

Terrorism Risk Forecasting by Ideology

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Abstract The purpose of the present study is to produce foresights on terrorism. For the first time in the literature, we test the predictive validity of risk terrain modeling to forecast terrorism. Because the relevant literature suggests that target selection and the places where terrorist attacks occur are related to a group's strategies, we also investigate whether and how violent terrorist acts vary with respect to their surroundings in the same jurisdiction when the ideology is the point of comparison. Separatist and leftist terrorist groups committed 1152 violent terrorist acts between 2008 and 2012 in Istanbul, Turkey. Our analysis begins with a comparison of targets and risk factors by the ideology of the perpetrators for 857 separatist and 295 leftist terrorist incidents. After identifying high-risk locations, we test the predictive validity of risk terrain modeling. The study results showed that context and spatial influence—the risky areas of terrorism—vary by the nature of the ideology in the jurisdiction. Practical implications also are discussed.

Keywords Terrorism · Risk-forecasting · Geography · Ideology · Target

Introduction

The Role of Location in Terrorism

Terrorist acts have been dramatically ubiquitous in major urban areas of the world. While larger cities contain a juxtaposition of wealth and misery or tourism and terrorism (Savitch and

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Ardashev 2001), it is relatively unpredictable who could be the next victim when political violence targets a particular location. For example, large cities are relatively static entities over time, and the geography is both a backdrop for and a constraint on terrorists. Some urban areas, however, are target-prone simply because of variations in physical design.

In the same vein, location is among the factors for terrorists to consider before putting their plans into action. For terrorists resorting to political violence, numerous major cities have iconic features that are of symbolic value to a city, region or country. Such settings also shelter vital targets that are key to the day-to-day operation of a community (Brandt and Sandler 2010; Berrebi and Lakdawala 2007; Ekici et al. 2008). For example, Kliot and Charney (2006) reported that 119 suicide attacks targeted or occurred around markets, shops, places of entertainment (e.g., bars and pubs, restaurants, fashionable coffee shops) and shopping malls in Israel between 1994 and 2005. Likewise, Gruenewald et al. (2015) examined terrorist attacks by environmental and animal-rights extremists in the United States between 1987 and 2012 and found that nearly 74% of the targets were buildings of nongovernmental organizations (NGOs) or businesses. However, even when military and governmental entities are targeted, members of the public can be injured or killed (Braithwaite and Johnson 2012). Regardless, the coexisting features of occupied places in cities make some locations more risky than others. The physical design of an urban setting, therefore, makes it possible to forecast the risk of terrorism in terms of geography.

Although space plays an important role in the occurrence of terrorism, Bahgat and Medina (2013) has argued that the geographical aspect of terrorism needs further study in existing literature. Also lacking in the literature are empirical investigations of the relationship between location and political violence at the geographically micro level (LaFree and Bersani 2014; Onat 2016; Wormeli 2014). Past studies on the spatial aspect of terrorism mostly used larger units of analysis at the country or city level (Behlendorf et al. 2012; Blomberg et al. 2011; Findley et al. 2015; LaFree et al. 2012; Nemeth et al. 2014; Savitch and Ardashev 2001). Analyses of micro geographies focused on the network of energy infrastructure (e.g., a waterline) on a campus (Patterson and Apostolakis 2007), suicide bombings in a city (Brown et al. 2004; Schmidt et al. 2007), improvised-explosive-device attacks (Johnson and Braithwaite 2009; Townsley et al. 2008) and the distance between the locations of the attack and the terrorist-cell site (Rossmo and Harries, 2011). One limitation of these studies is that the researchers generally conducted event-dependent analyses to retrospectively examine the locations where attacks occurred. Therefore, a context-dependent approach has rarely, if at all, been applied to terrorism. That is, the current literature has not addressed the association of terrorist behavior (e.g., bombing) with the surrounding physical features (e.g., bars or restaurants) to the same extent as traditional crimes (e.g., robbery) have been explored (Onat 2016).

Unlike most street crimes, terrorist acts are committed in concert with others who have similar goals and motives. In this respect, terrorism differs from traditional crimes, as ideology plays a key role in the foundation, recruitment, strategies, and acts of terrorist groups. Four ideological categories have been commonly used to group terrorist organizations; left wing, ethnonationalist/separatist, religious, and right wing groups (Drake 1998; Jones and Libicki 2008; Piazza 2009). Terrorist operations are bound by ideology, and that ideology interacts with the group's targeting strategies (Blomberg et al. 2011; Drake 1998). At the country level, terrorist ideology is viewed as the antecedent of where a particular terrorist group targets an attack (Blomberg et al. 2011; Clauset and Gleditsch 2012). In the same vein, Anarumo et al. (2011) suggested that the risk of a subsequent attack would be different for each terrorist

group. Drake (1998), for instance, suggested that the Provisional Irish Republican Army professed that its primary targets in the 1970s were the security forces and economic buildings such as shops and offices (p. 62).

Intuitively, terrorists have always added geography into the equation to make a rational choice of their attacks, and the choice-making is ideology-dependent. Based on a review of the literature, however, no attempt has been made to explore how the ideology and spatial risk of terrorism interact in the same jurisdiction. In one study, Behlendorf et al. (2012) compared terrorist attacks of a separatist group (ETA-Euskadi ta Askatasuna, or Basque Homeland and Freedom) to a leftist terrorist organization (FMLN- Farabundo Martí para la Liberación Nacional, or National Liberation Front) in Spain and El-Salvador, respectively. They reported that the groups' strategies were substantially associated with the location of their acts and that the attacks were significantly clustered in the two different geographical areas. Unlike the FMLN, the ETA targeted provincial/regional capital cities. Furthermore, the FMLN prioritized military and diplomatic targets in its attacks; a similar significant association with the ETA's incidents was not found. The study, however, was limited in three aspects. First, it could not examine geographic units smaller than cities. Second, the analysis compared two different ideologies in two separate countries. Third, the scholars did not investigate the context-dependent and dynamic nature of terrorism by adding more spatial variables such as non-residential features in the cities; instead, they suggested the use of risk terrain modeling (RTM) to explore the relationship between terrorism, ideology, and geography.

