RISK TERRAIN MODELING: A TOOL FOR CRIME PREVENTION & REDUCTION IN NEW YORK CITY?

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I. **Abstract:**

This project explored the validity and reliability of risk terrain modeling (RTM) in New York City. This study merged data on crime complaints from the NYPD with data on environmental factors (such as the locations of: public housing, bus stops, banks, public high schools, pawn shops, liquor stores, drug dealing areas, and night clubs) from a variety of sources to test the validity of the RTM approach in New York City across 110,891 micro-places. Results of the analyses suggested that risk terrain modeling, using the selected risk factors, correctly distinguished "risky" areas from "non-risky" areas for certain risk factors for each crime type. However, the RTM models suggest that not all of the risk factors had a significant effect on the crime rate, and indicate that risk factor choice is important in development of RTM analyses for NYC. These analyses should be expanded in future research to determine how the co-location of environmental factors may contribute to increased crime rates and to inform policing practices and crime reduction and prevention strategies.

II. **Introduction**:

This project explores the validity and reliability of risk terrain modeling (RTM) in New York City. RTM is a risk assessment tool which analyzes the physical features of the environment and how those features coincide to create "risky" or "not risky" settings for crime. (Caplan et. al, 2014). This tool allows an analyst to weight the spatial influence of risk factors for crimes and then combine them into a "total risk" layer which indicates areas where crime Is statistically more or less likely to occur. Studies of many urban areas indicate that environmental factors influence future occurrence of certain types of criminal events, but it remains to be seen whether comparable patterns are evident in NYC.

This study tests the validity of the RTM approach in NYC by integrating data on crime complaints from the NYPD with data on environmental factors, including the location of public housing, bus stops, banks, public high schools, pawn shops, liquor stores, drug dealing areas, and night clubs. Separate analyses are conducted for aggravated assault, robbery, and burglary, with theoretically relevant risk factors considered for each crime type. The findings contribute to understanding spatial variation in crime and can inform policing practices and other crime prevention/reduction strategies for the NYPD.

III. **Literature Review/Background**

Crimes contribute to a loss in business revenue, drops in property value, personal loss for crime victims, and give areas a "bad reputation" overall, decreasing the quality of life in communities across the city. Previous research has found that residents' fear of crime was related to an individual's knowledge of crime occurring in their communities (Snowden et al. 2016). In January 2017, NYPD Commissioner James O'Neill announced that "2016 was the safest year ever in the history of New York City" (Eversley, 2017). There was a 4.1 percent decrease in crimes overall from 2015 to 2016, which has been credited by NYC Mayor Bill de Blasio and Police Commissioner James O’Neill to targeted policing strategies which focused on specific populations of people committing violent crimes in New York City (Eversley, 2017). Due to the purported “early success” of these targeted methods, as cited by Commissioner O’Neill, it is important to study other factors with novel methodological approaches, such as RTM, to further assess the factors associated with crime.

A. *Criminological Theories related to Aggravated Assaults, Burglaries, and Robberies*

Environmental criminology is a branch of criminological study that looks to explain human behavior in the context of the physical environment. Researchers have found that people may act or react differently in the same environment, and therefore it is important to not only study the individuals who commit crimes, but also to consider the context in which these crimes occur. Using RTM, the following environmental criminology theories can be operationalized and applied to the geographic study of aggravated assaults, burglaries, and robberies.

In many urban environments a small minority of streets (about 5 percent of the total number of streets) tend to be the source of approximately half of the crimes reported, and about "1 percent of streets account for 25 percent of crimes" (Weisburd, Groff, & Yang 2014). Why does such a small percentage of streets and total area account for such a large portion of total crime in a city? Researchers studying urban environments and crimes which occur in urban neighborhoods, such as those in NYC's Bronx, Brooklyn, Manhattan, and Queens boroughs, have found that these street segments serve as micro-communities that may have high levels of poverty, and experience ethnic and racial heterogeneity. Those factors in addition to physical environmental factors such as public bus stops and outlets for alcohol may yield elevated crime rates. The mixed use of land, the social disorganization of people using the area (residents, visitors, customers, etc.), and the lack of bonding within these communities and micro-areas may compromise collective supervision efforts and/or lead to a development of social norms and behaviors which are not acceptable in the larger society. By doing so, higher crime rates may result (Shaw and McKay 1942).

