The Local Geography of Transnational Terrorist Attacks*

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Abstract

Why are some locations more attractive targets for transnational terrorism than others? We know that transnational terrorist attacks occur in all regions and a majority of countries globally; yet intuition tells us also that not all locations within each country are equally likely to host an attack. Remarkably little is known about the local-level conditions and attributes that determine more precisely where transnational terror attacks occur. In this paper, we examine the determinants of transnational terrorist attack locations, specifically contending that individual locations can be characterized in two respects that directly impact the likelihood with which they will host terrorist attacks: vulnerability and value. In order to test these expectations, we regress newly geocoded data on transnational terrorism against two sets of covariates that are operationalized as proxies for vulnerability and value. Our analyses confirm that attacks are most likely at locations with recent civil violence, proximity to the capital city and international borders, low levels of forest cover but mountainous terrain, and locations with larger populations and higher levels of economic activity. Collectively, these findings corroborate our vulnerability and value hypotheses.

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Introduction

On September 21, 2013, Al Shabab operatives attacked the Westgate shopping center in Nairobi, Kenya, killing over 65 individuals and injuring more than 200 others. Al Shabab targeted Kenya because the Kenyan government supported the fight against Islamist insurgents in Somalia. They chose the specific location in Nairobi for a number of strategic reasons. Shopping centers in Nairobi, including the Westgate center, had previously been considered secure locations. They are frequented by considerable numbers of consumers. They reflect the heartbeat of an economically-vibrant capital city. In other words, the Westgate represented an attractive target, because it was both vulnerable and valuable.

The kinds of locations targeted by notable terrorist attacks—what Arce and Sandler (2010) refer to as "terrorist spectaculars"— rarely surprise us, even if their outcomes do shock. Densely populated urban centers, areas of significant economic activity, iconic political and religious sites all appear to make for attractive locations. Yet, most transnational terrorist attacks are not on the scale of the spectacular.[1] Accordingly, much less is said systematically about the location of the bulk of terrorist attacks. Indeed, we know that transnational terrorist attacks occur in all regions and a majority of countries globally; yet intuition tells us also that not all locations within each country are equally likely to host attacks.

Extant research highlights state- and regional-level covariates of terrorism (Enders and Sandler 2006, Li 2005, Piazza 2008), identifies clusters of terrorism in space and time (Braithwaite and Li 2007, LaFree, Morris, Dugan, and Fahey 2006, Johnson, Carran, Botner, Fontaine, Laxague, Nuetzel, Turnley, and Tivnan 2011), and demonstrates that transnational terrorism displays substitution—or spatial displacement—effects (Enders and Sandler 2006). However, remarkably little is known about the local-level conditions and attributes that determine more precisely *where* terrorism occurs.[2] Utilizing a recently geocoded version of

[1] We follow the convention of distinguishing *transnational* terrorist attacks from *domestic* attacks as discussed in Enders, Sandler, and Gaibulloev (2011).

[2] See Nemeth, Mauslein, and Stapley (2014) for one attempt at looking at subnational variation in terror

the ITERATE dataset (Mickolus, Sandler, Murdock, and Flemming 2003) and the new PRIO-GRID dataset (Tollefsen, Strand, and Buhaug 2010), we address this notable lacuna. Specifically, we claim that individual locations can be characterized in two respects that directly impact the likelihood with which they will host terrorist attacks. First, locations vary in terms of the extent by which they facilitate or hinder the preparation and conduct of terrorism—we refer to these as *vulnerability* characteristics. Second, locations vary with respect to their *value* to potential attackers. Very simply, we contend that locations that can be characterized as being vulnerable and/or valuable are more likely to experience increased levels of terrorism than those that display neither of these characteristics.

In order to test these expectations, we regress newly geocoded data on transnational terrorism against two sets of covariates that are operationalized as proxies for vulnerability and value. In this initial version, each of these covariates is operationalized at the local (0.5 decimal degree x 0.5 decimal degree grid cell) level. They include measures of mountainous terrain, forest coverage, distance to international borders, and level of civil conflict as indicators of vulnerability, and distance to capital cities, local economic activity, and population density as indicators of value.

Given that our grid cell analyses generate in excess of 64,000 observations per year and our analyses are conducted on data across a thirty-nine year period (1968—2007), terrorism proves to be a rare event in time and space. Accordingly, we employ two techniques designed to take account of this rarity. First, we dichotomize the outcome variable–differentiating between location-years in which there is no terrorism and those in which there is at least one terrorist attack. We then employ rare events logit (ReLogit) to assess patterns in this form. Second, we generate a count of the total number of attacks at each location in each year. Given the preponderance of zero counts, we employ the Zero-Inflated Negative Binomial

attacks. Their approach differs from ours in several respects. First, they examine domestic attack and thus use different data than we do. While some questions have been raised that domestic terror is difficult to distinguish from violence in civil war, focusing on transnational terrorism should mitigate these concerns somewhat. Second, they focus on hot spot analysis. This method has a long tradition in crime mapping, for example. Since identifying hotspots often needs to be coupled with analyzing why they cluster, we do not focus on this tool.

(ZINB) model to analyze this second form of the dependent variable. Both sets of analyses confirm that attacks are most likely at locations with recent civil violence, proximity to the capital city and international borders, low levels of forest cover but mountainous terrain, and locations with higher populations and levels of economic activity. Collectively, these findings provide some support for both the vulnerability and value hypotheses.

The paper proceeds as follows. First, we discuss the extant literature so far as it pertains to the question of what makes some locations more likely to host terrorism than others. We then layout the simple logic regarding the vulnerability and value of locations, deriving testable hypotheses from both. We then move to design a research strategy to test these hypotheses empirically. Finally, we discuss results and concomitant policy implications.

The Geography of Terrorism

The literature on the causes of terrorism is neatly summarized elsewhere (Hoffman 2006, Kydd and Walter 2006).[3] Our priority here is to discuss—as is most pertinent to the objectives of this study—extant research addressing where transnational terrorism attacks occur and the key determinants of these geographic patterns of locations.

In a seminal study—and by way of an illustration of traditional approaches to the geography of terrorism—Midlarsky, Crenshaw, and Yoshida (1980) investigate the diffusion and contagion of terrorist tactics and events. They argue that the global temporal and spatial distribution of terrorist incidents can follow four possible patterns: (1) "randomness", by which terrorist events may be distributed randomly in space and time; (2) "heterogeneity", by which the propensities of different countries to experience terrorism are disparate across space but constant over time; (3) "contagion", by which the occurrence of a terrorist incident in one country increases the probability of a neighboring country experiencing an incident in a subsequent period; and (4) "reinforcement", by which the occurrence of a terrorist incident

[3] Sandler (2014) offers a recent survey of some of the accomplishments of the analytical approach to understanding these causes and consequences.

in one country increases the probability that the same country will experience terrorism in a subsequent period. The authors conclude that the most striking pattern observed in their sample is one of contagion from Latin America to Europe. In a response article, Heyman and Mickolus (1980) argue that this pattern results from a process of mimicry, with Latin American terrorist groups[4] leading the way and being copied by groups emerging at a later stage in Europe.

Enders and Sandler (2006) study the distribution of transnational terrorism among countries by income class and geography, with a focus upon comparing patterns from the periods before and after 9/11. They find no evidence of an income-based, post-9/11 transfer of attacks to low-income countries. Contrary to common intuition, efforts by wealthy countries to counter terrorism do not appear to have resulted in the transference of these acts to poorer states, presumably less capable of launching effective counterterrorism efforts. This research also demonstrates that the post-9/11 period witnessed a significant transference of terrorist incidents from North America and West Europe to the Middle East and Asia following the adoption of dramatic new counter-terrorism measures in the United States and the United Kingdom. Adopting a different approach to the analysis of regional clustering of events, Braithwaite and Li (2007) identify country-level hot spots of transnational terrorist attacks and demonstrate that these play a crucial role in subsequent patterns of diffusion in space and time.

These studies have offered insights into the diffusion and contagion of terrorist activities and have successfully identified regional patterns of heterogeneity and dependence in the distribution of terrorist incidents. This evidence suggests that it is possible to identify and forecast regional and country-level terrorist hot spots. However, analysis that aggregates data at the country- or regional-level misses much of the important potential geographic variation in terrorist attacks. In response, this study is motivated by an expectation that the locations of terrorism hot spots do not coincide perfectly with conventional boundaries

[4] For a discussion about how to conceptualize a *terrorist group*, see (Phillips 2014) and (Young and Dugan 2014).

of regional and country units. As not all states share an equal likelihood of hosting attacks, this insight suggests that not all sub-state spatial units within any given state are equally likely to host those attacks that target the state.

There is a precedent for the employment of more fine-grained location data in the study of a range of related topics. In the study of civil war, a literature has developed that addresses how local geography affects the propensity of civil war onset (Buhaug and Rød 2006, Raleigh and Hegre 2009, Buhaug, Gleditsch, Holtermann, Østby, and Tollefsen 2011), duration (Buhaug and Lujala 2005), and rebel capability (Buhaug, Gates, and Lujala 2009). Studies of social conflict using georeferenced conflict data have shown that cell phone coverage (Pierskalla and Hollenbach 2013), environmental factors like rainfall levels (Hendrix and Salehyan 2012), and weather conditions (Carter and Veale 2013) each increase the propensity of social conflict at a more micro level.

