# Describing Temporal Correlation Spatially in a Visual Analytics Environment

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**ABSTRACT**

In generating and exploring hypotheses, analysts often want to know about the relationship between data values across time and space. Often, the analysis begins at a world level view in which the overall temporal trend of the data is analyzed and linear correlations between various factors are explored. However, such an analysis often fails to take into account the underlying spatial structure within the data. In this work, we present an interactive visual analytics system for exploring temporal linear correlations across a variety of spatial aggregations. Users can interactively select temporal regions of interest within a calendar view window. The correlation coefficient between the selected time series is automatically calculated and the resultant value is displayed to the user. Simultaneously, a linked geospatial viewing window of the data provides information on the temporal linear correlations of the selected spatial aggregation level. Linear correlation values between time series are displayed as a choropleth map using a divergent color scheme. Furthermore, the statistical significance of each linear correlation value is calculated and regions in which the correlation value falls within the 95% confidence interval are highlighted. In this manner, analysts are able to explore both the global temporal linear correlations, as well as the underlying spatial factors that may be influencing the overall trend.

**Keywords:** Visual analytics, temporal correlation, spatial aggregation, crime analysis.

## 1 MOTIVATION

In multivariate spatiotemporal data, the relationships between temporal trends and spatial locality become an important factor in analysis. Time series of variables are often generated and analyzed as a precursor to creating predictive models of the data. However, when analyzing temporal trends of spatiotemporal data, it is often most mathematically tractable to aggregate the data over a particular collection repository (i.e., a financial institution, hospital, police station, etc.). As the number of variables in a dataset increases, the number of linear correlations available to calculate and explore quickly becomes intractable. Given a multivariate dataset with N variables, the number of pairwise correlative factors to be explored are $\frac{N\times(N-1)}{2}$. Thus, the amount of information regarding correlative properties between variables is of the order of $O(n^2)$. However, understanding the relationships between variables within a dataset can provide analysts with valuable insights and aid them in hypothesis generation and exploration. As the analysis of competing hypotheses depends on complete (i.e., sufficiently complete to be reasonably accurate) mental models of considered concepts, and that those models are wholly dependent on all pertinent information being considered, new ways of disseminating and exploring information are needed.

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This need provides an impetus to the field of visual analytics. Visual analytics is the science of analytical reasoning assisted by interactive visual interfaces[16, 22]. This interactivity, especially in large and semantically complex sets, provides an immersive technique for exploring information relevant to the mental models [13, 14] developed by analysts. By combining this interactivity with intuitive visual displays, analysts can ingest information, form, explore, and validate hypotheses, as well as generate supporting data for reports.

In this paper, we present a visual analytics system for exploring temporal correlations within a given data set over various levels of spatial aggregation. Our system, shown in Figure 1, provides interactive filters and linked views in which analysts can test their mental models by exploring only the relevant data components. Furthermore, given a spatiotemporal dataset, various levels of spatial aggregation exist at which one may analyze the data. Our system presents an overall summary aggregation of the data and plots the temporal history of the dataset. Users are able to interactively select a set of time series data and using their specific domain knowledge, interactively explore correlations in the temporal domain and visualize the correlations at various spatial resolutions on a choropleth map (a map in which area are colored in proportion to the measured variable being displayed).. Such a system provides the user with an insight into the predictive value of a given set of time series data as well as an insight into which spatial areas in the data show strong signs of temporal correlation.

Our correlative analysis system focuses on categorical spatiotemporal event data (e.g., financial data, crime reports, emergency department logs). In such data, events consist of locations in time and/or space, and each event fits into a hierarchical categorization structure. These categories can be filtered by linked data, and the events may be mapped to a particular spatial location. Data categories are typically processed as either time series aggregated over some spatial location (county, zip code, collection station), or spatial snapshots of a small time aggregate (e.g., day, week). In order to facilitate the discussion of our visual analytics system, we frame our work around an application of exploring correlations within criminal incident reports from West Lafayette, Indiana, USA. Such a dataset is representative of a variety of spatiotemporal data that consists of fields including date and time of occurance, crime types, geographic location, street address, description of crime events, etc. Currently, our work has focused on four case studies: 1) an analysis of the correlative factors between criminal incidents and large events such as football and basketball games, 2) the spatial exploration of temporal correlations between semester criminal incidents, 3) the spatial exploration of the aggregate of noise and vandalism incidents between semester weekends, and 4) a correlative analysis between criminal incidents over semester holidays.

