

AN APPLICATION OF RISK TERRAIN MODELING TO RESIDENTIAL BURGLARY

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ABSTRACT

Using dispatch data from the Lawrence Township Police Department (LTPD), this study examines the extent to which indicators of "risk," as identified by the prior research and routine activities theory, correlate with the geospatial distribution of burglary via the application of risk terrain modeling (RTM). Risk is operationalized in this study by the geospatial concentration of bus stops, calls for suspicious vehicles, and calls for suspicious persons in Lawrence Township. Results indicate that those areas in Lawrence Township with highest concentration of bus stops, calls for suspicious vehicles and calls for suspicious persons also have the highest concentration of burglary events.

INTRODUCTION

In 2010, burglary offenses resulted in an estimated \$4.6 billion of lost property, averaging a loss of \$2,119 per burglary (Federal Bureau of Investigation, 2011). In 2008, there were 3,188,620 self-reported household burglary victimizations, only slightly more than half (56.2%) of which were reported to the police (US Department of Justice Statistics, 2011). While law enforcement agencies devote a significant amount of time and resources, including money and personnel, to thwarting burglary and arresting suspects, only 12.4 percent of all burglaries in 2010 were cleared by an arrest (Federal Bureau of Investigation, 2011). Given constraints on police funding, it is important that police departments be able to maximize their resources to combat burglary. Police resource maximization begins with a determination of what areas within a locale are most at risk for burglary.

A relatively recent development in the geospatial analysis of criminal events - risk terrain modeling - may provide police with a more informed assessment of burglary risk (Caplan & Kennedy, 2010). Risk Terrain Modeling (RTM) is a method that potentially offers police agencies and criminologists the ability to identify certain locations most at risk for crime by not relying merely on the retrospective concentration of criminal events in a geographic space but instead by offering a forward-looking approach to identifying the location of criminal events. RTM, developed by Caplan and Kennedy, is a method used to understand crime and the physical and spatial settings in which it may occur (Caplan & Kennedy, 2010). In this study, I utilize RTM to examine the risk factors that correlate with burglary events within a suburban community.

Spatial analyses of residential burglary have identified a variety of correlates of residential burglary (see, e.g., Chang, 2011; Bernasco, 2009; Johnson *et al.*, 2007; McLaughlin, Johnson, Bowers, Birks & Pease, 2006; Malczewski & Poetz, 2005). According to Chang, burglaries occur, not because of any specific, vulnerable space, but because an entire spatial structure of a certain area is vulnerable (2011). Johnson *et al.* concluded that when a burglary occurred at a location, it was likely that another burglary would occur in close proximity soon after (2007). Finally, Malczewski and Poetz explored police perceptions of hotspots for burglary and found that police could identify long-term hotspots for burglary, but were unable to identify where crime occurred in the recent past.

Prior research further shows that several factors either significantly increase or decrease the risk of burglary in an area. According to Moreto (2011), proximity to police stations decreases

the risk of burglary in the surrounding area because there is an increased likelihood of being caught in the act of committing the offense or a faster response time by police. A car being present at a residence and the lights being on in a residence represent the “capable guardians” dimension of routine activities theory and lowers the risk of burglary at a specific residence (Snook, Dhimi & Kavanagh, 2010; Nee & Meenaghan, 2006). Additionally, a property’s physical features, such as footpaths, alleys and roads, can significantly influence the risk of burglary at a particular residence or location (Chang, 2011).

Prior research also shows that burglars, in selecting their target, utilize a limited rational perspective (Snook, Dhimi & Kavanagh, 2010; Nee & Meenaghan, 2006). A burglar selecting a target using the limited rational choice perspective does not meticulously plan his or her act, nor does he or she act impulsively; rather a burglar searches for a target that presents a safe opportunity to commit the offense (Snook, Dhimi & Kavanagh, 2010; Nee & Meenaghan, 2006).

In an effort theoretically to explain residential burglary, routine activities theory has been frequently applied. According to routine activities theory, there are three components that are required for a crime, in this case residential burglary, to occur: (1) a motivated offender; (2) a suitable target; and, (3) a lack of capable guardians (Clarke & Felson, 1993). An offense is most likely to occur when these three variables coincide at one time and in one location (Akers & Sellers, 2004). Capable guardians have been operationally defined as anything from a person to a dog to an automobile at a residence (with the idea that a person may be present at the home) to an alarm system or to neighbors.

