Justice Quarterly

ISSN: 0741-8825 (Print) 1745-9109 (Online) Journal homepage: www.tandfonline.com/journals/rjqy20

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To cite this article: Joel M. Caplan, Leslie W. Kennedy & Joel Miller (2011) Risk Terrain Modeling: Brokering Criminological Theory and GIS Methods for Crime Forecasting, Justice Quarterly, 28:2, 360-381, DOI: 10.1080/07418825.2010.486037

To link to this article: https://doi.org/10.1080/07418825.2010.486037

Published online: 25 May 2010.

JUSTICE QUARTERLY VOLUME 28 NUMBER 2 (APRIL 2011)

Risk Terrain Modeling: Brokering Criminological Theory and GIS Methods for Crime Forecasting

Joel M. Caplan, Leslie W. Kennedy and Joel Miller

The research presented here has two key objectives. The first is to apply risk terrain modeling (RTM) to forecast the crime of shootings. The risk terrain maps that were produced from RTM use a range of contextual information relevant to the opportunity structure of shootings to estimate risks of future shootings as they are distributed throughout a geography. The second objective was to test the predictive power of the risk terrain maps over two six-month time periods, and to compare them against the predictive ability of retrospective hot spot maps. Results suggest that risk terrains provide a statistically significant forecast of future shootings across a range of cut points and are substantially more accurate than retrospective hot spot mapping. In addition, risk terrain maps produce information that can be operationalized by

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Routledge Taylor & Francis Group
ISSN 0741-8825 print/1745-9109 online/11/020360-22

DOI: 10.1080/07418825.2010.486037

police administrators easily and efficiently, such as for directing police patrols to coalesced high-risk areas.

Keywords GIS; risk; shootings; crime; modeling

Introduction

Spatial analysis using mapping techniques has become integrated into the day-to-day strategic and operational processes of police agencies (Boba, 2005; Mamalian & La Vigne, 1999). The identification of crime hot spots through mapping, and the targeting of police activity to these places, has been recognized in high-quality evaluation research as an effective crime-fighting technique (Braga, 2005). Despite the evident success of this technology in operational policing, there is a manifest disconnect between the conventional practice of mapping and the demands by police agencies to be responsive to the dynamic nature and needs of the communities they serve. Mapping applications, in most police agencies, are restricted to fairly simple density maps based on the retrospective analysis of crime data (Groff & La Vigne, 2002). The reactive approach that this entails makes analysts less attuned to the idea of crime risk or potential, and it essentially assumes that crime will most likely always occur precisely where it did in the past (Johnson, Birks, McLaughlin, Bowers, & Pease, 2007). There is little evidence of police agencies using crime forecasting methods that make use of theory and modeling. This is true despite evidence to suggest that future crime patterns can be predicted in ways that can improve upon retrospective mapping. In real-world settings, as these locations evolve and as police respond to problems in them, crime patterns also change. An alternative approach involves identifying factors that enhance or reduce the likelihood of future crimes in particular locations.

In research and academic circles, we have seen in recent years the emergence of techniques that have begun to spatially forecast crime to good effect (e.g., Bowers, Johnson, & Pease, 2004; Gorr & Olligschlaeger, 2002; Groff & La Vigne, 2002). Yet, the slow adoption of these methods in operational policing suggests that criminologists have thus far failed to present them in ways that are accessible and convincing to police analysts and police leaders. The research reported here attempts to move the conversation beyond this impasse. By adapting existing forecasting methods to a new and compelling crime problem—shootings in urban New Jersey—we seek to demonstrate how effective forecasting can be achieved by thinking about crime events as hazards for which risk can be assessed using some intuitively simple principles within the analytical reach of crime analysts. Our approach can be seen as a geographical adaptation of offender-based risk assessment, now commonplace in the criminal justice system, in which the attributes of suspects and offenders are used to anticipate their likelihood of future behaviors (Miller & Lin, 2007). Because our units of analysis are geographical places rather than offenders, our risk factors are concerned with aspects of place rather than only characteristics of individuals. Importantly, we go on to demonstrate the superiority of the place-based forecasting method known as "Risk Terrain Modeling" (RTM) to conventional retrospective hot spot mapping when applied to this serious crime problem.

The Concentration of Crime

That crime takes place in specific, select areas, or "hot spots" is well supported by research (e.g., Eck, 2001; Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Harries, 1999; Sherman, Gartin, & Buerger, 1989) and comports with the daily experiences of crime analysts in law enforcement agencies across the nation. The identification of crime hot spots tell us where behavior is clustered. Connecting this to environmental context is more challenging for spatial analysis. Efforts to forecast future crime locations need to take this issue seriously. As Abbott (1997, p. 1152) states,

> the Chicago School thought that no social fact makes any sense abstracted from its context in social (and often geographic) space and social time … Every social fact is situated, surrounded by other contextual facts and brought into being by a process relating it to past contexts.

Abbott derides the efforts in contemporary urban studies to look for single causal factors. To him, the importance of the ecological approach was in its accounting of social interactions that occur in context (an empirical fact that was difficult to test, given the data and technology available at the time, but is now possible with modern analysis packages and better data).

Common to many ecological approaches (Eck & Weisburd, 1995) is the view that opportunities for crime are not equally distributed across locations (Block & Block, 1995). Brantingham and Brantingham (1981) provide important conceptual tools for understanding relationships between space and crime. They refer to the "environmental backcloth" that emerges from the confluence of routine activities and physical structures overlaying urban areas. The Brantinghams (1995) suggest that this backcloth is dynamic and, importantly, can be influenced by the forces of "crime attractors" and "crime generators"—both of which contribute to the existence of hot spots. Attractors are those specific things that attract offenders to places in order to commit crime. Generators, meanwhile, are concerned with the greater opportunities for crime that emerge from the collection of more people into areas simply as a result of the increased volume of interaction taking place in these areas. Drug markets provide an example of how crime both concentrates in certain spaces but also evolves in a way that sustains risky places and promotes violent behavior, acting as both attractors and generators of illegal activity (Eck, 1995; Ritter, 2006). The clustering of such activity in particular areas is supported by the unique combination of certain factors that make these places opportune locations for crime occurrence (Eck, 1995; Mazerolle, Kadlek, & Roehl, 2004); that is, where the potential for, or risk of, crime comes as a result of all the characteristics found in these places.