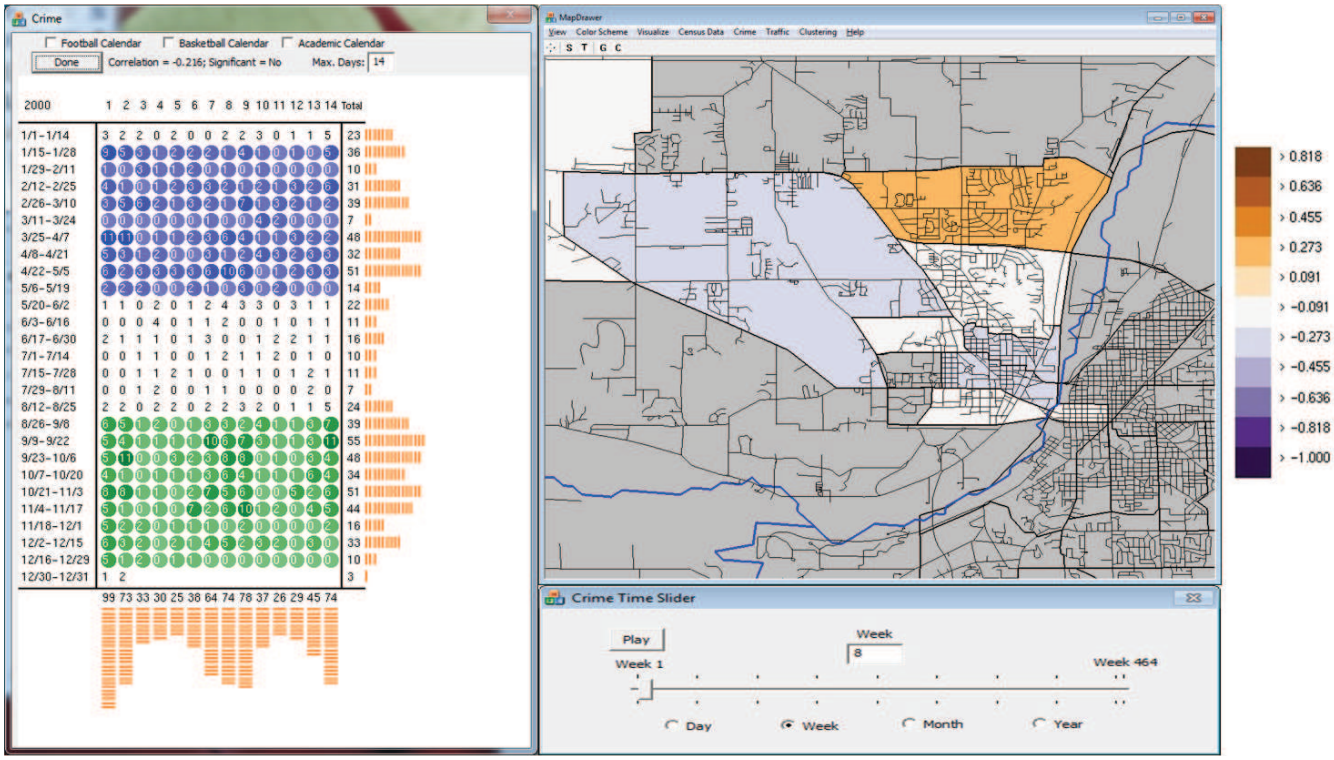


Figure 1: A screenshot of our system showing an interactive user date selection in the temporal calendar view, the resultant Pearson's correlation choropleth map, and a color legend showing the range of correlation values from -1.0 to 1.0. In the calendar view on the left, the user has interactively selected one temporal region (in blue) and is analyzing the correlation to the equal length temporal selection (in green). The correlation coefficient is displayed on the top of the calendar view. In this case, it is -.236. On the Right, we show the geospatial map view illustrating the temporal correlations with respect to census tract areas. The choropleth colors represent the correlation coefficients for each region. If regions are statistically significantly correlated, their boundaries will appear as thicker black lines.

## 2 Related Work

In recent years, researchers have explored different methods of analyzing temporal data to discover and analyze trends and correlations. The analysis of time series data is one of the most common problems in any data domain, and the most common techniques of visualizing time series data (sequence charts, point charts, bar charts, line graphs, and circle graphs) have existed for hundreds of years. Recent work in time series visualization has produced a variety of techniques, an overview of which can be found in [1]. Early work by van Wijk and Selow [24] looked at using calendar view visualizations to enable users to identify patterns and trends on multiple time scales simultaneously and provided a simple cluster analysis method. More recent techniques include the theme river [15], the spiral graph [26], and the time wheel [23]. These techniques looked at new ways to visualize temporal data to try and emphasize repeating patterns.

