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ORIGINAL ARTICLE

STAMP: spatial–temporal analysis of moving polygons

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Abstract Research questions regarding temporal change in spatial patterns are increasingly common in geographical analysis. In this research, we explore and extend an approach to the spatial–temporal analysis of polygons that are spatially distinct and experience discrete changes though time. We present five new movement events for describing spatial processes: displacement, convergence, divergence, fragmentation and concentration. Spatial–temporal measures of events for size and direction are presented for two time periods, and multiple time periods. Size change metrics are based on area overlaps and a modified cone-based model is used for calculating polygon directional relationships. Quantitative directional measures are used to develop application specific metrics, such as an estimation of the concentration parameter for a von Mises distribution, and the directional rate of spread. The utility of the STAMP methods are demonstrated by a case study on the spread of a wildfire in northwestern Montana.

Keywords Spatial pattern analysis · Spatial–temporal analysis · Polygons · Events · Geocomputation · Spread

JEL classification C0 · C69 · C69 · C0 · Q0

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1 Introduction

Increasingly, spatial data are being collected as part of systematic environmental monitoring programs. Advances in automated spatial data collection technologies have enabled standardized measurements to be taken for the same location at regular time intervals. For instance, satellites image the same region repeatedly through time. A growing interest in monitoring the human and physical environment has lead to the production of multi-temporal, spatially referenced data sets. However, data collected to meet operational needs on an ongoing basis is often not integrated temporally to investigate multi-temporal trends in spatial patterns. As an example, forest pest surveys in Canada are conducted annually to map the spatial extent and severity of forest disturbance, yet few studies have integrated these datasets for spatial–temporal analysis (Gillis and Leckie 1996).

The availability of multi-temporal geographic data has out paced the development of spatial–temporal analysis methods. In part, this is due to the limitations of current geographic information system (GIS) data models for representing spatial–temporal data (Langran 1992; Peuquet 2001; Christakos 2002). Presently, each data layer in a GIS database represents only one temporal snapshot of a phenomenon and links between layers are not natively supported. Most research into temporal GIS (TGIS) has therefore focused on developing the conceptual basis for GIS data structures and data models (Christakos 2002; Egenhofer and Golledge 1998; Peuquet 1994; Langran 1992; Worboys 1994). Despite the problem of spatial–temporal data representation in GIS, methods do exist for analyzing the changes in spatial patterns over time. Many of the available methods have been developed to address specific problems, such as the detection of land use changes or disease clusters in space and time. As such, the existing methods may be categorized based on their respective lineages.

Space–time statistics grew out of epidemiology and are mainly concerned with detecting space–time interaction in point observations of disease (i.e., Knox 1964; Mantel 1967). In epidemiology, the spatial–temporal clustering of disease incidence has implications about the contagiousness of the disease, and may be informative of disease causes. Space–time statistics also tend to be spatially global. In other words, a single value is used to quantify the spatial–temporal pattern in the entire study area. Some computational approaches developed in epidemiology are available for local analysis, such as GAM style cluster detection algorithms (Openshaw et al. 1987), and extensions to space and time (Kulldorff et al. 2005). While these advances allow for the identification of clusters, they provide no mechanism for exploring variations in the shape, orientation, size, or movement of raised incidences of disease, or to map locations where there have been temporal changes in identified spatial patterns of disease.

Another group of methods applicable with spatial–temporal data are those designed for raster-based change detection. This approach has a long history in remote sensing, with most methods being pixel level comparison operations to produce new layers depicting change between two temporal snapshots (Gong and Xu 2003). Other approaches model change by interpolating values between temporally successive snapshot datasets (Dragicevic and Marceau 2000). Newer raster based change detection methods have recently been developed for categorical map comparison (Visser 2006; Hagen 2003) which incorporate fuzziness into comparison statistics. Raster methods have the advantage of being spatially local; however, spatial–temporal methods for raster data are not easily extended to multi-temporal analysis or non-raster data.

For vector line and polygon data, fewer methods are available for analyzing spatial patterns through time. Line data are generally conceptualized as graphs and analyzed using methods from graph theory and network analysis (O'Sullivan and Unwin 2003). For polygons, area overlap statistics (Maruca and Jacquez 2002) are based on a calculation and comparison of area overlap between polygons in two datasets and can be used to detect change between two sets of polygons; however, lack the ability to describe local changes explicitly or extend to multi-temporal scenarios.

Rey and Janikas (2006) recently developed software for the analysis of attribute changes in areal units, yet their approach does not account for spatial changes in the areal units themselves. McIntosh and Yuan (2005) describe a framework for spatial–temporal analysis of polygon distributions derived from fields, linking vector polygons to their internal attribute values in their associated field data (conceptual objects) for spatial–temporal queries. Their focus is on the analysis of the internal values of the field attributes, rather than changes in the spatial properties of the polygons. For a multi-temporal set of polygon distributions, the primary method available was developed by Sadahiro and Umemura (2001) which uses overlays to derive polygon change events for temporal intervals. This approach provides a useful method for the spatial–temporal analysis of immobile polygons, and forms the basis for the extension and implementation presented in the current research.

Given that many geographic phenomena are represented as polygon data in GIS, there is a need to expand on existing methodologies for spatial–temporal change detection and quantification. Anthropogenic objects such as parks, administrative areas, market areas, buildings, and vehicles all lend themselves to a polygon representation. In the natural world, lakes, watersheds, animal home ranges, and flood zones are all commonly represented as polygons. The ability to analyze multi-temporal sets of polygons (many polygon layers) has utility in a wide range of application areas. In ecology for example, multiple layers of animal home range polygons could be analyzed to help determine the changing pressures on an animals' habitat, or to gain a better understanding of predator–prey relationships. In marketing, the spatial–temporal analysis of multiple sets of market area polygons could be informative about the changing local business environment, and provide clues about future competitive trends. In climatology, tracking the spatial changes in storm formations can lead to a greater understanding of the formative processes, and eventually inform predictive modelling efforts. The large array of potential uses for methods of spatial–temporal analysis for polygons is an impetus for their timely development. Further, as these datasets are already being collected, spatial–temporal analysis tools provide for additional insights to be derived from existing data.

In this paper we present the development, implementation, and extension of methods for the exploratory spatial–temporal analysis of polygon datasets. The focus here is on the detection, quantification, and representation of the spatial changes occurring through time in polygons. The basis for this research is the work of Sadahiro and Umemura (2001) and Sadahiro (2001) which describes an event based approach to the analysis of changes in the spatial distributions of polygons. These methods have received attention in spatial analysis literature (Maruca and Jacquez 2002; Fortin et al. 2005; Fortin and Dale 2005), yet lack of availability in software has limited their application (Boots 2000). The goal of this research is to expand upon the original method of Sadahiro and Umemura (2001) by quantifying new events (several types of movement), developing new measures of polygon change at both the global and local level, and demonstrating the application of these methods in a new domain area (environmental management). This expansion extends the original methods to include moving polygons thereby allowing a greater variety of phenomena to be supported. A complimentary component to this research is the development of freely available code that can be integrated with a popular commercial GIS package (ArcInfo 9.0). The implementation and utility of several methods developed and programmed for the spatial–temporal analysis of moving polygons (STAMP), are demonstrated in this manuscript through a case study on the spread of a wildfire in northwestern Montana.