For more than three decades, 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. Although well developed theoretically, research has been constrained in its ability to operationalize "opportunity" and to develop a metric for assessing it. Cohen and Felson (1979) explained in routine activities theory that crime occurrence can be more easily facilitated if there are motivated offenders, suitable targets of victimization, and an absence of capable guardians. They also admitted that "the risk of criminal victimization varies dramatically among the circumstances and locations in which people place themselves and their property" (Cohen & Felson, 1979, p. 595). Felson's recent work (2006) has focused on the ecological distribution of crime opportunities, which has obvious ties to routine activities theory, but he pays little direct attention to operationalizing (for empirical measurement) the spatial distribution of criminogenic opportunities. Cohen, Kluegel, and Land (1981) re-fashioned the routine activities theory, renaming it "opportunity" theory, to include concepts of exposure, proximity, guardianship, and target attractiveness as variables that increase the risk of victimization. But they too have yet to develop a metric for operationalizing "opportunity." Lee and Alshalan (2005) improved on prior research in the area of criminal opportunity by introducing multiple measures for each of the central concepts of opportunity theory and testing them using rates of property thefts at the US county level to explain cross-sectional variation. A common thread among opportunity theorists and related scholarly thinkers is that the unit of analysis for "opportunity" is a place, and that the dynamic nature of that place constitutes opportunities for crime. For example, Eck (2001, 2002), Mears, Scott, and Bhati (2007), Brantingham and Brantingham (1995) all directly state or imply the place-based nature of criminogenic opportunities. Crime control and prevention activities, then, must consider not only who is involved in the criminal events, "but also the nature of the environments in which these activities take place" (Kennedy & Van Brunschot, 2009, p. 129) because opportunity for crime is at least partly an attribute of all places.

As an attribute of places, opportunity is not an absolute value, a dichotomous variable, or a static quotient. It is rarely or never 0. Opportunity varies in degrees and changes over time as public perceptions about environments evolve; as new crimes occur; as police intervene; or as motivated offenders and suitable targets travel. Assessing spatial criminogenic opportunity requires a conceptual framework that is attuned to incorporating multiple dynamic factors and producing intelligence that serves strategic decision-making and tactical responsive action. Risk assessment—"a consideration of the probabilities of particular outcomes" (Kennedy & Van Brunschot, 2009, p. 4)—serves this purpose. The concept of risk is not new or unique to the criminal justice community (Andrews, 1989; Burgess, 1928; Glueck & Glueck, 1950; S. D.

Gottfredson & Moriarty, 2006), and risk assessment has a long history of being used to identify, prevent or control crime (Kennedy & Van Brunschot, 2009). Risk models provide tools for identifying hazards that can lead to crime outcomes. Kennedy and Van Brunschot (2009, p. 11) surmised that risk provides a metric that can help tie different parts of the crime problem together and offers a probabilistic interpretation to crime analysis

> that allows us to suggest that certain things are likely to happen and others can be prevented based on our risk assessments. It provides a framework, a common structure to our approach that has been missing in previous work on crime.

When "opportunity for crime" is thought of in terms of "risk of crime," places can be evaluated in terms of varying degrees of criminogenic risk relative to other nearby or far places, and the burden of measuring opportunity in absolute terms is removed. Considering criminogenic opportunity as place-based risk makes theoretical and intuitive sense to all participants: offenders and victims know they take risks and that these risks increase in certain locations; police consider risks in doing their jobs; and they are often deployed to certain geographies to combat crime and manage other real or perceived hazards (Kennedy & Van Brunschot, 2009).

While a crime event occurs at a finite place, risk is a continuous dynamic value that increases or decreases intensity and clusters or dissipates in different places over time, even places remote from a crime event. Valuations of risk are tied to geography and, regarding crime, risk values are the measure of a place's potential for a crime event to occur. Geographic risk is determined by a nexus of certain factors and it changes only as the characteristics and interactions of those factors vary. Sometimes all of those factors must interact at the same place and time for the event to occur. For example, individual meteorological factors that are incorporated into weather forecasting do not necessarily produce rain, thunder storms or hurricanes by themselves. It is only when they intersect in space and time that they have the greatest potential to yield a particular outcome. Other times, only one or a few factors may be required to interact about the same geography and at certain times for a particular event to occur. Understanding the spatial-temporal interaction effects of certain factors of crime is key to assessing and valuing criminogenic risk. Fortunately, decades of criminological research have identified a variety of independent variables to be significantly correlated with a variety of crime outcomes. It is about time that we simultaneously apply all of these empirical findings to practice.

Risk Terrain Modeling

We propose RTM as an approach to risk assessment to aid in crime forecasting by incorporating underlying causes of crimes and standardizing all of these factors to common geographic units over a continuous surface. It is similar to the approach adopted by Groff and La Vigne (2001) looking at burglary in that it avoids the complex statistical modeling used by Gorr and Olligschlaeger (2002), Johnson et al. (2007), and others (see Groff & La Vigne 2002) in favor of more user-friendly raster data models, which divides spatial layers into grids of equally sized cells such that the layers can be added together. Importantly, it can be seen as a variation of conventional offender-based risk assessment whose principles were established many decades ago as research began to demonstrate that the characteristics of offenders were correlated with their subsequent behavior (Burgess, 1928; Glueck & Glueck, 1950; Miller & Lin, 2007): offender characteristics are scored and combined to form a scale that is indicative of "risk"—such as the risk of rearrest or reconviction, the risk of absconding while on bail, or the risk of violating conditions of parole or probation (Clear, Wasson, & Rowland, 1988; M. R. Gottfredson & Gottfredson, 1979, 1984; S. D. Gottfredson & Moriarty, 2006). These methods do not reliably predict who will and who will not reoffend, all having substantial margins of error in this regard (Ashford & LeCroy, 1990; M. R. Gottfredson & Gottfredson, 1984; S. D. Gottfredson, 1987; S. D. Gottfredson & Moriarty, 2006; Klein & Caggiano, 1986; Wiebush, Baird, Krisberg, & Onek, 1995). Instead, they are concerned with the classification of offenders into higher and lower risk groups for the purposes of allocating appropriate criminal justice interventions and resources (Ashford & LeCroy, 1990; Baird, 1984; Juvenile Sanctions Center, 2002; Loeber & Stouthamer-Loeber, 1987; Marczyk, Heilbrun, Lander, & DeMatteo, 2003; Office of Juvenile Justice Delinquency Prevention, 1995; Wiebush et al., 1995). RTM is consistent with this tradition as it combines actuarial risk prediction with ecological criminology.