While such visualizations are able to provide insight into temporal data sets, many temporal data streams also contain spatial components. In order to facilitate the exploration of the spatial components of data, geographical visualization tools and techniques were developed. Geographic visualization utilizes sophisticated, interactive maps to explore information, guiding users through their data and providing context and information with which to generate and explore hypotheses. In more recent years, it has expanded to include increasingly complex data, new spatial contexts, and information with a temporal component. Relevant summaries on work in the field can be found in texts by Peuquet [20], Dykes and MacEachren [9], and Andrienko and Andrienko [4]. These books detail thoughts on knowledge discovery and the exploratory analysis of spatial and temporal data. Other reviews on spatiotemporal data mining and analysis can be found in [2, 5, 11].

Many of the geovisualization methods described in these textbooks [4, 9, 20] have been leveraged to create systems for data exploration combining both interactive mapping techniques and statistical methods. Dykes et al. [10] utilized web services to deliver interactive graphics to users, and introduced an approach to dynamic cartography supporting brushing and dynamic comparisons between data views in a geographical visualization system. Andrienko et al. [3] developed the Descartes system in which users were able to select suitable data presentation methods in an automated map construction environment. Edsall et al. [12] created a system that decomposed geographic time series data using a three-dimensional Fourier transformation of the geographic time series, allowing users to explore the three-dimensional representation of the physical and spectral spaces. Carr et al. [8] utilized a two-way layout of choropleth maps to enhance a user's ability to compare dataset and explore data hypotheses.

Such systems have paved the way for the emergence of visual analytics as a field formed at the intersection of analytical reasoning and interactive visual interfaces [22]. Visual analytics is concerned with presenting large amounts of information in a comprehensive and interactive manner. By doing so, the end user will be able to quickly assess important data and, if required, investigate points of interest in detail. While the formulation of the term visual analytics is relatively new, there has been much work in the realm of exploratory data analysis, particularly with regards to geographi-

Figure 2: Screenshots of the user selection process in the calendar view mode. Our system allows for contiguous selection by row (Left) or column (Right) in the calendar and the creation of a disjoint time series pattern (Middle).

cally located data. Work by MacEachren et al. [18] emphasized the use of visual techniques in areas of decision making and argued that a use-based approach was needed in developing information processing environments for a given user, which is of fundamental concern under the concept of visual analytics. These concepts were further explored in work by MacEachren et al. [19] in which a conceptual framework for the integration of knowledge discovery using geographical visualization was proposed in order to enable users to explore their data in the context of a spatiotemporal environment. More recently, the development of visual analytics systems for data analysis and exploration has been rapidly growing (e.g., [7, 17, 21, 25]). Techniques common across these systems include the probing, brushing and linking of data in order to help analysts refine and explore their hypotheses.

## 3 Visual Analytics Environment

Our system utilizes many of the aforementioned techniques to create an interactive environment for exploring temporal correlations spatially. By using domain knowledge of the data, analysts can form hypotheses about correlative relationships between variables in the dataset. Our work adopts the calendar view idea presented by van Wijk and Selow [24] and extends this work for interactive multivariate data correlation analysis. We incorporate linked views and brushing, thereby facilitating user interaction between the spatial and temporal domains of the data.

Figure 1 shows a snapshot of our system. The main window (Figure 1 - Right) of the system shows the geospatial view that supports the overlay of different maps and criminal incidents along with interactive panning and zooming tools. The left-most window is the calendar view of the selected CTC incidents that shows the sum of crime incidents for each day of a calendar year. The calendar view enables the users to visualize special events like football and basketball games on the calendar further allowing them to make a connection between the reported CTC activities and these events. The bottom-rightmost window contains the time slider that is used to temporally scroll through the data while dynamically updating all the other linked windows to reflect the change.

