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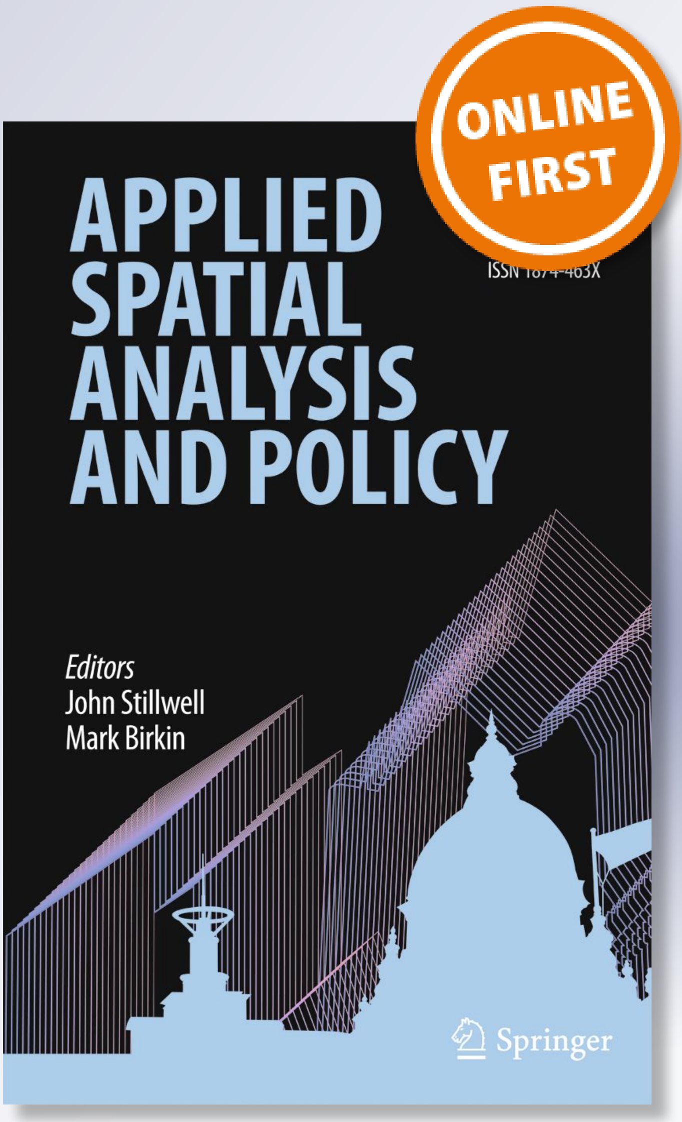

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Using Vulnerability and Exposure to Improve Robbery Prediction and Target Area Selection

Joel M. Caplan[1] · **Leslie W. Kennedy**[1] · **Eric L. Piza**[2] · **Jeremy D. Barnum**[1]

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Abstract
A large body of research has found that crime is much more likely to occur at certain places relative to others. Attempting to capitalize on this finding to maximize crime prevention, many police administrators have sought to narrow their department's operational focus and allocate resources and attention to the most problematic locations. However, in the face of a growing number of technological advances in crime forecasting that have facilitated this trend, it is still unclear how to best identify the most appropriate set of places to which resources and attention should be directed. Our goal was to examine this issue by exploring the ways in which spatial vulnerabilities and exposures could be used to identify the best target areas for policing. Using the Theory of Risky Places as a guide, we employed kernel density estimation (KDE) to measure crime exposures and risk terrain modeling (RTM) to identify crime vulnerabilities with the expectation that crime would be predicted more accurately by integrating the outputs from these two methods. To test this hypothesis, our analysis utilized 1 year of data on street robbery in Brooklyn, New York. A common metric, the prediction accuracy index (PAI), was computed for KDE, RTM, and the integrated approach, over 1 month and 3 month intervals. We found that the integrated approach, on average and most frequently, produces the most accurate predictions. These results demonstrate that place-based policing and related policies can be improved via actionable intelligence produced from multiple crime analysis tools that are designed to measure unique aspects of the spatial dynamics of crime.

Keywords Risk terrain modeling · Kernel density estimation · Prediction accuracy index

✉ Joel M. Caplan
jcaplan@rutgers.edu

1 School of Criminal Justice, Rutgers University, Newark, 123 Washington Street, Newark, NJ 07102, USA

2 John Jay College of Criminal Justice, City University of New York, New York, NY, USA

Introduction

The crime and place perspective suggests that police resources should not be randomly distributed among large beat, sector or municipal areas (Eck and Weisburd 1995). Deploying resources according to macro areas without priority to micro places within them assumes that crime is equally likely to occur everywhere within the macro geography (Sherman and Weisburd 1995). However, a line of research that burgeoned in the late 1980's, and continues to grow today, found that uniform distributions of crime are far from the reality and that resources can be allocated in a much more efficient and effective manner. Sherman et al. (1989), for instance, found that just 3% of places within Minneapolis, MN accounted for roughly half of all demand for police service. Though several prior studies had already reported uneven spatial distributions of crime across broad geographic areas (e.g., Guerry 1833; Shaw and McKay 1942; Quetelet 1842), the results of Sherman and colleagues were novel in that they extended the finding of crime concentration to 'places,' or micro units of analysis equivalent to street segments, block faces, addresses, or groups of addresses (Weisburd 2008, 2). Several recent studies have since corroborated the findings of Sherman and colleagues (e.g., Andresen et al. 2016; Braga et al. 2011; Braga et al. 2010; Caplan et al. 2011; Weisburd et al. 2012). These studies have helped to usher in a new era of policing that capitalizes on the influential role of geographic landscapes in facilitating crime (see Andresen 2014). Further, they have demonstrated the practical value of geographic information system (GIS) tools, spatial data acquisition, and spatial analysis.

The contemporary consensus among scholars and practitioners is that policing should not be implemented randomly; some places should receive greater priority than others for the greatest public safety return (Skogan and Frydl 2004). More specifically, police resources are best utilized when allocated to places where crime is most likely to happen (Braga et al. 2014; Kennedy et al. 2015a). The issue then, is how to best identify these places in the interest of allocating limited police resources to manageable areas that are likely to be the most problematic. While recent advancements in data and technology have proffered a number of tools to facilitate this endeavor, there is much room for improvement.

In this study we examine the ways in which spatial vulnerabilities and exposures to crime can be used to accurately identify probable places for future occurrence. "Spatial vulnerability" refers to the context of environmental risk, or the probability of particular outcomes (Caplan and Kennedy 2016). A place's vulnerability to robbery is measured through risk terrain modeling (RTM) as a score of the weighted influences that nearby attractors and generators of illegal behavior have on it (Brantingham and Brantingham 1995). "Exposure" refers to the historical facts and collective memories people have about places and the events that occurred there (Caplan and Kennedy 2016). It is the existing knowledge about past offending behaviors and crime hot spots, as measured through kernel density estimation (KDE) (Chainey et al. 2008). We evaluate these two common crime analysis methods independently and jointly to compare their crime prediction efficacy. Whereas police want to predict[1] and prioritize places that

[1] Although crime 'forecasting' and 'prediction' are technically different concepts, they are often used synonymously in practice (see RAND, 2013). Therefore, we use the two terms interchangeably throughout this paper.

disproportionately experience crime, and whereas a focus on micro places is the evidence-based modern day best practice, often resulting in measurable crime reductions merely through strategic assignments of officer presence (Ariel and Partridge 2016; Kennedy et al. 2018; Koper 1995; Koper et al. 2013; McGarrell et al. 1999; Piza and O'Hara 2014; Ratcliffe et al. 2011 Rosenfeld et al. 2014; Sherman and Weisburd 1995; Taylor et al. 2011), we sought to identify a viable method for police analysts to define target areas for police resource allocation and intervention in the face of two common options: hot spot analysis and risk terrain modeling. We hypothesized that crime would be predicted at places more accurately by considering the information produced by integrating the two methods instead of relying on a single method alone. This paper presents why this expectation turned out to be true for the crime of street robbery in Brooklyn, New York.