The technical approach to RTM is straightforward: identify, through meta-analysis or other empirical methods, literature review, professional experience, and practitioner knowledge (Ratcliffe & McCullagh, 2001), all factors that are related to a particular outcome for which risk is being assessed. Then, operationalize—standardize—each factor to a common geography. Essentially, RTM assigns a (weighted or un-weighted) value signifying the presence, absence or intensity of each factor at every place throughout a given geography. Each factor is represented by a separate coverage (raster) map of the same geography. When all map layers are combined in a Geographic Information System (GIS), they produce a composite map—a risk terrain map—where every place throughout the geography is assigned a composite risk value that accounts for all factors associated with the particular crime outcome. The higher the risk value the greater likelihood of a crime event occurring at that location. RTM of crimes produces maps that show places with the greatest risk or likelihood of becoming spots for crime to occur in the future (Caplan & Kennedy, 2009; Groff & La Vigne, 2001; Johnson, Bowers, Birks, & Pease, 2009). Not just because police statistics show that reported crimes occurred there yesterday, but because the environmental conditions are ripe for crime to occur there tomorrow.

Risk terrain modeling assumes a step that is basic to the development of geographic information systems in assuming that certain spatial locations can acquire attributes that, when combined in prescribed ways, create context in which certain outcomes are made more likely. So, as an example, the combined attributes of open space, presence of children, and proximity to schools may indicate a playground. These attributes combined can be used to anticipate the types of behavior that we would expect in a playground—reducing the uncertainty that our forecasts about what would transpire here are wrong. In this way, we use attributes as a means of assigning risk (or likelihood) that certain events will happen in a particular place. Now, these outcomes may be benign (e.g., children playing) or they may take on a more sinister character where a combination of certain types of factors creates a context in which the risk of hazardous outcomes (including crime) can occur. The advantage of an approach such as RTM is that it provides a landscape that can be considered in terms of factors that contribute to negative outcomes, such as crime, that are more enduring than just the characteristics of the people who frequent these places. This observation about enduring characteristics resonates with the work done by human ecologists (e.g., Holland, 1998) who set out to construct what they called natural areas; that is, locations that had certain characteristics that should lead to expected behavioral outcomes, regardless of the character of the people living in or passing through these areas. RTM suggests the formation of locations that are more malleable than those the ecologists saw in natural areas, but that share the characteristic that they are not pre-defined by the attributes of the people who live or travel there.

Risk Terrain Modeling and Forecasting Crime Places

As pointed out earlier, retrospective hot spot mapping is the operational default for police agencies in their attempts to anticipate the location of future similar crimes. Certainly, commonsense suggests that this is a reasonable method and research confirms its predictive power (Berk, 2009; Chainey, Tompson & Uhlig, 2008). However, research indicates that the predictive effectiveness of mapping can be improved over the conventional approaches (Johnson et al., 2007) using multivariate methods (Gorr & Olligschlaeger, 2002), raster data (Groff & La Vigne, 2001) and diverse techniques such as RTM, which builds in part on the theoretical insights already reviewed that seek to explain the clustering of crime. Forecasting approaches undertaken to-date are diverse, some more explicitly embracing theory than others and some relying on more complex statistical techniques. From our point of view, an important consideration for the development of forecasting models is replicability of the approach by police analysts using existing and common GIS tools. Also, it should enhance their ability to inform strategic decision-making and operational policing that can prevent or suppress crime without subsequently limiting perpetual forecasting efforts that rely solely on past crime events. That is, the identification of risky areas should permit police to intervene and allocate resources to reduce risk independent of the success or otherwise of the police in dealing with the crime problems predicted. By contrast, retrospective maps produce indicators of risk that are directly affected by police operations, making them less reliable.

Study Objectives and Research Setting

Our research presented here has two key objectives. The first is to apply RTM to the crime of shootings. The composite maps that were produced from RTM use a range of contextual information relevant to the opportunity structure of shootings to estimate risks of future shootings as they are distributed through a geography. The second study objective was to test the predictive power of the risk terrain maps over two six-month time periods. In addition to measuring its overall predictive power, RTM was compared against the predictive ability of retrospective hot spot maps. This test of efficacy is critical: if RTM is to be useful in operational policing, it needs to show substantial improvement upon conventional retrospective mapping techniques.

This study emerged out of collaboration with the New Jersey State Police. The focus of this collaboration, and the analysis presented henceforth, is Irvington, NJ, an urban community of 2.8 square miles with a population of 65,000 that has become a particular concern of local and state law enforcement over the last five years. Murder rates for 2007 were 38.7 per 100,000, compared to a national average for similar size cities across the country of 4.9 (UCR, 2008). The community is adjacent to a slightly larger suburban township and the larger city of Newark. The town has a large number of shootings and other violent crimes and it contains a large, vibrant drug market. In addition, it is also the hometown of a large number of known gang members. The combination of these factors and the growth of violence within Irvington without noticeable or alarming dispersion or displacement to other nearby towns led the State Police to set up a special task force to police this area as a supplement to the small and overtaxed township police.

This task force consists of uniformed troopers who patrol targeted areas based on prior acts of violence and a shooting response team that investigates all shootings where a victim was actually injured by gunfire. The patrol force may act in a highly visible saturation capacity or in aggressive patrols focusing on the suppression of open air drug markets. The shooting response team conducts shooting investigations and works with the uniformed troopers and undercover operatives by pointing them toward areas of potential violence such as gang-related retaliatory shootings. The task force is unique for a state police agency in that these troopers work out of a station house in the center of the city and are assigned fulltime to this detail, often for a period of several years. As a result of this task force operation, there has been an increase in drug arrests and a reduction of shootings in this area. This reduction in violence was dramatic at the onset of the operation; however, it has leveled off and remained fairly constant. State Police executives are now looking for more robust analyses of the data, specifically the ability to use forecasting to direct police operations. It is in this context that we have developed and tested RTM.

