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Final Summary Overview
NIJ FY17 Research and Evaluation on Domestic
Radicalization to Violent Extremism

INNOVATIVE METHODOLOGIES FOR ASSESSING RADICALIZATION RISK: RISK TERRAIN MODELING AND CONJUNCTIVE ANALYSIS

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I. Introduction

This project examines the spatial contexts of where terrorism incidents occur, where terrorists plan and prepare for their crimes, and where terrorists reside in the United States. Terrorism-related activities occur in diverse communities across the nation (Fitzpatrick et al., 2016; LaFree & Bersani, 2014) and perhaps increasingly so with the more prominent role of the internet in spreading and diversifying where these activities are occurring. We expect that different types of places where terrorism-related activities occur are associated with different profiles. We explore this question empirically by addressing two issues with prior spatial research on terrorism. First, we suggest that making inferences about where terrorists reside and plan and prepare for attacks based on where terrorism incidents occur can be misleading. That is, where terrorism incidents occur is not necessarily where other terrorism-related activities occur. For instance, we know from prior research that the majority of terrorists do not live where they commit their attacks (Smith et al., 2006; 2009). Therefore, we examine how spatial risks are patterned across different types of terrorism-related activities.

Second, we have found that most studies investigating the relative risks of terrorism in particular places rely on statistical main effects models to demonstrate how single variables increase or decrease the likelihood of terrorism occurring, net the effects of other factors. One concern is that main effects models are not capturing complex spatial profiles of different types of terrorism-related activities. It is not usually a single factor that influences terrorists' decisions, but instead an amalgamation of factors shaping opportunities that are more or less conducive for terrorists to reside, plan and prepare, and commit attacks. In other words, it is expected that multiple configurations of social characteristics and physical infrastructure attributes, each situated within unique socio-political contexts, are more or less conducive to different types of terrorism-related activities.

To address these gaps in prior research, we explore the utility of two different analytical tools for assess relative levels of risk presented by combinations of the physical/built infrastructure and broader community risk factors – Risk Terrain Modeling (RTM) and Conjunctive Analysis of Case Configurations (or "conjunctive analysis"). First, we rely on conjunctive analysis to identify demographic and social characteristics of communities (i.e., counties and census tracts) that, when considered in combination, form dominant profiles for communities at most risk for experiencing terrorists' pre-incident and incident activities. Second, we use RTM to identify situational, place-based risk factors most associated with places where terrorists' pre-incident and incident activities are most likely to occur. Drawing from the tenets of ecological, situational, and environmental criminology, our study is guided by six research questions:

> **1)** How are terrorists' pre-incident (residence and preparatory locations) and incident activities (successful attacks/crimes and unsuccessful plots) spatially distributed across the U.S.?
>
> **2)** What are the most prominent combinations of community characteristics in places where terrorists' pre-incident and incident activities are most likely to occur? How do these pre-incident and incident characteristics differ?
>
> **3)** What are the similarities and differences in prominent case configurations across different levels of aggregation (i.e., county and census tract)?
>
> **4)** What is the distribution of risk across micro-level places?
>
> **5)** What built, physical infrastructure characteristics contribute to the risk associated with pre-incident and incident activities?
>
> **6)** What prominent case configurations (or patterns) emerge when accounting for micro-level places nested within communities?

In answering these questions, we seek to further analytical approaches that can uncover the common trends in domestic radicalization and provide intelligence and law enforcement agencies with novel methods to diagnose, anticipate, and respond to localized sets of risks.

The next section provides an overview of our theoretical orientation and a review of relevant research. We then shift to the current project by introducing several research questions and the multiple sources of data relied on to explore terrorism-related activities, their macro-level socio-demographic contexts, and the micro-level environments of places where these activities occur. Next, conjunctive analysis and RTM are introduced along with illustrative findings for each analytical approach. We conclude the report by reflecting on the utility of conjunctive analysis and RTM for studying spatially oriented risk profiles of terrorism-related activities.

II. Theoretical Orientation and Prior Research

Our research draws from the tenets of several complimentary criminological perspectives, including and ecological, situational, and environmental criminology. Together, these perspectives provide a comprehensive framework for understanding how macro-level social conditions and micro-level interactional dynamics operate within particular spatial contexts to increase (or decrease) the risks of terrorism-related activities. It is suggested that the integration of macro- and micro-level perspectives and methodologies provides a more complete picture of how social and environmental factors intersect in unique and patterned ways, and in ways that may vary across communities.

Criminologists have long believed that “place matters” for preventing crime, as some places or *hot spots* consistently experience more crime in ways that are clearly not random (Sherman, Gartin, & Buerger, 1989; Weisburd et al., 1992). Structural theories of crime causation are based on the premise that crime varies by how places, including communities, neighborhoods, and counties, are structured and change over time, irrespective of who is residing in those places (Park et al., 1925; Shaw & McKay; Bursik & Gramsick, 1993). One of the most prominent macro-level perspectives is social disorganization, which suggests that transitory communities tend to have their own "criminal careers" (Shaw & McKay, 1942) that are plagued by a lack of social capital and a breakdown of social institutions and social control mechanisms which contribute to elevated levels of crime (Bursik, 1988). Studies have consistently found that indicators of community instability and deterioration (e.g., residential mobility, and poverty) to be linked to serious forms of crime, such as homicide (Pratt & Cullen, 2005; Pridemore, 2002).

Serving as an alternative macro-level perspective, group threat theory suggests that certain types of crime increase in more stable communities when dominant groups believe that their social position, resources, and space are threatened by subordinate groups (Blalock, 1967; Blumer, 1958). While little research has applied group threat perspectives to terrorism, studies have found significant relationships between group threat indicators and certain types of bias crime (Allison & Harris, 2018; Levin & Reichelmann, 2015; Stacey, Carbone-Lopez, & Rosenfeld, 2011) and lynchings (Beck & Tolnay, 1990; Corzine, Huff-Corzine, & Creech, 1988; Corzine, Creech, & Huff-Corzine, 1983).

Though still in its infancy, the existing literature on what types of community-level conditions structure opportunities for terrorism has grown in the last few years. Relying on data from the Global Terrorism Database (GTD), LaFree and Bersani (2014) found evidence that terrorist incidents clustered in 65 different U.S. county-specific "hot spots," though attacks were scattered across the entire country. Some of the key community characteristics predicting increased attacks included language diversity, larger proportion of foreign-born residents, greater residential instability, and higher urbanization. Interestingly, economic disadvantage and having relatively high racial and ethnic minority populations did not emerge as strong community-level predictors of the location of terrorist incidents. Another recent study by Freilich et al. (2015) utilized data from the U.S. Extremist Crime Database (ECDB) to examine the types of places where perpetrators of far-right extremist homicide resided. They found that far-right murderers were relatively more likely to live in counties with higher divorce rates and sizes of Jewish and Mainline Protestant congregations, though socioeconomic factors did not have such an effect.

Rather than focus on U.S. counties, Fitzpatrick et al. (2016) examined macro-level predictors of radicalization at the neighborhood - level (census tracts). The purpose of the study was to identify community markers indicative of residence and preparatory activities of terrorists. They found that terrorist residences and precursor activities clustered in the Western region of the country, and in places experiencing lower education levels, household poverty, and more urbanicity.

To summarize, approaches and findings to studying terrorism in America at the aggregate level have been disparate, including varying levels of analysis, data sources, community level measures, and terrorist outcomes. Nonetheless, some patterns have already started to emerge, such as the relative importance of urbanization and social diversity measures, and the unimportance of economic measures, for predicting the location of terrorism **incidents**. The current study contributes to this growing area of research by encompassing multiple types of terrorist behaviors and levels of analysis to advance a more comprehensive understanding of how social, economic, and other macro-level conditions shape risk of terrorism-related activities across American communities.

Environmental Criminology and Terrorism

This study also draws from environmental and situational criminology to help identify micro-level profiles of situated incident (terrorism attack or attempted attack), pre-incident (preparatory and residences), and how they might result in more or less opportunities for terrorists across a variety of environmental contexts. We draw from the criminal event perspective (CEP) as a broad framework for understanding domestic radicalization and terrorism, conceptualizing these behaviors as multi-dimensional events that unfold over a series of situated junctures (Block, 1981; Meier, Kennedy, & Sacco, 2001). These precursor activities are viewed as dynamic interdependencies between criminal actors and the situational and social contexts in which they interact. While it is assumed that terrorists are rational actors (Becker, 1968; Cornish & Clarke, 1986), situational factors can increase or decrease opportunities for terrorists' criminal behaviors (Hindelang, Gottfredson, & Garofalo, 1978). The likelihood of behaviors associated with terrorism-related activities may increase when certain types of environmental conditions are present, including motivated offenders, suitable targets, and a lack of capable guardians (Cohen & Felson, 1979). The criminal event perspective also maintains that, like crime, terrorism events are processes that develop through a series of stages that encompass pre-incident factors, dynamic transactions (incidents), and incident aftermaths (Meier, Kennedy, & Sacco, 2001). Our focus in this report is on both the activities occurring during the pre-incident and incident stages of terrorism events, assuming that terrorists' activities in all stages of an event cannot be separated from their social and physical settings (Brantingham & Brantingham, 1993; Miethe & Meier, 1994; Sacco & Kennedy, 2002).

Recognizing the many similarities in crime and terrorism, Clarke and Newman (2006) have been at the forefront of applying environmental criminology to the study of terrorism, suggesting that environmental factors and structured opportunities play key roles in causing terrorism. In their research, Clarke and Newman propose the "EVIL DONE" approach (and acronym) for assessing the desirability of targets based on eight criteria. This approach maintains that targets are increasingly attractive to terrorists when they are **e**xposed and accessible, **v**ital to the community or society at large, **i**conic, **l**egitimate in the eyes of sympathizers, **d**estructible, **o**ccupied by human targets, **n**ear where terrorists reside and operate, and **e**asy, or have lax security. While few have tested the tenets of this perspective in empirical terrorism research, the findings of several studies have shown promise for utilizing an environmental perspective to assess risks associated with targets based on their qualities of attractiveness and vulnerability (Gruenewald et al., 2015; Klein et al., 2016; Ozer & Akbas, 2011). Other research has also applied environmental approaches more broadly to the study of far-right terrorism (Parkin & Freilich, 2015), hijackings (Fahey, LaFree, Dugan, & Piquero, 2012), and improvised explosive devices in Iraq (Johnson & Braithwaite, 2009).

In recent years, research shifted toward understanding terrorism patterns at smaller units of analysis, including counties and census tracts (e.g., Fitzpatrick et al., 2016; Freilich, Adamczyk, Chermak, Boyd, & Parkin 2014; LaFree & Bersani, 2014; Smith & Damphousse, 2009). The expansion in datasets towards collecting and analyzing data at smaller, micro-levels provides an opportunity to advance our understanding of spatial patterns of terrorism events and their precursors. Investigating spatial patterns provides a novel solution to identifying when and where terrorism-related activities are at most risk of occurring. This framework offers the tools to concentrate counterterrorism efforts by identifying locations where risks are high (LaFree & Bersani, 2014). As Pelfrey (2014, p.483) states, "[b]ecause terrorism is manifested as a local act, understanding local predictors has important deterrence and prevention implications." Analyzing pre-incident activities and terrorist incidents for correlates at more local and micro levels of analysis will inform law enforcement agencies in the development of risk assessments for potential threats and build reasonable suspicion (Ferguson, 2012) to open cases that require further investigation. Morris (2015) reinforces this point in a recent essay and explains the importance of understanding terrorism events at micro-places, which allow for situational crime prevention efforts and target hardening by law enforcement. The important caveat presented by Morris (2015, p.420) was the application of a theoretical framework focusing "on identifying the environmental features of micro-places that result in suitable targets for terrorist events."

Examining terrorism at the micro-level from a vulnerability and exposure framework (Kennedy, Caplan, Piza, & Buccine-Schraeder, 2015) can provide a valuable perspective for the current study and terrorism research moving forward, assisting law enforcement agencies with the tools to identify potential terrorist threats. Consistent with the need to increase evidence-based approaches to counterterrorism initiatives (Lum, Kennedy, & Sherley, 2006), Lum (2009) suggests that the most effective strategies for managing crime, and by extension terrorism, are those that focus on the role of the spatial dynamics that govern the role of place in influencing criminal behavior. These spatial approaches take the emphasis off targeting offenders and consider the importance of location in explanations of crime and terrorism. To understand terrorism events at the micro-level, three propositions from a vulnerability and exposure framework are proposed. If one were to replace 'crime' with 'terrorism', the hypothetical relationships identified by Kennedy and associates (2015, p.5) remain relevant to the current study:

- All places are at risk for crime, but because of the spatial influence of certain criminogenic features of a landscape, some places are riskier than others;

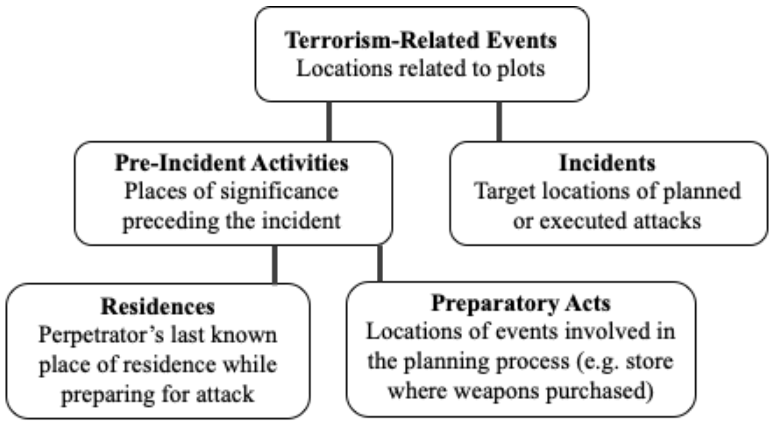
- Crime emerges at places when there is high vulnerability based on the combined spatial influences of multiple criminogenic features at said places; and
- The overall effect of risky places on crime is a function of differential vulnerability and exposure throughout the landscape.

Despite advances in applications of environmental approaches to studying terrorism, critical gaps in existing research remain that are addressed in the current study. In particular, prior research has not separately examined the how risk is structured in locations where terrorists live, plan and prepare, and commit attacks, failing to recognize potential heterogeneity in risk profiles across various terrorism settings. Another limitation of prior statistical research on risk of terrorism attacks occurring is the overreliance on statistical main effects models that tell us how single variables increase or decrease the likelihood of terrorism occurring. Useful in their own right, these approaches cannot capture complex spatial risk profiles of various terrorism-related activities, specifically the amalgamation of factors shaping opportunities situated within unique socio-political contexts that are more or less conducive for terrorists to reside, plan and prepare, and commit attacks. We now turn to the current study.

III. The Current Study

This study extends prior research on the spatial risks of terrorism by using an exploratory approach encompassing two methodologies designed to uncover underlying dynamics of terrorists' *pre-incident* activities (terrorist residences and preparatory activities) and *incidents* (successful attacks/crimes and unsuccessful plots). There are two major objectives for the current study. First, we identify demographic and social characteristics of communities (i.e., counties and census tracts) that, when considered in combination, form dominant profiles for communities at most risk for experiencing terrorists' pre-incident and incident activities. Second, we identify situational, place-based risk factors most associated with places where terrorists' pre-incident and incident activities are most likely to occur. By accomplishing these objectives, we provide straightforward analytical approaches that can uncover the common trends in domestic radicalization and provide intelligence and law enforcement agencies with novel methods to diagnose, anticipate, and respond to localized sets of risks.

Figure 1. Types of Terrorism-Related Events



Research Question(s):

Drawing from the tenets of environmental and situational criminology, our study is guided by a series of exploratory research questions:

1) How are terrorists' pre-incident (residence and preparatory locations) and incident activities (successful attacks/crimes and unsuccessful plots) spatially distributed across the U.S.?

2) What are the most prominent combinations of community characteristics in places where terrorists' pre-incident and incident activities are most likely to occur? How do these pre-incident and incident characteristics differ?

3) What are the similarities and differences in prominent case configurations across different levels of aggregation (i.e., county and census tract)?

4) What is the distribution of risk across micro-level places?

5) What built, physical environment characteristics contribute to the risk associated with pre-incident and incident activities?

