Methods for Space-Time Analysis and Modeling: An Overview

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ABSTRACT

With increasing availability of spatio-temporal data and the democratization of Geographical Information Systems (GIS), there has been a demand for novel statistical and visualization techniques which can explicitly integrate space and time. The paper discusses the nature of spatio-temporal data, the integration of time within GIS and the flourishing availability of spatial and temporal-explicit data over the Internet. The paper attempts to answer the fundamental question on how these large datasets can be analyzed in space and time to reveal critical patterns. The authors further elaborate on how spatial autocorrelation techniques are extended to deal with time, for point, linear, and areal features, and the impact of parameter selection, such as critical distance and time threshold to build adjacency matrices. The authors also discuss issues of space-time modeling for optimization problems.

Keywords: Autocorrelation, Geographic Information Systems (GIS), Optimization, Pattern Analysis, Spatio-Temporal Modeling

INTRODUCTION

With an increasing availability of geospatial information over the last fifty years, spatial scientists have dedicated their efforts to the development of tools and techniques for the spatial and temporal analysis of georeferenced data (Anselin, 1999; Fischer & Getis, 2010). Analytical and geovisualization methods have proved critical in a growing number of spatially integrated application domains such as ecology, population geography, crime analysis, urban planning, location modeling, economic, environmental and health sciences. Consequently, there is now an abundance of robust statistical and data mining methods specifically designed to deal with geospatial data. These methods have facilitated the extraction and detection spatio-temporal patterns, eventually leading to the understanding of complex spatial relationships.

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Developments in computational science and mapping technologies have enabled effective and efficient visualization of large geospatial data sets such as social media data on the Web. To that end, Geographical Information Systems (GIS) provide a unique platform to integrate these methods and visualization capabilities (Longley, Goodchild & Maguire, 1999).

The purpose of this paper is to provide an overview of methods that can be used for space-time analysis and modeling. We start by situating our discussions in a context of the uniqueness of spatio-temporal data, its increasing availability through the Internet and social media, and the increasing need of methods to extract space-time patterns. We then review critical methods for spatio-temporal analysis, applied to point and areal features (with and without attributes) and linear features, with an emphasis placed on how to extend the concept of spatial autocorrelation in time. We focus our discussion on space-time modeling using an example of spatial optimization for planning and environmental modeling, where GIS and location modeling can be coupled together for data acquisition, analysis and result visualization. We conclude the paper with a revisit of the broad issues in space-time methodology.

SPATIO-TEMPORAL DATA

The Uniqueness of Spatio-Temporal Data Unique and the Critical Role of GIS

Spatial data is characterized by a set of longitude and latitude coordinates (or x and y), and usually modeled from an object-based or location-based approach (Peuquet, 2002). These modeling approaches are not contradictory, but rather complimentary. For instance point data is used when mapping crime events and disease occurrence (McElroy et al., 2003; Chainey & Ratcliffe, 2005) and can easily be overlaid with raster data, while linear features are used for network modeling. An interesting question is whether the spatial distribution of these events is clustered or not, leading to the identification of hot spots. Increasingly however, spatial data has also been augmented with attributes and temporal coordinates, for instance the time stamp associated with an event.

Researchers (Peuquet, 2002; Andrienko & Andrienko, 2006) have proposed two approaches to incorporating time in spatial data. In an object-based approach, temporal extent is attached to each entity as an attribute, while in a continuous approach individual objects are considered as attributes and attached to a given location in space and time. In the object based approach for instance, GIS provide a unique platform that facilitates the linking of temporal and non-spatial attributes to geospatial locations by means of a unique identifier (ID). By means of structured query language (SQL), events occurring within a certain time interval can be extracted, and statistical techniques applied to test whether they exhibit space-time patterns.

Due to the unique nature of space-time data, it is thus straightforward to combine temporal and spatial queries. Consequently GIS is undergoing a new phase where two critical issues are in (1) the development and applications of techniques for the identification of clusters of spatial association in space and time -or in the attribute space, and (2) the development of space-time visualization techniques. These issues can be very challenging for large datasets. Our paper fits directly into the first concern, which is the development and application of space-time methods to identify clusters in space and time.

The Increasing Availability of Spatio-Temporal Data on the Internet

Spatial temporal analysis of Web-based data has been explored extensively in recent years mainly with focus on topics such as space time query over the Internet using spatial temporal conditions (Tezuka & Tanaka, 2005), attribute extraction combined with spatio-temporal queries (Perry et al., 2007), knowledge organization of space time data (Janowicz, 2010) and the handling of vagueness in spatial temporal data (Schockaert et al., 2010). These efforts have drawn important research attentions on exploring the spatiotemporal aspects of online information, especially user-generated contents.

