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What is This?

Joint Utility of Event-Dependent and Environmental Crime Analysis Techniques for Violent Crime Forecasting

Joel M. Caplan[1], Leslie W. Kennedy[1], and Eric L. Piza[1]

Abstract

Violent crime incidents occurring in Irvington, New Jersey, in 2007 and 2008 are used to assess the joint analytical capabilities of point pattern analysis, hotspot mapping, near-repeat analysis, and risk terrain modeling. One approach to crime analysis suggests that the best way to predict future crime occurrence is to use past behavior, such as actual incidents or collections of incidents, as indicators of future behavior. An alternative approach is to consider the environment in which crimes occur and identify features of the landscape that would be conducive to crime. Thanks to advances in geographic information system technology and federally funded (free) software applications such as CrimeStat III or the Near Repeat Calculator, these methods have recently been made more accessible to "average" users. This study explores the information products that each method offers for the purposes of place-based violent crime forecasting and resource allocation. Findings help to answer questions about where, when, and why violent crimes occur in a jurisdiction. Ways in which event-dependent and environmental crime analysis techniques can be utilized as complementary instruments in a crime analyst's tool kit are discussed in detail.

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Introduction

Work on crime hotspots has generated a great deal of interest in the spatial analysis of crime, leading to a revolution in the ways in which scholars and practitioners consider the origins and dispersion of crime. An extension of hotspot analysis has been the examination of "near repeats" (Bowers & Johnson, 2005) or contagion effects that explain how past crime incidents can serve as predictors of new crime incidence (Johnson, Bernasco, et al., 2007). Hotspot mapping and near-repeat analysis have allowed police to more efficiently target criminogenic places, but crime suppression and prevention efforts at these places cannot succeed outside of an understanding of the combined effects of the social and physical environments in which the offender operates (Weisburd et al., 2009). In Cohen and Felson's (1979) original article on routine activities, they wrote that "the risk of criminal victimization varies dramatically among the circumstances and locations in which people place themselves and their property" (p. 595). Criminologists have begun to address the importance of concentration effects of crime patterns based on underlying social contexts (Brantingham & Brantingham, 1998; Caplan, Kennedy, & Miller, 2011). This type of research is based on a form of analysis pioneered in criminology by Brantingham and Brantingham (1995) that considers the underlying social and physical "fabric" or environmental backcloth as a framework for action and is now appearing in studies of risk terrains or opportunity structures (Caplan et al., 2011; Groff & La Vigne, 2002).

Two elements need to be clarified to move forward. The first relates to the fact that event dependence is not a linear process but rather, in the interaction that takes place between crime incidents and context, a constantly changing risk dependence that emerges from the actions of all parties and criminogenic features about a location. The second relates to the role that crime incidence has on supporting future crime occurrence. With a better understanding of these elements and how they fit into the broader evolution to crime analysis and forecasting, it becomes clear that each method has unique operational utility for policing, even if the end analytical goals are the same.

It is likely that a hybrid method, to examine clustered events and environmental risk factors, could provide a more stable and spatially anchored approach to place-based crime control efforts. In other words, the vulnerability of areas

defined by the presence of factors that correlate with crime can be combined with the exposure that comes with past crime incidents to enhance the picture of crime occurrence and to better focus strategies for place-based interventions. In this study, we explore the combined practical utility of point pattern analysis, hotspot mapping, near-repeat analysis, and risk terrain modeling (RTM). We demonstrate that resilient crime hotspots are a function of the presence of motivated offenders as well as the attractive and/or generative qualities of the environment that serve as cues to offenders that certain places are suitable to commit crimes (Cohen & Felson, 1979).

Conceptual Framework

Crime Concentration

That crime concentrates at specific, select places or "hotspots" is well supported by research (e.g., Braga & Weisburd, 2010; Eck & Weisburd, 1995; Weisburd & Mazerolle, 2000) and comports with the daily experiences of crime analysts in law enforcement agencies around the world (Weisburd, 2008). The identification of crime hotspots tells where past behavior clustered. Connecting this to precursory environmental context is more challenging, but criminologists have stressed the influence of environmental features on crime for some time (e.g., Burgess, 1928; Shaw & McKay, 1969). A common thread among ecologists, opportunity theorists, and related scholarly thinkers argues that the unit of analysis for a crime event is a place—not the incident itself—and that the dynamic nature of that place constitutes opportunities for crime (Eck, 2001). In addition, common to many of these studies (Eck, 1995) is the view that opportunities for crime are not equally distributed across locations (Block & Block, 1995; Sherman & Weisburd, 1995). The clustering of illegal activity in particular areas is supported by the unique combination of certain factors that make these places opportune locations for crime occurrence (Eck, 1995; Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Harries, 1999; Kennedy, Caplan, & Piza, 2011; Mazerolle, Kadleck, & Roehl, 1998; Sherman, Gartin, & Buerger, 1989; Weisburd et al., 2009). Hotspots of crime, then, serve more as a proxy measure of places where the dynamic interactions of underlying criminogenic factors exist or persist over time. In this way, groups of past crimes serve as predictors of new crimes because their common denominator is a criminogenic geography. A sole analytical focus on crime hotspots is like observing that children frequently play at the same place every day and then calling that place a hotspot for children playing, but without

acknowledging the presence of swings, slides, and open fields—features of the place (i.e., suggestive of a playground) that attract children there instead of other locations absent such entertaining features.

Environmental Risk

Location matters because crimes cluster at certain locations (Eck et al., 2005; Harries, 1999; Sherman, 1995; Sherman et al., 1989; Weisburd, 2008; Weisburd & Eck, 2004). Environmental characteristics of these places influence and enable the seriousness and longevity of crime problems and ensuing hotspots (Sherman, 1995). The identification of crime hotspots tells us where illegal behavior is clustered but not necessarily why. Crime explanations may be accounted for by different factors that tie different components of environmental risk together to explain individual, group, and institutional influences and impacts on crime events (Caplan et al., 2011; Kennedy & Van Brunschot, 2009).