6) What prominent case configurations (or patterns) emerge when accounting for micro-level places nested within communities?

Moving forward, we first describe the data sources we obtain for the project. We then separate our findings based on analytical approach, beginning with a discussion of the spatial distribution of terrorism-related events at three different spatial units: State, County, and Tract. We supplement the county and tract descriptions with one-sample Z tests to identify if where the terrorism-related events occur are significantly different than the overall population (counties and tracts, respectively). This leads to our overview of findings of Conjunctive Analysis and the Risk Terrain Modeling. Given many study sites have small counts of terrorism-related events, we provide an approach the produces neighborhood profiles based on the social characteristics and count of different physical infrastructure facilities.

Data Sources

Data for this project come from multiple sources. First, data on terrorists' pre-incident behaviors (i.e., residences and preparatory) and incident activities are obtained from the American Terrorism Study (ATS). Second, community and environmental data are derived from open-access data portal, InfoGroup, and the U.S. Census Bureau. Each of these data sources is discussed in more detail below. Following the discussion of data, two proposed approaches comparatively examining the geospatial risk profiles of terrorism-related activities, Conjunctive Analysis of Case Configurations ("conjunctive analysis") and Risk Terrain Modeling (RTM), and the results stemming from these approaches are discussed.

American Terrorism Study (ATS)

This project relies on data collected through the American Terrorism Study (ATS), which is a compilation of data based on federal criminal cases resulting from indictment under an FBI investigation for "terrorism or terrorism-related activities." Sources for the data include court documents from official terrorism federal court cases as designated by the Federal Bureau of

Investigation and/or the Executive Office for United States Attorneys, U.S. Attorney websites, and open-source media documents. A large amount of these data has been collected through funded NIJ projects,[1] as well as for the current study. The ATS database contains variables capturing both the nature of terrorism and its treatment in the criminal justice system, including 170 incidents involving either ISIS or AQAM adherents, 167 eco-terrorism incidents, and 233 extreme far-right incidents. For the current study, we rely on ATS data for geocoded addresses of terrorists' residences, places of preparatory events, and incidents' locations (captured down to a street address level when possible and other event-level attributes (see Table 1). For a complete list of descriptive statistics and description of the dataset and variable coding, please see the attached playbook and data guide (Appendix A).

Table 1. Event-Level ATS Variables & Recodes for Conjunctive Analysis

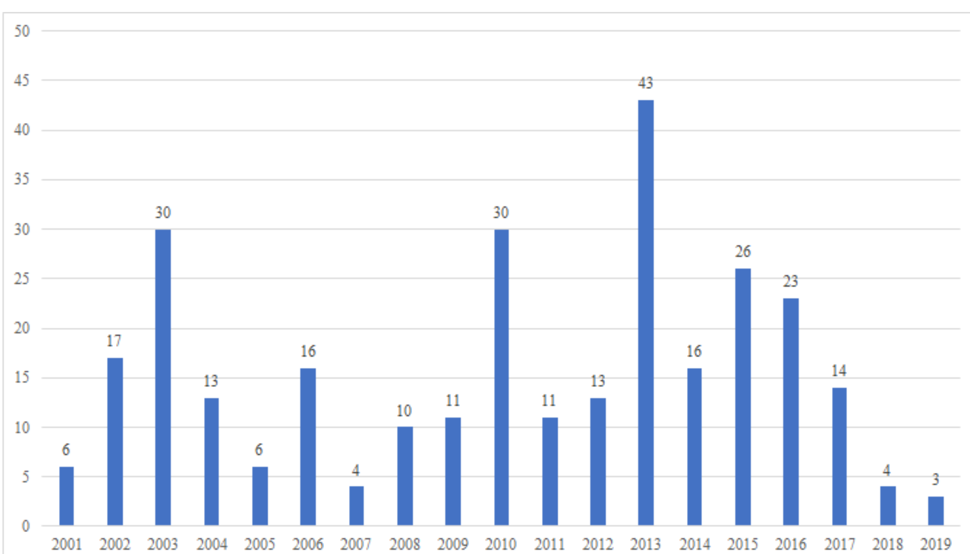
Category	Ideological category connected to the incident.	1 = Environmental 2 = Far-left 3 = Far-right 4 = Islamic Extremist 5 = Affiliation Unclear
Weapon	Type of weapon used or intended to be used in the attack, with preference given to the most destructive type of weapon.	1 = Explosives 2 = Firearms 3 = Incendiary 4 = Melee, Other, & Unknown
Lone Actor	Group structure of the perpetrator(s) of the incident.	1 = Loner, Loner Affiliated, & Lone Conspirator 2 = Group 3 = Unknown

[1] The projects including "Pre-Incident Indicators of Terrorist Activities: The Identification of Behavioral, Geographic, and Temporal Patterns of Preparatory Behavior." NIJ Award # 2003-DT-CX-0003; "Geospatial Analysis of Terrorist Activities, NIJ Award #2005-IJ-CX-0200; "Identity and Framing Theory, Precursor Activity, and the Radicalization Process, NIJ Award #2012-ZA-BX-0003; "Terrorism in Time and Space, NIJ Award # 2006-IJ CX-0026; Sequencing Terrorists' Precursor Activities, NIJ Award #2013-ZA-BX-0001.

Table 1. Continued		
Target Type	Characterizes the general category of target	1 = Government 2 = Military 3 = NGO or Business 4 = Private Property/Citizen 5 = Education, Financial, Medical, Religious, Transportation, Other, & Unknown
Success	An incident is considered at least partially successful if at least one of the weapons was delivered to the intended target. Unsuccessful incidents are those that are either foiled or do not occur on the intended target for reasons other than human intervention.	1 = Successful & Partial Success 2 = Unsuccessful

The current project focuses on terrorism-related pre-incident activities and incidents from following 9/11 through 2019 for analyses. The ATS data for the present study includes information on 420 terrorist residence to incident links, 617 pre-incident activities associated with 296 terrorism incidents during this time frame. The most common of these identifiable preparatory behaviors involve acquisition of materials or storage (23.8 percent), and acquisition or storage of weapons (14.3 percent).

Figure 2. Distribution of Terrorism Incidents by Year



American Community Survey (U.S. Census)

Data from the American Community Survey 2012 - 2016 – 5year estimates are utilized to construct community-level factors expected to relate to terrorism events based on extant literature (see LaFree & Bersani, 2014). We used this year to reflect the majority of incidents occurring in the latter half of the time frame. We utilized Social Explorer to assist in the data download through our affiliation with the University of Arkansas. Community factors are obtained for two different operationalizations of 'community'- county- and tract-level. We are using two levels of community to explore how robust findings are at the county-level compared to smaller units of communities (i.e., tract-level). Measures explored relate to urbanization, concentrated disadvantage, education level, marital status, residential instability, and population heterogeneity. The U.S. Census provides shapefiles and geodatabases with many of these measures already included, allowing for ease when merging multiple datasets. The variable break values are determined by the quartile values being recoded with three categories: under 25% being Low, between 25% and 75% Moderate, and above 75% (*note: tract-level has missing values depending on variable).

Table 2. County and Tract-Level Socio-Demographic Variables with Category Break Counts

Variable Name	**Variable Category Counts – Terrorism – Related Events only**		
County – Level	*Low*	*Moderate*	*High*
Population Density (Per Sq. Mile)	7	26	103
Percent White	70	63	3
Percent Less than High School Diploma	48	70	18
Percent Unemployed	12	82	42
Percent Families Below Poverty Line	37	82	17
Percent Living in Same Household 1 Year Ago	60	59	17
Percent Vacant Houses	82	46	8
Percent Foreign Born	3	35	98
Gini Index	22	64	50
Tract - Level	*Low*	*Moderate*	*High*
Population Density (Per Sq. Mile)	54	159	116
Percent White	102	174	50

Table 2. Continued			
Percent Less than High School Diploma	100	156	70
Percent Unemployed	83	157	84
Percent Families Below Poverty Line	74	168	79
Percent Living in Same Household 1 Year Ago	141	137	48
Percent Vacant Houses	78	166	80
Percent Foreign Born	42	161	123
Gini Index	73	135	113

Reference USA-InfoGroup

We also relied on historic nationwide business data through Reference USA: InfoGroup. InfoGroup, Data Axle, a leading commercial provider of public record information for reference, research, and marketing purposes that has been utilized in prior RTM research (Caplan, Kennedy, Barnum, & Piza, 2015) and is used by Esri® (Esri, 2015). The dataset consists of verified business records, and included geographic identifiers: address, city, state, and census tract, allowing for merging with other datasets (ATS, U.S. Census). We use the 2016 InfoGroup records for RTM and the 2017 InfoGroup records to aggregate to tracts. The 2017 data are directly linked to the 2010 Census Tract FIPS while 2016 and prior are coded to the 2000 census. We rely on the NAICS description to select out our business records (e.g., commercial bank and religious organization; see infogroup.com). For complete list, see Play Book (Appendix A). This allowed us to categorize different elements of the built, physical infrastructure to use in analyses.

IV. Terrorism-Related Events Across the U.S. by Spatial Unit

This section focuses on examining our first and fourth research questions:

> *1) How are terrorists' pre-incident (residence and preparatory locations) and incident activities (successful attacks/crimes and unsuccessful plots) spatially distributed across the U.S.?*
> *4) What is the distribution of risk across micro-level places?*

State-Level Distributions

The focus of the study is to explore the spatial attributes of terrorism-related events from a macro- to micro - lens. With that, address specific information is not always available or known at the time of coding. Because of this, we provide a state-level description as we move towards smaller spatial units (e.g., county, tract, and address). The data provided from ATS are separated into three categories: incident (ie., event locations), preparatory activities, and residences. Each of these categories are examined separately first then, when appropriate, joined for analysis. For the sake of consistency, we kept Washington, D.C. within the analysis so the total potential would be 51 rather than 50. We will refer to the grouping as states, including D.C. in this language.

Incidents: There are 296 terrorism incidents with at least a state identifier. These incidents occurred in 35 different states. The top five states, California, New York, Virginia, Texas, and Utah account for 50 percent (148 / 296) of all incident locations. At this level, 9.8 percent (5/51) of the potential locations (i.e., states) account for 20 percent of the target locations, indicating a macro-level concentration of incidents. More broadly, 35 out of 51 potential states had incidents occur (68.6 percent). Of the 296 incidents, 153 were successful (52.03 percent) in 32 different states.

Preparatory Activities: There are 617 terrorism preparatory activities that are linked to a specific state, representing 34 unique states. When examining the top five states, New York, Illinois, California, Virginia, and Washington, they together account for approximately 58 percent of the preparatory activities (357 / 617). Again, 9.8 percent of the potential locations accounted for over half of the preparatory activities (5 / 51). More broadly, there are a total of 34 states where preparatory events occurred, 66 percent of the potential total (34 / 51). This indicates an extent of macro-level concentration of preparatory activities.

Residences: Focusing on known residences of terrorists, 420 are linked to a state. The 420 residences are located within 34 states (66.6% of total). Across the states, the top five, California, Virginia, New York, Florida, and Texas account for 49 percent of all terrorist related residences (9.8% of states). Like preparatory activities, this indicates there is a macro-level concentration of known terrorist residences at the state-level.

Overall, there are 1,333 terrorism-related events that had at least a state identifier (296+617+420) for the relevant time frame. The top 5 states, based on percent of total, are California, New York, Illinois, Virginia, and Florida. These five states (9.8%) contain just over half of all terrorism related data points (50.86% incidents, preparatory activities, and residences). After 9/11, there is identifiable concentration of terrorism-related events at the state-level with the top 10 states accounting for around 69 percent of terrorism-related events. Additionally, given 50 potential states plus D.C., only 40 states (including D.C.) had state-level terrorism-related events. Even at a state-level, data indicate terrorism-related events are not equally spatially distributed, leading to certain states being more likely to contain terrorist incident targets, having known terrorists reside, and/or having more preparatory activities occur within the respective state.

Figure 3. State-Level ATS Categories Combined

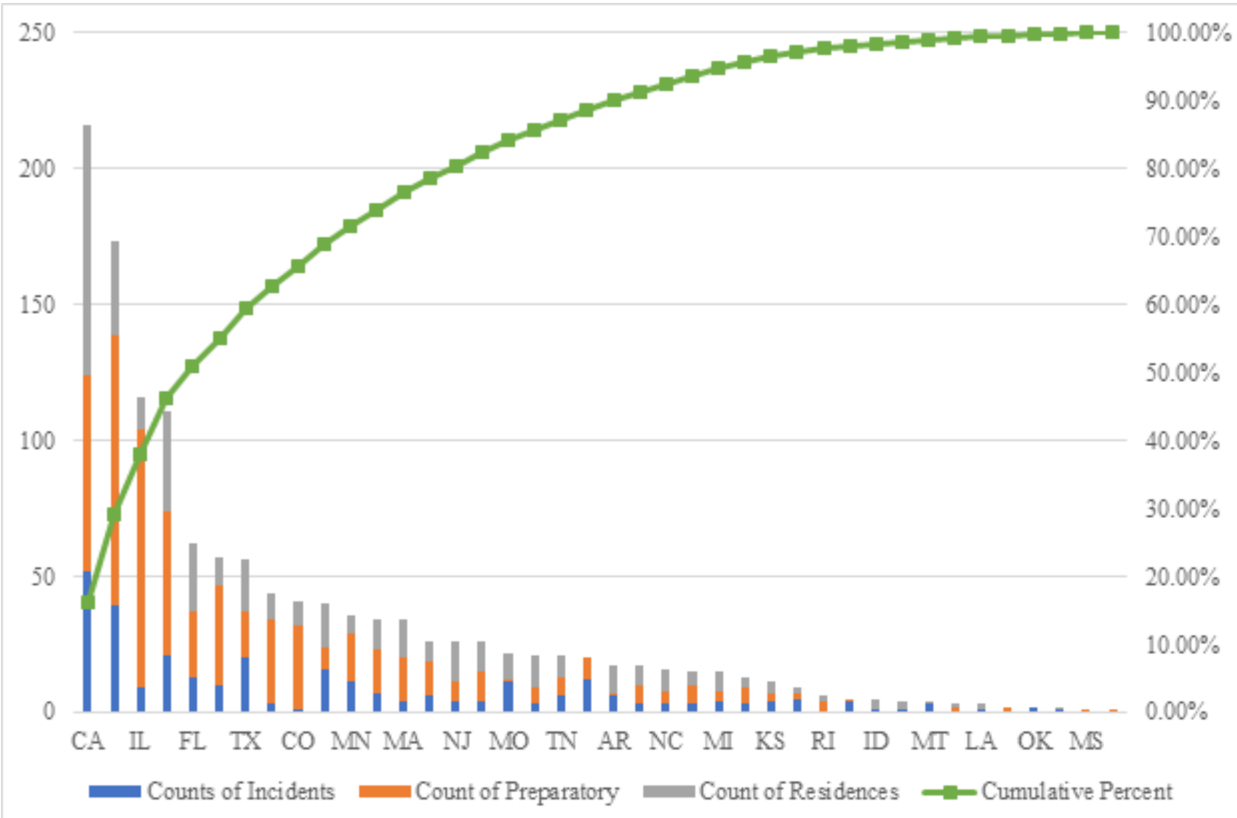
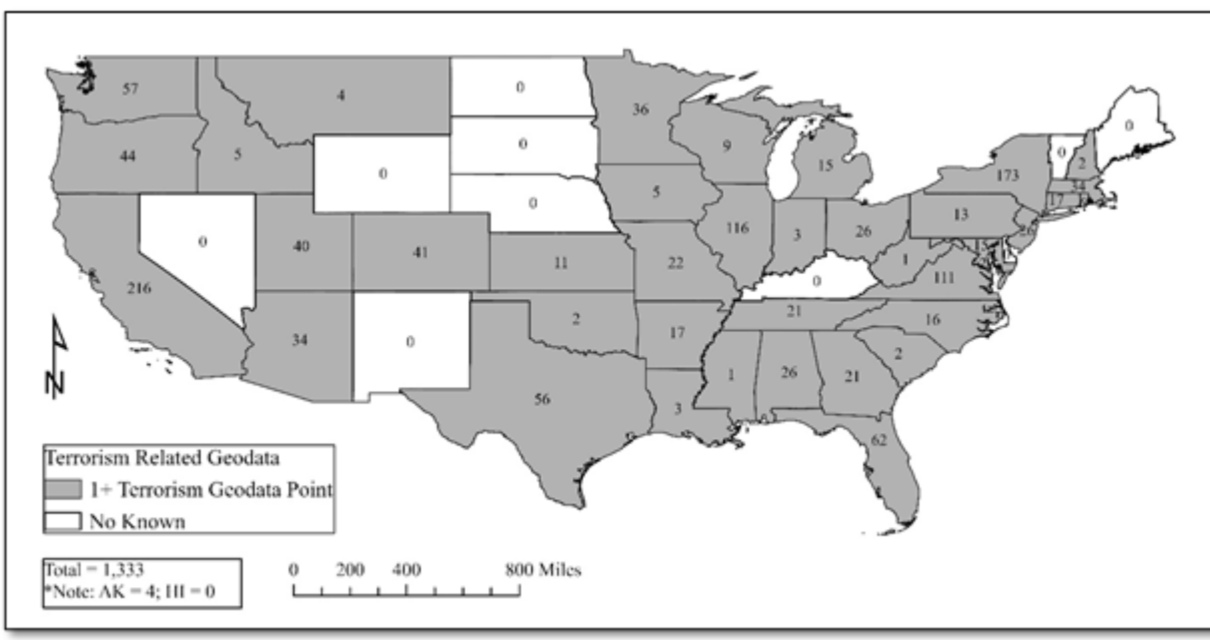


Figure 4. Combined ATS Categories for any State Level Terrorism Related Identifiers



County-Level Distributions

Moving down to a smaller spatial unit, we examine the distribution of terrorism-related events across U.S. Counties. Within the United States, there are 3,142 counties. Our terrorism-related events occurred in just 220 counties. These 220 counties contained 1,333 events, similar to the State-Level Distribution, and constitutes 16.5 percent of potential counties (220 / 1,333). The top ten counties in Table 3 represent 32.03 percent of all terrorism related geo-data points at the county-level. Stated another way, 4.5 percent (10 / 220) of the counties contained almost a third of all terrorism-related events (32.0 percent; 427 / 1,333). This indicates a degree of clustering with terrorism-related events in space. Figure 5 outlines the counties throughout the United States containing any terrorism-related event. Furthermore, there were 39 counties containing each separate category of terrorism-related events, as seen in Figure 6. These 39 counties account for 49.06 percent of the terrorism-related events (654 / 1,333).

