Conjunctive Analysis Report: 2012 Residential Burglary in Arlington, TX

PIs Leslie Kennedy, Joel Caplan & Eric Piza

Completed in partial fulfillment of National Institute of Justice (NIJ) award #2012-IJ-CX-0038

Background and Overview

Research suggests that crime is not evenly distributed throughout the environment (Sherman, Gartin, and Buerger, 1989). This can be explained through the presence of *attractors* and *generators* of crime (Brantingham and Brantingham, 1995), or “risk factors,” that co-locate to create unique “behavior settings” (Taylor, 1997) that are conducive to illegal activities. Risk terrain modeling (RTM) is an approach to risk assessment that uses existing technology, data, and GIS (geographic information systems) to diagnose the underlying characteristics of the environment that produce crime-conducive behavior settings. RTM standardizes risk factors to common geographic units over a continuous surface and combines multiple risk factors to produce a composite map showing the presence or absence of risk at micro-level places (Caplan, Kennedy, Miller, 2010). It is used to empirically test ideas about emerging conditions leading to crime problems, to develop interventions that deploy police officers to high risk places, and to help prioritize crime risk factors for mitigation efforts. However, the conditions that influence crime are highly complex.

It is likely that some interaction effects among certain risk factors in a RTM are stronger than other interactions on the attraction of criminal behavior, even for weighted risk terrain models. Missing from the current outputs of RTM methods and statistical validation tests is an easy way to determine which combination of risk factors account for the greatest relative frequency of crimes compared to all other risk factor combinations. For example, regression modeling (i.e., to test predictive validity) provides information about the likelihood of crime occurring at places with every increased risk value. If we can imagine an un-weighted 5-factor RTM, places with all 5 risk factors present will have the greatest risk, or likelihood, of crime occurring there. However, places with risk values of "4" should not be treated equal because it is unclear which factors’ absence makes the "best" 4-factor model. Should places with factors A, B, C, D be prioritized over places with factors B, C, D, E or vice versa? In this example, several places can have risk values of “4” but have meaningfully different combinations of risk factors. We need a way to test which behavior settings (e.g., bars + parks + schools *or* bars + parks + fast food restaurants) account for the most crime events.

Conjunctive analysis can be used to explore the relative interaction among risk factors by allowing for the comparison of cross-case configurations and by providing empirical evidence demonstrating the interrelationships between factors of the location in question. It provides a multivariate analysis of discrete categorical data that can be used for various criminal justice applications, such as to examine the risks of imprisonment for federal drug offenders (Miethe, Hart, and Regoeczi, 2008). The end product or output of a conjunctive analysis is a data matrix of behavior settings, which include every possible combination of risk factor interactions and the relative frequency of crimes associated with each setting. Conjunctive analysis can be used to enhance the practical value of RTM by addressing the interrelationships among different factors. More specifically, RTM can be used to empirically identify and validate environmental risk factors. These significant risk factors can then be incorporated into a conjunctive analysis to assess interaction affects among them.