Routine Activities Theory (RAT) and Crime Pattern Theory (CPT) can also explain the spatial patterning of certain crimes such as burglaries and robberies. Cohen and Felson (1979) suggested that crime is the product of the co-occurrence of three key elements - the lack of a capable guardian, the presence of a suitable target, and the presence of a motivated offender - during the course of daily routine activities. In urban environments with dense populations, such as New York City, population density necessitates the crossing of paths of potential offenders and potential victims and in some cases, the absence of capable guardians, through the "normal everyday activities of offenders and victims" (Groff, 2007). CPT supports and builds on RAT, citing that criminal opportunity is not randomly distributed throughout space and time. Rather, this theory suggests that certain areas at certain times are more likely to provide the co-occurrence of the elements necessary for crime to occur (Brantingham, 2010).

IV. Risk Terrain Modeling & Risk Factors

A review of the literature has identified several risk factors and the spatial influence of those risk factors for the crimes being studied. There is overlap in risk factors across crime types, but some are likely to have unique impacts on specific crimes.

A. *Aggravated Assault (Felony Assault) Risk Factors*

Aggravated assault, or felony assault in NYC, has several risk factors, but the three examined in this study are the location of liquor stores, bus stops, and public high schools. Jennings et al. (2013) studied the relationship between alcohol outlets, such as liquor stores, and violent crime. They found that as the number of alcohol outlets increased, so did the percentage of violent crimes. This positive correlation between alcohol outlets and violent crime such as aggravated assault suggests that liquor stores would be an appropriate risk factor for this study. RAT and CPT can explain the relationship between alcohol and aggravated assault. Both assault victims and crime perpetrators may frequent establishments where alcohol can be obtained. In these cases, the victim's behavior and movement, patterns of alcohol consumption or purchase puts them in an environment where they are exposed to motivated offenders, and perhaps the absence of a capable guardian, such as a sober friend or a police officer.

Bus stops are also associated with aggravated assault (Drawve and Barnum, 2017). Throughout the course of their routine activities, aggravated assault perpetrators in urban environments may use public transportation and therefore their mental maps store location information for these transportation hubs. When the time comes for them to escape from the crime scene, offenders may access their mental maps and choose a route that is familiar to them. Bus stops allow access to and escape from the scene of aggravated assaults. Potential assault victims also utilize public transportation and do also internalize these hubs in their mental maps. Through the course of both the offender and victim's routine activities, their paths may cross and increase the risk of the assault occurring. In terms of aggravated assaults, public high schools act as crime generators. Crime generators are places where large crowds are attracted and as such offer many potential victims (Paulsen, 109). Public high schools in NYC house hundreds of students during the school day, providing potential victims and perpetrators who are going about their routine activity of attending school. Additionally, these students' decision-making and self-control skills often are not yet fully developed, and these factors may lead to the occurrence of violent crimes such as aggravated assault.

B. *Burglary Risk Factors*

Three risk factors strongly associated with burglary are public housing developments, pawn shop locations, and bus stop locations (Caplan and Kennedy, 2012). The areas in proximity to public housing developments are locations characterized by high residential mobility (tenants move in or out frequently), which may undermine bonding between residents and the community. This lack of attachment and concern for the community and for fellow members of the community is one of the physical embodiments of the social disorganization concept and may be one reason that the areas around public housing developments tend to be at higher risk for burglary than areas with single-family residences. Pawn shops represent potential places to offload stolen goods, and the locations of these pawn shops may be discovered through primary spatial learning, which takes place during the commission of our routine activities. Again, busses are commonly used by urban residents, and therefore are built into the movement and behavior patterns of both victims and perpetrators. There are peak or high traffic times for bus use as well, and therefore a potential burglar may be able to plan his or her burglary based on the comings and goings of the residents' bus commute schedules.