Opportunities for crime are not equally distributed across places, or "small micro units of analysis" (Weisburd, 2008, p. 2), and so the analytical approach to forecasting crime locations plays a critical role in the reliability and validity of efforts to assess vulnerabilities and future crime locations. Opportunity theorists (e.g., Cohen, Kluegel, & Land, 1981; Simon, 1975) have suggested that variations in crime are explained by opportunities to commit crime at locations that are accessible to the offender. "Perceptions of space, spatial cognition, and spatial behavior are scale-dependent and experience-based," explained Freundschuh and Egenhofer (1997, p. 362), so regions, such as cities, are learned by humans piecemeal over time (Montello, 1993). Motivated offenders may assess their own risks as a function of their knowledge about areas where they or other offenders committed crimes successfully in the past (e.g., hotspots) as well as their perceptions of features of the landscape that could help to facilitate new crimes. Risk defines the likelihood of an event occurring given what is known about the correlates of that event, and it can be quantified with positive, negative, low, or high values (Caplan et al., 2011). RTM utilizes a geographic information system (GIS) to attribute criminogenic qualities of the real world to places on a digitized map (Caplan et al., 2011; Kennedy et al., 2011). It operationalizes the spatial influence (Caplan, 2011) of crime risk factors to common geographic units and then combines separate map layers to produce a risk terrain map showing the presence, absence, or intensity of all risk factors at every place throughout the landscape. It "paints a picture" of place-based environmental context for criminogenesis. Although RTM is a relatively new method, much research (e.g., Caplan, 2011; Caplan et al., 2011; Caplan &

Kennedy, 2011; Kennedy et al., 2011) has shown it to be a statistically valid approach to environmental crime analysis and forecasting.

Near-Repeat Victimization

Farrell, Phillips, and Pease (1995) offer two suggestions as to why it is that particular targets are more likely to be repeatedly involved in crime. The first explanation for repeat victimization is what they refer to as *risk heterogeneity*. Victims (or targets) may have certain characteristics that increase the possibility that they will be victimized and victimized repeatedly. These characteristics are thought to exist prior to the initial victimization and are enduring—lasting both before and after initial and later victimizations, regardless of steps that might be taken to reduce a risk profile. A second explanation focuses on the context in which the victimization takes place. Farrell et al. (1995) refer to this as *state dependence* and note that "in the context of re-victimization presumed to be state-dependent, the basic question concerns reasons for the choice of the same [or different] perpetrators offending more than once against the same target[s] in preference to other targets" (p. 386). Rather than enduring traits characterizing victims as in the first explanation, state dependence implies that victimization changes victims to make them increasingly attractive.

The "state-dependent" situation may apply to locations as well as to individuals. Locations may contain characteristics that make them more likely to promote crime than other, less suitable, areas. This attraction would likely be based on a number of factors. If we consider the past experience with crime as an isolated indicator of future victimization, this would parallel crime analysis approaches based on event dependence, such as hotspots (discussed above). As an extension of, or companion to, hotspot analysis, the phenomenon of contagion effects has been labeled *near repeats* (Ratcliffe & Rengert, 2008) and explains how past crime incidents can serve as predictors of new crime incidence (Bowers & Johnson, 2005). Near-repeat models assume that if a crime occurs in a location, the chances of a future crime occurring nearby increases. In the studies that have been done to-date, researchers have found evidence to support the near-repeat phenomenon in a variety of crime types and settings (e.g., Johnson, Bernasco, et al., 2007; Ratcliffe & Rengert, 2008; Wells, Wu, & Ye, 2011). Investigations of near repeats provide an important extension of hotspot analysis as they account for the temporal link between crime events and do not just assume that behavior that takes place in close proximity at whatever time in a set frame (e.g., a month, a year) has anything to do with other behavior located nearby.

Research Setting and Crime Forecasting Scenario

This study emerged out of collaboration with the New Jersey State Police (NJSP) in 2007 in Irvington, New Jersey (NJ), an urban community of 2.9 square miles with a population of 65,000. Murder rates in 2007 were 38.7 per 100,000 persons, compared with a national average of 4.9 for similar size cities (Uniform Crime Report, 2008). The town has a lot of gang-related violence and contains a vibrant drug market. The combination of these factors led to the formation of a special NJSP task force to supplement the smaller municipal police. A reduction in violence[1] was dramatic at the onset of task force operations; however, it leveled off and remained fairly constant since.

Violent crime data include aggravated assaults, homicides, robbery, shootings, and weapon possession (i.e., the targeted violent crime types in Irvington during the study time frame). Data were provided by the NJSP through the Regional Operations Intelligence Center. There were 57 types of violent crime incidents from April to August 2007 and 32 violent crime incidents from April to August 2008. Although they are relatively small numbers for statistical purposes, these counts of violent crimes used in this study are the entire population of violent crimes known to police in Irvington during the 5-month time periods. These address-level data were geocoded to a street-centerline shapefile of Irvington, obtained from the Census 2000 Topologically Integrated Geographic Encoding and Referencing (TIGER/Line) shapefiles that were created by the U.S. Census Bureau. Geocoding match rates were 91% and 94%, respectively, well above the minimum reliable geocoding hit rate of 85% recommended by Ratcliffe (2004).

