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A Metric Comparison of Predictive Hot Spot Techniques and RTM

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There are numerous hot spot mapping techniques that can be used in research and in practice for predicting future crime locations. Due to differences in the varying techniques, metrics were developed to compare the accuracy and precision of these techniques. The predictive accuracy index (PAI) and recapture rate index (RRI) were used to assess six different hot spot techniques. Spatial and Temporal Analysis of Crime, Nearest Neighbor Hierarchical, Kernel Density Estimation, and Risk Terrain Modeling were the general techniques compared in relation to their PAI and RRI values for short-term and long-term prediction of robberies. The results of the study were discussed with an emphasis on the utility of using multiple techniques jointly for analysis.

Keywords hot spots; crime prediction; crime analysis; Predictive Accuracy Index; Recapture Rate Index

Introduction

The geography of crime has become a stronghold within police departments because of the advancements in technology. The various applications of crime mapping have made it a mainstay within police agencies (see Chainey & Ratcliffe, 2005). This could partially be the result of Sherman, Gartin, and Buerger's (1989) findings that crime is not random in space, limiting the geography of crime (Sherman et al., 1989). With the growth of crime mapping over the years, numerous techniques have been designed to examine the geographical distribution of crime.

The implementation of hot spot mapping into police initiatives has become a popular technique. Hot spots are considered small areas where the crime

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frequency is high, allowing for greater predictability of crime location (Sherman, 1995). Braga (2005) provided a review of hot spot policing studies and the effectiveness of the strategies in reducing crime and/or calls for service. Additionally, hot spot mapping becomes useful when predicting where crime is likely to occur since hot spot mapping is based upon past crime locations. As Chainey, Tompson, and Uhlig (2008) discussed, hot spot mapping is a basic retrospective technique that is useful for predicting future patterns of crime.

Within hot spot mapping, there are numerous techniques that are capable of identifying hot spots of crime. Eck, Chainey, Cameron, Leitner, and Wilson (2005) provided a review of these techniques and the applicability of them for hot spot mapping, but as Chainey et al. (2008) identified prior literature had not compared techniques to determine which is the most useful for predicting future crime. Because of the different mapping techniques (i.e. raster vs. vector output), it is difficult to compare hot spot techniques because of how the hot spots are geographically constructed, limiting the comparison to a hit rate (amount of crime predicted in hot spots compared to the overall amount of crime) or visual inspection. Chainey et al. (2008) proposed a metric measure of the predictive accuracy index (PAI) to assess the accuracy of hot spot techniques in predicting future crime. This measure allowed for comparison of varying techniques beyond visual inspection or the hit rate. When comparing various hot spot techniques, different studies came to contradictory conclusions (see Chainey et al, 2008; Dugato, 2013; Hart & Zandbergen, 2012; Levine, 2008; Van Patten, McKeldin-Coner, & Cox, 2009). Van Patten et al. (2009, p. 28) brought up a valid point that necessitated reiteration when answering what was the best hot spot technique, "It depends." As they indicated, different hot spot techniques were useful in different situations. While these studies compared similar techniques with varying parameters, there is a prospective technique, risk terrain modeling (RTM), which merits comparison to traditional hot spot techniques.

RTM is often used as a predictive technique that includes multiple environmental risk map layers based on a specific crime (see Caplan, Kennedy, & Miller, 2011). Risk layers are combined based on a grid system and corresponding areas of each map are lined up (risk factors are based on past literature). The combination of multiple risk layers creates a risk assessment of a study area that is interpreted as a higher risk value associated with a high risk for crime. Rather than relying on past crime solely, as is common within hot spot techniques, RTM incorporates physical and social characteristics of the environment.[1]

Since RTM constructs a risk assessment of an area based on a grid system, the highest values within the scale are considered the riskiest for future crime and

1. Levine (2005) discussed how the concentrations of crime create the label of a crime "hot spot" but these applications only take crime locations into context (phenotype). The cause of the formation of the hot spots needs to be examined, which Levine (2005) discussed could be a result of land-use patterns or behavioral patterns (genotype).

referred to as hot areas. The high-risk value cells become "hot areas" for future crime, not unlike hot spots, but they are conceptually different. Both traditional hot spots and RTM indicate areas that are expected to have crime occur within them in the future. While RTM can include a crime density risk measure, RTM differs from traditional hot spot techniques by including measures that reflect the study area's physical and social environment. With the view point that RTM can be implemented to identify "hot areas" for crime prediction, RTM can be compared to more traditional hot spot techniques (see Dugato, 2013). RTM has been compared to density maps (see Kennedy, Caplan, & Piza, 2011) and concluded RTM performed better than density maps[2]; however, Kennedy et al. (2011) did not use a metric to compare the techniques, rather a hit rate. When using a metric comparison, Dugato (2013) found density maps were more accurate but less reliable compared to RTM. Because of this, further research is needed comparing density maps and RTM using a metric comparison.

Additionally, when Kennedy et al. (2011) compared RTM with density maps, predicting future crime occurring within the following year (divided into four-, three-month time frames), the researchers could have used a hot spot technique that was more suited for this time frame. Van Patten et al. (2009) indicated that the Nearest-Neighbor Hierarchical (Nnh) hot spot technique excelled at shorter term prediction periods, such as one year to the following year. Essentially, Kennedy et al.'s (2011) study examined a shorter term prediction time frames within a year. This is not to say that Kennedy et al. (2011) should have examined different prediction time periods but included a comparison technique that excelled at this type of time frame prediction. The present study extends the prediction time frames to include short- and long-term time frames.

The current study supplements the extant literature by comparing multiple hot spot techniques similar to prior studies (Chainey et al., 2008; Dugato, 2013; Hart & Zandbergen, 2012; Levine, 2008; Van Patten et al., 2009), but including the comparisons with the RTM technique. The goal of the current research was not to suggest that one technique was superior to another but to simply compare multiple techniques on their predictive capabilities. It should also be stated that Kennedy et al. (2011) made no assertion that RTM should replace hot spot mapping but that both techniques should be used simultaneously. To compare the varying techniques the PAI (Chainey et al., 2008) and the recapture rate index (RRI) (Levine, 2008) were examined for robberies that occurred in Little Rock, Arkansas.

Review of Literature

While Sherman et al. (1989) is often associated with the clustering of criminal activity, prior literature indicated that crime clustered at varying levels

2. Kennedy et al.'s (2011) study did not use the PAI and RRI measures for comparison of techniques.

(see Balbi & Guerry, 1829; Guerry, 1833; Quetelet, 1842; Shaw & McKay, 1942). There are varying definitions of hot spots, but essentially a hot spot is a geographical location that contains a high amount of crime compared to the distribution of crime across the study area (see Block & Block, 1995; Chainey & Ratcliffe, 2005; Sherman, 1995; Sherman et al., 1989). Past research suggested that there could be variation in crime from street to street (see Weisburd, Bushway, Lum, & Yang, 2004; Weisburd, Morris, & Groff, 2009). For policing interest, areas where crime clustered became important for strategy implementation.

