Event Data on Armed Conflict and Security:
New Perspectives, Old Challenges, and Some Solutions[1]

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This article presents the Event Data on Conflict and Security dataset (EDACS), discusses the inherent problems of georeferenced conflict data, and shows how these challenges are met within EDACS. Based on an event data approach, EDACS contributes to the growing number of novel georeferenced datasets that allow researchers to identify causal pathways of violence and the dynamics of (transboundary) violence through spatiotemporal disaggregation. However, the unreflected use of any of these datasets will give researchers unjustified confidence in their findings, as the pitfalls are many and propagating errors can result in misleading conclusions. In order to identify and handle the different challenges to overall event data quality, we reflect upon key problems and argue in favor of transparency in data collection and coding process, to empower analysts to challenge the data and avoid cascading errors. In particular, we investigate how the choice of news sources, the handling of geographic precision, and the use of auxiliary data can bias event data. We demonstrate how the EDACS dataset design enables the analyst to deal with these issues by providing a set of variables indicating the news sources, possible sources of bias, and detailed information on geographic precision. This allows for a flexible usage of the data based on individual analytical requirements.

Recent conflict research has focused more and more on geographically and temporally disaggregated conflict data. A variety of datasets containing detailed, georeferenced information on violent conflict events have emerged (Dulic 2010; Melander and Sundberg 2011; Raleigh et al. 2010). These datasets provide the opportunity to open the black box of war by allowing more precise analyses of time-dependent variations of warfare and geographical differences in the occurrence of violent events (see Buhaug 2010; Weidmann 2010; O'Loughlin et al. 2010). In particular, the disaggregation of warfare contributes to our scientific understanding of the micro mechanisms of armed conflicts within or across states, as well as to our knowledge on the evolution of fragmented security environments in zones of civil wars and areas of limited statehood.

Despite the welcome availability of a growing number of georeferenced event datasets, several practical and analytical issues remain controversial or unresolved. In particular, data collection efforts may lack transparency about subjectivity, uncertainty, or inter-coder consistency of coding results (Gleditsch and Beardsey 2010). Hence, the unreflected use of any of these datasets will give researchers unjustified confidence in their findings, which in turn may result in misleading conclusions. In other words, since the "world of violence is what researchers make of it" (Eberwein and Chojnacki 2001),[2] users should be aware that the existing datasets only portray the world of violence that is accessible (as reported by the selected news services) and conceptually relevant (as based on operational definitions of violent events). Thus, by assuming that both event data and the research strategies to collect information are inherently biased, the overall scientific objective is not the completeness of events, but a proactive problem-oriented approach to deal with biased information and transform source data into event data.

Focusing on georeferenced conflict event data, this article aims to identify and cope with core challenges to overall event data quality.[3] We reflect upon key problems and argue in favor of transparency in data collection and coding process, to empower analysts to challenge the data and avoid cascading errors. Furthermore, we present the new *Event Data on Conflict and Security* (EDACS) dataset and show how the issues discussed are addressed within EDACS. In order to highlight certain issues, we will also draw comparisons between EDACS and the two different, georeferenced conflict event datasets currently available for comparison:[4] the *Armed Conflict Location and Events Dataset* (ACLED) (Raleigh et al. 2010) and the recently published beta version of the *Uppsala Conflict Data Program – Georeferenced Event Dataset* (UCDP-GED) (Melander and Sundberg 2011).

We distinguish between four different categories of challenges to data quality (see Figure 1): errors and bias contained in the source (news) or the auxiliary data (maps, etc.) and faults in the processes of transformation of source data into event data (misinterpretation, oversights, etc.) or in the contextualization of the events using auxiliary data (event localization, actor identification, etc.).

(Figure 1 about here)

Data quality, in turn, can be broken down into several aspects: completeness, accuracy, consistency, and relevancy (Batini and Scannapieca 2006, 40; Thion-Goasdoué et al. 2007). For instance, inter-coder reliability – which prevents oversights and misinterpretations – helps to achieve consistency, while higher resolution settlement data enhance accuracy. Considering the complexity of the subject matter, there are boundaries to every quality dimension in the resulting data. Whenever there is no optimal solution to a challenge to data quality, the resulting shortcomings have to be made visible to the end users, to allow for a considered analysis and prevent cascading errors.