We recognize that environmental risk factors could be located away from streets and that crime events could conceivably occur at any location in Irvington (Caplan, 2011). So, when spatial units of analysis are called for in this study, we use raster map cells to represent microlevel places and to serve as the standard unit of analysis. Raster mapping was specifically developed to model continuous landscapes in a GIS (Tomlin, 1991; Tomlin, 1994) and, as Couclelis (1992) explained, can communicate the reality of how crime occurs at microlevel places better than vector street maps (see also, for example, Freundschuh & Egenhofer, 1997; Groff & La Vigne, 2002). Consistent with the work of Weisburd et al. (2009) and others (e.g., Braga, Green, Weisburd, & Gajewski, 1994; Groff, Weisburd, & Yang, 2010; Weisburd, Bushway, Lum, & Yang, 2004), the cell size was selected as a function of street segments: A 100-ft cell size was selected because it represents about
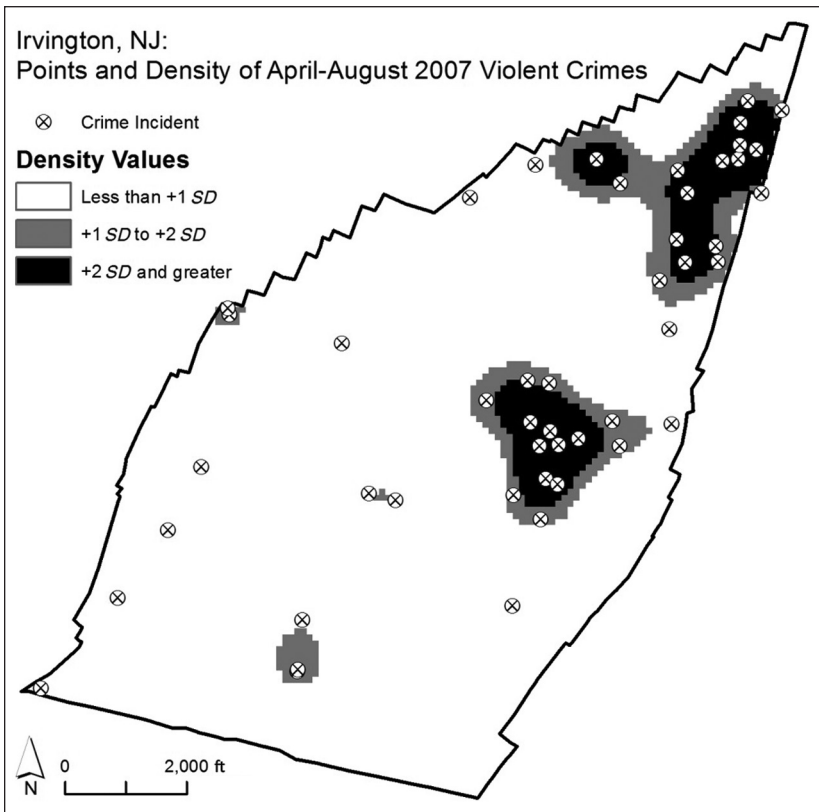
Figure 1. Points and density values

one third the average length of street segments in Irvington. This allowed us to model the environmental risks of crime as precisely as one corner or the middle of a street block, and is likely to be the smallest spatial unit to which police could reasonably be deployed.

Method and Results

Event-Dependent Analysis

Point pattern analysis and hotspot mapping. Visual inspection of the points in Figure 1 suggests that violent crimes are not uniformly distributed

throughout Irvington and may be clustered in certain areas. We conducted a Nearest Neighbor (NN) analysis for spatial randomness by calculating the distance from each point in a collection to its nearest neighboring point. These distances are then compared with the expected mean NN distance for a random distribution of points to determine whether points are statistically closer than expected under spatial randomness.[2] Results of a NN analysis suggest that the distribution of violent crimes in Irvington is significantly clustered (observed $M = 492.27$, expected $M = 601.95$, NN ratio = 0.82, z score = −2.51, $p = .01$). Density mapping serves as a useful follow-up to visual reviews of pin maps and NN analysis because it identifies where the highest concentrations of crime incidents are occurring at more localized places within the study area. Hotspot mapping is the use of cartographic techniques to create and visualize crime clusters (Braga & Weisburd, 2010; Eck & Weisburd, 1995; Groff & La Vigne, 2002; Sherman, 1995; Sherman et al., 1989). A conventional hotspot map of violent crimes is a raster density map calculated from the locations of violent crimes from a recent past time period that would then be used to identify existing problematic areas or to suggest the areas where violent crimes will occur in the future (Harries, 1999).

Figure 1 presents a density map of violent crimes in Irvington, NJ, from April through August 2007. The density map is symbolized according to standard deviational breaks, with all places colored in black having density values greater than $+2$ *SD* from the mean density value—which statistically puts these places (i.e., raster cells of 100 ft × 100 ft) in the top 5% of the most densely populated with violent crimes. Because seasonality correlates with crime incidents and should be controlled for with long-term forecasting, a conventional hotspot analysis, or density map, might suppose that violent crimes from April through August in 2008 would occur at the same hotspot locations as existed in 2007. As Table 1 shows, density hotspot mapping yields respectable place-based forecasts of 2008 violent crimes. In the 100 ft × 100 ft places on the map in Figure 1 that had a density value above $+2$ *SD* in 2007, 17% of violent crime incidents between April through August 2008 occurred within these same places,[3] which total 7% of the area of Irvington.

Near-repeat analysis. Conventional hotspot mapping is a-temporal. Brantingham and Brantingham (1981/1991) refer to this as the *stationarity fallacy* that emphasizes the fact that hotspots are combinations of unrelated incidents that occurred over time and are plotted in hotspots as though they are somehow connected beyond sharing a common geography. In overcoming this fallacy, the study of criminogenic places should incorporate time.

Table 1. Chi-Square Results

Place type (n = 4,039)	p value	Any violent crime in 2008 (yes, n = 30)	Coverage area of Irvington	Crimes per area
Density > +1 *SD*	Fisher's < .01 Pearson < .001	12 (41.4%)	1,162/8,240 cells (14%)	12/1,161 = 0.0103
Density > +2 *SD*	Fisher's = .098 Pearson = .095	5 (17.2%)	581/8,240 cells (7%)	0.0086
Risk value ≥ 3	Fisher's < .001 Pearson < .001	13 (44.8%)	831/8,240 cells (10%)	0.0156

Note: At least one cell has expected counts less than 5.

Near-repeat analysis adds a temporal aspect to point pattern and hotspot analysis by suggesting with a certain level of statistical confidence that new crimes happen within a certain distance of past crimes and within a certain period of time from the prior incident (Short, D'Orsogna, Brantingham, & Tita, 2009). According to results of a near-repeat analysis of Irvington's violent crime incidents during April through August 2007 using the Near Repeat Calculator,[4] Version 1.3 (Ratcliffe, 2009), there is evidence of an overrepresentation of violent crimes at the same place up to 7 days after an initial incident ($p < .05$); the chance of another violent crime incident was about 500% greater than if there were no repeat victimization pattern.[5] Near-repeat violent crimes were also overrepresented between 8 and14 days and within 801 to 900 ft of the initial incident ($p < .01$),[6] and there was a 153% greater chance of a new violent crime incident occurring within 0 to 14 days at 801 to 900 ft away from the initial incident ($p < .05$).[7] A total of 800 ft is about two blocks in Irvington.

There is no guarantee that new near-repeat crimes will happen in these "near-repeat rings," but history suggests that the spatial–temporal nature of crime incidents in Irvington made certain locations riskier for new crimes to occur than other locations, at certain times. If April through August 2008 violent crimes occurred with the same near-repeat pattern as April through August 2007 violent crimes, then near-repeat analysis could inform the allocation of police resources to prevent near-repeat crimes during 2008. Near-repeat analysis can be used to rule out concern about a "stationarity fallacy" (Brantingham & Brantingham, 1981/1991) and to strengthen the construct validity of these techniques.