Methods: Developing Risk Terrains for Shootings

Our technical approach to building risk terrains involved re-conceptualizing multiple layers of criminogenic risk factors within a spatial context. Data from Irvington were combined in a GIS to produce a composite risk terrain map showing the potential, or risk, for crimes to occur at each place in the future (Caplan & Kennedy, 2009; Groff & La Vigne, 2001). Raster mapping uses grids made up of equally sized cells to represent discrete or spatially continuous data. Each cell is assigned real world coordinates and an attribute value. When different raster maps have the same sized cells, these maps can be combined by adding, subtracting, multiplying, or dividing the values of congruent cells among each map. This "map algebra" (Tomlin, 1994) makes raster maps ideal for creating risk terrains, which are the composite of multiple raster map layers within a common geography.

One of the challenges of doing this work was that, in general, shootings are not a common form of violence and there is—perhaps as a result of this—a relative lack of literature compared to other types of crime. However, in certain areas of inner city neighborhoods such as Irvington, shootings frequently occur. For this study, we chose to operationalize three key variables that, based on literature (and local hunches), we felt confident would spatially predict shootings: dwellings of known gang members (n = 722; Brantingham & Brantingham, 1981; Fagan & Wilkinson, 1998; Klein, 1995), locations of retail business infrastructure (n = 108; Brantingham & Brantingham, 1995; Roncek & Maier, 1991), and locations of drug arrests (n = 496; a proxy for police intervention activities; Blumstein, 1995; Lum, 2008). These three variables are not an exhaustive list of the likely predictors that our review identified. However, they had the distinction of being operationalizable using data obtained from the New Jersey State Police.[1] Specifically, data on these three variables were available in address-level datasets from 1 January 2007 through 30 June 2008. Dwellings of known gang members referred to addresses where police had information about one or more gang members residing; retail business infrastructure referred specifically to bars, strip clubs, bus stops, check cashing outlets, pawn shops, fast food restaurants, and liquor stores; drug arrests referred to arrests by police for drug sales or possession.

Operationalizing these datasets to raster map layers was done using standard tools available in ArcView's Spatial Analyst Extension. Data were first geocoded to street centerlines of Irvington, NJ (obtained from Census 2000 TIGER/Line

1. Data was provided by the NJ State Police through the Regional Operations Intelligence Center and the many datasets they maintain, validate and update regularly to support internal crime analysis and police investigations.

Shapefiles) to create point features representing the locations of gang members' residences, retail business outlets, and drug arrests, respectively on three separate maps. The Density Tool in ArcView's Spatial Analyst Extension was then used to create a raster grid for each map and assign values to identically sized raster cells based on the intensity, or local concentration, of points near each cell's location. The Density Tool uses a method called the "moving window" in which a circular search area with a predetermined radius (referred to as the bandwidth) is drawn from the midpoint of each cell; points that fall within the circle are used to generate the value for each cell (Johnson et al., 2007; Mellow, Schlager, & Caplan, 2008). A new raster map is then created where higher cell values represent areas with heavier concentrations of points. Density values were calculated for this study so that points lying near the center of a cell's search area were weighted more heavily than those lying near the edge, in effect smoothing the distribution of values. The specific parameters for density calculations used in this study were a bandwith of 1,000 feet and a cell size of 100 feet.[2] This density method for operationalizing geocoded tabular data into risk terrain map layers was repeated for each variable, producing three raster maps with cell values assigned according to the immediate or nearby concentration of key variables in each respective cell.

Cells within each density map layer were classified into four groups according to standard deviational breaks. As shown in Figure 1 density maps (left) appear as a continuous surface when each cell is shaded from white to black according to its density value. In this figure, darker colored cells represent a higher density of gang member residences. The map on the right shows the same cells classified into four groups. White colored cells have values below the mean cell value; cells colored light grey have values between the mean and +1 standard deviation (SD); cells colored dark grey have values between +1 SD and +2 SD; cells colored black have values greater than +2 SD. In other words, the black colored cells have values in the top 5% of the distribution and were considered the highest risk. These four groups were coded 0 (white group; lowest risk) to 3 (black group; highest risk). This process was repeated for all three density map layers to produce three new raster maps of Irvington with all locations designated as low to high risk for shootings. All three map layers were considered aggravating factors (i.e., variables that increase the likelihood for shooting outcomes) and remained positive values. Since the cells of different map layers were the same size and were classified in a consistent way (i.e., standard deviations), they could be summed to form a composite risk terrain. Map layers of gang member residences, retail infrastructure, and drug arrests were summed

2. A 1,000 foot bandwidth was selected because it seemed a reasonable sphere of influence for shooters—the average blockface is approximately 350 feet (Felson, 1995; Taylor, 1997; Taylor and Harrell, 1996). 100 $\times$ 100 foot cells were the smallest area that our computers could process reasonably fast and, for this proof of concept of RTM, if a Risk Terrain could predict locations of shootings at the smallest (but reasonable) geographic units, it would best exemplify the utility of RTM for operational policing compared to larger, less specific, units of analysis.

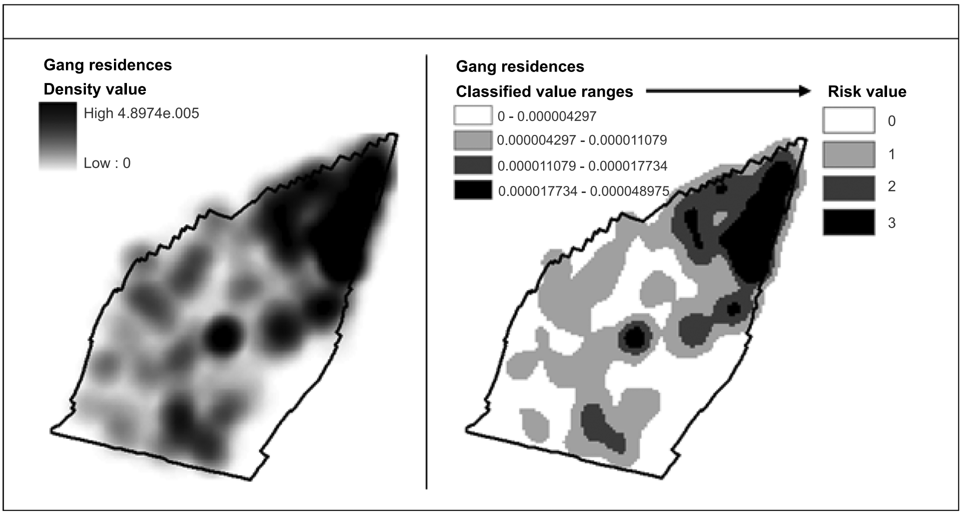

Figure 1 Example of risk value determination from Standard Deviation classification schema.

together using the Raster Calculator Tool in ArcView's Spatial Analyst Extension; cell values could range from a low of 0 to a high of 9.