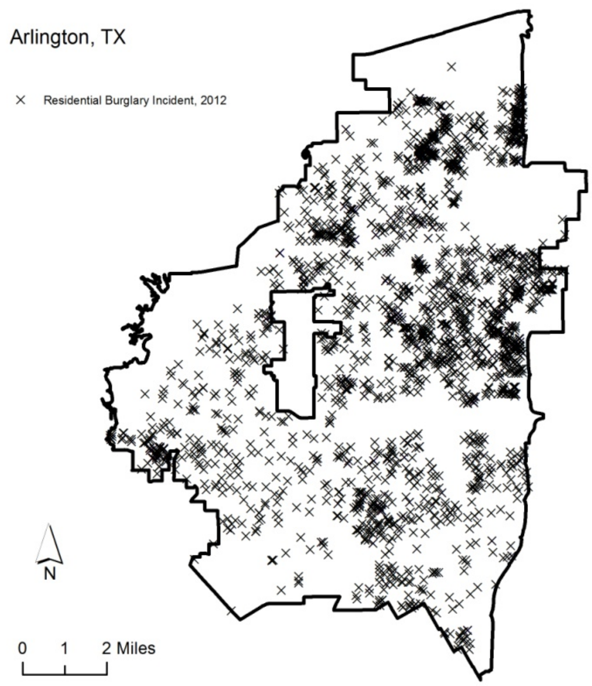
The purpose of this report is to combine the power of RTM and conjunctive analysis to examine the spatial context of residential burglary in Arlington, TX. This report will first describe the steps involved in building a RTM for residential burglary in Arlington, as well as the results of this model. Subsequent sections will present the conjunctive analysis process, along with the results of a conjunctive analysis that was informed by results from the RTM. Finally, the practical implications of using conjunctive analysis and RTM to inform targeted police interventions are discussed.

Building the Risk Terrain Model

As discussed above, RTM identifies the risky features of a landscape and models how they help to create unique behavior settings for crime. The Risk Terrain Modeling Diagnostics (RTMDx) Utility was used to produce a risk terrain model[1] for the 2,525 incidents of residential burglary that occurred in calendar year 2012. The RTMDx Utility is a software app produced by Rutgers University that automates the RTM process[2].

Figure 1 is a pin map displaying the distribution of residential burglary incidents in the jurisdiction of Arlington, TX. It appears that incident locations of this crime do not distribute evenly throughout the jurisdiction. As depicted on the map, crimes seem to cluster at certain areas. By diagnosing the underlying spatial factors of residential burglary at existing high-crime places, RTM helps to forecast where crime is statistically most likely to occur in the future and provides actionable information for focused interventions. The following sections will discuss the basic steps of building the RTM used for this conjunctive analysis, including selecting likely risk factors, setting parameters in the RTMDx Utility, and operationalization of the risk factors. The results of the risk terrain model are then presented.

Figure 1. 2012 Incident Locations of Residential Burglary in Arlington, TX



Selecting Likely Risk Factors

With any RTM analysis, the product of this task should be a comprehensive list of risk factors related to the outcome event. The RTMDx Utility can accept up to 30 risk factors as inputs for testing. Three methods were used to identify the final "pool" of risk factors that should be tested for inclusion in the RTM. 1) Existing empirical research literature was reviewed, which identified a variety of risk factors that have been found to correlate with residential burglary. 2) Professional/practitioner insights also played an invaluable role in determining which factors are likely relevant for this particular jurisdiction. Jurisdictions may have specific crime problems that relate to a unique set of factors that are best identified by local officials who work in these environments on a regular basis.

Once a pool of potential risk factors were compiled, 3) visual inspection in a GIS was used to explore which features appear to co-locate with crime incident locations. Using ArcGIS, each potential risk factor data set was layered, respectively, with point features of residential burglary incidents and visually inspected for spatial relationships. Risk factors that generally appeared to share a spatial relationship were retained for empirical testing in the RTMDx Utility. This process was used to exclude risk factors that very obviously did not visually appear to spatially relate to the crime incidents, in order to create a more parsimonious model.

Risk Factors and Data Sources

Risk terrain modeling relies on valid and reliable data sources. Data used for this study was collected from InfoGroup and the Arlington Police Department (APD). InfoGroup is a data and marketing services company that provides detailed information about public entities. Some of the risk factor data sets used in this case study were obtained from InfoGroup at the address-level: apartment complexes, convenience stores, foreclosures, gas stations with convenience stores, pawn shops, recreation centers, sit-down restaurants, retail stores, schools, senior high schools, variety stores and grocery stores. Crime and other data sets were provided at the address-level by the APD: residential burglary incidents.

