

# The Impact of Hurricanes on Crime: A Spatio-Temporal Analysis in the City of Houston, Texas

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**ABSTRACT:** The impact that natural disasters have on crime is not well understood. In general, it is assumed that crime declines shortly after the disaster and slowly increases to pre-disaster levels over time. However, this assumption is not always confirmed by the few empirical studies that have been conducted to date. In this paper we analyze the impacts that Hurricane Rita, and for the purpose of comparison, Hurricane Katrina had on the temporal and spatial distributions of reported crimes in the city of Houston, TX. Crime data were collected before, during, and after the landfall of both hurricanes. The modeling part of this paper focused on primarily spatio-temporal and local regression models at the local scale. Spatio-temporal models were applied to identify potential spatio-temporal crime clusters associated with the hurricanes. A local regression model in the form of a geographically weighted regression was applied to explore relationships between crime clusters and possible underlying factors leading to the creation of said clusters.

The results show that while Hurricane Katrina did not have any apparent impact on crime, Hurricane Rita led to a significant short-term increase in burglaries and auto thefts. The most important result was the identification of a large, highly significant spatio-temporal burglary cluster located in the northeastern part of Houston. This cluster lasted from a few days before to a few days after the landfall of Hurricane Rita. Empirical evidence was found that the mandatory evacuation order that was issued prior to the arrival of Hurricane Rita led to a short-time spike in burglaries. It was assumed that these crimes were committed by individuals who did not follow the evacuation order, but instead burglarized the residences of individuals who did evacuate. No mandatory evacuation order was issued for Hurricane Katrina. Altogether, three variables including the percentage of African Americans, the percentage of persons living below the poverty level, and the distance to the nearest police station was identified as having a positive relationship with the increase in burglaries associated with Hurricane Rita

**KEYWORDS:** hurricanes, crime, spatio-temporal analysis, geographically weighted regression, Houston

## Introduction

Between 1999 and 2005, the yearly crime totals in the city of Houston, TX ranged between 130,000 and 150,000, with crimes moderately increasing during this time period. This paper investigates the impact that natural disasters, specifically hurricanes have on the spatial and temporal distributions of crimes at the local scale, and possible explanations for this impact. In general, it is believed that crime generally trends downward during the recovery stage, with the exception of domestic violence (Enarson 1999; Tucker 2001), and gradually returns to pre-disaster levels during the reconstruction stage (Leitner et al. 2011). The downward trend during the recovery stage is due in

part to emergent pro-social behaviors which create an atmosphere of altruism among the members of the community (Quarantelli 1970; Drabek and McEntire 2003). Cromwell et al. (1995) refers to this behavior as informal guardianship. It is speculated that in the case of post-Katrina New Orleans, the presence of a large number of National Guard troops and the influx of billions of dollars in governmental aid have contributed to the reduction in crime rates (Roman, Irazola, and Osborne 2007). After some time, the altruism of the community fades away and crime returns to pre-disaster levels (Bailey 2009). One phenomenon that has attracted much attention in the literature is whether looting occurs during the emergency stage of a disaster. Some researchers argue that the belief that citizens will begin looting simply because the opportunity presents itself in the wake of a disaster is a myth and largely promulgated by media reports (Quarantelli 1970; Wenger and Friedman 1986; Sunseri 2005). In contrast, other researchers believe that looting following a domestic disaster is not a myth (Frailing and Harper 2007), or

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they found support both for and against the “looting myth” (Manusinghe 2007).

Until today, just a handful of empirical studies exist that have tested whether the different theories expressing the relationship between crime and natural disaster can be supported. Of those, quite a few have investigated the impact of Hurricanes Katrina and Rita on crime in New Orleans, or other major cities directly “hit” by either one or both hurricanes, for example Houston, and/or receiving large numbers of New Orleans evacuees, for example Atlanta, Baton Rouge and Houston (Leitner et al. 2011). Of all studies, most of them are small-scale, time-series analysis, usually covering a multi-year time period, focusing exclusively on a single urban neighborhood. One exception is the study by Bass (2008) which compared crime trends in New Orleans with crime trends in ten major evacuation cities, and ten other cities of similar size that did not receive large numbers of evacuees from New Orleans after Hurricane Katrina. In addition, the focus of empirical studies is on one crime type, only (Frailing and Harper 2007; VanLandingham 2007; 2008) or on several different crime types (Wenger and Friedman 1986; Cromwell et al. 1995; Suar and Kar 2005; Lawton and Schulenburg 2007; Munasinghe 2007; Bailey 2009; Leitner and Helbich 2009). Most studies discuss changes in crime during the emergency and reconstruction stages with the length of both stages depending on the severity of the disaster. According to Kates et al. (2006) the emergency stage for New Orleans after Katrina is the longest on record at six weeks, while the reconstruction stage is predicted to last for about eight to eleven years. The study by Leitner et al. (2011) is the only large-scale study to date that investigates the relationship between one specific natural disaster (Hurricane Katrina) and crime in both urban and rural parishes of Louisiana. The same study also discussed violent and non-violent crime trends, both temporally and spatially during the four stages of a disaster: mitigation, preparedness/planning, emergency/recovery, and during reconstruction in both the hardest hit areas of Orleans Parish and neighboring parishes, and in areas outside this disaster zone that received large numbers of evacuees. In contrast the study presented here investigates the spatial and spatio-temporal impact that Hurricane Rita has on the spatial and spatio-temporal distributions of crime at the local scale in an

urban area, in this case Houston, TX. In addition, possible reasons for the change in certain crime types associated with the landfall of Hurricane Rita will be provided.