Data were divided into three six-month time periods: January to June 2007 (Period 1), July to December 2007 (Period 2), and January to June 2008 (Period 3). Two risk terrain maps were created using data from Periods 1 and 2. The predictive validity of these risk terrains was tested using counts of shooting incidents during Periods 2 and 3 that were appended to the cells of Period 1 and Period 2 risk terrains, respectively, using the Spatial Join function in ArcView. Cells of final risk terrain maps, then, had two values attributed to them: (1) risk value (from 0 to 9), and (2) number of shootings during the consecutive time period. These values were used in subsequent statistical analyses.

Shooting incidents were located by street addresses in the dataset. Therefore, their exact locations were unknown beyond the street name and number that was assigned to each incident. For example, if a shooting occurred in a back yard that was several hundred yards from the street in front of the house, the location of the shooting would nonetheless be recorded as the dwelling's street address. This is common practice for most police departments. However, for the purpose of modeling and testing risk terrains with real data, it was supposed that shootings could only occur on streets to which the data was geocoded. Given this limitation of administrative police records, all risk terrain cells that did not intersect with a street were excluded (using "Select by Spatial Location" in ArcGIS) to produce two new risk terrains. Cells (i.e., 100 × 100 foot places) within these new risk terrains (n = 4,046 in each) served as the unit of analysis for subsequent statistical tests.

Figure 2 illustrates risk terrains for the two time periods, together with the shootings for the subsequent six-month time periods. The future shooting incidents appear to be located in areas that risk terrain maps forecasted to be higher risk, and their movement appears to be heading south and west. Risk values for each cell of the Period 1 risk terrain of Irvington, NJ ranged from zero (0) to eight (8); the mean was 2.37 (SD = 2). Shootings per cell ranged from 0 to 2 (n = 28). Risk values for each cell of the Period 2 risk terrain ranged from 0 to 8; the mean was 2.39 (SD = 2). Shootings per cell ranged from 0 to 2 (n = 26).

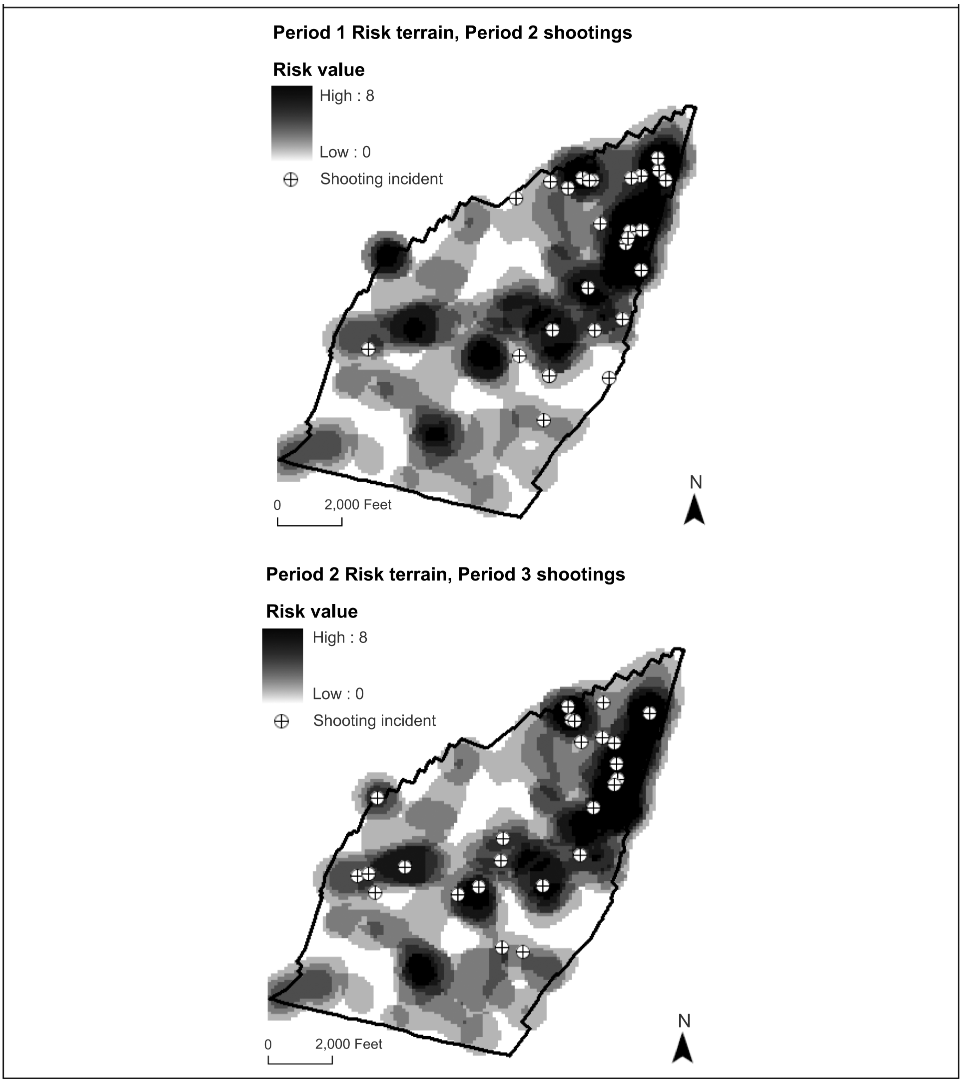

Figure 2 Risk terrain and shooting overlay.

Results: Testing Risk Terrains

We used a number of techniques to assess the predictive efficacy of the risk terrain models.