### 3.1 Temporal Correlation Exploration

For the temporal correlation exploration, we provide several interaction methods within the calendar view window widget of Figure 2. The users can select date ranges by simply clicking on the start and end dates of the first date range and then choosing the start date of the second range using a mouse. To ensure that the length of the two selected time series remains the same (a requirement for calculating the correlation coefficient), the system automatically calculates the ending date of the second range. This method selects all the dates between the selected starting and ending dates. This mode of selection can be seen in Figure 2 (Left). The users can also select individual dates and form two arbitrary date ranges for performing correlative analysis. Figure 2 (Middle) shows this mode of selection. This method can be used, for example, to analyze the spatial and temporal correlations between the crime occurences on major calendar events like football and basketball games. Finally,

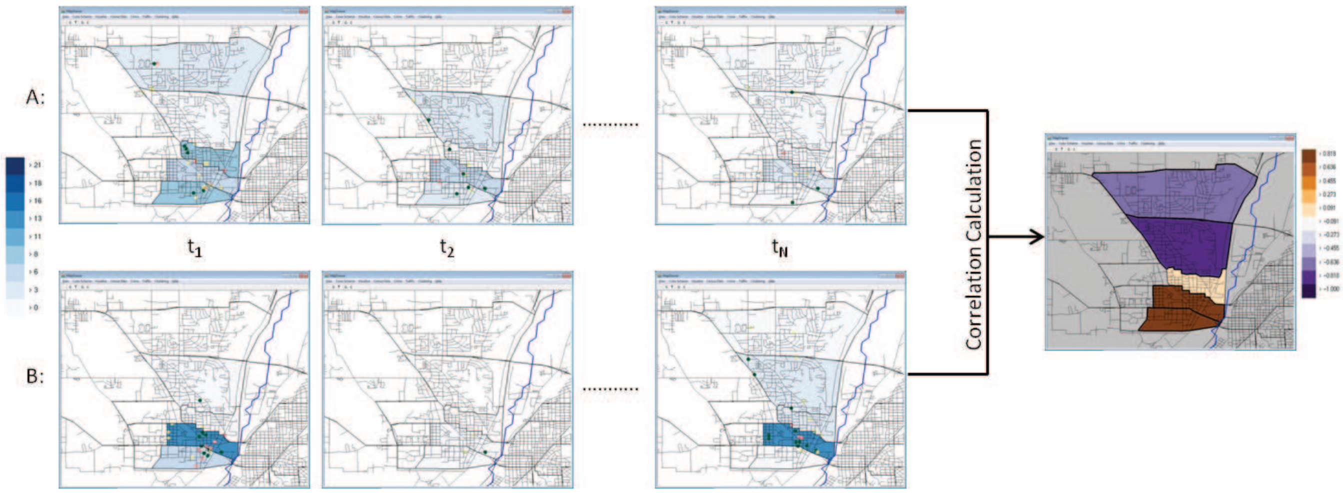


Figure 3: Our temporal correlation analysis with respect to spatial aggregation. The user has selected a time series ($A$ and $B$) and for each temporal unit, the number of events in areal unit $g_i$ are calculated. Then for each $g_i$, there exists two time series $g_{iA}$ and $g_{iB}$ which are used to calculate Pearson's correlation. The correlation value is mapped to a color and the resulting temporal correlations with respect to spatial aggregates are plotted as a choropleth map.

we also include a feature by which users can select an arbitrary range of dates by clicking on a start date and choosing an end date which selects all the dates between the columns or rows of the starting and ending dates. Figure 2 (Right) shows this mode of selection where the analyst intends to perform correlative analysis between the two selected range of weekends. This type of selection is especially useful if, for example, the analyst wants to analyze the correlation between only the weekends of two different times of a year (or of different years). In each of the selection methods, the system colors each calendar day with a color shade that corresponds to the relative count with respect to the maximum crime count for that particular calendar year. This further allows the users to observe trends in their selected date ranges. After selecting the two date ranges, the system provides the users with the option of selecting the time aggregation (by day, week or month) over which it automatically aggregates the data. Moreover, to facilitate the selection of dates, we allow the users to change the width of the calendar to range from 7 to 30 days. This action further provides the users with more options of selecting the dates for correlative analysis by using any of the described methods above.

Once the temporal ranges to be compared are selected, the correlation calculation is performed. Correlation is a single number used to describe the linear relationship between two variables. In the case of time series analysis, we use correlation to describe the degree in which certain periods of time can be used to predict future events. For example, a police official may be interested in knowing whether crime activity levels at a certain period of a year are related to those of a different year thus indicating a pattern in criminal activity. As such, we choose to apply the Peasron product-moment correlation coefficient (*Pearson's correlation* - $r_{xy}$) as part of our hypothesis analysis which is defined as

$$r_{xy} = \frac{N\sum_{i=1}^{N} x_i y_i - \sum_{i=1}^{N} x_i \sum_{i=1}^{N} y_i}{\sqrt{N\sum_{i=1}^{N} x_i^2 - (\sum_{i=1}^{N} x_i)^2}\sqrt{N\sum_{i=1}^{N} y_i^2 - (\sum_{i=1}^{N} y_i)^2}} \quad (1)$$

where N is the length of time series $x$ and $y$ (note that to calculate $r_{xy}$ $x$ and $y$ must be of equal length), and $x_i$ and $y_i$ are the values of the respective time series at time $i$. Once $r_{xy}$ is calculated, we then apply a two sided t-test:

$$t = r_{xy}/\sqrt{(1-r_{xy}^2)/(N-2)} \quad (2)$$

We then use the t-distribution with $N-2$ as the degrees of freedom to determine if the calculated correlation coefficient is significant within the 95% confidence interval. The correlation coefficient for the temporal selection is then displayed at the top of the calendar view dialog box and we correspondingly show whether the two sided t-test implies temporal significance or not.