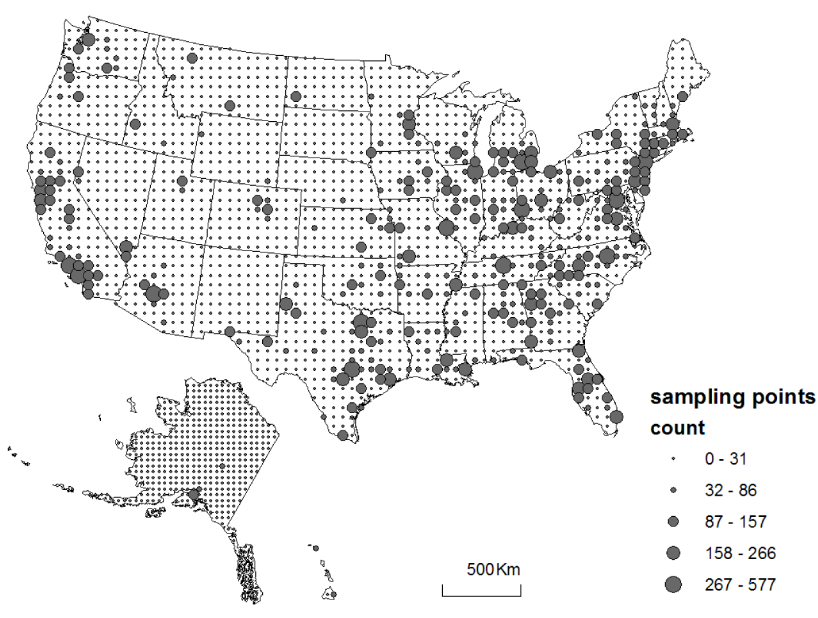
Spatio-Temporal Data on the Internet

There are generally two types of online data that can be used in space-time analysis. A first type is vector data representing the geometries of graphical features; these data are often contributed by users to sites such as OpenStreeMap. This type of online geographic data uses data formats that can be directly integrated in GIS. These data are known as Volunteered Geographic Information (VGI) and has drawn mainstream research attentions regarding utilizing online spatial data (Elwood, 2008; Goodchild, 2008). Li et al. (2010) showed an example of utilizing VGI is to analyze trajectory GPS data where users upload their GPS routes as online maps to help understand the pattern of moving individuals. A second type of online geographic data often uses a text format with explicitly embedded spatio-temporal information; these data include status updates on social network sites (e.g., Twitter and Facebook) and various web pages. An example of using this type of data is illustrated in Figure 1.

SPATIO-TEMPORAL ANALYSIS

Hagerstrand (1970) brought time and geography together when he proposed a space-time prism to represent the mobility of an individual in the geographic space. This technique has proved particularly suitable to understand the space opportunities for each individual. Since Hagerstrand, several methods have been proposed to integrate time in spatial analysis, for instance for the monitoring of disease or crime patterns. Different models have been suggested to handle the temporal dimension in a GIS,

Figure 1. The spatial distribution of tweets about Barack Obama during the week from August 17 to 24, 2011. The area of the United States is discretized into a grid of 2,500 cells and real-time tweets about Obama were counted for each cell, with a total of about 62,000 tweets. The location of each tweet was represented using the location of the user who initiated that tweet.



see for instance Peuquet and Duan (1993) and more recently Kwan (2004) and Miller (2005). Although it is relatively straightforward to visualize changes in GIS, the discipline has been slow at embracing time as a unique dimension, and only a handful of these recent methods have been integrated in GIS (Goodchild, 2000; Jacquez et al., 2005; Andrienko & Andrienko, 2006), resulting mostly in ad hoc applications.

Recent research in spatio-temporal analysis has focused in two arenas: (a) theoretical spatio-temporal data modeling and (b) spatiotemporal visualization. Theoretical spatiotemporal data modeling is a growing field in GIS, especially developing framework for the management of complex geographic data. Pultar et al. (2009) developed a platform, Extended Dynamic GIS, for spatiotemporal data representation, storage, and query. Pultar et al. (2010) implemented the space-time point (STP) data structure facilitating the querying of spatio-temporal data location, time, and attribute. Huang & Peng (2008) proposed an object-oriented data model that coherently represents space, time, and dynamics of transit networks. Recent works include Khalesian and Delavar (2008) to model micro-simulation of highway traffic, and Di Martino and Sessa (2011) for the spatio-temporal evolution of fire hotspots. Using multidimensional map algebra, Mennis (2010) developed a technique for analyzing spatio-temporal data and for processing algorithms. Kang and Scott (2008) developed an integrated spatio-temporal GIS toolkit for the exploration of intra-household interactions.

Exploring patterns in large individual-level spatiotemporal datasets is made possible by the space-time prism framework (Demsar & Virrantus 2010, Andrienko et al. 2011). An example includes Chen et al. (2011) for a space-time path based multi-level clustering method. Shaw and Yu (2008) analyzed the complex spatio-temporal relationships among activities and interactions taking place in both physical and virtual spaces. Shaw et al. (2008) presented a generalized space-time path (GSTP) approach to facilitating visualization and exploration of spatiotemporal changes among individuals in a large dataset. Their approach provided a useful exploratory analysis and geovisualization environment to help researchers effectively search for hidden patterns and trends in such datasets.

In the area of visualization, GIS software have made some progress in the management and display of temporally varying data through frame animations and 3D data representations (Andrienko et al., 2011), but significant research has yet to come in the area of temporal modeling at large, for instance space-time clustering and space-time autocorrelation. One point of focus which has received and continues to receive considerable attention is the development of techniques to rapidly detect space-time patterns and unusual values, outliers or trend, for instance through *Exploratory Spatial Data Analysis* (ESDA). These methods facilitate the exploration of spatial data in various ways, helping to discover spatial patterns, identify clusters and suggest hypotheses of causal relationships (Tukey, 1977; Anselin, 1996; Anselin, 1999). Along with these methods come a suite of techniques to visualize spatial data such as scatter plots, kernel density, graduated symbol and choropleth mapping (Chang, 2011). *Confirmatory analysis* usually forms a second step after ESDA, which is used to statistically test whether the pattern of the phenomenon under study is not a product of a random process. Exploratory and confirmatory methods can be repeated (and extended) in time.