Regression Analysis

Logistic regression analyses were used to determine the extent to which shootings were significantly more likely to occur in higher risk cells. A Binary Logistic Regression was run for each of the two risk terrain forecast periods using "Risk Value" (0-8) as the independent variable and "Presence of Any Shooting" (Yes or No) as the dependent variable. As shown in Table 1, odds ratios suggest that for every increased unit of risk, the likelihood of a shooting significantly increases by at least 56% ($p < 0.001$); the Period 1 risk terrain attained an even higher odds ratio to suggest a shooting likelihood of 69% ($p < 0.001$). Calculation of Moran's I indicated there was no spatial autocorrelation, so we present here models that do not include a spatial lag.[3]

Table 1 Logistic regressions for risk value on shooting

							95% CI for Exp(*B*)	
	B	SE	Wald	df	Sig.	Exp(*B*)	Lower	Upper
Period 1 risk terrain[a]								
Risk value	.52	.097	29.06	1	<.001	1.69	1.397	2.048
Period 2 risk terrain[b]								
Risk value	.44	.094	22.31	1	<.001	1.56	1.297	1.876

[a]–2 Log likelihood = 280.824; Nagelkerke R square = .11; n = 4046 street-intersected cells. [b]–2 Log likelihood = 280.695; Nagelkerke R square = .08; n = 4046 street-intersected cells.

3. Moran's I is an area-wide analysis that was used to measure spatial autocorrelation in the distributions of shootings within cells of the Period 1 and Period 2 risk terrains of Irvington, NJ. Distributions among geographical units, such as grid cells, are usually not independent, meaning that values found in a particular cell are likely to be influenced by corresponding values in nearby cells (Anselin, Cohen, Cook, Gorr, & Tita, 2000). Moran's I measures this autocorrelation, with values approaching 1 when geographical units are situated near other similar geographical units, and approaching –1 when geographical units are situated near dissimilar geographical units. A Moran's I value of 0 indicates the absence of autocorrelation, or independence, among geographical units. GeoDa, a freestanding software application, was used to calculate Moran's I values for each risk terrain with a Queen Contiguity Weight matrix (Anselin, 2003). A permutation process "in which a reference distribution is calculated for spatially random layouts with the same data (values) as observed" permitted generating pseudo p-values for assessing the statistical significance of the Moran's I values (Anselin, 2003, p. 91). The value of the global Moran's I score for the Period 1 Risk Terrain was 0.014; the value of the Moran's I score for the Period 2 Risk Terrain was 0.011. These values near 0 indicate that no spatial autocorrelation was present in the distributions of shootings across cells in either risk terrain. Though, neither value was statistically significant ($p > 0.05$ after running 999 permutations).

Comparing Risk Terrains to Retrospective Maps

This research also sought to examine whether the risk terrains would improve upon retrospective maps in their ability to correctly forecast places where shooting incidents will occur. If the risk terrain methodology does not show any improvement to retrospective hot spot mapping, its added value to police operations is negligible.

To do this analysis, we had to build retrospective maps for comparison. Retrospective mapping is defined by using the locations of past events to predict locations of future similar events. In police work, this univariate analysis assumes a static environment—that the locations of crimes do not change over time and is operationalized as the production of density maps for visual analysis. A retrospective map of shootings, therefore, is a density map calculated from the locations of shooting incidents from Period 1 that would then be used to forecast the locations of shootings that will occur during Period 2. This type of procedure is widely used by crime analysis units in police departments across the country (Harries, 1999).

Risk terrain maps and retrospective maps must be produced and classified with the same parameters in order for direct comparisons to be made. Thus two retrospective maps were produced using the same technical procedures as described previously with regard to risk terrain maps, and only cells that intersected with streets were included. Shooting incidents from Periods 1 and 2 produced Period 1 and Period 2 retrospective maps, respectively. Cells in each map were classified using standard deviational breaks and then each category was coded with a "risk" value from 0 to 3 (highest risk). Since retrospective maps are based solely on one variable (e.g., shootings) their cells' risk values only range from 0 to 3. Clusters of cells with values of three are what might commonly be referred to as hot spots. It was assumed that a Period 1 retrospective map would correctly forecast the locations of some Period 2 shootings, and that a Period 2 retrospective map would correctly forecast the locations of some Period 3 shootings. While the predictive validity of retrospective maps was expected to be significant, as the existing literature suggests, it was hypothesized that risk terrain maps would have higher percentages of correct predictions.

To ensure that the same number of risky cells was tested across the two methods (i.e., for comparison purposes) the top 10% (405), top 20% (810), top 30% (1214) and top 40% (1618) of cells were selected and designated as "High Risk" among four dichotomous variables, respectively.[4] Additionally, for each map, the count of shootings per cell was recoded into a dichotomous variable that noted the presence or absence of "any shootings."

4. Random numbers were necessary to randomize the sorting of cells with the same risk values. For example, if 11 out of 100 cells had a risk value of eight, and they were sorted in descending order, the top 10% of cells to be designated as "high risk" would all have values of eight. But, the 11% cell would be excluded due to a rather arbitrary sorting algorithm. The random number ensured that every cell had an equal chance of being sorted above or below each cut point.

The associations between high-risk cells and shootings were tested for significance using 2 × 2 tables and Fisher's exact tests.[5] Results for each cut point are presented in Table 2. As much as 21% more shootings occurred in high-risk cells predicted by the risk terrain map compared to the retrospective map. The top 10% of high-risk cells in the Period 1 risk terrain map correctly predicted 42% of future shootings, compared to 21% that were identified by the Period 1 retrospective map. The risk terrain innovation therefore doubles the number of shooting incident locations that were correctly predicted compared with the conventional approach. It is possibly a conservative estimate of the risk terrain's potential because only three data layers were used to create risk terrains, while we imagine that many more layers might also be included. As depicted in Figure 3, results suggest that risk terrains provide a statistically significant forecast of locations of future shootings across a range of cut points, and are substantially more accurate than retrospective hot spot mapping.

Testing the Cohesiveness of Risk Terrain High-Risk Cells

As a final step in examining the utility of risk terrain maps, we sought to test the cohesiveness of forecast hot spots they generate. This is important because risk terrains will be of most operational utility to the police if they can create clearly defined clusters of high-risk cells that can be easily patrolled, as opposed to only a large number of dispersed isolate cells

Table 2 Fisher's exact tests—Comparative predictive validity for risk terrains and retrospective maps, Periods 1 and 2

		% of cells with shootings during the following six months that were designated as high-risk (Period 1 n = 24; Period 2 n = 25)	
	High-risk cell designation method (n = 4046)	Risk terrain map	Retrospective map
Period 1	Top 10%	42**	21
	Top 20%	54**	42*
	Top 30%	71**	63**
	Top 40%	75**	67*
Period 2	Top 10%	40**	28**
	Top 20%	56**	40*
	Top 30%	68**	52*
	Top 40%	80**	72**

*$p < 0.05$; **$p < 0.01$

5. This test is an alternative to Chi-square for 2 × 2 tables when predicted cell counts are low, which is the case with shootings. The lack of spatial autocorrelation means that assumptions of independence of spatial units are legitimate in this case.

