Simulating Spatial-Temporal Pulse Events in Criminal Site Selection Problems

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Abstract

Previous academic research has identified the correlation between special events and crime rates within cities. However, in much of the previous work, the focus was either on spatial *or* temporal analysis related to the evolution of local crime patterns in conjunction with the special events. This research uses a hybrid agent-based simulation to examine the impact of temporal pulse events on the criminal site selection process. The simulation provides researchers with a method for adjusting both the temporal and spatial patterns in response to a series of a-priori special events. Using the data from this simulation, we illustrate the effectiveness of a new modeling approach. Initial results show that adding a hierarchical framework to a feature-space regression model improves crime prediction accuracy and offers the law enforcement analyst better insight into both the temporal *and* spatial considerations of criminals. Improving the ability of law enforcement to identify, and prepare for, spatial-temporal shifts in crime patterns will significantly enhance proactive policing operations and resource allocation planning in support of large special events.

1. INTRODUCTION

Research and practical experience have identified the correlation between special events, such as football games and concerts, with changes in the spatial-temporal distribution of crime in cities. While analytic tools exist for modeling dynamic changes in either the temporal, or the spatial, patterns of crime, effective approaches for predicting the *spatial-temporal* changes in criminal activity around special events are not readily available. This article reviews the use of agent-based modeling to demonstrate the efficacy of using hierarchical modeling to predict the impact of spcial events on the criminal site selection process.

Using an agent-based simulation model allows to integrate spatial-temporal considerations into a criminal site selection process while still allowing for the probabilistic nature of crime. We use the simulation to generate a series of scenarios with varied pulse events that impact the criminal agent's site selection preferences. Using the data from these simulations, we illustrate the effectiveness of a new modeling approach. This modeling approach first identifies both the spatial *and* temporal patterns in the data and then uses hierarchical spatial choice modeling to predict areas of potential criminal activity. We compare the performance of models that do not consider temporal information to a hierarchical model that accounts for the impact of special events on criminal activity. The use of the simulation model demonstrates that this new modeling approach provides law enforcement personnel with a framework for identifying, and understanding, the impact of special events on the criminal site selection process.

The remainder of this section provides a quick review of applicable crime theory, criminal site selection, pulse events, and agent based modeling for crime studies. The subsequent section discusses the base simulation and the research design while also introducing the hierarchical framework used to account for the spatial-temporal impact of pulse events on the criminal's site selection process. Section 3 reviews the initial and exploratory results of the simulation data. In the final section, we review conclusions, discuss the applicability to modeling law enforcement data, and propose paths for future research.

1.1. Crime Theory

Rational criminal theory assumes that individuals have specific reasons for committing a crime at a certain time and a certain place (Clark, 1980). The underlying assumption is that there are patterns to the historical criminal activity data within a spatial region (Brantingham and Brantingham, 1984). Spatial choice models offer analysts a methodology for identifying a criminal's preference for one site over another within a spatial region.

Spatial choice models assume an actor will select a site (for migration, retail establishment, or criminal event) based on the perceived utility, or worth, of that site from a set of alternatives (Ewing, 1976; McFadden, 1986). The use of spatial choice models nests well within the rational criminal theory since it assumes that spatial point processes involving actors are a result of the actors' mental processes and perceptions (Burnett, 1976). This article expands on the spatial choice problem to examine the impact of both geographic and temporal features on the criminal's site selection (CSS) process.

1.2. Criminal Site Selection

CSS is the process by which a criminal selects the time and space to execute an event based on their preferences (Porter, 2006; Xue and Brown, 2006). Early work on CSS used spatial distances to environmental features and spatial representations of social demographics to examine which locations are preferred by criminals for certain types of crimes (Bannatyne and Edwards, 2003; Liu and Brown, 2003). Rather than using a latitude and longitude to describe each location in a study region, we measure the spatial distance from each location to a set of environmental features such as streets, buildings, entertainment districts, banks, or schools (Huddleston and Brown, 2009).