Space-Time Analysis for Point Events with No Attribute Data

A spatial pattern refers to the tendency of a spatial variable (or phenomenon) to form some type of clusters that can be identified through visual or statistical analysis. Point events such as disease, traffic accidents, and crime usually exhibit such a spatial pattern, and also tend to repeat over time at same. In the case of spatial epidemiology, for example, knowledge on the strength of spatial clusters and their locations can assist health care decision makers on where to locate additional workforces to prevent further disease from occurring, while maintaining location-specific prevention measures. There exists a palette of exploratory and confirmatory methods to identify and test whether these patterns occur by chance (see Delmelle, 2009 for a review). As an example, Figure 2a and 2b illustrates the spatial distribution of dengue cases for January in the city of Cali, Colombia from January 2010 to August 2010, with significant clusters in different parts of the city (see also paper by Delmelle et al., this issue). To map these clusters, the *Kernel density* map (Figure 2b, Equation 3) uses a bandwidth of 750m, which is computed from a *K-function* (Equations 1, 2 in Table 1 and Figure 3), a count statistic, where we essentially test whether the observed point pattern is significantly different than what would be expected under random circumstances (see Bailey & Gatrell, 1995 for mathematical explanation; Casas et al., 2010 for an application to medical information; and Delmelle & Delmelle, 2012 for an application to commuters).

Several techniques have been devised for the detection of patterns in temporal datasets (e.g. multiple time series analysis); however these techniques are not always adequate for the analysis of space-time datasets. A methodological challenge resides in the proper definition of a metric for space-time "contiguity", that is to define which combinations of locations and time periods are "neighbors" to a given observation in space-time. To model the temporal component one approach consists of partitioning the data into different time intervals, and applies the same technique. For instance, it is possible to repeat the *K-function* and *Kernel density* estimation for different months, revealing if the strength and location of clusters change over time (see Casas et al., 2010 and Delmelle et al., this issue). Table 2 summarizes various techniques for the analysis of space-time data, and these are explained below.

One extension of the spatial K-function is the *temporal K-function* (Equations 6 and 7), which provides a measure of temporal dependence over varying time-scales. It is one-dimensional since only time is considered. A time interval t is used instead of a distance radius h (Delmelle et al., 2011). Space-time interaction among data points can be tested by the *Space-Time K-function* (Equations 8, 9, 10), which estimates whether nearby events also exhibit

Figure 2. Spatial distribution of dengue cases in the city of Cali, January 2010. The map in b) is the kernel density estimation with a bandwidth (search radius) of 750m.

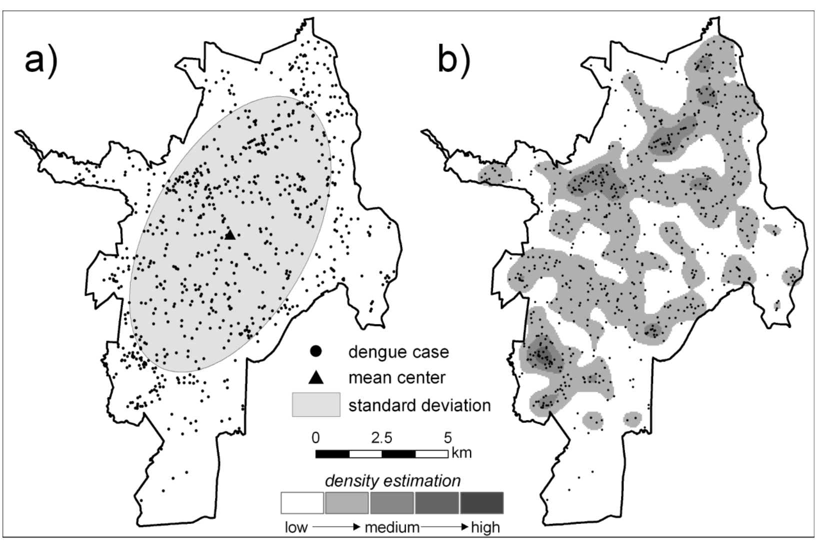


Table 1. General methods for point pattern analysis and spatial autocorrelation

Method	*Mathematical Expression*	*Parameters*	*Eqn*	*References*
K-function	$K(h) = \frac{A}{n^2} \sum_{i \neq j} \sum I_h(d_{ij})$	d_{ij} = distance between two point events *i* and *j*, *A* = size of the study region	1	Bailey and Gatrell (1995)
	$I_h(d_{ij}) = \begin{cases} 1 & if \quad d_{ij} \leq h, \\ 0 & o.w. \end{cases}$		2	
Kernel density	$\hat{\lambda}_\tau(g) = \sum_{h_i \leq \tau} \frac{3}{\pi\tau^2}\left(1 - \frac{h_i^2}{\tau^2}\right)$	τ = Bandwidth g = Gridcell h_i = Separating distance between event *i* and *g* $\hat{\lambda}_\tau(g)$ =Kernel estimate at *g*	3	Bailey and Gatrell (1995)
Moran's I	$I = \frac{n \sum_i^n \sum_j^m w_{ij} \left(u_i - \overline{u}\right)\left(u_j - \overline{u}\right)}{\sum_i^n \sum_j^m w_{ij} \sum_i^n \left(u_i - \overline{u}\right)}$	u_i = attribute value at *i* u_j = attribute value at *j* $\overline{u}$ = average attribute value w_{ij} =weighting function *n* = total number of observations *m*= total number of neighbors for observation *i*	4	Bailey and Gatrell (1995), Moran (1948), (1950)
Getis-Ord Gi*	$G_i^* = \frac{\sum_j^m w_{ij} u_j - \overline{u} \sum_j^m w_{ij}}{\sqrt{\frac{\sum_j^m u_j^2}{n}} \sqrt{\frac{\left[n \sum_j^m w_{ij}^2 - \left(\sum_j^m w_{ij}\right)^2\right]}{n-1}}}$		5	Getis & Ord (1990)

