Chapter 2
Assessing and Comparing Data Sources for Terrorism Research

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Introduction

A journey of a thousand miles begins with a single step. Lao Tzu

Much of the early work on terrorism was based on "small-*n*" qualitative case studies. Little by little narrative chronologies were added. Today, large-*n* quantitative databases of terrorist events containing thousands and even tens of thousands of events and a wide range of variables are only a click way on the Internet. These databases have provided enormous opportunities for terrorism researchers to identify cases and test hypotheses that are relevant to the field. But how good is the quality of the data? And how should terrorism researchers go about choosing between competing datasets?

One of the assumptions behind this chapter is that insights gained from the study of small-*n* data may be relevant to the development of standards to assess and compare large-*n* terrorism datasets. Ever since Geddes' paper on "how the cases you choose affect the answers you get" (Geddes, 1990), small-*n* qualitative researchers have quite self-consciously tried to improve the quality of small-*n* data. One result has been the growth of a large body of scholarship around the concept of "best practices" norms and standards to maximize transparency, reliability, and validity in this kind of data (Brady & Collier, 2004).

At the same time recognition has been growing that large-*n* datasets, including data on political events and processes, are often riddled with the same problems that plague small-*n* data. Collier, Brady, and Seawright (2004), for example, have drawn attention to the problems large and small-*n* researchers both face in making contextually sensitive judgments in terms of coding. Others have gone a step further suggesting that large-*n* datasets should be able to convey the kind of "detailed knowledge

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and sensitivity to context" that are the hallmarks and strength of case-oriented studies (Munck & Verkuilen, 2002). Still others have argued that improving data quality in databases such as *Polity IV* requires heightened critical attention to questions normally raised by qualitative researchers on subjects such as data construction and what Herrera and Devesh call "data supply chains":

> Who produced the data? Why? What were the producer's incentives and capabilities? Did they work as an independent agency or were they influenced by external actors? (2007, p.366)

These observations have led to increased calls for *shared* standards to evaluate small-*n* and large-*n* research. In this context, John Gerring (2001, 2010) introduced the concept of a "criterial framework" that bridges small-*n*/large-*n*, qualitative/quantitative chasms. Drawing on this concept, Evan Lieberman (2010) has shown that normative criteria commonly associated with the evaluation of small-*n* studies (e.g., citation transparency and handling of issues of uncertainty) can potentially improve political datasets such as *Polity IV*, the *Annual Survey of Freedom* (Freedom House index), the *Minorities at Risk* dataset (*MAR*), and the *Uppsala Conflict Data Program* dataset (UCDP).

In this chapter I will build on the concept of a "criterial framework" by extending it to large-*n* terrorism datasets and by proposing a best practices framework to help users evaluate the validity and reliability of a range of terrorism datasets. I will begin by discussing why we need norms or best practice standards to compare and evaluate quantitative terrorism data sources. I will then make a case for extending the concept of a "criterial framework," such as the one described by Gerring (2001, 2010), to terrorism data. I will highlight challenges and problems that occur in applying such a framework to five of the most well-known and respected terrorism events datasets in the field. All five of the databases selected are translations of narrative records (usually news reports) into numerical data in the form of counts, indexes, or dummy variables indicating the presence or absence of a phenomenon related to a coded terrorism event. In selecting the databases I have chosen ones that are publically available on the Internet and could be considered elite or the best in the field. I will conclude with proposals for implementing best practices in terrorism databases.

Developing Standards for Terrorism Data

Why Do We Need Them?

There are practical as well as methodological reasons for developing standards to assess and compare large-*n* terrorism datasets.

Practical Reasons

Terrorism datasets are unique in that most of them were first developed, maintained, and used *outside* universities in the intelligence and defense communities. First published in 1975, the *RAND Terrorism Chronologies*, which later became the basis for the well-known *RAND-MIPT* terrorism database, now subsumed into the *Rand Database of Worldwide Terrorism Incidents* (RDTWI), were originally developed by policy analysts such as Brian Michael Jenkins under a defense department grant for intelligence purposes (Fowler, 1981). The RAND chronologies were subsequently used by CIA analyst, Edward Mickolus, to produce the *International Terrorism*: *Attributes of Terrorist Events* dataset (ITERATE), a dataset that later formed the basis for the CIA's annual terrorism report, *Patterns of Global Terrorism* (Schmid, 1983, p. 257). Much of the *Global Terrorism Database* (GTD) originated with reports made by Pinkerton Global Intelligence Service (PGIS), a private global security firm (La Free, 2010), and the *World Incident Tracking System* (WITS) is a replacement for the previous annual *Patterns of Terrorism* report put out by the U.S. National Terrorism and Counter Terrorism Center (NCTC) (Wigle, 2010).

Because of these origins, *outside* an academic environment, terrorism data were not always subjected to the kinds of rigorous norms in terms of collection or coding that are usually expected in academia (Schmid, 2004). This situation led to considerable embarrassment when two Princeton scholars reviewed the data tables at the end of the State Department's annual *Patterns of Global Terrorism* report for 2003 and found that the numbers in the tables did not add up and that the conclusion of the report, namely that global terrorism had decreased that year, was in error and that terrorism had actually increased. When they subsequently published that information in an op-ed piece in the *Washington Post* (Krueger & Laitin, 2004a) and in an article in *Foreign Affairs* (Krueger & Laitin, 2004b), the State Department admitted that the report was wrong and retracted it.

Today large numbers of the users of terrorism data, however, are academic scholars. Many of these academics were nurtured in programs that emphasized the importance of best practices in collecting data and while they may agree with Gerring that the objects of social science often "refuse to lie still in the manner of rocks, animals, cells and atoms" (Gerring, 1999, p. 393) there is a much greater expectation that terrorism data should be based on solid norms and that it should be subjected to evaluation and questioning.

Terrorism datasets differ from other political and social science data in another important way. Since much of the data is derived from media sources in real time, and since its developers have frequently used different definitions and coding rules, no one dataset is completely comprehensive or exhaustive and there is a great deal of variability across datasets. For example, in a previous comparison of transnational terrorism events data from two terrorism databases, ITERATE and RAND-MIPT, this author found several large discrepancies in quarterly events counts for the time period 1993–2004. As shown in Fig. 2.1, there were distinct differences in counts at the outset of the series in 1993 and again between 2001 and 2002 and in 2004. A likely explanation for these differences was that the databases operationalized what constituted a "transnational" event very differently. In general, transnational terrorist events are viewed as ones that involve perpetrators and victims from different countries.[1] However, what constitutes a country may be differently defined