Predicting the most likely locations of instigator events (i.e., precursor crimes for near-repeat incidents) requires an understanding of the environment that is most conducive for violent crimes to occur within (Johnson, Birks, et al., 2007). Target selection for violent crimes is likely a sequential, multilevel process and typically involves general site selection first (e.g., microlevel places within a jurisdiction) and then the selection of a specific target (e.g., a person/victim). "In general however," explains Johnson, Birks, et al. (2007), "our understanding of offenders' localized use of time and space together is underdeveloped" (p. 202). But place-based characteristics of the environment will likely affect individual-level decisions and criminal behaviors (and vice versa), and ultimately the locations of instigator events.

Environmental Crime Analysis Using RTM

Figure 2 presents a risk terrain map for violent crimes that was produced in accordance with the steps described by Caplan and Kennedy (2010). The map was produced using five risk factors that previous empirical research found to be correlated with said violent crimes. These risk factors are gang members (Braga, 2004; Kennedy, Piehl, & Braga, 1996), bus stops (Golledge & Stimson, 1997; Loukaitou-Sideris, 1999; Roman, 2005), schools (Roncek, 2000; Roncek & Maier, 1991), public housing (Eck, 1994; Newman, 1972; Roncek, Bell, & Francik, 1981), and facilities of bars, clubs, fast food restaurants, and liquor stores (Block & Block, 1995; Brantingham & Brantingham, 1995; Kennedy et al., 2011; Roncek & Bell, 1981; Roncek & Maier, 1991). Data on gang members were obtained from a NJSP database that is maintained, validated, and updated regularly to support internal crime analysis and police investigations. The gang intelligence data set comprised addresses of all known gang members' residences, which were operationalized as a density map because the spatial influence of these features was understood as "areas with greater concentrations of gang members residing will increase the risk of those places having shootings and other violent crimes since gang members are often both the perpetrators and intended targets of these events in Irvington."[8] Highest risk places were defined as having density values above +2 *SD* from the mean density values in Irvington. Addresses of all public bus stops were obtained from NJ Transit and operationalized as a distance map up to 555 ft away because the spatial influence of these features was understood as "up to one and a half blocks away from bus stops—transportation resources that motivated offenders and targeted victims use regularly—are at greater risk for violent crime because they 'set the stage' for
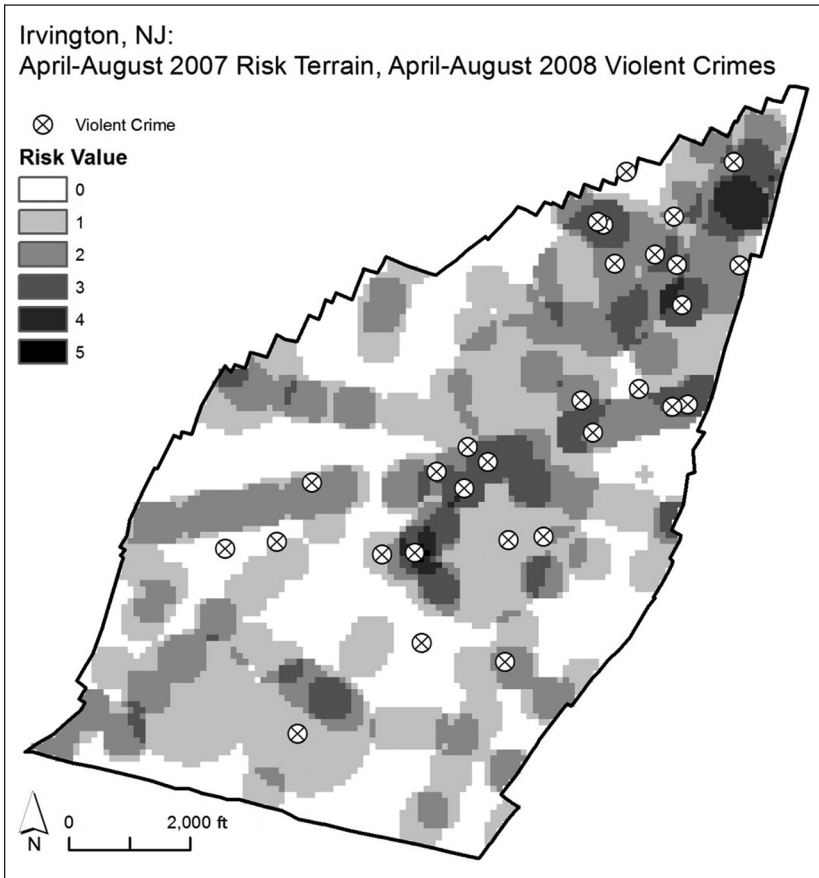
Figure 2. Risk terrain map showing environmental criminogenic context of 2007

criminal events since targeted victims are most vulnerable when they arrive at or leave these destinations" (Golledge & Stimson, 1997; Roman, 2005). Addresses of all public and private school buildings were obtained from the NJ Department of Education through the NJ Geographic Information Network and operationalized as "distances up to three blocks (up to 1,110ft) are at the greatest risk for violent crimes" (Xu, Kennedy, & Caplan, 2010). Addresses of bars, clubs, fast food restaurants, and liquor establishments were obtained from the NJSP and operationalized as "distances up to one block (up to 370ft) are at greatest risk for violent crimes" (Clarke & Eck,

Table 2. Logistic Regression Results for 2007 Environmental Risk Values on 2008 Violent Crimes

							95% CI for Exp(*B*)	
Variable	*B*	*SE*	Wald	*df*	Significance	Exp(*B*)	Lower	Upper
Risk value (0-5)	0.653	0.172	14.381	1	<.001	1.920	1.371	2.691

Note: CI = confidence interval; −2 log likelihood = 330.0; Nagelkerke R^2 = .043; *n* = 4,039.

2005; Roncek & Bell, 1981; Roncek & Maier, 1991). Parcels of public housing were obtained from the Irvington and Newark Housing Authorities and operationalized as distances up to one block (up to 370 ft) are at greatest risk for violent crimes (Roncek & Francik, 1981). The risk terrain map is symbolized according to unique risk values, which range from 0 (lowest, white) to 5 (highest, black). Higher risk places in 2007 should host violent crime incidents in 2008, unless one or more risk factors are mitigated at these places.