Table 3: Top 10 County-Level Terrorism-Related Events

	County, State	Count Any
1	New York, NY	58
2	Cook, IL	58
3	Queens, NY	50
4	Placer, CA	44
5	Los Angeles, CA	44
6	Alameda, CA	40
7	Arapahoe, CO	37
8	Monroe, NY	37
9	Multnomah, OR	31
10	Loudoun, VA	28

Figure 5. Any Terrorism-Related Events at the County-Level

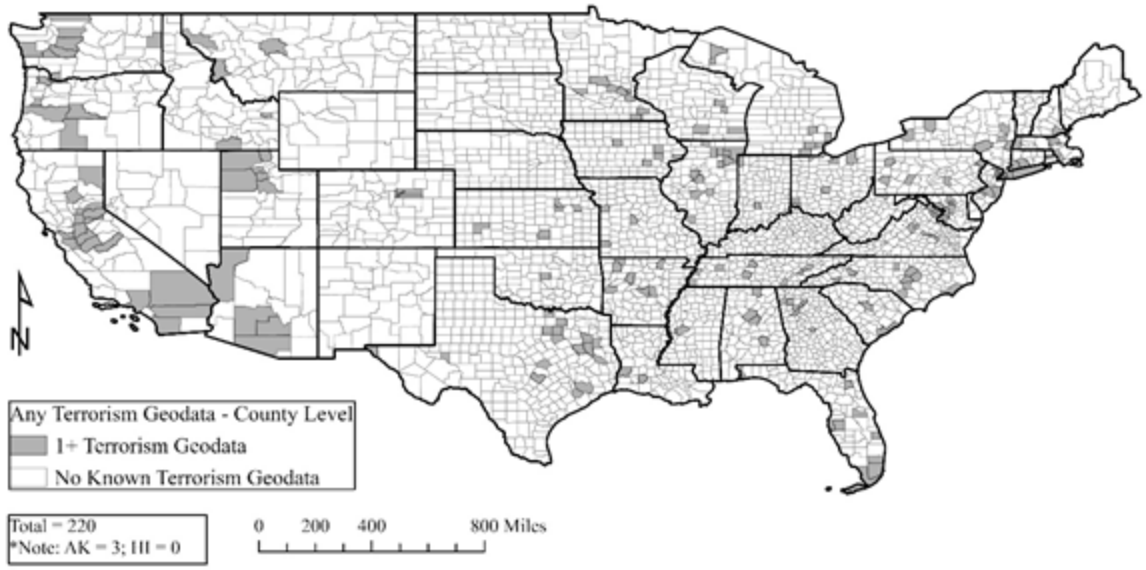
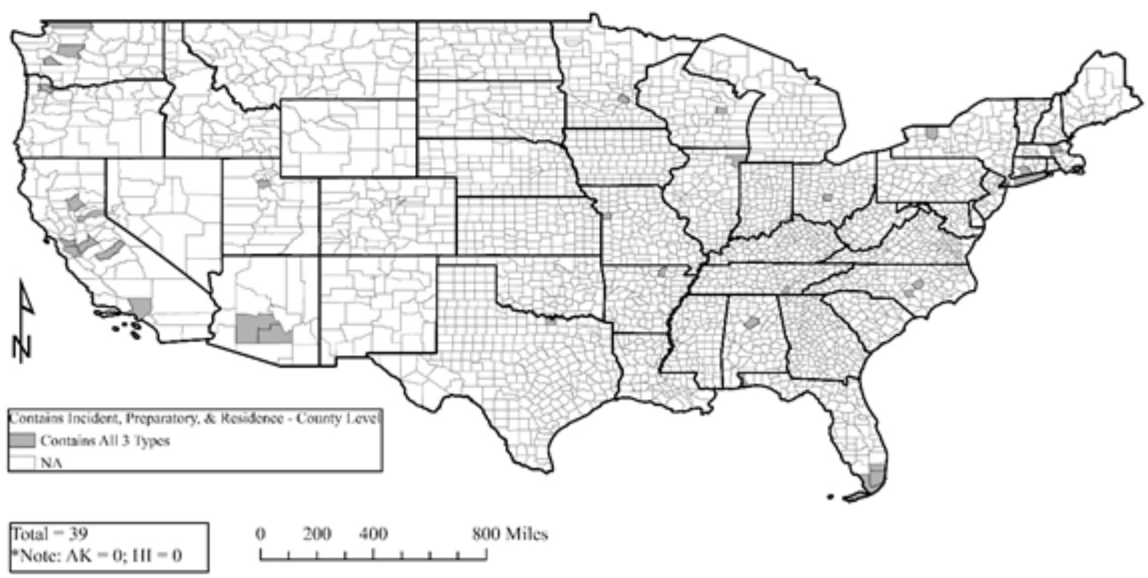


Figure 6. Counties Containing Each Terrorism-Related Event Category



Incidents: There were 296 terrorism-related events that were joined to counties across the United States. The 136 counties containing the 296 terrorism incident locations represent 4 percent of all counties in the United States. It is worth noting here that there were only 296 incidents, so there is no possibility that all counties could ever have an incident occur. If we change the denominator to reflect potential equality of the 296 incidents occurring in truly 296 counties, then we can better represent the spatial distribution at the county-level. The 136 counties where terrorism incidents occurred/planned constitutes about 46 percent of potential counties if spatial equality is the counter. Based on this, we see that at the county-level, there is an unequal distribution of terrorism target locations. The top five counties for target locations include: New York, NY (25), Washington, D.C. (12), Los Angeles, CA (12), Alameda, CA (10), and Salt Lake, UT (8). These five counties contained 67 incident locations, equating to 22.6 percent of all incidents post 9/11. While 136 counties contained incident locations, only 84 counties contained the 154 successful incidents.

Preparatory Activities: The 617 County-Level Preparatory Activities are linked to a specific county. The 617 preparatory activities occurred in 101 different counties. If we treat 617 as our denominator for spatial equality, each county has 1 preparatory activity, then we find that the preparatory activities concentrated in just 16.4 percent of potential counties (101 / 617). Furthermore, when examining the highest count counties, about 10 percent (10 / 101) of the counties contained about 46 percent (283 / 617) of the preparatory activities. The top five counties for preparatory activities include: Cook, IL (50); Monroe, NY (33), New York, NY (32), Queens, NY (31), and Arapahoe, CO (31).

Residences: At the County-Level, there were 420 terrorist related residences that are linked to a county. The 420 residences were linked to 137 different counties throughout the United States. This represents 32.6 percent (137 / 420) of potential counties contained terrorist residences, indicating concentration within counties (i.e., not equally spatially distributed). The top 11 counties (8 percent) had a total of 155 residences, 36.9 percent of the total county-level residences. The top five counties are: Alameda, CA (21), San Diego, CA (19), Los Angeles, CA (18), Henrico, VA (18), and Placer, CA (17).

One-Sample Z Test: We provide an overview of county-level descriptives along with one-sample z-tests to identify if the mean social characteristics of counties with terrorism-related events are significantly different (non-directional) than the mean social characteristic of the population (all counties). In short, are the terrorism-related communities different than the norm. The formula is provided in Figure 7. The numerator of the formula subtracts the population mean from the sample mean. This number is then divided by the standard error of the mean, which is the population standard deviation divided by the square root of the sample size.

Figure 7. One Sample Z-Test Formula

$$z = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

Our focus here is limited to the counties where incidents occurred and counties containing *any* terrorism-related event (incident or pre-incident). Since we are interested in any non-directional significant change in the sample mean compared to the population mean, the critical value necessary at $p < 0.05$ is $\pm$ 1.96. The null hypothesis in each of the z-tests is that the county mean does not significantly differ from the population county mean for each social characteristic. In Table 4 the sample of counties consisted of counties with any terrorism-related event, compared to all US counties.

Table 4. One Sample Z-test and Cohen's *d* for U.S. Counties with *Any* Terrorism Geodata

	All Counties			Any Terrorism Counties					
	N	**Mean**	**Std. Deviation**	**N**	**Mean**	**Std. Deviation**	**Obtained Z**	**Cohen's *d***	**Effect Size**
Population Density (Per Sq. Mile)	3142	267.915	1797.845	220	1949.087	6359.431	**13.870**	0.935	Large
Percent White	3142	83.382	16.779	220	74.571	16.012	**-7.789**	-0.525	Large

Table 4. Continued									
Percent Less than High School Diploma	3142	14.190	6.542	220	11.985	5.351	**-4.997**	-0.337	Medium
Percent Unemployed	3142	4.029	1.693	220	4.562	1.273	**4.669**	0.315	Medium
Percent Families Below Poverty Line	3142	11.955	5.764	220	10.750	4.618	**-3.101**	-0.209	Medium
Percent Living in Same Household 1 Year Ago	3142	86.487	4.369	220	84.354	4.462	**-7.239**	-0.488	Medium
Percent Foreign Born	3142	4.648	5.684	220	11.465	9.276	**17.788**	1.199	Large
Percent Vacant Houses	3142	18.209	10.940	220	11.670	7.747	**-8.865**	-0.598	Large
Gini Index	3142	0.444	0.035	220	0.455	0.037	**4.518**	0.305	Medium

There are 220 counties containing either, or a combination of, an incident, preparatory activity, or residence. The presence of a preceding negative z-score sign indicates the direction of the deviation compared to the population. All differences in sample mean to population mean are statistically significant (bolded). For instance, we find that the average percentage of White persons in our sample is significantly less than the population average of percentage of White persons. We also find that the mean for percent of population with less than high school education is significantly less than the mean of the population more generally. Further, we find that the mean percentage of foreign born in our sample is significantly greater than the county population mean.

To further our understanding of the differences between the mean values of counties where any terrorism-related event occurred compared to the population of U.S. counties, we also calculate Cohen's *d* for effect size. To calculate the effect size, the population mean is subtracted from the sample mean then divided by the population standard deviation (see Figure 8). Generally, a small effect size ranges from 0 - .2; medium effect size ranges from .2 - .5; and large effect size is any value greater than .5.

Figure 8. Cohen's *d* Effect Size Formula

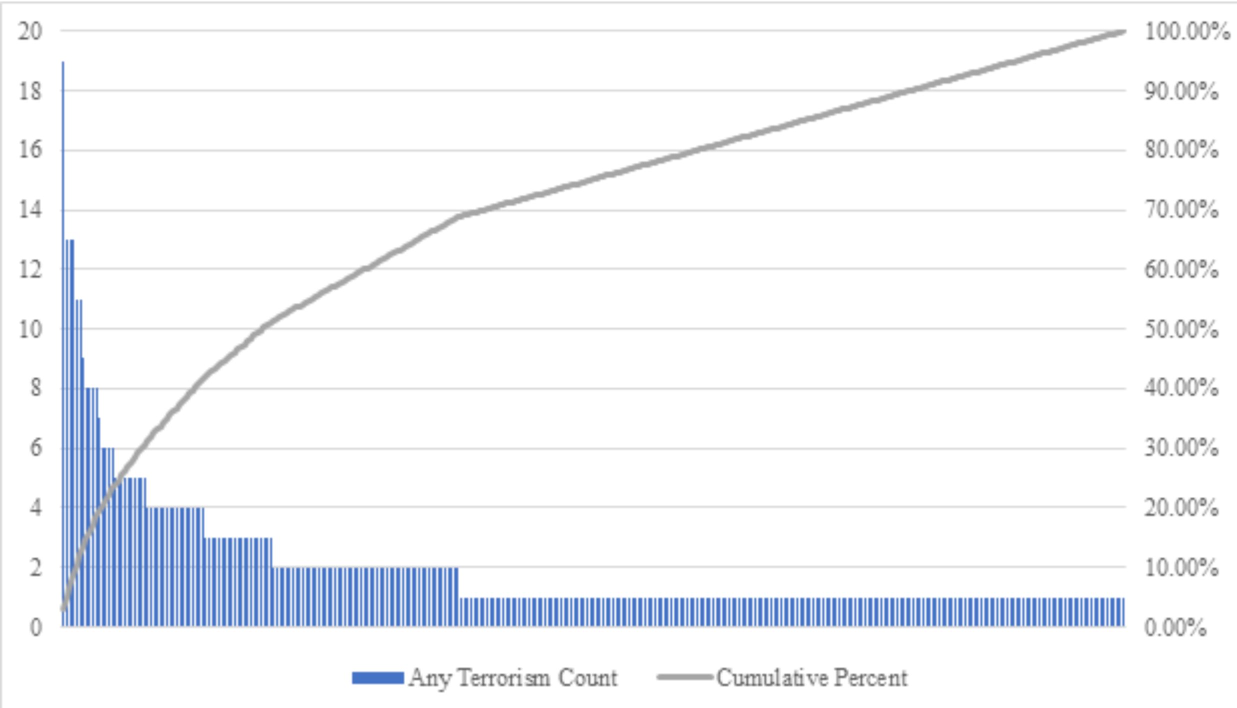
$$\textbf{Cohen's } d = \frac{(\bar{x} - \mu)}{\sigma}$$

As indicated in the Cohen's *d* values in Table 4, the effect sizes range from medium to large. In short, the further the effect size moves away from zero, be it positive or negative, the less similar the groups (sample and population). Put differently, there is less overlap between the groups the larger the Cohen's *d* obtained value. Focusing on the largest differences between the counties experiencing terrorism-related events and the population of U.S. counties, findings suggest that terrorism-related events are more likely to occur in counties that are more densely populated, more racially heterogenous, have a relatively larger foreign-born population, and have less vacant houses in the county. These findings generally support the conclusion that terrorism-related events occur in counties that are relatively more urbanized and socially disorganized at a macro-level.

Tract-Level Distributions

When moving towards a smaller unit of analysis often described as neighborhoods, census tracts, there is a reliance on full address information to join the address of the incident, preparatory activities, and/or residence. This reduced our number of terrorism-related events to 659 including incidents: 208 incidents, 252 preparatory activities, and 199 residences. All terrorism-related events occurred within 329 census tracts. Figure 9 provides a cumulative distribution of terrorism-related events across the census tracts.