proximity in time. For contagious disease, it would be expected that patients living close to one another would exhibit similar symptoms at small time intervals, while cases far away from one another would probably be less likely to be correlated to one another (Bailey & Gatrell, 1995). When no space-time interaction exists, Equation 8 becomes the product of Equations 1 and 6. Substracting the product of separate spatial and temporal K-function tests for spatial independence (Gatrell et al., 1996). Figure 4 illustrates the space-time interaction among dengue cases for the month of January 2010. A clear cyclical pattern is observed (6 and 11 days), while the greatest interaction is observed at distance lags of 1000 and 1600meters.

The *Knox test* (Knox, 1964) is used to test the statistical strength of the space-time interaction at a particular distance and time. The statistic counts the number of adjacent events (defined by the time t_{crit} and distance window d_{crit}) around each observation, and evaluate by how much this count is different from what would be expected under complete spatial randomness. The number of events is also called space-time pairs ST (Equation 11). A Chi-square statistic $Ç^2$ is then used to measure by how much the observed count of pairs differs from its expected number (Delmelle et al., 2011). That expected number can be estimated through Monte-Carlo simulations (Levine, 2005). The observed count of pairs close in space (1600 meters) and time (6 days) is significantly above the lowest and highest simulated (expected) values, indicating a statistical preference for

Figure 3. Variation in K-function value for the dengue cases (Figure 2) with increasing separating distance; L-function at the bottom

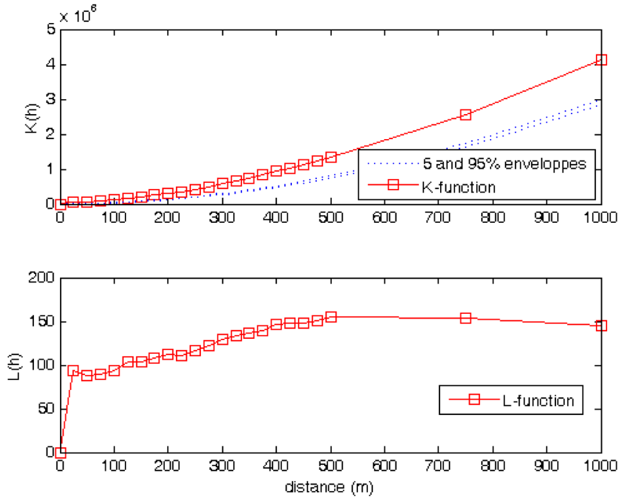
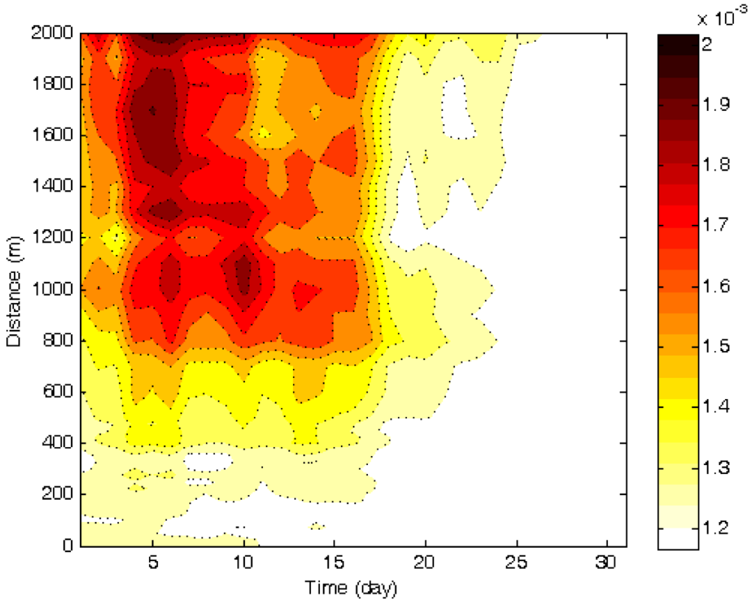


Table 2. Space-time point pattern method

Method	Mathematical Expression	Parameters	Eqn	References
Temporal K-function	$\hat{K}(t) = \frac{L}{n^2} \sum \sum_{i \neq j} I_t(t_{ij})$	t_{ij} = difference in time occurrence between *i* and *j* L = maximal temporal difference among all events	6	Bailey and Gatrell (1995), Casas et al. (2010)
	$I_t(t_{ij}) = \begin{cases} 1 & if \quad t_{ij} \leq t, \\ 0 & o.w. \end{cases}$		7	
Space-time K-function	$\hat{K}(h,t) = \frac{L \cdot R}{n^2} \sum \sum_{i \neq j} I_{h,t}(t_{ij}, d_{ij})$	$I_{h,t}(t_{ij}, d_{ij})$ indicator function $\hat{D}(h,t)$ - test for spatial dependence	8	Bailey and Gatrell (1995), Delmelle et al. (2011)
	$I_{h,t}(t_{ij}, d_{ij}) = \begin{cases} 1 & if \quad (t_{ij} \leq t \; AND \; d_{ij} \leq h), \\ 0 & o.w. \end{cases}$		9	
	$\hat{D}(h,t) = \hat{K}(h,t) - \hat{K}(h) * \hat{K}(t)$		10	
Knox test	$ST = \sum_{i=1}^{n} \sum_{j=1}^{i-1} x_{ij} y_{ij}$	$x_{ij} = \begin{cases} 1 & if \, d_{ij} < d_{crit} \\ 0 & o.w. \end{cases}$	11	Knox (1964)
		$y_{ij} = \begin{cases} 1 & if \, t_{ij} < t_{crit} \\ 0 & o.w. \end{cases}$	12	