Neighborhood watch associations have been built on the notion that an aware public can reduce the desirability of homes to be targeted for burglary within a neighborhood. Neighbors who watch for suspicious cars and persons and who report suspicious cars and persons can theoretically influence the occurrence of burglary in an area. In line with routine activities theory, potential burglars will be less likely to continue their enterprise in areas with a perceived high number of capable guardians. An increased police presence in a neighborhood, either through officer-initiated patrols and/or due to calls for suspicious persons and suspicious vehicles would theoretically reduce the likelihood that continued burglary would occur in those locales with an increased police presence.

Risk can be measured through an evaluation of the correlates of burglary and other influential factors of the offense (Caplan & Kennedy, 2011). This study will operationally define burglary risk via three items. The first risk item, public transportation hubs and stops, specifically bus stops, has been shown to increase the risk of burglary in an area (Moreto, 2011). Access to public transportation allows an offender to enter and leave an area quickly and anonymously (Rengert, 1991). Employing dispatch data provided by the Lawrence Township Police Department in Lawrence Township, Mercer County, New Jersey, I will also examine the influential risk of the geospatial distribution of calls for suspicious persons and for suspicious automobiles in relation to calls for burglary. While prior studies have considered the geospatial distribution of residential burglary in urban areas, few studies have examined the geospatial characteristics associated with residential burglary in suburban settings. Moreover, no RTM study to this point has been conducted in a suburban community such as Lawrence Township.

METHODOLOGY

The data for this study were taken from the 2009 dispatch detail file from the Lawrence Township Police Department (LTPD) in Lawrence Township, Mercer County, New Jersey. Lawrence Township is a small suburban community that borders Trenton, the state capital. To conduct the geospatial analysis of the data fields from the dispatch detail used in this study, I obtained Topologically Integrated Geographic Encoding and Referencing (TIGER) line shapefiles for Mercer County, New Jersey from the United States Census Bureau website (<http://www.census.gov/cgi-bin/geo/shapefiles2010/main>) (United States Census Bureau, Geography Division, 2010). All geospatial analyses for this study were conducted in ArcMap version 9.3.1 and the ArcMap Spatial Analyst Extension package (ESRI 2009). The Mercer County

was clipped using the clip tool in the extract menu in the ArcMap Toolbox so that only Lawrence Township, New Jersey remained.

The initial task was to geocode the addresses listed in the dispatch detail. Geocoding refers to the process of assigning latitude and longitude values for each call location in the dispatch detail file. The LTPD does not have the technology to locate the calls for service via the use of a global positioning system in the police car. The responding officer must provide an address for the location at each call to the police dispatcher. Thus, the address for each call had to be geocoded using the geocoding tool in ArcGIS 9.3 (ESRI 2009). The latitude and longitude for each call location was stored. Geocoding of all calls for burglary, suspicious vehicles, and suspicious persons was performed and the xy coordinates for each call were stored in the file.

The analysis began with the formation of a pin map (not shown) whereby addresses with their corresponding x and y coordinates (in decimal degrees) were added to the Lawrence Township shapefile. The image on the pin map did not reveal any particular clustering of observations in any one location. Pin maps, however, unless they are adjusted to reflect multiple calls at a single location, do not provide an accurate image of clustering of observations. A test of spatial randomness was undertaken for the 2009 burglary calls. The null hypothesis for the test of spatial randomness is that the points are not autocorrelated with one another. If the null hypothesis is rejected, in other words, there is evidence of spatial autocorrelation. The Moran's I statistic for spatial autocorrelation indicated spatial randomness in the distribution of 2009 burglary events.

The next step in the analysis was to project the data from a geographic coordinate system to a projected coordinate system (i.e., Universal Transverse Mercator Zone 18 North). The projected data were then used to generate a kernel density image of residential burglary calls for 2009 using the point data (in decimal degrees) for each burglary call from the dispatch detail file. The raster image that was generated from the density analysis contained 100 square foot cells with a bandwidth of 1,000 feet. In order to generate the criminal event layer for burglary, I reclassified the density analysis information using a binary coding similar to that featured in the RTM manual for risk layers; specifically, I coded all burglary events at the 95th percentile as "1" and all other values, including blank data, as "0".