Predictive policing is a crime reduction approach that is taken by police organizations to predict where future crime is likely to occur and implement strategies to prevent the occurrence of crime (Bratton, 2011). This approach changes the nature of policing from being reactive to proactive. Being a proactive approach, predictive policing is a data-driven process and the reliability of the data can affect the results (Pearsall, 2010). An analytic tool that can be used for predictive policing is crime mapping via hot spots and geospatial risk assessments.

There are a multitude of different mapping techniques when examining the clustering of crime (see Eck et al., 2005), but in the current study limited techniques were utilized. The current study relied on the point pattern data and kernel density techniques for comparison to RTM. The choice in techniques was based upon past comparison studies (Chainey et al., 2008; Dugato, 2013; Hart & Zandbergen, 2012; Levine, 2008; Van Patten et al., 2009). These techniques were further discussed to provide a background on the techniques and why they were included for comparison.

Predictive Mapping

A common hot spot mapping technique is based on a type of mapping referred to as point pattern. Visually, point pattern mapping resembles older pin maps but with advancements in technology they can be displayed on computers allowing for more sophisticated analyses. Benefits from using these techniques are that the data are not limited to predefined boundaries (i.e. police districts and census boundaries). Outputs for these types of analyses can be displayed via spatial ellipses and/or convex hulls. An ellipse is an arbitrary boundary that encompasses the cluster of crimes while a convex hull connects the outer crime locations of a cluster (Levine, 2008). The output (ellipse or convex hull) indicates where crimes are clustered geographically but do not represent the actual distribution of crime within those clustered areas (see Ratcliffe & McCullagh, 2001). While the convex hulls are more accurate than the ellipses, the underlying crime clustering is not shown in the output.

A technique that has been used often in prior research is the Spatial and Temporal Analysis of Crime (STAC) technique developed by the Illinois Criminal Justice Information Authority (1996) (see Block & Block, 1995; Rengert, 1997;

Townsley, Homel, & Chaseling, 2000). Block and Block (2005) discussed how the STAC technique within CrimeStat (Levine, 2005) geographically locates the densest clusters of incidents on the map. Levine (2008, pp. 295–296) stated, "STAC is an older hot spot algorithm based on overlaying a search circle on the nodes of a grid and counting the number of events occurring within the circle." In Hart and Zandbergen's (2012) comparison of multiple hot spot techniques, they found that STAC was the most accurate within their analysis. While an older technique, STAC helped advance the examination of crime spatially and still required the examination in the current study.

With the assertion that there are better techniques that indicate high concentrations of crime, Levine (2008) suggested the use of the Nnh clustering technique. Numerous studies have incorporated this technique into their analyses within the criminology and criminal justice field (Calvo, Saler, & Matz, 2012; Newton & Hirschfield, 2009; Paulsen, 2004; Van Patten et al., 2009). This technique is based on a threshold distance to which the crime incidents are compared to identify clusters (meeting the minimum number of points necessary) and if the number of incidents is greater than a specified minimum. Crime points that are closer to one another than the user-defined threshold distance are selected for clustering (see Levine, 2005). This technique typically produces smaller and more concentrated clusters than STAC (Levine, 2008).

Moving from ellipses and convex hulls, Kernel Density Estimation (KDE) produces a continuous smoothed surface with variation of the density of crime over a study area (Eck et al., 2005). KDE operates on a grid that is overlaid on the study area that allows for calculating the number of crimes in each grid cell, providing a density estimate for each cell (see Levine, 2005). The values can be displayed geographically, identifying where hot spots are located. Chainey et al.'s (2008) comparison of multiple hot spot techniques concluded that KDE was best suited for predicting future crime. This was met with criticism (see Levine, 2008; Pezzuchi, 2008), but KDE is a technique that is commonly used in research (Chainey et al., 2008; Kennedy et al., 2011; Tompson & Townsley, 2010) and among police departments (Harries, 1999). Similar to STAC and Nnh techniques, parameters used within the KDE technique can be changed, altering the output (cell size and bandwidth).

The last technique included in the current study, RTM, is commonly used with point data. RTM is used to calculate a risk assessment of a study area based upon numerous physical and social factors resulting in higher risk values being associated with increased odds of a criminal event occurring there in the future (Caplan & Kennedy, 2011). To construct a risk assessment, a pool of potential risk factors have to be determined based on prior literature and operationalized based on the current study area. The risk factors are commonly operationalized via proximity to or density of each factor across an overlaid grid of the study area (see Caplan et al., 2011; Dugato, 2013; Kennedy et al., 2011). Each risk factor is expressed separately as a map layer because of differing spatial influences, and then combined to form an overall risk assessment. For example, high-density areas of alcohol outlets and being within a block of a pawn shop could be riskier for robberies. These two factors have different operational spatial influences but can be spatially joined (see Caplan & Kennedy, 2011). The spatial overlap of risk factors creates a more risky environment where crime would be expected to occur in the future. Being that RTM utilizes point data, it is possible for RTM to subsume other hot spot techniques as a risk factor (i.e. KDE). RTM operates on a similar grid system to KDE allowing for the density of past crime to be included as a risk factor for predicting future crime. When using a metric comparison between RTM and KDE, Dugato (2013) found KDE to be more accurate but less reliable than RTM. Similar to the traditional hot spot techniques, the parameters used in RTM can affect the risk assessment of a study area and could result in an unsatisfactory “best model” for prediction (see Caplan & Kennedy, 2011).

RTM does suffer from the modifiable area unit problem due to the boundaries of a grid system (see Bailey & Gatrell, 1995). RTM operates using a grid-based system, and Caplan and Kennedy (2011) discussed how the cell size defined by the user should be theoretically based. Diverging from previous RTM comparison studies (Dugato, 2013; Kennedy et al., 2011), the current study extends the application of the technique in comparison to various traditional hot spot techniques. The highest risk value within RTM can be treated as a “hot area” for future crime and requires examination similar to other studies. Using a metric comparison of the varying techniques allows for the accuracy and precision to be comparable.

Comparing multiple hot spot techniques has been often conducted visually or via a hit rate (percent of predicted crime in retrospective hot spots), leaving the subjectivity of it to the user. To overcome this issue Chainey et al. (2008) developed the PAI. The PAI examines the hit rate in relation to the area (hot spot) and overall study area. While the PAI measures accuracy, Levine (2008) argued it is still possible to be accurate without being precise. Because of the PAI measure not assessing the precision of the hot spots, Levine (2008) suggested the incorporation of the RRI. The RRI compares the rate of change from one time period to the predicted time period. A value lower than 1.0 is interpreted as a decrease in crime prediction from one time frame to another while a value above 1.0 is interpreted as an increase in crime prediction from one time frame to another. Thus, the RRI becomes a supplementary measure, supporting the PAI, and allows for comparison of multiple hot spot techniques.