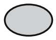
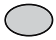
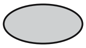
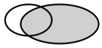
2 Context: event definitions for spatial–temporal relationships

Spatial–temporal analysis of polygon change requires relationships be defined for polygons that are temporal neighbors. In Sadahiro and Umemura (2001), events giving rise to changes in temporally neighboring polygons are deduced based on unioning two polygon layers together and coding the states or conditions of arcs and polygons in time period one (T_1) and two (T_2). In our implementation, possible arc states are boundary, interior, empty; polygons may be existing or non-existing.

Applying topological rules to the configuration of arc and polygon states in the unioned layer, we can characterize individual changes between polygons in T_1 and T_2 (Claramunt and Thériault 1996). These events (Table 1) individually describe changes occurring at one time interval (also called basic processes), or can be linked into sequences to describe the evolution of a polygon over multiple time periods (also called composite processes). The methods presented and developed in this paper are based on the assumption that polygon changes are discrete and that polygons are spatially distinct (no internal polygon partitions). This limits the possible change events to generation, disappearance, expansion, contraction, and movement.

Movement is a class of polygon change events that are an extension to the methods presented by Sadahiro and Umemura (2001). The addition of movement events enables spatial–temporal patterns of processes that spread and diffuse to be considered in the polygon change approach. As a result, these methods can now be applied to a much wider range of applications including the study of human disease, plant or animal disease, and fire. We conceptualize polygon movement for the analysis of spatial phenomena related by proximity. Movement occurs when a polygon does not overlap, but is within a distance threshold, of a another polygon. For example, polygons representing areas of a forest infested by insects could be

Table 1 Typology of events to describe geometric changes in polygons

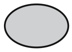
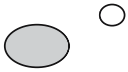
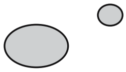
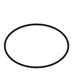
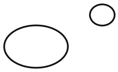
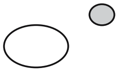
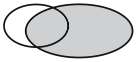
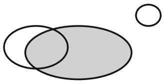
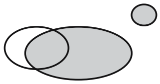
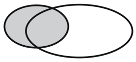
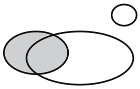
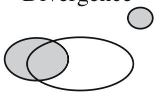
Event	T_1	T_2	$T_1 + T_2$
Generation	none		
Disappearance		none	
Expansion			
Contraction			

related over two time periods by overlap, indicating expansion or contraction of the infested area, or by proximity, indicating insect dispersal, perhaps past unsuitable habitat. In this case, polygons related by proximity would be categorized as movement events, representing a different spatial process (dispersal) than the expansion events (spread). Movement events are not designed for analysis of entities that move continuously through time, such as moving cars because we do not interpolate locations between time periods. However, if the temporal grain of the data is fine enough to warrant the assumption that changes are discrete, then continuously moving objects can be analyzed with the STAMP methodology.

There are many spatial processes that can generate spatial patterns of movement. To differentiate spatial processes associated with movement, movement events can be categorized based on the events of the polygons involved in the movement (Table 2). We consider the following movement patterns: displacement, convergence, fragmentation, concentration, and divergence. Displacement movement occurs when a T_2 polygon occurs within the movement distance threshold (d) of a T_1 disappearance polygon. Displacement may represent a process where a phenomenon disperses to a nearby region but does not persist in the originating location. For instance, in forest insect epidemics the insects may have utilized all hosts at the initial location and dispersed past unsuitable forests to a new location.

Convergence occurs when T_1 polygons disappear within d of an expansion polygon in T_2. Convergence may indicate that the spatial extent of the phenomenon is spreading from multiple locations and converging in a central region. Continuing the example of forest insect epidemics this could indicate that multiple small infestations have merged into a single larger infestation. Fragmentation is also associated with expansion but occurs when T_2 polygons appear within d of a T_2 expansion polygon. Fragmentation represents spatial processes that cause phenomenon to split from a central location to nearby peripheral or adjacent regions, with an overall increase in the area having the presence of the event. For a forest insect infestation this could occur when insects move from a central location with moderately suitable hosts, to multiple new locations that have abundant or highly suitable host trees.

Table 2 Types of movement based on polygon events involved in proximity relation. In each case, the unshaded polygons are from T_1 and shaded polygons are from T_2 and the movement type is based on a polygon being within a threshold distance (d) of the start event. For displacement events, both polygons are reclassified as displacement (one source, one destination). For other movement events, only the generation or disappearance events are reclassified as the new movement type

Start Event	**T_1 within d becomes**	**T_2 within d becomes**
Generation 	Displacement 	Generation 
Disappearance 	Disappearance 	Displacement 
Expansion 	Convergence 	Fragmentation 
Contraction 	Concentration 	Divergence 

The final two movement events, concentration and divergence, are both associated with contraction polygons. Concentration occurs when T_1 polygons disappear within d of a contraction polygon in T_1. In such cases the spatial pattern indicates events are moving and occurring over a smaller spatial extent than in the past. For forest insect infestations this could indicate that the insect populations are declining or concentrating in an optimal region. Finally, divergence occurs when a polygon in T_2 appears within d of a contraction polygon in T_1. Such patterns may be indicative of spatial processes that move from one region to several adjacent or peripheral regions indicating an overall decline in the spatial extent of event presence. Such spatial patterns could indicate a forest insect infestation spatial process when insects have utilized all suitable hosts at a central location and have moved to nearby regions with moderately suitable trees.

3 STAMP methods

3.1 Defining spatial–temporal associations

To define spatial–temporal association for polygons stored in a GIS database, we begin by unioning each pair of temporally neighboring polygon layers. Each of the resultant change layers represent the change occurring in the corresponding temporal interval (Fig. 1—Step 1). For each change layer, change events are deduced by examining the states of arcs and polygons in each time period and stored as feature attributes (Table 3). From the individual polygons in the change layer, we can represent all events taking place between T_1 and T_2.