Using a prospective forecasting methodology, the current study attempted to predict risk of terrorism and the interaction of ideology with risk, which has been a neglected topic in geographic research at the micro level. The analyses measured risk and tested the validity of forecasting to understand where terrorism occurs and remains endemic in Istanbul, Turkey.

Terrorism Risk Forecasting by Geographic Features

The built environment and human behavior are interdependent. Hence, a plausible risk assessment requires one to include opportunities that exist in a particular environment. The physical characteristics of a neighborhood or a city influence how land users socialize with others. For example, the presence of a stadium in a neighborhood is an opportunity for a leisure activity, but it also facilitates crimes such as pickpocketing or vandalism (Madensen and Eck 2008). At the macro level, various elements of a place are related to crime, and the clustering of these factors forms the "environmental backcloth" that influences the flow of both targets and offenders, resulting in an increased risk for crime and the emergence of hot-spot areas (Brantingham et al. 2009). As with traditional crimes, an urban layout influences the occurrence of terrorism (Onat 2016).

Empirical testing of the abovementioned theoretical propositions is possible with RTM, an analytical tool that uses a geographic information system (GIS) to study the features of an area's infrastructure. That information is used to understand the environmental contexts where crimes are clustered. More broadly, RTM probes whether places with concentrations of crime also have common patterns of infrastructure (e.g., government buildings or hotels). Then, it tests the significance of spatial association with respect to crime and different layers of infrastructure (Caplan et al. 2011; Caplan et al. 2013). When all significant layers are combined, the risk becomes a high probability of occurrence of crime in a particular location where these patterns exist. Although RTM is mainly interested in forecasting crime in space and time, the model enables one to identify risk values of a crime for particular spatial units,

which are the measure of a place's potential for an event of some sort to occur by taking landscape features into account, making a more accurate analysis possible (Kennedy et al. 2011).

Findings from empirical studies in different parts of the world have suggested that crime and terrorism alike concentrate in space. Over the last several decades, terrorists have targeted various features and places on a landscape, but the targets have some commonalities in different countries for different terrorist organizations. Recent empirical research has shown that terrorists attack governmental buildings (e.g., city halls, police-military facilities or court houses), banks, religious facilities (synagogues, churches or mosques), business facilities (stores, supermarkets or restaurants), political party buildings, NGOs, health facilities, diplomatic entities, media offices, and recreational spaces (Ekici et al. 2008; Gruenewald et al. 2015; Kliot and Charney 2006; Libicki et al. 2007; Nunn 2007; Ozer and Akbas 2011; Savitch 2014; Webb and Cutter 2009).¹ When all these nonresidential features co-locate in an area, the risk of terrorist activity is considerably increased.

In sum, terrorists stage their acts on a landscape with its diverse built environment. At the aggregate level, the incidence of terrorism is not random in space. A group's ideology also matters in terms of where attacks will cluster in a jurisdiction. For both practitioners and researchers, a micro-level analysis is more informative if the goal is to prevent the next attack. A pattern analysis of locations of terrorism, including the features of the surrounding environment, can help forecast where the next attacks will occur. Taking the built environment into account, RTM enables one to predict the risk of attack at the micro level. However, few terrorism studies (Rusnak et al. 2012; Onat 2016) benefited from this innovative method in the past. Therefore, the current research uses RTM to forecast overall terrorism risk and the varying spatial correlates by different ideologies in Istanbul, moving the literature forward in two ways. First, the predictive validity of RTM in terrorism is tested for the first time. Second, the study evaluates the way spatial risk factors of terrorist activity vary by ideology.

Research Questions

This study addresses the extent to which physical features across the landscape enhance the likelihood of terrorism, considers the importance of a terrorist group's ideology in this relationship and then tests how valid the risk forecast is for future terrorist attacks. The following questions were posed:

- 1) Do physical features targeted by terrorist organizations differ by ideology?
- 2) Are there key environmental features which increase the general risk of terrorist activity within Istanbul?
- 3) Do differences in ideology change the significance of the nonresidential environmental features used as predictors for the terrorism forecast?
- 4) How well does RTM predict locations of terrorist attacks?

¹ Also, the symbolic value of the targets has been important for terrorists, and one of the well-known rating methods was proposed by Clarke and Newman (2006) to predict what terrorists can target. Several studies benefited from Clarke and Newman's method to rate a number of physical features for the likelihood of being targeted in the city. The RTM analysis, on the other hand, is applicable to all places in a study area, though the symbolic nature of a particular feature is not weighted.

Data and Methods

Research Setting

The study area is the jurisdiction of Turkey's Istanbul Police Department (IPD).² Istanbul is one of two cities in the country that geographically connects two continents: Europe and Asia. Turkey's strategically distinct location has implications for security issues. The country has been struggling with different extremist ideologies against its democratic regime for many years and has been exposed to the activities of terrorist organizations operating on the basis of extreme leftist, rightist, religious, and separatist ideologies since the 1960s (Bal and Laciner 2001). The exposure to terrorism by different groups has amplified the violence in major cities. As the largest urban area in the country, Istanbul has been a hot spot for terrorism similar to New York, London, Paris, Mumbai, and Moscow (Savitch 2014).