Due to the relatively few violent crimes for the time frame studied, and the limited variability of violent crime counts per cell (e.g., there were not many cells with two or more violent crimes in them, partly a function of the very small unit of analysis), we dummy coded the violent crimes as being present or absent within each cell and used logistic regression throughout the study. Such adjustments to the data should not dramatically affect the statistical results because of the significant number of cells actually analyzed and because the normal distribution of crimes in each cell was originally predominately zero or one. Indeed, undercounting incidents within cells may result in underestimating the predictive validity of our model. We were aware that distributions among geographical units, such as raster cells, may not be spatially independent (Anselin, Cohen, Cook, Gorr, & Tita, 2000). A Moran's I test indicated no spatial autocorrelation present, so a spatial lag variable was not created as a control.[9]

Logistic regression results (Table 2) suggest that for every unit increase of a place's (i.e., 100 ft x 100 ft cell's) risk value, the likelihood of a violent crime occurring there during April through August 2008 increased by 92%. For places with one or more risk factors in 2007, we can be 95% confident that if violent crimes happen in 2008, the likelihood of them happening at these places are between 37% and 169% greater than other places in Irvington. Table 3 presents results of a logistic regression whereby environmental risk was treated as a categorical variable and dummy coded; zero (0) risk was the

Table 3. Logistic Regression for 2007 Environmental Risk Values on 2008 Violent Crimes

Variable	B	SE	Wald	df	Significance	Exp(B)	95% CI for Exp(B)	
							Lower	Upper
Risk value = 1	0.465	0.614	0.574	1	.449	1.592	0.478	5.300
Risk value = 2	0.038	0.708	0.003	1	.957	1.039	0.259	4.163
Risk value = 3	2.111	0.580	13.238	1	<.001	8.259	2.649	25.757
Risk value = 4								
Risk value = 5	4.927	1.323	13.866	1	<.001	138.000	10.317	1,845.883

Note: CI = confidence interval; −2 log likelihood = 316.579; Nagelkerke R^2 = .083; *n* = 4,039. Reference category: risk value = 0. No crimes during this time period occurred in cells with risk value of 4.

Table 4. Logistic Regression Results for 2007 RTM on 2007 Violent Crimes

Variable	B	SE	Wald	df	Significance	Exp(B)	95% CI for Exp(B)	
							Lower	Upper
Risk value (0-5)	0.821	0.139	34.921	1	<.001	2.272	1.730	2.982

Note: RTM = risk terrain modeling; CI = confidence interval; −2 log likelihood = 468.004; Nagelkerke R^2 = .07; *n* = 4,039.

reference category. Risk values equal to or greater than 3 appear to be significant predictors of future shootings compared with value of 0.[10] The order of magnitude for risk values' effect sizes confirms that the more the environmental risks present at a microlevel place, the greater the likelihood of a future violent crime occurring there.

According to results of a chi-square test in Table 1, nearly 45% of all violent crimes in 2008 happened at places with risk values of 3 or more, which comprised 10% of the area of Irvington.[11] Synthesizing all the results presented in Table 1, it appears that occurrences of violent crimes in 2008 at places where violent crimes produced hotspots in 2007 were attributable to criminogenic stagnation—Risk factors at microlevel places stayed the same or were not successfully mitigated over time. That is, the locations of schools, bars, and so on do not change drastically from year to year. This explains why the risk terrain map also has similarly strong predictive validity for April through August 2007 violent crimes, as shown in Table 4. If risk factors in the risk terrain model are not directly and successfully mitigated,

and crimes continue to occur, then they will likely cluster at the same criminogenic places over time, creating hotspots. In this way, crime hotspots were valid measures of where new crimes were likely to occur in the future because they were proxy measures of environments that were chronically most conducive for illegal violent behavior. This finding is consistent with recent work by Weisburd, Groff, and Yang (2012) in Seattle, Washington, that points to an extremely strong relationship between crime, place, and the characteristics thereof.

Joint Utility of Hotspot Mapping, Near-Repeat Analysis, and RTM

Results from the previously demonstrated crime analysis techniques suggest that police in Irvington could have strategically allocated resources to key crime-infested places—given their knowledge of where violent crimes were concentrating at hotspots and the time frame and general area within which near-repeat crimes were likely to occur. Once multiple suspected correlates of violent crime are identified, assumptions about their combined place-based effects on crime occurrence can be tested for statistical significance using RTM. The joint utility of these crime analysis techniques offers police a unique opportunity to suppress violent crimes immediately by allocating resources to existing hotspots. They can, in addition, prevent violent crimes through interventions at places that are most attractive to motivated offenders given certain characteristics of the environment, even if violent crimes are not yet occurring there (Baughman & Caplan, 2010; Weisburd, 2008). To test this proposition in Irvington, a logistic regression was used to measure the effect of the "presence of any violent crimes from April through August 2007" on the locations of violent crimes from April through August 2008. At the microlevel unit of analysis, 2007 violent crime incidents were a significant predictor of 2008 violent crime incident locations.[12] This finding is consistent with the conceptual framework of hotspot mapping, the conclusions of empirical research regarding hotspots (e.g., Chainey, Tompson, & Uhlig, 2008; Gorr & Olligschlaeger, 2002), and the decisions by police commanders to allocate resources to high-crime places. Including a measure of environmental risk yields an even better model of future violent crime locations compared with predictions made with past violent crime incidents alone. With a Nagelkerke R^2 value of .07, the logistic regression model inclusive of past violent crimes and an environmental risk value derived from RTM explains more than twice the variance (the other model's value was .025). As presented in Table 5, microlevel places in

Table 5. Results of Logistic Regression on 2008 Violent Crimes

Variable	B	SE	Wald	df	Significance	Exp(B)	95% CI for Exp(B)	
							Lower	Upper
Risk value ≥ 3	1.719	0.387	19.754	1	<.001	5.582	2.615	11.914
2007, violent crime present	1.755	0.655	7.182	1	<.01	5.782	1.602	20.864

Note: CI = confidence interval; −2 log likelihood = 318.826; Nagelkerke R^2 = .076; n = 4,039.