Events can be categorized into three levels of complexity based on the number of polygons involved in the event (Fig. 2). At the simplest level, single events do not interact with any other polygons (generation and disappearance). Each of these events has a one-to-one association with a polygon in the input layers. Two-polygon events occur when two polygons, one from each time period, are connected. Connectedness can be derived from two spatial relationships: overlap (expansion, contraction and stability events) and proximity (movement events). These events therefore have a one-to-two association with polygons in the input layers (one event per two input polygons). Multi-polygon events are based on the overlap of multiple polygons, having a one-to-many association with polygons in the input layers. This

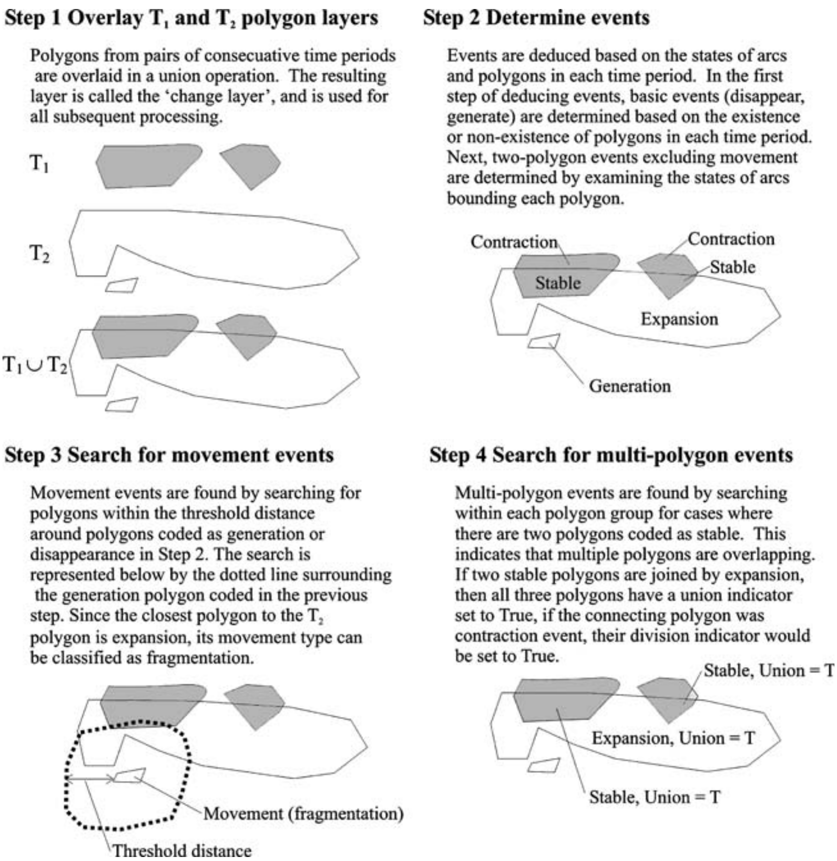


Fig. 1 Computational procedure for polygon event deduction for polygons from two time periods. For multiple time periods, this procedure is repeated for each pair of consecutive layers

Table 3 Change layer fields for storing event and polygon group information

Field name(s)	Description
S_1/S_2	State in T_1 and T_2 (existing, non-existing)
T_1/T_2	Polygon ID in T_1 and T_2
EVENT	Event occurring
TOPO	Polygon group the change polygon belongs to
UNI/DIV	Flags for UNION and DIVISION events

Unions occur when one T_2 polygon overlaps multiple T_1 polygons. Division occurs when multiple T2 polygons overlap one T_1 polygon

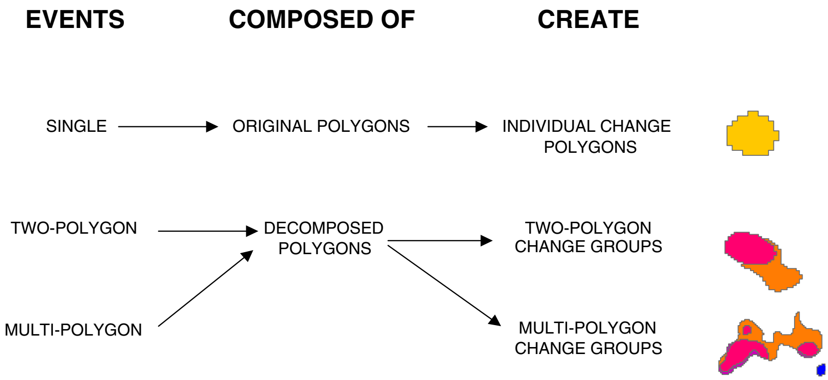


Fig. 2 Hierarchical diagram of polygon change events. Event complexity is defined by the number of polygons involved. Single events involve one polygon, two-polygon events involve two polygons, and multi-polygon events involve three or more polygons

occurs when multiple T_1 polygons overlap one T_2 polygon (union) or vice versa (division).

Based on the outlined spatial–temporal relationships in Table 1, new information about the change occurring between two sets of polygons can be extracted. Each change layer represents one instance of change. These layers can be queried to determine individual changes, and linked together to represent multi-temporal change patterns (histories).

3.2 Computing events

The general procedure for determining generation, disappearance, expansion, and contraction events (Fig. 1—Step 2) is as follows (Sadahiro and Umemura 2001). Polygons in each unioned layer are coded as existing (E) or non-existing (Ø) and arcs are coded as boundary (B), interior (I) or nothing (Ø) for both time periods. Rules can then be applied to these state variables to infer events. For example, a polygon coded as ‘Ø’ in T_1 and ‘E’ in T_2 can be classified as either expansion, generation, or a type of movement. If the arcs of this polygon were coded as ‘Ø’ in

T_1 and 'B' in T_2, expansion is ruled out because it is not touching any other polygons, and the polygon is temporarily classified as generation. In our implementation, movement events (Fig. 1—Step 3) are determined by a search performed around all generation and disappearance polygons. If another polygon is found in the search area, its event type is examined and a movement type is assigned based on the rule combinations of events outlined in Table 2. If multiple polygons are found within the search area, the closest polygon is used to define the type of movement occurring. The distance metric used is the minimum distance, which is best for transmission processes (Okabe and Miller 1996). The distance threshold is application specific, and alternative distance metrics could be employed such as the Hausdorff distance or average distance (Miller and Wentz 2003). Also, we define multi-polygon events as a special case of contraction (division) and expansion (union) events, involving a minimum of three original polygons (Fig. 1—Step 4).

3.3 Change metrics and analysis

Spatial properties of a single polygon may include size, shape, boundary properties and location, and for multiple polygons include overlap (Galton 1998), distance (Okabe and Miller 1996), directional relations (Peauquet and Zhan 1987; Frank 1992; Skiadopoulos et al. 2005; Yan et al. 2006), and density. Most research into changes of spatial objects has focused on qualitative models of change (for example, the four and nine intersection models of spatial relations, Egenhofer and Franzosa 1991; Egenhofer et al.1993, or its Voronoi based equivalent: Chen et al. 2001). Since our interest is in measurement of change, as well as the identification of change locations, we take a quantitative approach to the description of spatial changes by using change metrics.

Following Sadahiro and Umemura (2001), some simple global metrics can be calculated as follows. In Table 4, Γ_i is the set of polygons in time period i, *EVENT* denotes the set of all events in one time interval, and $event^x$ denotes one type of event (i.e., generation) in *EVENT*.