Figure 4. Space-time K-function for dengue cases in January 2010. Darker colors reflect stronger interactions with maximal values at six and eleven days of interval, and 1000 to 1600meters separation distance.



space-time interaction at those scales. Other significant methods for the detection of space-time clusters of point events, especially in the context of disease mapping, have been recently proposed and integrated within GIS applications, for instance the spatial scan statistic which is integrated in SaTScan (Kulldorf, 1997; Kulldorf, 2005), the development of Amoeba (Aldstadt & Getis, 2006), and Space-Time Intelligence Software (STIS) for the analysis of disease (Jacquez et al., 2005).

Space-Time Analysis for Point Events and Areal Data with Attribute Information

The previous paragraphs discussed general methods to evaluate the magnitude of space-time clustering for point data with no attribute information. This paragraph describes two well-known methods for the detection of spatial autocorrelation for point and areal data with attributes. Spatial autocorrelation measures whether nearby data observations are dependent on each other, that is observations closer to each other should exhibit similar attribute values. The *Moran's I* test (Moran, 1948, 1950) is a global measure which evaluates the degree of spatial autocorrelation among data points (see Table 1 for a definition, Equation 4). The term w_{ij} represents the weight between two observations, which is usually a function of their separating distance, while an alternative consists of determining whether polygons are adjacent to each other ($w_{ij} = 1$), that is contiguity. Moran's I value range from -1 to +1, with values of -1 and + 1 denoting total dispersion and perfect spatial correlation, respectively, while a value of 0 indicates a random pattern. Other statistical tests have been devised such as Geary C, similar in nature.

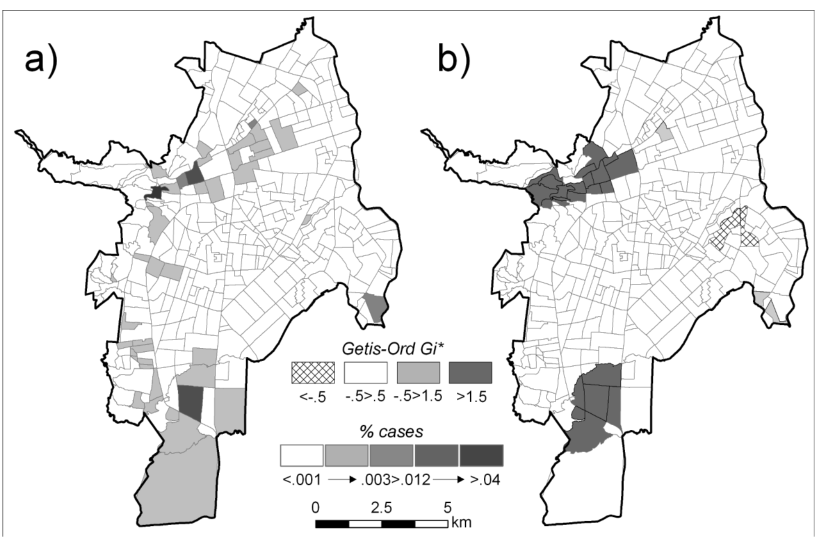
A weakness of both Moran's I and Geary's C tests is that they are global statistical measures and do not inform on where spatial autocorrelation occurs. *Local Moran's I* (Anselin, 1995) and the *Gi* statistic* (Getis & Ord, 1990) allow to detect local clusters of similar values. The Getis-Ord statistic evaluates the difference in data value of one unit *i* from its surrounding values *j*. To illustrate the concept of spatial autocorrelation, we use the percentage of dengue cases per population at the neighborhood level for the city of Cali in January 2010 (Figure 5). We observe a modest Moran's *I* value of .01 (suggesting a nearly random pattern), but the Getis-Ord local statistic (Equation 5) indicates statistically significant pockets of similar values in the center and southern part of town, that is the observed local sum of the attribute values is greater than what would be expected.