To estimate the criminal's spatial preferences, we mathematically represent the criminal's site selection process as a binary random variable where Pr $(Y_{s,t} = 1|X)$ is the probability that a crime occurred at a location s at a point in time t given a set of features X. We now model the likelihood of a criminal event at a given location and time as a function of the criminal's preferences for each set of features:

$$\Pr(Y_{s,t} = 1|X) = \frac{\exp[\beta_0 + \beta_1 X_{s1} + \ldots + \beta_k X_{sk}]}{1 + \exp[\beta_0 + \beta_1 X_{s1} + \ldots + \beta_k X_{sk}]} \quad (1)$$

Equation 1 uses a set of features X as a vector of length k for each location s in order to estimate β, a vector of coefficients that represents the criminal's preference for executing a crime at a location with the selected spatial features. Analyzing previous criminal event data enables us to model the criminal's preferences for selecting a certain location in feature-space for executing a crime. Previous research has shown that variations of this feature-space model (FSM) perform as well, or better, than traditional kernel models (Brown et al., 2001; Huddleston and Brown, 2009). However, just as the criminal's preferences for certain locations might change depending on distances to residential districts as compared to entertainment districts, the CSS process can also change depending on the time of day or depending on the temporal proximity to special events (Rossmo et al., 2005; Cohen et al., 2007).

1.3. Spatial-Temporal Pulse Events

Spatial-temporal pulse events are special events that are correlated with changes in the crime rates within a spatial region for a limited temporal interval. Pulse events may be known "one-time" events such as elections, school openings, or a major concert in a large urban venue. Additionally, pulse events may also include "recurring events" such as sporting events or weekly prayer meetings. Whether a recurring or one-time event, a pulse event is correlated with a shift in the spatial distribution of crimes across the region for a brief temporal interval. This type of analysis proceeds from the work of (Enders and Sandler, 2006) in defining the impact of intervention to patterns of terrorism.

To identify spatial-temporal pulse events, we use a two-step methodology that first examines the relationship between crimes rates and special events within a specific temporal horizon. The cross-correlation function (CCF) quantifies the strength of the relationship these special events might have on the criminal's site selection process. By comparing the criminal event time series with a time series built upon knowledge of special events, we identify potential spatial-temporal shifts in the site selection process that reflect increased opportunities for the criminal. The CCF is the statistical measure of the relationship between these two time series. We mathematically define the CCF using the notation provided by (Chatfield, 1975):

$$\rho_{wy}(\tau) = \frac{\gamma_{wy}(\tau)}{\sqrt{\gamma_{ww}(0)\gamma_{yy}(0)}} \quad (2)$$

This function measures the correlation between our incident time series Y_t and our potential pulse event, or special event, time series $W(t+\tau)$.

But the CCF does not identify the spatial impact of a pulse event on the CSS process. The second step in our methodology uses the geographic mean center to compare the distribution of the crime clusters within the pulse event temporal interval to previous temporal intervals (Unwin, 1981). We estimate the mean center of criminal events by calculating the mean x and y using the spatial coordinates of the event data. If during the temporal interval of the special event, the spatial distribution of criminal activity shifts from the normal geographic mean center, we hypothesize that the presence of the special event causes a shift in the CSS process. In Section 2, we expand Equation 1 to account for these spatial-temporal shifts in the CSS process by using hierarchial modeling.

1.4. Agent Based Simulation for Crime Studies

The crime simulation work presented by (Liu et al., 2005) served as the foundation for this research. Using a cellular automata approach, the authors simulate real crime patterns in an urban area. Section 2 provides additional details on the adaptations made to the work of Liu, et al. for this article. Additional research examines how agent based models integrated with geographic information systems (GIS) provide four unique relationships for interaction; identity, temporal, casual, and topographical (Brown et al., 2005). For this article, we focus mainly on the temporal and topographical interactions between the criminal agents as they relate to the site selection process used to select the time and space for crime. However, the criminal agent needs to encounter other agents for a criminal event to occur. Building on the conceptual model of "convergence", we develop the likelihood of a criminal act based upon the criminal agent's preferences for certain spaces at certain times given the presence of a target, or victim, agent (Groff, 2007).

2. METHODOLOGY

Although the feature-space model (FSM) introduced in Equation 1 has been shown to be effective in estimating criminal activity, the FSM does not account for changes in a criminal's site selection process as a result of special events. For this article, we use a small agent based simulation to create an environment where the introduction of special events impacts on the criminal agents' preferences for certain locations in feature-space. The remainder of this section describes the simulation model, reviews the research design, and introduces a hierarchical framework for Equation 1 that accounts for changes in the criminal site selection process during temporal intervals with special events.