After providing a brief introduction of the EDACS data, we will demonstrate ways to push the inherent boundaries of data quality, guided by our four analytical categories of challenges to data quality (see Figure 1): systematic errors in the source data (section Source Bias in Conflict Event Data), fault-tolerant transformation of source data into event data (section Event Extraction), errors contained in the auxiliary data, and possible faults in the processes of spatiotemporal contextualization (section Event Contextualization).

EVENT DATA ON CONFLICT AND SECURITY (EDACS)

The project *Event Data on Conflict and Security* (EDACS) provides one approach that allows users to disaggregate the institution of (civil) war and analyze the processes of armed conflict as well as spatiotemporal variations of (in)security. EDACS is based on similar ideas as ACLED (Raleigh et al. 2010) and UCDP-GED (Melander and Sundberg 2011), but focuses more explicitly on violence in areas of limited or failed statehood. The dataset currently contains detailed information on violent events in seven countries of Sub-Saharan Africa (Somalia, Democratic Republic Congo, Republic of the Congo, Burundi, Rwanda, Sierra Leone, and Liberia) between 1990 and 2009.

EDACS distinguishes itself fundamentally from the ACLED dataset by its stricter event definition (see the section Selection Bias). Conceptually, violent incidents with at least one fatality resulting from the direct use of armed force are coded with their location and timeframe. Among other factors, the type of military action (*fighting* or diverse forms of *one-sided violence*), the number and type of fatalities, as well as the involved *violent* or *non-violent actors* are coded. Furthermore, we provide a set of variables indicating the news sources, possible sources of bias, and detailed information on geographic precision to allow for flexible use of the data based on individual requirements. A more detailed description of the dataset can be found in the download section of our website.[5]

In contrast to UCDP-GED, which employs a similar event definition, EDACS covers events with unknown actor participation (see the sub-section Problems of Actor Differentiation) and includes actors and dyads not surpassing the minimum threshold of twenty-five conflict-related fatalities per year applied in UCDP-GED (Melander and Sundberg 2011, Sundberg et al. 2010). By not limiting our focus to well-observed actors and conflict dyads, EDACS provides a more comprehensive and detailed picture than UCDP-GED of patterns of violence in the observed countries and periods. In the following sections, we demonstrate how the EDACS dataset design enables the analyst to deal with the core challenges to georeferenced event data coding and usage as outlined above.

SOURCE BIAS IN CONFLICT EVENT DATA

Like other event datasets (e.g. ACLED, UCDP, WEIS), EDACS relies on news sources for gathering information on armed conflict. However, the biased nature of media-based (and other kinds of secondary) sources has implications for data reliability. Quantitative researchers have been studying these issues for almost forty years. Doran et al. (1973), Hazlewood and West (1974), and Jackman and Boyd (1979), just to name a few, have analyzed how the selection of different news sources affects data reliability for conflict events such as demonstrations, coups, or assassinations in cross-country conflict research. While Doran et al. (1973) detected contradicting trends in data collected from international versus regional newspapers, others have concluded that differences in event reporting are rather marginal, and that “increasing coverage beyond two sources is not likely to result in substantial changes to the ‘overall picture’ ” of event data trends

(Hazlewood and West 1974; Jackman and Boyd 1979, 457; Taylor and Hudson 1972).

More recently, a vast array of literature has emerged in the field of protest research that deals with the causes, consequences, and handling of reporting bias in media-based event datasets (e.g. Barranco and Wisler 1999; Earl et al. 2004; Hug and Wisler 1998; Mueller 1997; Ortiz et al. 2005). Unlike violent conflict event data projects, this literature mainly deals with (violent) protest events in ‘Western’ countries, where the circumstances differ significantly from war-torn countries in the Global South. Nonetheless, conflict research has to acknowledge the analytical concepts and methods from this literature to address media bias in the development and analysis of event data.

It is important to distinguish between causes and effects of selective event reporting (*selection bias*) and erroneous information on events (*description bias*) (Earl et al. 2004, 67). These different levels of news bias will be discussed in the following. However, only a few aspects can be considered here; for a more detailed discussion of various types of media bias in event reporting, see for example Öberg and Sollenberg (2011).

Selection Bias

Media-based event datasets are only a subsample of the “real” events (Barranco and Wisler 1999; Doran et al. 1973). This is especially true for armed conflict events, since reporting in war-torn areas is often limited due to censorship, security, and other reasons (Öberg and Sollenberg 2011). However, as Earl et al. (2004) point out, “a sample of even 5% of [real] events would not be problematic if it were truly representative” (Earl et al. 2004, 70). Researchers can only assume that the event data collected by them is representative and try to minimize the effect of potential sources of bias and miscoding.