Spatiotemporal Autocorrelation

One important challenge is to evaluate whether spatial autocorrelation varies temporally, in other words does the magnitude and the location of spatial clusters change over time? There has been a lot of recent work on spatiotemporal models, and a variety of approaches to better handle the temporal dimension have been proposed. Accordingly, geographic methods for spatiotemporal processes are also experiencing a period of rapid development. In particular, the methodological development for the analysis of spatiotemporal dataset has been motivated by the need to account for autocorrelation in spatial (Cliff & Ord, 1981) and temporal (Box & Jenkins, 1970) data. Properly identifying and quantifying the extent to which observations are autocorrelated with each other in time and space is essential in modeling spatial and temporal relationships

Moran's *I* and Scan statistics are good examples of local indicators of spatial association (LISA) statistics which describe areas of both positive and negative spatial autocorrelation. Moran's I can be extended in time to detect space-time autocorrelation (Goovaerts & Jacquez, 2005; Greiling et al., 2005), and spatial Scan statistics developed by Kulldorff and Nagarwalla (1995) can automatically identify clusters in space and time. However, they cannot detect moving clusters, and also suffer from computational complexity with large numbers of observations and with a difficulty of computing probability values if large numbers of variables are attempted to be analyzed (Leung et al., 2003). Other methods to identify spatiotemporal autocorrelation include space-time association methods such as serial autocorrela-

Figure 5. Percentage of dengue cases in January 2010 per population count in a). The map to the right displays the associated local G statistic using polygon contiguity as a measure of proximity.



tion and space-time autocorrelation. Research on space-time autocorrelation has focused on the static dimension of autocorrelation structure rather than its dynamic aspect (Kawabata, 2009), suggesting that the spatiotemporal autocorrelation can adequately be described by globally fixed parameters, assuming stationarity. However in practice, such assumptions of stationarity and fixed spatiotemporal neighborhood are violated for dynamic data, for instance information on traffic jams.

Recent studies which have attempted to capture the dynamics of space-time autocorrelation can broadly be separated into two categories: those that aim to capture the effective range of spatial neighborhood (Ding et al., 2011; Elhorst, 2003) and those that aim to capture the dynamic weight of correlation (Min et al., 2010). Table 3 summarizes some of the space-time autocorrelation techniques. In the study by Cheng et al. (2011a), the space-time autocorrelation function (Equation 13) is used for the global measures and the cross-correlation function (Equation 14) is used for local measures in order to gain an understanding of the complexity of spatiotemporal autocorrelations. In these Equations (13 and 14), the indices *i* and *j* represent spatial order which reflect the spatial configuration of the data. In a matrix format, row and column show the contiguity relationships for each other. For example, first spatial orders are coded as entries of one for areas that are adjacent to each other and zero otherwise. Their findings show that the spatiotemporal autocorrelation structure is dynamic in time and heterogeneous in space which is a direct reflection of dynamics and heterogeneity of network complexity. Their research has also underlined the critical need to define an appropriate space-time neighborhood (weight matrices) based on the strength of local autocorrelation. These can be incorporated into a model through the use of a dynamic spatial weight matrix. The space-time autocorrelation function defined in Equation (13) measures the N^2 cross-covariances between all possible pairs of locations lagged in both time and space (Pfeifer and Deutsch 1980). Equation (14) is the space-time cross-covariance given the weighted i^{th} order spatial neighbors of any spatial location at time t and the weighted j^{th} order spatial neighbors of the same spatial location s time lags in the future.

The space-time autoregressive integrated moving average (STARIMA) models space-time processes that exhibit stationarity in space and time by extracting global deterministic (nonlinear) space-time trends and local stochastic space-time variations in data (Cheng et al., 2011b). An example of a simple autoregressive model (AR) is given in Equation (15) with the series value at the current time point $y_{(t)}$ equals the sum of the previous series value, $y_{(t-1)}$ multiplied by a weight coefficient Φ_1. A definition of a simple moving average (MA) is given in Equation (16). Contrary to STARIMA, Generalized STARIMA (GSTARIMA) models can capture spatially heterogeneous autocorrelation structures by allowing the AR and MA parameters to vary by location (Min et al., 2010). The GSTARIMA model outperforms traditional STARIMA in terms of forecasting accuracy. Although the method allows for spatially dynamic parameter estimates, the spatial structure of the model is still fixed to an extent as the size of the spatial neighborhood considered is the same for each location. Its temporal structure is also fixed.

On the visual end, STARS (Rey & Janikas, 2006) enabled the depiction of multiple dimensions on a single view which contrasts two forms of covariance in a graph representation in addition to providing dimension specific views, such as a time path. The linkages reflected in a spatial weight matrix based on contiguity are used to show the strength of the temporal covariance between each pair of contiguous polygons. This type of interaction is useful for uncovering covariance relations that may not be obvious with traditional ESDA techniques. Hardisty and Klippel (2010) have created a method for exploring spatiotemporal structure using an extension to the local Moran's I (Anselin, 1995). They created LISTA-Viz, which

Table 3. Space-time autocorrelation

Method	Mathematical Expression	Parameters	Eqn	References
Space-time autocorrelation	$\rho_{ij}(s) = \dfrac{\gamma_{ij}(s)}{[\gamma_{ii}(0)\gamma_{jj}(0)]^{1/2}}$	N = *number of spatial locations* $W^{(i)}$, $W^{(j)}$ = spatial weight matrices i, j = spatial orders N*1 = vector of observations z at time t, $z(t+s)$ = the N *1 vector of observations z at time $t+s$ ` = matrix transposition	13	Pfeifer and Deutsch (1980)
	$\gamma_{ij}(s) = E\left\{\dfrac{[W^{(i)}z(t)]`[W^{(j)}z(t+s)]}{N}\right\}$		14	
Space-Time Autoregressive and Space-Time Moving Average	$y_{(t)} = \Phi_1 \cdot y_{(t-1)} \cdot + e_{(t)} + a$	Φ_1 = weight coefficient $e_{(t)}$ = error component a = series mean (constant)	15	Box et al. (1994)
	$y_{(t)} = \Phi_1 \cdot e_{(t-1)} \cdot + e_{(t)} + a$		16	

exposes the statistical method in a manner that offers tight integration with many other tools in the GeoViz Toolkit application[1]. With integration, the spatiotemporal structures uncovered by LISTA-Viz are analyzed visually and computationally by many other views and methods offered in the GeoViz Toolkit.