The third step in the analytical protocol involved operationally defining burglary risk. I have chosen to operationally define burglary risk in this study using three factors: (1) bus stop locations, (2) calls for suspicious persons and (3) calls for suspicious vehicles. Each risk layer was generated using the RTM methodology. I conducted kernel density analyses of each risk layer using 100 square foot cells and a 1,000 foot radius. Each risk layer raster image was clipped to the tract boundary for Lawrence Township. The density values were then reclassified where values at the 95th percentile for each risk layer were coded as "1" and all other values as "0".

To generate the composite risk image found in the RTM manual, the individual binary valued risk layers were combined using the raster calculator in ArcMap. The composite risk index in this study ranged from "0" representing that none of the risk factors were present in the 100 sq. foot cells to "3" representing that all three risk factors were present. The composite risk index was then symbolized and featured in Figure 2.

The unit of analysis in this study is the 100 square foot cell. Given the size of Lawrence Township, and the cell dimensionality, the data matrix contained 5,708 cells. The data layers were then spatially joined into one data table so that each cell contained a binary value for the 2009 burglary calls, bus stop locations, calls for suspicious persons, and calls for suspicious vehicles. The data table was then exported to SAS/STAT for statistical analysis.

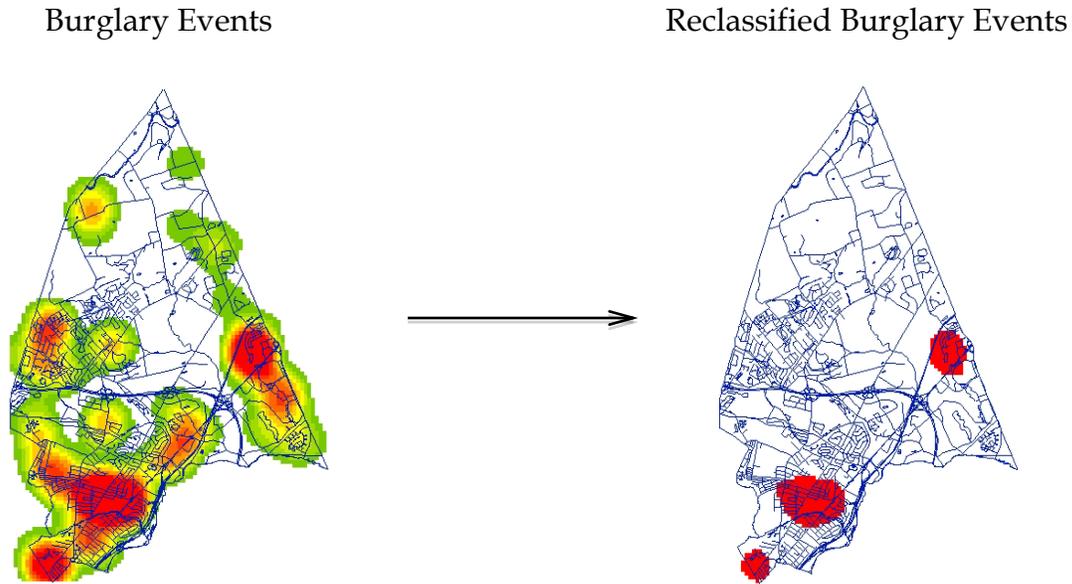


Figure 1.

Kernel density image of burglary events in Lawrence Township, New Jersey. Concentrated areas of burglary events (Red) appear most prominently in the southern part of Lawrence Township and in the northeastern corner of the township. The left panel features the kernel density image. The right panel features the binary-valued reclassified scoring where the 95th percentile of burglary events is featured (Red).

