

Risk Terrain Modeling for Spatial Risk Assessment

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Abstract

Spatial factors can influence the seriousness and longevity of crime problems. Risk terrain modeling (RTM) identifies the spatial risks that come from features of a landscape and models how they collocate to create unique behavior settings for crime. The RTM process begins by testing a variety of factors thought to be geographically related to crime incidents. Valid factors are selected and then weighted to produce a final model that basically paints a picture of places where crime is statistically most likely to occur. This article addresses crime as the outcome event, but RTM can be applied to a variety of other topics, including injury prevention, public health, traffic accidents, and urban development. RTM is not difficult to use for those who have a basic skillset in statistics and Geographic Information Systems, or GISs. To make RTM more accessible to a broad audience of practitioners, however, Rutgers University developed the Risk Terrain Modeling Diagnostics (RTMDx) Utility, an app that automates RTM. This article explains the technical steps of RTM and the statistical procedures that the RTMDx Utility uses to diagnose underlying spatial factors of crime at existing high-crime places and to identify the most likely places where crime will emerge in the future, even if it has not occurred there already. A demonstrative case study focuses on the process, methods, and actionable results of RTM when applied to property crime in Chicago, Illinois, using readily accessible resources and open public data.

Introduction

Several methods can aim to clarify the forces that create risky places. Evaluating the spatial influences of features of the landscape on the occurrence of crime incidents and assessing the importance of each feature relative to one another combine to make a viable method for assessing such risk (Caplan, 2011). For an analogy that is much more benign than criminal offending, consider a place where children repeatedly play. When we step back from our focus on the cluster of children, we might realize that the place where they play has swings, slides, and open fields. The features of the place (that is, a place suggestive of a playground), instead of the features of other locations that lack such entertaining qualities, attract children. Just as playground equipment can influence and enable playful behaviors, in a *similar* way, features of a landscape could influence the seriousness and longevity of illegal behaviors and associated crime problems (for example, Caplan, Kennedy, and Piza, 2013a, 2012; Drawve, in press; Dugato, 2013; Kennedy, Caplan, and Piza, 2011). Risk terrain modeling (RTM) identifies the risks that come from features of a landscape and models how they collocate to create unique behavior settings for crime (Caplan and Kennedy, 2010).

Risk Terrain Modeling

RTM is an approach to risk assessment whereby separate map layers representing the spatial influence of features of a landscape are created in a Geographic Information System (GIS; Caplan and Kennedy, 2010). Risk map layers of statistically validated features are combined to produce a composite risk terrain map with values that account for the spatial influences of all features at every place throughout the landscape. RTM offers a statistically valid way to articulate crime-prone areas at the microlevel according to the spatial influence of many features of the landscape, such as bars, parks, schools, foreclosures, or fast-food restaurants. Risk values in an RTM do not suggest the inevitability of crime. Instead, they point to locations where, if the conditions are right, the risk of illegal behavior will be high.

RTM is not difficult to use with the freely available resources provided by the Rutgers Center on Public Security.¹ To make RTM more accessible for private and public safety practitioners, Rutgers University developed the Risk Terrain Modeling Diagnostics (RTMDx) Utility, a free² desktop software app that automates RTM (Caplan, Kennedy, and Piza, 2013b). Many police agencies regularly use it. Some current applications of RTM include ongoing projects in cities across the United States funded by the National Institute of Justice (NIJ).³ Project sites (that is, police departments) include New York, New York; Newark, New Jersey; Chicago, Illinois; Kansas City, Missouri; Arlington, Texas; Colorado Springs, Colorado; and Glendale, Arizona. A key objective of these projects is to inform police-led interventions that address a designated priority crime type at target areas for each city.

¹ <http://www.rutgerscps.org/>.

² The educational version of the RTMDx Utility is free for noncommercial use. The professional version of the Utility is bundled with the RTM Training Webinar, offered biannually by the Rutgers Center on Public Security.

³ NIJ Award Nos. 2012-IJ-CX-0038 and 2013-IJ-CX-0053.

RTM diagnoses the underlying spatial factors that create risk at high-crime places. Police interventions are then designed to suppress crime in the short term and mitigate spatial risk factors at these areas to make them less attractive to criminals in the long term (Caplan, Kennedy, and Piza, 2014).

RTM has 10 steps—

1. Select an outcome event.
2. Choose a study area.
3. Choose a time period.
4. Obtain base maps.
5. Identify all possible risk factors.
6. Select model factors.
7. Map spatial influence.
8. Weight risk map layers.
9. Combine risk map layers.
10. Communicate meaningful information.