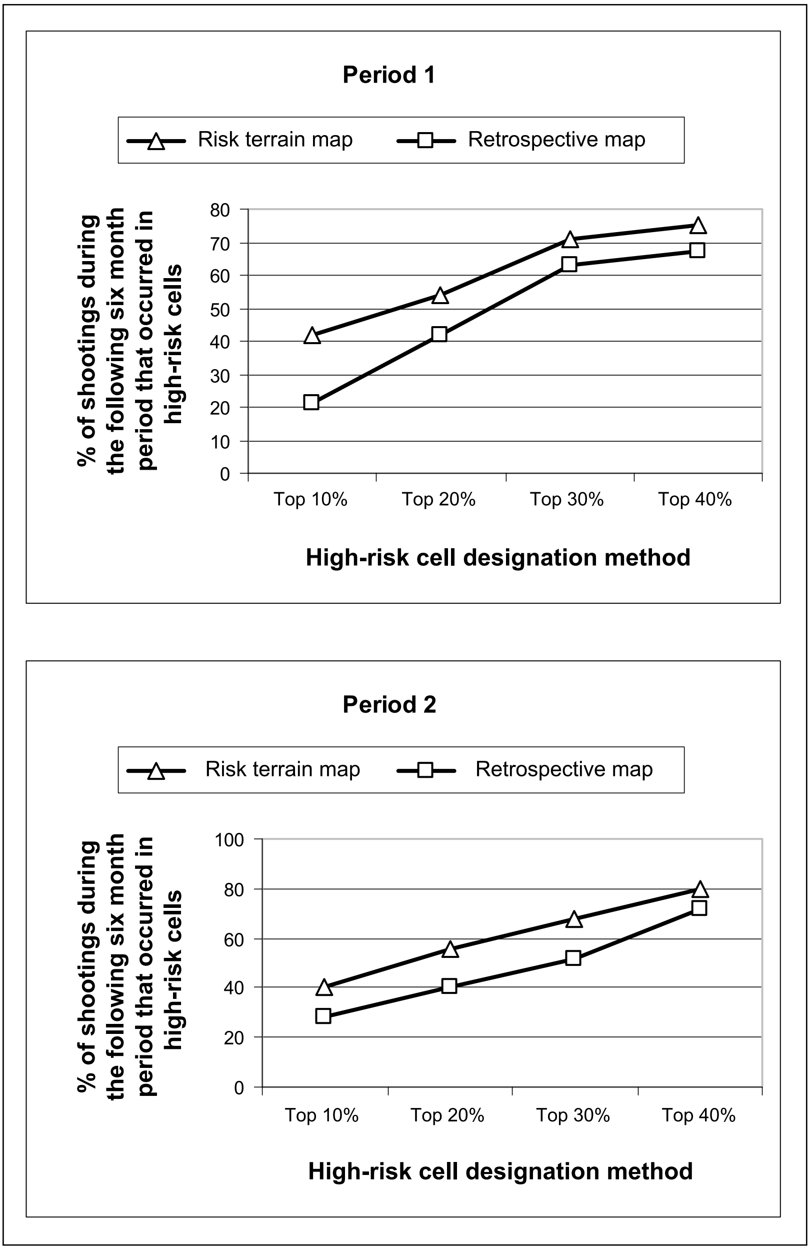

Figure 3 Comparative predictive validity for risk terrains and retrospective maps.

(Johnson et al., 2007). One way of measuring this is to conduct a Nearest Neighbor analysis, as suggested by Johnson et al. (2007) and who were among the first to use this approach to study hot spot coalescence. Nearest Neighbor (NN) analysis is a test of spatial randomness and works by calculating the distance from each cell in a collection to its nearest neighboring cell (Caplan,

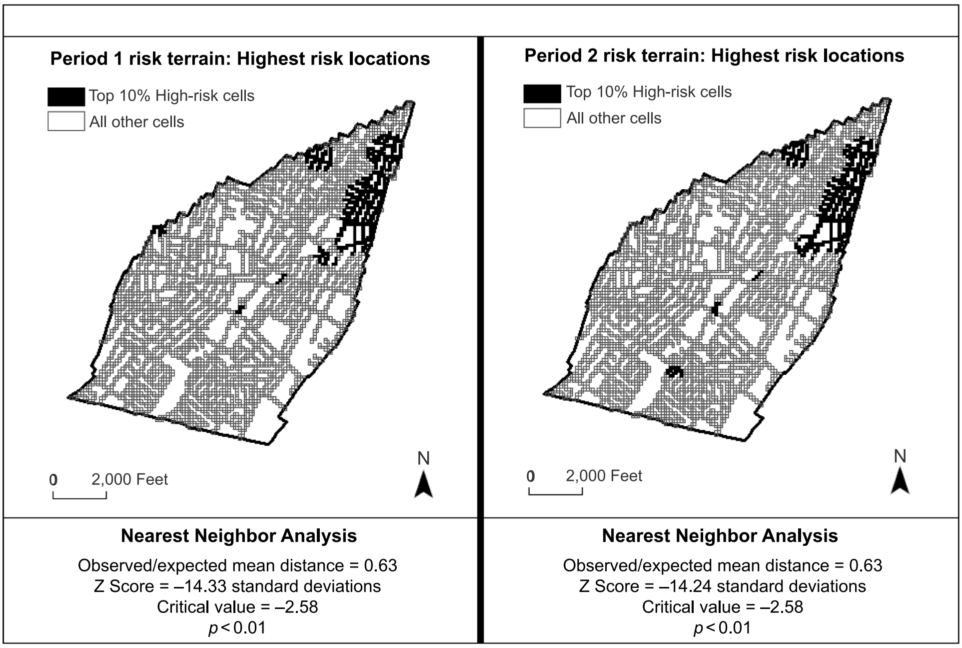

Figure 4 Clustering of top 10% high-risk locations in risk terrains.