Setting Parameters in the RTMDx Utility

Several parameters must be set in the RTMDx Utility before testing can begin. For this analysis, an "aggravating" model type was run to determine the underlying attractors of residential burglary in Arlington, TX. Other parameters include "block length," "cell size," "maximum spatial influence," "analysis increments," and "operationalization," which are discussed below.

Block Length, Cell Size, Maximum Spatial Influence, and Analysis Increments

Risk terrain modeling is typically concerned with the micro-level unit of analysis, such as a raster GRID cell. In this case, "block length" was set to twice[3] the mean length of a block face in Arlington (980 feet) and the "cell size" was set to half that length (490 feet). Previous empirical research suggests that the spatial influence of a given environmental feature extends no more than just a few street blocks. Therefore, the "maximum spatial influence" for this model was set to 4 blocks. The RTMDx Utility allows for testing either whole or half block increments. Each risk factor in this study was tested at whole block increments.

Operationalization

The "operationalization" parameter was custom selected for each risk factor tested. This parameter regards how each risk factor's spatial influence will be assessed; that is, as a function of "proximity," "density," or "both." "Proximity" proposes that being within a certain distance of the factor features increases the likelihood of crime. "Density" proposes that risk is higher at places where the factor features are heavily concentrated. The RTMDx Utility also allows for testing "both" proximity and density. This setting permits the Utility to empirically select the best operationalization. However, this doubles the number of variables to be tested and greatly increases the analytical run time. So, to purposefully make this parameter decision for each risk factor, output results from the Nearest Neighbor (NN) analysis tool in ArcGIS were consulted. Table 1 shows the results of the NN analysis and the corresponding "operationalization" parameter selected for each risk factor.

Table 1. Results of NN Analysis and Corresponding Risk Factor Operationalizations

Name	Operationalization	Observed Distance	p-value	Spatial Pattern
Apartment Complexes	Both	996.04	0.00	Clustered
Convenience Stores	Both	2059.74	0.00	Clustered
Foreclosures	Both	1875.25	0.00	Clustered
Gas Stations w/ Conv. Stores	Proximity	4263.26	0.02	Dispersed
Pawn Shops	Proximity	4544.78	0.31	Random
Recreation Centers	Proximity	5426.81	0.60	Random
Sit-Down Restaurants	Both	555.11	0.00	Clustered
Retail Shops	Both	1624.36	0.00	Clustered
Schools	Both	1969.45	0.00	Clustered
Senior High Schools	Proximity	10843.68	0.00	Dispersed
Variety Stores	Proximity	3826.74	0.81	Random
Grocery Stores	Proximity	2912.35	0.67	Random

To Produce Table 1:
First, a "nearest neighbor threshold" was calculated as: *NN Threshold = 2 * (Block Length * Number of Analysis Increments).* The NN threshold for this case study is 7,840. Then, for each set of risk factor feature points: If the features were not significantly clustered or if the observed mean distance reported by the Nearest Neighbor analysis was greater than the NN threshold, the operationalization was set to "proximity." If the points were significantly clustered and the observed mean distance was less than or equal to the NN threshold, "both" proximity and density was used, allowing the model to empirically determine the best one, if any. There were, however, some exceptions to this general rule. Risk factor data sets that represented a fleeting phenomenon (i.e., they occurred at a location, but did not remain a permanent feature of the environment), such as drug arrests or calls for service, were tested as a function of "density." And, because the RTMDx Utility supports only point features as inputs, some polygon shapefiles had to be converted to (representative) point features prior to being tested (e.g., parks were typically polygons shapefiles and were converted to point features). Given the method of conversion, these risk factors were tested as "proximity" only.