With any of the techniques, there are parameters that must be defined before completing the analyses. Chainey et al. (2008) and Hart and Zandbergen (2012) discussed the importance of parameter selection for each technique. Hart and Zandbergen (2012) demonstrated how applying different parameters could influence the output measures (for example, hit rate). The minimum number of events, search radius, and output cell size (among other parameters) are commonly subjective to the user, depending on which technique is being used. Altering these parameters can result in differences in the size, shape, and presence of hot spots within a study area. When selecting the parameters for a hot spot technique, while the selections are subjective, the parameters need to be based on theoretical reasoning in relation to the study area being analyzed.

In the current study, numerous hot spot mapping techniques were compared to one another within Little Rock, Arkansas. Using the PAI and RRI allows for comparison of the varying mapping techniques that would be difficult to compare without these measures. The current research extends the comparison of multiple techniques by incorporating the RTM technique that is often associated with predicting future crime. Traditionally, RTM has been compared to KDE due to similarities of a grid system, but the PAI and RRI allow for cross-comparison of different techniques. Viewing the high-risk areas of RTM as hot areas for crime is similar to hot spots in that those areas are expected to have higher frequency of future criminal activity. When comparing the different hot spot techniques, various temporal time frames were assessed to determine the short-term and long-term values of the techniques.

Data and Methods

The current study took place in Little Rock, Arkansas. Little Rock has a population of around 200,000 with an area of around 120 square miles. Robbery crime incident data were obtained from the Little Rock Police Department from January 2008 through December 2011. Additionally, the Treasury Department in Little Rock provided a spreadsheet of active businesses within Little Rock that had permits for 2008. These data contained the type of business, name, and address of the establishment.

All of the data were geocoded above the recommended 85% level that Ratcliffe (2004a) put forth in his examination of the acceptable minimum when geocoding (lowest geocode rate was 94%). Following the discussion of Hart and Zandbergen (2012), the data were geocoded to the street centerlines since they found that the geocoding quality effected prediction results. Crime and business data from 2008 were used to construct the base year hot spots for which future crime would be compared to in terms of the PAI and RRI values.

For comparison of the hot spot techniques used in the current study (discussed below), the PAI and RRI were measured for each predicted time frame. The PAI measure is expressed in the following formula (Chainey et al., 2008):

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

where n represents the number of predicted crimes within the hot spot(s), N is the overall number of crimes that occurred within the predicted time frame, a is the area of the hot spot(s), and A is the overall area of the study area. The numerator in the formula becomes the hit rate while the denominator becomes an area percentage. Van Patten et al. (2009) extended the application of the measure to account for comparison to historic data. The modified formula is:

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

where n' is the number of predicted crimes within the historic hot spot, N' is the overall number of predicted crimes for a time frame, a is the area of the historic hot spot, and A is the overall area of the study area. This extension allows for comparison of future crime locations over a number of temporal separations to base year (historical data) hot spot(s). The PAI is a measure of accuracy of the hot spot techniques and allows for comparison of varying hot spot mapping techniques.

As discussed before, the PAI is a measure of accuracy while the RRI is a measure of precision. Levine's (2008) RRI formula is expressed as:

$$\frac{\text{PAI}_t}{\text{PAI}_{t-1}} = \text{RRI}$$

where PAI_t is the value of the predicted time period to the previous time period. In the current study, PAI_{t-1} is the base year of 2008 in which all other time periods are compared back to within the analyses.

These measures of accuracy and precision were applied to six different techniques used within the current study. The measures included were based on similar comparison studies that incorporated the PAI measure and/or the RRI measure (Chainey et al., 2008; Dugato, 2013; Levine, 2008; Van Patten et al., 2009). With the limited metric comparison of RTM to other techniques (see Dugato, 2013), the current study extends prior comparisons by including point-pattern hot spot techniques. Dugato (2013) included kernel density as a comparison to RTM when predicting robberies in Milan, finding that kernel density was more accurate (PAI) but less precise (RRI) than RTM. The current study included the STAC and Nnh point pattern data hot spot techniques along with kernel density to comprise a metric comparison to RTM.

The point pattern data and kernel density hot spot techniques were constructed using CrimeStat IV (Levine, 2013) and the RTM was constructed within ArcGIS 10.1 after utilizing RTMDx (Caplan & Kennedy, 2013). Since the analyses were predicting crime over a three-year time span, multiple base (2008) hot spots were created. While steps were taken to construct the "best" traditional hot spot techniques, RTMDx (see Caplan, Kennedy, & Piza, 2013) is designed to provide the "best model" with the data provided. The various parameters that were set for each technique to identify clusters of crime made the operationalization of the concept of a "hot spot" difficult. The clustering was dependent upon the technique that was being used, STAC, Nnh, and KDE. Because of the differences between hot spot techniques, each technique had a slightly different operationalization of "hot spot." For RTM, the highest risk cells were referred to as "hot areas," referring to geographical areas that were formed by a multitude of robbery risk factors determined by RTMDx.

The different techniques were compared temporally over various prediction time frames. The PAI and RRI values were assessed for the following prediction periods: 2 days, 1 week, 1 month, 6 months, 12 months, 13–18 months, 13–24 months, and 25–36 months.[3] This approach allowed for comparing the different techniques in short-term and long-term prediction capabilities. The parameters for each technique were discussed below.

Spatial and Temporal Analysis of Crime

The parameters that need to be set for STAC are the search radius, minimum points per cluster, scan type, and number of standard deviation for the ellipses. To find the best STAC model for comparison some of these parameters were changed and compared to one another to determine the best STAC parameters (PAI and RRI values across all temporal periods). Levine (2010) discussed the usefulness of experimenting with various search radii. The search radius was set to 1290 ft (three blocks), 12 minimum points were used, and a triangular scan type. The 1290 ft search radius was chosen to be consistent between STAC and Nnh.[4] A triangular scan was used because many of the streets in Little Rock resemble a stem and leaf pattern. As Little Rock expanded, there was a change in street design from grid pattern to stem and leaf.

While the STAC technique indicates clustering within the data, the strength of the clustering is not identifiable without running Monte Carlo simulations. The simulations randomly place *n* cases throughout the study area (rectangular equivalent in area size) and use the same parameters to search for clusters. The parameters that were set to determine STAC clusters are replicated within the simulations to determine if clusters appear when cases are randomly placed in a study area (expected vs. observed clustering). Levine (2010) stated that the default is set to zero (0) simulations because of the calculation time increases, but the number of simulations ran can be determined by the user. In the current study, 1000 simulations were run when testing the strength of

3. Additionally, a one day prediction, 1 January 2009, was examined but no technique was able to predict the robberies that occurred on that one day.