RESULTS

A kernel density image of calls for residential burglary is featured in Figure 1. The density image was generated using a bandwidth of 1,000 feet and a cell size of 100 square feet. The density image represents areas where calls for burglary were most prominent in Lawrence Township in 2009. The density analysis was undertaken using the Spatial Analyst extension in ArcMap 9.3 (ESRI DATE). Burglary is densely concentrated in three different areas of Lawrence Township; thus, RTM may offer the potential to narrow the focus of residential burglary by targeting fewer areas. Density images for each of the risk factors are featured in Figure 2. There is a greater concentration of bus stops in the southwestern corner of Lawrence Township. The southwestern corner of Lawrence Township borders Trenton, New Jersey. And two major roadways, United States Route 1 and Route 206, converge in the southwestern corner. A raster image of bus stop density was generated and the cell wise information reclassified binary location intensity was stored in each row. A high concentration of calls for suspicious automobiles and calls for suspicious persons appear most prominently in the southern part of Lawrence Township and in the northeastern corner of the township.

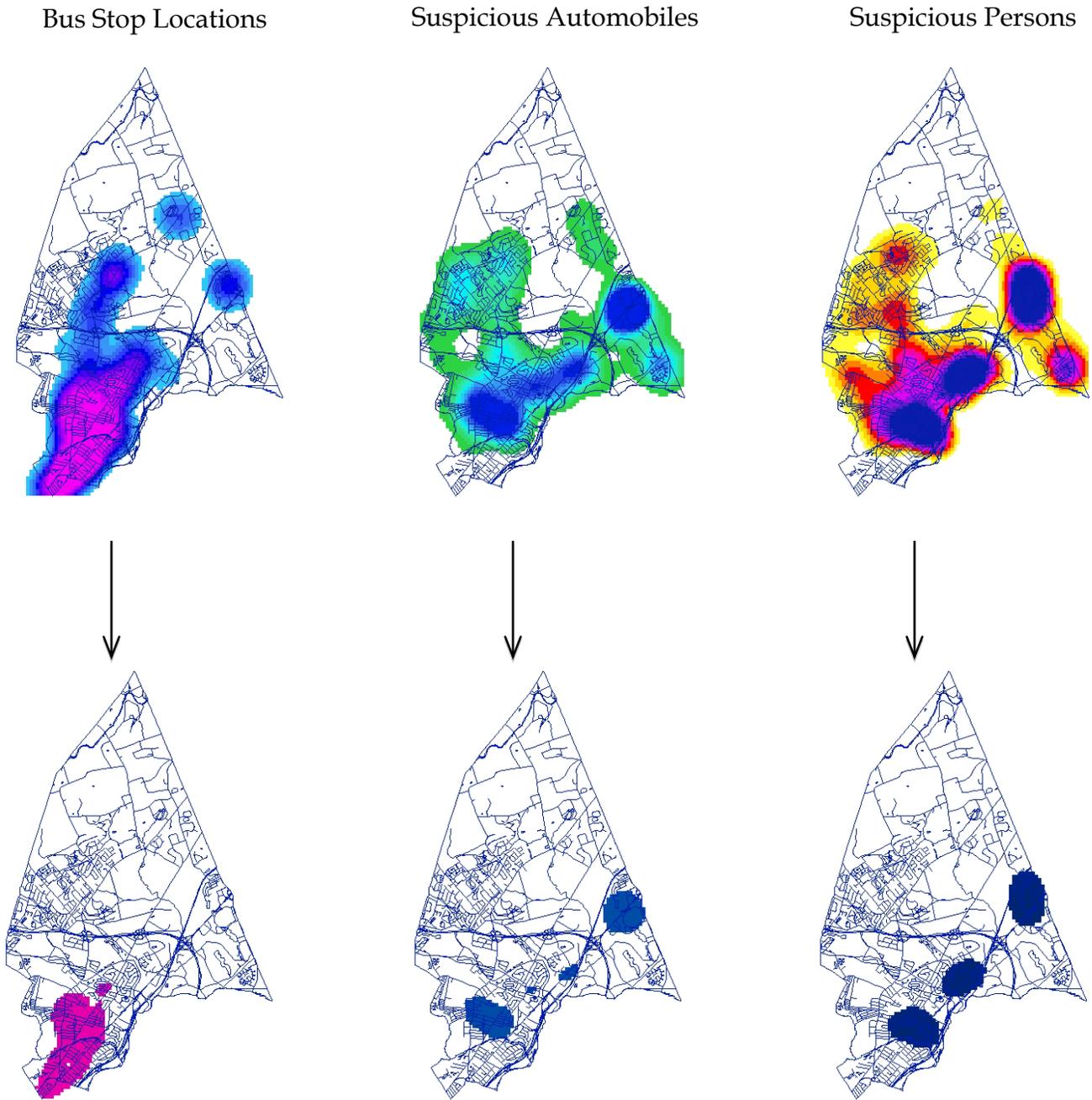


Figure 2. Kernel density images of risk layers are featured on the top panel. Binary-valued reclassified images are featured on the lower panel below the arrow corresponding to the density image above. Concentrated areas of bus stop locations (Pink) appear