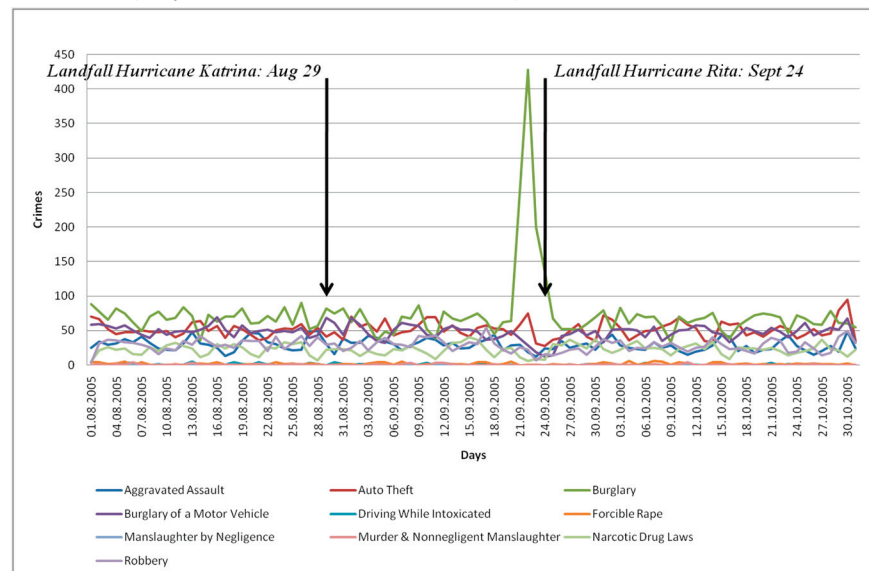
### Study Area and Data

The study area comprises of the jurisdiction of the Houston Police Department (HPD), which is located inside Harris County, one of 254 counties in the state of Texas. Crime data for this study area were downloaded from the Houston Police Department (HPD) website (<http://www.houstontx.gov/police/cs/stats2.htm>). The HPD is one of the ten largest police departments in the U.S., serving a population of over two million residents, and covering an area of approximately 600 square miles. Over 5,500 sworn full-time police officers and over 1,500 non-sworn full-time employees work for the HPD (Lawton and Schulenburg 2007).

Crime data were downloaded for the entire months of August, September, and October 2005. This time period covered several weeks before, during, and after the landfall of both Hurricane Katrina (August 29th) and Hurricane Rita (September 24th). The data included the offense date and time, offense type, police beat, and the address of the offense at the street block level. This allowed the geo-coding of crime locations using the TIGER street network data available from the U.S. Census website (<http://www.census.gov/geo/www/tiger/index.html>). Of the 26,746 crimes that occurred during the three-months time period, 25,092 (93.8%) were successfully geo-coded. As expected, the geo-coding rate varies by police district and ranges from a high of 100% to a low of 77%.

When creating a time series of daily crime totals for the three-months time period for all ten crime

**Figure 1.** Time series of ten different crime types for Houston, TX from August 1 - October 31 2005 (adapted from Leitner and Helbich 2009)

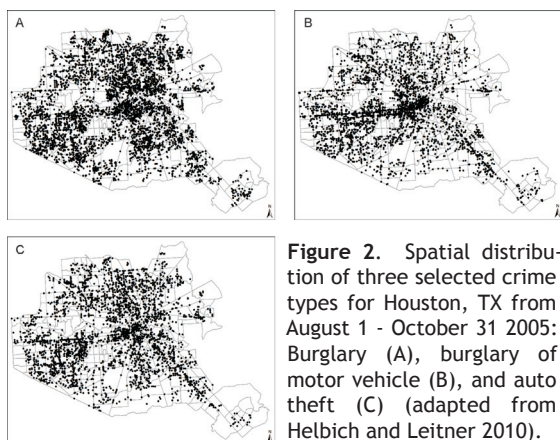


types, an intriguing feature is revealed, namely a significant spike in burglaries contemporaneous with the largest ever mandatory evacuation in Houston's history, approximately 40% of the total population due to approaching Hurricane Rita (Figure 1). Recall that Hurricane Rita made landfall on September 24. The significant increase in burglary cases lasted four days. It started on September 21 with 251 burglaries, reached a high of 428 burglaries on September 22, decreased to 200 burglaries on September 23, decreased further to 135 burglaries on September 24 and returned to pre-hurricane levels on September 25 with 67 burglaries. There was also a minor spike in auto thefts with a high of 75 cases on September 22. All other crime types show a slight decrease in daily totals during the evacuation period for Hurricane Rita (Figure 1). In contrast, no mandatory evacuation order was issued for Hurricane Katrina. This may be the main reason that no apparent change in the daily totals for any of the ten crime types can be observed before, during, and after Hurricane Katrina made landfall on August 29 (Figure 1) (Leitner and Helbich 2009). The spatial distribution of the three crime types, including burglary (n= 6,730), burglary from a motor vehicle (n=4,378), and auto theft (n=4,767) for the three-months time period is shown in Figure 2. While the spatial patterns of all three crime types seem to be similar, a visual interpretation and comparison is clearly limited.

In the discussion that follows, the main methods used in this research will first be discussed at a conceptual level and then applied to analyze the crime data that were collected for Houston from August 1 through October 31, 2005. The focus of the analysis will be on local techniques, since crime is mostly a local phenomenon and both crime and crime inducing factors and their relationship change across space. Such non-stationarity can only be captured with local techniques.

## Spatio-Temporal Cluster Methods

During the past few years, geographic information systems (GIS) and spatial statistical methods, including



**Figure 2.** Spatial distribution of three selected crime types for Houston, TX from August 1 - October 31 2005: Burglary (A), burglary of motor vehicle (B), and auto theft (C) (adapted from Helbich and Leitner 2010).