2.1. Model Description

Beginning with an agent based model used to examine relationships between citizens, violent actors and protectors (Huddleston et al., 2008), we create a small spatial region using the simulation software NetLogo to simulate temporal patterns within a criminal's site selection process. We identify six features within the spatial region to represent entertainment and business sectors. We populate the spatial region with only two breeds of agents: criminals and citizens. We base the ratio of criminals to citizens on empirical results from previous criminal studies with an adjustment in scale to match the limited spatial region of the simulation (Meeker et al., 2002).

2.1.1. Agents

We begin each simulation run with the citizen agents randomly distributed across the region with assigned home, work, and entertainment locations. Throughout the simulation, each citizen agent moves from their home location to their work, or entertainment, location with varied temporal patterns. The criminal agents begin each simulation in four distinct regions. Each criminal agent has a specified length of time for moving amongst the population. Within each daily temporal interval, the interaction between a criminal and citizen agent triggers the criminal agent's site selection process. If the criminal agent is sharing a location with more than one citizen, no crime will occur. Multiple citizen agents collocated at one location serve as defacto guardians. However, if a criminal agent shares a location with only one citizen, the criminal agent is more likely to initiate a crime if the location matches his preferences.

2.1.2. Simulation Scenarios

Although the criminals have separate spatial regions, they have a similar site selection process related to event initiation. During the week, the business districts serve as attractors to criminal activity. Given a convergence event between a criminal agent and a solo citizen, the criminal agents are more likely to initiate a crime if they are closer to the business districts. During the weekend interval, the business districts serve as repellers to criminal activity and the entertainment districts serve as attractors. For each simulation run, we introduce a series of special events that serve as spatial-temporal pulse events to the criminal agent's site selection process. During the temporal intervals of the special events, entertainment district three becomes the primary attractor for criminal activity. As criminal agents encounter solo citizens, they are more likely to commit a crime if they are closer in distance to entertainment district three.

Figure 1 offers a visual depiction of one simulation run including the preference for a spatial-temporal shift to entertainment district three during temporal intervals with special events. The white squares indicate crime events occurring on the 7th day of the weekly pattern. The black squares indicate criminal events that occur during the remainder of the weekly interval. The red squares indicate the crimes that occur on the day of the simulated cultural events. While the majority of the events associated with the simulated special event happen in the upper right quadrant vicinity entertainment district three, criminal agents still have a probability of executing a crime in areas that match their site selection preference.

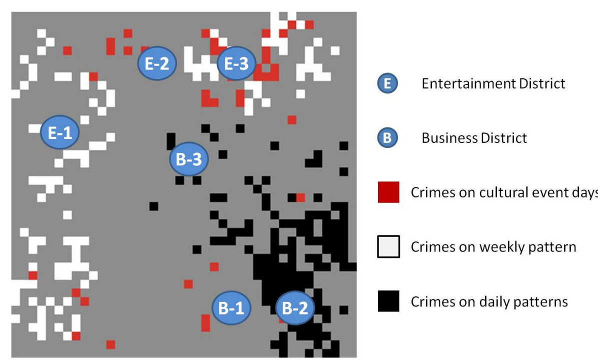


Figure 1. Sample simulation run with weekly crime patterns and a spatially adjusted crime pattern during temporal intervals with special events

2.2. Research Design

We establish three training and testing scenarios. For each simulation run, we introduce four possible spatial-temporal pulse events across a simulated temporal horizon of 120 days. We isolate the criminal events on each special event day to include the preceding seven days. We use the eight day interval around the first special event as the first training set. For each simulation run, we record a vector $Y_{s,t}$ such that a value of 1 indicates the presence of a crime at a location s at a point in time t while the value of 0 indicates the absecnece of crime. Using both the feature-space model from Equation 1 and the hierarchical model introduced in the subsequent section, we estimate the criminal agent's preference for a series of predictor features. We then evaluate each model against a test set using the eight day interval surrounding the second special event. The second training set includes the simulated data from both the first and second special events and predicts against the eight day period that includes the third special event. We build the final training set using the eight day windows preceding the first three special events and test against the final special event. Each test set represents a possible 12,800 possible space-time blocks for a criminal agent to consider as part of their site selection process in an eight day period that includes the programmed special event. Much as the feature-space model accounts for spatial preferences of the criminal agents by using distances to specific features, we hypothesize that modifying the feature-space model to include temporal distances from special events will account for the changes in criminal site selection motivated by the changes in activity surrounding the special event.