Irvington with past violent crimes had a 478% increase in the likelihood of future violent crimes compared with places that were not host to violent crimes in the previous year, when controlling for environmental risk ($p <$ .01). Places with risk values of 3 or more (as supported by the results presented earlier in Table 3) had a 458% increase in the likelihood of future violent crimes compared with places with lower risk values, when controlling for the presence of prior violent crime incidents ($p < .001$). These results confirm that violent crimes occur at places with higher environmental risks, especially if violent crimes occurred there already.

Knowing that the presence of past violent crimes can be a significant predictor of future similar crimes, we can use near-repeat analysis to categorize violent crime incidents according to their temporal nature, that is, as instigator or near-repeat event.[13] The spatial–temporal linkage of such incidents was identified here using the "other functions" tool of the Near Repeat Calculator (Ratcliffe, 2009). The joint application of RTM and near-repeat analysis can be used to anticipate the distal and temporal limits and locations of near-repeat events that follow unpreventable violent crime incidents. According to results of the near-repeat analysis, near-repeat violent crimes were most likely to occur between 801 and 900 ft and within 14 days of an instigator event. As shown in Figure 3 and Table 6, near-repeat incidents during April through August 2007 were most likely to happen at higher risk places within these bounds. Environmental risk remains significant to the locations of near repeats even when controlling for the presence of instigator events at micro-level places. This multivariate regression, as shown in Table 7, is the best model produced (i.e., in terms of explained variance: Nagelkerke R^2 = .363) for predicting where violent crime incidents were likely to happen. This finding supports the near-repeat phenomenon and the relationship it has with environmental risks above and beyond crime incidents themselves. "Risk heterogeneity" of environments, as articulated by risk terrain maps, exists
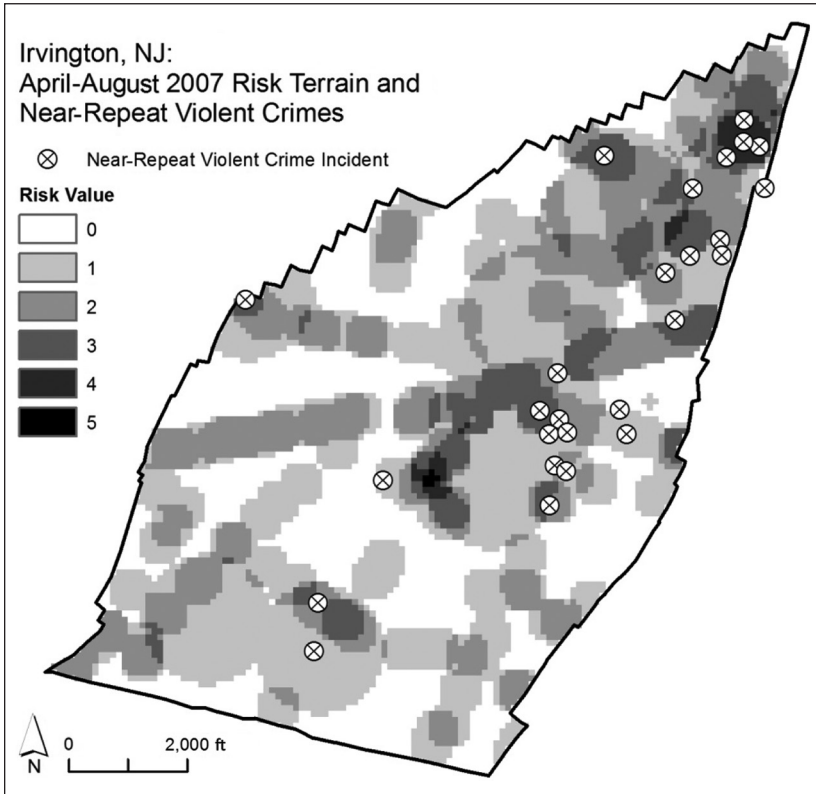
Figure 3. Near-repeat violent crimes and risk terrain map showing environmental criminogenic context of 2007

Table 6. Logistic Regression Results for 2007 RTM on 2007 Near-Repeat Violent Crime Incidents

							95% CI for Exp(*B*)	
Variable	*B*	*SE*	Wald	*df*	Significance	Exp(*B*)	Lower	Upper
Risk value (0-5)	0.881	0.184	23.016	1	<.001	2.413	1.684	3.459

Note: RTM = risk terrain modeling; CI = confidence interval; −2 log likelihood = 291.008; Nagelkerke R^2 = .077; *n* = 4,039; 26 near-repeat incidents.

Table 7. Results of Logistic Regression on 2007 Near-Repeat Violent Crime Incidents

Variable	B	SE	Wald	df	Significance	Exp(B)	95% CI for Exp(B)	
							Lower	Upper
Risk value ≥ 3	1.174	0.498	5.565	1	.018	3.235	1.220	8.581
2007, instigator crime present	5.550	0.518	114.882	1	<.001	257.241	93.236	709.739

Note: CI = confidence interval; −2 log likelihood = 203.105; Nagelkerke R^2 = .363; n = 4,039.
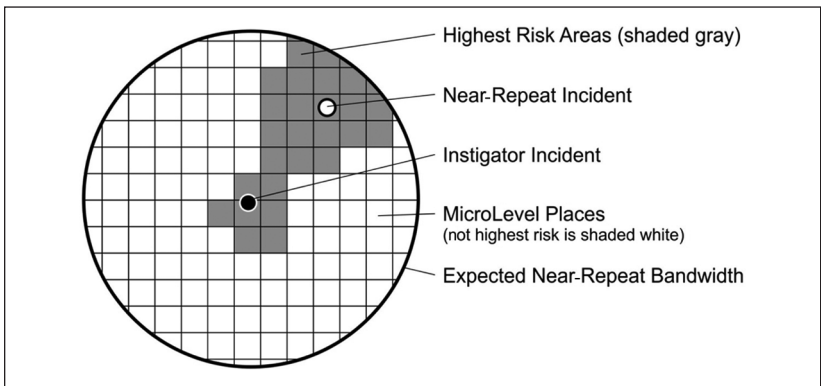

Figure 4. Instigator violent crimes create a bandwidth within which near-repeat incidents are most likely to happen at environmentally risky places

prior to the initial victimization and can be enduring without proper intervention efforts. "State dependence" exists at places with instigator crimes, which makes the same target or nearby targets especially attractive. Where risk heterogeneity and state dependence coexist, that is, when instigator events locate in risky environments, the emergence of new crimes is especially likely.