Conceptual Framework

Scholars and practitioners alike understand that police efforts to control and prevent crime are maximized when focused at micro-level places that are most likely to experience a disproportionate share of crime (Braga et al. 2014). More elusive, and arguably inconsistent in practice, is the best way to operationalize 'problem places' into 'target areas' that can be subjected to police interventions. Methods for crime mapping and analysis can take many forms (see Santos 2012), but a common approach involves identifying past spatial patterns of crime to make assessments about specific places where crime is likely to occur in the future. Rapid improvements in data and GIS technology have led to the creation of numerous analytic techniques to do this (Perry et al. 2013; Eck et al. 2005). For most methods the goal is to identify crime 'hot spots,' or places in a jurisdiction with a disproportionately high frequency of crime (Sherman 1995). Hot spot methods measure 'exposure,' or the historical crime facts about places and events that have occurred there, within a jurisdiction (Caplan and Kennedy 2016). Hot spots can provide a good measure of future crime places.

Some common methods for identifying crime hot spots include kernel density estimation (KDE) (Chainey et al. 2008), spatial and temporal analysis of crime (STAC) (Block and Block 2004), and nearest neighborhood hierarchical (Nnh) clustering (Levine 2004). A number of studies have compared these and other methods relative to one another with regard to their efficacy in predicting which places will generate the greatest share of crime in future time periods (Chainey et al. 2008; Drawve 2016; Drawve et al. 2016; Hart and Zandbergen 2012; Levine 2008; Van Patten et al. 2009). KDE often stands out among these studies and has become a frequently utilized hot spot mapping and crime prediction method. According to Hart and Zandbergen (2014), KDE is popular among researchers and practitioners given its accessibility in mainstream GIS or data management software, such as Esri ArcGIS or Microsoft Excel (Power Map), as well as the relatively simple and straightforward interpretation and aesthetic appeal of its outputs (306). Moreover, and perhaps more important, is the relative efficacy of KDE for identifying locations where crime will be most likely to occur. For example, research by both Chainey et al. (2008) and Drawve (2016) found that KDE outperformed other methods, such as STAC and Nnh, by predicting crimes over the smallest geographic areas. However, Levine (2008) found that Nnh produced the best predictions relative to other methods (including KDE), and research by Hart and Zandbergen (2012) determined that no single method is superior to another. Van Patten et al. (2009) suggested that different hot spot techniques are useful in different situations, so there is no single best option.

Although the KDE analysis is completed with a few clicks of a mouse in a GIS, KDE is a mathematically sophisticated way to calculate surface density. In ArcGIS, for example, KDE begins with an initial set of crime incident point locations distributed over a continuous surface of equally sized raster grid cells covering the study extent. The kernel density function draws a circular neighborhood around each sample point and then applies a mathematical function that goes from 1 at the location of the point to 0 at the neighborhood boundary. A kernel is a smoothly curved surface that is fitted over each point. Then, a density value for each cell in the grid that comprises the study area is calculated by adding the values of all the kernel surfaces where they overlap. Weights are calculated for each point within a specified search radius (i.e. bandwidth), with points near the center weighted more heavily than points near the edge (Johnson and Ratcliffe 2013). Places with exceptionally high density values are considered crime hot spots.

KDE, like other hot spot methods, is a retrospective approach to crime prediction, based on known recent past incident locations, i.e. exposures. Results are operationalized for practice with the expectation that new crimes will occur in the future at the same locations where exposures concentrated in the past. So, police resources and interventions are focused at hot spots because they have been the places for significant proportions of criminal activity and, thus, are believed to offer the greatest crime reduction potential (Braga and Weisburd 2010; Braga et al. 2014).

In a recent paper testing the Theory of Risky Places, Kennedy et al. (2015b) argued that crime vulnerability at any given place within a jurisdiction can be evaluated by understanding what features of the environment contribute to the emergence and persistence of hot spots. They calculated crime risk scores of places as a product of the weighted influences that nearby attractors and generators exerted on illegal behavior at each place. Within this context, place-based values of crime risk, or spatial vulnerability, offer a mechanism to forecast the emergence of crime problems at micro places within a study area. But, as demonstrated in Kennedy et al.'s paper, relying on spatial vulnerability alone to make predictions about locations for crime is problematized by the possibility of false positive predictions, or the chance that certain places will be identified as vulnerable (i.e., high risk) but never actually experience crime. Of course, the same can be true of KDE hot spots. This can hinder police operations by causing inefficient allocations of resources and intervention actions to places that are suitable for crime, but that are relatively less likely to be exposed to it compared to other places. To overcome this issue, assessments of exposure, such as hot spot analysis, can be incorporated into assessments of spatial vulnerability, such as risk terrain modeling, to make better place-based predictions. This is a key proposition of the Theory of Risky Places proposed by Kennedy and colleagues. When combined with vulnerability, exposure emphasizes a place's experience and history with crime; that is, places where crime tends to concentrate in the recent past will aggravate its spatial vulnerability and thus increase its risk (Kennedy et al. 2018).

Risk terrain modeling (RTM) is used to articulate spatial vulnerability (Caplan and Kennedy 2016). RTM relies on criminogenic features of the environment to identify risky places (Kennedy et al. 2012). In this regard, RTM builds on extant research demonstrating a relationship between crime and certain environmental features, such as bars, restaurants, and public transportation stops (e.g., see Bernasco and Block 2011). Rooted in the idea that criminal behavior is influenced by the physical environment (Brantingham and Brantingham 2008), RTM incorporates principles of environmental criminology (Wortley and Mazerolle 2008) and risk assessment (Kennedy and Van Brunschot 2009) to assess the probability of crime occurring among places within a jurisdiction based on attractors and generators of criminal behavior (Brantingham and Brantingham 1995). The probability of crime is estimated by testing the spatial influences of attractive/generative features of a landscape, and their spatiotemporal confluence at places, on crime outcomes within a jurisdiction (Caplan and Kennedy 2016). Several recent studies have incorporated RTM into evaluations of crime prediction techniques (e.g., Garnier et al. 2018; Ohyama and Amemiya 2018; Dugato 2013; Drawve 2016; Drawve et al. 2016; Irvin-Erickson 2014; Moreto et al. 2014; Yerxa 2013), finding RTM to have accurate predictions across a variety of crime types and study areas.

The basic process of RTM (see also Caplan et al. 2015) involves first identifying environmental features that are theoretically or have been shown empirically to be associated with a given crime type. Once a pool of potential risk factors has been identified, the next step involves creating a series of standardized raster grid (map) layers based on each feature's locations and spatial influences throughout a jurisdiction. Each layer is then empirically evaluated to identify statistically significant risk factors and their relative weights on crime location patterns. The final task involves combining the individual risk map layers into a composite risk terrain map with risk scores indicating the likelihood of crime across all places throughout the study area. Crime is highly probable at places with high risk scores – where problematic environmental features combine to create optimal conditions for offending. Police resources and intervention actions are allocated to these locations in order to maximize crime and risk reduction efforts (Kennedy et al. 2018; Caplan and Kennedy 2016; Kennedy et al. 2015a, b).