2.3. Hierarchical Feature-Space Modeling

In order to incorporate temporal distances from special events, we modify the FSM of (Brown et al., 2001) to include a hierarchical framework that accounts for temporal changes in a criminal actor's spatial preferences (Gelman and Hill, 2007; Huddleston and Brown, 2009):

$$\Pr\left(Y_{s,j}=1|X\right)=\frac{\exp\left[\alpha_j+\beta_{1j}X_1+\ldots+\beta_{6j}X_6\right]}{1+\exp\left[\beta_0+\beta_{1j}X_1+\ldots+\beta_{6j}X_6\right]}$$
$$\text{for } j=1,\ldots,\text{ temporal interval} \tag{3}$$

The above notation indicates that the probability of a criminal executing an event ($Y_{s,j}=1$) at a specific location s during a temporal interval j is a function of the six predictor features $x_1,\ldots,x_6$ that are the spatial distance to each business and entertainment district. β is a vector of coefficients that models the dynamic (changing in time) preferences for certain spatial features based on the temporal proximity to the special events. For this article, we set the temporal interval as the seven days preceding the special event such that $j=8$. A value of $j=1$ indicates the day of the special event. We are now modeling how the criminal agent's site selection process changes based on the decreasing temporal distance to the pulse event. This hierarchical feature-space model (HFSM) uses the temporal distance in days as the multilevel component. We continue to account for the distance to the location of the special event since we retain entertainment district three as one of the six features.

3. RESULTS

Since we know the criminal agent rule set contains a spatial shift within the temporal interval of the special events, we hypothesis that the cross-correlation function and the geographic mean center analysis will identify this relationship. The remainder of this section reviews the application of the two-step methodology and explores the performance of the hierarchical feature-space model in predicting changes in criminal activity using the simulated crime data.

3.1. Initial Analysis

Aggregating the simulated crime event data at the daily level allows us to examine the relationships between the presence of "a-priori" special events and the potential spatial-temporal preferences within the criminal agent's site selection process. Figure 2(a) depicts a daily count of crimes from one run of the simulation with four days acting as pulse events. The red line indicates the daily crime average over the entire run of the simulation. The blue line depicts the days of the simulation with the special event. Using the CCF, we examine the relationship between our daily time series data with the simulated special event time series data. Figure 2(b) depicts the visual result for the CCF exploration of the simulated crimes with the pulse event time series. The distinct spike in the CCF strongly supports the hypothesis of a relationship between the two time series.

While the CCF helps identify relationships between potential pulse events and temporal shifts in the criminal's site selection preference, we use the geographic mean center as a basic measure of central tendency to calculate changes in the spatial distributions over the temporal intervals. Figure 3 depicts the three distinct mean centers for crime clusters from the simulation based on the temporal patterns of weekly periodicity, daily activity, and the spatial-temporal pulse event.