Results of the Risk Terrain Model
There were 11,998 raster GRID cells (i.e., 490ft x 490ft) used in the analysis, 1,487 of which contained crime incidents. The RTMDx Utility identified 7 statistically significant risk factors for residential burglary incidents in Arlington, TX and produced a risk terrain map (Figure 2) with relative risk values at each micro-level place. For a more detailed explanation of the statistical procedures see the *RTMDx Utility User Manual*. Relative risk values (RRVs) ranged from 1 (for the lowest risk place) to 51 (for the highest risk place). The highest risk places are 51 times more likely to experience residential burglary than the lowest risk places. Locations that are two standard deviations above the mean RRV (i.e. places shaded black on the map) are considered the highest risk locations for residential burglary in Arlington, TX. The likelihood of crimes occurring at these places is more than 16 times higher than some other locations.

Figure 2. RTM for Residential Burglary in Arlington, 2012

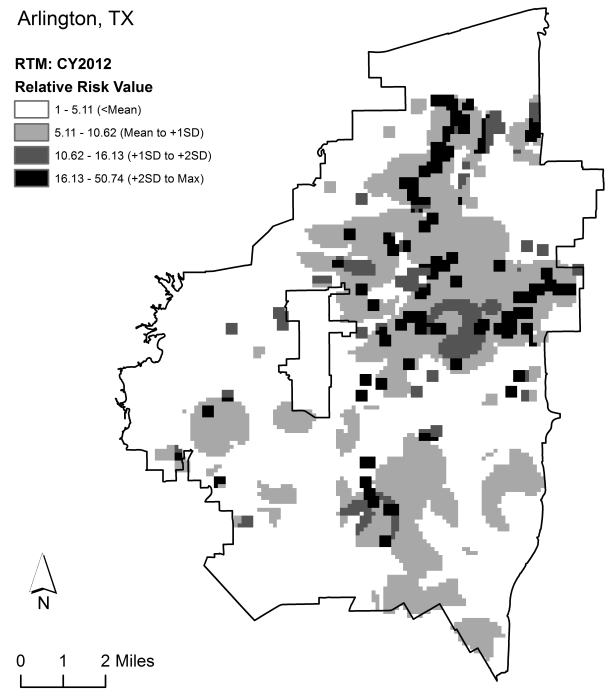
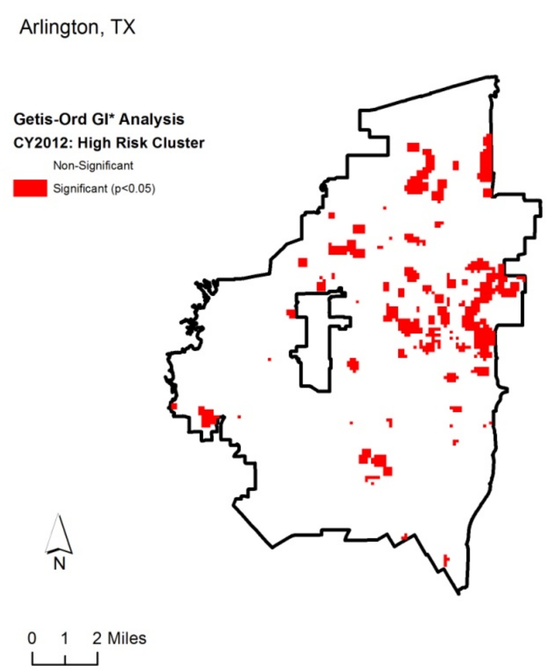


Figure 3. Getis-Ord Gi* Analysis of High Risk Clusters for Arlington, 2012



The Hotspot Analysis tool (Getis-Ord Gi*) in ArcGIS was used to identify statistically significant clusters of relative risk values (i.e., high-risk clusters). As Figure 3 illustrates, there are significant clusters of high-risk in Arlington, TX.

The 7 risk factors included in the risk terrain model are apartment complexes, schools, foreclosures, pawn shops, variety stores, convenience stores, and gas stations with convenience stores. The most meaningful operationalizations and spatial influential distances of these factors are presented in Table 2. The relative risk values can be interpreted as the weights of risk factors and may be easily compared. For instance, a place influenced by apartment complexes has an expected rate of crime that is more than 3 times higher than a place influenced by gas stations with convenience stores (RRVs: 3.88 / 1.19 = 3.26). The most important predictor of residential burglary occurrence is proximity to apartment complexes. Accordingly, all places may pose a risk of residential burglary to people in Arlington, TX, but because of the spatial influence of certain features of the landscape, some places are riskier than others.

