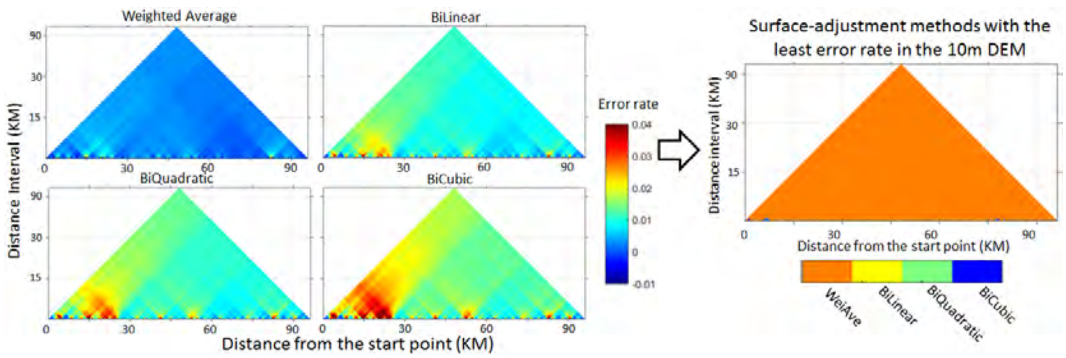



**Figure 4** Error rates of distance measurements in the 10m DEM represented in TM (left) and the overlaid TM showing the most accurate approach (right).

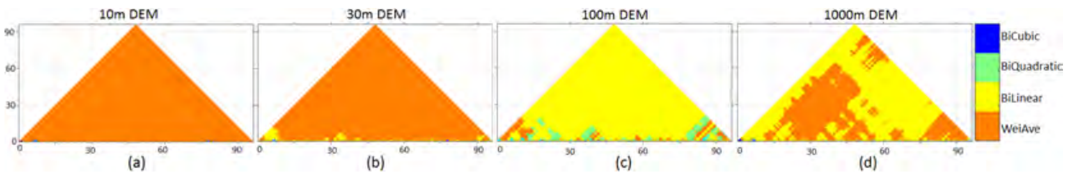



**Figure 5** Comparison of the four surface-adjustment methods for measuring different lengths of intervals in the TM. Colors indicate the most accurate approach.

error rate of distance (computed as (benchmark distance − measured distance)/benchmark distance) in every 100m interval along the transect, using different surface-adjustment methods and on DEMs of different resolutions. From the linear charts, it is also difficult to analyze the propagation of errors at different scales and to compare the surface-adjustment approaches in measuring different interval lengths.

The TM provides a compact view of error rates of measuring different lengths of intervals (Figure 4). By overlaying the TMs of different surface-adjustment approaches, we can identify the most accurate (lowest error rate) approach in measuring different lengths of intervals along the transect. The left side of Figure 4 demonstrates the error rates of the four surface-adjustment approaches in the 10m DEM. The right side is the result of overlaying the four TMs in the left panel, where the colors denote the most accurate surface-adjustment

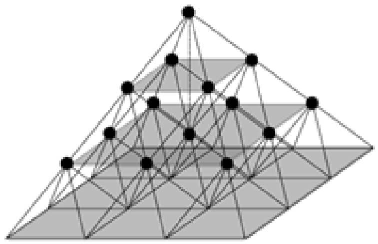


**Figure 6** A raster in a Pyramid Model (PM).

approach in measuring different lengths of intervals. The single color (orange) of the overlaid TM indicates that weighted average is the most accurate approach in measuring all intervals in the 10m DEM. However, as shown in Figure 5(b), the Bilinear approach outperforms weighted average in some short intervals (yellows in the bottom of the TM) in the 30m DEM. In the 100m DEM, Bilinear approach becomes the most accurate approach for long intervals, while Bilinear and Biquadratic have better accuracy in short intervals (Figure 5(c)). In the 1000m DEM, Bilinear and weighted average have competing accuracies in measuring distances in different intervals (Figure 5(d)). The measurement errors represented in the TMs inform the best surface-adjustment approach for measuring distance in different lengths of intervals. Next, the relationship between the measurement accuracy and terrain roughness will be explored in the framework of TM, which will be presented in the conference.