Whereas spatial vulnerability characterizes susceptibility to crime, or the likelihood that crime will emerge at a specific place, and exposure characterizes historical significance and experiences with crime, or the likelihood that crime will persist at a specific place, a vulnerability-exposure framework for target area selection is expected to yield the greatest value for policing policies and practices (Kennedy et al.2018). Though several studies have compared the efficacy of vulnerability and exposure methods *against* one another, none to our knowledge have examined the *combined* effects of multiple methods for target area selection. One study by Caplan et al. (2013a) explored the 'joint utility' of KDE and RTM to predict violence. They found that both methods produced actionable information that could enhance allocation of police resources. But their application of the two methods employed regression models whereby each was controlled-for the other when assessing a respective method's effects on outcomes. Caplan et al. (2013a) demonstrated a strong and valuable contribution of each method for purposes of crime prediction, but stopped short of operationalizing these findings for the purpose of selecting target areas for police patrol purposes. They did, however, attribute their high levels of variance explained and other significant findings to the 'joint utility' of event dependent crime prediction techniques that account for prior crime incidence as well as the surrounding environments that facilitate offending and create spatial vulnerabilities. This is further supported by Drawve et al. (2019) who used both methods to predict traffic crashes in Green Bay, Wisconsin. The current study builds on this work by creating a hybrid vulnerability-exposure measure, using KDE and RTM, to assess specific places where crime is most likely to occur and where resources could confidently and wisely be allocated.

Current Study

Study Setting and Crime Type

The study setting is Brooklyn, one of five boroughs in New York City, NY.[2] Brooklyn is situated east of Manhattan and south of Queens and totals approximately 71 mile^2 in size. Of the five boroughs, Brooklyn has the largest population with just over 2.6 million residents. After Manhattan, Brooklyn has the second highest population density of the boroughs, with nearly 37,000 residents per square mile.

We focus on robbery, a violent crime that involves force or threat of force to obtain something of value from another person (Wright and Decker 1997).[3] According to the Federal Bureau of Investigation (2014) robbery occurs frequently, and often in the streets, which makes it an ideal outcome event for spatially-oriented research (Van Patten et al. 2009). Robbery also has importance within the New York City Police Department (NYPD), as the agency has typically considered robbery a 'bell-weather' crime that gauges levels of other violent crime and, thus, has tended to design crime prevention interventions to target the occurrence of robbery (Maple and Mitchell 1999; Sousa and Kelling 2006). Robbery complaints were provided directly from the New York City Police Department (NYPD). Robbery complaints were obtained as XY coordinates and imported into ESRI ArcGIS for preparation and analysis.[4] Robbery data for this study refer to only those incidents that occurred in the streets (not inside buildings) over the course of 1 year from October 1, 2014 through September 30, 2015. To make our research practically meaningful, crime predictions are compared each month and every 3 months, which are commonly used time intervals for police departments to assess ongoing and emerging trends (Santos 2012). Robbery counts for each time period are displayed in Figs. 1 and 2.

Methods

Following prior studies (Chainey et al. 2008; Drawve 2016; Drawve et al. 2016; Dugato 2013; Levine 2008; Van Patten et al. 2009) our metric for comparing the

[2] See a reference map of Brooklyn, NY on Google Maps: https://goo.gl/maps/aE7no4KH3SR2

[3] This definition is consistent with New York State Penal Law, see CJI2d [NY] Penal Law §160.00. The NYPD classifies crime incidents using these definitions (see http://www.nyc.gov/html/nypd/html/crime_prevention/crime_statistics.shtml).

[4] Robbery and risk factor data provided to the research team by the NYPD were likely geocoded using a composite method that matched first to streets then to parcels (which would explain the points that were offset as much as 160 ft). Since XY coordinates were provided to us, we do not know more about the exact geocoding method used by NYPD. For the point risk factors we manually geocoded, we used a 15-ft offset. Polygon risk factors, conversely, pertained to parcel and building footprints in New York city and were not georeferenced according to street centerline.

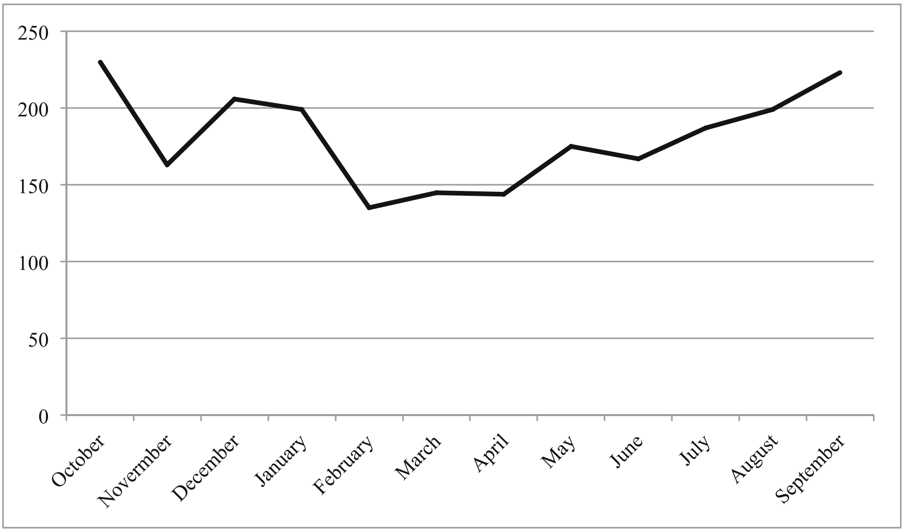

Fig. 1 Monthly robbery counts for Brooklyn, October 2014 – September 2015

individual and combined effects of exposure via KDE and vulnerability via RTM is the prediction accuracy index (PAI). The PAI is a measure of crime prediction accuracy that accounts for the size of the geographic area identified by crime from a previous time period that is required to predict crimes for a subsequent time period (Chainey et al. 2008). The PAI is calculated using the following formula (Chainey et al. 2008):

$$\mathrm{PAI} = \frac{\left(\frac{n}{N}\right) \text{ x } 100}{\left(\frac{a}{A}\right) \text{ x } 100}$$

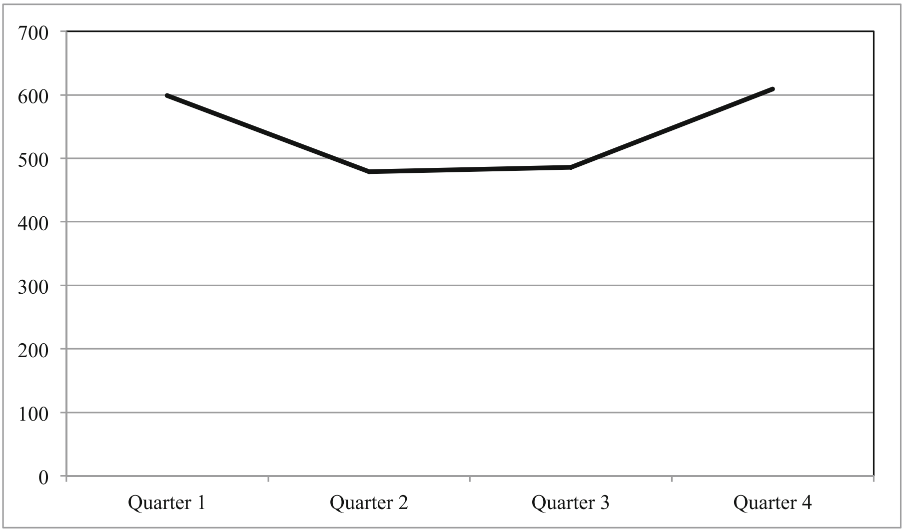

Fig. 2 Three month robbery counts for Brooklyn, October 2014 – September 2015

Where n represents the number of robberies in the hot spots or risky places, N is the total number of robberies in the study area, a is the area (e.g., mi^2) of the hot spots or risky places, and A is the area (e.g., mi^2) of the study area. The numerator is known as the 'hit rate' whereas the denominator is referred to as the 'area percentage.' The PAI is a useful metric for evaluating the utility of different crime prediction methods because it is relatively easy to compute and accounts for frequency of crime relative to geographic area required to predict crimes (Chainey et al. 2008). Higher PAI values indicate a greater degree of accuracy for a given method, or that more crime is accurately predicted within a smaller geographic area.