Media reporting is decisively influenced by varying news values, potentially resulting in selection bias (Hocke 1995; Mueller 1997). Several factors such as frequency and relevance influence the perceived newsworthiness of an event and the decision to report it or not (Galtung and Ruge 1965; Öberg and Sollenberg 2011, 57). Furthermore, these factors might change depending on location and time, making it difficult to assess the resulting selection bias. Violent events are generally considered to be relatively newsworthy (Barranco and Wisler 1999, 304; Woolley 2000, 158), as are armed conflicts in general (Öberg and Sollenberg 2011, 53). However, this assumption must be treated with caution, since other aspects such as abruptness or identification strongly influence newsworthiness as perceived by media outlets. In other words, the interest of international media in a specific armed conflict declines gradually over time, but increases with a great power military intervention or the involvement of UN-led multilateral forces.

Nonetheless, we argue that conflict events resulting in the loss of life are reported with higher consistency than those without fatalities, even if they, of course, remain susceptible to selection bias, but in a positive way – in the media they are selected over other events that do not involve loss of life. While ACLED includes lethal and non-lethal battles or one-sided attacks as events in an undifferentiated manner (Raleigh et al. 2010), we define an event as a *violent incidence at a specific location and a specific time with at least one fatality resulting from the direct use of armed force*. This lethality threshold of single events corresponds to the approach taken by UCDP-GED (Sundberg et al. 2010) and seems appropriate to obtain a more reliable and consistent data basis for studying patterns of violence and (in)security.

If certain regions or time periods have higher news coverage than others, systematic selection bias is likely to fake trends. If alternative datasets are lacking, the analyst has to address this problem through source criticism and a careful interpretation of the results, considering the nature of the information sources (Öberg and Sollenberg 2011). We therefore argue that consistency of the data sources across time and regions is a necessary precondition when interpreting empirical findings.

EDACS is based on a set of four predefined sources or media outlets that are used for all coded countries and years of observation. First, the archives of three international newspapers (The Guardian, The New York Times, and The Washington Post) and the broad collection of translated local news reports by BBC Monitoring were searched by keywords through LexisNexis. All sources had been pretested and were found to report relatively consistently for the cases selected and the period under study (1990 to the present). This approach of searching predefined news outlets is similar to UCDP-GED but contrasts with ACLED, where sources differ between regions and periods of observation, as shown in the following.[6]

When comparing EDACS for Somalia 1997-2009[7] with UCDP-GED events and battle- and one-sided violence against civilians events[8] of ACLED, the issue of source consistency becomes striking (see Figure 2): Until 2003, EDACS collected slightly more events (split by days[9]) than ACLED and UCDP-GED. From 2003 onwards, however, the number of ACLED events sharply increased, while EDACS and UCDP-GED followed a common trend of slightly declining event numbers until the Ethiopian invasion of Somalia in late 2006. One explanation for this strong discrepancy in the data may be that about 88% of the ACLED events from 2003 are based on data from the Worldwide Incidents Tracking System (WITS) and reports from the Security Preparedness and Support Program (SPAS). While they probably provide more detailed information than the news reports used for EDACS and UCDP-GED, this inconsistency overemphasizes violence after 2003, leading to artificial data trends.

(Figure 2 about here)

Even more extreme than the discrepancy in Somalia 1997-2009, where ACLED collected between two and four times as many events as EDACS or UCDP-GED (see Figure 2), in the case of Sierra Leone ACLED counted between five and eight times as many violent events (1287) as EDACS (194 events/276 event days) or UCDP-GED (156 events) for the years 1997-2003 (see Figure 3), the time period for which data is available in all three datasets. Like in Somalia, event numbers over time of EDACS and UCDP-GED appear to correlate during the period of observation in Sierra Leone. Clearly it is important to question whether the high deviation of ACLED event numbers can be explained by ACLED's inclusion of violent events not resulting in fatalities, in contrast to the other two datasets.

(Figure 3 about here)

If we suspected all three data projects to have similarly high event coding standards, this discrepancy would probably be a result of differing strategies of source selection. While EDACS and UCDP-GED follow a similar standardized approach in all countries of observation of searching the predefined media outlets, ACLED uses more than fifty different secondary sources or media outlets for Sierra Leone 1997-2003. While it may be questioned whether the sources used in EDACS and UCDP-GED neglect this region (compared to Somalia), source criticism and the detection of selection bias are not possible for the ACLED data, since there is no documentation available to explain the selection of this vast array of sources.