Dependent Variable: Terrorism

The current research aims to forecast the spatial risk of terrorism, which refers to a combination of the location of terrorist incidents and the features of the physical landscape in the surrounding environment. Before starting the risk analysis, it is important to explain how a criminal act is deemed a terrorist incident. The legal definition of terrorism in the domestic law is used.³ Essentially, the definition refers to the unlawful use of force for social and political objectives, though a nonviolent criminal act can be terrorism when committed for a terrorist organization. In the current study, the concept of incidence of terrorism is defined as "the incident of violent acts that a designated terrorist organization committed; and that was investigated by the counter-terrorism unit of the IPD."⁴

² Police are responsible for the safety of urban and suburban cities of Turkey while the gendarmerie serves in the rural areas. The current study examined the terrorist incidents within the boundaries of the IPD area of responsibility.

³ According to the Article 1 of Law No: 3713 (Anti-Terror Law in Turkey 1991), the definition of *terror* is described as follows: "The terror is an act, by using force and violence, perpetrated by any of the methods of extortion, intimidation, discouragement, menace and threat by a person or by persons belonging to an organization with a view of changing the nature of the Republic as defined in its Constitution and its political, legal, social, secular and economic order, impairing the indispensable integrity of the State with its country and nation, endangering the existence of the Turkish State and Republic, weakening or annihilating or overtaking the state authority, eliminating the basic rights and freedoms and damaging the internal and external safety, public order or general health of the country." For an act to be considered as a terrorist incident, the crimes stated in Article 4 of the Turkish Anti-Terror Act have to be committed with the intentions cited in Article 1. Accordingly, Article 4 of the Turkish Anti-Terror Act articulates that the offenses described in the different articles of Turkish Penal Code "shall be considered as terrorist offenses if they have been committed for the purposes described in Article 1 under the scope of the activities of a terrorist organization established with the purpose of committing crimes." For example, a defendant would be accused of violating the Anti-Terror Act if the person committed a burglary to provide monetary support to the operations of a terrorist group.

⁴ Most recent empirical research on the spatial aspect of terrorism have used different specific acts together to construct a dependent variable of terrorism (Baudains et al. 2012; Cothren et al. 2008; LaFree et al. 2012; LaFree and Bersani, 2014; Nemeth et al. 2014). For example, Nemeth et al. (2014) based their construct on five criteria: "the attacks are intentional; involve the use, or threatened use, of violence; and the perpetrating actors are subnational; the act must be directed towards a political, economic, religious, or social goal; there must be evidence of intent to coerce; and the action must be outside the realm of legitimate military activities." (p.308). To explore spatial and temporal patterns of terrorism, LaFree et al. 2012 used 1993 terrorist attacks attributed to the ETA from 1970 to 2007, and the data from GTD also include unarmed assaults and attacks to facilities or infrastructure. The spatio-temporal patterns were also examined with terrorist incidents that were designated by a law enforcement agency (see Cothren et al. 2008).

Data were gathered from the Turkish National Police (TNP) and from media reports. The TNP data had three categories of terrorism ideology: right-wing, left-wing, and separatist. The current research was focused mainly on the acts of left-wing and separatist terrorist organizations since the right-wing groups committed only one attack over the study period. While the separatist group is the PKK (Kurdistan Workers Party), the extremist left-wing groups are DHKP/C (Revolutionary People's Party/ Front), TIKB (Revolutionary Communist Union of Turkey), TKP/ML (Turkish Communist Party/Marxist Leninist), and MLKP (Marxist Leninist Communist Party).

To construct the dependent variable, incident summaries were reviewed to identify the locations of the terrorist incidents between 2008 and 2012.⁵ Quantitative Content Analysis was used to create a dataset compatible with GIS software. Riffe and her colleagues (2014) defined Quantitative Content Analysis as “the systematic assignment of communication content to categories according to rules, and the analysis of relationships involving those categories using statistical methods” (p. 18). Quantitative Content Analysis was used to find the addresses of terrorist incidents. These locations were entered into a Microsoft Excel file and then geocoded.⁶

For the accuracy of the geocoding, the geocoded incidents were revisited when online Turkish media reports of terrorist incidents were analyzed. The result was a dataset that included 1152 separatist or left-wing terrorist incidents with a component of material damage, injury or death. Of all the incidents, separatist terrorists committed 857 (74%) and the leftists 295 (26%). The specific acts were bombing, arson, placing explosives, illegal violent demonstrations, armed assault, armed robbery, and invasion.⁷

Independent Variables: Infrastructure

Infrastructure data were used to test the predictive validity of RTM and to determine the varying patterns of the environment around the locations of terrorist incidents based on ideology. The TNP provided the dataset. The geographic data included the administrative borders of the IPD's jurisdiction and the features of infrastructure in the form of nonresidential locations across Istanbul. Seventeen spatial correlates were used that Onat (2016) recently identified, as the potential variables to be associated with terrorism and geography. The spatial correlates of terrorism were identified in three steps. Initially, the spatial variables were reviewed in the empirical geography of

⁵ A sample incident summary is as follows: “On January 1st, 2008 at around 18.00, a bomb detonated in a waste container that was in front of the building at Inonu Street 122 in Cumhuriyet Neighborhood of the district of Kucukcekmece. Two persons were wounded, and some buildings around the address were damaged. An investigation was initiated to identify suspect(s).” In practice, counterterrorism units intervene in any investigation with the suspicion of terrorism. If the incident is not a terrorist act, then it is cleared from the database of the Counter Terrorism Department.

⁶ The addresses of the incidents were entered into a Microsoft Excel file and then geocoded using the ESRI's World Geocoding Service that requires an authorization by the producer. The matching scores in geocoding were quite high. Ninety-eight percent, or 1272 incident addresses, were matched successfully. Two percent, or 22 addresses, had more than one candidate with the same best match in different locations, and they were rematched to the correct addresses. The raw data included 1294 incidents over the study period. Some instances were nonviolent acts (e.g., unlawful demonstrations to propagandize a terrorist organization). The addresses of violent terrorist incidents provided by TNP were used to probe the spatial aspects of the activity.