We calculate PAI values at 1 month and 3 month intervals for KDE, RTM, and a combined measure (based on the two methods) to determine if accounting for both vulnerability and exposure of places to crime enhances prediction accuracy.[5] More specifically, a PAI value is calculated for each method and for each month (i.e., 1 month of robbery data to predict the next month's robberies) and for each method every 3 months (i.e., 3 months of robbery data to predict the next 3 months' robberies). This results in a total of 14 time periods (i.e., 11 one month intervals and 3 three month intervals) for which PAI values are calculated and compared for each method.

Analytic Approach

KDE requires several parameters to be specified a priori by the user, including interpolation method (i.e., triangular or quartic), bandwidth (i.e., search radius), and cell size (Hart and Zandbergen 2014). Both Drawve (2016) and Hart and Zandbergen (2014) found the quartic method to be optimal for crime prediction, which we use here.[6] With regard to bandwidth, Drawve (2016) determined that a 1-block bandwidth produces the highest PAI values. Therefore, we use a 362-ft bandwidth, which approximates the average block length in Brooklyn. Finally, Hart and Zandbergen (2014) found that cell size has little or no effect on PAI values. Therefore, to maintain consistency between the two methods (see discussion below) we use a cell size of 181 ft, which approximates half a block length in Brooklyn.

Each iteration of KDE utilized robbery incidents in one time period to identify hot spot places that were likely to experience robbery in the next subsequent time period. For our purposes, places were considered hot spots if they had kernel density values that were two standard deviations or higher above the mean kernel density value (Caplan et al. 2013a). A separate KDE was produced using robbery incidents for each month to predict robberies in the

[5] The robbery data used for this study was offset from street centerlines by as much as 160 ft. Most cells in the fishnet of Brooklyn were within this distance from streets. However, some other study settings may not be similar. For future research in other settings, we recommend that the fishnet used for testing predictive validity of KDE and/or RTM be limited to only those cells that intersect streets if the crime incident data used for the analysis are geocoded to street centerlines. Excluding non-intersecting cells before testing predictive validity would account for where crimes could actually occur within the study setting; It would exclude the cells that could never have a crime occur due to the technicalities of geocoding addresses to streets. This would likely enhance the results of future research.

[6] We use ArcGIS to perform each KDE, which by default employs interpolation based on the quartic method.

following month. For example, for the first time period we used October 2014 robbery incidents to identify hot spots. We then determined the area of October 2014 hot spots relative to the area of Brooklyn and counted the number of November 2014 robbery incidents that fell within them to calculate the PAI values. We continued this process, performing KDE and calculating PAI values for each month through August 2015 (predicting September 2015). This same process was also completed every 3 months beginning with October – December 2014 (predicting January – March 2015) through April – June 2015 (predicting July – September, 2015).

The RTM process began with the identification of potential risk factors for robbery. The search for potential risk factors was based on theory and existing empirical evidence that particular environmental features would be likely to attract or enable robbery (e.g., see Bernasco and Block 2009, 2011; Dugato 2013; Haberman et al. 2013; Hart and Miethe 2014; LaVigne 1996; Roncek et al. 1981; Roncek and Faggiani 1985; Roncek and Maier 1991; Smith et al. 2000; St. Jean 2007). In total, we include 27 environmental features of the Brooklyn landscape as potential risk factors in each risk terrain model, which are displayed in Table 1. Environmental feature data were obtained directly from the NYPD as shapefiles compiled from numerous local government agencies: the Department of Consumer Affairs, Department of Financial Services, Department of City Planning, Department of Environmental Conservation, Department of Information Technology and Telecommunications, Department of Parks and Recreation, the New York City Housing Authority, and the New York State Liquor Authority.

As with KDE, a separate risk terrain model was created each month and every 3 months to identify places where robbery was likely to happen in the next month and next 3 months, respectively. For example, for the first month, risk factors were validated and weighted based on October 2014 robbery data. The resulting vulnerable places based on October 2014 risk factors were identified and measured in terms of their area relative to Brooklyn. Finally, the number of November 2014 robbery incidents that fell within the vulnerable places was counted to calculate PAI values. We considered places to be vulnerable if their relative risk scores (RRSs), produced by the risk terrain model, were two standard deviations or higher above the mean RRS. We also completed this process every 3 months beginning with October – December 2014 (predicting January – March 2015) through April – June 2015 (predicting July – September, 2015).

All risk terrain models were created within the RTMDx software (Caplan and Kennedy 2013). Similar to KDE, we specified a cell size of 181 ft and a block length of 362 ft (the average block length in Brooklyn) as parameters for the RTM analysis (Caplan et al. 2013b). Additional parameters for the RTM included operationalization, maximum spatial influence, and analysis increments. Operationalization refers to how the spatial influence of each environmental feature will be tested. Caplan (2011) explains that the spatial influence of environmental features may be operationalized as proximity (i.e., being near a feature increases risk) or density (i.e., a cluster of features increases risk). Although RTMDx can test both operationalizations and empirically select the most

Table 1 Environmental features included as potential risk factors in risk terrain models of robbery in Brooklyn

Environmental feature	*n*	Observed mean distance	Spatial pattern	Operationalization
Banks	415	517.24	Clustered***	Both
Billiard Halls	7	5145.17	Random	Proximity
Check Cashing Businesses	143	2071.86	Dispersed***	Proximity
Chemical Dependency Facilities	83	1207.40	Clustered***	Both
Cinemas	11	4140.73	Random	Proximity
Clubs	40	2924.96	Random	Proximity
Colleges and Universities	16	3445.80	Random	Proximity
Food Pantries and Soup Kitchens	225	1252.81	Clustered***	Both
Gas Stations	249	1025.96	Clustered***	Both
Grocery Stores	2239	307.17	Clustered***	Both
Homeless Facilities	124	1486.28	Clustered***	Both
Hospitals	16	4708.05	Random	Proximity
Hotels and Motels	73	1772.22	Clustered***	Both
Laundromats	1375	353.58	Clustered***	Both
Mental Health Facilities	206	787.05	Clustered***	Both
Developments†	–	–	–	Proximity
Off Premise Liquor Establishments	546	757.69	Clustered***	Both
On Premise Liquor Establishments	1411	293.92	Clustered***	Both
Parking Facilities	208	799.24	Clustered***	Both
Parks†	–	–	–	Proximity
Pawnbrokers and Secondhand Dealers	1504	264.08	Clustered***	Both
Pharmacies	647	604.54	Clustered***	Both
Postal Facilities	77	2795.17	Dispersed*	Proximity
Schools	576	551.47	Clustered***	Both
Recreation Centers	7	9712.50	Dispersed***	Proximity
Restaurants	698	477.43	Clustered***	Both
Subway Entrances	545	176.49	Clustered***	Both