ACLED, similar to other event data projects (e.g. Nardulli et al. 2011), appears to reduce source selectivity by maximizing the number of sources used. However, it is unclear whether this reduces or only obscures selection bias. Using additional news sources does not necessarily reduce bias, since they might all be affected by the same biases (Hug and Wisler 1998). Other sources of selective news coverage, such as presence or absence of observers, censorship, or general media restrictions (Öberg and Sollenberg 2011) might be more pronounced. Considering the rapid spread of information and communications technology in the Global South over the last few years, the inclusion of all available sources would further intensify this bias towards recent conflict events. Furthermore, maximizing the number of sources lessens reproducibility and hinders source criticism. Besides, additional sources increase the costs of data coding and promote coding errors.

We currently conduct research on (semi-)automated event data coding (see below), which will provide opportunities to test the effects of including additional news sources. Though our data cannot be traced back to real events, we are able to compare data from different sources to estimate causes and patterns of selection bias. In order to allow for such comparative studies, event datasets must precisely indicate their sources and coding processes, and avoid interpretation of sources by coders via strict coding rules. Only through careful interpretation of results and source selectivity can research findings become meaningful.

Description Bias

Not only *that* an event is reported, but also *how* it is reported is crucial for event data quality. In order to carry out research using event data, one must assume that the given location and time of events are trustworthy (Abbott 2006, 17; Earl et al. 2004). However, it remains difficult to argue that specified actors can be considered "hard data" (Raleigh et al. 2010, 656). Going through the news reports it is often impossible to differentiate whether an actor is named or blamed by a source or cited witness. Likewise, fatality counts are highly susceptible to bias since they are often subject to government or rebel propaganda.

The issue of description bias is especially severe when media outlets retrieve information directly or indirectly from conflict actors. However, we would miss a large share of events and risk an even stronger media restriction bias if we excluded these reports. For each event, names and publication dates of the news sources are indicated. Furthermore, events are marked as *biased* in EDACS if the information on the event is provided by this type of source. We therefore enable the data user to exclude these events from their analysis. In the EDACS data on Sierra Leone, for instance, *biased* sources constitute about 20% of events in the early nineties in Sierra Leone – in the period 1990-1995, this share is almost 40%.

With the EDACS project we code actors as they are reported in the respective sources. However, when information is seemingly biased, we mark the specified actor as "unconfirmed". Specific coding rules regarding actors and coded variables are documented in detail in a downloadable codebook.[10]

The inherent bias in fatality counts, however, must be addressed in a more complex way. Since fatality numbers may constitute the least reliable information related to armed conflict events (Raleigh et al. 2010), their coding, analysis, and interpretation must be handled with care. We code minimum and maximum fatality numbers whenever different sources provide contradicting figures.[11] Further, we have developed a set of strict and conservative rules to code fatalities in order to ensure intersubjectivity and consistency of our data.

For instance, a violent event in southern Somalia was reported as follows in The New York Times:

> "Somalia's faltering government and powerful Islamists on Saturday exchanged artillery fire for the second day near the government seat … After an overnight lull, rival forces resumed clashes in villages south of Baidoa …

witnesses and officials said.

‘The fighting has resumed and it is raging in the same area as yesterday,’ Sheik Osmail Addo, an Islamic commander, said. Each side confirmed casualties, with the Islamists saying that 50 people had died – 30 government soldiers and 20 Islamists – but there was no independent confirmation. The government army said it had lost soldiers in Friday's fighting, but declined to give a figure. ‘We lost a lot of men,’ Commander Ibrahim Batari said.” (Agence France-Presse, 2006)

According to our coding rules, any claims regarding death figures by parties involved in the conflict are coded conservatively, with the minimum set at twenty-two and the maximum at the number stated in the claim. Since there is no optimal solution to this challenge, we provide a descriptive string variable citing the death figures’ description, which enables end users to apply their own coding rules.

EVENT EXTRACTION

Compounding the challenges to completeness (selection bias), accuracy, and consistency (description bias), there are also inherent obstacles to the generation of event data during the actual transformation of news articles into structured information. During the process of coding, or more precisely, event extraction, accuracy can be affected by oversights and inconsistency in the subjective judgments of human coders, as investigated more in detail by Laver et al. (2003), Rothman (2007), and Ruggeri et al. (2009).