As illustrated in Figure 4, violent crimes that cannot be prevented and that serve as instigator events (for near repeats) are most likely to attract near-repeat incidents at nearby places of high environmental risk—as opposed to microlevel places within the expected near-repeat bandwidth that have very low risk. Stated another way, instigator violent crimes may create a "pie" of a certain radius within which near-repeat incidents are most likely to happen

during a certain time frame. But within this pie, some "slices" are more likely to have violent crimes than other slices.

One advantage of knowing that a near-repeat phenomenon exists for violent crimes in a jurisdiction and that violent crimes are more likely to occur at high-risk places is the ability to prioritize each new crime incident according to its propensity for being the instigator event for near-repeat crimes. Assuming that every new violent crime incident is a potential instigator for near repeats, priority can be given to new crimes that occur at high-risk places with other high-risk places in close proximity. Place-based environmental risk assessment with RTM permits real-time evaluation of the propensity for a new crime to become an instigator for near repeats.

Discussion and Conclusion

We identified a three-part integration of these approaches for crime analysis and forecasting based on each step's information product, as exemplified in Figure 5. The first step (1 in Figure 5) is hotspot analysis to assess whether (and where) crimes cluster spatially in the jurisdiction. The second step (2 in Figure 5) is to model environmental risks with RTM to identify high-risk places for criminogenesis. The joint utility of information derived from Steps 1 and 2 (A in Figure 5) is to determine whether crime hotspots occur at high-risk places or within high-risk clusters. This knowledge can help to explain the underlying environmental risk factors that may attract and generate hotspots. The third step (3 in Figure 5) is near-repeat analysis to assess the spatial–temporal nature of past crimes. The joint utility of information derived from Steps 1 and 3 (B in Figure 5) is to help explain the event-dependent and temporal nature of crime hotspots in the jurisdiction. If a near-repeat phenomenon exists, then the joint utility of information derived from Steps 2 and 3 (C in Figure 5) is to evaluate the propensity for new crime incidents to become instigators for near repeats based on the proportion of high-risk places within the expected near-repeat bandwidth. The culmination of all three steps is information products that can inform short- and long-term strategic planning and at least three tactical deployment decisions. Information Product A enables police to respond immediately to places where crimes cluster and crime problems persist, and to respond preemptively to high-risk places. Information Product B gives police a temporal window for which near-repeat crimes are most likely to follow new crime events. This knowledge can help to reduce the costs of deploying extra resources for long or uncertain lengths of time following new crime incidents (Koper, 1995). This, in turn, can help to reduce alert fatigue
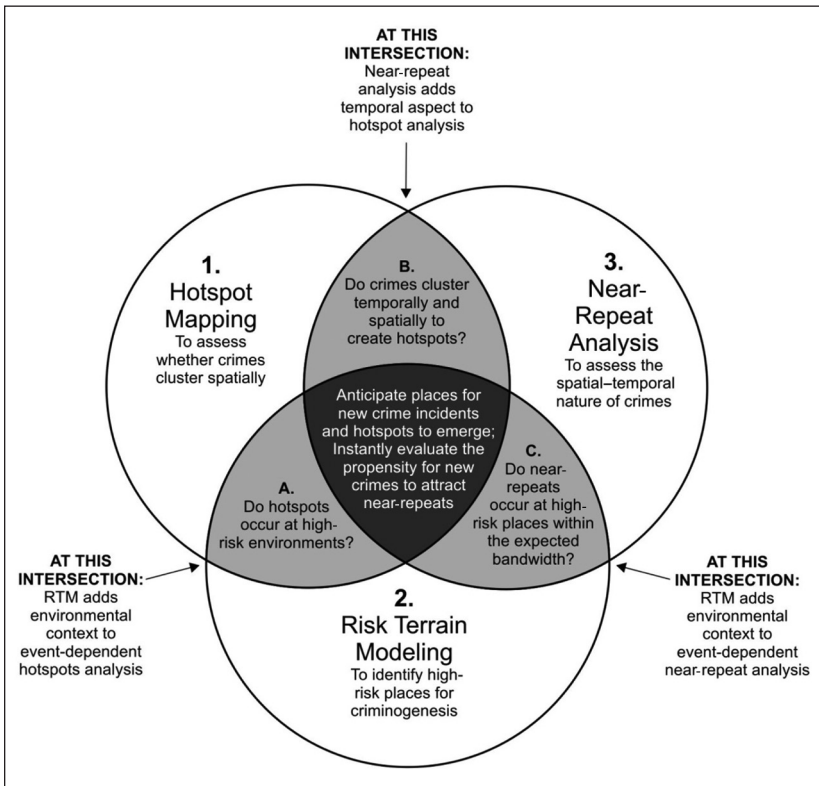
Figure 5. Three-part integration of hotspot mapping, near-repeat analysis, and risk terrain modeling
RTM = risk terrain modeling.

among patrol officers who are assigned to patrol places nearby to new crime incidents (Johnson, Birks, et al., 2007). Information Product C allows police to prioritize place-based deployments of resources by comparing new crime incidents relative to all others according to the surrounding environment's suitability for hosting new near-repeat incidents. Priority can be given—and limited resources (re)allocated—to new crime incidents that have more high-risk "slices of the pie" than other incident locations. This three-part crime analysis method was demonstrated to be empirically grounded for violent crimes in an urban setting. But caution should be had in generalizing this approach to other settings and crime types without local replication and

validation of the procedure. Future research should test whether this method, if implemented to practice, would prove more effective at mitigating crime problems than tactical or strategic decision making based on the observations or experience of police commanders. The method should also be compared with more traditional methods of crime analysis, such as pattern identification (see Boba, 2009, Chapter 9).

Some of the models had low predictive power, as measured by the Nagelkerke R^2, suggesting that additional variability of violent crime locations remains unexplained by this three-part approach. More research is required before relying fully on this method of analysis and tactical response. Tactical pattern analysis, for example, may be better at identifying short-term dynamic hotspot patterns and may allow for analysis products that are more actionable and immediate for police response (International Association of Crime Analysts, 2011). Integrating tactical pattern analysis into the proposed methodology might improve its viability for short- and long-term planning.