Despite the progress made in understanding the effects of local geography on civil conflict generally, the geography of terrorism remains, overall, a remarkably understudied topic of research (Bahgat and Medina 2013). The few studies conducted on this issue have been limited in geographic scope to analyses of attacks in particularly countries, including Israel (Kliot and Charney 2006, Berrebi and Lakdawalla 2007), Spain (LaFree, Dugan, Xie, and Singh 2009), and the United States (Cothren, Smith, Roberts, and Damphousse 2008, Webb and Cutter 2009). Space-time patterns have also been analyzed using point locations of insurgent and terrorist attacks in Iraq (Townsley, Johnson, and Ratcliffe 2008, Johnson and Braithwaite 2009, Braithwaite and Johnson 2012). Point locations have also been analyzed at the global-level in order to uncover hot spots of militarized disputes (Braithwaite 2006, Braithwaite 2010) and civil conflicts (Buhaug and Gates 2002). Research using changepoint regression models has shown that transnational terrorist attacks are increasingly aimed at *soft* or un-hardened locations within target countries, such as private actors, rather than property or public infrastructure (Brandt and Sandler 2010, Santifort, Sandler, and Brandt

2013).[5] Much less is known, however, about the process of geographic target selection—and, specifically, about the factors that determine *where* within the borders of independent states terrorist attacks are likely to occur. To our knowledge, Nemeth, Mauslein, and Stapley (2014) is the only other global, subnational geocoded study.

In summary, the extant literature has been limited from making more significant empirical advances in the study of the local geography of terrorist attacks by a dearth of fine-grained data on the location of terrorist activities on a broadly cross-national basis. Accordingly, this is the lacuna that we look to address in the sections that follow. Next, we discuss and outline expectations of the local correlates of terrorist attacks as a precursor of a discussion of a research design that represents the first study of the local geography of transnational terrorism.

Locating Terror

Our causal logic of the determinants of the local geography of transnational terrorist attacks centers upon the dual attributes of vulnerability and value. In a simple sense, these attributes overlap conceptually with what Most and Starr (1989) refer to as *opportunity* and *willingness* and Diehl (1991) refers to as *geography as context* and *geography as cause*.[6]

We begin by employing a fairly accepted definition in which '[t]errorism is the premeditated use or threat to use violence by individuals or subnational groups in order to obtain a political or social objective through intimidation of a large audience beyond that of the immediate victims.' (Enders and Sandler 2006, 3). In this instance, we are especially interested in transnational events—those in which at least two of the nationalities of the perpetrators, victims, or host state differ. The logic to be detailed below builds upon two simple assumptions: (1) that non-state actors typically consider terrorism a last resort, because they are

[5] Enders and Sandler (1993) begun this thinking about substitution effects, or that certain targets will be more attractive when others are hardened or become more costly to the group.

[6] The vulnerability/value distinction is also similar to what Berrebi and Lakdawalla (2007, 4-5) call *preferences* and *productivity*.

typically actors that are located on the 'wrong' side of a considerable power asymmetry in their relations with the government that they are challenging; and (2) the primary means by which terrorists will look to compensate for this asymmetry is by targeting in a manner that maximizes the media coverage of their attacks. This second assumption, especially, feeds directly into the decision calculus of target selection. In this respect, we suggest that targets must be (a) vulnerable and (b) valuable. By vulnerable, we simply mean that it must be possible for the target to be accessed sufficiently to enable attack. In practice, we consider that targets are, accordingly, more or less easily attacked. By valuable, we simply mean that terrorists will prefer, *ceteris paribus*, to target locations if they are more likely to attract greater media (and, therefore, public) attention.

The Vulnerability of Locations

The vulnerability of a location refers to the ways in which a particular location makes (im)possible the task of executing a terrorist attack. This can be thought of as a two stage process. From the terrorist's perspective, when selecting targets they must ask: is it possible to deploy force to a particular location? And is it possible to carry out a terrorist attack once at that location? In other words, vulnerability refers to the extent to which various "barriers" to attack are present/absent a particular location.

Conceptually, the vulnerability of a target is the product of three components. The first concerns the *security* of the target.[7] Factors such as the presence of military and policy personnel, barriers to entry, and technology that detects the movement of individuals near the perimeter of the target (surveillance equipment, etc) all serve to increase the security of the target.[8] However, ongoing civil conflict in a country may reduce and degrade the security infrastructure of a country, allowing for attacks on targets that may otherwise be

[7]Building on Enders and Sandler (1993), Nemeth, Mauslein, and Stapley (2014) are mainly concerned with this dimension of attracting domestic attacks.

[8]Increasing the security of public infrastructure has inadvertently shifted the focus of terrorist attacks towards private individuals, who are less easily secured from these attacks (Santifort, Sandler, and Brandt 2013, Mathews and Lowenberg 2012, Brandt and Sandler 2010).

less vulnerable. Secondly, the *accessibility* of the location influences the vulnerability of a target. Targets that are located in isolated, difficult-to-reach areas are less accessible, and thus less vulnerable, than targets in populated ones. Thus, we expect populated areas to experience more transnational terror events than less populated ones.[9] Finally, the level of *preparation* terrorist groups can achieve prior to launching an attack against a target shapes its vulnerability. Terrorists often seek access to safe havens, whether in neighboring countries or difficult terrain (such as mountainous or forest-covered regions) in which to prepare and plot attacks (Korteweg 2008, Kittner 2007).

[H_1]: *The greater (or lower) the vulnerability of a specific location, the higher (lower) the likelihood of an attack occurring locally.*

Along with the general relationship between vulnerability and the likelihood of a terror attack, we expect to observe the following specific relationships:

[H_1a]: *Ongoing civil conflict raises the likelihood of a terrorist attack.*

[H_1b]: *A decrease in distance to an international border increases the likelihood of a terrorist attack.*

[H_1c]: *Mountainous terrain raises the likelihood of a terrorist attack.*

[H_1d]: *Forest coverage raises the likelihood of a terrorist attack.*

The Value of Locations

The value of a location refers to the extent to which a particular location is home to assets of value to either the terrorists, the targets, or the audience. On the one hand, this means that such a target is likely to attract greater levels of public attention. This is crucial, because,

[9] Urban areas are frequently the main targets of terror attacks, both in the developed world (Glaeser and Shapiro 2001, Savitch and Ardashev 2001) and the developing world (Beall 2006).

as noted above, we assume that terrorists are looking to overcome a considerable resource disadvantage *vis-a-vis* the government that they challenge. One key way of doing that is to mobilise support by getting the group's message out to as wide a population as possible. Another way of doing this is to provoke a fearful response within as wide as possible an audience population. On the other hand, terrorists are also often keen to damage symbolic assets; perhaps these might be assets that represent the tyranny against which they perceive they are struggling.

Therefore, we argue that the value of a target is conceptually a product of two components. First, the *symbolism* of a target, whether cultural, political, or social, can enhance how attractive a target is. Attacking a symbolic target, such as those located in or near the national capital, enhances the significance of the attack beyond its immediate, direct effects. Secondly, the *material harm* that can result from attacking a target increases its attractiveness for terror groups. For example, one terrorist manual called for "blasting and destroying the embassies and attacking the vital economic centers" as well as destroying the "bridges leading into and out of cities" (Anonymous 2003, 12). Thus, we expect that more economically productive areas should be more attractive for terrorist attacks.

[H_2]: *The greater (or lower) the value of a specific location, the higher (or lower) the likelihood of a terrorist attack occurring locally.*

We should also observe the following specific relationships:

[H_2a]: *Higher levels of local population raise the likelihood of a terrorist attack.*

[H_2b]: *The closer a location is to the capital, the higher the likelihood of a terror attack.*

[H_2c]: *The higher the economic productivity of a location, the higher the likelihood of a terror attack.*

[H_2d]: *The closer a location is to an urban area, the higher the likelihood of a terror attack.*

Some of the variables that make a location valuable may also make it more vulnerable, and vice versa. For instance, populated areas are more vulnerable because there are more potential victims than unpopulated areas. Yet they are also more valuable, as launching indiscriminate attacks in these areas may contribute to a climate of fear in a country and may induce a general feeling that "anyone can be next."[10]

Finally, it is important to note the relationship between vulnerability and value is, at least to some extent, interactive. For instance, the fact that a target is less vulnerable may make it more valuable for some terrorist groups, as attacking it may be a way to demonstrate a terror group's prowess or the commitment of its members. In other words, decreased vulnerability can result in increased value for some terror groups.