⁷ Of all 1152 terrorist incidents, only one was invasion, seven were robberies, 28 armed assaults, 214 violent demonstrations, 280 explosives, and 622 arsons. The study area was very wide, and the number of incidents in the other types was not large enough to conduct statistical tests. Using the same variables and parameters (i.e., 110-m by 110-m cells within a two-block area), a separate model could only be tested for all terrorist arson incidents without an ideological dichotomy.

terrorism literature (Ekici et al. 2008; Libicki et al. 2007; Nunn 2007; Rusnak et al. 2012; Ozer and Akbas 2011; Savitch 2014; Webb and Cutter 2009). Then, the incident summaries were examined to identify targeted places. As the study used an incident-based identification process, some incidents also included more than one feature. Lastly, nonresidential features were categorized and counted in the neighborhoods with incidences of terrorism. As a result, each infrastructure variable was used as an independent variable in the statistical models.

Modeling Terrorism Risk

An RTM model shows the interaction of spatial influences and criminogenic features, while an RTM map combines the total effects of these factors at every places (i.e., cells) on a landscape (e.g., a city) (Caplan 2011; Kennedy et al. 2011). RTM uses raster maps that break the surfaces into equally sized cells as that helps to continuously analyze the landscape by adding the influence of each risk factor into the equation as an independent variable.

To operationalize risk factors to risk-map layers, the mean street-block length was measured (222 m with $SD = 281$) from the network of streets in the study area. One half of a street-block length (110 m) was appropriate to create 110-m by 110-m cells for RTM analysis of environmental risk values for terrorism. The spatial influence was set at a perimeter of two blocks. The analysis measured the risk of terrorism using the 110-x-110-m cells within a perimeter of 440 m. Risk Terrain Modeling Diagnostic Tool (RTMDx) software was used to identify statistically significant risk factors based on operationalization and spatial influence (i.e., proximity or density within two blocks).

Each independent variable might have a spatial influence on the occurrence of a terrorist incident based on proximity or density. For the risk factors operationalized by proximity, it was hypothesized that “distances from a particular feature up to two blocks (440 m) are at the greatest risk for terrorism as victims are often targeted when arriving at or leaving the establishment.” For other risk layers operationalized by density, it was hypothesized that “high concentrations of particular physical features (e.g., eateries) increase the risk of those dense places having terrorist incidents.” All risk factors also were operationalized in an aggravating model type in which the assumption was that the risk factors of the RTM model were correlated with the locations of outcome events in positive spatial relationships. To make it clear, the aggravating model type implies the risk factors would increase terrorism risk in a place.

In the next step of the analysis, the same model was used for three dependent variables: all separatist and leftist terrorism, separatist terrorism, and leftist terrorism. In the final step of the analysis, an RTM was conducted inclusive of both ideologies to determine if any environmental factors increase the general risk of terrorism. Additionally, previous research also suggests that terrorism targeting strategies may vary by ideology (Santifort et al. 2013; Wright 2013). Therefore, two additional models were also run for separatist and leftist terrorism independently and results compared.

Findings

Target Comparison by Ideology

Incident summaries ($N = 1152$) were used to determine the type of places terrorists targeted in the events studied. The summaries of 689 incidents contained no spatial information other than

the address for each incident. In the other 463 incidents, terrorists either directly targeted such places as government buildings, political party buildings and schools, or the incidents occurred in very close proximity to these features. Of the 463 incidents with target information, separatist terrorists committed 364 attacks and leftists 99. The separatist acts were mostly committed by the PKK that claims an independent state in the southeastern part of Turkey, and the separatist group bases this claim on the ethnic difference or ethnonationalism between Kurdish people and others in this region. For a comparable analysis, Fig. 1 demonstrates the percentages of targeted features by ideology for those attacks where features were mentioned in the incident summaries.

The separatist group differed from the leftist group by targeting parks, post offices, and media buildings. Unlike the leftist group, the ethnonationalist group more frequently targeted franchises. On the other hand, the leftists prioritized targeting political party buildings. For the purpose of the study, these features were considered to be potential correlates of terrorism and their co-existence composes attractor terrain because they might entice a left-wing or ethnonationalist terrorist group to attack a particular location or target (Rusnak et al. 2012). The current research assumes that the co-location of all of these features increases the risk of a terrorist attack in a particular place.

Comparison of Risk Factors by Ideology

Before the risk factors were modeled, it was important to know whether terrorist incidents committed between 2008 and 2012 were clustered in the study area, which measured 1772 km². This large area also includes rugged terrain inaccessible by the roadway network. The terrorist incidents and the risk factors were geocoded at their street addresses; however, places such as