C. *Robbery Risk Factors*

Robbery risk factors differ slightly from the burglary and aggravated assaults risk factors. Specifically, nightclubs, proximity to drug dealing areas, and proximity to banks are unique risk factors for robbery (Gaziarifoglu, 2010). Like the regular residential turnover of areas in proximity to public housing developments, nightclubs experience a high rate of client mobility, with people going in and out during business hours. This movement also embodies the concept of social disorganization. Also, nightclubs generally serve alcohol, which may make clients more vulnerable to victimization, and may embolden potential perpetrators with "liquid courage". Drug dealing areas are also risk factors for street robbery, as robbery can finance the purchase of drugs or help perpetrators to obtain drugs from other users. Through the routine, risky activities of drug users, potential victims and potential perpetrators may cross paths near these drug dealing areas. For this study, drug dealing areas were operationalized as locations of “dangerous drugs” complaints collected by the New York City Police Department. Finally, when individuals utilize bank facilities, they become attractive targets upon leaving the bank or area in which it is located. This elevates the risk of robbery in such areas, provided there are motivated offenders present and insufficient guardianship. The bank's security system – one dimension of capable guardianship - does not protect people who have just left the bank (a potentially attractive target) from the motivated offender who may be waiting outside for an opportunity to commit robbery.

V. **Methodology**

This study examined the validity and reliability of the Risk Terrain Modeling technique across 110,891 micro-level areas in the following four boroughs of New York City: Kings (Brooklyn) County, Bronx County, New York (Manhattan) County, and Queens County. Richmond (Staten Island) County was excluded from the study because it is separated by water from the other four boroughs and because it differs in terms of physical environment (for example, access to public transportation) and population features (population density of Staten Island differs notably from other boroughs). The micro-level areas examined were defined as raster cells of 254 feet by 254 feet, which is equivalent to the average half-block length in New York City [Pollak, 2006]). This conforms to previous studies that have applied RTM (Caplan and Kennedy, n.d.).

This study utilized crime data, transportation information, business locations, and school datasets to create "risk" surfaces, operationalizing the spatial influence (in feet) of these risk factors. The surfaces were then combined to define “risky” versus “non-risky” areas, with separate risk factors used for the three crime types examined in the study. An area was classified as “risky” if it was within the spatial influence of one or more risk factors for a certain crime. “Non-risky” areas were those that were not within the “spatial influence” (discussed below) of any of the risk factors for a certain crime. Crime levels were then compared across micro-areas classified as risky or non-risky. The main tools for data analysis came from Esri's ArcGIS Suite and IBM's SPSS.

VI. Data Collection and Geoprocessing

Risk factor data, study area geography shapefiles, and New York City crime datasets were collected from several data repositories. Also, a processing environment in ArcMap was set up, using the correct geographic and projected coordinate systems and processing environment for necessary vector and raster geoprocessing. New York University’s Spatial Data Repository (SDR) was the source of the study area shapefile. The researcher downloaded an NYC Boroughs shapefile and then selected the study area boroughs of New York, the Bronx, Brooklyn, and Queens, to create a custom study area shapefile.

The NYC OpenData platform was the source of the “NYPD Complaints Data Current YTD”, a dataset provided and managed by the NYPD, from which data were gathered on crime counts for the year 2016.

The crime complaint dataset contained attributes regarding the date of the complaint, offense description, and the location of the complaint indicated by latitude and longitude coordinates. Data were collected for the dependent variables in the study—aggravated assault, robbery, and burglary—and one independent variable, dangerous drug crimes (defined below). The crime complaints were filtered in Microsoft Excel by crime type into one CSV file. The filtered CSV file was imported into ArcMap and created a point file using the "Get XY Data" option for CSV files. The point shapefile was then divided into four separate shapefiles, one for each study crime type examined as dependent variables and one for the drug crimes risk factor (a key independent variable), and confined to the study area using the Clip geoprocessing tool.

Other independent variables used to define the micro-areas in the study as "risky" or "non-risky" were drawn from a variety of sources. NYC OpenData houses the "School Points Locations" dataset for New York City, provided by the Department of Education in 2014, containing school names, types, and locations. This file was filtered in ArcMap to select only public high school points for the study area. A polygon shapefile of New York City Housing Authority (NYCHA) Developments, which contained locations of 2016 public housing developments in New York City, was obtained from NYC OpenData. The pawn shop data was also obtained from NYC OpenData, from the "Legally Operating Businesses" dataset provided by the Department of Consumer Affairs. The CSV file was filtered in Excel to include only pawn shops. That CSV file was then added to ArcMap where points were created using the "Get XY Data" tool and confined to the study area using the Clip geoprocessing tool. Next the five bus stop shapefiles for the study area, collected from NYU's SDR, were added to ArcMap. Bus stop shapefiles were then joined using ArcMap's Merge tool and were confined to the study area, using the study area shapefile and the Clip geoprocessing tool.