Modeling the Geography of Terrorist Attack Locations

Unit of Observation and Choice of Estimator

The PRIO-GRID dataset(Tollefsen, Strand, and Buhaug 2010) employed herein partitions global territories into 64,804 equally sized (0.5 x 0.5 degrees) grid cells. Given that we have data suitable to populate this data structure for each year from 1968 to 2007, the behavior of interest, terrorism, becomes an incredibly rare event. Accordingly, it is appropriate to employ an approach that takes account of the disproportionately high number of zero observations on the dependent variable. First, we employ the ReLogit estimator (King and Zeng 2001*a*, King and Zeng 2001*b*). Second, we use a negative binomial regression. Thirdly, we employ the Zero Inflated Negative Binomial event count model. Note that the table for the ZINB event count model includes a column for the event model and one for the inflation model, which estimates the likelihood that the cell experiences 0 attacks. We estimate these models at the

[10] Kliot and Charney (2006, 354-355), citing Cutter, Richardson, and Wilbanks (2003, 2), argue that '[i]t is important to stress that terrorism is successful in inducing fear because it exposes civilians to attacks which have a random quality, so that everyone feels less safe....The seeming randomness of terrorist attacks increases public anxiety concerning terrorism.'

cell-year level and at the cell level. Fourth, in order to take into account the nested structure of the data we estimate multilevel random effects negative binomial models with variables to measure attributes of the state. Finally, we match the sample on propensity for civil conflict and re-estimate our models.

Measuring Terrorist Attack Location

The recent geocoding of the vast majority of events in the ITERATE dataset provides a unique opportunity to model the local geography of terrorist attacks. Each of the over 13,000 transnational terrorist events from the iterate database that have been geocoded have been assigned a longitude and latitude pair of coordinates. These geocoded locations are paired with their corresponding grid cell location from the PRIO-GRID dataset using the *join* command in ARCGIS v10.0. As a result of this merging of two datasets, we have both a count and a binary indicator of terrorist attack locations. In the first instance, we have a simple count (0 or positive integer) of the total number of attacks within each cell in each year. In the second instance, the binary variable is assigned a value of "1" if at least one terrorist attack occurs within the cell in a given year and "0" otherwise.

Geocoding the Terrorism Events

The ITERATE project provides detailed data on the characteristics of transnational terrorist groups, their activities which have international impact, and the environment in which they operate (Mickolus et al. 2003). The database includes information from 1968 to 2007.

Geo-Coding Methodology

This project uses the UCDP/AidData geo-coding methodology, which is modified from Sundberg, Lindgren, and Padskocimaite (2010), to assign sub-national geographic information, where possible, to ITERATE terrorism event entries based on information provided by event descriptions. This includes latitude and longitude coordinates, location name and ID, administrative boundary information, and a precision code.

Sources vary with respect to the precision of information about locations of attacks that are reported in ITERATE. Sometimes the exact location is named and in other instances the general area is reported; therefore, we use the system of geo-referencing used by UCDP/AidData which identifies coordinates for information at four main levels, ranging from point locations, through two administrative divisions, to the country level. Eight precision categories are connected to the coordinates in order for researchers to select subsets of the dataset that contain different levels of precision. If the event description only gives information on the administrative division, and not the exact location, then the centroid point of the administrative division is entered into the latitude and longitude columns. If there is no direct mention of any location in the event description, the country coordinates are coded with precision "7", which indicates that the location is unknown.

In order to obtain the latitude and longitude of geographic locations mentioned in the documentation, a geographic gazetteer is necessary. This project has relied primarily upon geonames.org, which provides not only the latitude and longitude of a location, but also the administrative division under which it is governed (province, district, central government, etc.) and a geographic identifier that is unique to each location.

Precision Category Definitions

For the data to be useful for a wide range of applications it is crucial to make it possible to select sub-sets of the data based on varying criteria of precision. The first six categories detailed by the UCDP's Georeferencing Project Codebook (Sundberg and Lindgren, 2009, 13) are used here, with minor modifications. The seventh and eight precision categories are unique for the UCDP/AidData codebook.

- 1 = The coordinates correspond to an exact location, such as a populated place or a hill.

- 2 = The location is mentioned in the source as being "near", in the "area" of, or up to 25 km away from an exact location. The coordinates refer to that adjacent, exact, location.
- 3 = The location is, or is analogous to, a second order administrative division (ADM2), such as a district, municipality or commune.
- 4. = The location is, or is analogous to, a first order administrative division (ADM1), such as a province, state or governorate.
- 5 = The location can only be related to estimated coordinates, such as when a location lies between populated places; along rivers, roads and borders; more than 25 km away from a specific location; or when sources refer to parts of a country greater than ADM1 such as a National Park which spans across several provinces (e.g. Foret Classee de Gongon in Benin)
- 6 = The location can only be related to an independent political entity, meaning the pair of coordinates that represent a country.
- 7 = Unclear. The country coordinates are entered to reflect that sub-country information is unavailable.

The majority of observations are at the precision code 1 level (77.1 percent). Thus, the majority of the observations of terror attacks in the dataset are coded with a relatively high degree of precision as to where the attack occurred. As the precision code values increase, the degree of precision declines. These attacks are coded as occurring in the centroid of the corresponding administrative level. All observations, regardless of precision level, are included in the model.

- Number of 1s: 9929 (77.1 percent)
- Number of 2s: 604 (4.7 percent)

- Number of 3s: 210 (1.6 percent)
- Number of 4s: 429 (3.3 percent
- Number of 5s: 172 (1.3 percent)
- Number of 6s: 1240 (9.6 percent)
- Number of 7s: 286 (2.2 percent)
- Total: 12870

Mapping the Data

Figure 1 offers a visual representation of the geocoded ITERATE data.

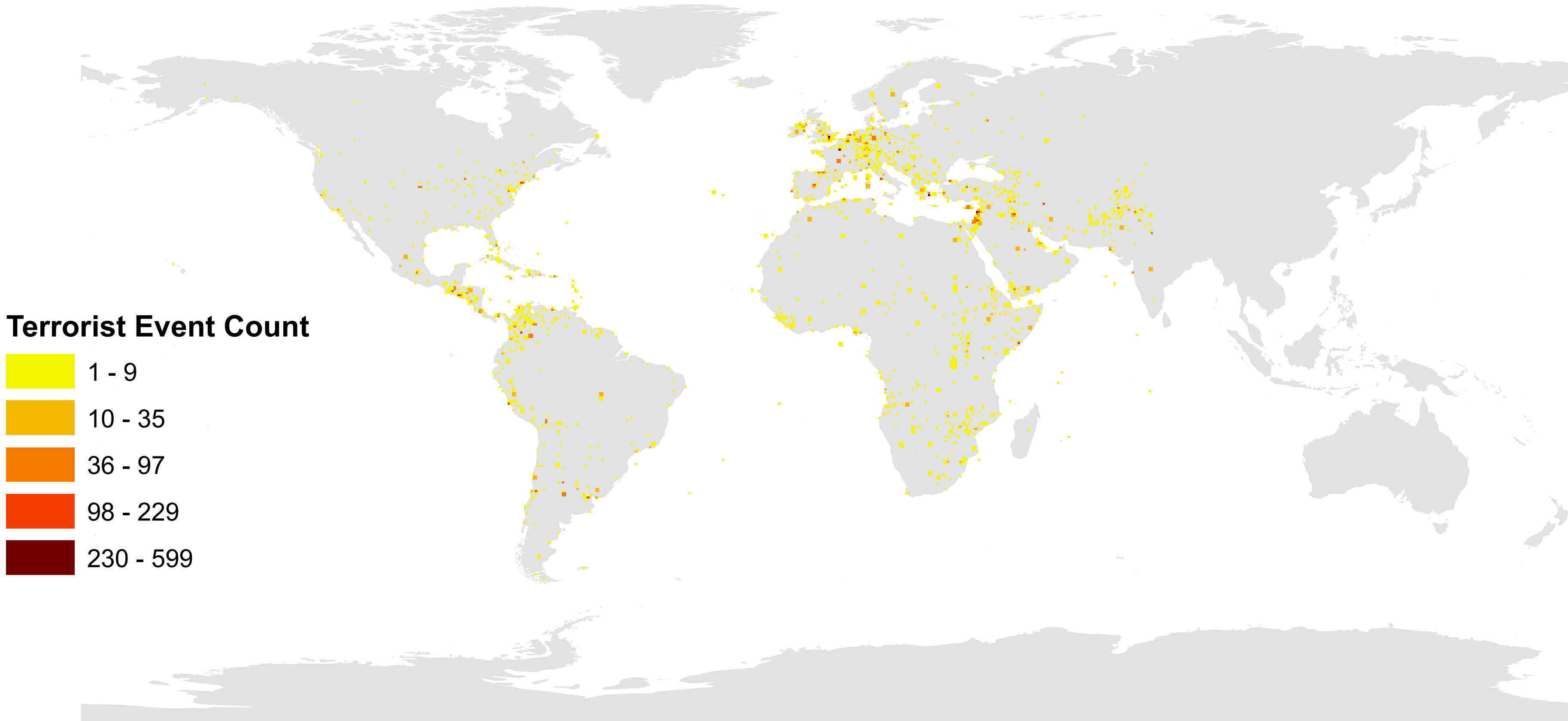

Figure 1: Global Locations of Transnational Terrorism

Measuring Vulnerability

All of the location-level data used to operationalize our key *vulnerability* and *value* explanatory variables are drawn from the PRIO-GRID dataset (Tollefsen, Strand, and Buhaug 2010). In the next two sections, we detail their operationalization and list, where appropriate, details of their original source.