4. The search radius and minimum number of points were altered numerous times in relation to the findings of the Monte Carlo simulations. For example, seven minimum points with a 1075 ft search radius resulted in clusters being found in the STAC technique but not in the Nnh technique. The parameters were altered until comparable significant findings were found. Additionally, smaller search radii resulted in convex hulls having an area equal to zero, suggesting a hotpoint rather than hot spot (see Ratcliffe, 2004b). Past research argued that there can be variation in crime from street to street so the current study sought to account for this by examining smaller search radii (see Weisburd et al., 2004, 2009).

the clusters found by the STAC technique. The simulations also acted as a recommendation for the search radius used for the STAC technique.

Overall, the search radius was set to 1290 ft (about three blocks) for comparison to the other techniques. The minimum points per cluster was set to 12 and the scan type was set to triangular because of the mostly irregular street patterns in Little Rock. A one standard deviational ellipse was constructed for each cluster (Levine, 2005) and can be displayed geographically within ArcGIS. Convex hulls were also used to indicate the clusters, but the output for convex hulls was a polygon that connects the outermost points of the cluster rather than an ellipse (Levine, 2005). By design, convex hulls cover less area, increasing the density and altering the PAI value (Levine, 2008). A STAC "hot spot" was operationalized as a cluster of robberies that had at least 12 incidents occur within a 1290 ft search radius (represented by ellipses or convex hulls).

Nnh Clustering

The parameters that need to be set for the Nnh technique were the threshold distance, number of standard deviations for the ellipses, and the minimum points per cluster (Levine, 2005). Similar to the STAC technique, the search radius was set to 1290 ft. A minimum number of 12 points was used to remain consistent with the STAC technique and to avoid similar area issues when comparing to the STAC, KDE, and RTM techniques. Within CrimeStat IV there were two types of output options, ellipses and convex hulls. Similar to the STAC technique output, a one standard deviational ellipse and convex hull were used for the base year (2008).[5]

Similar to the STAC technique, Monte Carlo simulations were used to test the strength of the clusters indicated by the Nnh technique. According to Levine (2010), the Monte Carlo simulations indicate if the number of clusters observed were significantly greater than what would be expected by chance since the simulations randomly distribute *n* cases. When running the Nnh technique, 1000 Monte Carlo simulations were run to determine the significance of the clustering observed. A search radius of 1290 ft resulted in no clusters being found in the Monte Carlo simulations, suggesting that the observed were not by chance. A Nnh "hot spot" referred to a cluster of robberies occurring within a 1290 ft search radius and was comprised of at least 12 robberies, which were visually displayed as either ellipses or convex hulls.

5. For the Nnh technique, it is possible to have second- and third-order clusters. Levine (2010) stated that first-order ellipses could cluster in space, allowing for a second-order ellipse to encompass multiple first-order ellipses. The third-order ellipse would include multiple second-order ellipses which are the result of clustering of first-order ellipses. The current analysis did not indicate the presence of second-order ellipses. Levine (2010) discussed the usefulness of the different order levels, and if second-/third-order ellipses were found in the current analysis they would have been included for comparison of PAI and RRI values.

Kernel Density Estimation

Within KDE single interpolation, the parameters that needed to be set were the method of interpolation, choice of bandwidth, and cell size.[6] When determining the "best model" for KDE, a similar approach was used from Hart and Zandbergen's (in press) study on the altering of the parameters within KDE. The study found that the interpolation method employed can have a considerable effect on the PAI value, the choice in bandwidth has some effect, and the grid cell size had little to no effect. In the current study, a grid cell size of 430 ft was used, which was about the average block length (430 ft is the same cell size used within the RTM technique). Within CrimeStat IV, there are five different types of interpolation methods: normal, uniform, triangular, quartic, and negative exponential (see Levine, 2013). Each interpolation method was utilized across five different bandwidth lengths: 215, 430, 645, 860, and 1075 ft, representing half block increases. Once the 25 iterations were run (five interpolation methods × five bandwidths), the cells with density values above two standard deviations from the mean were selected. The areas of these cells encompassed across the 25 iterations were above three square miles. Because of this, the top 10% of the cells with density values above two standard deviations from the mean were selected for comparison of PAI and RRI values.

To determine the "best model" for KDE, the average PAI and RRI values for each iteration were compared to determine the "best." While there were differences among the iterations, the triangular and quartic methods were generally the top two methods, similar to Hart and Zandbergen's results (in press). The two search radii that had high average PAI and RRI values for the triangular and quartic methods were 430 and 645 ft. The average PAI values were greater with 430 ft bandwidth and the average RRI values were greater with the 645 ft bandwidth (see Appendix A). The 430 ft bandwidth was used because of the higher average PAI value. The quartic interpolation method had the highest PAI value, providing support for the utilization of a quartic interpolation method with a bandwidth of 430 ft for comparison to the other predictive techniques.

While Levine (2013) suggested that normal interpolation should be used for samples that are below 10,000 because it avoids the possibility of indicating "false hot spots," the quartic method was used in the current analysis based on preliminary findings. The quartic function weights points closer to each other more then gradually declines until the user-defined bandwidth radius is reached (Levine, 2013). This function allows for peaks within the data to be distinguished rather than a more generalized smoothing. The top 10% of cells above two standard deviations from the mean were considered "hot spots" for

6. Van Patten et al. (2009) used the normal interpolation method in their hot spot technique comparison study using PAI and RRI values. Chainey et al. (2008) chose the quartic interpolation method, which Levine (2008) also used when supplementing the PAI with the RRI measure. Hart & Zandbergen (in press) recommended the triangular or quartic methods for prediction.

the KDE technique. These cells were selected out for comparison to the other techniques.[7]

Risk Terrain Model

The RTM technique included Little Rock business data and crime data to create a risk assessment for predicting future robberies. A grid was laid over Little Rock of 430×430 ft cells (resulting in 19,038 cells).[8] The RTM for the current study was based in a general violent crime model. Gaziarifoglu (2010) and Drucker (2010, 2011) provided reviews of risk factors associated with various types of violent crimes to incorporate within the RTM approach. Based upon past literature (Anderson, 1999; Bernasco & Block, 2011; Brantingham & Brantingham, 1982, 1995; Caplan et al., 2011; Fass & Francis, 2004; McCord, Ratcliffe, Garcia, & Taylor, 2007; Wright & Decker, 1996), the risk factors included in the model were pawn shops, check-cashing, fast food, on-site alcohol, off-site alcohol establishments, independent grocery stores, department discount stores, convenience stores, tobacco shops, tattoo parlors, and motel/hotel/motor home parks. On-site alcohol establishments were divided into two categories, beer permits, and mixed drink permits (12 physical risk factors in total). The spatial influence the risk factors had on the surrounding environment was operationalized in terms of proximity to or density of each factor.