most prominently in the southern part of Lawrence Township. Concentrated areas of calls for suspicious automobiles (Light blue) and calls for suspicious persons (Dark blue) appear most prominently in the southern part of Lawrence Township and in the northeastern corner of the township. The upper panels feature the

kernel density images. The lower panels feature the binary-valued reclassified scoring where the 95th percentile of each risk factor is featured.

Reclassified Burglary Events

Reclassified Risk Items

Predicted Probability

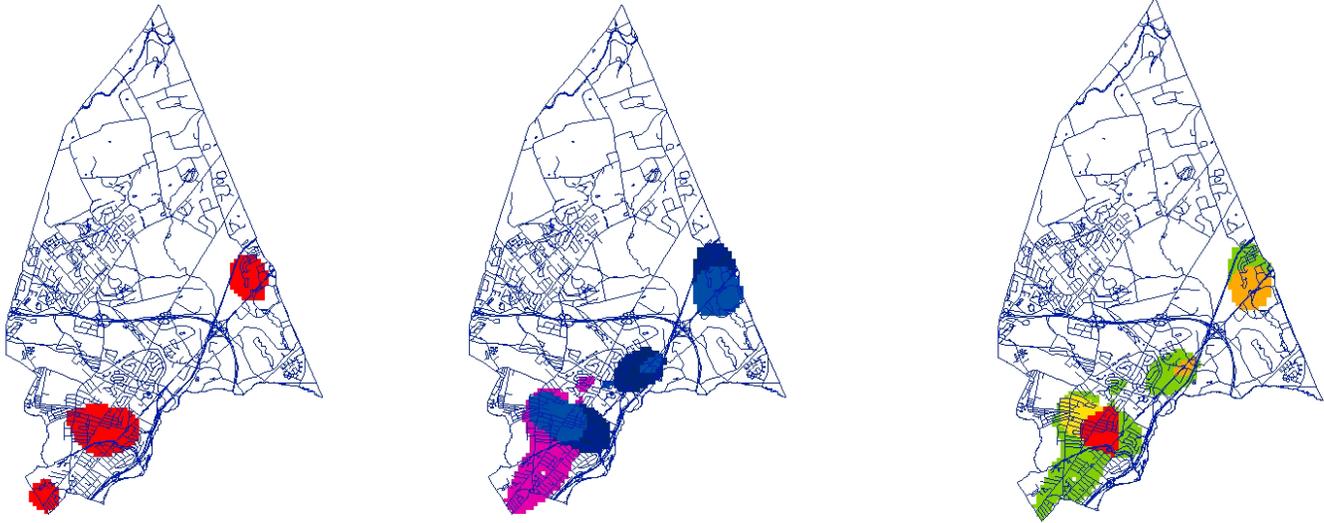


Figure 3.

The reclassified burglary events (featured on the left image), reclassified risk items (featured in the center image), and the predicted probability of each burglary event (featured in the right image). The red area in the predicted probability image represents the part of Lawrence Township with the highest predicted probability of burglary in 2009.

The data matrix of reclassified binary values for burglary and the risk factors was used to test the statistical association of burglary events and the individual risk factors. Given that the burglary event was reclassified using a binary scheme (1=95th percentile or above; 0=below the 95th percentile), it was necessary to employ a regression procedure that would model a binary dependent variable. I chose to estimate a binary logistic regression model where burglary would be regressed on the risk factors. The binary logistic regression model was estimated using the GENMOD procedure in SAS/STAT 9.3.