Terrain: Drawn from the United Nations Environmental Programme's Mountain Watch Report (UNEP 2002), these data provide the proportion of mountainous terrain within each cell.

Forest Cover: Drawn from the Globcover 2009 dataset (Arino et al. 2010), these data provide estimates of the percentage of forest cover in each cell.

Proximity to International Border: These data provide the distance in 100 kilometer units from the center of the cell to border of the nearest contiguous neighboring country.

Civil Conflict: This covariate is a dummy variable representing the presence or absence of an ongoing intrastate or internationalized intrastate conflict within the cell. These data reflect the conflicts detailed in the UCDP conflict dataset (Harbom and Wallensteen 2010). This variable is only available for 1989-2005.

Measuring Value

Proximity to State Capital: These data provide the distance in 100 kilometer units from the cell to the national capital in the corresponding country.

Economic Productivity: These data represent the per capita gross cell product in 1990 USD in each cell, drawn from the G-Econ dataset (Nordhaus 2006). For the purposes of estimation, GPC is divided into units of 1000 USD.

Population: These data, taken from the Gridded Population of the World (Center for International Earth Science Information Network (CIESIN)/Columbia University, (FAO), and de Agricultura Tropical (CIAT) 2005), provide population size for 1990, 1995, 2000, and 2005. The missing years were filled by log-scale extrapolation for years prior to 1990 and after 2005, and log-scale interpolation for years between 1990 and 2005 without data. The population is divided into units of 1000 for the purposes of estimation.

Infant Mortality Rate: These data represent the number of children per 1,000,000 that die before reaching their first birthday. These data were only available for the year 2000, and so those data were entered for all remaining years.

Urban: This variable, drawn from Nelson (2008), shows the estimated travel time in 100 minute units to a city with a population of greater than 50,000 within the cell. This variable does not vary over time. We multiply the distance by negative one so that the variable reflects proximity to an urban area.

Control Variables

Total Land Area in Grid Cell: This covariate represents the area of land in 100 square kilometer units within the grid cell.

Precipitation: These data provide yearly total precipitation in meters in each cell, based on meteorological data gathered by the University of Delaware.

Ethnic Fractionalization: Using the GeoEPR through PRIO-GRID we created a Herfindahl-Hirschman index of the amount of area each group controlled in a cell. The variable *Ethnic Fractionalization* is 1 minus this index and reflects the amount of ethnic diversity in territorial control.

State Level Variables

Regime Type: We used a diversity of measures of regime type including the Vanehanen Index of Democratization, Freedom House imputed polity index, and the revised combined polity score.

Capacity: To measure state capacity we used CINC score from correlates of war as well as the two factor measure of military capacity and bureaucratic capacity developed by Hendrix and Young (2014).

Political Terror: This is the Political Terror Scale published by Amnesty International.

Results: Location, Location, Location

Below we present the results of a variety of statistical models including rare event logit, negative binomial event count, zero-inflated negative binomial, multilevel, and propensity score matching models. These models are designed to test the vulnerability and value hypotheses described above. Overall, the results provide broad preliminary support for hypotheses one and two, with exception of hypothesis 1d which hypothesized that forested areas would be more likely to have terrorist attacks due to vulnerability. In fact, we find the opposite, that terrorist attacks are less likely to occur in forested areas.

Cell-Year Level Models

The results of the Rare Events Logit and negative binomial event count model at the cell-year level of analysis are presented in Table 1. We first discuss the variables associated with the vulnerability of local areas. Civil conflict and mountainous terrain both have a positive and significant effect on the likelihood of a terror attack. The effect of distance to an international border is negative and significant for each model. Contrary to the hypothesized relationship, the effect of forest coverage is negative and significant for all four models.

We also find support for the value hypothesis. The effect of distance to capital is negative and significant for all four models. The coefficients on economic activity and proximity to urban areas is positive and significant. Population is positive and significant for each model except the negative binomial event count model that does not include civil conflict.

The results of the cell-year level zero inflated negative binomial model are presented in Table 2. The event count stage is presented in the left column and the inflation stage is presented in the right column. Overall, the results support the vulnerability hypothesis. The effect of civil conflict is positive and significant in the count stage and negative and significant

	Rare Events Logit	Rare Events Logit	Negative Binomial	Negative Binomial
Civil Conflict in Cell	1.639***		1.822***	
	(0.120)		(0.136)	
Land Area	0.00728	0.0369	0.0180	0.0301
	(0.0191)	(0.0227)	(0.0173)	(0.0229)
Infant Mortality Rate	0.00665	0.0295	-0.000676	0.0210
	(0.0196)	(0.0222)	(0.0208)	(0.0269)
Distance to Capital	-0.183***	-0.173***	-0.158***	-0.161***
	(0.0250)	(0.0230)	(0.0194)	(0.0246)
Distance to International Border	-0.191***	-0.117***	-0.227***	-0.116***
	(0.0391)	(0.0235)	(0.0387)	(0.0300)
Population	0.000544***	1.52e-28***	0.00136***	-6.52e-31
	(0.0000820)	(9.84e-33)	(0.0000996)	(4.05e-31)
Urban	0.167***	0.437***	0.0779*	0.278**
	(0.0505)	(0.112)	(0.0320)	(0.0863)
Forest Coverage	-0.00807***	-0.0137***	-0.0111***	-0.0219***
	(0.00229)	(0.00263)	(0.00258)	(0.00310)
Mountainous Terrain	0.620***	0.983***	0.511**	1.245***
	(0.144)	(0.141)	(0.162)	(0.200)
Economic Activity	0.0591***	0.0766***	0.0651***	0.104***
	(0.00738)	(0.00727)	(0.00874)	(0.00871)
Precipitation	0.344***	0.557***	0.467***	0.963***
	(0.0688)	(0.0685)	(0.123)	(0.149)
Ethnic Fractionalization	0.172	0.335	0.174	0.0918
	(0.190)	(0.198)	(0.185)	(0.253)
Constant	-5.561***	-5.606***	-6.209***	-5.652***
	(0.469)	(0.541)	(0.439)	(0.602)
$\ln(\alpha)$			3.689***	4.671***
			(0.150)	(0.136)
Observations	764551	1577267	764551	1577267

Clustered Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1: Cell-Year Level Rare Events Logit and Negative Binomial

in the inflation stage, indicating that civil conflict makes it less likely that no events will occur, and increases the number of events. The coefficient on distance to international border is negative and significant in the count stage. However, the coefficients on mountainous terrain are not significant and forest coverage is positive and significant in the inflation stage, suggesting that forestation may actually reduce the likelihood of a terror attack contrary to the vulnerability hypothesis.

We also find mixed support for the value hypothesis. The effect of population is positive and significant in the count stage and negative and significant in the inflation stage. Distance to capital has a negative and significant coefficient in the count stage. The effect of economic activity is positive and significant in both the event count and inflation stage. However, proximity to an urban area did not have a significant effect in either stage.

Cell-Level Models

The results of the cell-level rare events Logit and negative binomial models are presented in Table 3. We find support for the vulnerability hypothesis from these cell-level models. Civil conflict and mountainous terrain have a positive and significant effect and distance to international border has negative and significant effect in both models, supporting Hypothesis 1. However, the effect of forest coverage is negative and significant in both models, contrary to the hypothesized relationship.

The cell-level models also provide evidence for the value hypothesis. Population, economic activity, and proximity to an urban area each have positive and significant effects as hypothesized. The effect of distance to capital is also in the hypothesized negative direction and significant in both models.