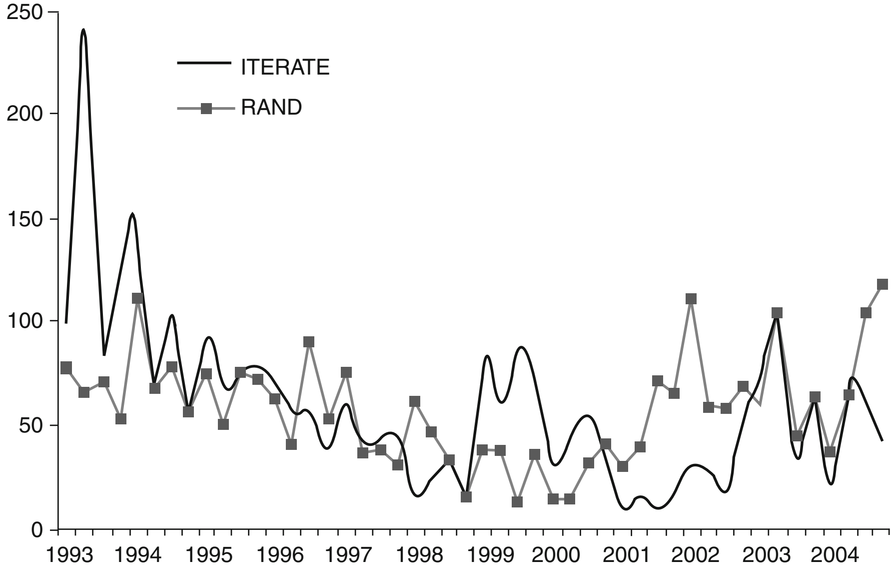

Fig. 2.1 ITERATE vs. RAND-MIPT: quarterly number of transnational terrorist incidents (1993–2004). *ITERATE* International Terrorism: Attributes of Terrorist Events; *RAND-MIPT* RAND-Memorial Institute for Prevention of Terrorism Database

when a territory is still disputed. A likely explanation for the discrepancy at the outset of the series in 1993 is that ITERATE counted more events that started in one of the newly formed Soviet states and ended in another or targeted people as transnational whereas RAND excluded those events under the assumption that they were not yet transnational. By contrast, closer inspection of the data for the period 2001–2002 and for 2004 suggests that RAND counted more incidents associated with

[1]When a terrorist incident in one country involves victims, targets, institutions, or citizens of another country, it is considered transnational or international and is included. The 9/11 hijackings, for example, are included as transnational terrorist incidents for at least three reasons. First, the perpetrators came from outside of the United States. Second, the victims were from over 80 countries. And third, the incidents had worldwide economic and security ramifications. The bombings of the US embassies in Kenya and Tanzania on August 7, 1998, as well as the suicide car bombings aimed at British and Jewish targets in Istanbul, Turkey on November 20, 2003, are similarly included as transnational terrorist incidents since they involve perpetrators and victims from different countries. On the other hand, the bombing of the Murrah Federal Building in Oklahoma City by Timothy McVeigh is not included since it is considered to be a purely domestic event. Similarly, bombings by the IRA in Northern Ireland are not included as transnational terrorist acts. However, IRA attacks in England would be included.

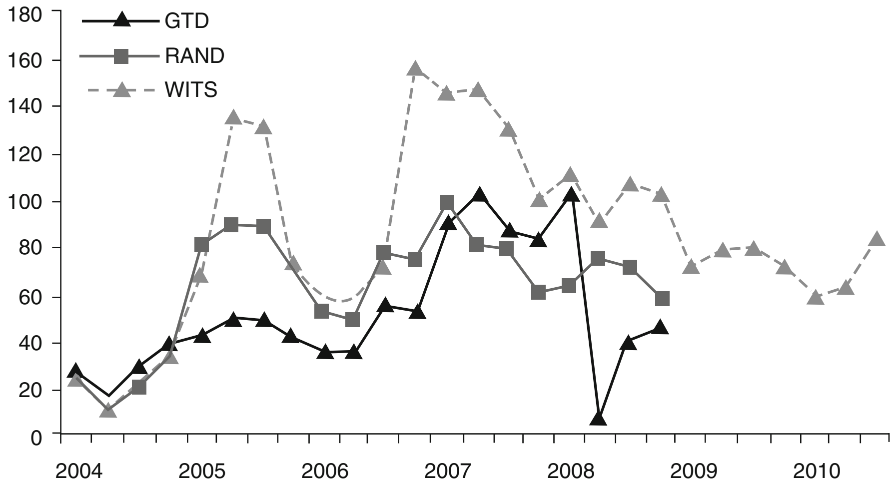

Fig. 2.2 GTD, RAND, and WITS (2004–2008): quarterly number of suicide attacks. *GTD* Global Terrorism Database; *RAND* Rand Database of Worldwide Terrorism Incidents (RDTWI); *WITS* Worldwide Incidents Tracking System

Palestinian uprisings against Israel (Intifada) as transnational whereas ITERATE, making the assumption that such events were domestic, did not include them (Sheehan, 2007, 2009).

Similar disparities are evident in more recent data. Figure 2.2, for example, shows the quarterly number of suicide attacks for more recent data on international and domestic terrorism events from three current terrorism datasets (the GTD, RAND, and WITS) for the time period 2004–2008. In this case the RAND and WITS datasets both show much higher frequencies of suicide attacks at almost every time point compared to the GTD.

Disparities like these can be a source of consternation for terrorism researchers. Just looking at the plots, we do not know if the disparities are a function of differences between the two databases in the ways they define terrorism, in the sources they use, in coding rules, or something else. And without more information, it is not possible to tell if one or the other dataset capturing more "true" events or including more "false" ones.

Part of the problem is that terrorism databases often tap into different data sources and information. The plot below (Fig. 2.3) of international terrorist incidents from ITERATE and RAND-MIPT for the years 1993–2004 illustrates this point.

The plot above shows that *unique* incidents, ones covered in only one of the two databases, outnumbered *overlapping* ones at almost every quarterly period shown. Overall for the time period, overlapping incidents constituted only about one third

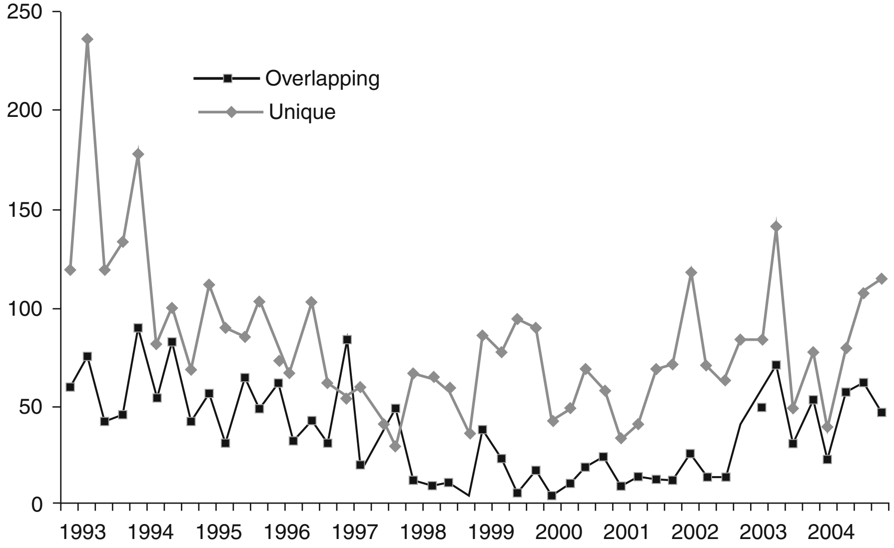

Fig. 2.3 ITERATE vs. RAND-MIPT (1993–2004): overlapping and unique international terrorist incidents. *ITERATE* International Terrorism: Attributes of Terrorist Events; *RAND-MIPT* RAND-Memorial Institute for Prevention of Terrorism Database