Despite the noted limitations of the current study, it is reasonable to believe that GIS and multimethod crime analysis procedures can shape police department policies and practices regarding officer deployments. A recent and much publicized example is in Santa Cruz, California, where officers deploy to places most likely to be at risk of future crime (Thompson, 2011). Other police departments are also known to focus activities on various situational and environmental risk factors at certain locations (Braga & Bond, 2008; Clarke, 1997; Taylor, Koper, & Woods, 2011). Incorporating such a holistic approach to crime analysis and resource deployment necessitates "buy in" from agency leadership. This commitment must be institutionalized in a manner that ensures that midlevel executives and those under their command incorporate the approach into daily operations. This could be established and reinforced through standard law enforcement management strategies, such as CompStat (Boba, 2009; Weisburd, Mastrofski, McNally, & Greenspan, 2001). Existing CompStat processes could be leveraged to ensure that commanders put commensurate effort toward mitigating the underlying problems that generate crime. In addition, the "SARA" (scanning, analysis, response, and assessment) model of problem-oriented policing could be embraced in a manner that encourages commanders to devise plans that directly address the risk factors identified in a risk terrain model.

The use of event-dependent and environmental crime analysis techniques will be highly dependent on the availability of data. Indeed, the analysis outlined in this article might have benefited from additional data that were unavailable to the researchers. Although all the risk factors included in this

analysis were "static" features of the environment, it is likely that dynamic characteristics of these features can further identify risk heterogeneity. A public housing complex experiencing a sharp increase in narcotics-related calls-for-service, for example, may be more criminogenic (at that moment in time) than complexes where reported narcotics activity is stable. Identifying common attributes linking the crime incidents comprising a hotspot may also be beneficial. For example, identifying a series—a "run of similar crimes committed by the same individual(s) against one or various victims or targets" (Velasco & Boba, 2000, p. 2)—can help police anticipate crime emergence when an incident with a similar modus operandi occurs outside of the existing hotspot (International Association of Crime Analysts, 2011). Modern GIS technology supports the real-time updating of data through the linking of mapping software and large databases that primarily contain information on crime, calls-for-service, and officer activity. Less is known about the manner by which crime risk factors are collected, stored, and updated. If a police department collects these data in an ad hoc manner (as opposed to the systematic collection of crime data), it may be challenging for the agency to routinely incorporate crime forecasting into its operations. However, the recent uses of RTM in various practical settings (Baughman & Caplan, 2010; Caplan et al., 2011; Caplan & Kennedy, 2011; Kennedy et al., 2011) suggest that police departments are able to access and incorporate risk data into their analytical framework.

Most often a crime analyst's measure of the presence of offenders is designated as the number of crime incidents reported or arrests that are made and tabulated by police in crime reports. But, there are other types of measures to use that are more enduring than the crime incident. Natural areas, according to human ecologists, are settings that have certain characteristics that lead to predictable behavioral outcomes, regardless of the character of the people living in or passing through these areas (Shaw & McKay, 1969). Tying predictions of crime to geographic locations and their characteristics provides the basis for connecting attributes of space to actual behavior that occurs at these places, such as high frequencies of crimes (i.e., hotspots) or near-repeat victimizations. It also takes the police beyond a tactical response to crime occurrence to one that is more strategic, anticipating where resources will be needed to respond to and prevent newly emerging crime problems.

Declaration of Conflicting Interests

Funding

Notes

1. According to the New Jersey (NJ) State Police Uniform Crime Reports, the violent crime rate in 2006—before the task force—was 22.4 per 1,000, with a murder count of 21. In 2009, the violent crime rate was 18.2 per 1,000, with a murder count of 17.
2. The nearest neighbor index is expressed as the ratio of the observed distance divided by the expected distance—the average distance between neighbors in a hypothetical random distribution. If the index is less than 1, the pattern exhibits clustering; if the index is greater than 1, the trend is toward dispersion or competition.
3. Pearson chi-square value = 2.78, $df = 1$, $p < .10$.
4. It uses the *XY* coordinate and date of criminal incidents to test for statistically significant spatial–temporal patterns between all points within the data set. The patterns found are then compared with an expected pattern if no near-repeat phenomenon were to exist using the Monte Carlo method.
5. Iterations requested: 99, spatial bands/bandwidth: 10/100, temporal bands/bandwidth: 24/7; Manhattan.
6. Iterations requested: 99, spatial bands/bandwidth: 10/100, temporal bands/bandwidth: 24/7; Manhattan.
7. Iterations requested: 99, spatial bands/bandwidth: 10/100, temporal bands/bandwidth: 12/14; Manhattan.
8. In addition to the observed nature of recent past violent crimes as described by the NJ State Police, the use and operationalization of "gang members residences," "retail infrastructure," and "housing" risk factors was informed by prior theory and research on contagion effects and near-repeat crimes. This was particularly important because a near-repeat phenomenon was found to exist in Irvington. Wells, Wu, and Ye (2011) found that near-repeat shootings cluster differently in Houston according to the presence of different features of the environment, including business facilities and housing; gang-related shootings were found to generate higher levels of subsequent violence than other incident types. None of these differences found by Wells et al. were statistically significant, but they were limited to data on only gun violence (i.e., location type and motivation) and lacked data on environmental features of places (i.e., crime generators and attractors) comprising the environmental backcloth of the near-repeat incidents. Despite this, it is evident that the spatial influence of particular features of the environment is an important component in understanding the occurrence

of near-repeat incidents as well as instigator incidents. Because the violence in Irvington is primarily gang related, we found Wells et al. work particularly insightful as we developed the risk terrain model.

9. Moran's index = -0.001583, expected index = -0.000248, variance = 0.000197, z score = -0.095161, and p value = $.924187$.

10. Conceptually, risk is rarely or never absolutely 0. Therefore, an environmental risk value of 0 should be interpreted as the risk for crime at these places is no greater than any other place under normal circumstances.

11. Pearson chi-square = 31.40, $p < .001$, $n = 4,039$.

12. -2 log likelihood = 335.789, Nagelkerke R^2 = $.025$, $B = 2.365$, $SE = 0.629$, Wald = 14.15, $df = 1$, $p < .001$, $\exp[B] = 10.645$, and 95% confidence interval = $[3.104, 36.502]$.

13. These are not necessarily mutually exclusive.

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