Figure 9. Any Terrorism-Related Event Count by Tract and Cumulative Percentage



There are no census tracts that contained each type of known terrorism-related event. Table 5 contains the descending counts of any terrorism geodata points across the census tracts. These 16 tracts represent 4.863 percent of the total tracts and account for 23.065 percent of the terrorism-related events. This indicates a level of neighborhood concentration that is evident in Figure 9. Furthermore, the categories of terrorism-related events are separated with top neighborhoods listed. Most of these tracts contain preparatory activities and residences rather than incidents. Additional contextual information was provided in Table 5 to indicate the county and state as well as the specific tract (i.e., FIPS).

Table 5. Tract-Level Descending Counts of *Any* Terrorism-Related Event

Counts	Cumulative Percentages		Categories Separated			Location Information		
Any	Terrorism Related Events	Terrorism Tracts	Incident	Preparatory	Residence	FIPS	County	State
19	2.883%	0.304%	0	0	19	06073020707	San Diego	CA
13	4.856%	0.608%	1	12	0	36081032000	Queens	NY

Table 5. Continued								
13	6.829%	0.912%	0	13	0	27109002300	Olmsted	MN
13	8.801%	1.216%	0	9	4	51107611004	Loudoun	VA
11	10.470%	1.520%	0	11	0	17201002100	Winnebago	IL
11	12.140%	1.824%	0	4	7	06061022013	Placer County	CA
9	13.505%	2.128%	0	3	6	08005086000	Arapahoe	CO
8	14.719%	2.432%	0	7	1	53073001000	Whatcom	WA
8	15.933%	2.736%	0	6	2	06037133100	Los Angeles	CA
8	17.147%	3.040%	0	8	0	08005007702	Arapahoe	CO
8	18.361%	3.343%	0	8	0	08005081400	Arapahoe	CO
7	19.423%	3.647%	0	6	1	53033026200	King	WA
6	20.334%	3.951%	0	6	0	06061021802	Placer	CA
6	21.244%	4.255%	0	2	4	25017352700	Middlesex	MA
6	22.155%	4.559%	0	6	0	34039039800	Union	NJ
6	23.065%	4.863%	0	1	5	09001073700	Fairfield	CT

Incidents. For the terrorism incidents, there were 208 geodata points associated with terrorism incidents in which full addresses were available that were linked to 177 tracts in the United States. Evident in Figure 9 (above), most of the tracts did not have multiple incidents (23 / 177 = 12.99%). These 23 tracts account for 25.96 percent of the total tract-level terrorism incidents (54 / 208). Table 6 provides a list of the top tracts with 3+ incidents.

Table 6. Tract-Level Descending Terrorism Incidents

Count	County	State	FIPS
5	Alameda	CA	06001403000
4	Crane	TX	48103950100
3	Arlington	VA	51013980100
3	D.C.	D.C.	11001006202
3	Prince William	VA	51153901100

Preparatory Activities. Terrorist preparatory activities occurred across 99 census tracts. These preparatory activities are more concentrated than the terrorism incidents. If the activities were equally distributed, this would result in 252 unique census tracts. The 99 census tracts preparatory activities occurred in represents 39.29 percent of potential tracts, indicating concentration. Of the 252 preparatory activities, 57 tracts had more than one activity. These 57 tracts contained 210 of the 252 activities (210 / 252 = 83.33%). The top six tracts in Table 7 represent 24.21 percent (61 / 252) of the total preparatory activities occurring in only 6.06 percent of the tracts (6 / 99).

Table 7. Tract-Level Descending Terrorism Preparatory Activities

Count	County	State	FIPS
13	Olmsted	MN	27109002300
12	Queens	NY	36081032000
11	Winnebago	IL	17201002100
9	Loudoun	VA	51107611004
8	Arapahoe	CO	08005007702
8	Arapahoe	CO	08005081400

Terrorist Residences. The 199 terrorism residences are contained with 103 census tracts. As a reminder, one residential address could be linked to multiple incidents, so the same address could be represented multiple times. The 103 census tracts where terrorists were known to reside represents 51.76 percent of the total possible tracts if equal spatial distribution is assumed. Of the 103 tracts, 66 (64.08 percent) had only one known residence. The remaining 37 tracts (35.92 percent) contained 66.83 percent of the known terrorist residences (133 / 199). The top 5 tracts in Table 8 represent 4.85 percent of the total tracts (5 / 103) while containing 21.11 percent of the known terrorist residences (42 / 199).

Table 8. Tract-Level Descending Terrorist Residence Counts

Count	County	State	FIPS
19	San Diego	CA	06073020707
7	Placer	CA	06061022013
6	Arapahoe	CO	08005086000
5	Fairfield	CT	09001073700
5	Placer	CA	06061020502

One Sample Z test. Using the statistics from the tracts, we calculate a one-sample z-test for all tracts containing any terrorism-related events. Table 9 provides the results of our one-sample Z-tests for *all* tracts. Again, we did not hypothesize a specific direction, so we treat this as non-directional and exploratory. Results indicate that the mean of population density, percent of population with less than high school education, percent unemployed, percent of families with income below the poverty line, percent same house one year ago, percent of foreign born, and the Gini index significantly differed from the population averages of all tracts. The sign indicates the direction of the difference. For instance, the mean population density of tracts with any terrorism-related event is significantly greater than the mean population density of all tracts. Similarly, the mean percentage of living in the same house 1 year ago weas significantly less than the population mean.

Table 9. One Sample Z-test and Cohen's d for U.S. Census Tracts with *Any* Terrorism Geodata

	All Census Tracts			Any Terrorism Census Tract					
	N	**Mean**	**Std. Deviation**	**N**	**Mean**	**Std. Deviation**	**Obtained Z**	**Cohen's *d***	**Effect Size**
Population Density (Per Sq. Mile)	72719	5392.421	12096.136	329	7617.708	14113.536	**3.337**	0.184	Small
Percent White	72399	72.873	25.315	326	69.370	22.746	**-2.499**	-0.138	Small
Percent Less than High School Diploma	72391	13.691	10.963	326	12.666	10.378	-1.688	--	--
Percent Unemployed	72289	7.981	5.343	324	7.892	5.175	-0.301	--	--
Percent Families Below Poverty Line	72172	12.512	11.424	321	12.561	11.404	0.077	--	--
Percent Living in Same Household 1 Year Ago	72399	85.098	9.145	326	78.561	14.788	**-12.905**	-0.715	Large
Percent Foreign Born	72246	11.863	10.706	324	11.250	9.576	-1.031	--	--
Percent Vacant Houses	72399	12.414	13.549	326	16.598	14.362	**5.576**	0.309	Med.
Gini Index	72146	0.424	0.062	321	0.440	0.077	**4.597**	0.257	Med.

We also provided the Cohen's *d* effect size in Table 9 to ease the interpretation. For the two prior examples, population density had a small effect size while percent living in the same house 1 year ago had a large effect.

V. Conjunctive Analysis of Case Configurations ("Conjunctive Analysis")

This section focuses on answering our second and third research questions:

2) What are the most prominent combinations of community characteristics in places where terrorists' pre-incident and incident activities are most likely to occur? How do these pre-incident and incident characteristics differ?

3) What are the similarities and differences in prominent case configurations across different levels of aggregation (i.e., county and census tract)?

Background of Conjunctive Analysis

In this section, we explore the utility of Conjunctive Analysis of Case Configurations (or "conjunctive analysis") for exploring the social and social-situational contexts of terrorism-related activities in the U.S. across multiple level of analysis. Conjunctive analysis was introduced to criminology by Miethe and colleagues (2008) and is based on comparative techniques used in qualitative and quantitative analyses of categorical data (see Qualitative Comparative Analysis (QCA) (Ragin, 1987). This approach differs from other, more traditional approaches, in that it allows for all possible combinations of variables or in other words, a fully saturated model (all potential interactions; see Miethe et al., 2008). Researchers like Drawve et al. (2017) have recently expounded on the analytical advantages of this approach and the limitations of traditional quantitative techniques by replicating a prior study utilizing logistic regression (Drawve, Thomas, & Walker, 2014). For example, significant direct effects were found for numerous independent variables on predicting the likelihood of arrest; however, conjunctive analysis findings indicated that the effects of the independent variables were not equal (i.e., the effect varied based on the overall situational profile of combinations).

Conjunctive analysis relies on variables being dichotomized or categorical to be able to aggregate into all combinations to determine profiles. The number of configurations is dependent upon the number of independent variables and the categories within each variable. For instance, if we have 6 variables -- 3 dichotomized, and 3 categorical variables with 4 categories each -- there would be potentially 512 case configurations (2x2x2x4x4x4=512). Conjunctive analysis explores the patterns of these variables in relation to an outcome of interest (e.g., Did a terrorist pre-incident or incident activity occur in this place? *Yes* or *No*) or can be used to develop configuration profiles related to subsets of data with no outcome indicator.

An initial step in conjunctive analysis is constructing a data matrix (or "truth table") that reflects all possible combinations of the independent variables (see Table 1 below). The Combination ID is just that, an ID for that specific configuration of cases (i.e., unique ID). The independent variables (X1-j) make up a majority of the table and, for example purposes, are limited to binary (0,1) responses. In Table 10, there are five binary measures, resulting in 32 configurations (=25). The "# of cases" refers to the number of cases that have that specific configuration. Lastly, "proportion" refers to the proportion of cases in each specific configuration where Y (binary dependent variable) is represented. In relation to our proposed study, the proportion of communities experiencing successful terrorism incidents. This is important to distinguish because the matrix provides a guide for what is contributing to higher or lower proportions. If you view the matrix of independent variables, think of it as turning on or off a light switch. How does this alter the proportion (i.e., outcome probabilities)? This highlights the importance of conjunctive analysis when compared to traditional methods since it accounts for all possible interactions. For example, when examining combination ID 1 and 2, the only difference is with variable Xj, so the difference in the proportion could be discussed in relation to that variable.

Table 10. Example Conjunctive Analysis Data Matrix*

Combination #	X1	X2	X3	X4	Xj	# of Cases	Proportion
1	0	0	1	1	1	nc1	y1/nc1
2	0	0	1	1	0	nc2	y2/nc2
3	1	0	1	1	1	nc3	y3/nc3
4	1	1	1	0	0	nc4	y4/nc4
5	0	1	1	0	0	nc5	y5/nc5

*Adapted from Miethe et al. (2008)

With Table 10, there are 32 possible case configurations. Of interest is what are considered dominant case configurations. The distinction of dominant case configurations relies on the sample size. Since we have smaller sample sizes, under 1,000, a dominant case configuration has a minimum of five cases per configuration (see Hart, 2015). Usually only the dominant case configurations are examined and compared to one another.

In the past, conjunctive analysis has been applied to a variety of criminal justice outcomes: bystander presence and intervention (Hart & Miethe, 2008), gun use (Hart & Miethe, 2009), college student victimization (Hart & Miethe, 2011), maritime piracy (Bryant, Townsley & Leclerc, 2013), rape against females (Rennison & Addington, 2015), likelihood of arrest for robbery (Drawve, et al., 2017), and terrorism incident outcomes (Gruenewald, et al., 2019).

We explore the applicability of conjunctive analysis to places with different types of terrorism-related events, specifically the configurations of social characteristics related to where these activities occur at the county-level. Instead of focusing on a binary outcome in this application, the sum of terrorism-related events is calculated. This step allows for identification of county-level social profiles and the corresponding number of terrorism-related events each specific profile contains. This analysis is limited to only counties that have at least one terrorism-related activity. The variables we include in our analysis are population density, percent White, percent less than high school diploma, percent unemployed, percent families living below the poverty line, percent living in the same household one year ago, percent vacant houses, percent foreign born, and the Gini Index. We chose to demonstrate the utility of conjunctive analysis by recoding each variable into three categories based on quartile percentages: below 25% (“low”), between 25% and 75% (“moderate”), and above 75% (“high”).

County – Level Conjunctive Analysis Findings

In Table 11, we present the most prominent county-level profiles while also distinguishing by type of terrorism-related activity. While a minimum of five is the conventional cutoff for a prominent configuration, we present all risk profiles associated with three or more counties to illustrate the utility of conjunctive analysis for especially rare forms of crime like terrorism and since we examine the sum of events rather than likelihood of an outcome. The "sum" column reflects the total number of specific types of terrorism-related activities occurring in counties associated with a particular sociodemographic risk profile.

Table 11. Most Prominent Configurations of County-Level Risk Factors

ID	Population Density	% White	% Less than HS	% Unemp.	% Families Below Poverty	% Same House 1 year	% Vacant	% Foreign Born	Gini Index	Sum	# of Counties
Any Terrorism-Related Event (Incident, Planning / Preparatory Activity, or Residence)											
1	High	Low	Mod.	High	Mod.	Mod.	Low	High	High	69.00	3
2	High	Low	Low	Mod.	Low	Mod.	Low	High	Mod.	53.00	6
3	High	Low	Low	Mod.	Low	Low	Low	High	Mod.	51.00	3
4	High	Low	Mod.	Mod.	Mod.	Mod.	Low	High	Mod.	47.00	4
5	High	Low	Low	Mod.	Low	Low	Low	High	High	38.00	3
6	High	Low	Mod.	Mod.	Mod.	Low	Low	High	High	17.00	3
7	High	Low	Mod.	High	Mod.	Low	Mod.	High	Mod.	10.00	3
8	High	Low	Mod.	High	High	Low	Mod.	Mod.	High	10.00	3
9	High	Mod.	Mod.	Mod.	Mod.	Mod.	Low	High	Mod.	4.00	3
Only Terrorism Incidents											
10	High	Low	Low	Mod	Low	Mod	Low	High	Mod	10.00	5
11	High	Low	Mod	Mod	Mod	Low	Low	High	High	4.00	3
Only Terrorism Planning and Preparatory Activities											
12	High	Low	Mod	Mod	Mod	Mod	Low	High	Mod	40.00	4
Only Terrorism Residences											
13	High	Low	Low	Mod	Low	Mod	Low	High	Mod	22.00	3
14	High	Low	Low	Mod	Low	Low	Low	High	Mod	19.00	3
15	High	Low	Low	Mod	Low	Low	Low	High	High	11.00	3
16	High	Low	Mod	High	Mod	Mod	Low	High	High	11.00	3
17	High	Low	Mod	Mod	Mod	Mod	Low	High	Mod	6.00	3
18	High	Low	Mod	High	Mod	Low	Mod	High	Mod	4.00	3

Examining prominent risk profiles across all terrorism-related events, it appears that all configurations are associated with high-density population areas. The presence or absence of other risk factors varied in patterned ways across configurations. The most prominent risk profile associated with any type of terrorism-related event associated with only six counties and 53 total events, reflecting in part the relatively small number of terrorism-related events in our study and the relatively large number of risk profiles reflected in our data. This county-level risk profile included a combination of high population density, low percentage White, low percentage of less than high school graduate, moderate percentage of unemployment, low percentages of families below poverty line, moderate percentage of families living in same house one-year prior, low percentages of vacant houses, high percentage of foreign born, and moderate Gini Index score. The risk profile linked to the most terrorism-related events, 69 events, varied from Profile 1, with lower education, higher unemployment, higher poverty, and higher inequality. In other words, more terrorism-related events are associated with this particular profile while also representing fewer U.S. counties.

As shown in Table 11, the most prominent risk profiles for all terrorism-related events directly align with the most prominent risk profile for terrorism incidents. In contrast, the most prominent risk profiles for preparatory activities diverged in distinct ways. That is, preparatory activities happened in counties that that were relatively less educated and more impoverished. The most prominent risk profile (n=22) also aligns with the most prominent profile for any terrorism-related activities; however, the second most prominent risk profile for terrorist residences (n=19) varies in terms of residential stability, reflecting less residential stability.

Tract-Level Conjunctive Analysis Findings

A unique ability of the conjunctive analysis is that we can identify the combinations of our social variables without an outcome selected. That is, by limiting our analyses to the tract-level, we can focus on the tracts containing terrorism-related events. This provides us with variation across neighborhoods that would be washed away if combined into an index such as residential stability or concentrated disadvantage. We provide general combination configurations at this level to provide an overview at the tract-level. Greater examination / attention to these will focus on the incident-level attaching these to characteristics / variable derived from the ATS, adding contextual information.