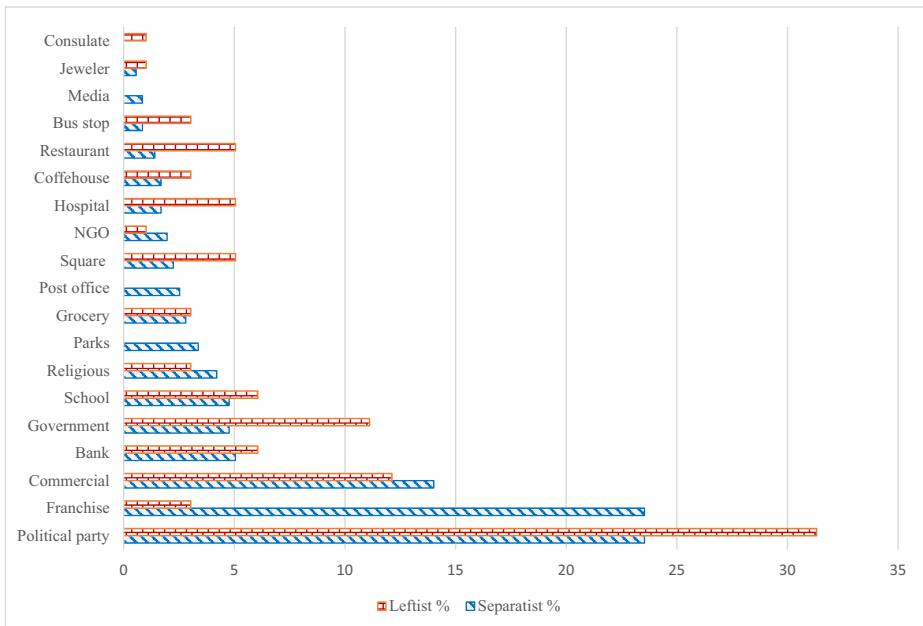


Fig. 1 Target comparison by ideology

ponds or cemeteries did not include any of the points in the incident and infrastructure datasets. Kennedy et al. (2011) argued that cells without any point of incident and risk factor would bias statistical tests by resulting in a negatively skewed dataset. Therefore, a blank vector grid of the study area was created with a cell size of 110-m by 110-m for a total of 149,134 cells. In the next step of the modeling process, cells that did not fall within a two-block distance of streets were excluded; 108,471 cells fell within this distance. Then, a new polygon of this smaller area was created by dissolving those 108,471 cells and analyzing the data within a 997 km² area.

For the cluster analysis, an average nearest neighborhood analysis was conducted using ArcMap 10.4 for 295 leftist and 857 separatist terrorist incidents. Given the *z*-scores (−19.66 for leftist and −31.42 for separatist, respectively, with $p < .001$), the results indicated a less than 1% likelihood that this clustered pattern could be the result of random chance. In other words, both leftist and separatist terrorist incidents were statistically significantly clustered over the study area during the study period.

In the next phase of the analysis, the influence of 17 spatial risk factors were modeled separately for leftist, separatist, and all terrorist incidents to empirically test the role of ideology in the same jurisdiction. Table 1 illustrates the results from three RTM models with different dependent variables: leftist, separatist, and all incidents.⁸

In each model, the RTMDx utility generated a model of terrorist incidents for the study area. A model was produced to represent the risk factors for the 1152 events in the dataset, taking into account the potential spatial influences of the variables listed in Table 1. All geographic calculations were conducted in the projection of the study-area boundary using 110-m by 110-m raster cells and an average block length of 220 m. Of the 108,471 raster cells used in the analysis, 906 contained outcome events in the overall model—710 in the separatist model and 229 in the leftist model.⁹

Simply put, two variables (for one block and two block distances) were created for each independent variable that was assumed to have a spatial influence by either proximity or density, and four variables were generated for the ones that may have an influence by both proximity and density. Accordingly, there were 44 variables to test the influence on terrorism. As a result of a stepwise elimination process and a subsequent selection by Bayesian information criteria, the best risk terrain model for each terrorism category was used to conclude where the respective risk was higher. Those variables noted as “tested, but not in

⁸ Religious facilities included mosques, synagogues, and churches. The bakery variable was constructed from the point locations of bakeries and patisseries where bread and cakes are made and sold. Franchises were convenience stores selling basic food items and consumer goods and included the locations of all branches of five franchise convenience stores (BIM, Kiler, HakMar, A101, and Carrefour) whose branches were targeted multiple times. Educational facilities were elementary schools, high schools, and universities. Eateries included cafés, coffeehouses, fast food establishments, and restaurants, where people can spend time on the premises. The government variable included police, military, and correctional facilities; courthouses; city hall; other municipal buildings; consulates; and post offices.

⁹ The models generated 44 variables from 17 risk factors to test for statistical significance. The testing process involved first using an elastic net penalized regression model assuming a Poisson distribution of events. Next, 21 variables were selected in the overall and separatist models and 23 variables in the leftist model through cross validation. The variables were then used in a bidirectional stepwise regression process starting with a null model to build an optimal model by optimizing the Bayesian information criteria (BIC). A BIC score balances how well the model fits the data against the complexity of the model. The stepwise regression process was conducted for both Poisson and negative binomial distributions with the best BIC score used to select between the distributions. The best risk terrain model was a negative binomial with eight risk factors for all incidents (BIC score = 10,265.0), seven risk factors for separatist incidents (BIC score = 8265.4), and six risk factors for leftist incidents (BIC = 3293.8). The models also included an intercept term that represents the background rate of events and an intercept term that represented overdispersion of the event counts.

Table 1 Comparison of influence of risk factors in models for overall, separatist, and leftist terrorism

Risk factor	Count	Operationalization	Spatial			Relative risk value (RRV)			Ranking by RRV in model		
			Influence	Overall	Separatist	Leftist	Overall	Separatist	Leftist		
Religious facility	3394	Proximity	2 blocks	2.51	2.86	<i>ns</i>	1	1	<i>ns</i>		
Grocery store	10,037	Density	2 blocks	2.22	2.42	2.09	2	3	4		
Bakery	7954	Density	2 blocks	2.18	2.50	2.01	3	2	6		
Pharmacy	5612	Proximity	2 blocks	1.79	<i>ns</i>	<i>ns</i>	4	<i>ns</i>	<i>ns</i>		
Office block	7360	Density ^a	1 block	1.73	1.74	<i>ns</i>	5	6	<i>ns</i>		
Educational facility	3567	Proximity	2 blocks	1.72	1.79	2.54	6	5	2		
Bar/nightclub	1279	Proximity ^b	2 blocks	1.64	1.55	3.67	7	7	1		
NGO	2290	Proximity	2 blocks	1.61	1.84	2.07	8	4	5		
Government building	2192	Proximity	2 blocks	<i>ns</i>	<i>ns</i>	2.36	<i>ns</i>	<i>ns</i>	3		
Tested, but not in the final models											
Bank	5624	Proximity	—	—	—	—	—	—	—		
Franchise	1366	Proximity	—	—	—	—	—	—	—		
Bus stop	6151	Density	—	—	—	—	—	—	—		
Eatery	15,400	Density	—	—	—	—	—	—	—		
Hospital	1449	Proximity	—	—	—	—	—	—	—		
Liquor store	2415	Proximity & density	—	—	—	—	—	—	—		
Park	2696	Proximity	—	—	—	—	—	—	—		
Political party	176	Proximity	—	—	—	—	—	—	—		
Total	78,962										