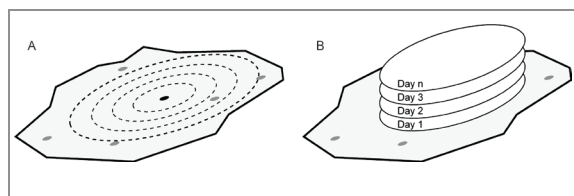
spatial cluster methods, have become increasingly important in spatial crime analysis (Eck et al. 2005). A variety of explorative and inferential methods exist for the analysis of spatio-temporal crime patterns for spatial point distributions. Such patterns include global statistics (Knox and Bartlett 1964; Mantel 1967; Diggle et al. 1995; Jacquez 1996), which evaluate the point pattern across the entire study area and local methods (Kulldorff et al. 1998; Takahashi et al. 2008), which allow to detect and quantify individual spatio-temporal clusters. From a statistical point of view, a spatial cluster is a spatially bounded group of cases of sufficient size and concentration to be unlikely to occur by chance alone (Knox 1989).

Kulldorff's scan statistic is a state-of-the-art method for the detection and evaluation of spatial, temporal, and spatio-temporal clusters (Kulldorff 1997; Kulldorff et al. 1998). Many applications can be found in the medical profession, especially epidemiology, with the focus on the identification of purely spatial clusters. Several studies (e.g., Kulldorff et al. 2003; Song and Kulldorff 2004) have emphasized the performance and efficiency of this statistic. Fewer applications have used the spatio-temporal scan statistic (Kulldorff et al. 1998), although it can be used in a prospective fashion or for prospective surveillance. Examples are Kulldorff et al. (1998), Elias et al. (2006), and Gaudart et al. (2006). While few applications of the scan statistic to model spatial clusters in criminology exist (Jefferis 1998; Ceccato and Haining 2004; Ceccato 2005), we do not know of any examples in the criminology literature using the spatio-temporal scan statistic to identify spatio-temporal crime clusters. In general, Kulldorff's statistics are popular because they can be adapted to different data types and probability models, such as the Poisson model (Kulldorff 1997), exponential model (Huang et al. 2007), and multinomial model (Jung et al. 2010). The following discussion focuses on the retrospective scan statistic with a spatio-temporal permutation probability model to detect significant spatio-temporal clusters (Kulldorff et al. 1998).

The input data for this model are the coordinates of the crime locations and their time stamps. No additional information, such as the population-at-risk or a background population is needed. The main reason is that the Poisson model used in this analysis is based on crime incident locations and not on rates. Clearly, crime rates could have been calculated with the available data for most of the time period that was analyzed. However, no information was available about the percentages of evacuated residents associated with the mandatory evacuation order issued ahead of Hurricane Rita for the different neighborhoods in Houston.

The scan window is a three-dimensional cylinder with the base area representing the spatial dimension (Figure 3, left) and the height the temporal dimension (Figure 3, right) of potential clusters. During the analysis, the cylindrical window moves from one

crime location to the next and continuously changes the radius of the base area and its height, allowing the detection of differently sized clusters. This results in a large number of differently sized and shaped overlapping cylinders, each representing a possible cluster of a different size. Kulldorff et al. (1998) recommend limiting the maximum size of the search window to 50% of the total number of incidents and to half of the length of the entire time period. For each possible cluster the observed number of crime locations is compared with the expected number of crime locations using a spatio-temporal permutation model. In general, a spatio-temporal cluster is identified by a cylinder that includes a significantly larger number of observed crime locations than



**Figure 3.** The two basic components of the scan statistics: Spatial dimension (A) and temporal dimension (B) (adapted from Tuia et al. 2009).

would be expected by chance for a certain time period.

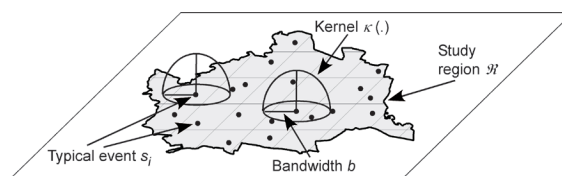
The number of expected crime locations is estimated using a Poisson distribution that exhibits a constant risk over space as well as time. The null hypothesis is thus based on the assumption that no spatio-temporal clustering exists. On this basis a likelihood ratio statistic is calculated for each cluster. The cluster with the highest likelihood ratio statistic is denoted as the most likely cluster and denoted as the primary cluster. This cluster possesses the highest significance. Secondary clusters exhibit lower likelihood ratio statistics and consequently lower statistical significance compared to a primary cluster.

The statistical significance of each cluster is determined by a Monte Carlo simulation. One point of criticism comes from Tango and Takahashi (2005), who argue that most geographic clusters are not circular. This resulted in the extension of the method to an elliptical scan window (Kulldorff et al., 2006) and the implementation of alternative statistics (Tango and Takahashi 2005). Further details about this method can be found in Kulldorff and Nagarwalla (1995), Song and Kulldorff (2003) or Kulldorff et al. (2004).

### Kernel Density Estimation

The kernel density estimation is an interpolation technique that generalizes individual point locations or events,  $s_i$  to an entire area and provides density estimates,  $\hat{\lambda}(s)$ , at any location within the study region  $R$  (Bailey and Gatrell 1995; Burt and Barber 1996; Fischer, Leitner, and Stauffer-Steinnocher 2001;

Knowles and Leitner 2007; Leitner and Helbich 2009). Density estimates are derived by placing a symmetrical surface, called the kernel function,  $\kappa(\cdot)$ , over each event, and summing the value of all surfaces onto a regular reference grid superimposed over the study region (see Figure 4). Typically, a symmetrical kernel function falls off with distance from each event at a rate that is dependent on the shape of the kernel function and the chosen bandwidth,  $b$ . The bandwidth determines the amount of smoothing. Kernel density estimates can also be applied to two different sets of point patterns or events at the same time and this is referred to as dual kernel density estimates. Additionally, density calculations can be carried out for events that are weighted or events that are not weighted (Fischer, Leitner, and Stauffer-Steinnocher 2001; Knowles and Leitner 2007; Leitner and Helbich 2009).