Reference USA was the data source for night clubs/bars, banks, and liquor stores datasets. These datasets were downloaded as CSV files and contained business names and locations in a US postal address format. The CSV files were added to ArcMap and an address locator for New York City, created by the NYC Department of City Planning and obtained from Columbia University's "New York City Numeric and Spatial Data" web page, was used to create point shapefiles for each dataset. Multiple rematches were conducted for each dataset until a match rate of at least 92 percent was reached for each dataset.

The next step was to create buffers around the vector features, indicating the spatial influence they tend to exert, as determined by prior research studies. For aggravated assaults, the risk factors are liquor stores, bus stops, and locations of public high schools (Drawve and Barnum, 2017). A single buffer was created to represent the spatial influence of liquor stores, which is 864 feet. A single buffer represented bus stops' spatial influence for aggravated assaults, with a radius if 1728 feet. Public high schools have a smaller spatial influence, with a single buffer of 216 feet radius. As explained in more detail below, each micro-place that fell within the specified spatial influence radius of a risk factor was classified as "risky" whereas the micro-places that did not fall within those radii were "non-risky". A parallel approach was adopted for both the burglary and robbery analyses.

Burglary risk factor buffering, as determined by Caplan and Kennedy (2012) involved creating multiple single buffers to represent their spatial influence. Public housing required only a single buffer of 300-foot radius. However, both pawn shops and bus stops required a buffer to represent a spatial influence of 300-900 feet away from each point. The Symmetrical Difference tool was used to create donut-shaped buffers to represent the spatial influence risk areas of 300 to 900 feet away from the bus stops and pawn shops.

Robbery risk factors required single buffers of varying radii (Gaziarifoglu, 2010). Night club buffers of 462 feet were created. Following that, the researcher created buffers for drug dealing locations and banks, with radii of 924 feet and 1386 feet, respectively. The spatial influences of the three robbery risk factors were operationalized as single-ring buffers. The spatial influence of nightclubs was represented by buffers with a radius of 462 feet. The spatial influence of drug dealing locations were represented by buffers of a 924-foot radius. In terms of robberies, banks have a larger spatial influence than the other two identified risk factors, with buffers of 1386-foot radius.

VII. Raster Geoprocessing

Following the vector geoprocessing, the vector buffer layers were converted into raster layers using raster geoprocessing. The conversions were completed using the Polygon to Raster tool in ArcMap.

Phase 1: Dichotomous Risk Raster Geoprocessing

During the first phase of analysis, the risk factor datasets for each crime type were reclassified into binary rasters using the Reclassify tool, indicating the presence or absence of the spatial influence of at least one risk factor in each micro-place. These binary rasters classified the cells that fell into the risk influence areas as “risky” (value = 1) and all other cells as “non risky” (value = 0).

After the analysis of each individual risk factor, ArcMap's Map Algebra tool was then used to combine the individual risk rasters, to develop one risk surface which indicated the presence of the spatial influence of one or more risk factors for each crime type, creating a dichotomous risk surface of “non-risky” (value = 0) and “at least 1 risk factor present” (value = 1) micro-places.

Phase 2: Full Scale Risk Raster Geoprocessing

In the second phase of the raster geoprocessing, the risk raster cells that fell into the risk influence areas were classified as “risky” on a scale of 1, 2, or 3, (value = 1, 2, or 3, respectively) indicating the number of risk factors present and all other cells as “non-risky” (value = 0). ArcMap's Map Algebra tool was again used to combine the risk rasters, to develop one risk surface which indicated the presence of the spatial influence of none, one, two, or three risk factors for each crime type. For the full scale risk analysis, these risk values ranged from 0 (no risk factor influence in the micro-place) to 3 (spatial influence of three risk factors present). The final raster risk surface was reclassified to combine the varying risk levels, creating a four level risk surface of “non-risky”, “1 risk factor present”, “2 risk factors present”, and “3 risk factors present” micro-places.