### 3.2 Spatial Correlation Exploration

Given the temporal correlation for a given time series, the next question that could be asked is, what influence do the spatial constraints in the data have on this correlation? To that end, our system automatically splits the time series into a set of $k$ new time series, where each of these new $k$ time series is based on the aggregate number of samples within a given areal unit. The system then calculates the Pearson's correlation coefficient for each areal unit and colors it based on its calculated correlation coefficient using a divergent color scale [6]. This generates a choropleth map, which is a thematic map with each geographic unit colored in proportion to the resulting correlation coefficient value mapped between the range of the minimum (-1.0) and maximum (1.0) attainable values. We also apply the two sided t-test to each areal unit and highlight the statistically significant regions by increasing the thickness of their boundary outlines.

This process of generating the spatial correlation map is explained in Figure 3. In this example, the analyst has chosen to see the correlation of the aggregate of noise, vandalism and theft crime incidents in West Lafayette, Indiana, USA over the two selected time series ($A$ and $B$) of $N$ weeks each from the calendar view by selecting a range of dates from which the system generates the data for the selected weeks automatically. After selecting the two desired date ranges on the calendar, the system calculates the Pearson's correlation coefficient for each areal unit and maps this value to a color with which the corresponding geographical unit is then colored. Moreover, for each areal unit, the system determines whether the calculated correlation coefficient is significant within

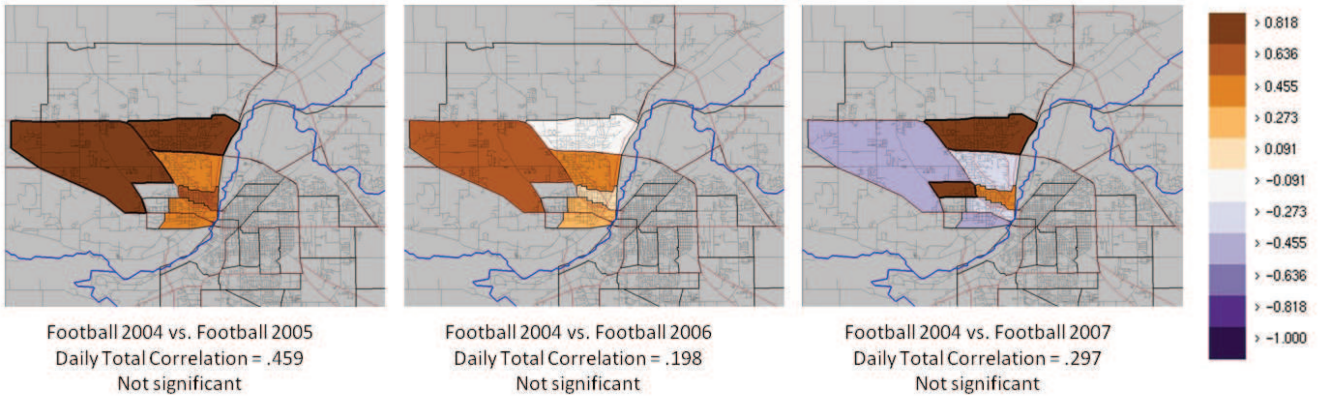


Figure 4: A comparison of temporal correlations in combined noise and vandalism incidents for West Lafayette, Indiana, USA between football weekends over the years. The spatial regions with statistically significant correlations are highlighted by increasing the thickness of their borders. No consistent correlation patterns are observed between football weekends over the years.