RTMDx (Caplan & Kennedy, 2013) is a software application designed for RTM and was used to create the "best model" for predicting robberies in Little Rock. Prior to the development of RTMDx the operationalization of risk factors was generally a user-defined parameter, which could result in a less than "best model." For example, without the use of RTMDx a user could expect the spatial influence of liquor stores to be three and a half blocks and express it as such in RTM, but through automated statistical iterations in RTMDx the spatial influence liquor stores had in the model was actually two blocks.[9]

Within RTMDx, certain parameters have to be set or input when creating a model: study area, block length, raster cell size, type of model, outcome event, risk factors, and the operationalization of the spatial influence (see Caplan et al., 2013). A shape file containing the boundaries of Little Rock was

7. Limiting the KDE to the highest value hot spot cells could result in an increase in the PAI and RRI values because the area KDE initially indicated as a hot spot was restricted to encompass smaller areas for comparison.

8. RTM is designed to include social measures as well as physical measures. Caplan (2010) discussed how to include Census data into the RTM at the block level. RTMDx operates using point-based data and expressing the point data via proximity or density. Higher level of aggregate data (i.e. block, block group, and tract) are not usable currently within RTMDx. Dugato (2013), while not using RTMDx, used physical, point-data, establishments as proxies for social characteristics (RTMDx was not available when Dugato's study was conducted).

9. That is not to say it is not possible to determine the spatial influence each risk factor has without RTMDx, RTMDx automates many of the steps that would determine the spatial influence and significance testing of risk factors (see Caplan et al., 2013).

added for the study area. The average block length in Little Rock was 434 ft and the raster cell size was set to 430 ft (similar to the KDE technique). The model type selected was Aggravating because the model is assuming the input risk factors correlate with the outcome event.[10] Caplan et al. (2013) stated that an Aggravating model tests for positive spatial relationships between the risk factors and outcome event. The outcome event in the current study was 2008 robberies because this was used as the base map to predict future robberies. Next, the 12 risk factors were added in the model within RTMDx. When inputting each risk factor, the operationalization of each factor has to be set. There are three options for operationalization of factors that should be theoretically based and tailored to the study area: density, proximity, and both proximity and density. The individual risk factors were further discussed below in relation to how they were spatially operationalized. The maximum spatial influence has to be set and it ranges from one to four blocks (based on the block length already input previously). In the current study, the maximum spatial influence was set to four blocks for each risk factor. The last subpart of the operationalization process is setting the analysis increments to half or whole. This pertains to the testing of spatial influences based on different increments. For example, if proximity, maximum spatial influence of two blocks, and half block increments were selected, that specific risk factor would be expressed by four different spatial influences: half block, one block, one and a half blocks, and two blocks. Each risk factor in the current study was set to half block increments, increasing the number of variables tested within RTMDx.[11] Each risk factor was further discussed to provide support for the selection of the operationalization type (density, proximity, or both).

Pawn shops, check-cashing stores, and tattoo parlors were operationalized as having a proximity spatial influence in Little Rock. That is, the presence of the businesses created a riskier area for robberies to occur. Pawn shops were separated from check-cashing establishments because pawn shops attract business beyond only cashing checks. Wright and Decker (1996) discussed how robbery offenders targeted victims that they perceived as carrying cash or victims that displayed wealth through jewelry. The offenders in Wright and Decker's (1996) typically targeted local business such as pawn shops where there could be more potential targets. Tattoo parlors were included as a risky place because of the similar cash at hand type of business they attract. Next, check-cashing establishments were used as a proxy for socially disorganized areas. Past research suggested that check-cashing establishments were located within inner cities and in areas that were typically low income and high minority (Graves, 2003; Squires & O'Connor, 1998). The number of actual business locations for these factors ranged from 12 to 14 in Little Rock, suggesting that the

10. Future research should examine the inclusion of protective factors that could affect the riskiness of an area. RTMDx only builds an aggravating or protective model. It would be beneficial to be able to include both types of measures within one analytic technique.

11. For greater detail on the steps and processes of RTMDx, see Caplan et al.'s (2013) manual.

relatively small amount would be better expressed via proximity. The presence of these three risk factors was expected to create a riskier environment for robberies and the operationalization of proximity was selected in RTMDx.

Next, beer-only, mixed-drink, and fast-food establishments were operationalized via density. Research concerning on-site alcohol establishments suggested that the presence of such type of establishments is met with an increase in violent crime (Brantingham & Brantingham, 1995; Homel & Tomsen, 1993; Roncek & Bell, 1981; Roncek & Maier, 1991; Roncek & Pravatiner, 1989). On-site alcohol establishments were not evenly distributed throughout Little Rock, creating clusters of establishments. Past research on fast-food establishments (Bernasco & Block, 2011; Brantingham & Brantingham, 1982; LaVigne, 1997; Spelman, 1995) recognized that crime location was influenced by the presence of fast-food establishments. For example, LaVigne (1997) attributed low crime rates to the prohibiting of fast-food restaurants in certain areas because these types of establishments increase the potential of victims for robbery. This could lead to clustering of fast-food establishments in certain areas of a city. These three measures were specifically operationalized as density risk factors within RTMDx.

The last six risk factors were operationalized as both proximity and density. This was done because the presence of a business could make the surrounding area more risky (proximity) or the clustering of a business type within Little Rock could create risky areas (density). Off-site alcohol establishments have been found to have higher levels of violent crime where there were more off-site stores (Gorman, Zhu, & Horel, 2005; Reid, Hughey, & Peterson, 2003). Furthermore, Wright and Decker (1996) found that robbers target liquor stores because victims usually had cash at hand for their purchases. Extant literature (Bichler, Schmerler, & Enriquez, 2013; LeBeau, 1997; Sherman et al., 1989) established that hotels and motels could influence crime and arrests, being labeled a risky place. Because of this, hotel, motels, and motor homes were included in the current study as a risky place.[12]

Social measures were included to account for socially disorganized areas via proxy measures. Prior research established that lower income minority neighborhoods typically had fewer supermarkets (Altschuler, Somkin, & Adler, 2004; Moore & Diez Roux, 2006; Powell, Slater, Mirtcheva, Bao, & Chaloupka, 2007). With the absence of supermarkets in lower income minority neighborhoods, there was a high prevalence of non-chain and smaller grocery stores (Moore & Diez Roux, 2006; Powell et al., 2007). Independent grocery stores, convenience stores, and discount stores were included as a proxy for socially disorganized areas within Little Rock. Additionally, tobacco shops were included based on Schaap and Kunst's (2009) literature review, which found that individuals from socially disadvantaged background were more likely to smoke. Based on this and researcher knowledge of Little Rock, the location of tobacco shops were utilized as a proxy for socially disorganized areas. These social disorganization

12. The coding of the data grouped hotel, motels, and motor home parks together.

proxy measures were operationalized as proximity and density to determine if the establishments were risky based on the proximity to one or the density of each type of risky place.