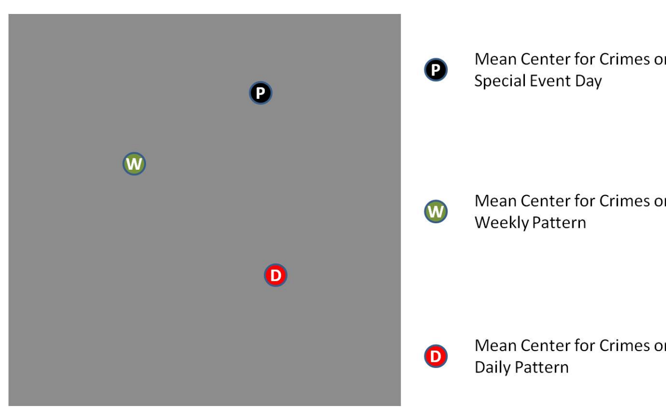
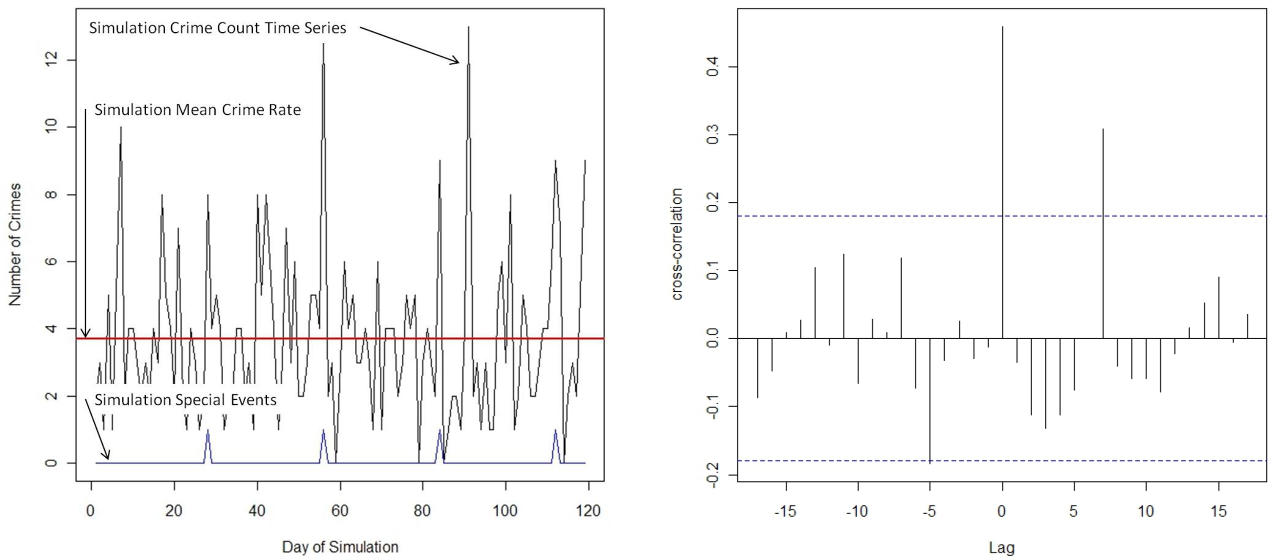


Figure 3. Geographic Mean Centers of Crime Clusters Based on Shifts in Criminal Agent Site Selection

The initial analysis identifies potential space and time pat-



(a) Time Series of One Simulation Run

(b) Cross Correlation for Simulated Crimes with Pulse Events

Figure 2. Time Series and Cross Correlation Plots

terns in the criminal agents' site selection process. Taking the temporal patterns found with the CCF and the spatial component identified with the mean center calculations, we adjust the hierarchical framework around the feature-space model to account for the impact of the spatial-temporal pulse event.

3.2. Exploratory Analysis

Using the hierarchical feature-space model (HFSM) from Equation 3, we generate predictive threat surfaces that offer promise for improving resource allocation especially with regards to the day of the pulse events. Significant change is seen with the HFSM for identifying shifts in criminal activity and an overall area reduction of the high threat space for the day of the pulse event. Figure 4 provides a clear view of how the HFSM adapts to the temporal patterns in the criminal agents' site selection process. Although the base feature-space model (FSM) accurately identifies three primary areas of high crime probability, the HFSM accounts for the temporal changes of the criminal agent's site selection process. The HFSM threat surface accurately identifies the northwest quadrant vicinity entertainment district three as the most likely area for crime on the day of the special event. Of special note is how the HFSM also accounts for the periodicity patterns in the criminal agents' site selection process by identifying both the daily and weekly patterns.

To compare the performance of the HFSM to the base FSM without temporal information, we use the surveillance plot. Similar to the receiver operating characteristic curve (ROC) developed in World War II, the surveillance plot allows us to compare the ability of a model to accurately predict the occurrence of crime while minimizing the number of false positive predictions (Swets et al., 2000; Gorr, 2009). We build the surveillance plot by plotting the rate of accurate crime predictions against the rate of crime incidents predicted where crimes did not occur.