Depending on the context, spatiotemporal analyses can be applied in hierarchical modeling methods within different frameworks such as repeated-measurement, longitudinal data models, multilevel models, and generalized linear mixed models. Software packages such as WinBUGS[2], SaTScan[3], MLwiN[4] among others have made it possible to estimate spatiotemporal dependencies.

Space-Time Analysis for Linear Features

As mentioned previously, traditional spatiotemporal studies are based on point or polygon features. Point-based analysis may be misleading in our understanding of the nature of events such as traffic accidents when these occur because those events are associated with network characteristic: nodes (intersection or junctures), road segments, road types, speed, traffic signs and traffic volumes among others. Okabe et al. (2006) have proposed a general framework for spatial analysis of network features. Nevertheless, one must keep in mind that network events also have a temporal component. Although the structure of spatiotemporal data is more complex than that of spatial data alone, spatiotemporal network data also consist of a time-ordered sequence of events where the observation process under study contains the temporal dimension as well as the spatial dimension.

We used traffic accidents to illustrate the significance of a segment-based approach where each segment is a measurement unit. A traffic accident is recognized as a point feature and is expected to form spatial clusters over time. Conventionally, point-based accident data are aggregated to investigate the changes in spatial pattern of accidents. In most cases, many longitudinal analyses use area-based spatial structures such as Traffic Analysis Zones (TAZs), census blocks, counties, and states. However, one must be careful when aggregating traffic accidents to statistical units (Delmelle & Thill, 2008). For instance, allocating a traffic accident to a certain spatial unit is often directly drawn upon the boundaries between spatial areas. Thus, a structure of segment-based networks would be appropriate for identifying accident-prone segments over multiple periods (Aguero-Valverde & Jovanis, 2008). More importantly, the segment on the network plays an important role as common spatial unit or norm for panel analysis. If a traffic accident is repeatedly referenced as a point with the exact spatial reference over multiple periods, spatial distribution of points such as Kernel density would be ideal for examining the accident patterns intuitively (Flahaut et al., 2003; Geurts et al., 2005; Steenberghen et al., 2010). The clusters of traffic accidents compared to the other types of spatial clusters in crime or disease, however, are generally formed on the transportation network. Specifically, most vehicle accidents occur linearly on road segments by reflecting the structures of road networks, which greatly enhance the understanding of the network property of accidents.

Spatial events are not likely to be independent on each other: a high accident frequency on a segment may impact the frequency of other, adjacent segments. This can be handled by incorporating line segments or networks into the analysis. Figure 6 shows network autocorrelation analysis of traffic accidents in Cincinnati, OH during 2004–2008, generated from the generalized linear mixed model using random and fixed effects with time included as a random component. The segment links in HH show the high-high network autocorrelation, reflecting statistically significant high concentration of traffic accidents. On the other hand, links in LH show low-high network autocorrelation where road segmentations are surrounded by high concentration of accidents. Those links are merged with roads segments of Interstate highways where relatively large number of accidents are observed. Segments in HL show the high-low network autocorrelation where concentration of accidents is found to be high-low compared to neighboring road segments, suggesting accidents in those segments are statistically higher than neighbors.