The 12 risk factors were input in RTMDx and the "best model" was calculated. Based on the operationalization of the 12 risk factors, 144 variables were created and tested for significance. The program builds from a null model and used stepwise regression to build the "best model." RTMDx operates based on building the optimal model, which is reflected in the Bayesian information criteria (BIC) value (see Caplan et al., 2013). The output from RTMDx stated that negative binomial regression elicited the best model with eight variables and a BIC value of 4429.4 (see Appendix B for "best model").[13]

Four risk factors, on-site beer, fast-food establishments, department discount stores, and on-site mixed drink, were operationalized as density values.[14] The KDE function within ArcGIS was utilized and the cells with density values above two standard deviations from the mean were assigned the value of one (risky) while all other cells were assigned a value of zero (not at the highest risk).[15] The remaining four risk factors, tobacco stores, independent grocery stores, convenience stores, and hotel/motel/motor, were expressed via proximity based on the spatial influence determined by RTMDx. The cells within the defined distance of each type of risk factor were assigned the value of one, and risky and all others were assigned zero, not at the highest risk. Since the eight risk factors were operationalized as separate raster layers, the raster calculator was used to calculate the relative risk score for each cell (see Caplan et al., 2013). Based on the number of cells above two standard deviations from the mean (264), the top 23% of the cells with a value above two standard deviations from mean were classified as a "hot area" (61 cells).[16]

13. Ratcliffe (2012) discussed the use of changepoint regression to determine the spatial influence around criminogenic places. This is a different method than the one utilized in the current study, yet future research can be directed at comparing the two methodologies to determine if there are differences in the operationalization of spatial influence for specific crime generators and crime attractors.

14. Caplan et al. (2013) noted that there is a difference in the type of kernel density function used by RTMDx and that which is used in ArcMap. While there are differences, Caplan et al. (2013) stated that relative risk values could vary slightly but generally this should not affect most research utilizing RTMDx.

15. It would be inaccurate to say that cells given a value of zero indicate no risk because only the highest risk cells were given the value of one based on the operationalization of the risk factors. The RTMDx output suggested that the range was from 1 to 820.4, interpreted as odds, but because of differences in the kernel density functions the range was 1 to 941.7. The average cell risk was 4.580 with a standard deviation value of 53.509.

16. The top 23% of cells were taken because if the top 20% of cells were used, there would be multiple cells with the same risk value. That is, the use of cut-off value of the top 20% would have arbitrarily excluded cells with the same risk values. There were 10 cells with the same value at the 20% mark and including those would have increased the hot area to 61 cells, 23% of the cells with values greater than two standard deviations from the mean. Additionally, if the 264 cells were used, the area would have been over one square mile, which is double to triple the other techniques area. By using the 61 cells, the area was .406 square miles, comparable to the other areas.

Table 1. PAI Values for predictive hot spot techniques

	2 Days	1 Week	1 Month	6 Months	12 Months	13–18 Months	13–24 Months	25–36 Months	Average value
STAC ellipse	50.776	32.497	16.694	29.015	24.159	20.457	27.398	24.968	28.212
STAC convex	51.911	33.223	17.067	32.960	29.294	23.902	30.447	30.086	31.111
Nnh ellipse	29.777	38.115	29.369	34.031	31.301	37.704	38.772	31.126	33.774
Nnh convex	30.241	38.708	33.141	41.601	39.819	47.863	47.179	34.114	39.083
KDE	97.475	93.576	58.752	77.361	73.342	82.748	80.038	56.493	77.473
RTM	37.552	60.083	45.268	46.095	43.213	30.258	31.275	34.588	41.041

Results

The different hot spot techniques covered varying amounts of area due to differences in their construction. While different areas were indicated, there was spatial overlap of hot spots and hot areas between all of the techniques (see Appendix C). The STAC hot spot technique identified six ellipses and convex hulls within the analysis (total = .299 and .292 square miles respectively). As previously discussed, the STAC and Nnh techniques vary by design, and the Nnh technique found 11 ellipses and convex hulls (.510 and .502 square miles respectively). With the more ellipses/convex hulls identified within the Nnh analysis, the area for the Nnh was greater than the STAC analysis. Additionally, as previously mentioned, ellipses, by design, cover more area than convex hulls. Next, once limiting the KDE to the top 10% of cells that had values above two standard deviations of the mean, there were 47 cells used for the PAI and RRI comparisons. KDE had an area of .312 square miles. Lastly, the RTM was limited to the top 23% of cells that had a value greater than two standard deviations from the mean. This resulted in 61 cells being selected out and encompassed .406 square miles. The area of the different techniques influenced the PAI value because it is used within the denominator of the PAI formula.

The PAI was a ratio of the hit rate and measurement area, while the RRI was a measure of precision over time. Higher PAI values indicated a more accurate technique when comparing techniques and the PAI values are provided in Table 1. Three shorter temporal time frames were first examined, 2 days, 1 week, and 1 month for predicting robberies (January 2009). The KDE technique had the highest PAI values for these time frames (97.475, 93.576, and 58.752, respectively).[17] The STAC techniques had the second and third greatest PAI val-

17. In fairness to the Nnh technique, Nnh was designed to indicate clustering within small distances. Using the default random nearest neighbor distance as the search radius instead of the 1290ft, the Nnh convex hull resulted in an average PAI value of 65.014 and a RRI value of 0.537. This was the second highest PAI value, behind KDE, and the lowest RRI value observed in the study. In short, the Nnh technique is best at identifying small, concentrated clusters.

ues for the two-day prediction phase, but once the prediction time frame was increased the STAC techniques were the least accurate. The RTM technique had the second highest PAI values when predicting 1 week and 1 month of robberies.

When the prediction time frame was lengthened to the first six months of 2009 and the entire year of 2009, the KDE technique had the greatest PAI values (77.361 and 73.342, respectively). During these prediction time frames, RTM remained the second most accurate technique with a PAI values of 46.095 and 43.213. RTM was followed by the Nnh techniques and STAC techniques. As the prediction time frames increased, RTM and Nnh were consistently the second and third most accurate techniques while KDE remained the most accurate (see in Table 1). The PAI value of KDE fluctuated compared to prior time frames but remained the most accurate in both short-term and long-term prediction. On average, KDE was the most accurate with a PAI value of 77.473 followed by RTM with an average value of 41.041. The average PAI values indicated that the STAC ellipses and convex hulls were the least accurate (28.212 and 31.111). Based on the PAI values, KDE excelled at short-term and long-term prediction compared to the other techniques included in the analysis. In many of the prediction time frames, KDE was about one and a half to two times as accurate as the other techniques.