The number, area, and average area ratios are simple descriptors of the original polygon layers. These can be computed prior to the creation of change layers for an initial view of the changes occurring between the datasets. The event measure is an indication of the frequency of change relative to the number of polygons. The area

Table 4 Global change metrics for simple and two-polygon events

Metric name	Type	Calculation	$n > 2$
Number ratio	Global	$r_{NUMBER} = \frac{\#(\Gamma_2)}{\#(\Gamma_1)}$	Calculate for T_1 and T_n
Area ratio	Global	$r_{AREA\_TOTAL} = \frac{A(\Gamma_2)}{A(\Gamma_1)}$	Calculate for T_1 and T_n
Avg. area ratio	Global	$r_{AREA\_AVG} = \frac{r_{AREA\_TOTAL}}{r_{NUMBER}}$	Calculate for T_1 and T_n
Event measure	Global	$m(EVENT) = \frac{\#(EVENT)}{\#(\Gamma_1)+\#(\Gamma_2)}$	$\frac{\sum_{i=1}^{n} m(EVENT)_i}{n}$
Area event measure	Global	$m(event^x) = \frac{A(event^x)}{A(EVENT)}$	$\frac{\sum_{i=1}^{n} m(event^x)_i}{n}$

event measure indicates the relative frequency of a particular type of event by its area relative to the area of all events. These measures are good starting points for initial exploration into the changes occurring.

Local metrics can also be calculated. Of particular interest are changes in size and direction in temporally related polygons. Temporally related polygons include those related by all events except for single events (generation and disappearance). Calculation of local metrics uses only polygons that have a space–time association, which we call a polygon group. For each polygon group (*PG*), summing the areas of expansion and contraction can yield two measures of change in size: $\mathrm{A}(event^{exp})^{PGj}$ and $\mathrm{A}(event^{contr})^{PGj}$, and for movement events, the summed area of movement gives a similar measure: $\mathrm{A}(event^{move})^{PGj}$, for polygon group *j*. These measures are calculated the same for all polygon groups.

The size measures for each polygon group provide information about local changes in the sizes of temporally related polygons. The combination of local size changes with measures of direction can provide a full description (metric and topological) of the characteristics of local change. Directional relationships between polygons are not commonly implemented in GIS software, as they are difficult to quantify due the impacts of size, distance, and shape on perceived directional relationships (Miller and Wentz 2003). An additional complexity is that each directional relationship requires a reference object and a target object, which doubles computational requirements of standard distance functions.

Our approach to detecting directional relationships among polygons is based on the cone-based model (Peuquet and Zhan 1987). In the simplest form a reference polygon centroid is used as the apex of an inverted triangle (the cone) that rotates clockwise from north to west (can be implemented for four 90° or eight 45° directions). The cone encompassing the greatest portion of the target polygon represents the directional relationship between the reference and target polygons. The underlying assumption in this model is that a one to one directional relationship exists between the reference and target polygons. Yet, if polygons are overlapping, multiple directional relations need to be represented.

The cone-based approach to quantifying direction relies on polygon centroids which can misrepresent relationships for irregular polygons, such as horseshoe-shaped polygons (for description, see Yan et al. 2006) and are problematic in situations where reference and target polygons have different orientations. Other approaches to quantifying directional relationships between polygons use generalization with minimum bounding rectangles to address the problem of irregularly shaped polygons (Skiadopoulos et al 2005; Skiadopoulos and Koubarakis 2004) and more recently, directional Voronoi diagrams (Yan et al. 2006).

After an extensive examination of the possible methods for computing directional relationships, we implemented a modified cone-based model that determines the amount of polygon area associated with each event with four feature attributes for representing multiple relations (i.e., Yan et al. 2006). A full review of our assessment of directional methods is beyond the scope of the current paper. However, it is worth mentioning that we found more sophisticated algorithms for quantifying directional relations resulted in little improvement to directional measures. An overview of the implementation of our direction algorithm for

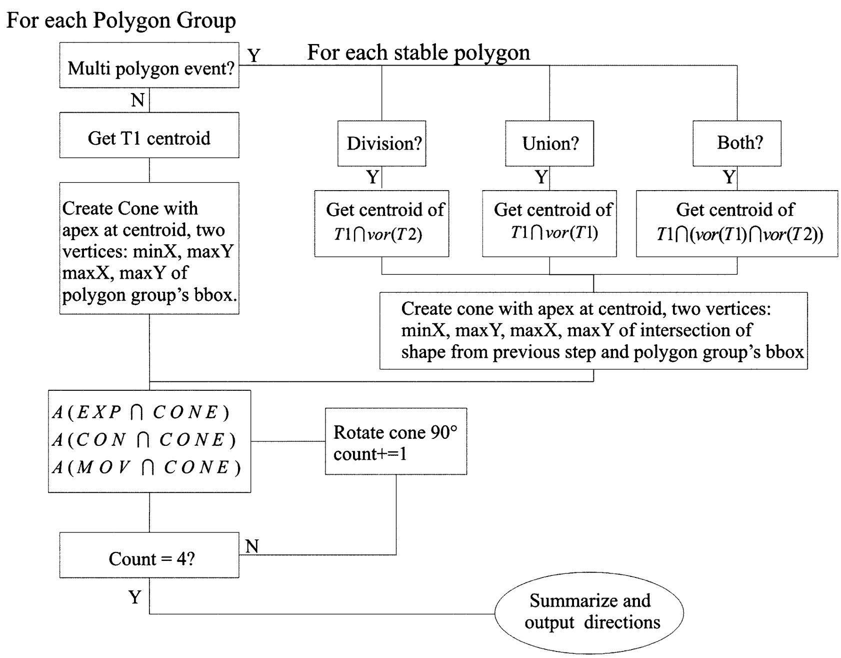


Fig. 3 Overview of approach to determine directional relations for polygons from different time periods. Polygon groups are defined as groups of related (by proximity or overlap) polygons from two time periods. Output directional measures for contraction, movement and expansion are stored as feature attributes, and summarized by polygon group

overlapping polygons is presented in Fig. 3. For two polygon event groups the shape of the cone corresponds to the centroid of the T_1 polygon, extended out to the appropriate vertices of the minimum-bounding rectangle of the polygon group (i.e., centroid(T_1), minX, maxY and maxX, maxY of the bounding box of $T_1 \bigcup T_2$ defines the cone for north, see Fig. 4a). By extending the cone to the vertices of the bounding box of $T_1 \bigcup T_2$, the cone becomes more sensitive to irregularly shaped polygons. For multi-polygon groups, the Voronoi diagram for areas is used to intersect the overlapping polygon, and separate cones are used for each of the T_1 polygons (Fig. 4b). The results of each cone are then summed for the whole group so results are comparable across all polygon groups. We do not alter the shape of the input polygons to ensure they are star-shaped, as in Sadahiro (2001), so it is possible for the Voronoi intersection method to exclude portions of the input overlapping polygon. In this case, the overlapping polygon area outside of the Voronoi polygons is attributed to an *unexplained direction* variable.