The combinations provided in Table 12 for tracts containing terrorism incidents represent tract configurations that are greater than two. Instead of a traditional dichotomous outcome event (will be discussed further later), we provide the sum of terrorism-related events. In this case, the Sum of Inc. refers to how many incidents occurred within the number of tracts. This is not to be confused with tracts with the greatest number of incidents.

Table 12. Most Prominent Configurations of Tract-Level Risk Factors

Population Density	% White	% Less than HS	% Unemp.	% Families Below Poverty	% Same House 1 year	% Vacant	% Foreign Born	Gini Index	Sum *ANY*	Number of Tracts
13 Terrorism-Related Event (Incident, Pre-Incident Activity, or Residence)										
Mod.	Mod.	Low	Low	Low	Mod.	Low	Mod.	Mod.	15	3
High	Mod.	High	Mod.	High	High	Mod.	High	High	12	3
High	Mod.	Low	Low	Low	Low	Mod.	Mod.	High	4	4
Low	--	--	--	--	--	--	--	--	3	3
Only Terrorism Incidents										
High	Mod.	Low	Low	Low	Low	Mod.	Mod.	High	4	4
Low	--	--	--	--	--	--	--	--	3	3
Only Terrorism Residences										
High	Mod.	High	Mod.	High	High	Mod.	High	High	4	3

Event-Level Findings

To assist in highlighting the importance of conjunctive analysis, we provide the likelihood of successful incidents based on ATS data only, with no spatial component. Table 13 provides the 23 dominant case configurations for likelihood of success with four independent variables: ideology, loner/group, weapon type, and target type. These profiles contain 197 of the 296 incidents (66.55%) and allow us to identify different combinations leading to a greater likelihood of success (closer to 100 percent) or more likely to be unsuccessful (closer to 0 percent). While this is valuable information, it excludes the larger contextual environment surrounding the incident location. The tradeoff with doing so is when increasing the number of variables considered, the potential number of configurations also increases, making it more difficult to obtain enough of the same profiles to be considered dominant.

Table 13. ATS Only Dominant Case Configurations for Terrorism Success

ID	Ideology	Loner/Group	Weapon Type	Target Type	Success Rate	# Incidents
1	Environmental	Loner	Other	Private Property/Citizen	100%	9
2	Environmental	Unknown	Other	NGO or Business	100%	7
3	Environmental	Group	Incendiaries	NGO or Business	100%	6
4	Far Right	Group	Other	Other	100%	5
5	Far Right	Group	Incendiaries	Other	92%	12
6	Environmental	Loner	Other	NGO or Business	88%	26
7	Islamic Extremist	Group	Other	Private Property/Citizen	80%	5
8	Far Right	Group	Other	Government	80%	5
9	Islamic Extremist	Group	Firearms	Military	78%	9
10	Far Right	Group	Firearms	Other	71%	7
11	Environmental	Loner	Incendiaries	NGO or Business	60%	10
12	Far Right	Group	Firearms	Private Property/Citizen	60%	5

Table 13. Continued						
13	Environmental	Loner	Incendiaries	Other	60%	5
14	Islamic Extremist	Group	Explosives	Private Property/Citizen	57%	7
15	Islamic Extremist	Loner	Explosives	Private Property/Citizen	40%	5
16	Islamic Extremist	Group	Explosives	Government	20%	5
17	Far Right	Group	Explosives	Government	13%	8
18	Islamic Extremist	Loner	Explosives	Other	7%	15
19	Islamic Extremist	Group	Explosives	Other	5%	21
20	Islamic Extremist	Loner	Firearms	Military	0%	7
21	Islamic Extremist	Group	Explosives	NGO or Business	0%	7
22	Islamic Extremist	Loner	Explosives	Government	0%	6
23	Islamic Extremist	Loner	Explosives	Military	0%	5

As seen in Table 14 the only difference is the addition of the population density at the county-level. In this instance, the dominant case configurations only contained high population densities. While this might present as an issue, by including one contextual variable, it changed many of the profiles when examining the number of incidents associated with each profile. For instance, lone environmental extremists with other/unknown weapon targeting an NGO or Business is successful 88% of the time with a total 26 incidents sharing this description (see ID 6). Once accounting for county-level population density, the number of incidents decreases to 20 for this profile (see ID 4), the likelihood of success actually increases to 95%.

Table 14. ATS Dominant Case Configurations Including County Population Density of Terrorism Success

ID	Ideology	Loner/Group	Weapon	Target	Pop. Density County	Success %	# Incidents
1	Environmental	Loner	Other/Unknown	Private Property/ Citizen	High	100%	8
2	Environmental	Unknown	Other/Unknown	NGO or Business	High	100%	7

Table 14. Continued							
3	Environmental	Group	Incendiaries	NGO or Business	High	100%	5
4	Environmental	Loner	Other/Unknown	NGO or Business	High	95%	20
5	Far Right	Group	Incendiaries	Other	High	88%	8
6	Islamic Extremist	Group	Firearms	Military	High	78%	9
7	Far Right	Group	Firearms	Other	High	71%	7
8	Environmental	Loner	Incendiaries	NGO or Business	High	60%	10
9	Far Right	Group	Firearms	Private Property/ Citizen	High	60%	5
10	Islamic Extremist	Group	Explosives	Private Property/ Citizen	High	57%	7
11	Islamic Extremist	Loner	Explosives	Private Property/ Citizen	High	40%	5
12	Far Right	Group	Explosives	Government	High	20%	5
13	Islamic Extremist	Group	Explosives	Other	High	5%	19
14	Islamic Extremist	Loner	Explosives	Other	High	0%	14
15	Islamic Extremist	Loner	Firearms	Military	High	0%	7
16	Islamic Extremist	Group	Explosives	NGO or Business	High	0%	7
17	Islamic Extremist	Loner	Explosives	Government	High	0%	6
18	Islamic Extremist	Loner	Explosives	Military	High	0%	5

Extending from the prior addition of the county-level population density, this approach allows for multiple levels. That is, we also include tract-level population density to distinguish potential variation, such as a less densely populated neighborhood within a highly populated county. Because we include tract-level information, our sample size decreases to the 208 incidents rather than the 296, so cross-table comparisons should be taken with caution. Table 15 highlights this type of variation and consistency from tract to county population density. While there is no low in either contextual variable, there are consistencies from high population density tracts within high densely populated counties.

Table 15. ATS Terrorism Success Dominant Case Configurations Including Tract & County Population Density

ID	Ideology	Loner/Group	Weapon Type	Target Type	Pop. Density Tract	Pop. Density County	Success Likelihood	# Incidents
1	Environmental	Loner	Other/Unknown	NGO or Business	Mod	High	100%	8
2	Far Right	Group	Incendiaries	Other	Mod	High	100%	7
3	Environmental	Unknown	Other/Unknown	NGO or Business	High	High	100%	5
4	Islamic Extremist	Group	Firearms	Military	Mod	High	86%	7
5	Environmental	Loner	Other/Unknown	NGO or Business	High	High	86%	7
6	Environmental	Loner	Incendiaries	NGO or Business	Mod	High	20%	5
7	Islamic Extremist	Group	Explosives	Other	High	High	0%	8
8	Islamic Extremist	Loner	Explosives	Other	High	High	0%	5

VI. Risk Terrain Modeling (RTM)

This section focuses on examining our fifth research question:

> *5) What built, physical environment characteristics contribute to the risk associated with pre-incident and incident activities?*

Background of RTM

Table 16. Prominent Configurations and Likelihood of Terrorism Incident Success

Ideology	Loner	Weapon	Pop Density	Foreign Born	Gini	Vacant Housing	Success Likelihood	# Incidents
Combined Event-Level and County-Level Configurations								
Environmental	Loner	Other	High	High	High	Low	1.00	14
Environmental	Unknown	Other	High	High	High	Low	1.00	6
Far Right	Loner	Other	High	High	Moderate	Low	1.00	5
Far Right	Group	Incendiary	High	Moderate	Moderate	Moderate	1.00	5
Far Right	Group	Firearms	High	High	High	Low	0.80	5
Islamic Extremist	Loner	Explosives	High	High	High	Low	0.29	7
Islamic Extremist	Group	Explosives	High	High	High	Moderate	0.08	12
Islamic Extremist	Loner	Explosives	High	High	Moderate	Low	0.00	5
Islamic Extremist	Group	Explosives	High	High	Moderate	Low	0.00	5
Combined Event-Level and Tract-Level Configurations								
Islamic Extremist	Group	Explosives	High	High	High	Low	0.17	6
Islamic Extremist	Group	Explosives	High	High	High	Moderate	0.00	5

RTM was developed by Joel Caplan and Leslie Kennedy (Caplan & Kennedy, 2016) as a spatial diagnostic technique designed to analyze and identify risk features of a landscape related to outcome events. RTM diagnoses how the environment influences behaviors and is often used for predictive purposes at the micro-level. Aggregate or higher-level analyses could mask variation at places (i.e., micro-level), overlooking variation within communities. We will distinguish between terrorists' pre-incident activities and terrorism incident locations, so we expect that certain places within communities will be riskier than others (i.e., provide greater anonymity, meeting places, access to weapons/equipment). Another focus will be on terrorist incidents, so we will hone our analysis on elements of target vulnerability and attractiveness, as well as other elements that make up structured opportunities for terrorism (e.g., weapon choices and number of offenders).

The presence or absence of certain elements of the environment will be tested to determine how risk factors co-locate in space, creating more conducive behavior settings for pre-incident activities and terrorist incidents to occur. RTM relies on determining the spatial influence that risk factors have on the environment through two processes: proximity and density. A common example in criminological literature is the influence bars have on violent crime; is it being within close proximity to a bar that creates risk for violent crime or is it the density of bars in a small geographical area that creates an increased likelihood for violent crime? When multiple risk factors have overlapping spatial influences, there is an increase in risk. For the purposes of the current study, the increase in risk is associated with expected future preparatory activities and completed terrorist incidents.

The RTM framework utilizes 9 steps to complete an analysis designed to assess risk and is outlined in Table 2 (see Caplan & Kennedy, 2016, p.12). ***Step 1*** is to choose an outcome event; for the current study, this involves the identification of pre-incident activities and terrorist incidents. In ***Step 2***, the study area will be determined by the most recent data available at the address level. Since the ATS is updated daily, we will identify high-risk places at the project start date. ***For Step 3***, the time period of the study will be terrorists' pre-incident and incident activities that occur following the September 11, 2001 terrorist attacks. ***For Step 4***, there is an important distinction when selecting risk factors. Everything we want to include in our RTM might not be available; this is expected based on data availability reflecting measures of interest.

Data reflecting potential risk factors will come from data portals and InfoGroup. RTM requires point level, or address level, data to test the potential relationship between risk factors and the outcome event. This will limit the data we can include specifically in the RTM analysis. With place-based approaches to understanding terrorism events relatively limited, ***Step 5*** requires an exploratory process using conjunctive analysis to understand community characteristics. For instance, the ATS has target categories related to place (e.g., nightclub, church, government building, and others). This will be explored to assist us in building a list of potential risk factors with a RTM framework.

Next, ***Step 6*** necessitates the mapping of spatial influence. Crimes have unique spatial distributions (Andresen & Linning, 2012) and with terrorism being rare, we will need to explore the appropriate spatial influence. ***Step 7*** requires the selection of risk factors through statistical testing to determine relationship and then the significant risk factors are weighted related to the outcome event. In ***Step 8***, each risk factor is given a relative risk value. ***Step 9*** is to combine the separate risk factors spatially (map algebra) to construct a spatial risk assessment with corresponding Relative Risk Scores (RRS). The minimum RRS is 1, so anything greater than one (to the maximum) is interpreted as riskier for experiencing terrorists' pre-incident and incident activities. Again, since this application of RTM differs from extant applications, we expect this process to be exploratory in nature.

Table 17: RTM Steps
1) Choose an outcome event
2) Choose a study area
3) Choose a time period
4) Identify best available risk factors
5) Obtain spatial data
6) Map spatial influence of factors
7) Select model factors
8) Weight model factors
9) Quantitatively combine model factors

**Adapted from Caplan & Kennedy (2016)*

RTM Current Study

Risk Terrain Modeling (RTM), specifically RTMDx, was used to explore the potential ability to diagnose the physical infrastructure of terrorism-related events. RTM is not new to terrorism applications (e.g., Marchment Gill, & Morrison, 2020; Onat, 2019); however, to the researchers' knowledge, the spatial tool has yet to be applied to United States – Domestic Terrorism. This is not too surprising given the rarity of terrorism events compared to other crime types and the limited spatial approaches applied to terrorism related data.

Given the rarity of terrorism related spatial attributes, especially at a micro-level, to achieve statistically significant models, we had to merge different categories to increase our sample. We acknowledge this as a limitation but given the heightened level of offense type, we believe this is an important contribution. As Hagan (2016) discusses in relation to RTM and terrorism specifically, there is a need for a more thorough list of potential risk indicators at the micro-level – moving away from the national and subnational levels. Data at the micro-level (address-level) were obtained from InfoGroup which is now Data Axle. The selection of potential risk factors was determined by the NAICS Description. Depending on the site/city, we included 65 different potential factors since micro-level spatial terrorism research is scant.

Our primary focus was on cities with highest terrorism incident counts with full addresses. The important part here, and we will continue to reiterate, is the full address aspect. Other terrorism-related events exist but with incomplete/partial location information, limiting the ability to be used within RTMDx. Given the event being studied, terrorism, we offer a different type of interpretation of the findings as more traditional crime related RTM approaches.

In relation to the RTMDx parameters, we used similar parameters across sites to remain consistent. We set each factor to be tested up to 4-blocks and tested both proximity and density at half-block increments.

New York City (Manhattan). There were 13 terrorism incidents in New York City, Manhattan borough, New York after September 11, 2001. The 13 incidents were all linked to Islamic Extremists and primarily included some type of explosive/bomb. Only 2 of the 13 incidents were successful and the target type for both was Private Property/Citizen. As seen in Figure 10 the terrorism incident/target locations were all south of Central Park. Interesting to visually identify, there are two areas of Manhattan where the incidents cluster (6 in the northern cluster and 7 in the southern).

Before delving into the RTM results, given the different types of terrorism geodata points, we examined the linkages between incidents, preparatory events, and residential locations when known. We indicate when there is a full-address known versus a general city and state location. Given the limited research on the spatial characteristics of terrorism spatial behaviors, this provides an overview of awareness space beyond the target location in Manhattan.

	Target Type	Residence Location	Preparatory Location	Preparatory Activity Type
Table 18. Manhattan Terrorism Target Types and Preparatory Locations				
1	6901 Transportation	Columbus, Ohio	Rochester, Minnesota*	Other
			Davie, Florida	Materials Acquisition/Storage
			Columbus, Ohio*	Acquisition of Expertise
			New York, New York*	Surveillance / Reconnaissance
2	7563 Private Property / Citizen	Bridgeport, Connecticut*	Matamoras, Pennsylvania*	Materials Acquisition/Storage
			Bridgeport, Connecticut*	Weapons Acquisition/Storage
			Shelton, Connecticut*	Weapons Acquisition/Storage
			New York, New York	Materials Acquisition/Storage & Other
			Ronkonkoma, New York	Materials Acquisition/Storage
3	9731 Transportation	Patchogue, New York	Unknown	
4	9740 NGO / Business	Unknown	Boston, Massachusetts*	Other
			Baltimore, Maryland	Materials Acquisition/Storage
5	10104 Financial	Unknown	Boston, Massachusetts*	Other
			Baltimore, Maryland	Materials Acquisition/Storage
6	10105 Transportation	Unknown	Boston, Massachusetts*	Other
			Baltimore, Maryland	Materials Acquisition/Storage
7	55040 Transportation	Bridgeport, Connecticut*	Shelton, Connecticut*	Weapons Acquisition/Storage
8	55041 NGO / Business	Bridgeport, Connecticut*	Shelton, Connecticut*	Weapons Acquisition/Storage
9	55042 NGO / Business	Bridgeport, Connecticut*	Shelton, Connecticut*	Weapons Acquisition/Storage
10	56221 NGO / Business	Brooklyn, New York	Unknown	
11	56307 Government	Jamaica, New York	Unknown	
12	56534 Private Property / Citizen	Paterson, New Jersey*	Unknown	
13	56564 Private Property / Citizen	Unknown	Unknown	

** Full-Address Known*

The application of RTMDx to these incidents was to identify if we could identify meaningful relationships between the physical infrastructure and the incidents. We explored a number of different types of combinations of business/infrastructure measures available through InfoGroup. Additionally, while traditional RTM applications rely on the average block-length in many circumstances to justify the "place" size, we explored different grid-cell sizes to explore how this would impact the findings.