Note: *ns* significant at least in one model but not in another model, — not significant in any models, $p < .05$

^a Office blocks significant by proximity in separatist model; ^b bars significant by density in leftist model

the final models” in Table 1 refer to risk factors that were ultimately found not statistically significant during the stepwise regression models. The RTM maps were produced from the best models with significant variables to identify the high risk places.¹⁰

To identify factors which influence the risk of terrorist activity, we employ relative risk values (RRVs) to compare across the overall, separatist, and leftist models. Some key similarities emerge, regardless of ideology. The proximity of educational facilities within two city blocks (440 m) was correlated with an elevated risk in terrorist activity across all three models (1.72 times greater risk of overall terrorism, 1.79 times greater risk for separatist terrorism, and 2.54 times greater risk for leftist terrorism). Locations with multiple grocery stores nearby, as well as multiple bakeries, were correlated with at least a doubling of terrorism risk across all three models. RRV also enables one to compare the risk factors within the same model. For example, religious facilities (RRV = 2.51) were about 1.5 times at risk as places with NGOs (RRV = 1.61) in the overall model. For other risk factors, ideology mattered. The risk of terrorist activity was elevated in areas with more office blocks in the overall and leftist models, but proximity to these places increased risk in the separatist model. The density of bars significantly increased risk of leftist terrorism, while proximity to these places elevated risk in both the leftist and overall models. Pharmacies were the fourth riskiest factor in the overall model, but statistically non-significant in their influence on the risk of separatist terrorism. Similarly, office blocks were correlated with an elevated risk of terrorism in the leftist model, but not significantly correlated in the separatist model. RRV further enables one to compare micro places based on their risk values. Based on the best model with significant risk factors, relative risk scores were assigned to cells ranging from 1 for the lowest risk cell to 155.9 (separatist model), 179.4 (overall model), and 193.5 (leftist model) for the highest risk. These scores allowed cells to be compared easily. For instance, a cell with a score of 155.9 had an expected rate of separatist terrorism that was 155.9 times higher than a cell with a score of 1.

To produce an RTM map for separatist and leftist terrorism, two composite maps were created with all significant risk factors in their respective models. Then, the top 5% highest risk places were overlaid for both ideologies. Figure 2 demonstrates the overlapping areas of the highest risk terrains, and for the most part, terrorism risk from separatist and leftist groups cluster in different places.

Predictive Validity Test

To test the predictive validity of the RTM model, we used a five-step process employing logistic regression and out-of-sample forecasting. In the first step, two separate datasets were created from all incidents by years without taking the ideology into account.¹¹ The 1152 incidents were divided into two sections by years. The first period dataset included all terrorist incidents from January 2008 to December 2010, and the second period dataset included the incidents between January 2011 and August 2012. In the first period 704 incidents occurred

¹⁰ The underlying correlation among the 44 variables generated from 17 risk factors may be a limitation. A potential intercorrelation of independent variables may make parameter estimates unreliable since it may produce large standard errors in the denominator, which could make a predictor insignificant in a model. On the other hand, our results could be only minimally-biased since the models include independent variables that had the strongest correlation with dependent variables.

¹¹ The predictive validity could not be tested by the current ideological dichotomy since the separatist groups committed around 480 incidents in the first period, and this number was around 190 for the leftist group. The RTMDx could not find any significant risk factor across 108,471 units with the two samples of incidents.

while the second period dataset included 539 incidents. In the second step, an RTM was modeled with the first period incidents, using the same 17 risk factors to identify risk of terrorism. In the third step, the risk values of the first period RTM were assigned to the 110-m by 110-m cells in the IPD jurisdiction. In the first period, the highest risk score was 184. Using ArcMap in the fourth step, the incidents in the second period were then aggregated into the cells that the RTM map produced for the first period. Five hundred thirty-nine terrorist incidents of the second period fell in 426 cells (110-m by 110-m) of the first period RTM map.

Using the tabular data from the RTM map in the fifth step, the occurrence of any terrorist event within a cell for the second period were regressed on risk values for the first period. The RTM model of places had high predictive validity in Istanbul. As displayed in Table 2, logistic regression results suggest that for every increased unit of risk, the likelihood of a violent terrorist incident happening at a particular place increases by 2.2% $[(1.022 - 1) \times 100 = 2.2\%]$. In other words, the likelihood of a violent terrorist incident in a 110×110 m place with a risk value of 184 increases by 404% $(2.2 \times 184 = 404.8)$ in respect to a place without significant risk factors.

The RTM map in Fig. 2 illustrates the top 10% highest-risk areas. To designate highest-risk places, the tabular data were imported from the RTM map into STATA. All cells were sorted ($N = 108,471$) by the risk values from the composite map, using 10% as the cutoff point.¹² The top 10% of the riskiest cells experienced 233 (43.2%) of all 539 incidents in the second period,¹³ and those 539 incidents occurred in 426 places (110-m by 110-m cells). Table 3 shows that the top 10% of the highest-risk places between 2008 and 2010 included more than 43% of the cells with at least one terrorist incident.