Table 1. Binary logistic regression estimates of the reclassified burglary events regressed on burglary risk items (n=5708).

Parameter	Estimate	Standard Error	Wald Chi-Square	P>Chi-Square	OR
Intercept	-5.8115	.2507	537.21	<.0001	
Bus Stops	4.6921	.2793	282.25	<.0001	109.082

Suspicious Persons	1.3303	.1807	54.19	<.0001	3.782
Suspicious Vehicles	4.9089	.2805	306.36	<.0001	135.490
Notes: OR=Odds Ratio Log Likelihood = -511.0233 Nagelkerke R Square = .662 Cox & Snell R Square = .243					

The binary logistic regression estimates of the binary valued burglary event variable regressed on the individual risk layer variables are presented in Table 1. All of the risk factors make statistically significant contributions to the outcome variable. Thus, areas with a high concentration of bus stop locations, calls for suspicious persons and calls for suspicious automobiles are associated with a higher concentration of burglary events. The odds ratios (OR) for bus stops and suspicious vehicles indicate that these two risk factors are more likely to be associated with burglary events than suspicious persons.

The parameter estimates from binary logistic regression represent the amount of change in the logarithm of the odds of burglary. A more intuitive interpretation for the parameter estimates for a binary logistic regression model comes from converting the parameter estimates to predicted probabilities. A predicted probability for a binary logistic regression model is obtained using the following formula (Hosmer and Lemeshow 1989, p. 11):

$$\hat{\pi} = \frac{\exp\left(\alpha + \sum_{i=1}^k b_i x_i\right)}{1 + \exp\left(\alpha + \sum_{i=1}^k b_i x_i\right)}$$

When the binary logistic regression estimates are converted to predicted probabilities, the difference in predicted probabilities represents a percentage difference in the dependent variable occurring between the values chosen for the independent variables. The predicted probability of a burglary event for areas with a high concentration of suspicious vehicles, for example, would be: $\hat{\pi} = .2885 = (\exp(-5.8115 + 4.9089)) / (1 + (\exp(-5.8115 + 4.9089)))$. The predicted probability for areas without a high concentration of vehicles (or bus stops or suspicious persons) would be: $\hat{\pi} = .0028 = (\exp(-5.8115)) / (1 + (\exp(-5.8115)))$. Taking the difference in these predicted probabilities (i.e., .2885-.0028) reveals that those areas with a high concentration of suspicious vehicles are approximately 28% more likely to have burglary events than those without a high concentration of suspicious vehicles.

The predicted probability for each covariate pattern was computed in PROC GENMOD in SAS/STAT using the "pred" subcommand. The predicted probabilities for each covariate pattern were added as a vector in the original data matrix. The updated data matrix was then exported from SAS/STAT as a .dbf file. The .dbf file was then imported back into ArcMap. The .dbf file was symbolized by using the raster features to polygon command in the ArcMap toolbox. The symbolized predicted probability image is featured in Figure 3 along with the image of the reclassified burglary events and the reclassified image of the burglary risk factors. The predicted probability of a burglary event is highest in cells where suspicious persons and suspicious cars were at the 95th percentile or above. The predicted probability image reveals that there is one area (symbolized in red) where the Lawrence Township Police Department may wish to focus their efforts with respect to burglary events.

CONCLUSION

This study employed risk terrain modeling to examine residential burglary data in Lawrence Township, New Jersey. Using the RTM methodology, I found that concentrations of bus stops, calls for suspicious persons and calls for suspicious vehicles all have statistically significant associations with areas with a high concentration of burglary events. Proponents of the RTM methodology claim that it offers police agencies with a prospective approach to fighting crime by identifying risk factors associated with criminal events. While the results of this study show that burglary events are associated with the risk factors used in this study, it does not mean that the risk factors are causes of burglary risk. All of the data used in this study came from the 2009 dispatch file. Holleran and Gale (2012) are examining the predictive validity of RTM using data from the 2010 and 2009 dispatch files from the LTPD. Results from Holleran and Gale suggest that burglary events in the following year are displaced to different, although nearby, locations.

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