Table 2. Risk Terrain Model Specifications

Name	Operationalization	Spatial Influence	Coefficient	Relative Risk Value
Apartment Complexes	Proximity	980	1.36	3.88
Schools	Proximity	3920	0.88	2.42
Foreclosures	Density	2940	0.58	1.78
Pawn Shops	Proximity	3920	0.34	1.40
Variety Stores	Proximity	3920	0.31	1.36
Convenience Stores	Proximity	3920	0.29	1.34
Gas Stations w/ Conv. Stores	Proximity	3920	0.18	1.19
Intercept	-	-	-3.21	-
Intercept	-	-	0.07	-

Conjunctive Analysis

Once a significant risk terrain model is identified, conjunctive analysis can begin. Conjunctive analysis is a fairly straightforward statistical technique. According to Miethe et al. (2008),

> "A conjunctive analysis of case configurations begins with an aggregated compilation of all possible combinations of attributes considered simultaneously. The number of possible case configurations depends on the number of independent variables and categories within them. For a conjunctive analysis involving 5 dichotomous independent variables, there are 32 qualitatively distinct case configurations (2^5=32)…Once the possible case configurations are identified, conjunctive analysis proceeds by aggregating each observation into their respective case configuration and exploring the relative distribution of particular categories of the outcome variables across these configurations" (p.229).

The data for the conjunctive analysis was prepared using ArcGIS. In this step, the spatial influence of each significant risk factor was coded as a dichotomous variable representing the presence (1) or absence (0) of highest risk at each micro-place (i.e., 490x490 raster cell) in the study area. Given 7 binary independent variables, the total number of possible case configurations for this conjunctive analysis is 128 (2^7=128). The final data was imported into SPSS (Statistical Packages for the Social Sciences) to perform a conjunctive analysis using the following formula (Miethe et al., 2008):

```
AGGREGATE
/OUTFILE = 'CA_Matrix_file'
/BREAK = A B C D
/Crime = SUM
/N_Cases = N
```

The resulting product is a conjunctive analysis data matrix (Miethe et al., 2008) that displays all of the possible case configurations of the aggregated compilation of risk factors. When displayed in a table of *i* rows and *j* columns, each row represents a particular case configuration. Each row also includes the number of observations (i.e., count of 490ft x 490ft cells) and the proportional distribution of outcome events for that unique case configuration. As explained by Miethe et al. (2008), "conjunctive analysis involves visual representations of case configurations that convey important information about their nature, diversity, and distribution for subsequent analysis" (p.229).