of all incidents. Overlapping terrorist incidents are the ones the databases agree on. In general they are more likely to be reported and more likely to be deadly (Sheehan, 2007). However, they constitute a relatively small proportion of all incidents. This may be because the databases have selection biases in terms of sources, because they use different operational definitions of terrorism, because they have different inclusion or exclusion rules, or simply because the enormity of capturing so much data in real time is so great that each database is only able to cover a segment of terrorism events. Unique events, however, constitute larger portions of each dataset and they are responsibile for the variability in terrorism datasets.

The point is that from a practical viewpoint to assess the quality and comparability of information across terrorism databases, researchers need some benchmarks or normative criteria.

Theoretical Reasons

There are also good theoretical reasons for developing best practices criteria for terrorism data. As Alex Schmid observes, scholars seek out terrorism data for a number of reasons. They may want to use the data to uncover underlying patterns or trends in terrorism, to compare terrorist campaigns cross-nationally and over time, to predict future events, to examine the causes, concomitants, or consequences of terrorism in relation to other phenomena, or to evaluate the success of counterterrorism (Schmid, 2004). To meet these different requirements, terrorism databases should ideally fulfill a number of criteria. In the best of worlds, it should be relevant and transparent. The definition of terrorism should be consistent over time and across regions. In addition, the data should be replicable and reliable and the validity and integrity of observations should be such that they can be checked (Drakos, 2009).

Unfortunately, terrorism data like much of what Colin Robson (2002) calls "real world" data rarely lives up to these expectations. However, to the extent that a terrorism database considers and at least tries to approach some norms and standards, we can have greater confidence in its credibility. The existence of norms and standards, moreover, can be a guide to particular researchers in their search for the best database for a particular project.

Developing Standards for Terrorism Data

The Case for a "Criterial Framework"

Users of large-*n* datasets usually look for tests of validity and reliability to evaluate a given dataset. Unfortunately, traditional tests of validity and reliability are problematic for terrorism data. Validity tests typically rely on a gold standard, but there is no gold standard for terrorism data. There is not even a universally accepted definition of terrorism. By one count there are as many as 109 definitions of terrorism (Schmid & Jongman, 1988). Reliability tests typically depend on consistency, but terrorism databases are often viewed as "living databases" (Wigle, 2010) that can be changed, even retrospectively, as new information emerges, as perspectives change or as the operational definition of terrorism is revised (Paull, 1982; Schmid, 1983; Wilkinson, 1986; Reid, 1997).[2] This means that inter-coder reliability tests, even if conducted at the time of collection of a discrete item of data (e.g., a terrorist event from a report in the media), are rendered meaningless and the conditions for test–retest may not exist. To complicate matters, terrorism databases have relied almost

[2] In the 1970s and 1980s, it was not at all uncommon for terrorism databases to redefine and reclassify terrorist incidents for political reasons (Paull, 1982, p. 46; Schmid, 1983, p. 260). This practice led to wide disparities in the annual Patterns of International Terrorism report across the Ford, Carter, and Reagan administrations. For example, although only eight types of incidents were classified as terrorism under Ford, as many as 17 were classified as terrorism under Reagan. Reclassification, moreover, was applied retrospectively. As a result the 1980 Patterns of Global Terrorism report estimated that the number of worldwide terrorism incidents for the period 1968–1980 was 6,714 although only a year earlier it estimated that terrorism incidents for approximately the same time period 1968–1979 were half that number or 3,336 (Wilkinson, 1986, p.44, cited in Reid, 1997).

exclusively on reports in the news media (Fowler, 1981) and all too often such reports have been accepted unquestioningly despite their known biases and unreliability (Wardlaw, 1982; Wilkinson, 1986; Herman & Chomsky, 1988).

Alternative criteria, developed for small-*n* research may be well suited to evaluating terrorism data with its naturalistic roots in "real world" inquiry and its emergent qualities (openness to adaptation and change as new information emerges). The mindset that informs these criteria is also well suited to terrorism data. Although large-*n* research is typically guided by a positivist belief that a real world of objects apart from people exists out there and that researchers can accurately describe it and compare their descriptions with this objective reality, this is not the case with small-*n* research. Small-*n* researchers, coming from post-positivist, constructionist, and interpretivist traditions, are more likely to take the position that researchers can only know the world from their own perspective of it.[3] One implication of this view is that researchers' and informants' own preconceptions, values, and biases are relevant to all phases of research and are critical to its credibility. Another implication of this view is that knowledge (the truth) can only be approximated, never fully known, and uncertainty needs to be acknowledged. This mindset may be particularly helpful in evaluating terrorism data where, because of the clandestine nature of the phenomenon, objective information is not always available.

At the same time, small-*n* researchers, mindful of the importance of validity, have developed criteria such as credibility, transferability, generalizability, and dependability that parallel the concepts of validity and reliability (see Guba, 1981). This situation has led to increasing recognition that shared norms for designing and evaluating research can be built across the two approaches (Brady & Collier, 2004).

The concept of a criterial framework was introduced and developed by Gerring (2001, 2010) as a means of helping social science researchers bridge small-*n*/large-*n* and other divides (qualitative/quantitative, positivist/interpretivist) to find common ground in designing research. It has since been extended to evaluating large-*n* political data (Lieberman, 2010). One of the advantages of applying such a framework large-*n* data is that it has the potential to bring rich detailed descriptions that can serve as an alternative to traditional validity and reliability testing when such testing is not possible.

Proposed Criteria

In this section, I propose six criteria derived from small-*n* research that could be used to evaluate and compare terrorism datasets. To make them easier to remember, I have chosen words that all start with the letter C. They include Conceptual clarity, Context and immediacy of observation, Citation transparency, Coding

[3] It should be noted that these approaches are not uniform. Post-positivists are more likely to accept the "objective" nature of reality than interpretivists and constructionists.