All environmental features' spatial influence tested to a maximum extent of 3 blocks at half block increments

†Data were originally acquired as polygon shapefiles. However, the RTMDx Utility only accepts point features as potential risk factors. Therefore, ArcMap 10.2.1. was used to convert each park polygon to a representative grid of points prior to inclusion in the risk terrain model

$*p < 0.05$;$***p < 0.001$

appropriate one, this is not always necessary (Caplan et al. 2013b). Basic visual inspection of environmental features on a map and supplementary nearest neighbor analyses can aid in the selection of which operationalization parameters to set (Caplan and Kennedy 2016). For example, it makes little sense to test the spatial influence of features as a function of density if they are randomly dispersed (i.e., not clustered) throughout a jurisdiction. Table 1 displays the operationalization(s) tested for each environmental feature.[7]

Maximum spatial influence defines the geographic extent to which environmental features' influences on crime extends (i.e., the influence of bars may extend to 1, 2, 3, or even 4 blocks). Because research has found that the spatial influence of features typically extends within just a few blocks (Groff and Lockwood 2014), we test the spatial influence of each environmental feature to a maximum extent of 3 blocks. Finally, analysis increments refer to the level of detail at which spatial influence is assessed (i.e., half-block or whole-block increments). Because whole blocks provide a cruder assessment, we tested the spatial influence of each environmental feature at half block increments to more precisely specify the dynamics of spatial influence across the landscape.

Integrating KDE and RTM

For each KDE or RTM analysis, Brooklyn was represented as a raster grid of 181-ft by 181-ft cells ($n = 61{,}361$). Each cell (the statistical unit-of-analysis) represented a micro place that may have been identified, during each one-month or three-month period, as a hot spot via KDE or a vulnerable place via RTM. To evaluate the co-effects of the two methods, we used a simple Boolean approach to create an integrated measure of exposure and vulnerability. Within ArcGIS, we created a single vector grid of cells with the same size and dimension as the raster grids employed in the KDE and RTM analyses. Within the accompanying attributes table, we created separate columns to indicate whether each cell was considered a hot spot or vulnerable place during each time period. Then for each time period, we 'selected by attributes' (in ArcGIS) cells that were considered both hot spots *and* vulnerable places. For cells that were both hot spots and vulnerable places, we measured their area relative to Brooklyn and counted the number of robberies in the subsequent time period to calculate PAI values. The PAI values were then compared across all three approaches to determine if robbery predictions improved when jointly considering the outputs of both approaches relative to those of the single method.

Results

Table 2 presents the descriptive information that was utilized to calculate PAI values for each time period. For example, each month RTM identified an average of 1557.82 cells (SD = 736.83) as highly vulnerable to robbery. This approximates 2.54% of places in Brooklyn. In contrast, each month KDE identified 2.20% of places in Brooklyn as hot spots, or 1347.82 cells (SD = 178.69) on average. The integrated measure (INT) of vulnerability-exposure identified the fewest places as problematic in Brooklyn each

[7] We use the Nearest Neighbor Threshold (NNT) to select operationalization parameters. The NNT can be calculated using the following formula: 2 * (Block Length * Number of Analysis Increments). This formula produced a NNT of 4344. If the features were not significantly clustered *or* if the observed mean distance (reported by the NN analysis) were greater than the NNT, the 'proximity' to features was tested. If the features were significantly clustered *and* the observed mean distance was less than or equal to the NNT, 'both' proximity to and density of features was tested.

Table 2 Number of cells, future crimes, and the hit rate for RTM, KDE, and the integrated measure at 1 month and 3 month time intervals

Method	Time period											AVG	SD
	1	2	3	4	5	6	7	8	9	10	11		
RTM (1 month)													
n future crimes	23	13	14	8	13	21	8	10	17	12	22	14.64	5.41
hit rate	14.11	6.31	7.04	5.93	8.97	14.58	4.57	5.99	9.09	6.03	9.87	8.41	3.35
n cells	3130	1748	1274	626	2361	1684	719	844	1717	1330	1703	1557.82	736.83
RTM (3 month)													
n future crimes	62	79	59	–	–	–	–	–	–	–	–	66.67	10.79
hit rate	12.94	16.26	9.69	–	–	–	–	–	–	–	–	12.96	3.29
n cells	1773	2811	1423	–	–	–	–	–	–	–	–	2002.33	721.86
KDE (1 month)													
n future crimes	15	14	15	14	8	5	7	14	12	13	18	12.27	3.95
hit rate	9.2	6.8	7.54	10.73	5.52	3.47	4	8.38	6.42	6.53	8.07	6.97	2.15
n cells	1632	1301	1518	1437	1084	1123	1137	1381	1287	1421	1505	1347.82	178.69
KDE (3 month)													
n future crimes	66	57	81	–	–	–	–	–	–	–	–	68	12.12
hit rate	13.78	11.73	13.3	–	–	–	–	–	–	–	–	12.94	1.07
n cells	3306	2823	2913	–	–	–	–	–	–	–	–	3014.00	256.85
INT (1 month)													
n future crimes	5	2	2	1	1	1	1	3	2	1	2	1.91	1.22
hit rate	3.07	0.97	1.01	0.74	0.69	0.69	0.57	1.8	1.07	0.5	0.9	1.09	0.74
n cells	257	145	98	42	146	98	46	46	138	116	131	114.82	61.84
INT (3 month)													
n future crimes	18	12	12	–	–	–	–	–	–	–	–	14	3.46
hit rate	3.76	2.47	1.97	–	–	–	–	–	–	–	–	2.73	0.92
n cells	299	359	189	–	–	–	–	–	–	–	–	282.33	86.22

Approximately 881 cells = 1 square mile in Brooklyn (total n cells = 61,361)

For one month intervals, Time Period 1 refers to October 2014(future crimes and hit rate pertain to November 2014). For three month intervals, Time period 1 refers to October – December 2014 (future crimes and hit rate pertain to January – March 2015)

month. On average, 114.84 cells (SD = 61.84) were considered to be problematic (i.e., both vulnerable and exposed) to robbery. This is equivalent to less than one-fifth of 1 % of places throughout Brooklyn. Overall, more places were identified by each method as problematic when considering 3 month intervals. This was expected as longer time frames account for a larger number of robbery incidents. Every 3 months, on average, RTM identified 2002.33 cells (SD = 721.86), or 3.26% of places in Brooklyn, as vulnerable to robbery. In contrast, KDE identified 3014 cells (SD = 256.85), or 4.91% of places, as hot spots in Brooklyn, on average, for each 3 month time period. The INT measure identified 282.33 cells (SD = 86.22), or less than one-half of 1 % of places, in Brooklyn as problematic for robbery. Whether 1 month or 3 month intervals are considered, the INT identifies the smallest geographic area as likely to experience robbery in subsequent time periods. Appendix presents maps of places throughout Brooklyn that were considered vulnerable to robbery overlaid on places that were considered hot spots for robbery for each 3 month time period to visualize the distribution and convergence of these locations.