**Figure 4.** Kernel density estimation of a point pattern using the quartic kernel function (courtesy of Fischer, Leitner, and Stauffer-Steinnocher 2001).

### Spatio-Temporal Crime Clusters Using Kulldorff's Scan Statistics

In this study a cylinder with circular base area was used as the scan window. The temporal unit was one day, although a more precise time stamp (minutes and hours) was provided in the original crime data. The coarser temporal unit (day) was chosen because the computing time with a finer temporal unit would have been too long. For example, the computing time was 94 hours for burglaries using a Dell Optiplex 745 Computer with Intel Core 2 CPU 6400, 2.13 GHz, 2 GB DDR2 RAM. The maximum size of the circular base area of the cylinder was set to 50% of the expected crime locations. Similar, the maximum time length was set to 50% of the entire observed time period from August 1 to October 31. All levels of significance are based on 999 Monte Carlo simulations.

In general results show that all crime patterns exhibit a different and heterogeneous spatio-temporal behavior. For burglaries, burglaries of a motor vehicle, and auto thefts the highest number of significant spatio-temporal clusters was found. For this reason the focus of the following discussion is on these three crime types. From all identified clusters, only those that were significant at  $p < 0.1$  were included in Figure 5 and Table 1. Of the 24 spatio-temporal clusters found for burglaries, four had a level of significance of  $p < 0.1$ . All clusters are dominated

by the large cluster C1 ( $p = 0.001$ ) located in the (north) eastern part of the study area. In contrast, the other three significant clusters, C2-C4, are much smaller and located in the center and western part of Houston. Cluster C1 lasts from September 21 to 27, which covers the time-period from several days before and after Hurricane Rita hit the city of Houston on September 24, 2005 (Figure 5 and Table 1).

Spatio-temporal clusters for the burglaries from motor vehicles show a pattern that is quite different from burglaries. While more spatio-temporal clusters (45) and clusters that are significant (8 with  $p < 0.1$ ) were found, none was as large and dominant as the burglary cluster C1. Most of the significant clusters for the burglaries of motor vehicle are located in the center of the study area. The primary cluster C1 and secondary clusters C3-C5 can mostly be found along the Southwest Freeway and Highway 59. Hurricane Katrina did not have any effect on cluster creation in Houston. All significant clusters lasted just a few days and were formed almost two weeks before or more than one week after Hurricane Katrina. The only significant cluster during the mandatory evacuation of Houston due to the approaching Hurricane Rita was cluster C4. This cluster is located almost in the center of the study area and lasted from September 22 to 25 (Figure 5, Table 1). A more detailed study needs to be conducted to find out whether or not this cluster was directly related to the mandatory evacuation. An analysis of auto thefts revealed the occurrence of seven small significant clusters at  $p < 0.1$ . While an overall increase in the total number of auto thefts happened during Hurricane Rita, none of those small significant clusters was found during that time period. Similarly, no significant cluster was identified

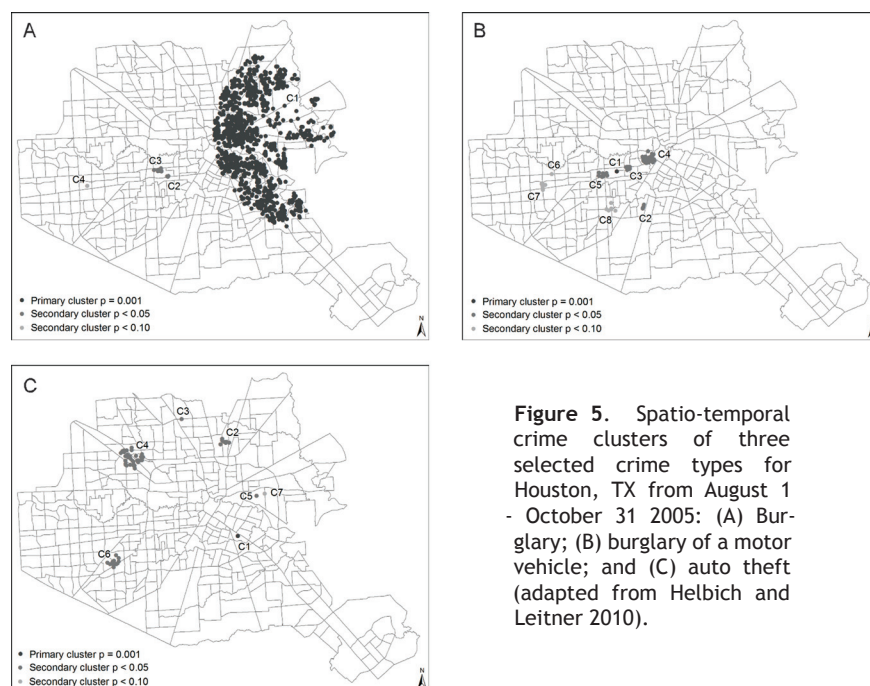
**Table 1.** Selected results from spatio-temporal scan statistic.