For each phase of the risk raster geoprocessing the final raster risk surface was converted to a vector polygon layer, then spatially joined, based on location, to a micro-place fishnet with 110,891 grid cells of 254 feet by 254 feet. This was done separately for the assault, robbery, and burglary risk layers to determine the “riskiness” for each crime within each micro-place covering the study area. Finally, for each crime type, the fishnet “riskiness” grid was spatially joined to the 2016 crime layers so that a crime rate attribute could be generated for each micro-place grid in the risk surface. The crime rate was derived using the number of crimes occurring in a micro-place divided by the population density. Population density was calculated as the number of people living in each micro-place (254ft^2). These risk polygons were symbolized based on risk value to provide a visual comparison of the crime locations to the predicted “risky areas. In addition, the researcher utilized IBM's SPSS statistical software to determine if there was any statistically significant difference in the average crime rates in the intensity-varying “risky” micro-places versus the “not risky” micro-places for each crime type.

Results/Outcomes

The current study examined the spatial influence of risk factors for three types of felonies in New York City using Risk Terrain Modeling (RTM). Based on previous research, it was expected that areas falling within the spatial influence of multiple risk factors for a crime would experience higher crime rates than other areas falling outside of those “risky” areas. Therefore, if the risk terrain model prediction is correct, this study should result in a higher mean rate of the three identified crimes occurring in the areas identified as "risky" than the areas identified as "no risk".

Aggravated Assaults

In 2016, there were 20,012 aggravated assaults reported in the four boroughs examined. This study examined the relationship of three risk factors for aggravated assaults (proximity to liquor stores, bus stops, and public high schools) and the occurrence of aggravated assaults, generating a crime rate based on population density in the micro-place. The results of the dichotomous risk terrain analysis for each of the risk factor for aggravated assaults identified that only the presence or absence of bus stops had a statistically significant influence on the average aggravated assault rate at the micro-place level, with a significance value less than 0.05, as seen in Table 1. The aggravated assault distribution overlying the bus stop spatial influence risk surface is displayed in Figure 1.

Table 1. *Differences in Aggravated Assault Rates per Micro-Place based on Spatial Influence of Bus Stops*

	N	Mean Aggravated Assault Rate	p
No Bus Stop Influence	15219	0.0109	0.005
Bus Stop Influence	95672	0.0426	

The dichotomous risk terrain analysis with the groupings of zero risk factors present or at least one risk factor present indicated that that there was a significant difference in the aggravated assault rates per micro-place between “risky” and “non- risky” micro-places. An independent samples T test was conducted to compare the mean average aggravated assault rates for each risk area type. A Levene’s Test for Equality of Variances reported a F statistic of 4.292 with a p value of 0.038, indicating a less than 5% chance that the results of the comparison of “risky” and “not risky” areas were due to chance. Based