In this article, we use a case study from Chicago to discuss the steps in the RTM process, including the statistical procedures that are automated by the RTMDx Utility (Caplan, Kennedy, and Piza, 2013b). This example is intended to diagnose the underlying spatial attractors (Brantingham and Brantingham, 1995) of burglaries (that is, step 1, select an outcome event) throughout the landscape of Chicago (that is, step 2, choose a study area) during calendar year 2013 (that is, step 3, choose a time period). Base maps and other datasets were downloaded from the Chicago Data Portal, provided by the Chicago Police Department (CPD), or purchased from Infogroup⁴ (that is, step 4, obtain base maps). Reported incidents of burglary in Chicago during 2013 were obtained from official CPD administrative data. All data were acquired at the address or XY coordinate level. The following sections discuss steps 5 through 10.

Possible Risk Factors

(that is, step 5, identify all possible risk factors)

Environmental risk factors for this study were selected based on empirical research evidence and the knowledge of CPD personnel, who provided practical experience-based justification for the use of some factors. As a consequence, the pool of factors selected for inclusion in the RTM is not only empirically driven but also is theoretically and practically meaningful. Exhibit 1 shows the factors used in this study.

⁴ Infogroup is a leading commercial provider of business and residential information for reference, research, and marketing purposes.

Exhibit 1

Risk Factors for Burglary in Chicago

Risk Factor	Count	Coefficient	Spatial Operationalization	Spatial Influence (feet)	RRV
In the risk terrain model					
311 service requests for street lights out	9,999	0.1595	Proximity	852	1.1730
311 service requests for alley lights out	9,995	0.4605	Proximity	852	1.5848
311 service requests for abandoned vehicles	7,137	0.6955	Proximity	1,704	2.0046
Apartment complexes	391	0.1434	Proximity	3,408	1.1542
Foreclosures	15,305	1.3849	Proximity	852	3.9944
Problem buildings	28,575	0.6645	Density	852	1.9434
Gas stations	140	0.1747	Proximity	3,408	1.1909
Grocery stores	933	0.2477	Proximity	1,704	1.2810
Laundromats	173	0.1202	Density	3,408	1.1278
Retail shops	235	0.1016	Density	3,408	1.1070
Schools	1,021	0.3264	Proximity	1,704	1.3860
Variety stores	124	0.1397	Density	3,408	1.1499
Bars	1,316	0.2013	Density	3,408	1.2230
Nightclubs	128	0.1946	Density	1,704	1.2148
Bus stops	10,711	0.2525	Proximity	1,704	1.2873
Intercept	—	- 4.1782	—	—	—
Tested, but not in the final model					
Banks	367				
Healthcare centers and gyms	176				
Homeless shelters	29				
Malls	29				
Parking stations and garages	218				
Post offices	53				
Recreation centers	33				
Rental halls	89				
Liquor stores	926				

RRV = relative risk value.

Sources: Chicago Data Portal; Chicago Police Department; Infogroup

This broad spectrum of factors, or features of a landscape, identified from a variety of sources, may pose general spatial risks of illegal behavior resulting in burglary. It is likely that only some of them will be significantly influential within Chicago, however. Therefore, it is hypothesized that (1) certain features of the physical environment will constitute significantly higher risk of burglary at micro-level places than at other places. And, furthermore, (2) the copresence of one or more risky features at microlevel places will have a higher risk of burglary incidents compared with places without those features.

Building a Risk Terrain Model (that is, step 6, select model factors; step 7, map spatial influence; and step 8, weight risk map layers)

Chicago was modeled as a continuous surface grid of 426 by 426 foot cells ($N = 36,480$), with each cell representing a microlevel place throughout the city. The approximate average block length in Chicago is 426 feet, as measured within a GIS. This spatial dimension has practical meaning because the cell size corresponds to the block face of the Chicago street network, representing the most realistic unit for police deployment at the microlevel (Weisburd and Groff, 2009). Moreover, empirical research by Taylor and Harrell (1996) suggests that behavior settings are crime-prone places that typically comprise only a few street blocks (Taylor, 1997). As opposed to perpetrators of other types of crimes, such as street robbery, burglars operate within a slightly larger behavior setting because of their mobility (Hesseling, 1992).

To determine the optimal spatial influence of each risky feature within a few street blocks in Chicago, several variables were operationalized from 24 potential features, or risk factors. For each risk factor, we measured whether each raster cell in the grid was within 852, 1,704, 2,556, or 3,408 feet of the feature point or in an area of high density of the feature points based on a kernel density bandwidth of 852, 1,704, 2,556, or 3,408 feet. These distances represent approximately two blocks, four blocks, six blocks, and eight blocks in Chicago. These incremental units resulted in as many as 8 variables of spatial influence measured as a function of Euclidean distance or kernel density for each risk factor, respectively.