Table 2.1 Criterial framework for evaluating terrorism databases

Criterion	Rationale	Assessment
Conceptual clarity	The relevance of a database depends on the definition(s) of terrorism used	Is the definition of terrorism used in construction of the database specified?
Context and immediacy of observations	Data collected from primary and secondary sources are often more valued than those collected from tertiary sources	Do the authors report the context and immediacy of the observations?
Citation transparency	The replicability of a dataset depends on citation transparency	Are the actual sources of the data described? Are clear references to original data provided?
Coding consistency	The reliability of a dataset depends on coding consistency over time and across raters	Do the authors provide a codebook? Do they discuss how they resolve coding conflicts and make decisions in ambiguous cases?
Certainty	The validity of observations depends on certainty. Contradictions and ambiguity in data should be reported	Are contradictory facts reported?
Conflict of interest issues	The integrity of observations can be compromised in the presence of competing interests	Are funding sources and other potential conflicts of interest reported?
Convenience/ functionality	Differences in data sources can be uncovered more easily when those sources are easily accessible and the data can be disaggregated	How accessible is the database? Can it be downloaded? Can it be disaggregated for fine analyses?

consistency, Certainty, and Conflict of interest. I have added an additional criterion, Convenience and functionality, since many users of terrorism data want data that they can find easily and that will fulfill different functions. My hope is that the criteria proposed here will help researchers be better able to evaluate the quality of terrorism data and be in a better position to choose between terrorism data sources (Table 2.1).

Conceptual Clarity

How well do the authors of the database communicate the underlying concept of terrorism they use to choose individual cases? How well do they define it? As Lazarsfeld and Barfeld (1951, p. 155) once wrote,

> Before we can investigate the presence or absence of some attribute… or before we can rank objects or measure them in terms of some variables we must form the concept of that variable.

Concepts, as Goertz (2005, p 5) observes, are ontological: "they are theories about the fundamental constitutive elements of a phenomenon." Traditionally, concepts implied necessary and sufficient conditions. In the last few decades, however, what Collier and Mahon (1993) call "family resemblance" approaches have often been used as a substitute for necessary and sufficient conditions. In these approaches, one condition substitutes for another. Such substitutions can lead to "conceptual stretching" or "traveling" and more permissive inclusion of cases (Collier & Mahon, 1993, p. 845).

While conceptual stretching and traveling may have benefits (ambiguous cases will not as easily be lost), they pose problems for researchers who want to generalize from a set of data. This was an issue when the U.S. State Department released its 2003 *Patterns of Global Terrorism Report*. This report specified terrorism as "premeditated, politically motivated violence perpetrated against noncombatant targets by subnational groups or clandestine agents, usually intended to influence an audience" (U.S. State Department, *Patterns of Global Terrorism 2003*, p. vii). It further specified that an international terrorist attack was an act committed by substate actors from one nation against citizens or property of another and that an incident was "judged significant if it results in loss of life or serious injury to persons, major property damage, and/or is an act or attempted act that could reasonably be expected to create the conditions noted" (U.S. State Department, *Patterns of Global Terrorism 2003*, Appendix A). The key problem here was the use of the word "significant." As Krueger and Laitin (2004a, 2004b) quickly pointed out, almost no information was provided about how the government authors distinguished significant from nonsignificant events. In the end, a reanalysis of the data with better specification of what the government authors meant by the word "significant" produced a very different set of data and one which embarrassingly contradicted previous findings that terrorism events had decreased that year. In fact, the new evidence indicated that terrorist events had increased.

Conceptual clarity has implications for inclusion rules. Different concepts of what constitutes an *event*, for example, can lead to different inclusion rules and widely varying estimates. This was the case when in its original database RAND counted 40 bombings by one group in one city as one event when ITERATE counted 40 separate events (Jenkins & Johnson, 1975). Similarly, different concepts of what is *international* or *transnational* can lead to other discrepancies. As discussed earlier in this chapter, RAND but not ITERATE appears to have treated incidents involving Palestinians and Israelis as transnational with the result that its estimates of total transnational terrorist incidents were much higher than ITERATE's at some intervals in the last 12 years.

Context and Immediacy of Observation

What is the context of the data? How was it collected? How close were the authors to the source? Terrorism data may be generated from primary sources, from secondary sources, tertiary ones, and from experts. Academic scholars often put a premium on data collected through direct observation because of its immediacy. Interview data, such as that collected by Merari (2010) in his interviews with suicide terrorists, is especially valued because of its immediacy. The value of such data, however, has to be weighed against the potential for selection bias. After direct observation, scholars usually value primary sources such as newspaper accounts at the time of an event over secondary sources (e.g., journal articles) and tertiary ones (e.g., textbooks, other datasets).

Citation Transparency

Do the authors provide the sources for the data they report? Terrorism data is derived from a wide variety of sources. The sources may include United States and foreign news and wire services. They may also include information from interviews, books, memoirs, and interviews with principals (Mickolus, 2002). Knowing the sources of a particular event matters since coders often have to make decisions. They may have to choose, for example, between conflicting estimates from different sources on the number of fatalities associated with an event. Confidence in data is heightened when the actual source of the data is provided. Citation transparency is also critical to correcting and replicating datasets.

Coding and Consistency

Do the authors use consistent rules to code data? Do they use a codebook? And have they institutionalized systems to ensure coding consistency across raters (inter-rater reliability) and over time (test–retest reliability)? If so, how do these systems work? In cases where there are conflicting reports for example, about claims of responsibility for an event, or the number of casualties, how are final decisions made? By fiat? By consensus, majority rule or some other way? Finally, is there an "audit trail" that users can follow if the operational definition of terrorism or inclusion rules is altered?

Certainty of Record

Do the authors report the presence of uncertainty in the coding of a particular variable or attribute of a terrorist event? Conflicting accounts, as discussed above, may lead to uncertainty about whether an event was actually a terrorist event or something else. Or, an attribute of an event may not quite fit within a given coding scheme. The scheme, for example, may allow coding of one or two targets, but the terrorist attack had multiple targets. How do the authors resolve such quandaries and do they highlight them?

Conflict of Interest

Do the creators and maintainers of the database have conflicts of interest and do they report them? This is tricky. Since terrorism is a national security concern and since the creation and maintenance of terrorism databases is costly, most of the databases we cover here have received significant funding from a government body and one, WITS, is a direct output of a government agency, the NCTC. The question is really the extent to which sponsors, funders, or others influence the content and the extent to which operators of the database are upfront about such real or potential influences. In election years, in particular, political pressure may be exerted to show that terrorism rates have diminished. How do the authors handle such potential conflicts of interest? For example, do they disclose funding? Do they discuss the extent to which the sponsors have control over the data?

Convenience/Accessibility/Functions

How convenient is the database to use? How accessible is it? Is it available online? Is it searchable with key words? How functional is it? Can users perform online searches with key words? Can they use the data to create graphs and tables online? Is the dataset fully downloadable so that researchers can conduct their own analyses on it? Can the data be disaggregated for fine analyses? And finally, is there a fee to use it?

Application of the Framework

Assessment of Existing Terrorism Databases

Below I review and assess a range of existing terrorism databases and try to apply the criteria developed above as a basis for comparison. The databases I cover include five terrorism events databases.