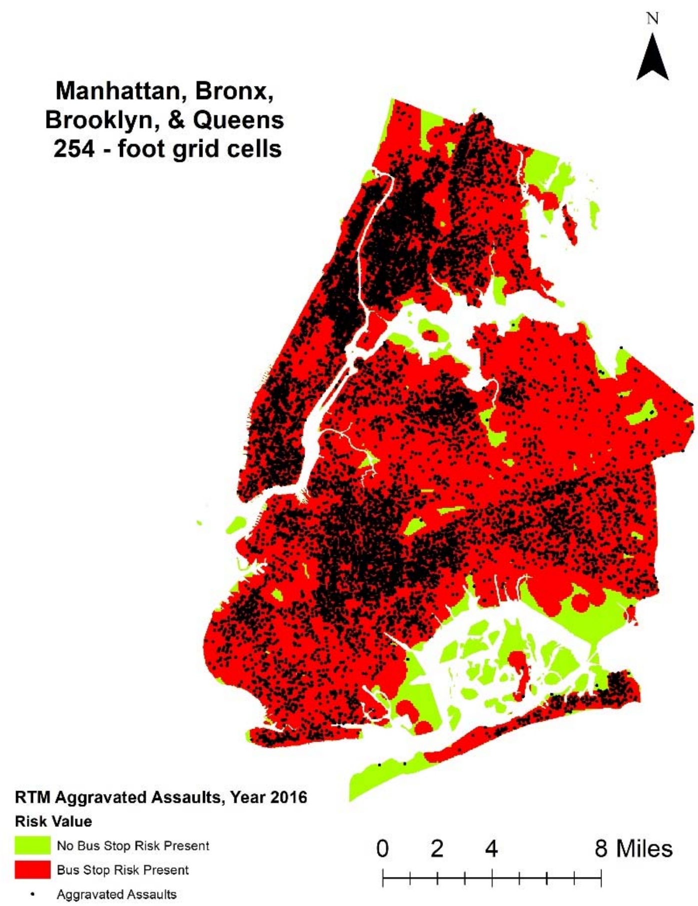

Figure 1: Micro-place Risk Terrain Map for Aggravated Assault Bus Stop Risks

on the results of the T test, “risky” areas experienced higher average aggravated assault rates than “not risky” areas, ($p = 0.004$).

The full scale (four risk groups total) risk factor RTM ANOVA identified no significant difference in mean aggravated assault rate between the four risk type groups. Equal variances in the means were not assumed, based on a Levene’s test and therefore post hoc tests were applied during the analyses. Post hoc Games-Howell tests did indicate there was a significant difference in mean aggravated assault rate between the micro-places experiencing only one risk factor and the micro-places experiencing three risk factors ($p < 0.05$).

Burglaries

The study area experienced 12,342 burglaries in 2016. This RTM analysis explored the spatial influence of three risk factors for burglaries (pawn shops, bus stops, and public housing), looking at average burglary rate based on population density in the micro-place. The results of the dichotomous risk terrain analysis for each of the risk factors for burglaries identified that only public housing had a statistically significant impact on the burglary rate, with a significance value of less than 0.05, as indicated in the independent samples T test results, as seen in Table 2. The mean burglary rate was greater in micro-places outside of the spatial influence of public housing areas than in areas within the spatial influence of public housing. Figure 2 shows the burglary distribution versus the spatial influence of public housing.

Table 2. *Differences in Burglary Rates per Micro-Place based on Spatial Influence of Public Housing*

	N	Mean Burglary Rate	P
No Public Housing Present	104250	0.0250	0.000
Public Housing Present	6641	0.0038	

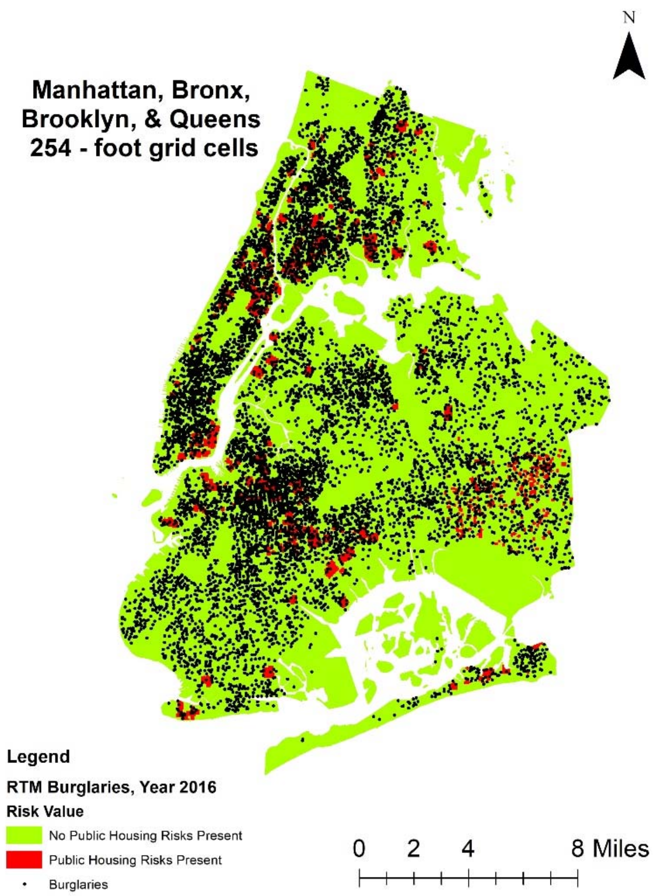

Figure 2 Micro-place Risk Terrain Map for Burglaries Public Housing Risks

The independent samples T test comparing the average burglary rate for the groups of zero risk factors present or at least one risk factor present indicated no significant difference in the variance of the burglary rates in the "risky" and "not risky" micro-places. This reveals that "risky" areas did not experience higher average burglary rates than "non-risky" areas, ($p > 0.05$).