Conjunctive Analysis Results

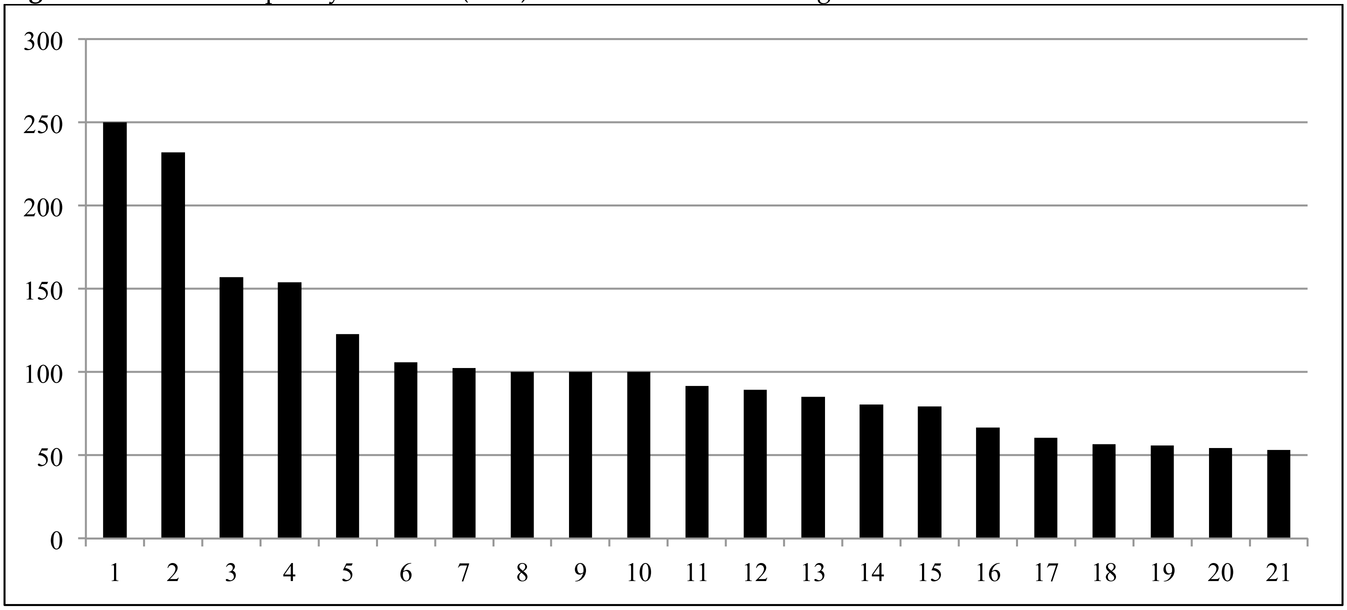
A conjunctive analysis data matrix for the 7 significant risk factors for residential burglary in Arlington, TX is displayed in Table 3. Of the 128 possible case configurations, a total of 88 were observed. However, only dominant case configurations (>9 observations) (Miethe et al., 2008, p.229) with a relative frequency of crime (RFC) above the mean (50.68) are displayed. This results in a total of 21 case configurations that are of particular interest to us. Each row under the case configuration column in Table 3 refers to a behavior setting defined by a unique set of attributes (i.e., presence or absence of risk factors). Each risk factor has a column containing a series of 1s and 0s indicating the presence or absence of that risk factor's spatial influence in each case configuration. For example, case configuration 1 is characterized by *the presence of* the spatial influences of apartment complexes, schools, foreclosures, pawn shops, variety stores, and convenience stores, and *the absence of* the spatial influences of gas stations with convenience stores.

Also from Table 3, we see that there are 12 observed instances (i.e., cells) of configuration 1, which were responsible for 30 of the 2,525, or 1.19%, of residential burglary incidents in 2012. The RFC of case configuration 1 is 250. This represents the most influential of all case configurations displayed in Table 3. Finally, Table 3 includes a break to denote case configurations with a RFC that is one or more standard deviations above the mean RFC. The 5 case configurations with a RFC greater than one standard deviation above the mean were responsible for 216 of 2,525 residential burglaries, or a total of 8.55%. Of the 11,998 raster cells analyzed, these 5 case configurations included 132 cells, or 1.1% of the total study area. The 21 case configurations with a RFC that was higher than the mean accounted for 1,015 of 2,525 residential burglaries, or 40.20%. These 21 case configurations included 1,148 cells, or 9.57% of the total study area. Thus, behavior settings covering about 9% of the study area account for nearly 40% of all crime incident locations.