Local measures of directional expansion and contraction can be extended to multi-temporal situations by connecting temporal sequences of spatially related polygons into histories, and summarizing metrics accordingly. This allows for extraction and comparison of spatial–temporal patterns. Additionally, the information provided by local and global metrics can be visualized in graphs and maps, and altered to calculate application specific metrics, such as the rate of spread or

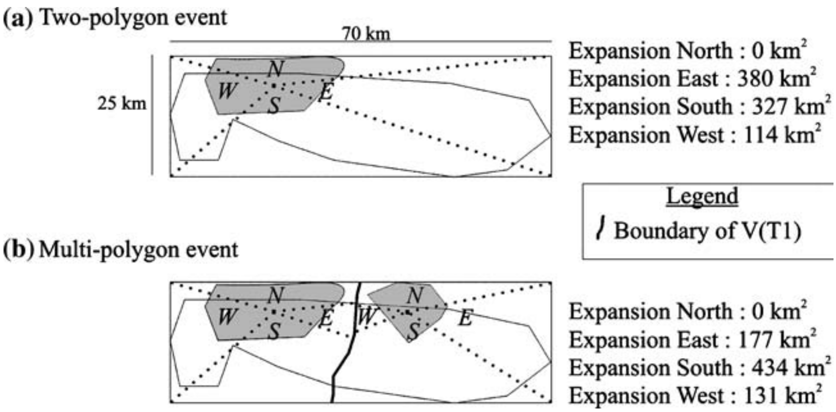


Fig. 4 Calculation of direction of expansion using a modified cone (*dotted lines*) based model: **a** for a regular polygon group consisting of only two-polygon events; **b** for a multi-polygon polygon group. The *dark centre line* is the boundary separating the Voronoi polygons of the two original T_1 polygons

frequency of multi-polygon changes. A particularly useful visualization for spatial–temporal patterns is the directed graph, which shows the spatial–temporal relationships deduced by the overlay procedure, and can be summarized statistically.

3.4 ArcGIS implementation

STAMP has been implemented as an ArcGIS version 9.0 toolbar. The functions making up this toolbar are packaged as a compiled dynamic link library (dll), programmed in Visual Basic.Net 2003. The compiled toolbar and the source code are freely available on our website, http://www.geog.uvic.ca/spar. Included in this implementation is functionality for the following tasks to enable STAMP analysis:

- Check if polygons are spatially exclusive
- STAMP overlay tool to generate events and polygon groups
- Build Voronoi polygons for areas
- Calculate local size and direction measures, global metrics, and summarized measures for spatial–temporal histories
- Create directed graphs as image files

4 Case study—wildfire spread analysis

4.1 Wildfire spread

Burning wildfires can quickly spread over larger areas. Increasingly GIS technology is being used in spatially explicit fire spread models that incorporate data on fuel load, wind, slope and aspect to determine the rate and direction of spread (Cova et al. 2005). Understanding the spatial–temporal patterns of advancing wildfires can reveal factors influencing spread, and inform more accurate spatial modelling of fire risk before and during wildfire events.

The goal of this case study is to quantify spatial–temporal patterns in polygons representing the spatial extent (perimeter) of wildfire in fourteen time periods. To achieve this goal we define spatial–temporal relationships between fire perimeter polygons, characterize polygons change events, visualize space–time relationships, and compute change metrics. Through this case study, we aim to demonstrate how STAMP methods may be employed for real time mapping and characterization of phenomena that spread, and highlight that STAMP methods may be used, in a research context, for assessing the performance of spatial–temporal models and simulations.

4.2 Data

The data for this case study was obtained from an online public data store managed by the Northern Rockies Multi Agency Command (data downloaded at http://www.fs.fed.us/r1/fireinfo/2003web/dataindex.htm). The website contains geospatial data for the 2003 fire season in the agency's geographic area of command. The fire perimeter polygons represent fire boundaries as digitized from thermal infrared images collected by the USDA Forest Service National Infrared Operations. Each fire perimeter has attributes indicating the date and time of capture. The changes in size and location of these perimeters are indicative of the fire's progression and are analyzed using the methods described in this paper. The Ball Creek wildfire data was collected approximately every second day over the course of the fire. While the temporal resolution of data is fine enough to depict spatial–temporal fire patterns, there are enough differences between the fire perimeter polygons to meet the assumption of discrete change. The case study is meant to illustrate the utility of the STAMP approach to spatial–temporal analysis, rather than an exhaustive study of the Ball Creek Fire.

4.3 Methods

At the outset of applying the STAMP methodology, it is critical to relate change events to spatial patterns of interest in the phenomena being analyzed. For wildfire spread, we are concerned mostly with rate and direction of spread of the existing fire, and the establishment of new fires. Thus, in the analysis of change events, we will focus on expansion, generation, and movements. Identifying these events and their changes through time will enable characterization of the nature and rate of spread. It will also be informative to explore the nature of multi-polygon events, union, and division, in the context of a spreading wildfire. Often, small fires will be started by spotting downwind of the main fire, which will then merge with the main wildfire (Finney 1998). A pattern where movement events are followed by multi-polygon unions will therefore be representative of this phenomenon.

As our data represents the progression of one wildfire, the global change metrics most informative for this analysis will be area based measures such as the area ratio and the area event measure. When data sets have many polygons in each time period, local change methods become a powerful tool for visualizing and exploring change. The threshold for the definition of movement events will be set to 2 km. This is a difficult parameter to estimate, as spotting distance varies with topography, vertical windspeed profile, and ember size (Finney 1998). In practice, it would be advantageous to vary this parameter multiple times to determine its actual sensitivity. For this case study, we focus on one wildfire, so the threshold is set large enough to capture any new fires within the vicinity of the main fire. If we were analyzing multiple burning fires across a landscape, the threshold would be set to differentiate between newly started fires (due to lightning strike) from fires started from spotting. The amount of expansion and movement will be calculated for each change layer, and summarized for individual histories. We also calculate the rate of spread for each change layer, based on the area of fire expansion divided by the duration of the temporal interval.

For each change layer, the mean direction and concentration parameter have been estimated based on the directional distribution of expansion. The quantitative directional measures generated by STAMP enable further analysis of directional trends. In this example, the concentration parameter is calculated using the CircStats Package for R (see Rao and SenGupta 2001) as the maximum likelihood estimate of the concentration parameter of a von Mises distribution of angular measurements, which describes the degree to which the mean angle is representative of the distribution of angles (Upton and Fingleton 1989). Expansion areas in each cardinal direction (N, E, S, W) are converted to directional observations (0, 90, 180, 270) and the concentration parameter is estimated for these distributions. A directed graph of temporal changes is also generated and summarized.