Crime Type	Cluster ID	Time Period	P
Burglary (n = 6,730)	C1	9/21 - 9/27	0.001
	C2	10/10	0.012
	C3	9/9	0.018
	C4	8/25	0.051
Burglary of Motor Vehicle (N = 4,378)	C1	8/13 - 8/14	0.001
	C2	9/20 - 9/21	0.001
	C3	9/12 - 9/13	0.002
	C4	9/22 - 9/25	0.002
	C5	9/26 - 9/28	0.048
	C6	9/29 - 9/30	0.061
	C7	10/16 - 10/19	0.070
	C8	9/8 - 9/13	0.099
Auto Theft (n = 4,767)	C1	8/1	0.001
	C2	9/12 - 9/13	0.007
	C3	9/10	0.012
	C4	10/8 - 10/10	0.016
	C5	10/29	0.018
	C6	10/3 - 10/4	0.027
	C7	8/25	0.083

during the landfall of Hurricane Katrina (Figure 5, Table 1). To sum up, the different crime types show a clear and distinct spatio-temporal pattern of clusters with little spatial overlap. This raises the question of the existence of spatio-temporal “crime niches” in Houston.

*Explaining the Overall Increase in Burglaries Associated with the Landfall of Hurricane Rita*

The most intriguing result from the previous section was the identification of a large, highly significant spatio-temporal burglary cluster located in the north-eastern part of Houston and lasting from September 21 through September 27, 2005. In this section, we will try to find out, which variables may have been responsible for the creation of said cluster and the overall increase in burglaries associated with the landfall of Hurricane Rita. For this analysis, eleven different variables from the 2000 U.S. Census, including some socio-economic





**Figure 6.** 2000 % Whites (A); 2000 % African Americans (B); 2000 % Hispanics (C); 2000 % Asians (D); 2000 % civilian labor force that is unemployed (E); and 1999 % persons below the poverty level (F).

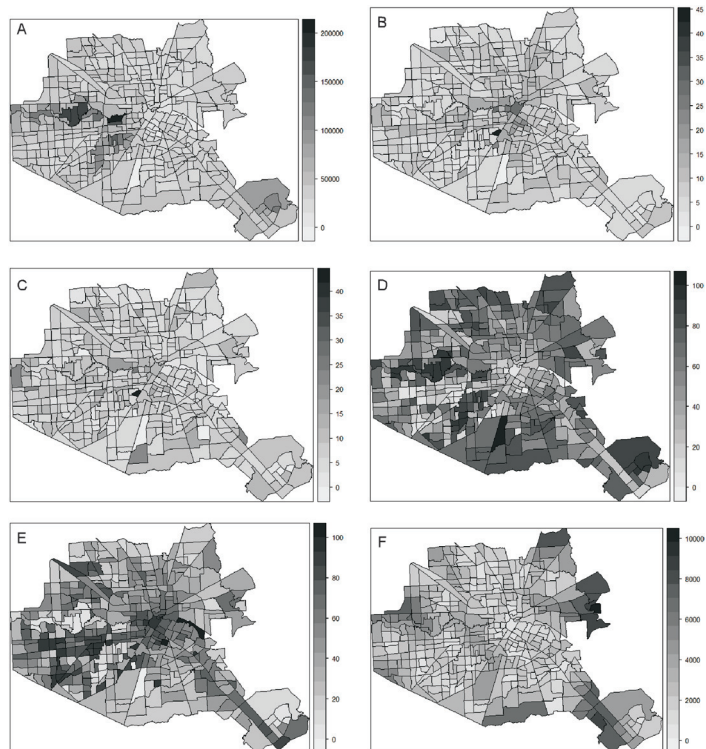
and housing variables, were selected at the census tract level (Figures 6 and 7). A pure visual comparison reveals that the primary spatio-temporal burglary cluster (Figure 5) is located in neighborhoods of Houston with high percentages of African Americans, persons living below the poverty level, and owner occupied housing units. Clearly, this visual comparison is rather limited. In order to better understand the possible reasons for the creation of the primary spatio-temporal burglary cluster and the overall increase in burglaries across Houston, regression analysis was conducted. The eleven socio-economic and housing variables plus one additional variable, namely the (euclidean) distance to the nearest police (sub) station (Figure 7), served as the independent variables. As the dependent variable, a dual kernel density estimate was calculated by subtracting the August 17 burglary incidents from the September 22 burglary incidents (Figure 8). Recall that September 22 marked the highest daily burglary total (428) that occurred during Hurricane Rita's evacuation and two days before Hurricane Rita made landfall. The number of burglaries that happened on August 17, namely 70, represents a typical daily burglary total for Houston during the three

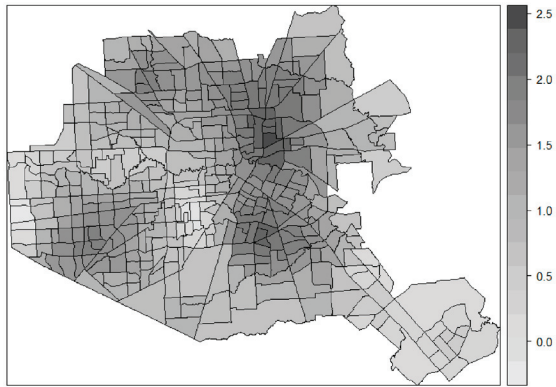
months observation period.

The dual kernel density estimation was calculated in CrimeStat 3.3 (Levine 2010). A quartic kernel function using an adaptive bandwidth with a sample size of 15 burglaries and a cell size of 500m were selected. Resulting density values for each grid cell were subsequently aggregated to corresponding census tracts (Figure 8). We acknowledge that the chosen parameter setting (type of kernel function, bandwidth type, and cell size) was one of many possibilities. For this unique setting, the resulting density surface (Figure 8) shows an increase in burglaries on September 22 (as compared to August 17) in the north, in the east and in a small pocket in the southwestern portion of the study area, partly overlapping with the large, primary spatio-temporal burglary cluster found by Kulldorff's scan statistic (Figure 5).