Terrorism events databases are systematic numeric records, usually derived from newspapers, wire, and other media, of the occurrence of individual terrorist events and the events' characteristics (e.g., date, location, name or type of perpetrator group when it can be identified, type of attack, and number of casualties). Terrorism events data can be linked in turn with other data to study the causes and consequences of terrorism. Events databases allow researchers to examine trends and patterns in terrorism over long periods of time and geographical space. They can be used in conjunction with other data (e.g., political or economic indicators) in analyses of the causes and consequences of terrorism and can contribute information to analyses of how, when and why and terrorism events and campaigns decline or end (Schmid, 2004).

Over the years, terrorism events databases have been used in time series analyses to assess impact of terrorist incidents on tourism (Enders, Sandler, & Parise, 1992; Fleischer & Buccola, 2002), on foreign investment (Enders & Sandler, 1996), and on gross domestic income and trade (Abadie & Gardeazabal, 2003; Nitsch & Schumacher, 2004). They have also been used to assess the impacts of such initiatives as the installation of metal detectors in airports on skyjackings (Enders & Sandler, 1993) and get tough police responses on violence in Northern Ireland (La Free, 2010).

Five of the best-known terrorism events databases are as follows:

1. International Terrorism: Attributes of Terrorist Events (ITERATE)
2. Rand Database of Worldwide Terrorism Incidents (RDWTI)
3. Global Terrorism Database (GTD)
4. World Incident Tracking System (WITS)
5. Terrorism in Western Europe: Events Data (TWEED)

Their scope, the time spans they include, and the numbers of incidents they cover are shown in Table 2.2. This table also provides an evaluation of how well each of the five databases meets each of the seven best standards criteria I set forth above.

General Comparisons

All of the databases with the exception of TWEED were created and are maintained in the United States. Although most were created outside academia (TWEED developed by Jan Engene at the University of Bergen is an exception), all are currently operated, directed, or at least partially managed by academics who provide consulting and oversight. ITERATE was started and continues to be maintained by former CIA analyst Edward Mickolus, but is now updated by Todd Sandler and his colleagues at the University of Texas at Dallas. Similarly, the RAND database, which originated with policy analysts such as Brian Michael Jenkins, is at least partially under the direction of Bruce Hoffmann at Georgetown University. The basis for the GTD was data collected by a private security service, PGIS, but the data is now under the direction of Gary La Free at the University of Maryland. WITS is a product of the US government National Terrorism and Counterterrorism Center (NCTC) but consulting oversight is provided by John Wigle at Johns Hopkins University.

As shown in Table 2.2, the five databases vary considerably in terms of the time spans they cover. With incidents dating back to 1950, TWEED spans almost 60 years. ITERATE, RAND, and GTD, with start dates in 1968, 1968, and 1970 respectively, each cover approximately 40 years. WITS, on the other hand, is relatively recent. With a start date in 2004, it only covers incidents for the past 7 years.

The five databases also differ in scope. ITERATE is uniquely restricted to transnational terrorist events, defined as incidents that start in one country and end in another or involve victims, targets, institutions, or citizens of more than one nationality (Sandler & Enders, 2004). In ITERATE, domestic incidents of terrorism, i.e., incidents which begin and end in the same country and which only have ramifications

Table 2.2 Evaluation of five databases on terrorist events

	ITERATE	RDWTI	GTD	WITS	TWEED
Overview					
	International Terrorism – Attributes of Terrorist Events	Rand Database of Worldwide Terrorism Incidents	Global Terrorism Database	Worldwide Incidents Tracking System	Terrorism in Western Europe: Events Data
DB Operator(PI)	University Michigan and Vinyard Software (Mickolus)	RAND (Original PIs: Jenkins, Hoffman)	START University Maryland (LaFree)	NCTC	University of Bergen (Engene)
Website	www.icpsr.umich.edu	http://www.rand.org/nsrd/projects/terrorism-incidents/	http://www.start.umd.edu/gtd	https://wits.nctc.gov	http://folk.uib.no/sspje/tweed.html
Unit of analysis	Events	Events	Events	Events	Events
Scope of events	International	International + domestic	International + domestic	International + domestic	Events in Western Europe
Time span	1968–2008	1968–2009	1970–2008	2004–2010	1950–2004
# of events	~13,000	~36,000	~88,000	~69,000	11,245
# of variables	42	15 + narrative description	~75 in 15 categories	~15	52
Assessment					
Conceptual clarity	Provides definition and criteria	Provides definition and criteria	Provides definition and criteria	Provides definition and criteria	Provides definition and criteria
Context/source type	Reports using primary sources: news articles, wire services, interviews with principals and secondary and tertiary documents: journals, books, and chronologies	Reports using primary documents including newspapers, journals, radio broadcasts, and foreign press	Reports using primary sources (news and wire services) in real time, secondary and tertiary sources (books, journals, existing datasets)	Reports using open sources including subscription news services, local news websites in English, and foreign languages	Reports using only one source, *Keesing's Record of World Events*. Most of the data (events from ~1950–1998) constructed retrospectively

Citation transparency	Reports generally using AP, UPI, Reuters, Foreign Broadcast Information, and major US newspapers	Reports using two or more sources for most events and that all source documentation is kept in paper form for each event	Reports using >3,500 news articles and 25,000 news sources for 1998–2007 alone. Clear citations to sources provided for recent events data	Reports using commercial subscription news services, the US government's sources, local news websites, and use of news websites in foreign languages	Reports using only one source, *Keesing's Record of World Events*, a world news archive that has recorded world events since 1931 and is updated monthly
Coding transparency and consistency	Provides detailed codebook Reports using identical criteria and maintaining continuity among coders through the use of overlapping coders and monitors	Provides basic information for coding of variables on website Procedures for achieving coding consistency provided in separate papers	Provides criteria for incident inclusion and coding scheme in a codebook. Cautions that data were collected in real time for GTD I (1970–1997), retrospectively for GTD 2 (1998–2007) and in real time again after 2007	Does not provide actual codebook Does address methodological issues in coding related to some variables on website and in papers	Provides detailed codebook Does not address who did the coding or how coding consistency was achieved on website
Certainty of record		No discussion of uncertainty at website	Includes a "doubt terrorism proper" field to record any reservation in the eyes of GTD analysts that the incident in question is truly terrorism for incidents after 1997	Addresses potential for uncertainty. Includes a "Confidence" field to designate whether attribution to a particular group is unknown, likely, plausible or inferred	

(continued)

Table 2.2 (continued)