Future crime counts and hit rates are also presented in Table 2. For example, RTM identified 3130 cells as vulnerable to robbery in time period 1 (October 2014). These 3130 cells predicted 23 robberies in the next month, which produced a hit rate of 14.11 (i.e., 14.11% of November 2014 robberies were predicted in these 3130 vulnerable cells). Overall, RTM predicted on average more future crimes, and yield higher hit rates than KDE, for each month and every 3 months (albeit just slightly). It is important to note that hit rate measures do not standardize for the size of the area required to predict crime. For example, higher hit rates are often a function of a larger geographic area identified as problematic (i.e., as a hot spot, vulnerable place, or both), which necessarily captures more crime incidents. Although considering an entire jurisdiction as problematic would produce a hit rate of 100 (i.e., all crimes predicted in the next time period), this would not be meaningful or actionable to police who must identify specific places to prioritize their limited resources. Therefore, we calculated PAI values to evaluate the performance of each method for each time period because PAI standardizes predictions by the size of the geographic area determined to be problematic; It standardizes hit rates by geographic areas. Higher PAI values indicate better performance, or more accurate predictions. Greater prediction accuracy reflects a higher hit rate over a small geographic area. Table 3 presents the PAI values for each method for 1 month and 3 month periods and includes averages and standard deviations across each time interval.

Table 3 PAI values for RTM, KDE, and the integrated measure at 1 month and 3 Month time intervals

Method	Time period											AVG	SD
	1	2	3	4	5	6	7	8	9	10	11		
RTM													
1 month PAI	2.77	2.22	3.39	5.81	2.33	5.31	3.90	4.35	3.25	2.78	3.55	3.61	1.16
3 month PAI	4.48	3.55	4.18	–	–	–	–	–	–	–	–	4.07	0.47
KDE													
1 month PAI	3.46	3.21	3.05	4.43	3.12	1.90	2.16	3.72	3.06	2.82	3.29	3.11	0.69
3 month PAI	2.56	2.55	2.80	–	–	–	–	–	–	–	–	2.64	0.14
INT													
1 month PAI	7.32	4.11	6.29	10.82	2.90	4.35	7.62	23.96	4.76	2.66	4.20	7.18	6.06
3 month PAI	7.71	4.22	6.40	–	–	–	–	–	–	–	–	6.11	1.76

For 1 month intervals, Time Period 1 refers to October 2014 (predicting November 2014). For 3 month intervals, Time period 1 refers to October – December 2014 (predicting January – March 2015)

First, considering the methods individually, the PAI values displayed in Table 3 suggest that RTM tends to outperform KDE in terms of prediction accuracy. In 7 of the 11 months, RTM produced a higher PAI value. Moreover, the average PAI value for RTM across all months was 3.61 (SD = 1.16). In contrast, KDE resulted in a higher PAI value in 4 of the 11 months. The average PAI value for KDE across all months was 3.11 (SD = 0.69). However, the results of an independent samples t-test reveal that these differences were not statistically significant.[8] The results tell a similar story when considering three-month intervals. In all three time periods, RTM produced a higher PAI value. The average PAI value for RTM across all three time periods is 4.07 (SD = 0.47) whereas the average PAI value for KDE across all three time periods is 2.64 (SD = 0.14). The results of an independent samples t-test reveal that these differences are statistically significant ($p < 0.05$). Overall, 3 month PAI values were higher than 1 month PAI values for RTM, and 3 month PAI values were higher for KDE than 3 month PAI values. Overall, these results complement findings reported by Drawve (2016).

Spatial crime predictions are more accurate when considering aspects of both crime vulnerability and exposure of places, at least when considering robbery incidents in Brooklyn. Specifically, PAI values are highest when employing an approach that identifies locations that are both hot spots via KDE and risky via RTM. According to Table 3, the integrated approach produced the highest PAI values in 8 of the 11 time periods. Moreover, the average PAI value for the integrated approach across monthly periods was 7.18 (SD = 6.06), twice as high as KDE or RTM alone. Results of independent samples t-tests reveal that these differences are statistically significant ($p < 0.05$). Two monthly time periods (5 and 10) found KDE to be slightly, insignificantly, higher than the INT measure, perhaps suggesting that robbery locations remained exceptionally stable (stationary) during this period. Time period number 6 found RTM to be significantly higher than the INT measures (KDE was exceptionally low, too), perhaps suggesting that robbery location patterns were drastically changing and emerging elsewhere from prior hot spots during this month compared to the previous month. Similar observations were made across three-month intervals in which the INT measure produced the highest PAI values for all three time periods. The average PAI value across these time periods was 6.11 (SD = 1.76), which was 1.5 times greater than RTM alone and more than 2 times higher than KDE alone. The differences between the INT measure and KDE are statistically significant ($p < 0.05$). The differences are only significant between RTM and the INT measure when broadening the level of confidence to $p < 0.10$. Figures 3 and 4 plot the PAI values for each month and every 3 months for visual comparison.

Discussion

This study sought to examine the independent and integrated efficacy of different crime analysis methods for producing actionable spatial intelligence to identify places most

[8] The two means of the average PAI values for RTM and KDE across all months were compared in t-tests with sample sizes of 11 months. The small size of sample ($n = 11$) could be a limitation to the statistical conclusion.

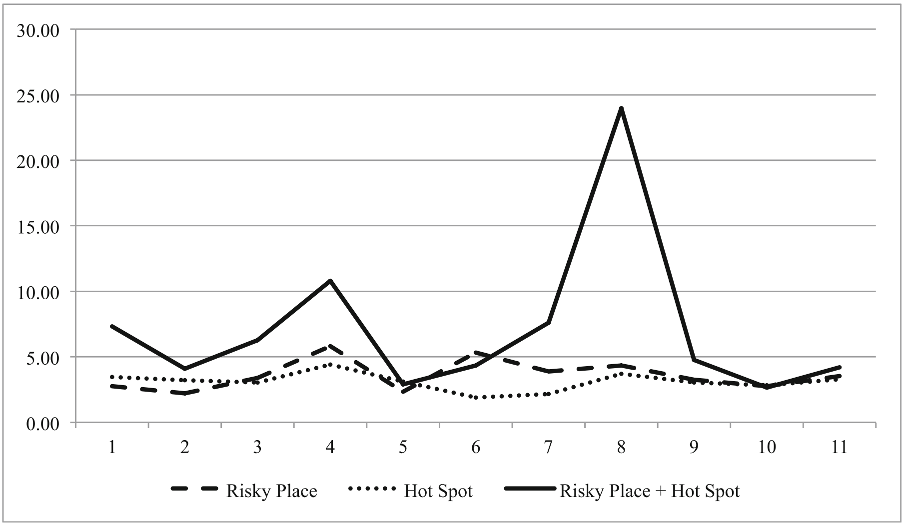

Fig. 3 Monthly PAI values for RTM, KDE, and an integrated approach

likely to experience crime and receive priority attention by police or other resources. We focused specifically on KDE and RTM, two methods commonly utilized in crime forecasting. Whereas KDE provides a measure of exposure to crime, RTM identifies a location's vulnerability to illegal behavior. Our goal was to determine if improvements in predictive accuracy over one- and three-month periods could be achieved by combining the outputs of KDE and RTM to produce a composite measure of vulnerability-exposure. These time periods were selected because they are operationally