As expected all twelve independent variables exhibited significant spatial autocorrelation, which is a possible indication of violating the independence assumption of global regression modeling. Using an ordinary least squares (OLS) regression, all twelve independent variables were regressed onto the dependent variable, namely the overall increase in burglaries

**Figure 7.** (A) 1999 median household income in \$1000; (B) 2000 % housing units vacant; (C) 2000 rental vacancy rate; (D) 2000 % owner occupied housing units; (E) 2000 % renter occupied housing units; (F) distance to the nearest police (sub) station.





**Figure 8.** Dual kernel density estimations calculated as the difference between September 22 and August 17 daily burglary incidents.

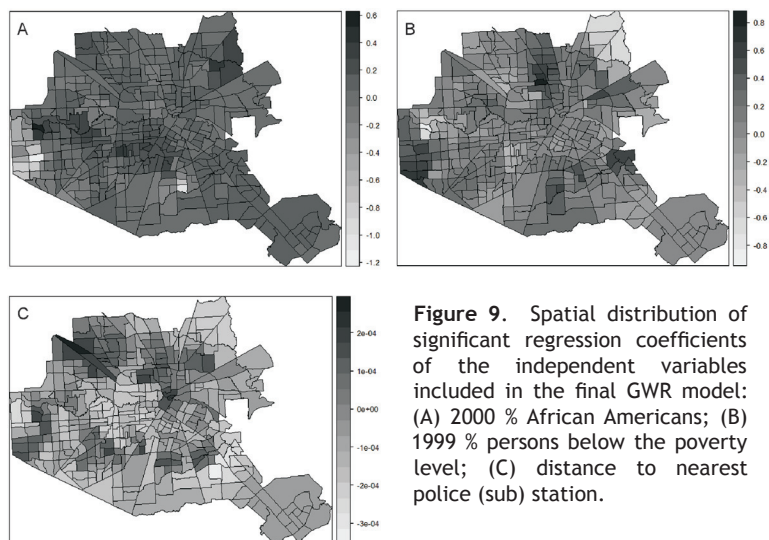
between August 17 and September 22 2005. The number of independent variables was subsequently reduced using the step-wise algorithm and residuals from the resulting model were tested for spatial autocorrelation. The Lagrange Multiplier diagnostics recommended the use of a spatial autoregressive model with an additional lag variable to account for the spatial dependence in the linear model (Anselin 1988). The next step involved the stepwise selection and inclusion of individual independent variables into the spatial lag model. The selection was stopped until all regression coefficients were significant at  $p = 0.1$ . The resulting spatial lag model showed much improvement over the original global OLS regression model, but still included some spatial autocorrelation, which can be the result of spatial heterogeneity. The final step involved running a geographically weighted regression (GWR) (Fotheringham et al. 2002), a local regression model, with the same independent variables as were included in the spatial lag model. While this final model still showed some weak residual spatial autocorrelation, it was the best model that we were able to find. Based on this final model, the following three independent variables plus the intercept had significant regression coefficients with the dependent variable and significant non-stationarity: 2000 % African Americans, 1999 % persons below the poverty level, and distance to nearest police (sub) station (Figure 9).

As expected, the relationship between each of the three independent variables and the overall increase in burglaries between August 17 and September 22 2005 varies across Houston, with the direction of this relationship being both positive and negative. The % African Americans and the % persons below the poverty level exert the strongest

influence on the number of burglaries, the distance to the nearest police (sub) station, exerts the weakest influence. The area in Houston occupied by the large, primary spatio-temporal burglary cluster (Figure 5) shows a mostly positive relationship between any of the three independent variables and the number of burglaries. This means that an increase in % African Americans and % persons below the poverty level results in an increase in the number of burglaries and vice versa. Similarly, a longer (shorter) distance to the next police (sub) station also leads to an increase (decrease) in the number of burglaries.

## Summary and Policy Implications

This paper investigates the influence that (primarily) Hurricane Rita had on the spatio-temporal distribution of crime clusters in the city of Houston, TX. The results show that the distribution of all crime types possesses a spatio-temporal heterogeneous behavior. The most spatio-temporal clusters were found with burglaries, burglaries of motor vehicles, and auto thefts. The most dominant cluster for burglaries lasted from September 21 to 27, which covers the time-span just a few days before and after Hurricane Rita. Factors contributing to this increase in burglaries were also identified in this study and included the percentage of African Americans, the percentage of persons living below the poverty level, and the distance to the nearest police (sub) station. The dominant burglary cluster is located in the (north) eastern part of Houston. One explanation for the creation of this cluster is that despite the issue of a mandatory evacuation before the landfall of Hurricane Rita, only 40% of Houston's population evacuated. Among the residents, who did not follow the evacuation order, were criminals, who then burglarized the temporarily "unprotected" homes of evacuees. This assumption is supported by an



**Figure 9.** Spatial distribution of significant regression coefficients of the independent variables included in the final GWR model: (A) 2000 % African Americans; (B) 1999 % persons below the poverty level; (C) distance to nearest police (sub) station.

important concept from environmental criminology (Brantingham and Brantingham 1981) which states that the number of crimes decreases with increased distance from the offender's anchor point (i.e., the offender's residence). This relationship can be shown with a distance-decay curve and it has been empirically proven many times. In other words, there is a high probability that homes of burglars' and homes being burglarized were located in the same or close-by neighborhoods of Houston. Not a single significant spatio-temporal crime cluster is found for Hurricane Katrina. This may have to do with the fact that no mandatory evacuation order was issued before the landfall of this hurricane.