This process generated 192 variables (that is, 2 operationalizations \times 4 blocks \times 24 factors) that were tested for significance with incident locations of burglary in Chicago. Raster grid cells within the study extent that were inside each Euclidean distance threshold were represented as 1 (highest risk); cells outside this distance were represented as 0 (not highest risk). Density variables were reclassified into highest density (density \geq mean + 2 standard deviations) and not highest density (density $<$ mean + 2 standard deviations) regions. Raster cells within the highest density regions were represented with a value of 1; cells not within the highest density regions were represented with a value of 0. All these values were assembled into a table in which rows represented cells within the Chicago study area grid and columns represented binary values (that is, 1 or 0, as described in the previous section). Counts of burglary incidents located within each raster cell were also recorded.

We used the RTMDx Utility (Caplan and Kennedy, 2013) to identify a statistically valid RTM. The testing procedure within the Utility began by using 192 variables, operationalized from the 24 aforementioned factors (that is, independent variables) and 2013 burglary incidents (that is, dependent variables), to build an elastic net penalized regression model assuming a Poisson distribution of events. Generating 192 variables presents potential problems with multiple comparisons, in that we might uncover spurious correlations simply because of the number of variables tested. To address this issue, the Utility uses cross-validation to build a penalized Poisson regression model using the penalized R package. Penalized regression balances model fit with complexity by pushing variable coefficients toward zero. The optimal amount of coefficient penalization was selected via cross-validation (Arlot and Celisse, 2010). This process reduces the large set of variables to a smaller set of variables with nonzero coefficients. It is important to note that using the model resulting from this step (that is, the penalized model) would be perfectly valid, in and of itself (Heffner, 2013), because all resulting variables from this process play a useful (significant) part within the model. Because the goal is to build an easy to understand representation of crime risk, however, the Utility further simplifies the model in subsequent steps via a bidirectional stepwise regression process.

The Utility does this regression process starting with a null model with no model factors, and it measures the Bayesian Information Criteria (BIC) score for the null model. Then, it adds each model factor to the null model and remeasures the BIC score. Every time the BIC score is calculated, the model with the best (lowest) BIC score is selected as the new candidate model (the model to surpass). The Utility repeats the process, adding and removing variables one step at a time, until no factor addition/removal surpasses the previous BIC score. The Utility repeats this process with two stepwise regression models: one model assumes a Poisson and the other assumes a negative binomial distribution. At the end, the Utility chooses the best model with the lowest BIC score between Poisson and negative binomial distributions. The Utility also produces a relative risk value (RRV) for comparison of the risk factors. Rescaling factor coefficients produce RRVs between the minimum and maximum risk values (Heffner, 2013). RRVs can be interpreted as the weights of risk factors. In sum, RTM with the RTMDx Utility offers a statistically valid way to articulate risky areas at the microlevel according to the spatial influence of many features of a landscape.

Results: Spatial Risk Factors for Burglary in Chicago

In 2013, 17,682 burglaries were reported in Chicago. The factors that spatially correlate with these crime incidents are presented in exhibit 1, along with the most meaningful operationalization, spatial influential distance, and relative risk value. Exhibit 1 demonstrates that, of the pool of 24 possible risk factors, only 15 are spatially related to burglaries in this study setting. The most important predictor of burglary occurrence is proximity to foreclosed properties. The RRVs for the model factors in exhibit 1 can be easily compared. For instance, a place influenced by foreclosures has an expected rate of crime that is more than three times as high as a place influenced by retail shops (RRVs: $3.99 / 1.11 = 3.59$). Places within one block of foreclosures pose as much as three times greater risk of burglary than what is presented by many other significant factors in the RTM. All places may accordingly pose risk of burglary but, because of the spatial influence of certain features of the landscape, some places are riskier than others.

Risk Terrain Map for Burglary in Chicago (that is, step 9, combine risk map layers)

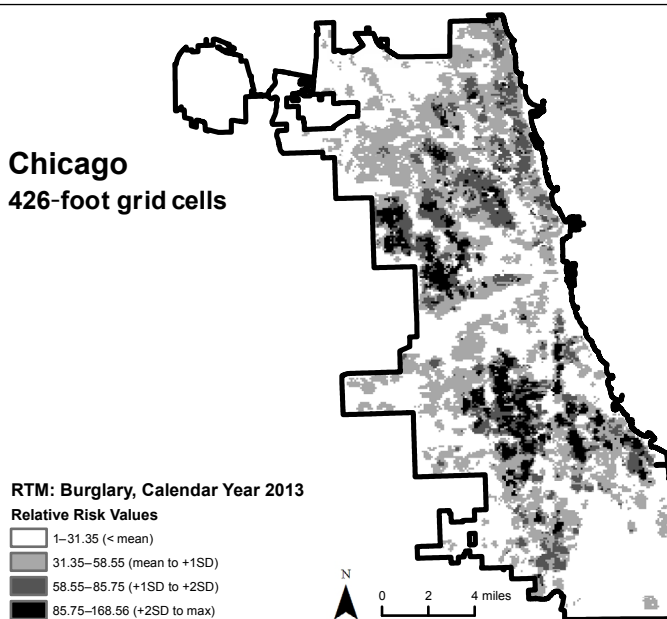
A place where the spatial influence of more than one model feature in exhibit 1 collocates poses higher risks. This proposition was tested by combining risk map layers of the 15 factors in the final model, using map algebra (Tomlin, 1994) and the ArcGIS for Desktop Raster Calculator, to produce a risk terrain map. The risk terrain map was produced using the following formula—