5 Results

Between August 23, 2003 and September 08, 2003, the Ball Creek Fire grew in size from an area of 1.29 to 30.70 km^2. The most dominant spatial–temporal polygon event throughout this period (beyond stability) was expansion. Between two time periods the mean area event measure for expansion was 21% (coefficient of variation [cv] = 0.86), with individual change years ranging from 1% in T_1–T_2 to 61% in T_6–T_7. Movement events occurred in intervals T_3–T_4 and T_{13}–T_{14}. Generation events did not occur. The area ratio for T_{14}/T_1 was 23.69, representing the large increase in size, and individual change layer area ratios ranged from 0.69 in T_1–T_2, to 2.55 in T_6–T_7. Fire merges (unions) occurred in T_3–T_4 and T_4–T_5 and multi-polygon divisions did not occur (Fig. 6).

Fire spread rates were calculated in m^2/h, and summarized for all expansion events only. Rates ranged from 603 m^2/h in interval T_1–T_2 to 642539 m^2/h in interval T_8–T_9. The mean rate of spread was 132628 m^2/h (cv = 1.42). Over all time periods, the most common direction of expansion was east (13.7 km^2), followed by south (8.3 km^2). The estimated concentration parameters ranged from 0.60 in T_{12}–T_{13} to 11.76 in T_6–T_7. Figure 5 shows the directional concentration parameter log(k) plotted (bottom line, right side scale) alongside the rate of spread (top line, left hand

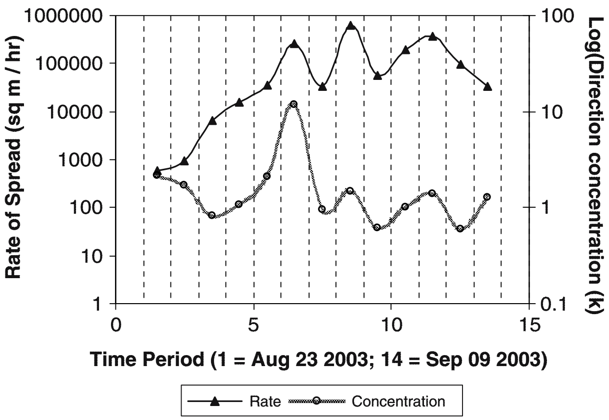


Fig. 5 Rate of spread and directional concentration for 14 time periods of the Ball Creek Fire, Montana, 2003. The *black line with triangles* indicates the rate of spread of expansion, and is measured on the left side scale. The *grey line with circles* indicates the directional concentration parameter for expansion, and is measured on the right side scale

scale) for expanding areas. Each vertical line on the graph represents one time period, so data points fall between vertical lines, representing the change intervals. The concentration parameter is plotted on a logarithmic scale to aid comparison with the trend in rate of spread.

The spatial distribution of the rate of fire spread is presented in Fig. 6. The map classes indicate the rate of spread the first time the fire expanded over each spatial location. Cases where the fire retreated, and re-expanded are not represented, although this is unlikely to happen because an area is unlikely to burn twice in quick

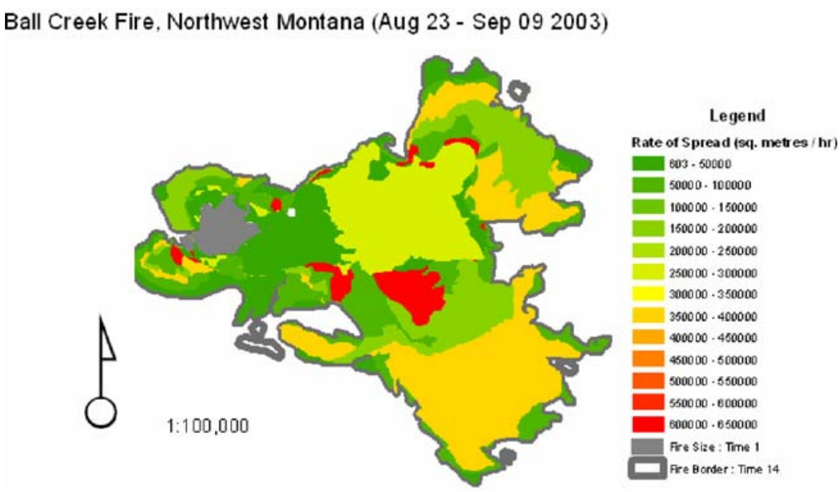


Fig. 6 Map of the rate of spread for 14 time periods of the Ball Creek Fire, Montana, 2003. Legend classifications are equal interval, 13 classes, 500,000 m^2/h intervals

succession. There are roughly five common rates of spread visible on the map. These different rates of spread are likely due to different fuel load and topography at spatial locations, and variations in wind and weather conditions at different times (Finney 1998). STAMP methods generate a powerful visualization of the spatial variation in spread rates. An additional use of these results could be to validate fire spread models, as STAMP provides observed values for comparison with model expectations. These types of comparisons could generate new information and lead to improvements in forest fire modelling and simulation.

The total area of the fire and total area of expansion events are shown in Fig. 7. Total area observations come from individual time periods, and expansion events are derived from change layers, so graphed data points are offset. Union events are flagged on the graph, indicating at least one fire merger occurred at the corresponding temporal interval.

A temporal directed graph of the wildfire represents the spatial–temporal relationships between polygons in each time period (Fig. 8). Each box represents one polygon (with unique polygon ID), and each arrow represents one relation. The summation of each of the arrows in one time interval represents the data in one change layer. In Fig. 8, two unions are represented, one in T_3–T_4, and one where the movement polygon (44411) merges with the main fire in T_4–T_5. From time period five onward, one main fire polygon remains. After the two fire mergers, a large increase in the size of the fire and amount of expansion occurred (Fig. 7).