We first started by including all 65 identified factors from InfoGroup. With this, we examined the factors at two different units of measurement: 1) Standard Value = 1,320ft (1/4 mile) and Place Size = 660ft (1/8 mile). When reducing the number of potential factors included and running combinations of subsets, many other infrastructure factors were significant. The subset RTMs identified many other significant factors such as: historical sites, civil and social organizations, human rights organizations, investment banking, news syndicates, international affairs, labor unions, political organizations, and many others. The significant risk factors were dependent on what was included in the model. It is worth nothing that RTMDx constructs the 'best' fitting model. This could lead to significant risk factors being excluded in the final model based on the BIC value.

Within RTMDx, it is possible to input as many factors as the user sees fit, but this approach also comes at a lack of interpretation. At the same time, with little known about risk of terrorism, exploratory analyses are needed in general to build a foundation. After running numerous combinations of potential factors in RTMDx, a pattern started to emerge when it came to places at-risk. That is, it is not necessarily that significant factors contribute to an increase of terrorism, rather the locations of that type of facility shares a similar micro-environment. Similar places continued to result as being risky places despite the potential risk factors included in the model. While this is a different takeaway from traditional RTM approaches, given the rarity of terrorism, the findings still have relevance. If certain types of businesses are found to share similar spaces as target locations, this could assist in prevention efforts since law enforcement cannot be present 24/7. This would allow for place-based training/resource allocation related to domestic terrorism from a community perspective.

We provide an overview of how we would argue RTMDx results could be used in relation to terrorism based on the physical infrastructure. For instance, we present the results a RTM that tested 29 different risk factors, resulting in two significant factors. Table 19 provides the spatial operationalization and relative risk values for each factor. To ease in the interpretation of this information, being in a place that has densely populated legislative bodies within ¾ of a mile is 29 times riskier. Figure 11 provides a spatial representation of above average risky places for terrorism target locations. Figure 12 limits the risky places to places with risk scores greater than two standard deviations from the mean and also contains prior target location(s).

Given the rarity of domestic terrorism in the United States all together, let alone a specific city, we argue RTM can guide community efforts. Given the broader Department of Homeland Security's See Something, Say Something campaign, directed efforts could target specific places. Keep in mind the risk maps shown and the identified risk factors are just one example. Across multiple models, the results indicated similar places being at-risk similar to the Above Average Risk presented in Figure 11. This information, coupled with NYPD having a Counterterrorism Bureau, could assist in their efforts. Additionally, Figure 13 overlays the tracts in Manhattan that contained *any* terrorism-related events. This could assist in further determining where to concentrate limited resources.

Table 19. RTMDx Results for ¼ RTM NYC Terrorism Incidents

Risk Factor	**Operationalization**	**Spatial Influence**	**Relative Risk Value**
Legislative Bodies	Density	4,620	29.041
Sightseeing – Land	Density	3,300	7.503

Figure 10. ATS Terrorism Incidents in Manhattan, New York with Full Address Available

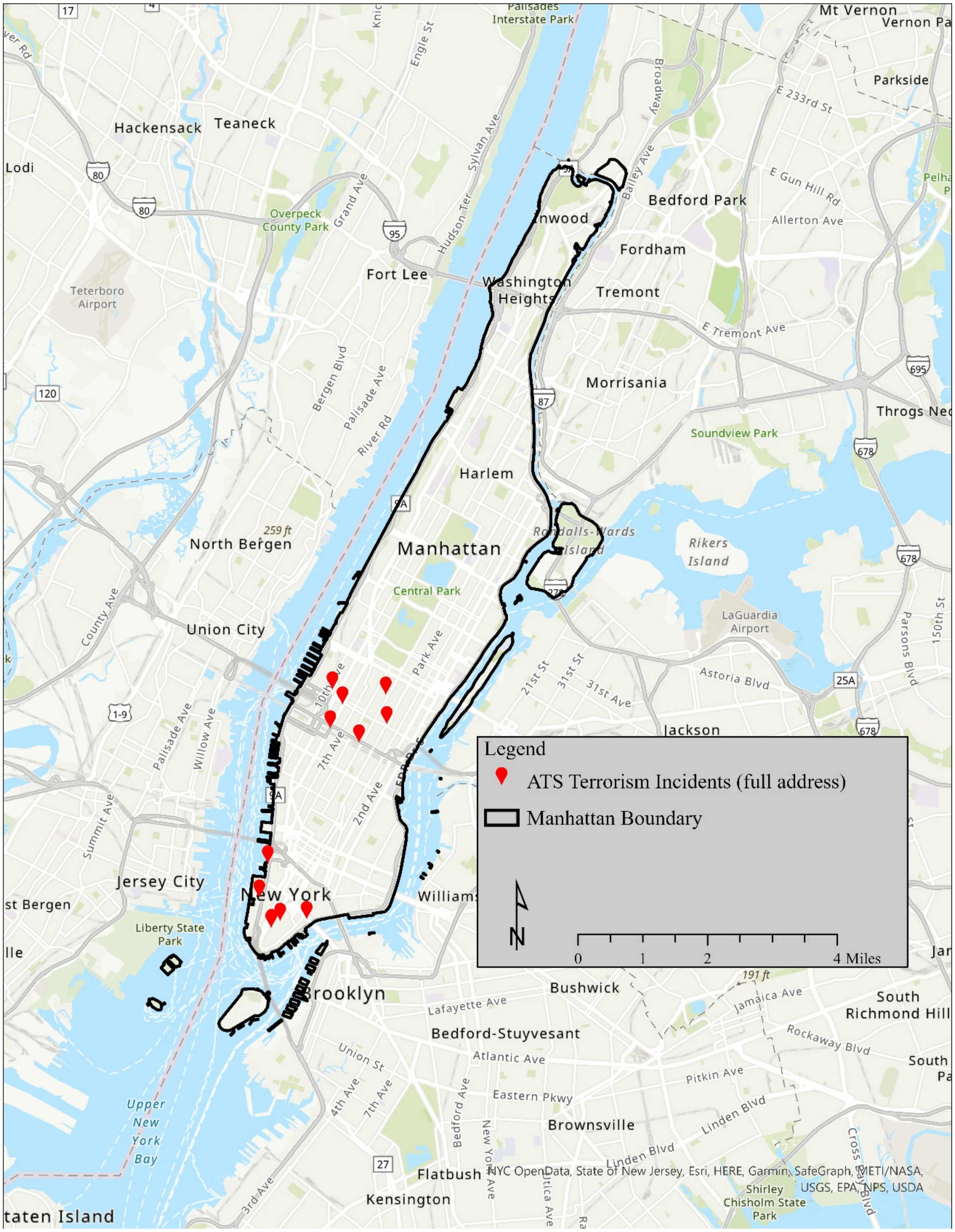


Figure 11. RTMDx Results for ¼ RTM NYC Terrorism Incidents – Above Average Risk

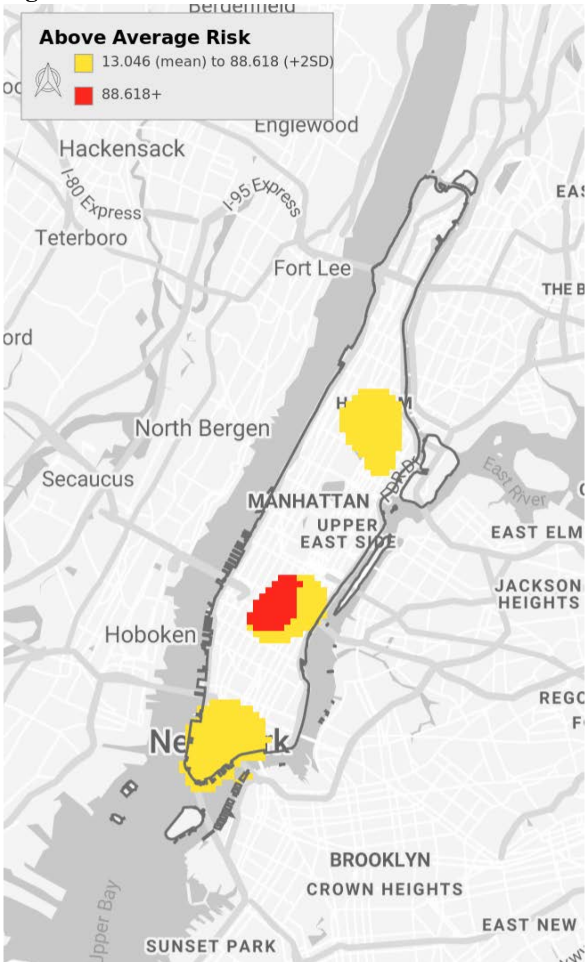
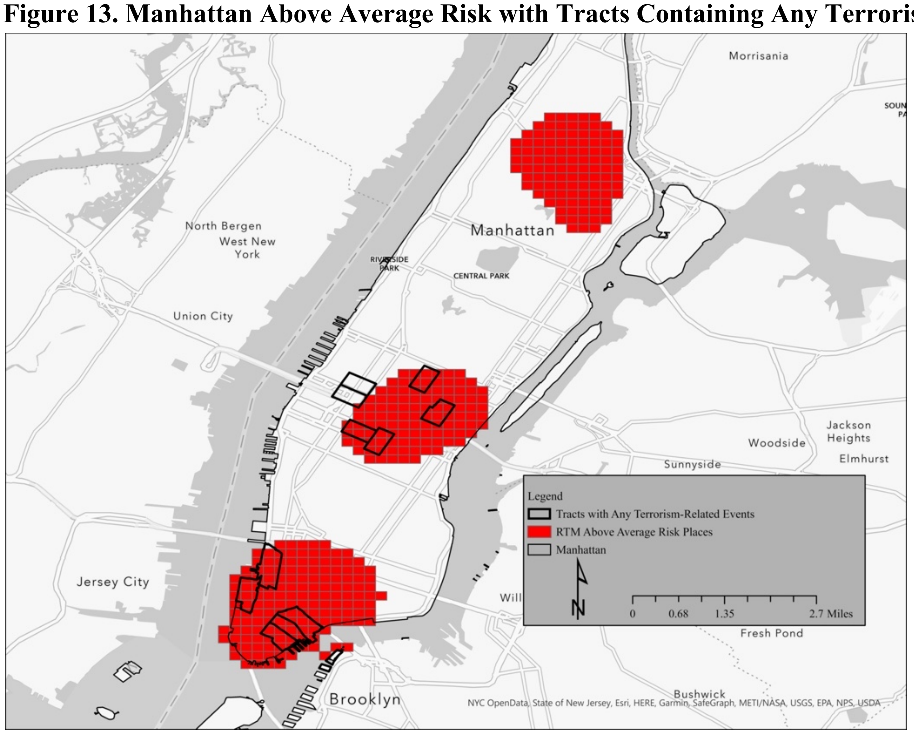


Figure 12. RTMDx Results for ¼ RTM NYC Terrorism Incidents – Priority Places

Figure 13. Manhattan Above Average Risk with Tracts Containing Any Terrorism Overlayed



Oakland, California. The city with the second highest incident counts with full addresses was Oakland, California with 9 incidents. Of the 9 incidents, 1 was Islamic Extremist while the other 8 were Environmental. The 1 Islamic Extremist incident was the *only* unsuccessful incident in Oakland and was the only incident in Oakland relying on explosives. The 8 successful Environmental terrorist incidents primarily relied on equipment sabotage (7) with one incident using a knife or other sharp object – all falling within our "other" category for weapon type given the vandalism linked to these incidents. Figure 14 identifies the target locations in Oakland, California.

We provide linkages based on incident id to preparatory activities and residential locations when known/identified. Duplicate locations were aggregated. For instance, the full address location in Hayward, California had multiple material acquisition/storage and weapons acquisition/storage activities. The Islamic Extremist incident had more known preparatory and residential information than the environmental incidents as seen in Table 19.

Since there were preparatory activities with full addresses in Oakland, we explored how those would potentially change the RTM results since it is a broader terrorism behavior rather than solely incident locations. With that, the two activities were surveillance / recon of the actual target location. This leads to the same address being represented three times rather than a single instance.

Table 19. Oakland Terrorism Target Types and Preparatory Locations

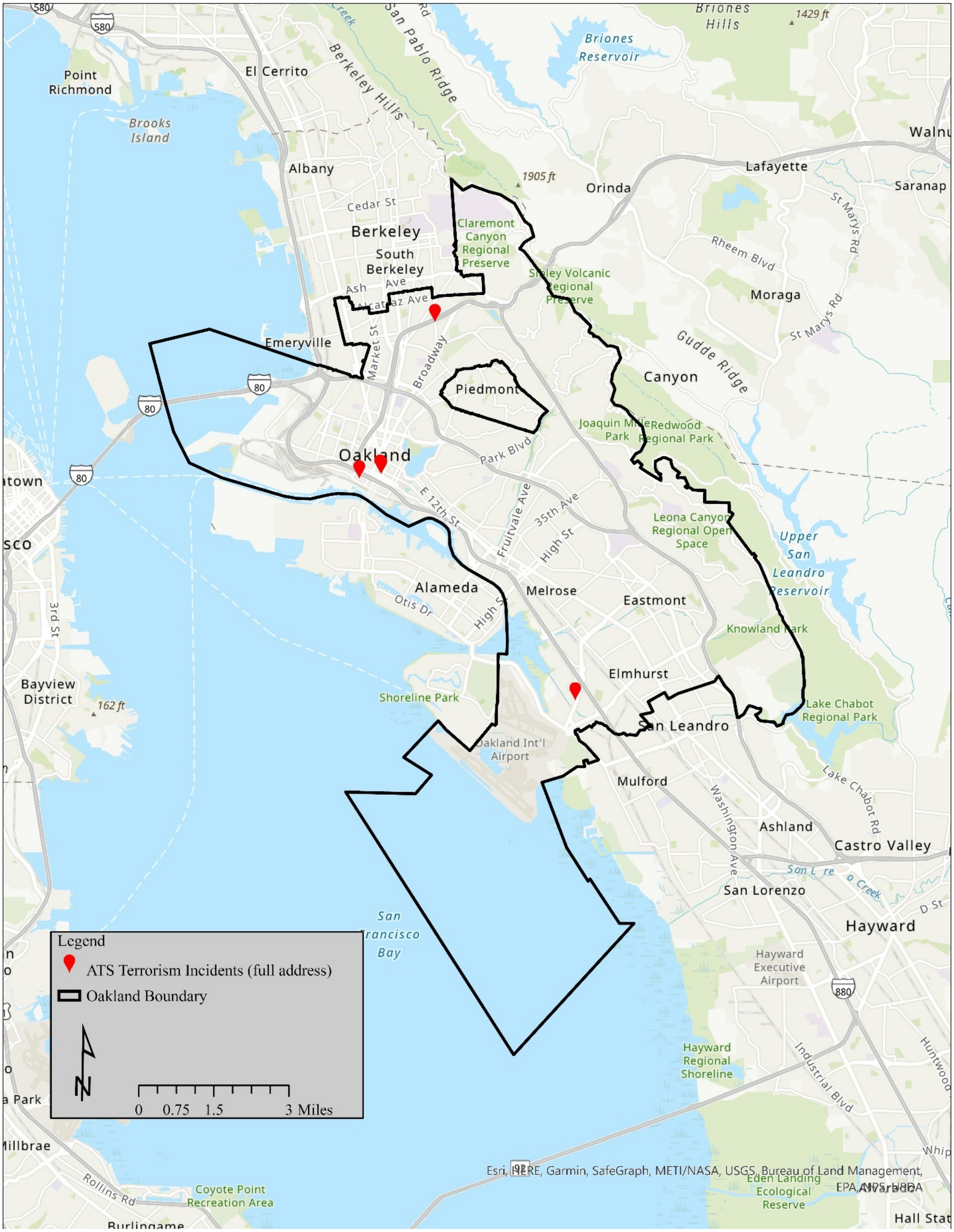
	Target Type	Residence Location	Preparatory Location	Preparatory Activity Type
1	54848 Financial	San Jose, California*	Hayward, California*	Materials Acquisition / Storage & Weapons Acquisition / Storage
			Hayward, California	Other
			Milpitas, California	Materials Acquisition / Storage
			Oakland, California*	Surveillance / Reconnaissance
			Union City, California	Weapons Acquisition / Storage

Table 19. Continued

2	56157 NGO / Business	Oakland, California Escondido, California*	Unknown
3	56158 NGO / Business	Oakland, California Escondido, California*	Unknown
4	56159 NGO / Business	Oakland, California	Unknown
5	56161 NGO / Business	Oakland, California	Unknown
6	56162 NGO / Business	Oakland, California	Unknown
7	56163 NGO / Business	Escondido, California*	Unknown
8	56164 NGO / Business	Escondido, California*	Unknown
9	56165 NGO / Business	Oakland, California Escondido, California*	Unknown

**Full Address Known*

Figure 14. ATS Terrorism Incidents in Oakland, California with Full Address Available



There were 55 different potential factors that were within Oakland. We input these in RTMDx to identify significant risk factors related to terrorism incidents and a combination of terrorism incidents and preparatory activities. When keeping the factors similar across models (testing 30 factors), RTMDx found two risk factors to be significant: 1. Credit Unions and 2. Mortgage & Nonmortgage Loan Brokers. The operationalization and spatial influence were the same across models with differences in the relative risk value (see Table 20). Keep in mind, the preparatory activities included for the Oakland models were surveillance/reconnaissance of the target location. This resulted with two addition geodata points at the target location. This assists in understanding why the relative risk value of credit unions doubled. With the same operationalization and spatial influence, the resulting figures of at-risk places were the same other than the range and descriptive statistics.