To address these issues, EDACS enforces certain constraints stored in a relational database. For instance, we have already mentioned that an event must be attributed to at least one news source. Therefore, our database model does not accept a data entry without the source name and the date of publication. Without these precautions, the transformation process would become less robust and might lead to artificial data. Furthermore, using the querying infrastructure provided by the database, ex-post checks are run to explore more complex reliability issues. This includes checks for potential duplicate events, potentially unreasonable values, and outlier detection.

Another significant, albeit labor-intensive precaution taken in EDACS is to code all data twice, by two different coders, automatically documenting which coder creates and which coder revises each entry. Conflicting results from the two coding rounds are reconciled by a supervising coder, which eventually leads to enhanced completeness and consistency.

As a consequence of the inherent susceptibility to inconsistency of manual coding, automated methods have been evaluated (King and Lowe 2003; Laver et al. 2003; Schrodt 2008). King and Lowe reported accuracy “virtually identical” to machine coding with human coders (King and Lowe 2003, 636). Upon closer examination, the results were very mixed: King and Lowe found a precision of 93% but also a false positive rate of 77%, i.e. 77% of sources were wrongly classified as containing an event. Such a high false positive rate would render any automated coding result useless. A similar strategy has been chosen by Nardulli et al. (2011) who employ manual coding supported by a more sophisticated document classification approach and achieve a false positive rate of 35%, which already “enables human operators to process huge amounts of text in an efficient manner” (Nardulli et al. 2011, 4). Nevertheless, 35% of all irrelevant articles have to be reviewed and dismissed manually – a high burden to human coders that devaluates the very low false negative rate of 1-4% (i. e. few relevant articles are erroneously excluded).

This strongly suggests going one step further: to use document classification in combination with machine coding to assist human coders whenever possible. Nardulli et al.

(2011) propose the same but are still in the development phase of such event extraction software. In EDACS, we have implemented and road-tested a combination of text classification and event extraction methods using supervised machine learning and natural language processing. This approach takes less time than manual extraction and allows for automated recoding using altered coding rules if desired (Wiesel and Ickler 2012).

EVENT CONTEXTUALIZATION

During the data generation process, researchers face problems that go beyond the mere transformation of news articles into event data. Using information such as maps, settlement data, and qualitative reports, data projects contextualize events, translate toponyms to geographic coordinates, determine actor alliances, and more.

Problems of Event Localization

All three data projects under investigation draw on the toponymic GEOnet Names Server (GNS) for event localization. The GNS database is maintained by the US National Geospatial-Intelligence Agency (NGA) and provides location names and coordinates in the World Geodetic System 1984 (WGS 84) on a global level (NGA 2011). GNS provides an extensive settlement dataset that is easily accessible at no charge. For micro-level analysis of conflict dynamics, however, GNS coordinates may be of limited use. Firstly, “GNS feature coordinates are approximate and are intended for finding purposes” (NGA 2011). Furthermore, large urban agglomerations are represented by a single vector point, even though cities cover large areas. Temporary settlements, which are common in the rapidly changing environment of civil wars, further complicate the matter. Toponym ambiguities are also frequent – for instance, the town of Koidu in Sierra Leone has seven entries in the GNS dataset, located up to fifty-five kilometers apart from each other but within the same district (Kono District, Eastern Province). In EDACS, we estimate locations in such cases after consulting additional map data such as GoogleEarth or Harvard's AfricaMap. Toponym ambiguities are indicated in an additional, event-specific text variable.

Newspaper articles often do not give the event location precisely. Instead, an article might indicate only a region or administrative unit, or mention relative geographic locations: e.g. "not far from A," "in between B and C," or "about twenty kilometers northeast of D." This is the case for about one third of all events (see Table 1) in the EDACS dataset. In ACLED and UCDP-GED, this problem is approached by specifying various levels of geoprecision, designating whether the coordinates refer to an exact location, an administrative division, or other approximate areas such as part of a region (Raleigh et al. 2009) or "near" an exact location (Sundberg et al. 2010, 14). Instead of predefining levels of accuracy, we quantify the accuracy. We specify buffers according to a set of strict buffer rules, while providing the original location description in an additional text variable. For instance, if a specific administrative unit is indicated, we code the coordinates of the centroid and specify a buffer relative to the size of the unit. If a location is described as "along the road between A and B," we code the central point along the respective road using auxiliary map data, and specify the distance to A or B as a location-specific buffer radius.