The spatial–temporal relationships (arrows) occurring in the main fire polygon from T_5–T_{14}, can be conceptualized as one continuous spatial–temporal history. As this history is the dominant process in this dataset (see area trend after T_5 in Fig. 7), summarizing size and directional measures for this history will not reveal different trends than those reported for the global measures. If there were multiple wildfires contained in this dataset however, each spatial–temporal history could be analyzed individually. As an example, the directional distribution of expansion areas for

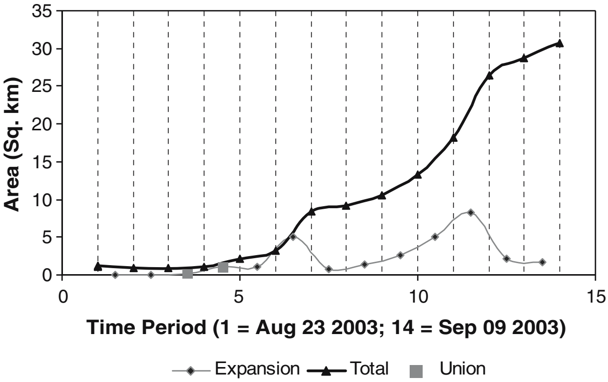


Fig. 7 Area of expansion (km^2) and total fire area (km^2) for 14 time periods of the Ball Creek Fire, Montana, 2003. The *black line with triangles* indicates the total fire size in each time period, from T_1 to T_{14}. The *grey line with dots* indicates the area of expansion, in each time interval

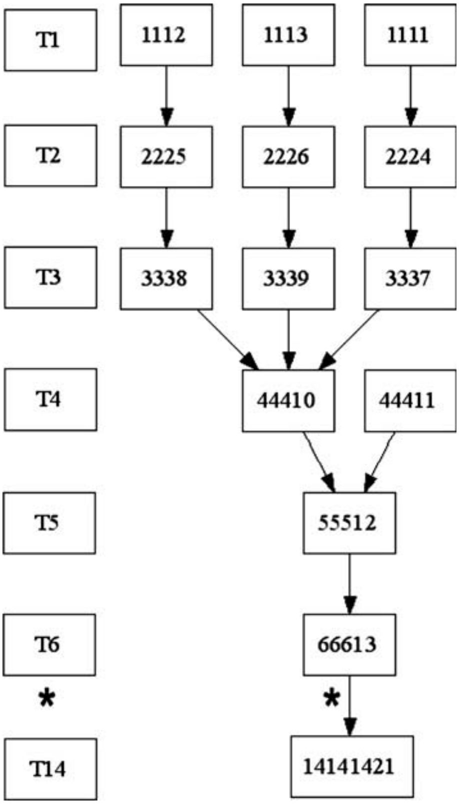


Fig. 8 Simplified temporal directed graph of spatial–temporal relationships occurring over fourteen time periods of the Ball Creek Fire, Montana, 2003. The * indicates multiple single relations occurred

history T_5–T_{14} is shown in Fig. 9. Again, the dominant directions of spread are east, then south.

6 Discussion

Results indicate that the fire grew largely unimpeded from T_1 through to T_{14}. However, the rate of spread was highly variable. Figure 4 shows how the fire expanded fastest in the T_6–T_7, T_8–T_9 and T_{11}–T_{12} intervals. It also appears that these high rates of spread were associated with peaks in the concentration of direction of expansion. This is probably related to wind direction and speed, and as wind became stronger and more unidirectional, the fire spread faster in the downwind direction. Interestingly, the overall size of the fire increased dramatically after T_5 until T_{12}. Prior to this period of rapid expansion, two fire mergers (T_3–T_4 and T_4–T_5) occurred which likely served to greatly increase the leading edge of the fire and create fire conditions suitable for rapid expansion.

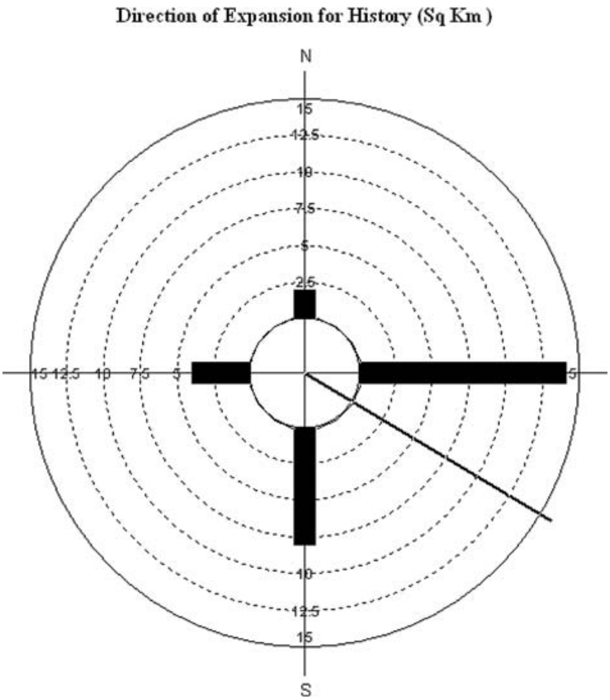


Fig. 9 Distribution of direction of expansion for history T_5–T_{14}. The size of the *black bar* indicates the amount of expansion in each direction. Each ring represents an area 2.5 km^2 in size. The line indicates the mean direction

7 Conclusion

STAMP extends methods for space–time polygon change analyses (Sadahiro and Umemura 2001; Sadahiro 2001), making them more general and suitable for a wider range of applications. A key extension is the introduction of new movement events, based on a distance threshold. Movement events can be distinguished based on pattern and allow the development of hypotheses regarding the nature of the spatial processes that lead to a specific spatial pattern of movement. Incorporation of movement enables the analysis of previously unsupported phenomena that travel, spread, or diffuse. As such, many new applications can be considered using STAMP methodologies including the transmission of disease in plants, animals, and people, the diffusion of ideas, the spread of fire, or wind driven processes. Conveniently, if movement is an inappropriate event for a given application, setting the threshold distance to zero will preclude movement events allowing STAMP software to still be used for analyses.

We also introduced new measures for directional change, based on a modified cone model for the calculation of directional relations among overlapping polygons. These measures enable the calculation of application specific metrics such as rate of spread, and have the potential for use in the validation of spatial simulation models.

This case study demonstrates the utility of the STAMP methods in quantitatively summarizing size and direction changes in spatial–temporal patterns of specific applications. New quantitative attributes and change measures include: the local area-based directional measure of expansion, contraction and movement; the total expansion, contraction and movement for each polygon group and local and global concentration parameters for directional measures of polygon groups. These events can be used to develop application specific measures of spatial–temporal polygon change. In the case study, derived metrics that were useful for examining the spread of a wildfire included the rate of spread of expansion, and an estimation of the concentration parameter for the expansion areas. The concentration parameter illuminated that there is a strong directional trend associated with expansion and large fire growth. This indicates that fast fire spread is likely associated with wind driven spatial processes. The flexible nature of the STAMP approach makes it ideal for exploratory analysis, as parameters and measures can be altered to suit the research question of interest.

Other advantages of the STAMP method include the local analysis of multi-temporal histories, the ability to rapidly summarize large amounts of data, and a standardized approach to the spatial–temporal analysis of polygon data. Finally, the computational procedure for the detection of events represented in Fig. 2 has been implemented using a popular GIS software package, and should, therefore, promote the use of spatial–temporal analysis of multi-temporal polygon datasets among GIS practitioners and researchers. This is a key contribution as, beyond areal overlap, the present functionality of GIS is limited for the analysis of multiple polygons layers.