While the KDE technique had the highest average PAI value across the prediction time frames, the RTM technique had the highest average RRI value, indicating that it was a more reliable and consistent measure. Robbery data from 2008 were used as the base year for the RRI values and the RRI was the ratio of the current prediction time frame PAI and the 2008 PAI value. The RRI values are presented in Table 2. For the first five prediction time frames within the first year, 2 days, 1 week, 1 month, 6 months, and year, RTM had RRI values greater than one (1). With values greater than one (1), this suggested that there was an increase in crime prediction compared to the base year, 2008. The RRI value for RTM fluctuated as the prediction time frames of the study but remained under a value of 1.00, a decrease in crime prediction. Beyond the one year prediction time frames, RTM and STAC ellipses had the highest RRI values. The high precision of the RTM technique could be because of the construction of the RTM model being based on the built environment rather

Table 2. RRI Values for predictive hot spot techniques

	2 Days	1 Week	1 Month	6 Months	12 Months	13–18 Months	13–24 Months	25–36 Months	Average value
STAC ellipse	1.640	1.049	0.539	0.937	0.780	0.661	0.885	0.798	0.911
STAC convex	1.215	0.777	0.399	0.771	0.685	0.559	0.712	0.704	0.728
Nnh ellipse	0.635	0.812	0.626	0.725	0.667	0.804	0.826	0.663	0.720
Nnh convex	0.475	0.608	0.521	0.654	0.626	0.752	0.741	0.536	0.614
KDE	0.894	0.859	0.539	0.710	0.673	0.759	0.734	0.518	0.711
RTM	1.036	1.657	1.248	1.271	1.192	0.834	0.862	0.954	1.113

than past crime (further discussed below). Overall, following the RTM technique in rank order RRI value were the STAC ellipses and convex hulls.

When comparing PAI and RRI values together for the hot spot techniques, there was not a technique that excelled for both measures. KDE outperformed the other techniques in terms of accuracy but had the second lowest average reliability value. While RTM was the most precise and reliable technique (average RRI = 1.113), it was also the second most accurate (average PAI = 41.041). RTM remained in the top for values for the PAI, but had an average PAI value of about 47% less than KDE's average PAI value. KDE had the highest PAI value on average (77.473), while having the second lowest average RRI value (.711), suggesting that it is an accurate technique but not the most precise. The STAC technique was the least accurate while having the second and third greatest reliability values. Levine (2008) argued how it was possible to be accurate without being precise, bringing forth the RRI measure to test the precision of the techniques, but as found in the current study it is also possible to be precise without being accurate. The importance of using both the PAI and RRI measures to compare predictive mapping techniques was apparent in the current findings.[18]

Discussion

The purpose of the current study was to explore the effectiveness of varying hot spot crime prediction techniques. The present study extended the comparison of techniques to include RTM using RTMDx. As Chainey et al. (2008) discussed, to compare varying hot spot techniques a common base was needed because of differences in the mapping techniques. Chainey et al. (2008) suggested the inclusion of the PAI to measure the accuracy and Levine (2008) proposed the use of the RRI for a reliability measure. The current study used these two measures to compare six different hot spot techniques. Additionally, the predictive time frames were divided into several short-term and long-term time frames allowing for variation in the effectiveness of predictability to be compared.

As the results indicated, KDE was the most accurate while RTM was the most precise. Dugato (2013) found similar results when metrically comparing RTM and KDE on a one-year prediction time period. Additionally, when examining just the accuracy, the current findings, with the inclusion of RTM, supported Chainey et al.'s (2008) results which found KDE to be the most accurate technique. The precision of RTM in the current study could be attributed to the integration of the built environment to expect where crime will occur, allowing for more consistent results.[19] The practical purposes are greater for

18. Additional maps are available for each technique and an overlay of all the techniques together to show similarities and differences; contact the corresponding author.

19. RTM is capable of using a hot spot technique such as KDE and supplementing the analysis with the density measure determined by KDE as a risk factor. Robberies from 2008, as a risk factor, were excluded from the pool of risk factors to keep from creating a biased model.

shorter time frame predictions rather than longer time frame predictions that can be affected by numerous social and physical dynamics (i.e. crime movement, city planning, and politics). Longer prediction time frames rely on crime being stationary or stable in certain areas to be accurately predicted. The stability of crime in an area was not the focus of the current study but offers a fruitful research area in relation to the environmental backcloth.

With the principle that crime generators and crime attractors (CGAs) increased crime in surrounding area, the built environment may not change as quickly as crime locations. While crime has been found to be limited geographical in space by numerous studies (see Braga 2005), over time crime could vary within the limited space. This may alter the PAI and RRI values in relation to crime prediction since crime may not occur within a predefined hot spot. The primary difference between RTM and the other hot spot techniques was that RTM accounted for areas where there were increased odds for robbery opportunities based on the built environment (i.e. CGAs), while the other techniques relied on past crime clusters.

While RTM excelled in reliability and precision, incorporating numerous measures of potential crime incident locations hindered the technique. When further examining the RTM map, there were numerous areas identified as risky, but no crime actually occurred in defined risky areas. While the current study limited the "hot areas" to a small percentage of the overall cells, this limitation requires further research. Levine, Wachs, and Shirazi (1986) and Block and Davis (1996) suggested the notion that the riskiness of an area could vary because of the environmental factors while remaining dangerous (Levine et al., 1986). Levine et al. (1986) asserted that there was a distinct difference between places being viewed as "risky" and/or "dangerous" when examining bus stops.[20] They found that environmental factors (i.e. types of businesses) varied around bus stops, contributing to the riskiness of the area. While the level of risk varied by land-use around bus stops, some less risky than others, all of the bus stops were still considered dangerous when examining crime. With the variation of riskiness in a study area, RTM becomes a helpful analytic tool since it can account for the different levels of risk.

When comparing the techniques in the current study, there was spatial overlap in hot spots and hot areas. This becomes useful since the techniques were constructed differently and was relatable to Chainey et al.'s (2008) findings that the hot spots identified for street crimes tended to occur where there were bars, restaurants, and other types of businesses. The RTM technique was based on CGAs while the other techniques utilized past crime. In the current study, crime was not included as a risk factor within the RTM model, distinctly separating it from the other techniques. Because of this, RTM could be used

20. Levine et al. (1986) suggested the incorporation of a "vice index" that would take into account a number of vice-related business establishments (i.e. liquor stores, strip clubs, and adult cinemas) in future research.

jointly with KDE since RTM indicated hot areas based on CGAs and KDE identified hot spots using past crime. This could be beneficial since KDE was the most accurate and RTM was the most reliable technique. The current findings also reiterate the assertion made by Van Patten et al. (2009), Kennedy et al. (2011), and Caplan, Kennedy, and Piza (2012) that the predictive techniques should be used jointly.

Although there was spatial overlap of the “hot spots” and “hot areas,” there were also spatial differences between techniques. For example, KDE and RTM were limited to their highest value cells (density and risk respectively), and this resulted in single cells or a few cells being grouped together in various locations of Little Rock. This differs from STAC and Nnh techniques, which relied on set parameters and were output as ellipses and convex hulls. The total area covered by each technique was represented differently visually and was unique because of the operationalization of “hot spots” and “hot areas.” With the identification of similar and different prediction areas, the spatial similarities could allow for targeted policing efforts because of the overlap of risk (RTM) and danger (hot spot techniques).