An ANOVA analysis was also completed for the full scale RTM analysis for burglaries. The results of this analysis suggest that there was no significant difference between the average burglary rates for the four risk groups.

Robberies

There were 15,038 robberies reported to the NYPD in 2016 in the study area. Nightclubs, drug crimes and banks were risk factors examined in this study, and average robbery rates were generated for each micro-place grid cell. The results of the dichotomous risk terrain analysis for each of the risk factor for robberies indicated that the presence of drug crimes had a statistically significant impact on average robbery rate, as shown in Table 3. In fact, the average robbery rate for micro-places inside of the spatial influence of drug crimes was over 4.5 times more than the robbery rates for micro-places outside of the

Table 3. *Differences in Robbery Rates per Micro-Place based on Spatial Influence of Drug Crimes*

	N	Mean Robbery Rate	P
No Drug Crimes Present	45082	0.0119	0.000
Drug Crimes Present	65809	0.0543	

"risky" areas. Figure 3 displays the distribution of robberies versus the spatial influence of drug crimes.

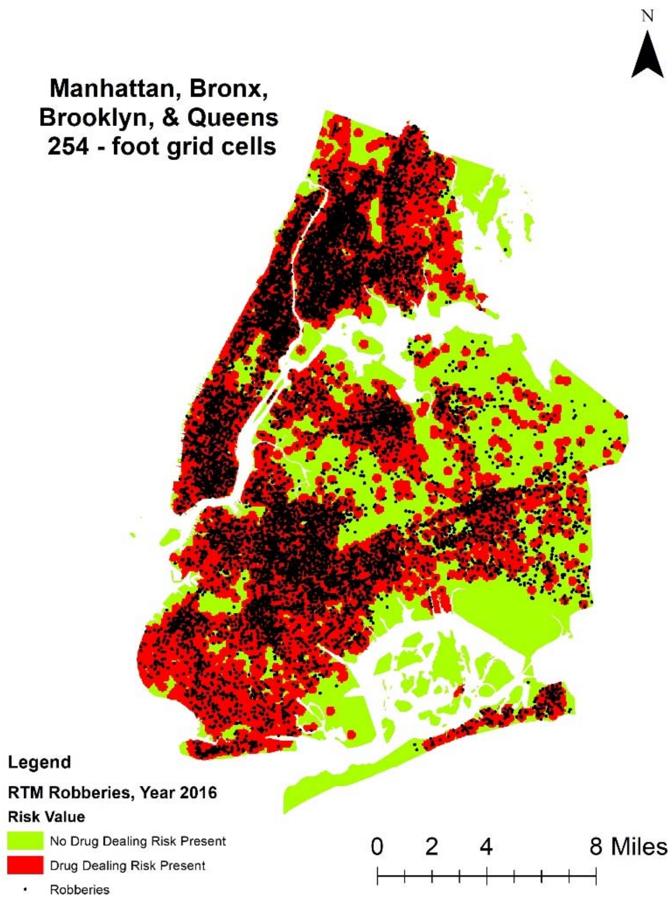

Figure 3: Micro-place Risk Terrain Map for Robberies Drug Dealing Risks

The results of the dichotomous risk terrain analysis of groups of zero risk factors present or at least one risk factor present indicated that there was no significant difference in the average robbery rates per micro-place between "risky" and "non risky" micro-places. Again, equal variances were assumed after the results of an independent samples T test. Based on that assumption, "risky" areas experienced higher aggravated assault rates than "not risky" areas ($p > 0.05$) in this study.

The results of the full scale risk RTM ANOVA for robberies indicate statistically significant differences in average robbery rates between the four risk groups and support the results of the comparison of zero risk factors present to at least one risk factor present. Table 4 displays the statistically significant results of a Games-Howell Post Hoc test, as the Levene's test indicated that equal variances could not be assumed.