Table 3. Conjunctive Analysis Data Matrix of Dominant Case Configurations with a Relative Frequency of Crime Above the Mean

Case Configuration	Apartment Complexes	Schools	Foreclosures	Pawn Shops	Variety Stores	Convenience Stores	Gas Stations with Convenience Stores	Crime Count (total n=2,525)	# of Case Configurations	% Crime	Relative Frequency of Crime (RFC)
1	1	1	1	1	1	1	0	30	12	1.19	250.00
2	1	1	1	0	0	0	1	58	25	2.30	232.00
3	1	0	0	1	1	1	1	33	21	1.31	157.14
4	1	1	1	0	0	1	1	20	13	0.79	153.85
5	1	1	0	1	0	1	1	75	61	2.97	122.95
One Standard Deviation								**216**	**132**	**8.55**	
6	1	1	1	0	1	1	1	35	33	1.39	106.06
7	1	1	0	1	1	1	1	174	170	6.89	102.35
8	1	0	0	0	0	1	1	27	27	1.07	100.00
9	1	0	0	0	0	1	0	11	11	0.44	100.00
10	1	1	1	1	1	1	1	11	11	0.44	100.00
11	1	1	0	1	1	1	0	22	24	0.87	91.67
12	1	1	0	0	1	1	0	60	67	2.38	89.55
13	1	1	0	0	1	1	1	174	204	6.89	85.29
14	1	1	0	0	0	1	0	45	56	1.78	80.36
15	1	1	0	0	0	0	1	35	44	1.39	79.55
16	0	0	0	1	0	1	1	10	15	0.40	66.67
17	1	1	0	1	0	1	0	17	28	0.67	60.71
18	1	1	0	0	0	0	0	34	60	1.35	56.67
19	1	1	0	0	0	1	1	46	82	1.82	56.10
20	0	1	0	1	1	0	0	6	11	0.24	54.55
21	0	1	1	1	1	1	1	92	173	3.64	53.18
Mean								**1015**	**1148**	**40.20**	

Figure 4. Relative Frequency of Crime (RFC) for each Behavior Setting



Discussion

Conjunctive analysis can be used to explore which unique combinations of risk factors identified via risk terrain modeling attract the most incidents of crime. Of the 128 possible configurations, we highlight 21 dominant case configurations with a RFC that is greater than the mean RFC. The most influential behavior setting (i.e., case configuration 1) is marked by the presence of six risk factors: apartment complexes, schools, foreclosures, pawn shops, variety stores, and convenience stores. When the spatial influential areas of these factors exist together, these behavior settings account for 1.19% of residential burglaries in Arlington, TX. While this seems like a small portion of residential burglaries, it is important to consider the RFC. For example, case configuration 34 (not displayed) accounts for the largest raw portion (7.13%) of residential burglary in Arlington, TX. However, RFC takes into account the amount of crime in relation to the relative size of the geography involved in its occurrence. Thus, case configuration 1 exerts nearly 10 times the spatial influence of case configuration 34 (250 / 25.07 = 9.97). The matrix produced by the conjunctive analysis provides a visual tool that highlights how risk factors co-locate at micro-level places to create unique behavior settings that are attractive to criminal behavior. These behavior settings can then be mapped in a GIS for analytic purposes or resource allocation.

Risk terrain modeling identified the 7 risk factors (apartment complexes, schools, foreclosures, pawn shops, variety stores, convenience stores, and gas stations with convenience stores) that pose the highest level of risk for residential burglary in Arlington, TX. Conjunctive analysis identified places with particular subsets of these 7 factors (e.g., A, B, C, D) to be prioritized over places with *different* and less risky combinations of these factors (e.g., B, C, D, E). Several places can have risk values of, for example, "6" but have meaningfully different combinations of risk factors. For example, case configurations 1 and 6 each have a set of six risk factors. However, case configuration 1 (apartment complexes, schools, foreclosures, pawn shops, variety stores, and convenience stores) is qualitatively different from case configuration 6 (apartment complexes, schools, foreclosures, variety stores, convenience stores, and gas stations with convenience stores). Using information obtained from the conjunctive analysis data matrix, we can see that case configuration 1 has nearly 2.4 times the relative frequency of crime as case configuration 6. From a practical perspective, conjunctive analysis verifies the important risk factor interactions, allowing police to make better decisions regarding the most effective allocation of resources and intervention strategies at specific behavior settings.