Figure 5 depicts a space-time surveillance plot and measures the % of the possible space-time blocks covered within the study region across the study horizon. The HFSM is in red and clearly dominates the base FSM in black especially within the first 20% of the space-time area. We quantify the difference in predictive performance by calculating the area under the curve for the two surveillance plots (Sing et al., 2005). Overall, the HFSM offers a 18% improvement in accuracy over the base FSM without temporal information.

Using the surveillance plot, we further examine model performance by focusing on how each model accurately identifies potential crimes in time and space. Using the partial area under the curve measure for the first 20% of the space-time area, we provide the law enforcement analyst with a measure that aids in resource allocation. Similar to the false positive point of interest introduced by (Kewley and Evangelista, 2007), a high partial area under the curve measure of the surveillance plot identifies a model which is more accurate in the higher threat areas. Given this information, law enforcement personnel can select the model with the low-

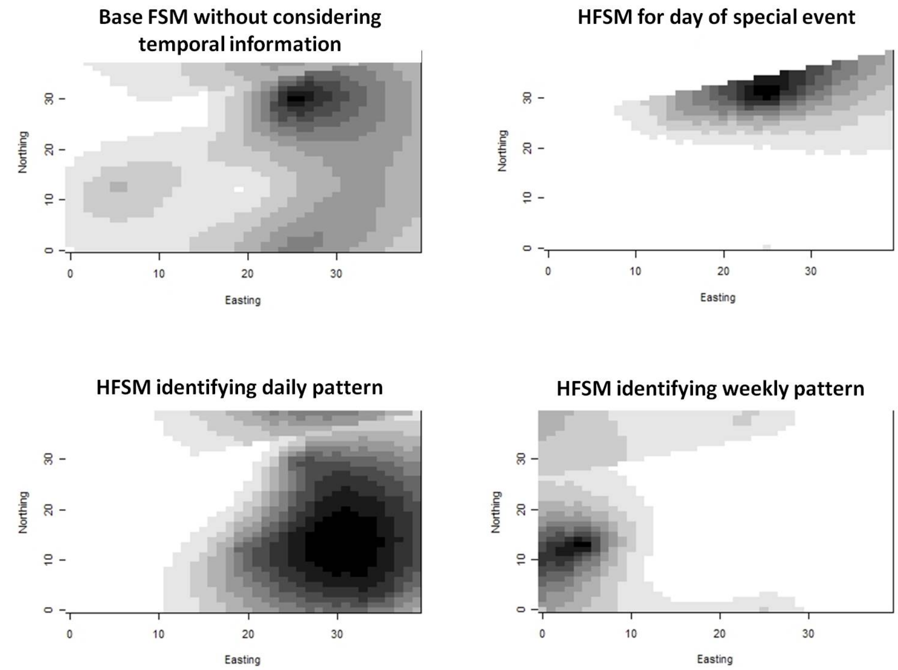


Figure 4. Comparison of Threat Surfaces from HFSM and the Base FSM without Temporal Features. Areas with higher probability of crime are shown with darker colors. The HFSM provides law enforcement personnel with a more focused threat surface to assist with resource allocation in high threat areas for specific temporal intervals.

est threat surface for the temporal interval surrounding the spatial-temporal pulse event.

Table 1. Partial area under the curve for surveillance plots of each modeling method

Training Events	Base FSM	HFSM
1 Event	0.034	0.041
2 Events	0.0163	0.0261
3 Events	0.0108	0.0326

Table 1 depicts the accuracy of the HFSM across all three scenarios for a sample simulation run. Regardless of the size of the training set, the HFSM offers better predictive performance on each test set when compared to the base feature-space without temporal information. And while the partial area under the curve measure seems higher for the first test set, the greatest improvement in performance is seen when using information from the three initial pulse events to predict against the fourth pulse event window. On the final test set, the HFSM offers significant improvement over the model built without considering temporal information. The performance of the HFSM over the base FSM holds across multiple simulation runs with varied special event locations and temporal patterns.