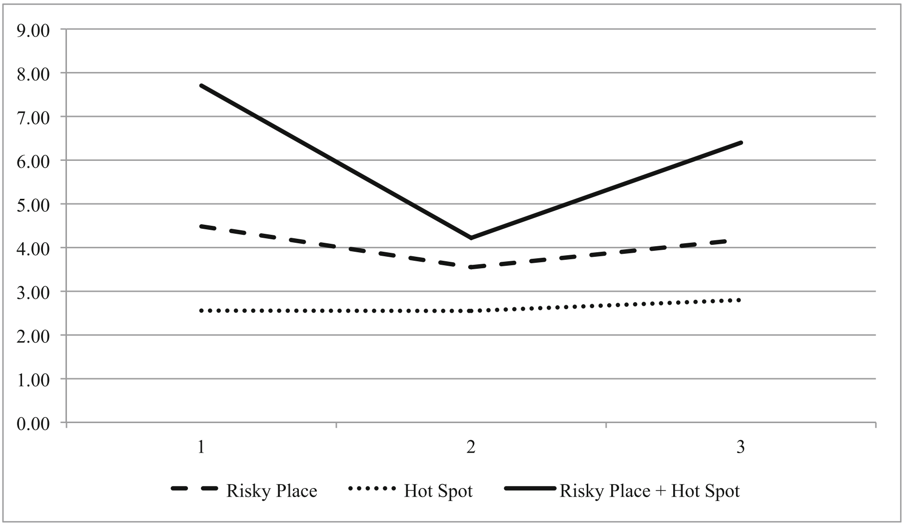

Fig. 4 Quarterly PAI values for RTM, KDE, and an integrated approach

meaningful and actionable temporal units of analysis (Rengert 1997) for police agencies, generally, and for the NYPD (and Brooklyn), specifically, because CompStat meetings often cover a 1-month period and other strategic interests often rely on quarterly reports. Results provide evidence to support using the vulnerability-exposure composite measure to enhance spatial crime prediction at micro places, and thereby to prioritize target areas for policing operations.

The predictive accuracy of KDE relative to RTM varied across the time intervals. Overall, RTM more frequently yielded higher PAI values across 1 month ($n = 7$) and 3 month ($n = 3$) time periods. Though, consistent with Dugato (2013), the differences between PAI values resulting from the two methods, particularly across months, was minimal. And, we tested over twice as many theoretically relevant environmental features in our RTM models, compared to Dugato's, which resulted in a more fully specified model of crime vulnerability in Brooklyn's risk terrain, and thus overall better potentials for forecast performance. However, given that the two methods performed differently over time, and that RTM performed more effectively overall over three-month time periods, further comparisons of these methods is necessary to determine the most optimal approaches given the conditions under which they are employed.

While RTM and KDE clearly have unique and meaningful values for crime analysis, PAI values were highest when considering qualities of vulnerability *and* exposure at locations, identified using both methods, combined. Overall, the integrated approach produced PAI values that were twice as high as KDE or RTM alone. These results are consistent with the exposure-vulnerability framework proposed by Kennedy et al. (2015a, b), but advance their research findings by demonstrating the implicit value of integrating these methods into a unified measure for target area definition. Alone, neither KDE or RTM fully capitalize on all the available empirically derived information about a place's suitability for ongoing or emergent crime problems. KDE identifies places where crime has concentrated in the past but does not account for the collection of environmental features that may facilitate offending or sustain its persistence. Likewise, RTM measures vulnerability by accounting for the presence of environmental features that create conditions suitable to offending, but it is limited by the potential that risky places may never be known to motivated offenders or utilized for criminal activities in the face of other places that are currently well known or 'reputable' options. Integrating the two techniques yields actionable information that can be used to anticipate new crime places with great efficiency.

Our findings are of practical value to police administrators who seek to prioritize problem places into target areas for resource allocation and intervention. The efficiency of police operations can be increased by maximizing crime prevention efforts at particular places most likely to experience crime problems, while minimizing the quantity and geographic area of relevant target locations. Our results demonstrate that a higher proportion of crime is captured in subsequent time periods relative to the geographic area required to address the spatial crime potential when considering both vulnerability and exposure at places. This information can enhance strategic and tactical allocation of resources and intervention actions intended to prevent and mitigate illegal behavior (Kennedy et al. 2011). Iterating the methods employed in this study on a monthly or quarterly basis would allow for dynamic identification of very small target areas that are likely to experience a meaningful portion of crime. Evidence-based dosages of directed patrols (Koper et al. 2013; McGarrell et al. 1999; Rosenfeld et al. 2014; Sherman and Weisburd 1995; Taylor et al. 2011) can be concentrated at these places. With a few confidently selected target areas that are manageable for patrol by fewer police units, extra (i.e. previously obligated) personnel can be utilized in other ways. For example, directed patrols might be paired with foot patrols (Piza and O'Hara 2014; Police Foundation 1981; Ratcliffe et al. 2011), who not only enhance police presence and community interactions, but who could also aim to directly address the spatial risk factors located within hot spots, identified by the risk terrain model. This might involve officers regularly visiting businesses with known problems, observing and reporting physical disorder such as unsecured vacant buildings or broken street lights to code enforcement, or fostering relationships with nonprofit organizations or social service providers who work with individuals at high risk for victimization. Criminal justice researchers regularly conclude that place-oriented approaches rooted in problem-oriented policing (Goldstein 1990) and situational crime prevention (Clarke 1980) are most likely to be effective in preventing and reducing crime in the long term (Skogan and Frydl 2004). An essential feature of these approaches is that they involve intentional activities tailored towards addressing the underlying characteristics of crime problems that cause places to be hot spots (Braga and Clarke 2014). Whereas measures of exposure can help to identify where and when crime concentrates over time, measures of vulnerability can diagnose what it is about places that allows crime to emerge and persist.[9] This is likely one explanation for the robust findings of this study, demonstrating the predictive power of a vulnerability-exposure framework for crime analysis.

While our findings advance theory and have practical implications for policing practices and policies, they should be generalized carefully in light of a few important qualifications. One pertains to the unavoidable subjective nature of parameter selection for both KDE and RTM. For example, studies by Drawve (2016) and Hart and Zandbergen (2014) note that certain changes in KDE parameters can lead to changes in PAI values. While we selected KDE and RTM parameters in accordance with theory and existing empirical research, specifically for the purpose of building optimal models, it is possible that alternative parameter specifications could be explored more fully in future studies and other settings.

It would also be worthwhile to explore the integration of additional hot spot techniques with RTM for crime prediction. We focus specifically on KDE because it is commonly used in practice and has been found to outperform other techniques for crime prediction (Chainey et al. 2008; Drawve 2016). However, other studies have found differently (Levine 2008). Future research should explore using other methods,

[9] Risk terrain models produced for this study identified the most problematic environmental features for each month and for each quarter over the course of 1 year. It is interesting to note that while some of the 27 environmental features tested in the models were rarely or never identified as risk factors, others were consistently found to increase the risk of robbery. In particular, grocery stores were risk factors for robbery every month and food pantries and soup kitchens and subway entrances were risk factors in most months. Conversely, banks, billiard halls, chemical dependency facilities, cinemas, clubs, colleges and universities, homeless facilities, hospitals, hotels and motels, mental health facilities, developments, parking facilities, parks, postal facilities, and recreation centers were never risk factors for robbery.

in combination with one another, to determine which technique or collection of techniques provide the best measure of exposure when integrated with measures of vulnerability. Moreover, such studies could be further enhanced by incorporating additional comparison criteria (e.g., see Adepeju et al. 2016).