Risk terrain modeling provides public safety practitioners with a tool to empirically identify which features of the environment influence illegal behavior. Moreover, it allows agencies to develop targeted, risk-based strategies according to the weights given to each significant factor in the model. However, the effectiveness of police interventions will likely vary as a function of the particular behavior setting that is being targeted because the interaction of some risky features from RTM are likely to be more prone to crime than the interaction of other risky features from the same model. Conjunctive analysis can be used to evaluate the un-weighted interactions among the risk factors within a RTM to determine which combination of features constitute the most influential behavior settings to be sure that resources are geographically targeted in the most efficient manner. Future research should evaluate the use of conjunctive analysis as a way for police to assess their long-term effectiveness in reducing crime. This can be done by conducting several conjunctive analyses over a length of time to determine which intervention activities were most effective at which behavior settings. Interventions can be updated and redeployed based on information obtained from each conjunctive analysis. Using conjunctive analysis in this way, police can continually ensure that they are employing the most effective strategies in the most appropriate places.

References

Brantingham, P., & Brantingham, P. (1995). Criminality of place. *European Journal on Criminal Policy and Research*, *3*(3), 5-26.

Caplan, J. M., Kennedy, L. W., & Miller, J. (2011). Risk terrain modeling: brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly*, *28*(2), 360-381.

Miethe, T. D., Hart, T. C., & Regoeczi, W. C. (2008). The conjunctive analysis of case configurations: An exploratory method for discrete multivariate analyses of crime data. *Journal of Quantitative Criminology*, *24*(2), 227-241.

Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, *27*(1), 27-56.

Taylor, R. B. (1997). Social order and disorder of street-blocks and neighborhood: Ecology, microecology and the systemic model of social disorganization. Journal of Research in Crime and Delinquency, 24, 113–155.

Taylor, R. B., & Harrell, A. (1996). Physical environment and crime (pp. 11-12). US Department of Justice, Office of Justice Programs, National Institute of Justice. Retrieved Mar 26 2014, From: https://www.ncjrs.gov/pdffiles/physenv.pdf

Endnotes

[1] The risk terrain model used for this conjunctive analysis was updated after the NIJ project intervention in the city had begun because there were recent improvements to the modeling process and new access to better data sets. So, the risk terrain model presented in this conjunctive analysis report might differ slightly from the model that originally informed the intervention in this city.

[2] http://www.rutgerscps.org/software/index.html

[3] The mean block length, based upon measurement of features within a street centerline shapefile, is generally used as the "block length" parameter within the RTMDx Utility. However, we expected features of the environment to influence behaviors resulting in burglaries differently than other types of crimes, such as assault, robbery, or motor vehicle theft. First, residential properties are stationary (i.e., they do not travel like people or cars can) and are likely located farther away from the commercial features used in this analysis. Second, a motivated offender's familiarity with potential/suitable targets for victimization is likely a function of the offender's travel patterns. These patterns are presumably influenced by "destination" features of the environment that attract them (e.g., shopping malls, preferred gas stations, grocery stores, gyms, etc.), and through areas that facilitate the best travel routes (e.g., local/residential roads). Travel patterns of motivated offenders, directly influenced by their desired destination, introduces them to new opportunities for burglary and exposes homeowners to unique risks based on their spatial locations in relation to certain features of the landscape. Given this mechanism through which we expect features of the environment to influence opportunities for burglaries, and given the "4 block" limit for the "maximum spatial influence" parameter in the RTMDx Utility, the mean block length was doubled for this parameter in order to allow the Utility to assess the spatial influence of environmental features within a larger radius -- beyond the immediate commercial zones of the features being tested. In this case, similar to a distance of up to 8 blocks, rather than 4.