In other words, more than 43% of all places with terrorist incidents in the second period overlapped with the top 10% highest risk-places of the first period. A chi-square test showed a statistically significant association between the proportion of violent terrorist incidents that occurred in the second period and the risk found in the first period (Pearson's chi-square = 464.59; $df = 1$; $p < .001$). Further analysis showed that 19.25% of the study area had a risk value 24 or higher, and 429 (79.6%) of all terrorist incidents occurred in what amounted to nearly 20% of all places studied.¹⁴

Discussion and Conclusion

The initial goal of the study was to contribute to the nascent literature on the geography of terrorism and forecasting the risk of a terrorist attack by taking a group's ideology into account. In a sample of 1152 incidents, the analysis found that one ethnonationalist group, the PKK, committed nearly three-fourths of the terrorist incidents during the study period, while the acts of four left-wing terrorist groups totaled one-fourth of the incidents. A review of the incident

¹² Initially, 10.8% percent of all 110-m by 110-m cells had highest values of risk in the first period, ranging from 62 to 184. The number of cells (11,618) with a risk value of 62 exceeded the number of cells (10,847) needed for the validity test. In total, 6529 cells had a risk value 62; however, 5758 cells needed to be included in the first-tier places. Therefore, 5758 cells with a risk value of 62 were randomly selected to ensure that every cell had an equal chance of being sorted into the pool of the top 10% of cells with the highest values of risk.

¹³ The total number of incidents in the second period was 94 in all cells with a risk value of 62 in the first period. The random sampling excluded three incidents in the process of designating high-risk places.

¹⁴ At the outset, the IPD jurisdiction contained 149,137 places; however, 108,471 were examined after excluding the places beyond two blocks from the street. Those 108,471 places under examination covered 72.7% of the entire jurisdiction.

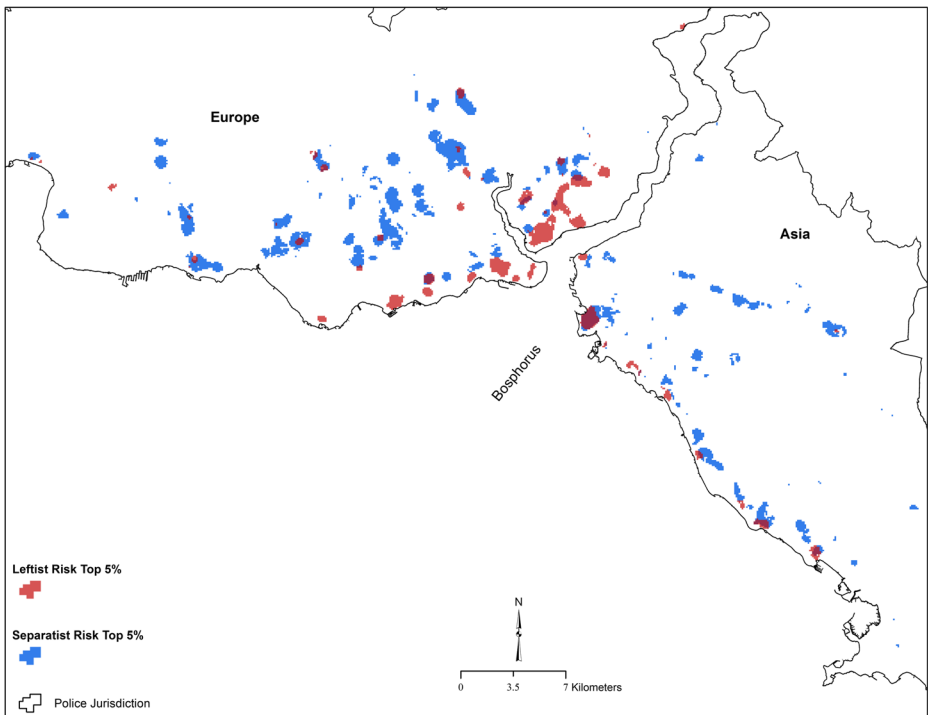


Fig. 2 Istanbul, 2008-2012: top 5% high-risk terrain—separatist and leftist terrorism

summaries revealed that 463 incidents included information of a physical feature, and target preferences were different for the two groups. Leftist terrorist groups primarily targeted political party and government buildings, while separatist groups heavily targeted private businesses.

The event-dependent analysis indicated that terrorism based on either ideology (i.e., separatist or leftist) was not random in space. The study benefited from the use of RTM, an innovative method of forecasting and exploring the environment in which a particular crime was committed. As a risk-foresight method, RTM enables one to test contextual correlates of outcomes of interest and to identify where small cells coexist and compare micro places based on their combined risk values. The context-dependent analysis found that the physical environment was patterned around both separatist and leftist terrorist attacks.

For risk factors operationalized by proximity, the results indicated that the terrorism risk is higher, in general, within a distance of two blocks (440 m) from religious facilities, pharmacies, educational facilities, bars, NGOs, and government buildings. For the risk layers operationalized based on density, a perimeter of 440 m around places with high concentration of grocery stores and bakeries was riskier, and this perimeter was 220 m for office blocks.

Grocery stores, bakeries, bars/clubs, and educational facilities were significantly associated with both types of terrorism. This commonality is a result of the fact that contemporary terrorists shifted their spatial strategies to the locations of everyday activity to target civilians (Braithwaite and Johnson 2012; Webb and Cutter 2009). Furthermore, the risk scores were not equal for every predictor in the RTM of the two different ideologies. Although each one of these features contributed to the spatial risk of terrorism across the landscape in Istanbul, the risk was highest

Table 2 Logistic regression for period 1 risk value on period 2 terrorist incidents

	Odds ratio	SE	Wald	df	Sig.	95% CI	
						Lower	Upper
Risk value	1.022	0.001	584.04	1	< 0.001	1.020	1.024

$N=539$, CI confidence interval, df degrees of freedom, SE standard error, Sig significance; $Wald$ Wald coefficient; Nagelkerke $R^2 = 0.073$

when all these features were present within a two-block radius in any part of the city. The RTM maps by the different ideologies showed where the opportunity existed in Istanbul.