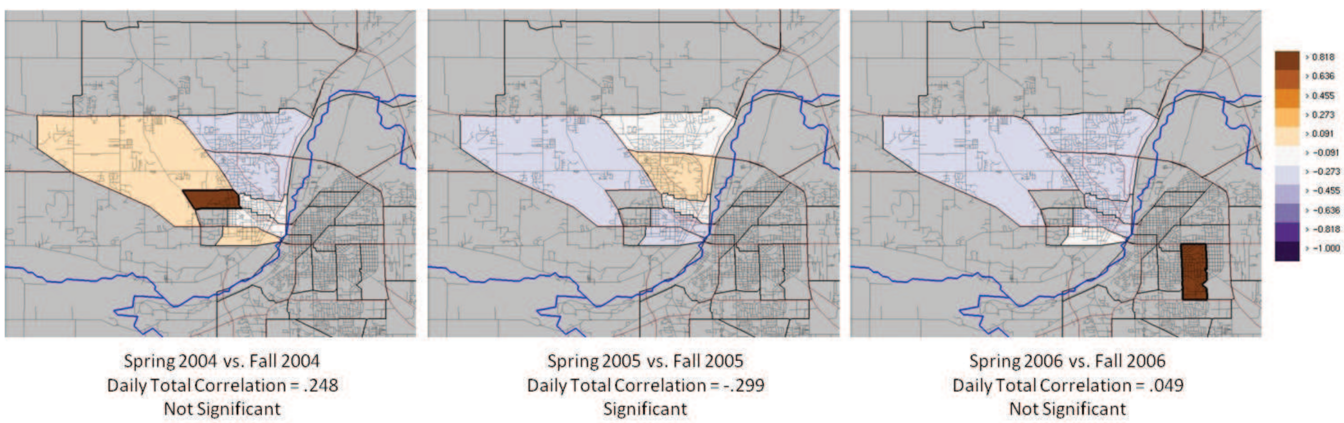


Figure 5: Temporal correlation comparison of an aggregate of noise and vandalism complaints between semester weekends.

the 95% confidence interval using a two sided t-test. If the test indicates that the spatial unit is significant, the system highlights it by increasing the thickness of its boundary outlines.

## 4 Exploring Correlations in Crime Data

To demonstrate the functionality of our system, we utilize the criminal incident reports from West Lafayette, Indiana, USA for the years 2000 to 2008. These crime reports have been categorized into different crime categories and as such we generate a calendar view of the crime incidents to facilitate the selection of the date ranges for correlative analysis. Our system allows users to interactively filter by crime category, and in this section, we cover four examples of using our system to explore correlations in West Lafayette, IN, USA.

### 4.1 Correlations between football weekends

The first example looks at noise and vandalism reports with respect to home football games. Here, the analyst believes that noise and vandalism reports during home football games may be consistent from year to year. The analyst selects the home football games from 2004 and those from 2005. This process is repeated to compare 2004 to 2006 and 2004 to 2007. Results of the analysis are shown in Figure 4.

The overall temporal correlation is found to be insignificant with respect to the two-sided t-test. In the 2004 to 2005 image, we can see that the two dark brown areas are spatially correlated, and the dark border indicates that this is a statistically significant correlation. Unfortunately, this correlation pattern does not hold when comparing 2004 to 2006. Furthermore, a different trend set emerges when comparing 2004 to 2007. This indicates that football game schedules will not be a good predictor of noise and vandalism complaints.

### 4.2 Correlations between semester weekends

Our second example demonstrates the correlative trends of the aggregates of noise and vandalism reports for West Lafayette, Indiana, USA occuring on the weekends (Friday to Sunday) between two semesters. As can be seen from the results (Figure 5), we observe that none of the areas show consistent significant correlative trends over the semesters. We also find that one region is highly positively correlated and statistically significant when comparing the weekends between the spring and fall 2004 semesters (Figure 5-Left), even though the temporal correlation for this case is not significant. This analysis indicates that even though noise and vandalism complaints are more frequent on the weekends (as can be observed from the weekly histogram plots of Figure 2-Right), semester weekends are not good predictors of noise and vandalism complaints over the