The results of the cell-level zero-inflated negative binomial model are presented in Table 4. The left column is the event count stage, modeling the number of attacks, given that at least one attack occurs and the right column is the inflation stage, modeling whether no attacks occur. Overall, the results concord with the vulnerability hypothesis. The effect of

	Event Count Stage	Inflation Stage
Civil Conflict in Cell	0.948***	-1.397***
	(0.225)	(0.418)
Land Area	-0.0134	-0.0181
	(0.0271)	(0.0309)
Infant Mortality Rate	0.0247	0.0329
	(0.0398)	(0.0448)
Distance to Capital	-0.160***	-0.0316
	(0.0216)	(0.0358)
Distance to International Border	-0.194**	0.0694
	(0.0630)	(0.123)
Population	0.000397***	-0.00396***
	(0.000117)	(0.00100)
Urban	0.00669	-0.0524
	(0.0688)	(0.0661)
Forest Coverage	0.00887	0.0213**
	(0.00661)	(0.00823)
Mountainous Terrain	0.125	-0.490
	(0.593)	(0.761)
Economic Activity	0.103***	0.0488**
	(0.0170)	(0.0187)
Precipitation	-0.388*	-1.284***
	(0.155)	(0.344)
Ethnic Fractionalization	-0.00670	-0.427
	(0.520)	(0.489)
Constant	-3.050***	3.708***
	(0.763)	(0.680)
lnalpha		
Constant	2.625***	
	(0.343)	
Observations	764551	

Clustered Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Cell-Year Level Zero-Inflated Negative Binomial

	Rare Events Logit	Negative Binomial
Civil Conflict in Cell	1.046***	1.154***
	(0.0828)	(0.151)
Land Area	0.00477	0.0374*
	(0.0115)	(0.0166)
Infant Mortality Rate	-0.00279	-0.0554**
	(0.0150)	(0.0208)
Distance to Capital	-0.0800***	-0.101***
	(0.00688)	(0.0102)
Distance to International Border	-0.149***	-0.103***
	(0.0167)	(0.0309)
Population	0.00118***	0.00178***
	(0.0000695)	(0.000166)
Urban	0.116***	0.0584**
	(0.0222)	(0.0193)
Forest Coverage	-0.00486***	-0.0176***
	(0.00134)	(0.00381)
Mountainous Terrain	0.703***	0.578**
	(0.0954)	(0.183)
Economic Activity	0.0569***	0.0668***
	(0.00372)	(0.00916)
Precipitation	0.453***	0.796***
	(0.0686)	(0.170)
Ethnic Fractionalization	0.134	0.0861
	(0.124)	(0.278)
Constant	-3.606***	-3.583***
	(0.279)	(0.457)
ln(α)		
Constant		3.058***
		(0.113)
Observations	39582	39582

Clustered Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Cell Level Rare Events Logit and Negative Binomial

civil conflict is significant and positive in the count stage and significant and negative in the inflation stage. Distance to international border has a negative and significant coefficient in the count stage. Mountainous terrain is negative and significant in the inflation stage. However, as in the above models, forest coverage has a significant effect that is in the opposite of the hypothesized direction.

The zero-inflated cell-level model also supports the value hypothesis. Population has a positive and significant coefficient in the count stage and negative and significant coefficient in the inflation stage. Distance to capital has a negative and significant coefficient in the count stage. Economic activity has a positive and significant coefficient in the count stage. Proximity to an urban area had a negative and significant coefficient in the inflation stage, however its coefficient is also negative and significant in the count stage.

Sensitivity Analysis: Multilevel Models

As our data has both state and lower levels data, we examine whether modeling this multilevel structure influences the inferences of the original models. The results for the multilevel random effect negative binomial models are presented in Tables 5 and 6. Table 5 includes country CINC score (state capacity) while Table 6 includes bureaucratic and military capacity.[11] Each column includes a different measure of regime type. The left column includes the Vanehanen Index of Democratization. The middle column includes the Freedom House imputed polity index. The right column includes the revised combined polity score.

In each of the multilevel models, civil conflict has a positive and significant effect. Distance to border is negative and significant in each. Mountainous terrain is not significant for any of the multilevel models. Like the above models, forest coverage has a negative and significant effect in each of the multilevel models.

The coefficients on cell population, economic activity and urban are significant and positive for all of the multilevel models. The effect of distance to capital is negative and significant

[11] See Hendrix and Young (2014) for why disaggregating state capacity can help explain cross-national incidents of terrorism.

	Event Count Stage	Inflation Stage
Civil Conflict in Cell	0.726***	-1.122***
	(0.196)	(0.234)
Land Area	0.0135	-0.00711
	(0.0177)	(0.0217)
Infant Mortality Rate	-0.0700***	-0.0385
	(0.0212)	(0.0280)
Distance to Capital	-0.102***	-0.00602
	(0.0120)	(0.0129)
Distance to International Border	-0.117***	0.0537
	(0.0346)	(0.0400)
Population	0.000879***	-0.00988***
	(0.000133)	(0.00206)
Urban	-0.119***	-0.135***
	(0.0319)	(0.0254)
Forest Coverage	-0.00437	0.0110**
	(0.00487)	(0.00385)
Mountainous Terrain	0.0110	-0.853**
	(0.247)	(0.270)
Economic Activity	0.0885***	0.00568
	(0.0134)	(0.0121)
Precipitation	-0.0458	-1.376***
	(0.168)	(0.218)
Ethnic Fractionalization	0.0324	-0.534
	(0.311)	(0.357)
Constant	-1.425*	3.273***
	(0.577)	(0.564)
Observations	39582	

Clustered Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Cell Level Zero-Inflated Negative Binomial

in each of the multilevel models. In sum, the results are not sensitive to this modeling choice.

Of the state level variables, the coefficient on Political Terror Scale is positive and significant for all of the multilevel models. The coefficient on CINC score is negative for all three models in Table 5. The coefficient on Military capacity and bureaucratic capacity are also negative and significant for each model in Table 6. These results suggest that state capacity has a negative effect on transnational terrorism. None of the effects of regime type are significant in any of the models.

Interestingly, while the effect of ethnic fractionalization is not significant in any of the single level models the effect of ethnic fractionalization is positive and significant in all of the models which take into account the hierarchical nature of the data. The random effect for country is significant across each of the multilevel models.

Sensitivity Analysis: Propensity Score Matching

The results from the civil conflict propensity score matching models are presented below. Table 7 presents the results for matched data using rare events logit and matched data using a negative binomial model. The effect of civil conflict is positive and significant in both the rare events logit and negative binomial model. The effect of distance to an international border is negative and significant. The effect of mountainous terrain and forest coverage are not significant in either model.

The matched models in Table 7 provide further evidence for the value hypothesis. The effect of population, economic activity, and urban proximity is positive and significant. The effect of distance to capital is negative and significant.

Table 8 presents the results from the matched zero-inflated negative binomial model. The effect of civil conflict is positive in the event count stage and negative in the inflation stage. The effects of distance to border and forest coverage are positive and significant in the inflation stage. The coefficients on mountainous terrain are not significant.

Table 8 also shows support for the value hypothesis. The effect of population is positive

	Negative Binomial	Negative Binomial	Negative Binomial
Civil Conflict in Cell	0.869***	0.890***	0.924***
	(0.119)	(0.119)	(0.121)
Land Area	-0.00353	-0.00272	-0.00139
	(0.0125)	(0.0125)	(0.0127)
Infant Mortality Rate	-0.0475	-0.0318	-0.0363
	(0.0268)	(0.0266)	(0.0265)
Distance to Capital	-0.0618***	-0.0616***	-0.0608***
	(0.00927)	(0.00927)	(0.00931)
Distance to International Border	-0.0535*	-0.0527*	-0.0537*
	(0.0217)	(0.0216)	(0.0217)
Population	0.00148***	0.00149***	0.00151***
	(0.0000639)	(0.0000637)	(0.0000651)
Urban	0.130***	0.129***	0.128***
	(0.0188)	(0.0188)	(0.0188)
Forest Coverage	-0.0103***	-0.0104***	-0.0103***
	(0.00187)	(0.00187)	(0.00188)
Mountainous Terrain	0.0643	0.0533	0.0443
	(0.125)	(0.124)	(0.125)
Economic Activity	0.0654***	0.0636***	0.0636***
	(0.00688)	(0.00683)	(0.00688)
Precipitation	0.380***	0.376***	0.380***
	(0.0795)	(0.0795)	(0.0803)
Ethnic Fractionalization	0.975***	0.977***	0.968***
	(0.202)	(0.201)	(0.203)
Political Terror Scale	0.318***	0.339***	0.339***
	(0.0602)	(0.0606)	(0.0609)
CINC	-32.81***	-33.96***	-33.45***
	(6.822)	(6.802)	(6.702)
Index of Democratization	-0.0125		
	(0.00781)		
Freedom House Imputed Polity		0.0383	
		(0.0327)	
Revised Combined Polity Score			0.00644
			(0.0148)
Constant	-6.210***	-6.735***	-6.578***
	(0.442)	(0.474)	(0.422)
$\ln(\alpha)$	2.742***	2.733***	2.785***
	(0.0639)	(0.0637)	(0.0647)
$\sigma^2_{Country}$	1.998***	1.999***	1.915***
	(0.352)	(0.350)	(0.341)
Observations	451054	451067	450824

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Multilevel Negative Binomial Models