## 4 Multi-Scale Spatial Analysis in the Pyramid Model

The concept of the Pyramid Model (PM) is similar to an image pyramid, which represents a raster image across multiple resolutions by smoothing and resampling. Image pyramids were originally developed in computer vision, image processing and signal processing, but are now used more widely to enhance the efficiency of multi-scale raster rendering in GIS. In our approach, the construction of a PM is similar to that of the TM in the sense of developing a hierarchy; but the PM represents 2D space across scales instead of linear time. To construct a PM, every pixel in the base raster can be represented as a point at the lowest level in the pyramid. Points at the second level represent square region of four pixels (2×2) in the raster. Points at the nth level represent square regions of $n^2$ pixels. In constructing this hierarchy, all square regions of different sizes in the base raster are represented as a pyramid containing uniformly arranged points in a 3D space (Figure 6). The pyramid can be represented as a 3D raster that consists of numerous equal-size voxels, each of which is associated with an aggregated statistic of the attributes or spatial metrics (e.g. density, texture, spatial dependence) for the square region it represents. The PM can also represent vector features (e.g. point, line, and polygon), in which points represent square regions in the base layer.

The utility of the PM is demonstrated in analyzing wetland fragmentation in coastal Louisiana. Published evidence shows that fragmented wetland habitats may accelerate wetland erosion and wetland loss (e.g. Lam et al. 2018). However, fragmentation indices calculated for different sizes of focal windows may lead to different results. Similar issues exist in other spatial pattern indices such as density, spatial autocorrelation, and terrain roughness. Figure 7 illustrates PM representations of fractal dimension (a commonly used fragmentation index) of a binary land cover raster clipped from coastal Louisiana. Using the land cover raster as the base (Figure 7(b)), local fractal dimensions for different sized focal windows can be stacked into a 3D PM (Figure 7(c)) in which lower layers represent

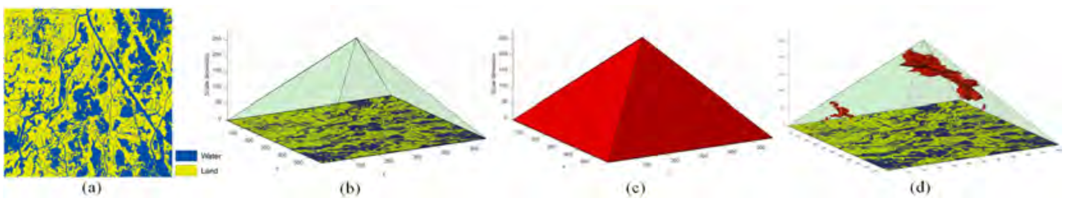



**Figure 7** Representing local fractal dimensions of land cover raster in a PM. (a) A binary land cover raster. (b) The land cover raster in the base of a PM. (c) A 3D Pyramid Model built from the land cover raster. (d) Voxels with a fractal dimension in the 99th percentile.

fractal dimensions for smaller regions, and higher layers represent fractal dimensions for larger regions. The internal variation of the PM can be visualized using ‘spatial query’. For instance, Figure 7(d) displays the voxels in the 99th percentile (i.e. the highest 1%) fractal dimension calculated in different sizes of focal windows, indicating the most fragmented regions at different scales. Extending map algebra into the 3D space, the variation in the PM can be further analyzed and multiple PMs can be compared or correlated. For instance, subtracting PMs of fractal dimension calculated at two time points, one can identify land areas where fragmentation has accelerated significantly. Moreover, regression analysis can be conducted between the PM of the land fragmentation and density of man-made structures to discover the scales at which human activities have most impact on wetland erosion.

## 5 Summary and Future Work

This study demonstrates the applications of the TM and the PM in multi-scale spatial analyses. Compared with traditional analytic tools that are limited to a single scale, the PM and TM can represent spatial patterns and relationships in a full dimension of continuous changing scales, and facilitate queries across spatial and temporal scales. This study demonstrates the use of two multi-scale models in evaluating distance measurement in DEMs and analyzing landscape fragmentation respectively. Beyond these, our future research plan includes developing a unified modeling framework that integrates TM and PM to fully support multi-scale spatio-temporal analyses. Within the unified modeling framework, an atomic element ($x$) consists of four dimensions including spatial location ($s$), spatial scale ($s$’), temporal location ($t$), and temporal scale ($t$’) [6]. Compared with prevalent GIS that focus on spatial analysis (i.e. $f(s)$) and single-scale spatio-temporal analysis (i.e. $f(s,t)$), the unified framework will fundamentally resolve the issue of multi-scale spatio-temporal analysis by providing 15 types of analyses using one or more of the four dimensions (i.e. $\binom{4}{1} + \binom{4}{2} + \binom{4}{3} + \binom{4}{4} = 15$).

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