4. CONCLUSIONS

This article expands the use of agent-based modeling to generate a series of scenarios replicating a criminal site selection process impacted by the presence of spatial-temporal pulse events. The agent-based crime simulation model enables us to integrate varied temporal patterns into the criminal site selection process while still allowing for the probabilistic nature of crime. Using the data from these scenarios, we demonstrate the effectiveness of a new modeling approach that provides insight to both the spatial *and* temporal patterns within the criminal site selection process.

The two-stage analytical process suggested by (Schabenberger and Gotway, 2005) identifies the spatial-temporal impact of the simulated pulse events. We use the cross correlation function to identify potential relationships between our simulated crime time series and a time series of special events. Using the geographic mean center conditioned on the temporal windows surrounding the special events helps us in identifying changes in the spatial distribution of the simulated criminal activity. We compare the performance of the base feature space model with the hierarchical feature space model against a series of three training and test sets for multiple simulation runs. While the HFSM outperforms the base model across all three scenarios, the most significant gain comes with using training data aggregated across multiple pulse event windows to develop a predictive model. Against

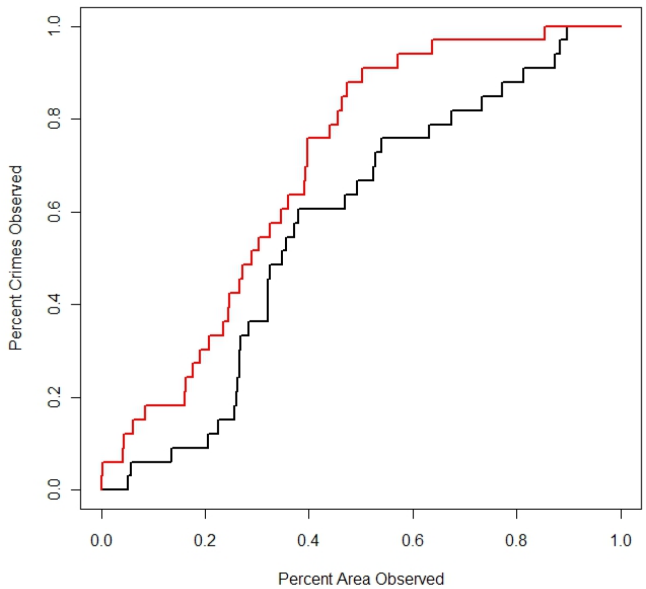


Figure 5. Surveillance Plot - HSFM (red line) versus Base FSM (black line) without Temporal Information

the simulated data, the HFSM provides an 18% improvement in predictive accuracy when compared to the performance of the base FSM without temporal information.

While the use of the simulation model demonstrates that this new modeling approach provides law enforcement personnel with a framework for identifying and understanding the impact of special events on spatial-temporal crime patterns, several challenges remain. The simulation developed for this article, while based loosely on empirical data, would benefit from integration with a geographical information system. Similar to the work of (Groff, 2007), the use of Agent Analyst software for simulation development would allow a more realistic depiction of identified criminal site selection preferences (Liu and Brown, 2003). Integrating both spatial and demographic information into the criminal agent utility function would also assist with sensitivity analysis between simulation variables and crime event patterns.

REFERENCES

Bannatyne, J. C. and H. P. Edwards (2003). A Bayesian explorations of the relationship between crime and unemployment in New Zealand for the time period: 1986-2002. In *International Workshop on Bayesian Data Analysis*, Santa Cruz.

Brantingham, P. J. and P. L. Brantingham (1984). *Patterns in Crime*. New York: Macmillan Publishing Company.

Brown, D. E., H. Liu, and Y. Xue (2001). Mining preferences from spatial-temporal data. In *Proceedings of the SIAM Conference*, Chicago. Society for Industrial and Applied Mathematics.

Brown, D. G., R. Riolo, D. T. Robinson, M. North, and W. Rand (2005). Spatial process and data models: Toward integration of agent-based models and gis. *Journal of Geographical Systems 7*, 25–47.

Burnett, P. (1976). Behavioral geography and the philosophy of mind. In R. Golledge and G. Rushton (Eds.), *Spatial Choice and Spatial Behavior*, pp. pp. 23–50. Columbus: Ohio State University Press.

Chatfield, C. (1975). *The Analysis of Time Series: Theory and Practice*. London: Chapman and Hall.