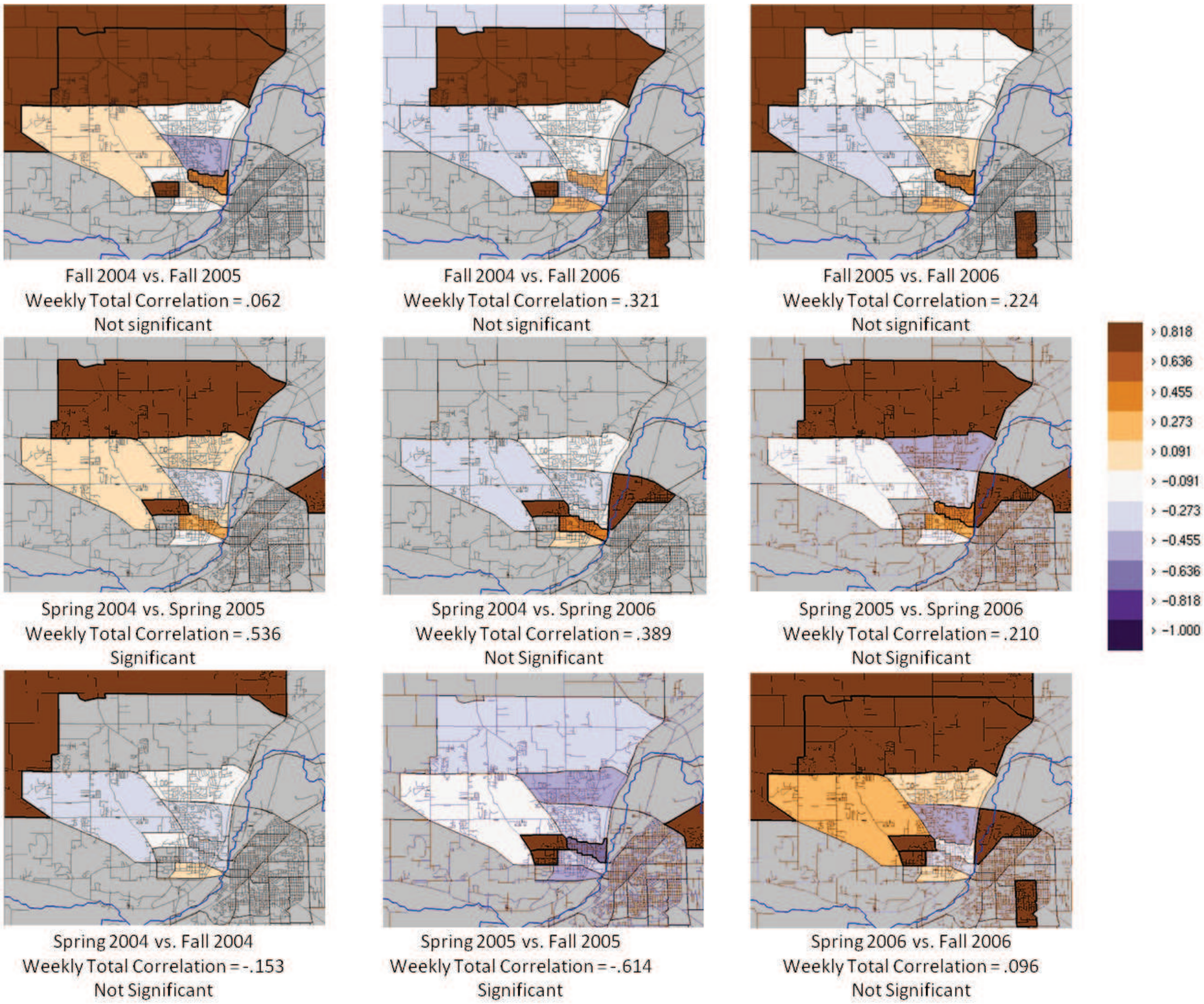


Figure 6: A semester to semester comparison of temporal correlations in combined noise and vandalism reports for West Lafayette, Indiana, USA. (Top) Comparison of correlations between fall semesters. (Middle) Comparison of correlations between spring semesters. (Bottom) Comparison of correlations between fall and spring semesters.

subsequent semesters.

### 4.3 Semester to semester analysis

Our third example looks at the weekly correlation between combined noise and vandalism complaints. We compare yearly across semesters and between semesters across years. The results of the analysis are shown in Figure 6. Here we find that the temporal correlation between semesters is not significant; however, in both the Fall (Figure 6-Top) and Spring (Figure 6-Middle) semesters, there are areas of West Lafayette, IN, USA that show considerably high correlation values from Fall to Fall and from Spring to Spring. Unfortunately, in the three year period chosen, there seems to be no area that is consistently statistically significantly correlated across all three years. Finally, when comparing Fall semester to Spring semester (Figure 6-Bottom), we see that the correlation values are negative for two of the three comparisons, with one having a global significance. Again, however, there are no significant correlative trends that can be extracted between these components consistently.