Table 20. RTMDx Results for Oakland Terrorism Incidents and Incidents & Preparatory Merged

Risk Factor	Operationalization	Spatial Influence	Relative Risk Value
Oakland Terrorism Incidents			
Credit Unions	Proximity	1,320	97.057
Mortgage & Nonmortgage Loan Brokers	Proximity	3,300	35.502
Oakland Terrorism Incidents & Preparatory Activities Merged			
Credit Unions	Proximity	1,320	200.959
Mortgage & Nonmortgage Loan Brokers	Proximity	3,300	14.708

Figures 15, 16 display the above average risk places for their respective terrorism-related events and Figures 17, 18 provide the priority places. Priority places account for past events, reducing the risky places between the respective figures. This can also be assisted by viewing the incident map with the above average risk, which leads to the priority places (without getting into the analytical side of how they are overlapping).

Similar to Manhattan, when running RTMs with various combinations of factors, many factors were identified as significant. Common ones that were identified in the best fitting models included (outside of the larger models): courts, charter bus, civil & social organizations, and police protections. There were other factors that appeared, dependent on what was included. All models held constant the parameters of a standard value of a quarter mile (1,320ft) and a place size of an eighth of a mile (660ft).

While there was a financial target in Oakland, similar spatial patterns emerged when running different combinations of factors. Although at-risk places are identified through RTMDx, if the significant risk factors of the models presented are rotated out, the new significant factors identify similar places at-risk.

Figure 15. RTMDx Results for 1/4 RTM Oakland Terrorism Incidents – Above Average Risk

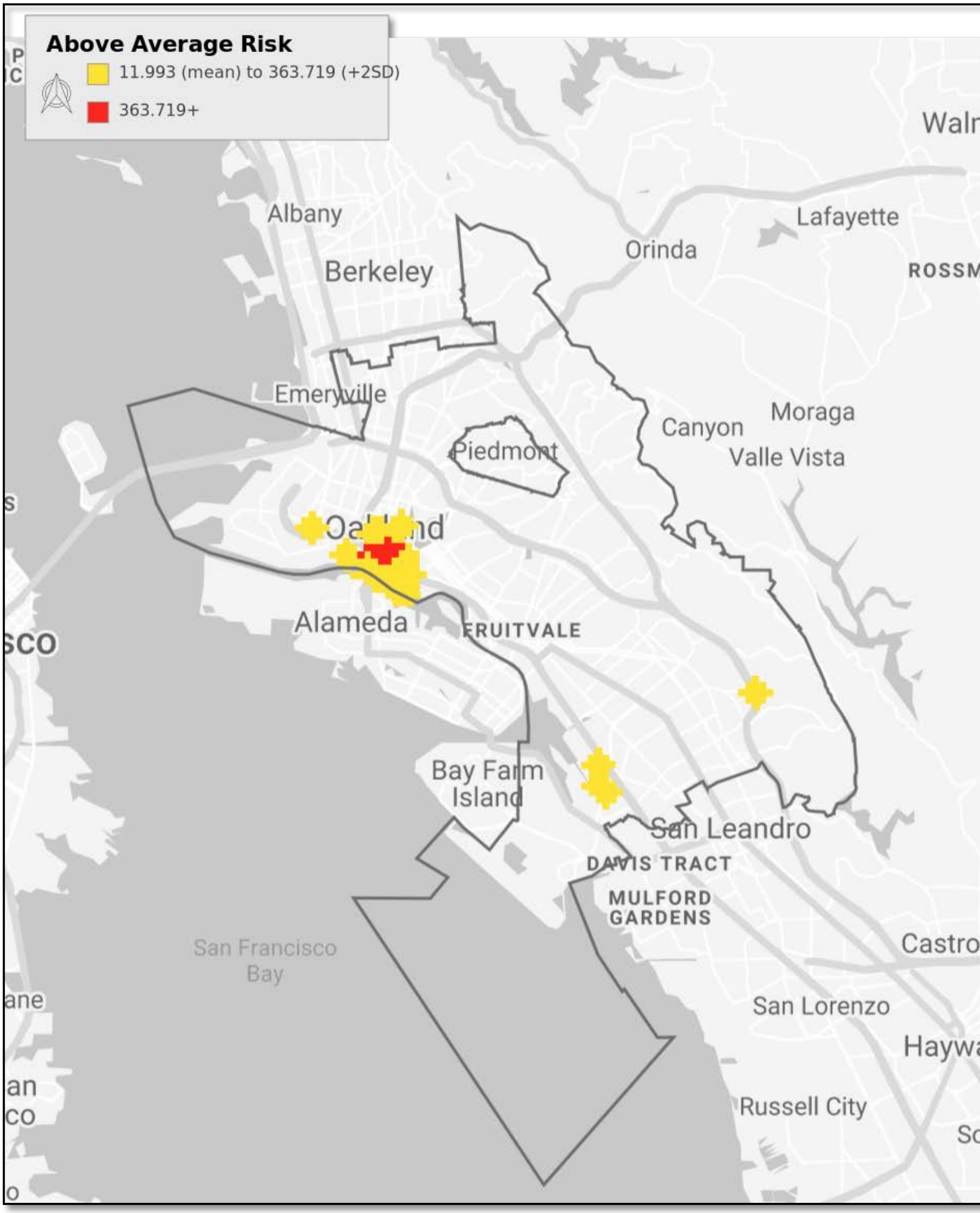


Figure 16. RTMDx Results for 1/4 RTM Oakland Terrorism Incidents & Preparatory Activities – Above Average Risk

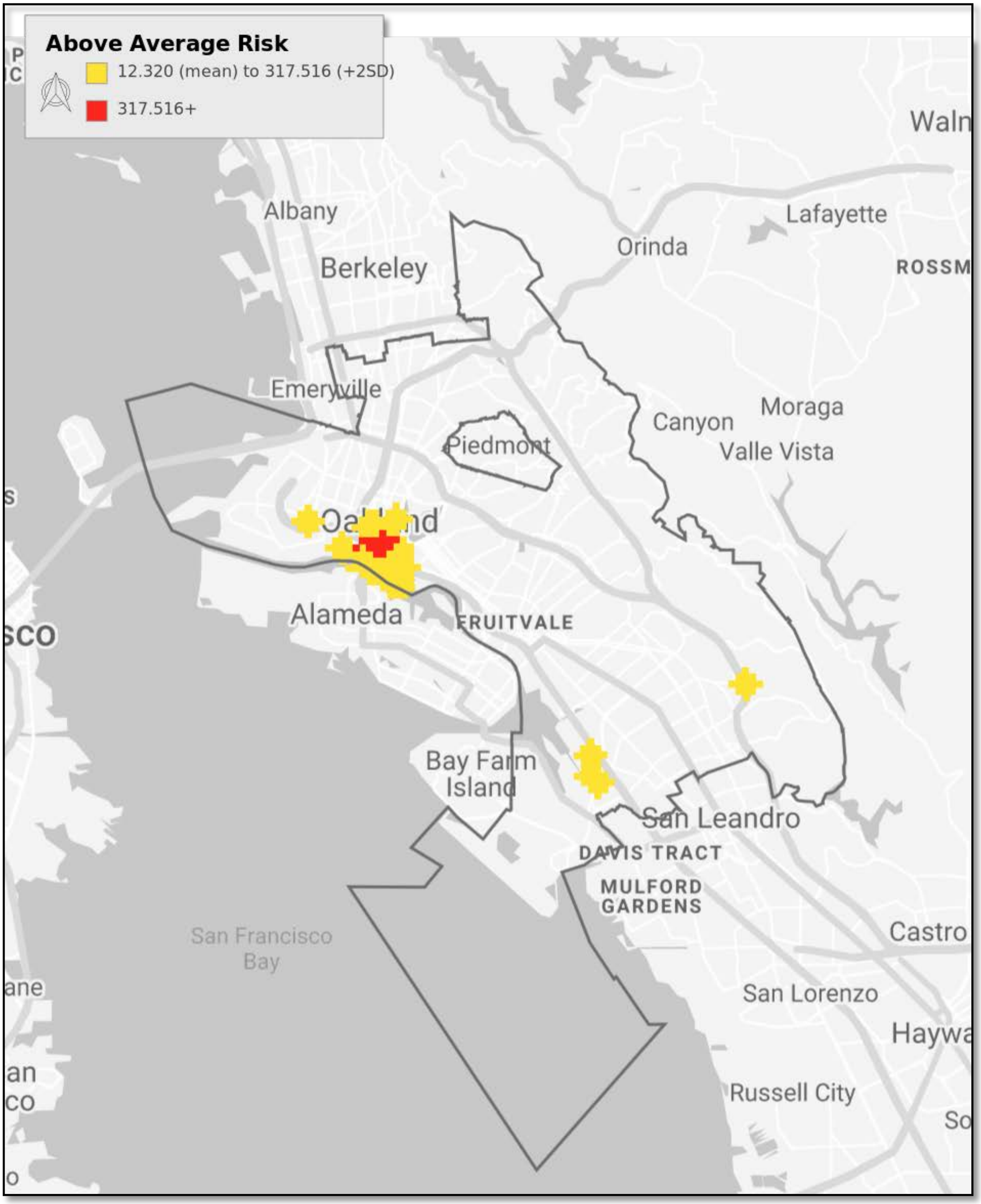


Figure 17. RTMDx Results for 1/4 RTM Oakland Terrorism Incidents – Priority Places

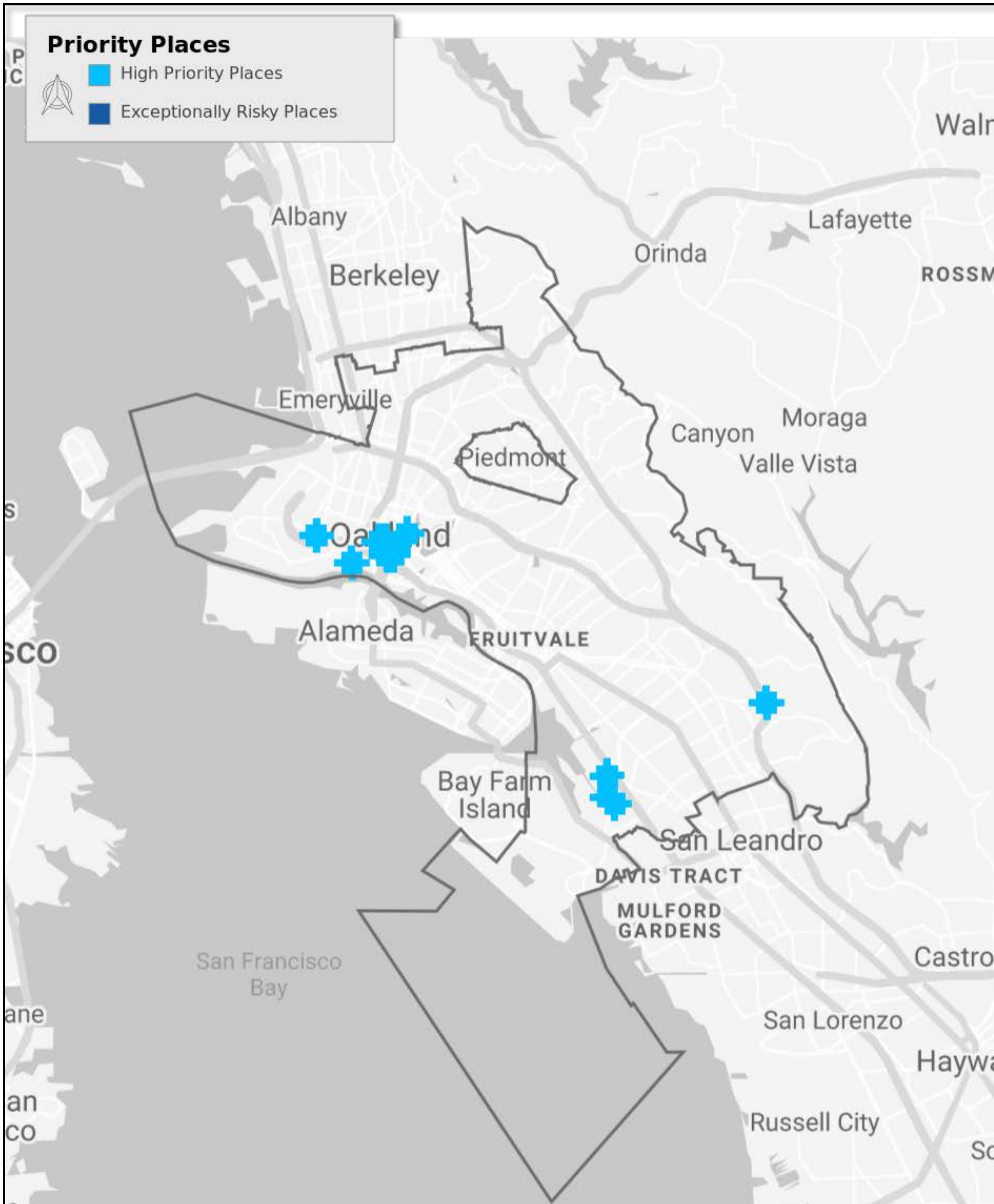
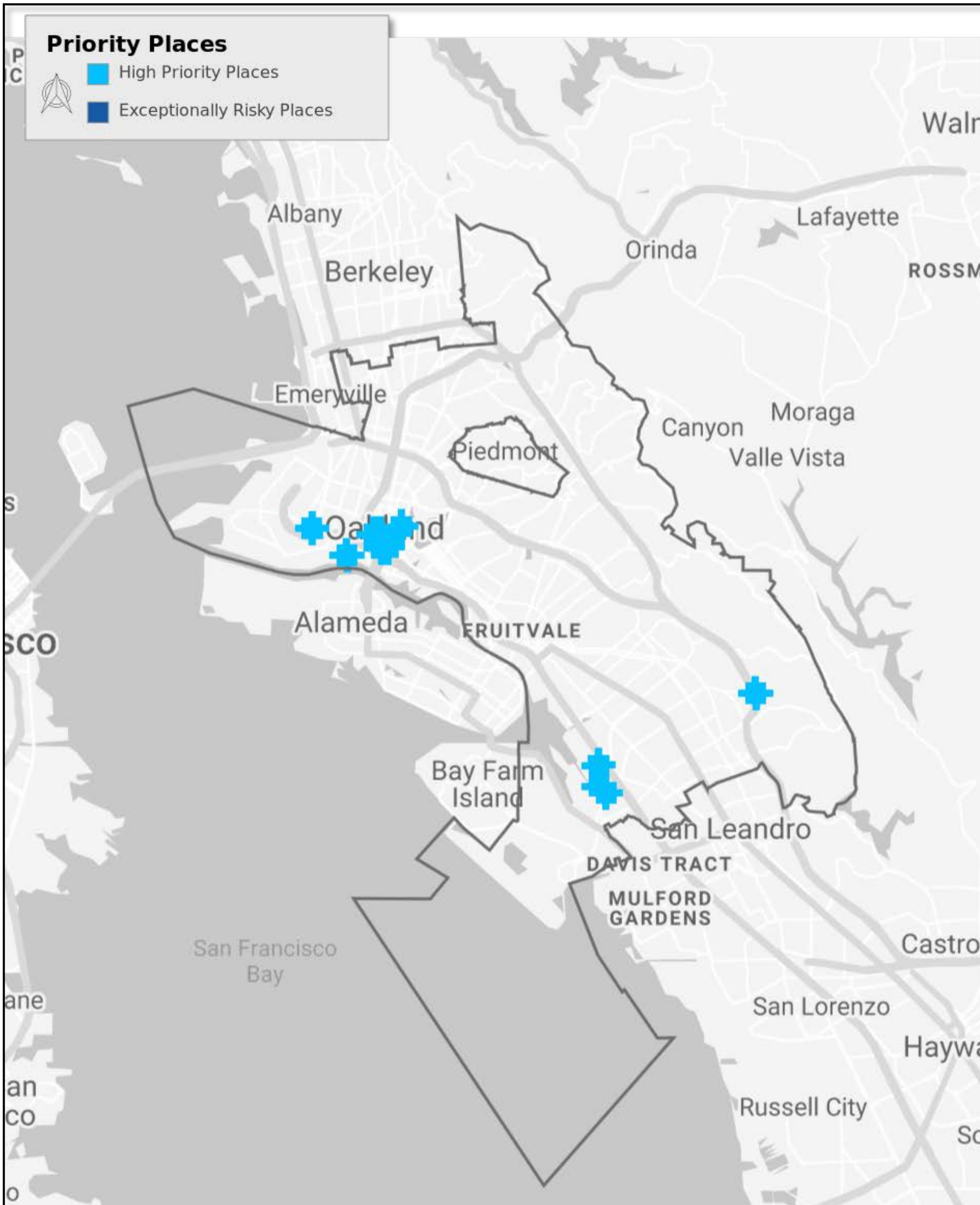