Clark, R. V. (1980). Situational crime prevention: Theory and practice. *British Journal of Criminology*, 136–147.

Cohen, J., W. Gorr, and A. Olligschlaeger (2007). Leading indicators and spatial interactions: a crime forecasting model for proactive police deployment. *Geographical Analysis 39*, 105–127.

Enders, W. and T. Sandler (2006). *The Political Economy of Terrorism*. Cambridge: Cambridge University Press.

Ewing, G. O. (1976). Environmental and spatial preferences of interstate migrants in the United States. In R. G.

Golledge and G. Rushton (Eds.), *Spatial Choice and Spatial Behavior*, pp. pp. 250–270. Columbus: Ohio State University Press.

Gelman, A. and J. Hill (2007). *Data Analysis using Regression and Multilevel / Hierarchical Models*. Cambridge: Cambridge University Press.

Gorr, W. L. (2009). Forecast accuracy measures for exception reporting using receiver operating characteristic curves. *International Journal of Forecasting 25*(1), 48–61.

Groff, E. R. (2007). Situating simulation to model human spatio-temporal interactions: An example using crime events. *Transactions in GIS 11*(4), 507–530.

Huddleston, S. and D. E. Brown (2009). A statistical threat assessment. *Systems, Man, and Cybernetics, Part A. 39*, 1307–1315.

Huddleston, S., G. Learmonth, and J. Fox (2008). Changing knives into spoons. *Systems and Information Engineering Design Symposium 2008*, 255–260.

Kewley, R. H. and P. Evangelista (2007). Evaluating machine learning methods for geospatial prediction problems. being prepared for submission to IEEE.

Liu, H. and D. E. Brown (2003). Criminal incident prediction using a point-pattern based density model. *International Journal of Forecasting 19*, 603–622.

Liu, L., X. Wang, J. Eck, and J. Liang (2005). Simulating crime events and crime patterns in a RA/CA model. In F. Wang (Ed.), *Geographic Information Systems and Crime Analysis*. Hershey, PA: Idea Group Publishing.

McFadden, D. (1986). The choice theory approach to market research. *Marketing Science 5*, 275–297.

Meeker, J. W., K. J. Parsons, and B. J. Vila (2002). Developing a gis-based regional gang incident tracking system. In S. H. Decker and W. L. Reed (Eds.), *Responding to Gangs: Evaluation and Research*, pp. 289–329. Washington DC: National Institute of Justice.

Porter, M. D. (2006). *Detecting Space Time Anomalies in Point Process Models of Intelligent Site Selection*. Ph. D. thesis, University of Virginia, Charlottesville.

Rossmo, K., I. Laverty, and B. Moore (2005). Geographic profiling for serial crime investigation. In F. Wang (Ed.), *Geographic Information Systems and Crime Analysis*, pp. 137–152. Hershey: Idea Group Publishing.

Schabenberger, O. and C. A. Gotway (2005). *Statistical Methods for Spatial Data Analysis*. Boca Raton: Chapman and Hall / CRC.

Sing, T., O. Sander, N. Beerenwinkel, and T. Lengauer (2005). ROCR: Visualizing Classifier Performance in R. *Bioinformatics 20*, 3940–3941.

Swets, J. A., R. M. Dawes, and J. Monahan (2000, October). Better decisions through science. *Scientific American 283*(4), 82–87.

Unwin, D. (1981). *Introductory Spatial Analysis*. London: Methuen.

Xue, Y. and D. E. Brown (2006, March). Spatial analysis with preference specification of latent decision makers for criminal event prediction. *Decision Support Systems 41*, 560–573.

Biography

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Donald E. Brown is a Professor of the Department of Systems and Information Engineering, University of Virginia. He received the B.S. degree from the United States Military Academy, West Point, the M.S. and M.Eng. degrees in operations research from the University of California, Berkley, and the Ph.D. degree in industrial and operations engineering from the University of Michigan, Ann Arbor. He is a Fellow of the IEEE and a past President of the IEEE Systems, Man, and Cybernetics Society. He is the recipient of the Norbert Wiener Award for Outstanding Research and the IEEE Millennium Medal. His research focuses on data fusion, statistical learning, and predictive modeling with applications to security and safety.