### 4.4 Correlations between aggregate of theft and burglary crimes over semester breaks

In our final example, we compare the correlations between an aggregate of theft and burglary crime reports for West Lafayette, Indiana, USA occuring during the semester breaks when most of the university students leave for their homes for the holidays. In particular, we compare the correlative trends between crime occurances occuring on spring breaks and thanksgiving breaks over different years. The results of the analysis are shown in Figure 7. These results highlight regions that are spatially significant, even though their corresponding temporal correlations are not. We also find certain geographic regions that have consistently high spatial correlation over the years for these crime types. For example, the regions maked by arrows in the figure show positive spatial correlation over their respective time periods, and their highlighted borders indicate statistical significance. So the regions marked by arrows across the years over spring break (and correspondingly over fall break) show high positive correlation indicating an increase in crime incidents

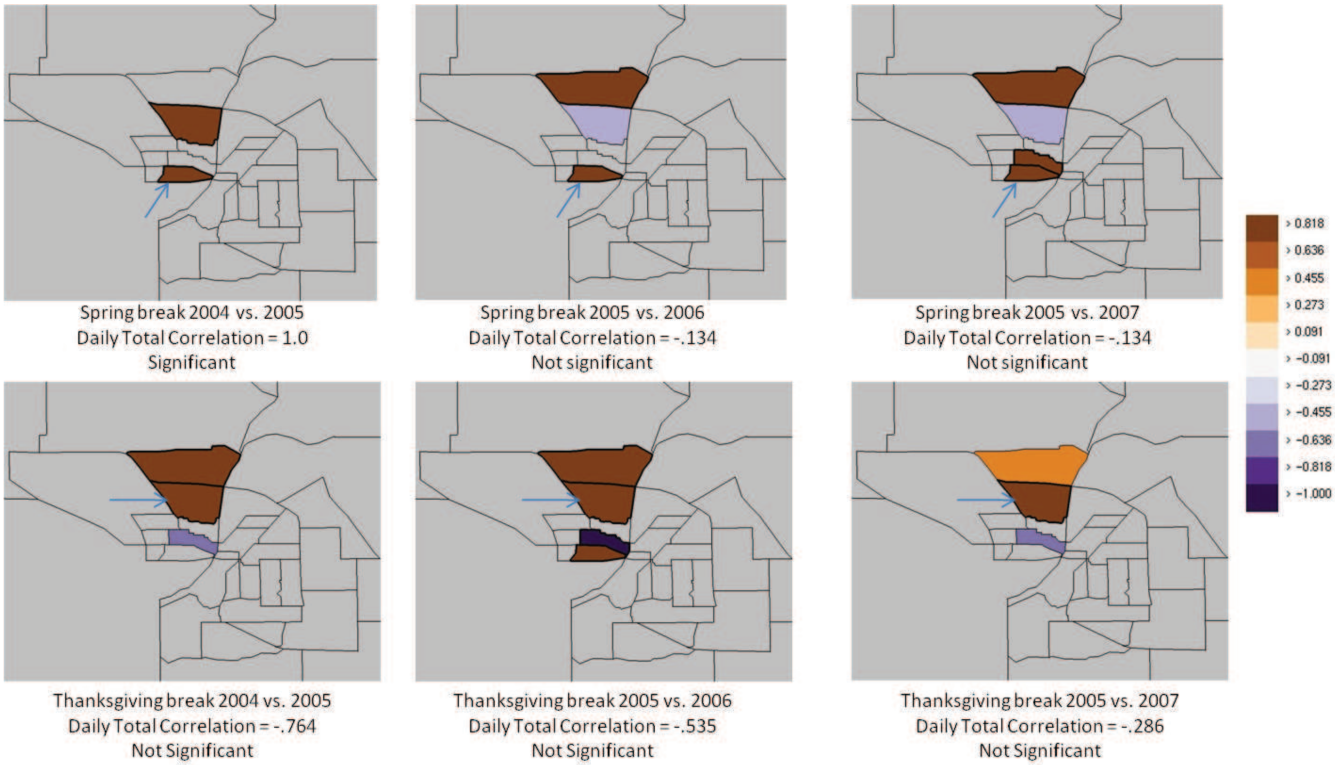


Figure 7: A comparison between an aggregate of thefts and burglaries over spring and thanksgiving breaks over the years.

over the years. This allows the analysts to point out the spatial regions that influence the overall global temporal trend. This example further shows that semester breaks are a good predictor of theft and burglary crimes.

## 5 Conclusions and Future Work

In this work, we presented a method of exploring temporal correlations spatially through an interactive visual analytics environment. Our system provides analysts with both a means of generating and exploring hypotheses along with tools to provide statistical tests of these hypotheses. We have demonstrated the functionality of our system using criminal reports from West Lafayette, Indiana, USA. Future work will include the incorporation of temporal lags and allow analysts to automatically find the optimal correlation coefficients within a given time range.

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