2010). This distance is then compared to the expected mean NN distance for a random distribution of cells.

The Average Nearest Neighbor tool in ArcGIS was used to perform a NN analysis on the highest risk cells in each risk terrain (Period 1 and Period 2) to determine if these cells were closer than expected under spatial randomness. As shown in Figure 4, there is less than 1% likelihood that the clustered pattern of the top 10% highest risk cells could be the result of random chance. Significant clustering was found for top 20%, top 30%, and top 40% high-risk cut points as well. Upon visual analysis of the maps in Figure 4, the top 10% highest risk cells appear to cluster into a low number of hot spots. Therefore, in addition to risk terrain maps improving upon retrospective maps, they appear to produce information that can be operationalized by police administrators easily and efficiently, such as for directing police patrols to coalesced high-risk areas.

Discussion and Conclusion

Risk terrain modeling suggests a way of looking at behavioral outcomes as less deterministic and more a function of a dynamic interaction that occurs at places. The attributes are not necessarily constant interactions set in place over time. However, the ways in which these factors combine can be studied to reveal consistent patterns of interaction. The computation of these rules is a key component of RTM, with the ability to weight the relative importance of different factors at different geographic points in influencing behaviors and events. The attributes themselves do not create the crime; they simply point to locations where, if the conditions are right, the risk of crime or victimization will go up. This might often be influenced by factors outside of the context that we are studying, such as the general level of social control that is in place across locations. But, this, too, can be added as an attribute, or factor, to be considered in RTM.

Risk terrains assume a wide divergence in the extent to which locations contain attributes that are likely to contribute to criminogenesis. We cannot simply assume, though, that because a location is high in risk according to these types of attributes, that crime will always ensue (any more than we can assume that a location that is a high risk for disease will experience an outbreak, as a matter of course). Important in these considerations is the extent to which we are likely to find that these locations are susceptible or exposed to conditions that promote criminal behavior. There is a long standing debate in criminology concerning what promotes these outcomes and it is not really enough to say that risk of crime increases when the number of criminals increase. What is more likely to occur is that the risk of crime in places that share criminogenic attributes is higher than other places as these locations attract offenders and are conducive to allowing certain events to occur. This is different from saying that crime concentrates in highly dense hot spots. Rather, it suggests that individuals at greater risk to committing crime will congregate in riskier locations. Oddly enough, this is not to say that there are more or better targets (Cohen & Felson, 1979) of crime here (as there may be less to steal and fewer rewards from robbing individuals) but rather that the conditions for criminal behavior (e.g., lower risk of apprehension or retaliation) are better in these places than in others.

This research sought to apply RTM to a contemporary social problem—shootings. In doing so, it has demonstrated the character and value of a spatial risk assessment technique that is within the reach of many operational crime analysts in practical law enforcement settings. Key steps in the process of developing our risk terrains included spatially operationalizing theory about the causes of shootings using three sources of available local criminal justice data: dwellings of known gang members, locations of retail business infrastructure, and locations of drug arrests. By combining raster map layers that incorporate these three types of information, we arrived at risk terrain maps that successfully forecasted crime at places.

The identification of risky areas permits public safety practitioners to intervene and allocate resources to reduce risk at the unit of analysis that they are operationally conditioned for—the geography. The impact of interventions to reduce risk (and avert negative events such as shootings) can be evaluated by regularly re-assessing risk, and then measuring changes in risk values among different risk terrain maps at micro or macro levels using basic inferential statistics. For example, when evaluating the impact of a police intervention that was taken in response to assessed risk, subsequent risk terrain maps might be expected to show certain results, such as an overall reduction in risk values throughout the intervention area; a fragmentation or shift of high-risk hot spots; or, an equalization (or smoothing) of risk throughout the study area—with a decreased intensity of high-risk hot spots and a slightly increased or constant intensity of risk at previously cooler spots. In this way, the risk assessment model and the interventions performed by public safety practitioners to reduce risk can be appropriately and mutually exclusively credited with success or failure—a major improvement upon other crime forecasting methods discussed earlier.

Although the effort put into RTM was more than that required to produce a conventional retrospective crime map, we suggest that with routinization of the process, such as with ArcView's ModelBuilder (ESRI, 2000), the time taken to regularly build these maps need not be beyond the resources and timeframes of operational crime analysts. The flexibility of RTM methods and the scales to which they can be applied would allow the police to strategically incorporate known areas of concern in their assessment of locations that might generate violence—a practical reality suggested by Ratcliffe and McCullagh (2001). Then police could assign resources accordingly to address one or more of the factors in the risk terrain model at the regional and/or local levels. For example, they might institute community policing strategies that engage other municipal agencies and address problems of social disorganization, including the strict enforcement of ordinances related to vacant properties; public works departments might be instructed to limit roadway access to troubled areas, such as drug markets; and, parole officers might be consulted to better evaluate reentry plans of incarcerated offenders who will return to high-risk areas. As these examples suggest, RTM has the potential to enhance short- and long-term strategic decision-making activities regarding such things as tactical operations, case management, and resource allocation. Risk terrains can be particularly valuable to police agencies when fiscal budgets are tight because they do not require new or exceedingly great investments in hardware or software. They only require a dynamic way of thinking about crime problems, their causes, and situational impacts of police interventions.

The extra effort to develop risk terrains has a significant payoff—it allowed us to identify cohesive and tightly defined geographical areas in which future shootings took place. Critically, it did this more effectively than retrospective crime mapping, and at a level of detail that could measure even subtle changes of risk at locations over relatively short six-month periods of time. While it remains a hypothesis, we might imagine that directing police patrols to a risk terrain's high-risk hot spots in place of the historical crime hot spots could further enhance the already effective strategy of hot spot policing—with greater potential impacts on crime reduction. In the context of shootings, which run a high risk of fatality, this would be a significant dividend.

Further steps in the development of risk terrains involve doing more work to elaborate, operationalize and test variables not addressed in the current paper, and to extend RTM to other types of crimes and settings. It will also be important to develop strategies for incorporating risk terrains into operational policing and test the impact of emergent operational strategies on targeted crimes. If refined further, RTM may enable police to be more effectively proactive and identify areas with the greatest probability of becoming hot spots for crime in the future. Not just because police statistics show that crimes occurred there yesterday, but because the environmental conditions are ripe for crimes to occur there tomorrow.

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