	ITERATE	RDWTI	GTD	WITS	TWEED
Conflict of interest (website report)	Data was originally developed by a CIA analyst, E. Mickolus. ICPSR website does not report government funding	RDWTI website reports US government contract to develop original database and continuous advising to US government on terrorism	GTD website reports current funding from DOJ, DHS. Clearly states that the GTD does not purport to represent inclusion decisions of DHS, DOJ, or other funding agencies		No funding sources reported on website
Convenience/functionality					
Online availability	Partial	Full	Full	Full	Full
Browsing features	No	Yes	Yes	Yes	Yes
Key word searching	No	Yes	Yes	Yes	No
Graphing features	No	Yes	Yes	Yes	No
Downloadable	No	Yes	Yes	Yes	Yes
Linkages	Numeric dataset is linked to narrative (text) database	Yes (through a code number). User can lease or purchase textual database	Short narrative included with data		
Pricing	Free to students/faculty at subscribing universities; charges otherwise apply	No cost to user	No cost to user	No cost to user	No cost to user

The RDWTI is composed of two earlier databases, the RAND Terrorism Chronology (1968–1997) which contained ~10,000 incidents and was limited to international incidents and the RAND-MIPT Terrorism Incident Database (1998–2008) which contained about 26,000 incidents and included both national and international incidents (check numbers) for that country, are specifically excluded. For example, the Oklahoma City bombing on April 19, 1995 is excluded, as are terrorist attacks by ethno-national groups within their own countries. This exclusion explains the relatively low number of incidents in ITERATE compared to the other databases. It has been estimated that domestic terrorist events outnumber international ones by eight to one (Sandler & Enders, 2008). By contrast, TWEED is limited to acts of internal terrorism in Western Europe. That is, it only includes events initiated by agents originating in the18 countries of Western Europe it covers. TWEED expressly excludes terrorist acts "imported" from outside the West European countries (Engene, 2007). The other three databases include both domestic and international incidents but do so for different time spans. The RAND database provides international incidents dating back to 1968 but contains domestic incidents only for the past 13 years, since 1997. The GTD provides domestic *and* international incidents dating back to 1970 while WITS provides domestic and international incidents only from 2004 to the present.

As shown in Table 2.2, the number of variables ranges from about 15 in the RAND database to 75 in the GTD. These differences, however, are partially a function of how variables are counted. The date of an incident may be shown as one variable or as three distinct ones that include day, month, and year. Similarly, the location of an incident can be presented as one variable or three (city, state or province, and country). Although ITERATE and the GTD do provide many more variables than the other databases, not all are what might be called "usable." ITERATE, for example, includes separate variables for the number of terrorists and the number of nationalities of terrorists in an attack force. Because of the clandestine nature of terrorism and the fact that a large majority of them are unclaimed, information like this is often unknown and it is not uncommon to have large numbers of missing values for such variables (Table 2.3).

How Well Do the Five Events Databases Clarify the Concept of Terrorism That Informs Their Selection of Terrorist Acts or Incidents?

All five of the databases we cover here give fairly clear definitions of the concept of terrorism they employ in selecting cases (see Appendix). ITERATE and RAND have consistently used the same or approximately the same definition of a terrorist incident since they began collecting incident data in the early 1970s. TWEED and WITS have also employed one definition since their inceptions. As discussed in a separate article in this monograph (La Free, 2011), the GTD is based on three datasets. GTD1 (1970–1997) was collected in real time by the PGIS, a private security firm. GTD2 (1998–2007) was collected by START at the U Maryland retrospectively, and GTD3 (2007-present) has been collected in real time by START. The GTD clearly provides the definition used by PGIS for GTD1 data and it also provides the definition used by START for GTD2 and 3 data. As discussed below, START uniquely allows the researcher to apply his or her own definition to select cases from the full GTD.

Table 2.3 Comparison of variables included in five terrorism databases

Variable	ITERATE	RAND	WITS	GTD	TWEED
Date					
Incident start date (year/month/day)	√	√	√	√	√
Incident end date (year/month/day)	√	√			
Location					
City			√	√	
Country	√	√	√	√	√
Province or state			√	√	
Region		√		√	√
Site of attack for example, home, office, car, airplane	√				
Attack type					
Type of attack	√	√	√	√	√
State sponsorship if known	√	√	?	?	√
Suicide attack (yes/no)	?	√	√	√	
Part of multiple incident/ coordinated attack		√		√	
Logistical success of attack (yes/no)	√			√	
International incident (yes/no)	√	√			
Perpetrator					
Perpetrator group name(s)	√	√		Text	√
Perpetrator group type/or ideological profile			√		√
Number of perpetrators in attack force	√			√	
Number of female perpetrators	√				
Nationalities of perpetrators in attack force	√				
Number of perpetrators captured				√	
Claim(s) of responsibility		√		√	
Weapon					
Means or weapon type used	√	√	√	√	√
Victims					
Number of victims	√				
Nationalities of victims	√		√		
Number killed	√	√	√	√	√
Number wounded/injured	√	√	√	√	√
Number US citizens killed	√	√	√	√	
Number US citizens wounded	√			√	
Number of perpetrators killed	√			√	
Type of target/victim					
Type of victim/target	√	√	√	√	√
US victim (yes/no)	√	√			
Type of US victim	√				
Nationality of target			√		

(continued)

Table 2.3 (continued)

Variable	ITERATE	RAND	WITS	GTD	TWEED
Consequences					
Property damage (yes/no)	√		√	√	
Extent of property damage	√			√	
Value of property damage	√		√	√	
Logistic success	√			√	
Hostage/kidnapping					
Hostages (yes/no)	√			√	
Number of hostages	√			√	
Number of US hostages	√				
Doubt/uncertainty				√	
Multiple incident				√	
Source citation(s)				√	
Government reaction					
Armed response					√
Arrest					√
Conviction					√
Demonstration control					√
Number killed by state institution					√
Number wounded by state institution					√

Examples for type of attack = assassination, bombing, hostage taking
Examples for type of target = business, government, airports, journalists and media, private citizens, and property
Examples of weapon type = biological, chemical, nuclear, firearms, explosives
Some databases (e.g., ITERATE and GTD) allow coding of group information for up to three "terrorist" groups
Some databases (e.g., GTD) allow coding of target characteristics for >1 type of target
Citations to sources available in GTD for incidents from 1997 onward

As shown, in Table 2.4 the databases do differ in terms of operational inclusion rules. For example, although ITERATE, RAND, WITS, and GTD restrict inclusion to terrorist acts committed by substate actors (substate terrorism), TWEED allows inclusion of terrorist acts by states (state terrorism). TWEED also differs from the others in its omission from its definition of the word violence and its use instead of the concept of "personal injury" or "attacks against material targets (property)." While this difference may appear semantic, it suggests a slightly lower level of tolerance for inclusion (an injury is not necessarily the result of violence). As another example, some but not all of the databases specify that the act must be premeditated or intentional. Some but not all include threats of violence and some but not all specify that the act must be committed against a civilian or noncombatant target (see Appendix).