Finally, we studied a single outcome event, robbery, over the course of a single year in a single jurisdiction. Although robbery is particularly amenable to spatial crime analysis and has been utilized in many previous studies (e.g. Drawve 2016; Dugato 2013; Hart and Zandbergen 2014; Levine 2008; Van Patten et al. 2009) it is not the only crime of interest to the police or their constituents. Moreover, some studies have incorporated multiple crime types (Chainey et al. 2008; Hart and Zandbergen 2014; Levine 2008) and found that a given method's performance varies depending on the crime type under consideration. Although we calculated PAI values over one-month and three-month time intervals, we used only a single crime type. Finally, Brooklyn is a very large urban jurisdiction with local dynamics that may influence crime differently than those in suburban, rural, or even smaller urban jurisdictions. Additional research is necessary to test the generalizability of our results to other crime types, across more temporal parameters, in other jurisdictions.

Conclusion

Consistent with a large and continuously growing body of research demonstrating that crime is much more likely to occur at some places relative to others, police administrators have sought to narrow their operational focus by allocating their department's finite resources to the most problematic locations to maximize crime prevention efforts. Modern advances in crime forecasting and prediction have complemented this trend towards 'refinement' in policing, yet it has been unclear how to best identify the most appropriate set of places to which resources and attention should be prioritized. In this study, our goal was to examine this issue further by exploring the ways in which spatial vulnerabilities and exposures could be used to identify the 'best' target areas for police resource allocation. We focused on two common crime analysis tools, kernel density estimation (KDE) and risk terrain modeling (RTM) with the expectation that crime would be predicted more accurately by integrating the outputs from both of these methods, rather than relying on information produced from a single method alone. We found support for this hypothesis using 1 year of data on robbery in Brooklyn as reflected in improvements in the prediction accuracy index, over one-month and three-month time periods, when utilizing an integrated approach that measures exposure via KDE and vulnerability via RTM. These findings suggest that more actionable intelligence can be created to enhance place-based policing by simultaneously considering information outputs from multiple crime analysis methods that are designed to measure unique aspects of the spatial dynamics of crime.

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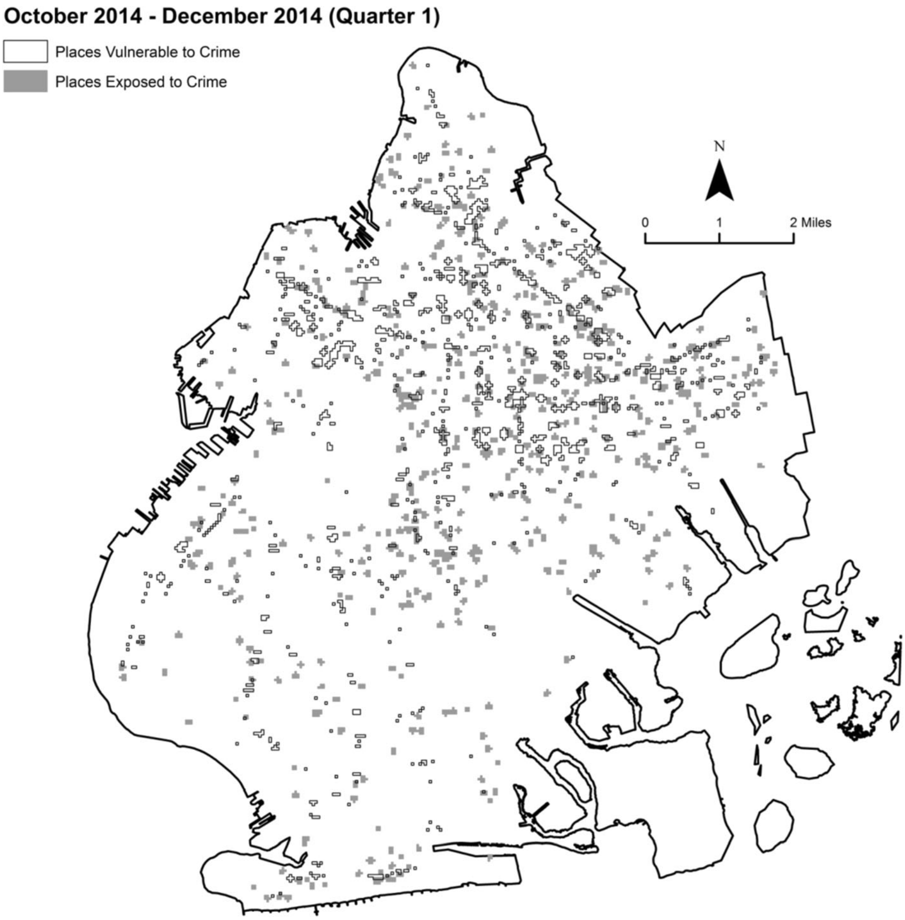
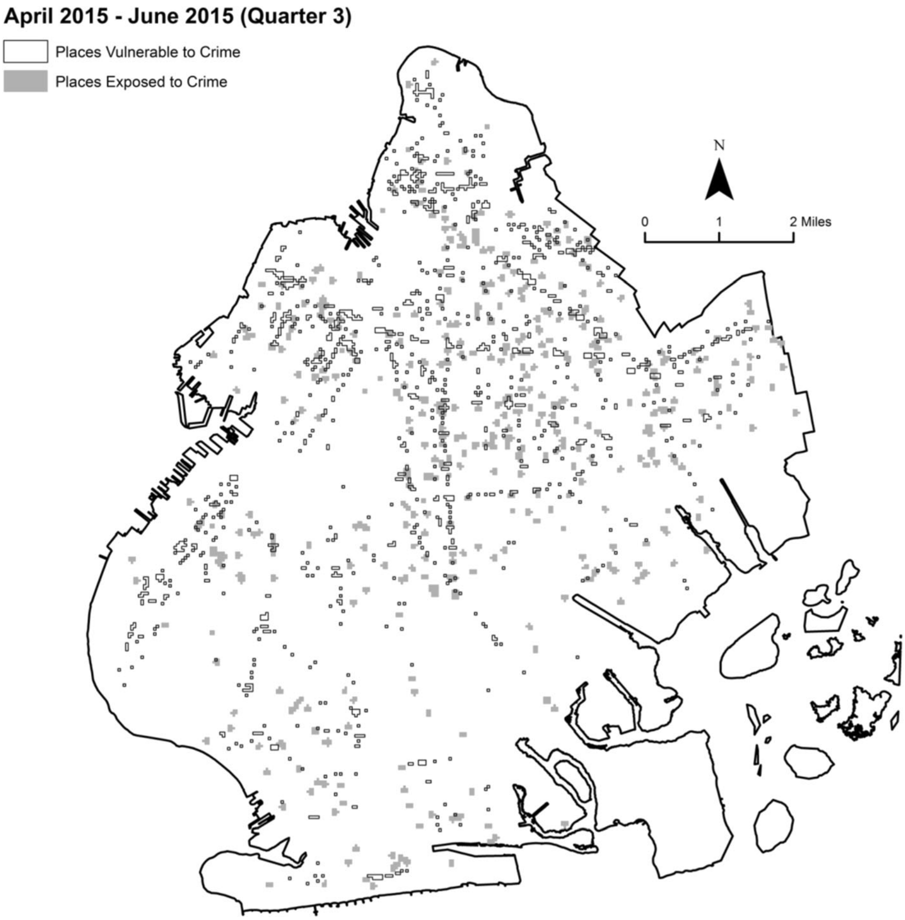
Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Appendix



January 2015 – March 2015 (Quarter 2)



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