There is a wide body of literature that discusses the effectiveness of varying police strategies on targeted hot spots. For example, directed patrols with license plate readers (Koper, Taylor, & Woods, 2013), foot patrols (Braga & Bond, 2008; Ratcliffe, Taniguchi, Groff, & Wood, 2011), directed police saturation (Sherman & Weisburd, 1995; Taylor, Koper, & Woods, 2011), and problem-oriented policing strategies (Braga et al., 1999) within crime hot spots were found to reduce calls for service and/or crime in the target area. This was where RTM can be used jointly with other hot spot techniques. RTM was capable of identifying risky areas for criminal activity while other hot spot techniques account for where crime clusters. With this distinction, policing strategies can be tailored to a smaller environment that accounts for both the built environment and the crime environment. The targeted police strategies could work to reduce the amount of police resources used and may help lead to more proactive crime strategies than reactive strategies.

The different techniques used in the current study have various applications for policing implications. For example, Levine (2008) stated that for regular police car patrolling of an area, KDE was capable of identifying the general areas where crime was concentrated, and therefore was a useful technique. An issue with KDE was that because of the smoothing effect of the technique, surrounding areas where crime may not have been present were represented as having crime present (a similar argument could be made about RTM). Additionally, another issue pertaining to KDE and RTM was that the area where both techniques identify as concentrated or risky were usually much greater than other techniques. In the current study, the KDE and RTM techniques were limited on their spatial output area defined as a hot spot or hot area. The STAC and Nnh techniques were capable of identifying boundaries of a high-risk area, which could also be troublesome, but could be useful for targeted patrols for various policing/prevention strategies.

Moving beyond strictly policing efforts, the inclusion of RTM and other hot spot techniques identified another strategy that could alter crime in an area. Eck (1994) extended routine activities theory (Cohen & Felson, 1979) to encompass a concept of place managers. Place managers influenced the opportunity of crime through ineffective managing and/or being absent from the place.[21] Eck and Weisburd (1995) provided an example of how lifeguards were put in place to prevent drowning but also to make sure patrons behaved themselves outside the water, managing the environment. The role of place managers has been researched in regards to bars (Madensen & Eck, 2008), rental properties (Eck & Wartell, 1998), and street blocks where people live or work (Mazerolle, Kadleck, & Roehl, 1998), all suggesting that effective management can lower crime in an area. For example, Mazerolle et al. (1998) found that street blocks where residents and business management engaged in collective crime control activities had significantly less disorder. With the inclusion of businesses from the built environment via RTM in the current study, the city can approach place managers of businesses to become more involved in creating a safe environment. Taking a similar position as Madensen and Eck (2008), policy-makers can target businesses to increase/encourage accountability of property management for crime reduction purposes while police focus on crime reduction efforts of their own; thus, the utility of using RTM jointly with another technique allowed for a dual focus of crime reduction (place management and policing).

With any of these hot spot techniques, there was the possibility of making errors. Type I errors refer to the false positives made by the different techniques. More specifically, a hot spot technique identifies a phenomenon belonging to a hot spot when in actuality the phenomenon does not belong to the hot spot. Another way of understanding false positives is precision without accuracy. For a technique like RTM, this could become an expensive issue for police departments due to the technique possibly identifying numerous risky areas that were not dangerous, allowing for more false positives. False positives could come with a significant cost but true positives could offset this, resulting in a net gain. True positives refer to a technique identifying a phenomenon belonging to a hot spot and the point belonging to the hot spot. Because of the various techniques used in the current study, the implications needed to be taken with caution when forming policing and/or prevention strategies.

Throughout the study, the parameters for the analyses were discussed with the goal of providing transparency in the decision-making process. Hart and Zandbergen (2012) identified how the change in parameters can alter the output, further changing the PAI and RRI values used to assess accuracy and reliability. The parameters chosen in the current study were based in

21. Felson (1995) expanded upon Eck's (1994) concept of place managers in greater context in relation to different types of people who are capable of discouraging crime.

environmental criminology literature with theoretical reasoning, past comparison studies, and knowledge of Little Rock. Hart and Zandbergen (2012) also found that different hot spot techniques performed better in different cities. Study areas could vary on the distribution of crime, social characteristics, and layout of the built environment, making certain techniques more useful than other. Future research should base parameter selection based upon their study area, purpose of research, and prior criminological research.

Additionally, only one type of crime was examined in the current study, leaving comparison of other types of crime for future research. The results for robbery found in the current study may differ when examining residential burglary, and because of this these techniques need to be further compared across numerous crime types such as Chainey et al. (2008) conducted. Hart and Zandbergen (2012) furthered this notion when they found that the crime type analyzed had a moderate effect on the accuracy of each technique. Due to this, future research needs to examine various techniques across multiple crime types to account for variations in the patterning for where crime occurs in space.

The focus of the current study was to extend the comparison of predictive spatial techniques to incorporate RTM using PAI and RRI measures. With RTM increasing in popularity among researchers and practitioners, RTM requires comparison to established spatial prediction techniques commonly used in research. While the focus of the present study was to compare RTM to traditional hot spot techniques, future research using RTM should take a similar approach. Past crime was not included in the pool of risk factors for the RTM model, resulting in a model being built strictly from CGAs. With the notion that to predict where crime will occur, past crime has to occur, RTM is capable of differentiating itself from traditional hot spot techniques by excluding crime as a risk factor. An effort should be directed at constructing "best models" that do not rely on past crime and examine how "best models" without crime compare to "best models" with crime.

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Appendix A. KDE iteration averages

KDE	PAI	RRI
215 ft		
Normal	75.368	.727
Uniform	68.248	.605
Triangular	59.253	.539
Quartic	58.242	.550
Neg. Expon.	73.632	.653
430 ft		
Normal	42.131	.754
Uniform	54.383	.789
Triangular	77.448	.719
Quartic	77.473	.711
Neg. Expon.	54.768	.768
645 ft		
Normal	23.025	.611
Uniform	35.967	.836
Triangular	65.812	.764
Quartic	70.782	.780
Neg. Expon.	37.795	.799
860 ft		
Normal	19.605	.643
Uniform	18.029	.624
Triangular	45.776	.732
Quartic	57.681	.868
Neg. Expon.	24.259	.775
1075 ft		
Normal	18.535	.692
Uniform	19.334	.758
Triangular	38.918	.763
Quartic	37.871	.759
Neg. Expon.	19.053	.758

Appendix B. RTMDx significant risk factors

Risk Factor	Operationalization	Spatial influence	Coefficient	Relative risk value
Beer Permit	Density	430	1.413	4.107
Tobacco Stores	Proximity	434	1.80	3.596
Fast Food	Density	430	1.241	3.458
Dept. Discount	Density	430	1.093	2.982
Ind. Grocery Stores	Proximity	1736	.875	2.399
Convenience Marts	Proximity	1736	.809	2.246
Mixed Drink Permit	Density	430	.672	1.958
Motel/Hotel/ Motor	Proximity	1736	.559	1.749
Intercept	–	–	−4.271	–

Appendix C. Spatial comparison of techniques