There were differences in predictors of terrorism by ideology. The two variables, religious facilities and office blocks, were the significant predictors of spatial terrorism risk in separatist model, but they were not significant in the leftist model. This outcome might be a function of the differing strategies in acting. As an ethnonationalist group, the PKK stands against the integration of the migrated Kurdish people in the metropolitan cities such as Istanbul. Although our data is limited to test whether the separatist terrorist acts were committed in the Kurdish populated neighborhoods, the attacks might have been committed in the areas that are the attraction centers for the migrated Kurdish residents, which lends support to the selection of soft targets by ethnonationalists (Gaibulloev et al. 2012; Wright 2013). Such a strategy is beneficial for the separatists since the post-attack period follows further government reaction in these neighborhoods, which contributes to the ethnic discrimination argument of the terrorist group. The left-wing terrorists, on the other hand, prefer officials and passive military targets rather than private parties in the hopes of attracting popular support (Brandt and Sandler 2010: p. 217). Accordingly, the government buildings construct was a significant predictor only in the leftist model.

However, there might be a difference between what the terrorists intend as a target and the type of infrastructure that is affected by the attack. In other words, regardless of the terrorists' intent, the significantly associated entities such as grocery stores are increasing the risk in the surrounding areas where such features are located. The spatial differentiation in the attacks for both ideologies is in line with the ideology-geography argument since each group under study has its own strategies and therefore its own behavior settings.

Lastly, tests of predictive validity of the RTM model in terrorism risk-forecasting showed that a model consisting of a 36-month period predicted the locations of more than 43% of terrorist incidents in the highest 10% risky places and nearly 80% of terrorism in the less than top 20% riskiest areas during the following 20-month period. Five hundred twenty-nine incidents occurred in 426 places in the second period, and 233 of the incidents (43%) fell within the top 10% of high risk cells and 429 incidents (79.6%) within the top 20%. The results were provided to understand how predictive the RTM was in the study period, and the

Table 3 Terrorist incidents in highest-risk cells

Top 10% highest risk ($N=10,847$ cells)	Presence of terrorist incident in 2011 and 2012 (% Yes; $N=426$ cells)
Yes	43
No	57

Pearson's chi-square = 464.59; $df=1$; $p < .001$

entire area of high risk places is still relatively large for a place-based policing strategy. However, the RTM map also informs which specific places (i.e., cells) with subsequent terrorist attacks are within the top 20%, and such a forecast makes it more reasonable to assign a police strategy in these places.

Given that terrorist groups act collectively and that they plan their attacks within the boundaries of their rationality, precision in predicting attacks is invaluable because terrorist groups will need to constantly change their target preferences following the responses to their attacks from the criminal justice system and mainstream society.

The study, however, does have limitations. First, agency incident data were used, and such data may have contained input errors. To eliminate this and other problems associated with the use of secondary data, the summaries of the incidents were compared with media reports on the Internet where such incidents are covered extensively. Furthermore, the number of incidents of leftist terrorism was relatively fewer in comparison to the size of the jurisdiction; therefore, it was not possible to test the predictive validity of the RTM models in terms of the ideological dichotomy. The collection of more incidents from the years before 2008 could help with the validity test. In the same vein, modeling each leftist group with more incidents may produce different results, as the construct of separatist terrorism included one-group incidents.

Another limitation to the current study is that the influence of a generator or attractor of terrorism was equal on the outcome event in their respective category. For instance, the RTM results indicated that proximity to a mosque significantly increases the risk of terrorism in Istanbul, but this influence of the mosques could differ from one mosque (e.g., Hagia Sophia in the tourist attraction area) to another (e.g., a mosque in a residential area) because of the symbolic nature that would attract the terrorists as well.

Although the study has limitations, it proves that, similar to traditional crimes, the risk of terrorist activity can be forecasted across space and time. Unfortunately, one of the places that the RTM map designated as high-risk experienced a deadly attack by separatist terrorists on the evening of December 10, 2016, and two explosions caused 48 fatalities and 168 injuries in Istanbul. Indeed, the RTM analysis identified the location of the attack in the top 5% of high-risk places, though the variance explained by the model was statistically low. Substantively, the RTM maps would help counterterrorism experts focus their attention and resources on these particular places. Given that the counterterrorism unit of the IPD has a structure and specialization according to the ideological categories of terrorism, focusing on these places would improve the quality and effectiveness of counterterrorism services in the face of scarcity of resources in such a large and densely populated city. In addition, the physical environment in these places may need to be redesigned to regulate and control public behavior in these locations.

To conclude, the findings of the current study lend support to previous studies on the nonrandomness of political violence in space (Bahgat and Medina 2013; Braithwaite and Li 2007; Nemeth et al. 2014), even when a micro unit is applied to the analysis. As such, the urban context in which terrorist groups perpetrate their attacks can be useful in helping to identify vulnerable places at a micro level (e.g., street blocks). Although terrorist groups have different target preferences based on their ideology, the geographic concentration of their illegal behavior makes it possible to forecast the locations of the next attacks with better precision. Such forecasts can help guide policy-makers to implement place-based intelligence to prevent terrorism. Therefore, a regular reassessment of risk is important for an evidence-based approach to safety-related issues in the public sphere. RTM is a practical and useful tool for forecasting variations in risks. The current analysis and similar ones can provide more precision for the effective application of place-based prevention of terrorism in the future.

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