The results of this empirical study are important for law enforcement for proactive planning and resource distribution in the preparation for a natural disaster. In case of future mandatory evacuation orders, city police should not only focus on planning for and coordinating traffic along evacuation routes. In addition, law enforcement should also place some personnel into specific neighborhoods of the city to watch out for criminal activities, especially burglaries, conducted by criminals, who did not evacuate. One such area that the police should focus on is in the (north) eastern part of Houston, an area mostly occupied by an economically disadvantaged population. The authors of this article are currently repeating this same analysis with crime data from Houston for the 2008 hurricane season, when Hurricane Ike (partial mandatory evacuation) and Hurricane Gustav (no mandatory evacuation) impacted the city. Results from the 2008 hurricane season will then be compared with the 2005 season to provide city officials and law enforcement with an even clearer picture about the impacts of hurricanes on the city's spatial crime distribution and its determinants.

## REFERENCES

- Anselin, L. 1988. *Spatial Econometrics. Methods and Models*. Dordrecht: Kluwer.
- Bailey, T.C. and A.C. Gatrell. 1995. *Interactive Spatial Data Analysis*. Essex: Longman.
- Bailey, K.L. 2009. *An Evaluation of the Impact of Hurricane Katrina on Crime in New Orleans, Louisiana*. Unpublished Applied Research Project for a Masters of Public Administration, Department of Political Science, Texas State University, San Marcos, TX.
- Bass, L. 2008. A pooled time series analysis of Hurricane Katrina evacuees and their effect on crime rates. In: *Proceedings of the 66th Midwest Political Science Association Annual National Conference*, Chicago, IL. [http://www.allacademic.com/meta/p266793\\_index.html](http://www.allacademic.com/meta/p266793_index.html) (accessed 23 February 2011).
- Brantingham, P.J. and P.L. Brantingham (eds.). 1981. *Environmental Criminology*. Beverly Hills, CA: Sage.
- Burt, J.E. and G.M. Barber. 1996. *Elementary Statistics for Geographers*. New York: The Guilford Press.
- Ceccato, V. and R. Haining. 2004. Crime in border regions: The Scandinavian case of Öresund, 1998-2001. *Annals of the Association of American Geographers* 94(4): 807-26.
- Ceccato, V. 2005. Homicide in São Paulo, Brazil: Assessing spatial-temporal and weather variations. *Journal of Environmental Psychology* 25(3): 307-21.
- Cromwell, P., R. Dunham, R. Akers and L. Lanza-Kaduce. 1995. Routine activities and social control in the aftermath of a natural catastrophe. *European Journal of Criminal Policy and Research* 3(3): 56-69.
- Diggle, P., A. Chetwynd, R. Häggkvist and S. Morris. 1995. Second-order analysis of space-time clustering. *Statistical Methods in Medical Research* 4(2): 124-36.
- Drabek, T. E., and D. McEntire. 2003. Emergent phenomena and the sociology of disaster: Lessons, trends and opportunities from the research literature. *Disaster Prevention and Management: An International Journal* 12(2): 97-112.
- Eck, J., S.P. Chainey, J. Cameron, M. Leitner and R. Wilson (eds.). 2005. *Mapping Crime: Understanding Hotspots*. Washington DC: National Institute of Justice.
- Elias, J., D. Harmsen, H. Claus, W. Hellenbrand, M. Frosch and U. Vogel. 2006. Spatiotemporal analysis of invasive meningococcal disease, Germany. *Emerging Infectious Diseases* 12(11): 1689-95.
- Enarson, E. 1999. Violence against women in disasters. *Violence Against Women* 5(7): 742-68.
- Fischer, M.M., M. Leitner and P. Stauffer-Steinnocher. 2001. Spatial point pattern analysis - some useful tools for analyzing locational data. *Geographischer Jahresbericht aus Österreich* 58: 49-65.
- Fotheringham S, C. Brundson and M. Charlton. 2002. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Chichester: Wiley.
- Frailing, K. and D.W. Harper. 2007. Crime and hurricanes in New Orleans. 51-68. In: D.L. Brunsmas, D. Overfelt and J.S. Picou (eds.), *The Sociology of Katrina: Perspectives on a Modern Catastrophe*. Landham, MD: Rowman & Littlefield Publishers.
- Gaudart, J., B. Poudiougou, A. Dicko, S. Ranque, O. Toure, I. Sagara, M. Diallo, S. Diawara, A. Ouattara, M. Diakite and O. Doumbo. 2006. *Space-time Clustering of Childhood Malaria at the Household Level: A Dynamic Cohort in a Mali Village*. *BMC Public Health* 6: 286.
- Helbich, M. and M. Leitner. 2010. Auswirkungen der Hurrikans Katrina und Rita auf raum-zeitliche Kriminalitätscluster in Houston, TX. Ein Scan Statistik Ansatz. In: *Proceedings Applied Geographic Information Technology XIV*, Salzburg.
- Huang, L., M. Kulldorff and D. Gregorio. 2007. A spatial scan statistic for survival data. *Biometrics* 63(1): 109-18.
- Jefferis, E. 1998. *A Multi-method Exploration of Crime Hot Spots: SaTScan Results*. Washington DC: National Institute of Justice.
- Jacquez, G.M. 1996. A k Nearest Neighbor Test for Space-time Interaction. *Statistics in Medicine* 15(18):