The extent to which each of the databases stretches the concept of terrorism is difficult to evaluate. Schmid and Jongman (2005, p. 146), however, contend that even in ITERATE, long considered the most authoritative database on terrorist

Table 2.4 Similarities and differences in factors included in database definitions of terrorism

	ITERATE	RAND	WITS	GTD	TWEED
Premeditated, intentional, or deliberate			√	√	√
Use of violence	√	√	√	√	
Threat of violence	√	√		√	
Act must be politically motivated	√	√	√		
Intended to influence or coerce an audience	√	√		√	√
Civilians or noncombatants targeted		√	√		
Perpetrators are substate groups or clandestine agents	√	√	√	√	√
Perpetrators are states or state agents					√
Calculated to cause anxiety, fear, or terror	√	√			
Can be motivated by political, religious, economic, or social goal				√	
Carried out to achieve publicity		√			
Act is outside the context of legitimate warfare or a coup d'état	√	√	√	√	√

Note: GTD includes incidents that meet elements #1, 2, 7 and at least 2 of #5, 10, and 12

events, there is sometimes a "strained relationship" between the cases it includes and its "operational definition" of terrorism.

> While some types of incidents – such as kidnappings, letter bombings, assassinations and murders and aerial hijackings – fit the general notion of terrorism and are compatible with the working definition, other types of incidents – such as sabotage, arms smugglings shootouts with police, occupations, thefts or break-ins, conspiracies and snipings – are not.

As noted earlier in this chapter, stretching of the definition was common in the early years of *Patterns of Global Terrorism* (the predecessor of WITS) when the definition was redefined several times to make it more inclusive.

What Is the Context of the Data? How Was It Collected? Where Does It Come from? How Immediate Were the Sources?

Most of the data for ITERATE, RAND, GTD, and WITS was collected by analysts in real time shortly after an incident occurred and was reported in the media. This is not the case with TWEED. For this database, created as part of the author's doctoral dissertation (1998), all of the data was collected retrospectively from one source. Also, as discussed above, although the bulk of the GTD dataset was collected in real time, a portion of it was collected retrospectively. These differences can affect the numbers of events included since not all sources that are available in real time are still available or accessible years later.

The extent to which the databases rely on primary vs. secondary and tertiary sources is difficult to assess. Sandler, Arce, and Enders (2008) report that the ITERATE dataset is derived from sources such as the AP, UPI, Reuters tickers, the Foreign Broadcast Information Service (FBIS), Daily Reports, and major US newspapers. Such sources are usually classified as primary, but Edward Mickolus has indicated that earlier data is also based at least in part on direct observation (interviews with principles), secondary sources (journals), and tertiary sources (books). The RDWTI website reports that most events included in its dataset are based on at least two sources and that all source documentation is kept in paper for each event record. The website for the GTD indicates that over 3,500,000 news articles and 25,000 news sources were reviewed to collect incident data for its database from 1998 to 2007 alone. According to John Wigle, the NCTC gathers data for WITS from open sources manually using commercial subscription news services, the U.S. Government's Open Source Center (OSC), local news websites reported in English, and, as permitted by the linguistic capabilities of the team, local news websites reported in foreign languages. TWEED data is uniquely based on one source, *Keesings Record of World Events*, an archive of articles on political, social, and economic events around the world that has existed since 1931 is updated monthly (Engene, 2007).

Do the Authors Cite Their Sources?

Most of the databases provide facts about their sources but do not go beyond referring to a general range of sources. At this time, only the GTD has made an attempt to cite sources for individual incidents and then only for its most recent incidents (see GTD website, home page announcements).

How Consistent Is the Coding?

All five of the databases provide a codebook or basic information on coding of variables associated with incidents. Most, however, give only limited information about who does the coding, how coding consistency over time is achieved, whether multiple coders are used, and if so whether tests of inter-coder reliability are performed. According to Sandler et al. (2008), coding consistency over time is sought in ITERATE by applying identical criteria and maintaining continuity among coders through the use of overlapping coders and monitors. According to Wigle (2010), the WITS team strives to maintain consistency in collection by having a central intelligence officer maintain knowledge of the search strings and Internet web sites commonly used by the analysts. This "knowledge capital," writes Wigle, provides consistency during turnover on the team. To reduce interpretation bias further (or increase inter-rater reliability), NCTC analysts maintain account notes of commonly used terms and phrases found in the press, recurring political and ethnic issues, terrain notes, weather-related trends, and other factors that influence a mastery of context surrounding acts of violence in countries assigned to their area of responsibility.

What About Handling of Uncertainty?

Almost all of the authors address this issue. For most of the databases covered here, uncertainty is addressed by omitting information that cannot be verified. The GTD is unique in building issues of uncertainty into its coding. For post 1997 data, it includes a field labeled "Doubt Terrorism Proper." This field allows the coder to indicate uncertainty about whether an incident meets all of the criteria for inclusion in the database. Users can filter the data and exclude cases in which there is a doubt. As indicated above, users can also filter results based on whether they meet all or only some of the criteria for its definition of terrorism.

Do the Authors Disclose Funding and Potential Conflict of Interest?

Conflict of interest occurs when an individual or organization is involved in multiple interests, one of which could corrupt the motivation for the act of another. Many of the events databases covered here were originally developed with government grants or under government sponsorship for specific political purposes. The RAND database, begun in the early 1970s, was first developed under a US government contract. RAND data was subsequently used as a basis for ITERATE, which later became a basis for the CIA's annual terrorism report in 1977 (Schmid, 1983, p. 257–260). The WITS database is a much more recent product of a US government agency, the NCTC, and the GTD has received funding from the DOJ and DHS. Most of the databases we cover here do disclose their funding sources. Some are more explicit than others about the extent to which they have independent control over the data they produce. Ultimately, the extent to which government sponsorship or funding has in fact produced biases in content is not known.

How Convenient and Accessible Are the Different Databases?

Is there a cost? Are the databases available online? Are they searchable, interactive, and can datasets be downloaded?

ITERATE: The ITERATE database is not fully accessible online. ITERATE datasets and documentation for incidents from 1968 to 1977 can be downloaded at no cost from the Inter-University Consortium for Political and Social Research (ICPSR) at www.icpsr.umich.edu/icpsrweb/ICPSR/studies/7947 at the University of Michigan. More recent data (1978 to the present), however, are available at no cost only to students and faculty of subscribing universities or for a fee from Vinyardsoftware@hotmail.com or via postal services at Vinyard Software, Inc. 2305 Sandburg Street, Dunn Loring, VA 22027–1124.

WITS: The WITS database is available online at no cost at http://www.nctc.gov/wits/witsnextgen.html. Researchers can search this database. This database can be searched using a variety of parameters (date, location, attack type, weapon type) to generate subsets of data and reports. The data can also be exported in subsets or in its entirety in a tab-delimited data file from the RAND website.

RDWTI: The full RDWTI database is available online at no cost at http://www.rand.org/nsrd/projects/terrorism-incidents/. This database can be searched using a variety of parameters (date, location, attack type, weapon type) to generate subsets of data and reports. The data can also be exported in subsets or in its entirety in a tab-delimited data file from the RAND website.