(Table 1 about here)

Other problems originating from the lack of accuracy of digitized maps and context data in civil war areas include, but are not limited to, incomplete data, lack of remote sensing data (especially in tropical regions due to cloud coverage), incompatible scales (due to generalization-impeding data pooling), accessibility (due to military restrictions, privacy laws, etc.), accuracy (expensiveness in acquisition and generation), temporal dynamics, propagation of errors (caused by miscoded information which cascades through the data – and renders results useless), and the Modifiable Areal Unit Problem (MAUP) (erroneous belief that a data attribute is homogenous) (Cressie and Wikle 2011, 197; Wu and Hobbs 2007, 117ff.). Coding events in remote or rural areas, as well as border or coastal regions, is also highly problematic due to the imprecision of underlying base maps and imprecise source indications. These problems can only be addressed via a multi-data approach and interpolation techniques, but they are far from solved.

When comparing the degree of spatial-temporal similarity of EDACS, UCDP-GED, and ACLED events in Somalia (1997-2009) (see Figure 4) coded with the highest temporal and geographical precision,[12] the results show a high overlap between EDACS and UCDP-GED, while both EDACS and UCDP-GED largely differ from ACLED. Only 8.47% of EDACS event days occur on the same day as ACLED violent events within a distance of five kilometers, whereas 33% of EDACS event days match UCDP-GED events (see Figure 4).

(Figure 4 about here)

Problems of Temporal Inaccuracy

The temporal dimension of violent events is essential for the analysis of conflict dynamics, but the coding of start and end dates of events is a highly problematic issue. First, reports of violence are often not accurate enough to distinguish between single and aggregated events and to determine exact time spans. Imprecise wording such as “last week” or “recently” makes estimations necessary. Again, we defined a set of coding rules to handle such specifications in a consistent way. To allow for deviating interpretations by the analyst, EDACS indicates such cases using the Boolean variable *estimated date* (see time-estimated events in Table 1) and stores the original source description for further use.

Temporal disaggregation is further complicated by events that span several days – for instance, when fatality counts per day are necessary. We provide two versions of EDACS data: a standard version and a version disaggregated by day. Temporally disaggregated, the number of fatalities is divided by the number of days, enabling the researcher to analyze "event days" instead of events. We do not consider this an ideal solution, but rather a practicable attempt to reduce the problem.

Problems of Actor Differentiation

As mentioned earlier, the identification of violent actors by news sources must be treated with caution. However, an exclusion of reported events, as in UCDP-GED (see above), with one of the participating actors not identified, harms data completeness and creates a selection bias towards well-documented events. Similar to ACLED (Raleigh et al. 2010), we therefore code these events using generic actor categories such as "rebels," "bandits," "clan militia," or else "unspecified actor." Of course, most categories are highly problematic since they are often created by the media. However, the informed researcher might be able to identify actors that are most likely to be responsible for a specific event. In order to assure data consistency and allow for source criticism, we generally refrain from judgment and leave such educated guesses to the analyst.[13] In some cases, however, interpretation based on auxiliary data is necessary in order to avoid redundancy in the actor database. While one source might name a particular actor by its self-declared name (e.g. “Somali National Alliance”), another might specify the actor by its leading commander (e.g. “fighters loyal to warlord Mohamed Farah Aidid”) or by its involvement in previous events (e.g. “militia alliance fighting the UNOSOM II mission in the Battle of Mogadishu”). Consulting qualitative conflict reports as well as consolidated actor databases, for instance provided by UCDP or the Institute for Strategic Studies (IISS), actors are coded in EDACS by their most commonly used name. We are aware that this approach can introduce new bias into our data. However, the consequent literal coding of actors as indicated in the sources would maximize data replicability, but also minimize its utility for research. Again, there is no optimal solution. Consequently, possible shortcomings have to be made visible to end users and analysts, thereby enabling them to challenge our coding decisions and gain new insights and more credible conclusions.