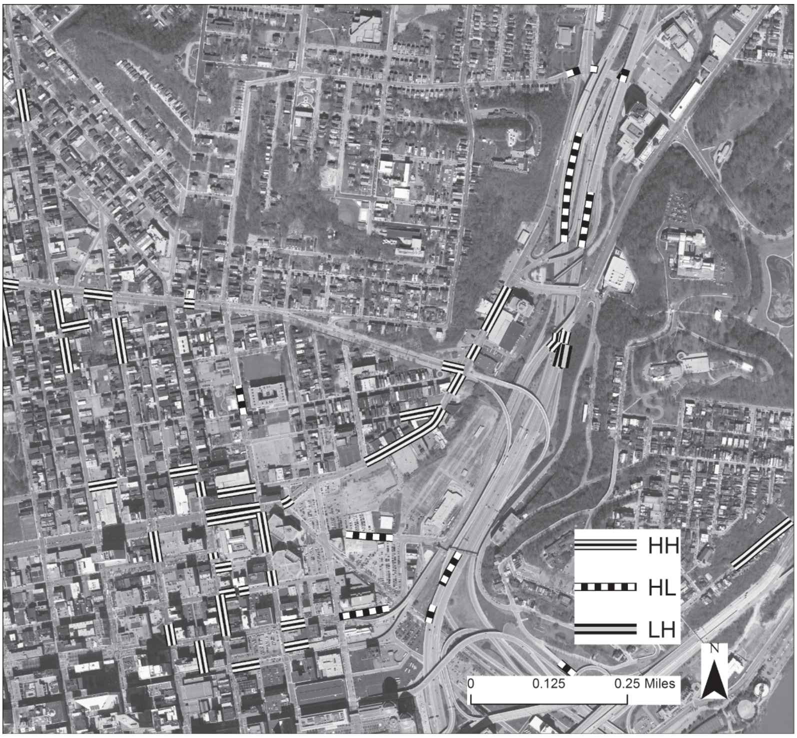
SPATIO-TEMPORAL OPTIMIZATION

Though the main focus of this review is placed on the development of statistical methods that can be applied to analyze spatial and temporal patterns of geospatial data, it is worth discussing normative models that can be used to help decision making in both spatial and temporal dimensions. In spatial epidemiology, for example, it is critical to predict when and where a disease will occur to allocate additional workforce through point-source modeling (Bailey & Gatrell, 1995). In many planning and environmental management applications, it is important to identify a set of activities related to each location through time (Church & Murray, 2008). For example, a goal in forest harvest planning is to determine whether one location is scheduled to harvest at a specific time (Öhman & Eriksson, 2008). Similarly, in environmental conservation, researchers often need to identify the placement and timing of habitat protection in order to maximize the population of protected species across areas and over time (Hof et al., 1999). In rapidly expanding areas, it may be necessary to build additional public facilities such as schools, post offices, libraries as well as emergency services to meet anticipated demand (Antunes & Peeters, 2001; Ribeiro & Antunes 2002).

To handle space-time challenges such as the ones mentioned above, a diversity of models has been developed in the literature and there may not be a “one-size-fit-all” recipe for all applications. However, it is possible to generalize many of the existing models by focusing on the essence. In general, we assume a discrete land use model where the space is partitioned into a limited number of land parcels and each parcel will be assigned a land use. In a forest harvest setting, the land use types can be harvest and no-harvest. The overall goal of these assignments is to maximize the total utility of the land over time.

To formulate our general model, we use the following notation:

Figure 6. Network autocorrelation in Cincinnati, OH



i = index of a land parcel,
j = index of land use,
t = index of time,
u_{ijt} = utility or benefit of location i at time t for land use j,
c_{ijt} = cost associated with location i at time t for land use j, and
b_t = the budget allocated to time period t.

The decision variables can be denoted below:

$$x_{ijt} = \begin{cases} 1 & \text{if location } i \text{ is acquired for land use } j \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

A general formulation of a utility model can be written as follows:

$$\text{Maximize} \sum_t \sum_i \sum_j u_{ijt} x_{ijt} \tag{17}$$

$$\text{Subject to} \sum_i \sum_j c_{ijt} x_{ijt} \le b_t \qquad \forall t \tag{18}$$

$$\sum_j x_{ijt} = 1 \qquad \forall i, t \tag{19}$$

$$x_{ijt} = \{0,1\} \qquad \forall i, j, t \tag{20}$$

In this formulation, objective (17) maximizes the total benefit over time, constraint set (18) ensures that at each time period, the total cost must not exceed the budget, constraint set (19) ensures that each parcel can only be assigned to one land use at a time, and constraints (20) indicate binary decision variables. This model can be rewritten as a cost model by minimizing the cost (the left term of Equation 18) subject to a predefined minimum total utility (Equation 17) either for each time period or all time. A number of spatial or nonspatial constraints can also be applied. For example, the spatial contiguity models developed by Williams (2002) or Shirabe (2005) can be adopted into the above modeling framework.

Spatiotemporal optimization models are often computationally intensive and require a significant amount of computing to reach an optimal solution (Antunes & Peeters, 2001). For this reason, spatio-temporal optimization applications often rely on a course resolution to represent the space in order to maintain a tractable problem size. Heuristic search methods such as evolutionary algorithms (Xiao, 2008) or simulated annealing (Aerts & Heuvelink, 2002) can be used to yield high quality solutions in a relatively small amount of time.

CONCLUDING REMARKS

The increasing availability of spatially- and temporally-explicit data there has led to a pressing need to develop and integrate methods that can be used to reveal useful patterns. GIS is now a matured field that has the ability to integrate geospatial data of different spatial scales and temporal granularity into a unified framework for a wide range of analysis. Within this broad context, this paper has stressed the importance of GIS, geospatial data, and reviewed traditional methods for the spatial analysis of point, line, and areal data, and its theoretical extensions to handle time as a unique dimension. Specifically, the paper provides several methodological frameworks in which data and model can be used to gain geographic knowledge. We have focused on two types of methods: spatio-temporal statistical methods that can be used to describe and infer the pattern from the data and normative methods that can be used to search for optimal spatio-temporal patterns given a set of objectives.

The development of methods for space and time analysis and modeling is an evolving process. Similar to other disciplines such as hydrological and ecological modeling (Beven, 1985; DeAngelis & Gross, 1992), space and time modeling has undergone different phases, especially from the traditional "global" version where one parameter is used to capture the entire area for all time periods to a current "localized" version where spatially and temporally varying parameters can be obtained. We argue that such a trend will continue, especially given the increasing computing power that enables a reductionist perspective of representing space and time. Such a trend also presents a challenge to existing methods for space-time analysis. We identify a few salient challenges that may lead to future developments. First, to fully understand spatial and temporal patterns in a large data set (space-time data mining), an exploratory visualization tool will be necessary. Existing tools, however, are typically derived from the concept of Hagerstrand's space-time prism (Hagerstrand, 1970) and are mainly designed to explore the space-time paths of a limited number of individuals. Second, many existing methods are typically not designed to handle potential uncertainty, in space and time, in data. Developing methods that incorporate error will significantly advance our understanding of spatial and temporal patterns. This perspective also applies to spatiotemporal optimization methods so robust solutions can be generated for decision making.

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ENDNOTES

1 http://www.geovista.psu.edu/geoviztoolkit/
2 http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml
3 http://www.satscan.org
4 http://www.bristol.ac.uk/cmm/software/mlwin

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