Table 4. *Differences in Robbery Rates per Micro-Place based on Scaled Risk Factors*

Risk Factor (A)	Risk Factor (B)	Mean Robbery Rate Difference (A-B)	P
0	1	- 0.0459	0.000
	2	- 0.0430	0.008

VIII. **Discussion**

Having an informed understanding of the spatial risks and influences of the physical landscape on the occurrence of crime can help law enforcement officers adjust and improve their policing strategies. Some features of an environment can be changed, and using the results from a risk terrain analysis can provide empirical support for those physical changes, whether it be adding more street lights or adding safety resource officers to schools. However, it is not always easy to adjust the physical environment. Instead, law enforcement officials must adjust their strategies and the distribution of their resources to best handle the uneven distribution of crime occurrences.

The results of the aggravated assault risk terrain model supported the hypothesis that the average rate of aggravated assaults (based on population density in each micro-place) would be higher in areas experiencing the spatial influence of at least one aggravated assault risk factor than areas that did not fall into the spatial influence of any aggravated assault risk factors. Further examination of the three different risk factors revealed that bus stops were more relevant in the study of aggravated assaults than the other two risk factors studied. Additionally, when the risk factors were combined and then compared across the four possible risk categories, results suggested that the number of risk factors present could have an impact on the aggravated assault rate, with the co-occurrence of three risk factors having more impact than the presence of only one risk factor.

The results of the burglary RTM did not support the hypothesis that the average rate of burglaries based on population density would be higher in areas experiencing at least one burglary risk factor than areas that did not fall into the spatial influence of any of the burglary risk factors. Instead, the analysis indicated that the type of risk factor was relevant to the study, not simply the quantity of the risk factors. Contrary to the initial hypothesis of this study, the burglary rate in micro-places outside of the spatial influence of public housing was statistically significantly higher than the burglary rate within the spatial influence of public housing. However, this variation may in part be due to the very small spatial influence of public housing (216 feet around the building), which is a shorter distance than the half-block length used to create the micro-places for this study. Also, once multiple risk factors were combined, there was no statistically significant difference between the "risky" and "non risky" micro-places. These findings may indicate that some of the chosen risk factors do not have as great an influence as other risk factors that could have been considered.

In terms of the robbery RTM, the results of this study suggest that the spatial influence of drug crime locations on their own had a statistically significant impact on the robbery rate. However, the other risk factors tested did not indicate such significant different. These results may imply that drug crime locations are more relevant to the locations of robberies than the other two chosen risk factors. Additionally, from the RTM results we can infer that if at least one risk factor was present, robbery was more likely to occur than if no risk factors were present. A full scale ANOVA of the four risk categories revealed more granular detail, showing that there was a significant difference between zero risk factors present and one or two risk factors present, but that the addition of a third risk factor did not impact the robbery rate.

IX. **Conclusion**

The results of a risk terrain analyses can inform the decision-making about where to deploy officers on foot patrol, for example, or where to focus special crime-fighting units. The results of this study can help to educate law enforcement on the influence of the identified spatial risk factors. For example, the results reported in this study suggest that certain risk factors should weigh more heavily in the predictions of where future crimes may occur. Understanding how the spatial influence of crime risk factors can impact the occurrence of crime and that some risk factors are more important than others can help with resource allocation and strategic planning for future law enforcement maneuvers. However, there are limitations of the study that should be considered before drawing strong policy conclusions. The study was limited to assessing only three risk factors per crime type. Future studies should be conducted to analyze a greater spectrum of spatial risk factors which may influence the occurrence of crimes. Additionally, future research should explore both aggravating and mitigating factors for these crimes, as mitigating factors could have played a role in reducing the likelihood of the occurrence of crimes, which could have played a role in the results of the RTM analyses for both burglaries and robberies in this study. Furthermore, researchers may utilize larger databases or more targeted databases to find more accurate data to represent or operationalize the risk factors for the different crime types. Finally, an expansion of this type of RTM study to geographic locations outside of urban areas could serve to determine the influence or relationship between spatial risk factors and crime occurrence, and explore the possible utility of risk terrain modeling outside of an urban environment.

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