	Negative Binomial	Negative Binomial	Negative Binomial
Civil Conflict in Cell	0.997***	0.992***	1.001***
	(0.126)	(0.127)	(0.127)
Land Area	-0.00525	-0.00503	-0.00245
	(0.0129)	(0.0128)	(0.0131)
Infant Mortality Rate	-0.0594	-0.0588	-0.0562
	(0.0310)	(0.0310)	(0.0308)
Distance to Capital	-0.0552***	-0.0548***	-0.0543***
	(0.00868)	(0.00867)	(0.00870)
Distance to International Border	-0.0714***	-0.0707***	-0.0707***
	(0.0210)	(0.0209)	(0.0210)
Population	0.00142***	0.00142***	0.00143***
	(0.0000599)	(0.0000599)	(0.0000611)
Urban	0.128***	0.128***	0.127***
	(0.0185)	(0.0185)	(0.0185)
Forest Coverage	-0.0117***	-0.0116***	-0.0116***
	(0.00186)	(0.00186)	(0.00187)
Mountainous Terrain	0.107	0.105	0.106
	(0.125)	(0.125)	(0.125)
Economic Activity	0.0678***	0.0674***	0.0673***
	(0.00670)	(0.00668)	(0.00673)
Precipitation	0.516***	0.516***	0.521***
	(0.0778)	(0.0778)	(0.0784)
Ethnic Fractionalization	0.782***	0.784***	0.773***
	(0.204)	(0.204)	(0.206)
Political Terror Scale	0.256***	0.253***	0.258***
	(0.0606)	(0.0612)	(0.0609)
Bureaucratic Capacity	-0.302**	-0.312**	-0.298**
	(0.110)	(0.109)	(0.110)
Military Capacity	-1.050***	-1.077***	-1.043***
	(0.155)	(0.154)	(0.154)
Index of Democratization	-0.00756		
	(0.00852)		
Freedom House Imputed Polity		-0.0262	
		(0.0330)	
Revised Combined Polity Score			-0.00962
			(0.0145)
Constant	-6.491***	-6.450***	-6.710***
	(0.474)	(0.506)	(0.455)
$\ln(\alpha)$	3.012***	3.010***	3.060***
	(0.0657)	(0.0657)	(0.0661)
$\sigma^2_{Country}$	2.542***	2.566***	2.420***
	(0.541)	(0.548)	(0.519)
Observations	624467	625475	625414

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Multilevel Negative Binomial Models

	Rare Events Logit	Negative Binomial
Civil Conflict in Cell	1.368***	1.539***
	(0.134)	(0.150)
Land Area	-0.00326	0.00195
	(0.0248)	(0.0220)
Infant Mortality Rate	-0.0236	-0.00572
	(0.0196)	(0.0238)
Distance to Capital	-0.285***	-0.254***
	(0.0352)	(0.0332)
Distance to International Border	-0.265***	-0.238***
	(0.0494)	(0.0536)
Population	0.000424***	0.000854***
	(0.0000478)	(0.000102)
Urban	0.174***	0.103*
	(0.0521)	(0.0412)
Forest Coverage	0.00129	-0.00328
	(0.00321)	(0.00371)
Mountainous Terrain	0.185	0.0438
	(0.172)	(0.197)
Economic Activity	0.0473***	0.106***
	(0.0113)	(0.0245)
Precipitation	0.104	0.273*
	(0.0841)	(0.110)
Ethnic Fractionalization	0.353	0.476
	(0.227)	(0.267)
Constant	-4.028***	-4.867***
	(0.690)	(0.649)
ln(α)		3.416***
		(0.163)
Observations	100994	100994

Clustered Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Matching Models: Rare Events Logit and Negative Binomial

in the event count stage and negative in the inflation stage, as hypothesized. The event count stage coefficient on distance to capital is negative and significant. The coefficients on economic activity show mixed results, being positive in both the event count and inflation stage. The coefficient on proximity to urban area is not significant.

	Event Count Stage	Inflation Stage
Civil Conflict in Cell	0.705*	-1.303***
	(0.303)	(0.368)
Land Area	-0.0261	-0.0139
	(0.0349)	(0.0435)
Infant Mortality Rate	0.0447	0.0553
	(0.0379)	(0.0394)
Distance to Capital	-0.230***	0.00550
	(0.0345)	(0.0411)
Distance to International Border	-0.0927	0.311***
	(0.0731)	(0.0874)
Population	0.000218***	-0.00286***
	(0.0000605)	(0.000445)
Urban	0.0464	-0.0510
	(0.0600)	(0.0567)
Forest Coverage	0.0148	0.0187*
	(0.00781)	(0.00816)
Mountainous Terrain	0.0801	0.208
	(0.488)	(0.495)
Economic Activity	0.173***	0.0589**
	(0.0305)	(0.0220)
Precipitation	-0.418*	-0.890*
	(0.186)	(0.404)
Ethnic Fractionalization	-0.135	-0.672
	(0.562)	(0.635)
Constant	-2.275*	2.601*
	(0.922)	(1.069)
$\ln(\alpha)$	2.308***	
	(0.227)	
Observations	100994	

Clustered Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Matching Models: Zero-Inflated Negative Binomial

We also estimated the multilevel models on the matched sample. Table 9 and 10 presents the results of this analysis. The results are substantively similar to those in Table 5 and 6 and support the value and vulnerability hypothesis.

In support of the vulnerability hypothesis, the effect of civil conflict in a cell is positive and significant for each of the matched multilevel models. Distance to an international border is negative and significant for each of the models. Mountainous terrain is positive for each of the models, but the effect is only statistically significant for the models in Table 9. Contrary to our expectations but consistent with the results above, the effect of forest coverage is negative and significant for each of the models. As found in the full sample multilevel models, ethnic fractionalization is found to have a positive and significant effect.

The matched sample multilevel models also provide support for the value hypothesis. Population, economic activity, and distance to urban area is positive and significant in each of the models. The effect of distance to capital is negative and significant in the models presented in Table 9, but is not significant for those presented in Table 10.

The state level results for the matched sample are similar to those found in the full sample. The coefficient on political terror scale is positive and significant in each of the models. The effect of CINC score, military capacity, and bureaucratic capacity are negative and significant. Of the regime type variables, only the Vanhanen index of democracy has a significant effect.

	Negative Binomial	Negative Binomial	Negative Binomial
Civil Conflict in Cell	0.891***	0.957***	1.001***
	(0.173)	(0.173)	(0.177)
Land Area	-0.0237	-0.0250	-0.0245
	(0.0196)	(0.0194)	(0.0195)
Infant Mortality Rate	-0.0672*	-0.0456	-0.0468
	(0.0300)	(0.0299)	(0.0298)
Distance to Capital	-0.0778**	-0.0822**	-0.0816**
	(0.0261)	(0.0262)	(0.0263)
Distance to International Border	-0.0110	-0.0106	-0.0113
	(0.0400)	(0.0402)	(0.0403)
Population	0.000999***	0.00102***	0.00102***
	(0.0000751)	(0.0000748)	(0.0000754)
Urban	0.102***	0.0982***	0.0977***
	(0.0246)	(0.0244)	(0.0244)
Forest Coverage	-0.0130***	-0.0132***	-0.0131***
	(0.00276)	(0.00276)	(0.00277)
Mountainous Terrain	0.281	0.250	0.239
	(0.169)	(0.168)	(0.168)
Economic Activity	0.118***	0.109***	0.109***
	(0.0142)	(0.0136)	(0.0137)
Precipitation	0.275**	0.267**	0.265**
	(0.0944)	(0.0944)	(0.0949)
Ethnic Fractionalization	0.709**	0.709**	0.696**
	(0.259)	(0.258)	(0.259)
Political Terror Scale	0.350***	0.353***	0.364***
	(0.0833)	(0.0834)	(0.0844)
CINC	-33.85***	-36.34***	-36.13***
	(8.365)	(8.460)	(8.426)
Index of Democratization	-0.0353**		
	(0.0116)		
Freedom House		0.00721	
Imputed Polity		(0.0405)	
Revised Combined			-0.00154
Polity Score			(0.0182)
Constant	-5.271***	-5.717***	-5.743***
	(0.661)	(0.675)	(0.643)
$\ln(\alpha)$	2.602***	2.592***	2.609***
	(0.0851)	(0.0849)	(0.0857)
$\sigma^2_{Country}$	1.609***	1.670***	1.642***
	(0.381)	(0.392)	(0.390)
Observations	66877	66888	66794

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Matching Models: Multilevel Models

	Negative Binomial	Negative Binomial	Negative Binomial
Civil Conflict in Cell	0.929***	0.945***	0.966***
	(0.184)	(0.184)	(0.185)
Land Area	-0.0472*	-0.0472*	-0.0449*
	(0.0204)	(0.0202)	(0.0205)
Infant Mortality Rate	-0.117***	-0.108**	-0.102**
	(0.0338)	(0.0336)	(0.0334)
Distance to Capital	-0.0435	-0.0443	-0.0437
	(0.0242)	(0.0241)	(0.0241)
Distance to International Border	-0.0366	-0.0343	-0.0344
	(0.0389)	(0.0388)	(0.0387)
Population	0.000927***	0.000937***	0.000942***
	(0.0000709)	(0.0000708)	(0.0000714)
Urban	0.116***	0.114***	0.114***
	(0.0263)	(0.0262)	(0.0262)
Forest Coverage	-0.0154***	-0.0154***	-0.0154***
	(0.00289)	(0.00288)	(0.00289)
Mountainous Terrain	0.492**	0.478**	0.468**
	(0.174)	(0.173)	(0.174)
Economic Activity	0.129***	0.123***	0.123***
	(0.0147)	(0.0143)	(0.0144)
Precipitation	0.387***	0.383***	0.382***
	(0.0918)	(0.0918)	(0.0921)
Ethnic Fractionalization	0.722**	0.724**	0.694**
	(0.265)	(0.264)	(0.266)
Political Terror Scale	0.410***	0.407***	0.413***
	(0.0904)	(0.0908)	(0.0904)
Bureaucratic Capacity	-0.418**	-0.467**	-0.475**
	(0.146)	(0.144)	(0.145)
Military Capacity	-1.055***	-1.167***	-1.151***
	(0.186)	(0.182)	(0.182)
Index of Democratization	-0.0369**		
	(0.0131)		
Freedom House Imputed Polity		-0.0475	
		(0.0404)	
Revised Combined Polity Score			-0.0125
			(0.0174)
Constant	-5.084***	-5.265***	-5.628***
	(0.712)	(0.727)	(0.693)
$\ln(\alpha)$	2.846***	2.851***	2.877***
	(0.0908)	(0.0906)	(0.0908)
$\sigma^2_{Country}$	1.535***	1.478***	1.421***
	(0.419)	(0.400)	(0.385)
Observations	82202	82310	82298

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Matching Models: Multilevel Models

Illustrations

While we have displayed statistical correlations using a variety of methods connected to an argument about the value and vulnerability of a location, we also want to illustrate the process of how these factors influence the actual outcome of terrorist events. We offer an illustration of how a sample of events matches the variables in the model. These descriptions are organized by variables in the vulnerability and value categories and come from the ITERATE event narratives.