- 1935-49.
- Jung, I., M. Kulldorff and O.J. Richard. 2010. A Spatial Scan Statistic for Multinomial Data. *Statistics in Medicine* 29(18): 1910-18.
- Kates, R.W., C.E. Colten, S. Laska and S.P. Leatherman. 2006. Reconstruction of New Orleans after Hurricane Katrina: A research perspective. *PNAS* 103(40): 14653-60.
- Knox, E.G. and M.S. Bartlett. 1964. The detection of space-time interactions. *Applied Statistics* 13(1): 25-30.
- Knox, E. 1989. Detection of clusters. 17-20. In: P. Elliott (ed.), *Methodology of Enquiries into Disease Clustering*. London: Small Area Health Statistics Unit.
- Knowles, J. and M. Leitner. 2007. Visual representations of the spatial relationship between Bermuda High strengths and hurricane tracks. *Cartographic Perspectives* 56: 37-51.
- Kulldorff, M. 1997. A spatial scan statistic. *Communications in Statistics: Theory and Methods*, 26(6): 1481-1496.
- Kulldorff, M. and N. Nagarwalla, 1995. Spatial disease clusters: Detection and inference. *Statistics in Medicine* 14(8): 799-810.
- Kulldorff, M., W. Athas, E. Feuer, B. Miller and C. Key. 1998. Evaluating cluster alarms: A space-time scan statistic and brain cancer in Los Alamos. *American Journal of Public Health* 88(9): 1377-1380.
- Kulldorff, M., T. Tango and P. Park, 2003. Power comparisons for disease clustering tests. *Computational Statistics and Data Analysis* 42(4): 665-84.
- Kulldorff, M., Z. Zhang, J. Hartman, R. Heffernan, L. Huang and F. Mostashari. 2004. Benchmark data and power calculations for evaluating disease outbreak detection methods. *Morbidity and Mortality Weekly Report* 53(Suppl): 144-151.
- Kulldorff, M., L. Huang, L. Pickle and L. Duczmal. 2006. An elliptic spatial scan statistic. *Statistics in Medicine* 25(22): 3929-3943.
- Lawton, B.A. and J. Schulenburg. 2007. Assessing the impact of Hurricane Katrina on space-time clusters of crime patterns in Houston. In: *Proceedings of the Ninth Crime Mapping Research Conference*, Pittsburgh, PA.
- Leitner, M. and M. Helbich. 2009. Analyzing, modeling, and mapping the impact of Hurricanes Katrina and Rita on the spatial and temporal distribution of crime in Houston, TX. In: *Proceedings of the GL Forum 2009*, Salzburg.
- Leitner, M., M. Barnett, J. Kent and T. Barnett. 2011. The impact of Hurricane Katrina on reported crimes in Louisiana – A spatial and temporal analysis. *The Professional Geographer* (forthcoming May 2011).
- Levine, N. 2010. *CrimeStat: A Spatial Statistics Program for the Analysis of Crime Incident Locations* (v 3.3). Ned Levine & Associates, Houston, TX, and the National Institute of Justice, Washington, DC.
- Mantel, N. 1967. The detection of disease clustering and a generalized regression approach. *Cancer Research* 27 (2 Part 1): 209-20.
- Munasinghe, M. 2007. The importance of social capital: Comparing the impacts of the 2004 Asian Tsunami on Sri Lanka, and Hurricane Katrina 2005 on New Orleans. *Ecological Economics* 64(1): 9-11.
- Quarantelli, E. and R. Dynes. 1970. Property norms and looting: Their patterns in community crisis. *Phylon* 31(2): 168-82.
- Roman, C., S. Irazola and J.W.L. Osborne. 2007. After Katrina: Washed away? *Justice in New Orleans. Urban Institute Research Report*. [http://www.urban.org/UploadedPDF/411530\\_washed\\_away.pdf](http://www.urban.org/UploadedPDF/411530_washed_away.pdf) (accessed 23 February 2011).
- Song, C. and M. Kulldorff. 2003. Power evaluation of disease clustering tests. *International Journal of Health Geographics* 2: 9.
- Suar, D. and S. Kar. 2005. Social and behavioral consequences of the Orissa Supercyclone. *Journal of Health Management* 7(2): 263-74.
- Sunseri, S. 2005. *Review of Literature on Response Behaviors in Overseas Disaster Events*. Gracefield, New Zealand: Opus International Consultants Limited. <http://www.resilience.org.nz/O2%20M1%20Review%20FINAL.pdf> (accessed 23 February 2011).
- Takahashi, K., M. Kulldorff, T. Tango and K. Yih. 2008. A flexibly shaped space-time scan statistic for disease outbreak detection and monitoring. *International Journal of Health Geographics* 7: 14.
- Tango, T. and K. Takahashi. 2005. A flexibly shaped spatial scan statistic for detecting clusters. *International Journal of Health Geographics* 4: 11.
- Tucker, E. 2001. Crime and disaster. *Business Recovery Managers Association Newsletter* 12(2).
- Tuia, D., C. Kaiser, A. Da Cunha and M. Kanevski. 2009. Detection of urban socio-economic patterns using clustering techniques. 19-36. In: B. Murgante, G. Borruoso A. Lapucci (eds.), *Geocomputation and Urban Planning*. Berlin: Springer.
- U.S. Census Bureau. 2007. *Population Estimates Program*. Online documentation: <http://www.census.gov/popest/estimates.php> (accessed 23 February 2011).
- VanLandingham, M.J. 2007. Murder rates in New Orleans, LA, 2004-2006. *American Journal of Public Health* 97(9): 1614-16.
- VanLandingham, M.J. 2008. 2007 Murder rates in New Orleans, Louisiana. *American Journal of Public Health* 98(5): 776-77.
- Wenger, D. and B. Friedman. 1986. Local and national media coverage of disaster: A content analysis of the print media's treatment of disaster myths. *International Journal of Mass Emergencies and Disasters* 4(3): 27-50.