There are numerous areas for future development of the STAMP methods. Firstly, the method of detecting directional change for multi-polygon polygon groups currently leaves an unexplained amount of area for certain configurations of irregular polygons. A more systematic treatment of this problem is needed to address these situations. Secondly, one major problem in dealing with polygons in GIS is the problem of indeterminate boundaries (Burrough and McDonnell 1998). Fuzzy boundaries should be incorporated into the event deduction procedure to handle situations where actual boundaries are not discrete. Thirdly, other spatial properties of interest could be developed into change measures. For example, we examined the utility of a polygon density metric, based on the area of each polygon divided by its Voronoi polygon. While informative of density, the method was too sensitive to edge effects for implementation. Further research into change metrics at both the local and global level would allow for a broader range of spatial–temporal questions to be explored. Lastly, the STAMP methods described in this paper focus solely on the spatial properties and relations of polygons. A logical extension would be the incorporation of attribute information into the event deduction procedure, perhaps for deriving functional events such as succession, production and transmission described by Claramunt and Thériault (1996). For example, multi-temporal sets of animal home range polygons for multiple species could be analyzed to detect spatial–temporal patterns in predator–prey interactions. This could then shed light onto hypothesized ecological theories such as spatial density dependence. In sum, we feel the methods for detecting and exploring local spatial–temporal change in this paper offer a useful starting point for future extension and use in a wide variety of applications.

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References

Boots B (2000) Using GIS to promote spatial analysis. J Geograph Syst 2:17–21

Burrough P, McDonnell R (1998) Principles of geographical information systems. Oxford University Press, New York

Chen J, Li C, Li Z, Gold C (2001) A Voronoi-based 9-intersection model for spatial relations. Int J Geograph Informat Sci 15:201–220

Christakos G., Bogaert P., Serre M.L. (2002) Temporal GIS: advanced functions for field-based applications. Springer, New York

Claramunt C, Thériault M (1996) Towards semantics for modelling spatio-temporal processes within GIS. In: Kraak M, Molenaar (eds) 7th international symposium on spatial data handling. Taylor and Francis, London, pp 47–63

Cova TJ, Dennison PE, Kim TH, Moritz MA (2005) Setting wildfire evacuation trigger points using fire spread modeling and GIS. Transactions in GIS 9:603–617

Dragicevic S, Marceau D (2000) A fuzzy set approach for modelling time in GIS. Int J Geograph Informat Sci 14:225–245

Egenhofer MJ, Franzosa RD (1991) Point-set topological spatial relations. Int J Geograph Informat Syst 5:161–176

Egenhofer M and Golledge R (eds) (1998) Spatial and temporal reasoning in geographic information systems. Oxford University Press, New York

Egenhofer MJ, Sharma J, Mark DM (1993) A critical comparison of the 4-intersection and 9-intersection models for spatial relations: a formal analysis. Auto-Carto 11:1–11

Finney MA (1998) FARSITE: fire area simulator—model development and evaluation. Res. Pap. RMRS-RP-4, USDA, Forest Service, Rocky Mountain Research Station, p 47

Fortin M-J, Dale M (2005) Spatial analysis: a guide for ecologists. Cambridge University Press, Cambridge

Fortin MJ, Keitt BA, Maurer ML, Kaufman D, Blackburn TM (2005) Species' geographic ranges and distributional limits: pattern analysis and statistical issues. Oikos 108:7–17

Frank AU (1992) Qualitative reasoning about distances and directions in geographic space. J Vis Language Comput 3:343–371

Galton A (1998) Modes of overlap. J Vis Language Comput 9:61–79

Gillis M, Leckie D (1996) Forest inventory update in Canada. Fores Chronicle 72(2):138–156

Gong P, Xu B (2003) Remote sensing of forests over time: change types, methods, and opportunities. In: Wulder MA, Franklin SE (eds) Remote sensing of forest environments. Kluwer Academic Publishers, Norwell, pp 301–334

Hagen A (2003) Fuzzy set approach to assessing similarity of categorical maps. Int J Geograph Informat Sci 17:235–249

Knox E (1964) The detection of space–time interactions. Appl Stat 13:25–29

Kulldorff M, Heffernan R, Hartman J, Assuncao RM, Mostashari F (2005) A space–time permutation scan statistic for the early detection of disease outbreaks. PLoS Med 2:216–224

Langran G (1992) Time in geographic information systems. Taylor & Francis, New York

Mantel N (1967) The detection of disease clustering and a generalized regression approach. Canc Res 27:209–220

Maruca S, Jacquez G (2002) Area-based tests for association between spatial patterns. J Geograph Syst 4:69–83

McIntosh J, Yuan M (2005) A framework to enhance semantic flexibility for analysis of distributed phenomena. Int J Geograph Informat Sci 19:999–1018

Miller HJ, Wentz EA (2003) Representation and spatial analysis in geographic information systems. Ann Associat Am Geograph 93:574–594

O'Sullivan D, Unwin J (2003) Geographic information analysis. Wiley, Hoboken, NJ

Okabe A, Miller HJ (1996) Exact computational methods for calculating distances between objects in a cartographic database. Cartograph Geograph Informat Syst 23:180–195

Openshaw S, Charlton M, Wymer C, Craft A (1987) A mark 1 geographical analysis machine for the automated analysis of point data sets. Int J Geograph Informat Syst 1(4):335–358

Peuquet D, Zhang CX (1987) An algorithm to determine the directional relationship between arbitrarily-shaped polygons in the plane. Pattern Recognition 20:65–74

Peuquet D (1994) It's about time: a conceptual framework for the representation of temporal dynamics in geographic information systems. Ann Associat Am Geograph 84:441–461

Peuquet D (2001) Making space for time: Issues in space–time data representation. GeoInformatica 5:11–32

Rey SJ, Janikas MV (2006) STARS: space–time analysis of regional systems. Geograph Anal 38:67–86

Rao JS, SenGupta S (2001) Topics in circular statistics. World Scientific, Singapore

Sadahiro Y (2001) Exploratory method for analyzing changes in polygon distributions. Environ Plann B: Plann Des 28:595–609

Sadahiro Y, Umemura M (2001) A computational approach for the analysis of changes in polygon distributions. J Geograph Syst 3:137–154

Skiadopoulos S, Koubarakis M (2004) Composing cardinal directions relations. Artific Intell 152:143–171

Skiadopoulos S, Giannoukos C, Sarkas N, Vassiliadis P, Sellis T, Koubarakis M (2005) Computing and managing directional relations. IEEE Trans Knowledge Data Eng 17:1610–1623

Upton G, Fingleton B (1989) Spatial data analysis by example: categorical and directional data. Wiley, Chichester

Visser H, de Nijis T (2006) The map comparison kit. Environ Modell Software 21:346–358

Worboys M (1994) A unified model of spatial and temporal information. Comput J 37(1):26–34

Yan H, Chu Y, Li Z, Guo R (2006) A quantitative description model for the direction relations based on direction groups. Geoinformatica 10:177–196