GTD: The GTD is also fully accessible online at no charge. It can be accessed at http://www.start.umd.edu/gtd/. Researchers can browse the GTD and use search terms and filters to generate subsets of data and produce graphs and tables. They can also download the dataset in different formats.

TWEED: The TWEED database is not interactive online. However, the full TWEED dataset in SPSS format and the accompanying codebook can be downloaded for educational and research purposes at http://folk.uib.no/sspje/tweed.htm.

Conclusion and Challenges for the Future

This chapter has reviewed the need for norms and standards to assess the quality of terrorism data and to help researchers choose between competing datasets. Using insights from scholarship on small-*n* qualitative data and the concept of a criterial framework (Gerring, 2001), the chapter proposes a set of criteria for evaluating large-*n* terrorism data and applies these criteria to five existing terrorism datasets. The findings suggest that despite remarkable strides in the construction and availability of terrorism data, there is still room for considerable improvement. There is a need in some cases for better specification of the definition of terrorism. There is a need in almost all cases for greater transparency in source citation and almost all of the databases could benefit from more explicit descriptions of coding rules and acknowledgement, where relevant, of doubt and uncertainty.

Going forward, the author has several recommendations.

1. In the long run, terrorism databases are only as good as the concepts they are built on. There is still a need to fine-tune our conceptualizations of terrorism. In the meantime, greater recognition of *conceptual* differences in the definitions of terrorism used in existing datasets will also benefit researchers struggling with the problem of interpreting differing results from different datasets.
2. Greater transparency in terms of the *context* and *citation* for sources of terrorism data would generate increased confidence in data and give researchers an opportunity to check original citations. It could also facilitate more mixed method analyses in which researchers, for example, perform additional tests of the truth of quantitative findings using qualitative case study analyses. The GTD's explicit citation of actual sources for its most recent events data is an important step in this direction.
3. More explicit acknowledgement of *coding* issues (who does the coding, how many coders are used, what is the process, how are coding conflicts resolved?) will help researchers better evaluate discrepancies in results and have greater confidence in the data.

4. More widespread recognition and acknowledgement that absolute *certainty* in coding terrorist events is not always possible will enrich interpretation of data. The inclusions by the GTD of a "doubt terrorism proper" field and by WITS of a "confidence" field are both valuable steps in this direction.
5. More transparency in acknowledgement of funding sources and who controls terrorism data will help researchers better evaluate potential *conflicts of interest*.

Finally, the near canonical reputation of datasets such as ITERATE needs to be reevaluated in light of the valuable contributions of newcomers to the field. Over the years ITERATE data has been used so often in academic publications that it has come to be seen by some as the only authoritative database on terrorism. But ITERATE is confined to international or transnational events and it is becoming much more obvious that distinctions between international and domestic terrorist events are not as clear-cut as previously thought. Moreover, ITERATE data is only available to subscribing universities and is not otherwise accessible on the web.

Appendix

Definitions of Terrorism

ITERATE: For the purpose of the dataset, ITERATE defines a terrorist event as

> . . . the use, or threat of use, of anxiety-inducing, extra-normal violence for political purposes by any individual or group, whether acting for or in opposition to established governmental authority, when such action is intended to influence the attitudes and behavior of a target group wider than the immediate victims. (Mickolus, 2003, p. 2)

RAND: For the RAND database terrorism is defined as

> …violence calculated to create an atmosphere of fear and alarm to coerce others into actions they would not otherwise undertake, or refrain from actions they desired to take. Acts of terrorism are generally directed against civilian targets. The motives of all terrorists are political, and terrorist actions are generally carried out in a way that will achieve maximum publicity. (RAND)[4]

[4] The RAND website clarifies its definition further with this excerpt from Defining Terrorism by Bruce Hoffman….We may therefore now attempt to define terrorist as the deliberate creation and exploitation of fear through violence or the threat of violence in the pursuit of political change. All terrorist acts involve violence or the threat of violence. Terrorism is specifically designed to have far-reaching psychological effects beyond the immediate victim(s) or object of the terrorist attack. It is meant to instill fear within, and thereby intimidate, a wider "target audience" that might include rival ethnic or religious group, an entire country, a national government or political party, or public opinion in general. Terrorism is designed to create power where there is none or to consolidate power where there is little. Through the publicity generated by their violence, terrorists seek to obtain the leverage, influence and power they otherwise lack to effect political change on either local or international scale.

RAND specifies that terrorism is defined by the nature of the act, not by the identity of the perpetrators or the nature of the cause. For RAND the key elements are as follows:

- Violence or the threat of violence
- Calculated to create fear and alarm
- Intended to coerce certain actions
- Motive must include a political objective
- Generally directed against civilian targets
- Can be a group or an individual

GTD: GTD data for 1970–1997, collected by the Pinkerton Global Intelligence Service (PGIS) used the following definition of terrorism:

> the threatened or actual use of illegal force and violence by a non state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation. (START, 2011)

GTD Data for 1998–2007 coded incidents in a way to allow users to identify cases that met their own definition of terrorism. Using the original definition, each incident had to be *an intentional act of violence or threat of violence by a non-state actor*. In addition two of the following three criteria had to be met to be included.

- The act was aimed at attaining a political, economic, religious, or social goal.
- There included evidence of an intention to coerce, intimidate, or convey some other message to a larger audience (or audiences) than the immediate victims.
- The act was outside the context of legitimate warfare activities.

These criteria continued to be included for data collected in real time after 2007 (START, 2011).

WITS: For its database WITS uses the definition of terrorism prescribed in the congressional reporting statute 22 U.S.C. § 2656f (d)(2). This statute reads

> …the term ‘terrorism’ means premeditated, politically motivated violence perpetrated against noncombatant targets by subnational groups or clandestine agents.

TWEED: For its database, TWEED uses the following explanation

> An act of terrorism is counted an act that has inflicted personal injury or attacks against material targets (property) if the act is of a nature that could have led to personal injury or in another way would have a noticeable impact on an audience, while at the same time the act was committed to direct demands of or raise attention from others than those immediately inflicted with personal or material injury. (Engene, 2006)

For TWEED the following events are counted as “violent actions of a terrorist nature: bombings, explosions, arson, fires, rocket attacks, killings, attempted killings, abductions, kidnaps, shootings, sieges, violent actions, violent attacks, attacks and similar violent actions.” Further, the event must be brought about “by an agent that has deliberately initiated the action.” While TWEED excludes events in which the purpose might be a coup d'état, it includes events in which government authorities engage in actions against terrorist or put the public in a state of fear:

> …events in which state authorities, police, secret services, military institutions, etc. are involved in actions directed against terrorists and terrorist groups are to be included. Also violent acts of state institutions directed against civilians are to be included, for instance in conjunction with demonstrations, strikes, and the like, when the state institution acts in a way that might put the public or sections of it in a state of fear. (Engene, 2006)

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