Figure 18. RTMDx Results for 1/4 RTM Oakland Terrorism Incidents & Preparatory Activities – Priority Places



VII. Combining Analytical Approaches

In this last section of our analyses, we focus our attention on the sixth, and final, research question:

> *6) What prominent case configurations (or patterns) emerge when accounting for micro-level places nested within communities?*

Background to Using Multiple Tools

Both conjunctive analysis and RTM can be used as separate analytical tools, but given the overlap of approaches, it is not uncommon to use the two approaches together. For instance, RTM and CACC have been used to examine robbery in Denver, Colorado (Connealy & Piza, 2019), robbery in Glendale, Arizona (Caplan, Kennedy, Barnum, & Piza, 2017), and traffic incidents in Green Bay, Wisconsin (Drawve, Grubb, Steinman, & Belongie, 2019). Most of these applications have been with common crime/public safety issues producing a larger risk map across an entire study area. As indicated in our examples previously, the risk is relatively limited within our two cities.

Now, taking the analysis from above for Manhattan, we are able to identify risky places throughout Manhattan and where risk overlaps with tracts with any known terrorism-related events. Since we are able to identify these tracts overlapping risky places, we can link these back to the social characteristics previously coded for CACC. Table 21 provides an outline of the tracts located in the identified risky areas and joins the social characteristics of those neighborhoods. This provides greater insights into a neighborhood profile that is at-risk within Manhattan.

Table 21. Above Average Risk Tracts (RTM) Social Characteristics from CACC										
	36061031703	36061011500	36061010400	36061010100	36061009200	36061007600	36061003900	36061001502	36061001501	36061000700
Any Terrorism-Related Events	1	1	1	1	5	1	1	1	3	2
Incidents	1	1	1	1	1	1	1	1	2	2
Preparatory	0	0	0	0	4	0	0	0	1	0
Residences	0	0	0	0	0	0	0	0	0	0
Population Density	High	High	High	High	High	High	High	High	High	High
% White	Mod	Low	Mod	Low	Mod	Low	Mod	Mod	Mod	Mod
% Unemployed	Low	Mod	Mod	Mod	Low	Low	Low	Low	Mod	Low
% Less than HS Education	Low	Mod	Low	Low	Low	Low	Low	Low	Mod	Low
% Families Living Below Poverty	Mod	Mod	Mod	Low	Low	Low	Low	Low	Mod	Low
% Same House 1-year ago	Low	Low	Low	Low	Mod	Low	Mod	Low	Low	Low
% Vacant Housing	Mod	High	High	High	High	High	High	High	Mod	Mod
% Foreign Born	High	High	High	High	High	High	Mod	High	High	High
Gini Index	High	High	High	High	High	High	High	Mod	High	High

Given the amount of cities that do not have enough incidents or terrorism-related events to run within RTMDx, we provide an approach that can accomplish similar tasks as the prior joint utility in a different manner. We focus the attention on Washington, D.C. to provide an example of how the neighborhoods experiencing terrorism-related events can still be joined with our datasets to understand the profile of specific neighborhoods and locations.

Washington, D.C. Given the symbolism and prominence of potential targets in Washington, D.C., greater attention could be spent on this site alone. The issue that arises when focusing on specific sites/cities is the often-small count of incidents given the rarity of domestic terrorism. From a RTMDx standpoint, it is recommended to examine a spatial outcome that has at least 10 events so there are enough non-zero cells/units to run the multiple steps of the approach. While there is partial address information known for more incidents in Washington, D.C., only 5 incidents had full addresses (e.g., street/block). Instead of introducing potential human error or uncertainty based on street centroid (I.e., has not been tested with RTMDx), we provide an overview of how similar factors from the social environment and physical infrastructure could be used jointly.

That is, we provide neighborhood profiles of the three tracts the five incidents occurred in within Washington, D.C. This same approach could be applied to any tract. Similar to how we use conjunctive analysis, we include the factors at the neighborhood-level to gain a count of each physical infrastructure factor type per neighborhood. By doing so, we can identify what is present/absent from the neighborhood. Figure 19 identifies the three tracts within Washington, D.C. containing the given incidents. For those familiar with D.C., these neighborhoods, especially tract 11001006202, contain numerous federal buildings, such as the White House.

Greater context is found for these neighborhoods when examining the social characteristics and physical infrastructure. Continuing with tract 006202, socially, the neighborhood has low population density, low unemployment, low percentage of population with less than high school education, low percentage of being in the same house 1 year ago, low household vacancy, and low percentage of foreign-born population. This neighborhood is high in percent White population. Given the location of this neighborhood, these findings make sense at face value. Beneficial to these social characteristics is the linking of the physical infrastructure of the neighborhood. Legislative bodies are common in this neighborhood, comprising 39 of the 67 facilities located in the neighborhood (58%). Not surprising given the focus on D.C., the three incidents in this neighborhood were all government targets.

Figure 19. Washington, D.C. Tracts Containing Terrorism Incidents

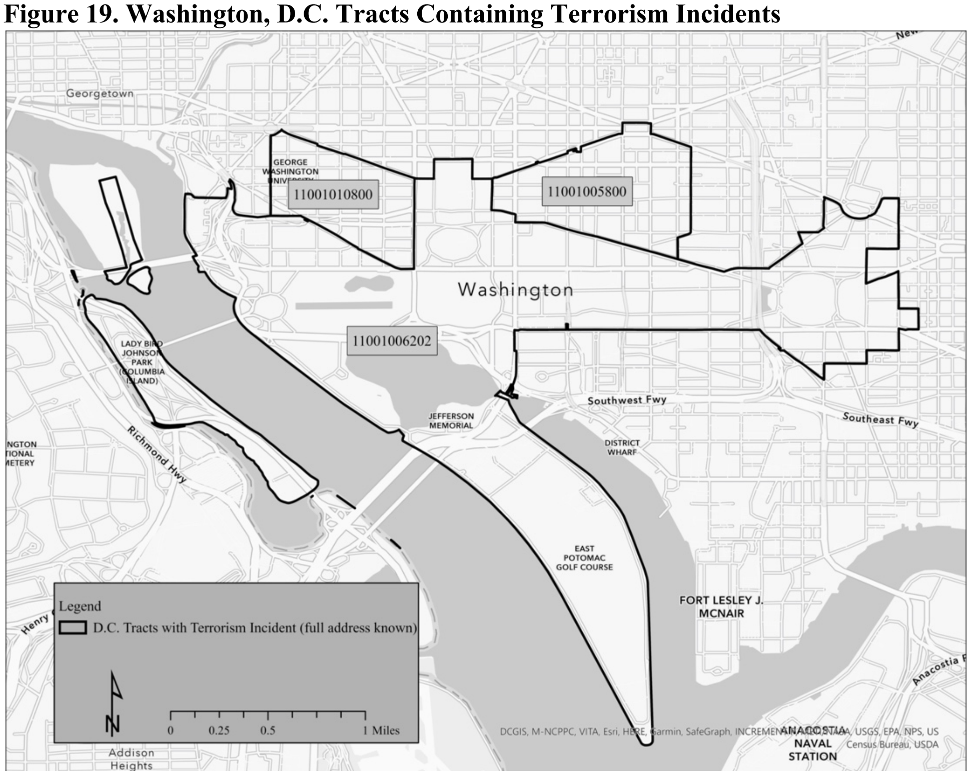


Table 22. Washington D.C. Tract Profiles Containing Terrorism Incidents

	11001005800	11001006202	11001010800
Number of Incidents	1	3	1
Social Characteristics (2016 ACS 5-year Estimates)			
Population Density	High	Low	High
% White	Mod	High	Mod
% Unemployed	Mod	Low	Mod
% Less than HS	Mod	Low	Low
% Families Below Poverty Line	Mod	--	High
% Same House 1 year	Low	Low	Low
% Vacant	High	Low	High
% Foreign Born	High	Low	Mod
Gini Index	Mod	--	High
Physical Infrastructure (InfoGroup 2017 – NAICS Descriptions)			
Total Number Facilities	315	67	81
Beer, wine, & liquor stores	4	--	2
Bowling	1	--	--
Civil & Social Orgs.	15	1	7
Collection Agency	--	--	1
College, University, & Professional Schools	7	1	14
Commercial Banking	85	2	20
Consumer Lending	3	--	--
Courts	1	--	--
Credit Unions	6	1	4
Environment, Conservation, and Wildlife Orgs.	3	1	--
Fitness and Rec/Sports Centers	8	1	1
General Medical and Surgical Hospitals	1	--	1
Gift, Novelty, and Souvenir Stores	11	3	--
Golf Course and Country Clubs	--	2	--
Historical Sites	--	1	--
Human Rights Orgs.	9	1	2
International Affairs	3	--	1
Interurban and Rural Bus Transportation	2	--	1
Investment Banking and Securities	3	--	1
Junior College	1	--	--
Labor Unions and Similar Orgs.	5	--	1
Language Schools	2	--	--
Legislative Bodies	31	39	3
Libraries and Archives	11	1	2
Limited-Service Restaurants	8	--	1

Table 22. Continued			
Medical Laboratories	--	--	2
Museums	17	3	6
National Security	1	--	--
Nature Parks and Other Similar Institutions	1	5	--
News Syndicates	4	--	--
Newspaper Publishers	3	--	--
Other Gasoline Stations	13	--	1
Petroleum Refinery	2	1	--
Police Protection	3	--	1
Political Organizations	13	1	--
Postal Service	1	1	1
Psychiatric and Substance Abuse Hospitals	--	--	2
Religious Orgs.	21	--	4
Scenic and Sightseeing Transportation - Water	2	1	--
Scheduled Passenger Air Transportation	3	--	--
Securities and Commodity Exchanges	2	--	--
Securities Brokerage	--	--	1
Sports and Recreation Instruction	1	--	--
Temporary Shelters	--	--	1
Theater companies and Dinner Theaters	8	--	--
Tour Operators	--	2	--

VIII. Implications for Policy and Practice

Overall, we are able to identify spatial patterns of terrorism-related events across the U.S. at multiple geographical units. In about 19 years, there were 296 domestic terrorism events, averaging to about 10 events a year, that we were able to include in our analysis. We bring this point up to help realize the rarity of domestic terror events. For instance, if we take the 2016 FBI Crime Clock numbers for murder, 1 every 30.6 minutes, there are about 47 murders per day in the US (30.6 / 1,440). In one week (47 * 7 = 329), there are more murders in the U.S. than there have been domestic terrorism incidents in 19 years. This is important to understand when trying to contextualize our findings.

We were able to identify that terrorism-related events are not equally spatially distributed across the U.S. at the State, County, and Tract levels. Because of this, law enforcement agencies could use the findings to inform the allocation of limited resources. As Pelfrey (2007) discusses, prevention and response to terrorism are two different concepts and each are associated with specific training needs, costs associated with them, and varying planning needs. From a prevention standpoint, law enforcement can only do so much on their side leading to response preparedness.

Terrorism-related behaviors are embedded within communities and places, indicating the necessity of law enforcement to develop and sustain reciprocal relationships. Community and place approaches to crime prevention is nothing new to law enforcement agencies. With a focus on terrorism-related events, Conjunctive Analysis assists in identifying community characteristics related to risk of terrorism-related events, while Risk Terrain Modeling can identify relevant businesses and attributes of physical infrastructures. We suggest that law enforcement could benefit from connecting these two types of information to inform their prevention efforts. That is, this information could be used in law enforcement training and spreading awareness to place managers (see Eck, 2015) of those facilities located in especially risky communities.

Community members and place managers become the social control mechanism when police are not present. As we found in the current study, certain locations have a disproportionate number of events. In Aurora, Colorado for instance, there were 23 preparatory activities with full-address information but these 23 activities occurred at 4 distinct locations. These start to resemble hotpoints (see Ratcliffe, 2004) for terrorism-related events that are often times not known until after the fact (I.e. a response). Building trust and cooperation within the communities and at certain places could assist in moving from reactive to proactive. In combination, conjunctive analysis and RTM can be used to direct efforts to specific communities and places by providing the law enforcement and intelligence community with novel methods to diagnose, anticipate, and respond to localized sets of risks.

Given the approaches used in our current study, in pair with the rarity of terrorism, we argue that conjunctive analysis could be better suited to assist with understanding what factors related to risk for terrorism-related events. The ability to examine profiles, be it county-level or neighborhoods, provides valuable insights into how prevention efforts could be developed and preparedness protocols. We are able to demonstrate the interplay between the physical infrastructure and social characteristics of neighborhoods throughout the United States experiencing terrorism-related events.

When exploring the utility of an RTM approach to terrorism, we focused on identifying it if was possible to construct risk models and what factors were associated with increased risk. We were able to identify risky places for terrorism target locations; however, we are not able to assess the predictive power of these models. The good and bad of this is that we are reliant on future terrorist events to evaluate our model. Given the rarity of terrorism events within specific locations, this could take time before it is possible to gain statistical power.

RTM provides an analytic framework to identify environmental factors that create vulnerability to future events, such as terrorism. The flexibility of this approach is evident in its ability to combine multiple datasets for a full study of terrorism-related events and locational preferences of activities to terrorism. The insights produced take us a long way forward in building prevention strategies to curtail these attacks. It is important to note that with RTM we are extending beyond an analysis that focuses specifically on the hot spots of events in one time period to one that takes place over time and over situations and environmental contexts that are conducive to terrorism events and their precursors.

Overall, we are able to identify that place does matter for terrorism-related events in the United States. We linked event characteristics and neighborhood/county characteristics to determine how those align with potential success. By understanding profiles related to successful and unsuccessful terrorism incidents, we can take what we know and prepare for the future. Inevitably, there will be future terrorism incidents that necessitate both prevention and responses.