$$\text{Exp}(-4.1782 + [1.3849 \times \text{Foreclosures}] + [0.6955 \times 311 \text{ Service Requests Abandoned Vehicles}] + [0.6645 \times \text{Problem Buildings}] + [0.4605 \times 311 \text{ Service Requests Alley Lights Out}] + [0.3264 \times \text{Schools}] + [0.2525 \times \text{Bus Stops}] + [0.2477 \times \text{Grocery Stores}] + [0.2013 \times \text{Bars}] + [0.1946 \times \text{Nightclubs}] + [0.1747 \times \text{Gas Stations}] + [0.1595 \times 311 \text{ Service Requests Street Lights All Out}] + [0.1434 \times \text{Apartment Complexes}] + [0.1397 \times \text{Variety Stores}] + [0.1202 \times \text{Laundromats}] + [0.1016 \times \text{Retail Shops}]) / \text{Exp}(-4.1782).$$

RRVs for each cell in the risk terrain map shown in exhibit 2 ranged from 1.00 for the lowest risk cell to 168.60 for the highest risk cell. The highest risk cells have an expected rate of burglary that is 168.60 times higher than a cell with a value of 1.00. The mean risk value is 31.35, with a standard deviation of 27.20. This microlevel map shows the highest risk cells symbolized in black (that is, greater than 2 standard deviations from the mean). These places have an 85.75 percent or greater likelihood of experiencing burglary compared with other locations.

Exhibit 2

Microlevel Risk Terrain Map for Burglary in Chicago



max = maximum. RTM = risk terrain map. SD = standard deviation.

Discussion **(that is, step 10, communicate meaningful information)**

As the RTM demonstrates, one or more features of the physical environment can elevate the risk of crime. Comparing RRVs across model factors is useful for prioritizing risky features so that mitigation efforts can be implemented appropriately. For instance, foreclosed properties may be the direct targets of burglary; however, other properties within close proximity to foreclosures may also be at high risk because of the absence of invested caretakers who would otherwise serve as eyes and ears within the area. After risk factors are identified, stakeholders can explore the (likely) mechanisms through which risks are presented and then initiate mitigation efforts, such as improved community surveillance and new homeowner investment campaigns. In Chicago, for example, the CPD developed strategies to work with other city agencies, including the Chicago Housing Authority, to target problem buildings using city ordinances to improve conditions conducive to crime. The city agencies are also working with private lenders to address the broader scope of the foreclosure crisis.

Using environmental factors for crime forecasting has many benefits, such as enabling intervention activities to focus on places—not just people located at certain places—that could jeopardize public perceptions and community relations. Another benefit is that RTM is a sustainable technique because past crime data are not needed to continue to make valid forecasts. Police use RTM to be problem oriented and proactive in their effort to prevent new crimes without having to be concerned that a high success rate (and no new crime data) will hamper their ability to make new forecasts. In fact, the researcher-practitioner collaborations forged through the aforementioned NIJ projects have led to new approaches to police productivity that go beyond a heavy reliance on traditional law enforcement actions, such as stops, arrests, or citations. The police are now able to measure their effects on mitigating the spatial influences of risky features—with the goal of reducing one or more risk factor weights in postintervention RTMs or, better yet, suppressing their attractive qualities completely and removing them from the post model altogether.

All places may pose risk of burglary but, because of the spatial influence of certain features of the landscape (not simply past crime locations), some places are riskier than others. As demonstrated here, RTM helps to explain why spatial patterns of crime exist in a jurisdiction and what can be done to mitigate risks, not just chase the hotspots. With such spatial intelligence (Kennedy and Caplan, 2012), key stakeholders can identify the most vulnerable areas in a jurisdiction, enabling them to predict, with a certain level of confidence, the most likely places where crimes will emerge in the future—even if they have not occurred there already.

Conclusion

Giving high regard to place-based risk assessments makes theoretical and intuitive sense: offenders know they take risks and that these risks increase in certain locations, and police are often deployed to certain geographies to combat crime and manage other real or perceived public safety and security threats (Caplan, Kennedy, and Miller, 2011; Kennedy and Van Brunschot, 2009). In

future work, additional research is needed to assess the temporal dynamics of burglary incidents, as well as the social and situational factors. In addition, RTM can be applied to a variety of other topics, including injury prevention, public health, traffic accidents, and urban development.

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