Vulnerability

Civil Conflict:

Former Sierra Leonoese soldiers and rebel fighters kidnapped 34 UN employees and West African peacekeepers near Freetown in 1999. The hostages were later freed, along with 200 other civilian hostages.

Kashmiri Muslim separatists took several British and American tourists hostage in Delhi, demanding the release of other Kashmiri militants or threatening to kill the hostages.

Fifteen members of the Liberation Front for Southern Sudan raided a Christian mission in Boma, taking 11 Westerners hostage. The rebels demanded ransom and supplies in exchange for the release of the hostages. While some hostages were allowed to go free, the remaining hostages escaped after their captors were attacked and routed by Sudanese security forces.

RENAMO fighters allegedly killed a couple and 5 of their 6 children in a village located 6 miles from the Mozambiquan border.

Terrain:

A luxury resort located in the mountains 8 miles east of Harare (then Salisbury) resulted in the deaths of two white Rhodesian woman and injured three others, including an American visitor. The assailants attacked the Montclair Hotel with grenades and automatic rifles.

Mozambique National Resistance Movement (RENAMO) fighters were accused of bombing the Small Lebombo Dam, located in the Lebombo mountains. Italians workers at the Dam left after the attack.

A bomb went off on a train traveling through the Apennine Mountains in Italy while the train was in the 11.6 mile tunnel under the mountains in 1984. Some 17 people died and another 115 were injured. Three neofascist groups claimed credit.

A French intelligence officer was found murdered in the mountains near Nice. Some suspected that his death was due to his knowledge of Soviet Bloc espionage operations in the South of France and Italy.

Forest:

Indian river pirates kidnapped 22 Bangladeshi fishermen near the Sundarbans forest.

Distance to international border:

A motorized hang glider from 50 miles across the border flew over an Israeli Defense Forces camp, firing machine guns and throwing hand grenades. 6 IDF soldiers were killed and seven injured before it was shot down. A second hang glider was launched several hours later, but was shot down soon after.

Zimbabwean media claimed that RENAMO fighters had attacked a village 16 kilometers from the border of Mozambique. A family of four was killed, including a 7-year old boy and a 2-year old girl. 15 homes were then looted.

Members of the Free Papua Movement kidnapped three Indonesians in a raid on a settlement near a border crossing. The hostages were later handed over.

Value

Proximity to State Capital:

The 1977 explosion of a bomb in a taxi near the Sovietskaya Hotel in Moscow caused little damage to the building, which often housed foreign dignitaries. But the media coverage of the event was a rare acknowledgement of a terror attack in the Soviet Union. The hotel administrator denied hearing the blast, but claimed that 'even if I did I could not tell you because we do not release such information.'

IRA firebombed four stores on Oxford Street and The Strand in London in 1993. The IRA said "The right of the Irish people to the ownership of Ireland and to their unfettered control of Irish destinies is a sovereign and indefensible right, and the sooner British generals and politicians convince themselves of our absolute determination to assert that right through force of arms until final British disengagement, the better for all. They will not, and cannot prevail."

Ali Hassan Salameh, the alleged planner of the 1972 Olympics massacre of Israeli athletes by Black September, was killed by a bomb which exploded near his home in Western Beirut in 1979. While the case remains unsolved, the Palestinian Liberation Organization claimed Israel planned the assassination.

Annie Kuzmuk, American wife of an American businessman, was killed by a bomb attack in downtown Manila that wounded at least 30 Filipinos. The April 6 Liberation Movement claimed responsibility for the attacks, which took place soon after President Ferdinand Macros' 63rd birthday.

Population:

A man in a sedan through a grenade into a My Place disco in Panama, killing a US soldier and injuring 17 Panamanians. The 20 December Movement (M-20) claimed credit.

Fighters from the United Revolutionary Front in Sierra Leone killed two Red Cross nurses in an ambush on a convoy near the village of Golahun. The rebels then burnt the convoy, which was carrying aid for the 10,000 refugees displaced by the rebellion.

Proximity to Urban Area:

Poles armed with automatic rifles seized the Polish embassy in Bern and took 13 people hostage. The seizure of the embassy lasted some 73 hours, which was finally ended in a raid. No injuries were reported.

A 55-pound bomb exploded in a South African-owned First National Bank in Oshakati, killing 26 persons and injuring 31. The South West African Peoples Organization (SWAPO) was blamed for the attack, which it denied.

Level of Economic Activity:

A bombing of a Banque Pastor in Paris and a Spanish consulate in Saint-Denis in 1976 marked the one year anniversary of the execution of 5 alleged Basque terrorists in Spain.

Members of the National Union for the Total Independence of Angola (UNITA) raided a diamond-mining town in 1986, captured some 197 foreign workers at the mind. The purpose of the attack was allegedly to cripple the Angolan economy, which was dependent upon its diamond exports for its supply of foreign exchange. Members of UNITA had made a similar raid of the Quando diamond mine back in 1984.

In 1990, eleven South Korean students, armed with home-made bombs and metal pipes, were arrested for attempting to enter the US Embassy to protest the Uruguay round of trade negotiations and to protest agains the alleged damage the US was causing the Korean economy.

Muslim extremists attacked two buses in 1993 that were carrying tourists on holiday in the south of Egypt. Egypt had had a profitable previous year due to record-high tourism levels, which disturbed some Muslims due to the increased presence of foreigners.

Conclusion

This paper has explored the implications of the variability in subnational locations on the likelihood of terrorist attacks occurring locally. From a global perspective, it is clear that not all locations are equally likely to host a transnational terrorist attack. We have offered an organizing framework involving *vulnerability* and*value* that allows locations to be differentiated. With increasing degrees of each attribute, we expect the prospects of an attack occurring locally to increase. Our analyses offer some initial evidence that this is a reasonable contention.

This approach could be used for risk analysis or to predict out-of-sample locations that are particularly attractive to groups that utilize terrorism. Our approach here is part of a growing group of studies that examine local level geo-coded conflict data (Findley and Young 2012, Nemeth, Mauslein, and Stapley 2014). In the future, we will address potential endogeneity problems associated with target countries interfering in other countries that may, in turn, provoke return attacks. To do properly, we may need to adjust the unit of analysis to include directed dyads. Next, there are a number of more complex, potentially interactive relationships such as whether civil conflict is occurring across the border in the neighboring state that could unpack some future results. Finally, a future direction is to examine the sub-national variation of different modes of transnational terror attacks.

References

Anonymous. 2003. "Al-Qaeda Training Manual.".

Arce, D.G., and T. Sandler. 2010. "Terrorist spectaculars: Backlash attacks and the focus of intelligence." *Journal of Conflict Resolution* 54(2): 354.

Arino, Olivier et al. 2010. "GlobCover 2009.".

Bahgat, Karim, and Richard M Medina. 2013. "An Overview of Geographical Perspectives and Approaches in Terrorism Research." *Perspectives on Terrorism* 7(1).

Beall, Jo. 2006. "Cities, terrorism and development." *Journal of International Development* 18(1): 105–120.

Berrebi, C., and D. Lakdawalla. 2007. "How does terrorism risk vary across space and time? An analysis based on the Israeli experience." *Defence and Peace Economics* 18(2): 113–131.

Braithwaite, A. 2006. "The geographic spread of militarized disputes." *Journal of Peace Research* 43(5): 507.

Braithwaite, A. 2010. *Conflict hot spots: emergence, causes, and consequences.* Ashgate Pub. Co.

Braithwaite, A., and Q. Li. 2007. "Transnational terrorism hot spots: Identification and impact evaluation." *Conflict Management and Peace Science* 24(4): 281–296.

Braithwaite, Alex, and Shane D Johnson. 2012. "Space–Time Modeling of Insurgency and Counterinsurgency in Iraq." *Journal of Quantitative Criminology* 28(1): 31–48.

Brandt, Patrick T, and Todd Sandler. 2010. "What do transnational terrorists target? Has it changed? Are we safer?" *Journal of Conflict Resolution* 54(2): 214–236.

Buhaug, Halvard, and Jan Ketil Rød. 2006. "Local determinants of African civil wars, 1970–2001." *Political Geography* 25(3): 315–335.

Buhaug, Halvard, and Päivi Lujala. 2005. "Accounting for scale: Measuring geography in quantitative studies of civil war." *Political Geography* 24(4): 399–418.

Buhaug, Halvard, and Scott Gates. 2002. "The Geography of Civil War." *Journal of Peace Research* 39(4): 417–433.

Buhaug, Halvard, Kristian Skrede Gleditsch, Helge Holtermann, Gudrun Østby, and Andreas Forø Tollefsen. 2011. "It's the local economy, stupid! Geographic wealth dispersion and conflict outbreak location." *Journal of Conflict Resolution* 55(5): 814–840.

Buhaug, Halvard, Scott Gates, and Päivi Lujala. 2009. "Geography, rebel capability, and the duration of civil conflict." *Journal of Conflict Resolution* 53(4): 544–569.

Carter, Timothy Allen, and Daniel Jay Veale. 2013. "Weather, terrain and warfare: Coalition fatalities in Afghanistan." *Conflict Management and Peace Science* 30(3): 220–239.

Center for International Earth Science Information Network (CIESIN)/Columbia University, United Nations Food, Agriculture Programme (FAO), and Centro Internacional de Agricultura Tropical (CIAT). 2005. "Gridded Population of the World, Version 3 (GPWv3): Population Count Grid.".

Cothren, J., B.L. Smith, P. Roberts, and K.R. Damphousse. 2008. "Geospatial and temporal patterns of preparatory conduct among American terrorists." *International Journal of Comparative and Applied Criminal Justice* 32(1): 23–41.

Cutter, SL, DB Richardson, and TJ Wilbanks. 2003. *The Geographic Dimension of Terrorism*. New York and London: Routledge.

Diehl, Paul. 1991. "Geography and War: A Review and Assessment of the Empirical Literature." *International Interactions* 17(1): 11–27.

Enders, W., and T. Sandler. 2006. *The political economy of terrorism.* Cambridge Univ Pr.

Enders, Walter, and Todd Sandler. 1993. "The Effectiveness of Antiterrorism Policies: A Vector-Autoregression-Intervention Analysis." *American Political Science Review* 87(4): 829–844.

Enders, Walter, Todd Sandler, and Khusrav Gaibulloev. 2011. "Domestic versus transnational terrorism: Data, decomposition, and dynamics." *Journal of Peace Research* 48(3): 319–337.

Findley, Michael G, and Joseph K Young. 2012. "Terrorism and civil war: A spatial and temporal approach to a conceptual problem." *Perspectives on Politics* 10(02): 285–305.

Glaeser, Edward L., and Jesse M. Shapiro. 2001. Cities and Warfare: The Impact of Terrorism on Urban Form. Working Paper 8696 National Bureau of Economic Research.

Harbom, Lotta, and Peter Wallensteen. 2010. "Armed Conflicts, 19462009." *Journal of Peace Research* 47(4): 501–509.

Hendrix, Cullen S, and Idean Salehyan. 2012. "Climate change, rainfall, and social conflict in Africa." *Journal of Peace Research* 49(1): 35–50.

Hendrix, Cullen S, and Joseph K Young. 2014. "State Capacity and Terrorism: A Two-Dimensional Approach." *Security Studies* 23(2): 329–363.

Heyman, E., and E. Mickolus. 1980. "Observations on" Why Violence Spreads"." *International Studies Quarterly* 24(2): 299–305.

Hoffman, B. 2006. *Inside terrorism.* Columbia Univ Pr.

Johnson, N., S. Carran, J. Botner, K. Fontaine, N. Laxague, P. Nuetzel, J. Turnley, and B. Tivnan. 2011. "Pattern in Escalations in Insurgent and Terrorist Activity." *Science* 333(6038): 81.

Johnson, S.D., and A. Braithwaite. 2009. "Spatio-Temporal Modelling of Insurgency in Iraq (From Reducing Terrorism Through Situational Crime Prevention, P 9-32, 2009, Joshua D. Freilich and Graeme D. Newman, eds., see-NCJ-229596).".

King, Gary, and Langche Zeng. 2001*a*. "Explaining Rare Events in International Relations." *International Organization* 55(3): 693–715.

King, Gary, and Langche Zeng. 2001*b*. "Logistic Regression in Rare Events Data." *Political Analysis* 9(2): 137–163.

Kittner, Cristiana C Brafman. 2007. "The role of safe havens in Islamist terrorism." *Terrorism and Political Violence* 19(3): 307–329.

Kliot, Nurit, and Igal Charney. 2006. "The geography of suicide terrorism in Israel." *GeoJournal* 66(4): 353–373.

Korteweg, Rem. 2008. "Black holes: On terrorist sanctuaries and governmental weakness." *Civil Wars* 10(1): 60–71.

Kydd, A.H., and B.F. Walter. 2006. "The strategies of terrorism." *International Security* 31(1): 49–80.

LaFree, G., L. Dugan, M. Xie, and P. Singh. 2009. "Spatial and Temporal Patterns of Terrorist Attacks by ETA 1970 to 2007." *Journal of Quantitative Criminology* pp. 1–23.

LaFree, G., N. Morris, L. Dugan, and S. Fahey. 2006. "Identifying Cross-National Global Terrorist Hot Spots." *Tangled roots: social and psychological factors in the genesis of terrorism* 11: 98.

Li, Q. 2005. "Does democracy promote or reduce transnational terrorist incidents?" *Journal of Conflict Resolution* 49(2): 278.

Mathews, Timothy, and Anton D Lowenberg. 2012. "The Interdependence Between Homeland Security Efforts of a State and a Terrorist's Choice of Attack." *Conflict Management and Peace Science* 29(2): 195–218.

Mickolus, EF, T. Sandler, JM Murdock, and PA Flemming. 2003. "International Terrorism: Attributes of Terrorist Events (ITERATE) Data Code Book." *Inter-University Consortium for Political and Social Research, Ann Arbor, Michigan* .

Midlarsky, M.I., M. Crenshaw, and F. Yoshida. 1980. "Why violence spreads: The contagion of international terrorism." *International Studies Quarterly* 24(2): 262–298.

Most, Benjamin A., and Harvey Starr. 1989. *Inquiry, Logic and International Politics.* Columbia, SC: University of South Carolina Press.

Nelson, A. 2008. "Travel time to major cities: A global map of Accessibility." *Ispra: European Commission* .

Nemeth, Stephen C, Jacob A Mauslein, and Craig Stapley. 2014. "The primacy of the local: Identifying terrorist hot spots using geographic information systems." *The Journal of Politics* 76(02): 304–317.

Nordhaus, William D. 2006. "Geography and macroeconomics: New data and new findings." *Proceedings of the National Academy of Sciences of the United States of America* 103(10): 3510–3517.

Phillips, Brian J. 2014. "What is a terrorist group? Conceptual issues and empirical implications." *Terrorism and Political Violence* (ahead-of-print): 1–18.

Piazza, J.A. 2008. "Incubators of Terror: Do Failed and Failing States Promote Transnational Terrorism?" *International Studies Quarterly* 52(3): 469–488.

Pierskalla, Jan H, and Florian M Hollenbach. 2013. "Technology and Collective Action: The Effect of Cell Phone Coverage on Political Violence in Africa." *American Political Science Review* pp. 1–18.

Raleigh, Clionadh, and Håvard Hegre. 2009. "Population size, concentration, and civil war. A geographically disaggregated analysis." *Political Geography* 28(4): 224–238.

Sandler, Todd. 2014. "The analytical study of terrorism: Taking stock." *Journal of Peace Research* 51(2): 257–271.

Santifort, Charlinda, Todd Sandler, and Patrick T Brandt. 2013. "Terrorist attack and target diversity Changepoints and their drivers." *Journal of Peace Research* 50(1): 75–90.

Savitch, HV, and Grigoriy Ardashev. 2001. "Does terror have an urban future?" *Urban Studies* 38(13): 2515–2533.

Sundberg, Ralph, Mathilda Lindgren, and Ausra Padskocimaite. 2010. "UCDP Georeferenced Event Dataset (UCDP GED Codebook)." *Department of Peace and Conflict Research* .

Tollefsen, Andreas Forø, Håvard Strand, and Halvard Buhaug. 2010. "PRIO-GRID: A Unified Spatial Data Structure.".

Townsley, M., S.D. Johnson, and J.H. Ratcliffe. 2008. "Space time dynamics of insurgent activity in Iraq." *Security Journal* 21(3): 139.

UNEP. 2002. "UNEP World Conservation Monitoring Centre Annual Report.".

Webb, Jennifer J, and Susan L Cutter. 2009. "The geography of US terrorist incidents, 1970–2004." *Terrorism and Political Violence* 21(3): 428–449.

Young, Joseph K, and Laura Dugan. 2014. "Survival of the Fittest: Why Terrorist Groups Endure." *Perspectives on Terrorism* 8(2).