CONCLUSIONS

The attraction of developing event datasets has resulted from the lack of existing research programs to account for the mechanisms and dynamics of violent conflict and warfare on the local or sub-state level. Today, a new generation of event data on armed conflict and security sheds light on patterns of who fights where and under what local conditions, and allows researchers to test hypotheses that highlight spatial and temporal dynamics of violence. Paying theoretical and empirical attention to the complex relationship between time, spaces, actors, and violent behavior is a necessary condition not only to advance the scientific study of conflict and war in general, but also to better understand regional or local variations of one-sided and mutual violence. However, we should be aware of serious errors resulting from the sources and auxiliary data used, as well as of shortcomings in the processes of transforming source data into event data (misinterpretation, oversights) and faults in the contextualization of events. In this sense, the growing diversity of georeferenced event datasets becomes a chance to enhance data quality by comparing sources, events, and results. It could, at least to some degree, minimize the 'one-stop shopping' problem that typically arises from (unjustified) confidence in the quality of large data collections.

Nevertheless, even an increase in collected information on violent events cannot portray the 'real world' of violence or war. The methodological problem remains of how to confirm causal relationships of single events or between a series of events. If one assumes that the occurrence of a particular event is always better reflected as "a matter of chance" (Lebow 2000, 592), then conclusions drawn from a recorded sequence of violent events concerning the mechanisms and dynamics of armed conflict become illusive.

At the end of the day, there is no guarantee that the collection of more and more events or the cyclical development of new data projects will improve our knowledge of the etiology and dynamics of violence. On the contrary, there is a high risk that both coders and users underestimate challenges to the accuracy, consistency, and relevancy of event data. The consequential problem is one of credibility. What conflict research needs and what EDACS offers is transparency and a proactive problem-oriented approach to empower analysts to question the data and avoid cascading errors. Overcoming the 'one-stop shopping' problem means striking a balance between quantitative and qualitative methods, confirming the correctness of computed event clusters by crosschecking them with qualitative reports,[14] and being aware of the uncertainty of conflict environments and the limitations of scientific knowledge.

REFERENCES

Abbott, Marianne 2006. Dangerous Intervention: An Analysis of Humanitarian Fatalities in Assistance Contexts. Dissertation, Graduate School of The Ohio State University.

Agence France-Presse December 10, 2006. "Islamists and Somali Troops Exchange Fire." *The New York Times.*

Barranco, José, and Dominique Wisler 1999. "Validity and Systematicity of Newspaper Data in Event Analysis." *European Sociological Review* **15**(3):301-322.

Batini, Carlo, and Monica Scannapieca 2006. Data quality: Concepts, methodologies and techniques *(Data*-Centric Systems and Applications*).* Secaucus, NJ, USA: Springer-Verlag New York, Inc.

Buhaug, Halvard 2010. "Dude, Where's My Conflict? LSG, Relative Strength, and the Location of Civil War." *Conflict Management and Peace Science* **27**(2):107-128.

Cleveland, William S. 1981. "LOWESS: A program for smoothing scatterplots by robust locally weighted regression." *The American Statistician* **35**, 54.

Cressie, Noel, and Christopher K. Wikle 2011. Statistics for Spatio-Temporal Data. Wiley Series in Probability and Statistics. John Wiley & Sons, Inc., Hoboken, New Jersey.

Doran, Charles F., Robert E. Pendley, and George E. Antunes 1973. "A Test of Cross-National Event Reliability: Global Versus Regional Data Sources." *International Studies Quarterly* **17**(2):175-203.

Dulic, Tomislav 2010. Geocoding Bosnian Violence: A note on methodological possibilities and constraints in the production and analysis of geocoded event data. Paper presented at the annual meeting of the *Theory vs. Policy? Connecting Scholars and Practitioners*, New Orleans, Feb 17, 2010.

Earl, Jennifer, Andrew Martin, John D. McCarthy, and Sarah A. Soule 2004. "The Use of

Newspaper Data in the Study of Collective Action." *Annual Review of Sociology* **30**:65-80.

Eck, Kristine 2012. "In Data We Trust? A Comparison of UCDP GED and ACLED Conflict Events Datasets." Forthcoming in *Cooperation and Conflict* **47**(1).

Eberwein, Wolf-Dieter, and Sven Chojnacki 2001. "Scientific necessity and political utility. A comparison of data on violent conflicts." *Discussion Paper P01-304*, Social Science Research Center Berlin.

Galtung, Johan, and Marie H. Ruge 1965. "The Structure of Foreign News: The Presentation of the Congo, Cuba and Cyprus Crises in Four Norwegian Newspapers." *Journal of Peace Research* **2**(1):64-91.

Gleditsch, Nils Petter and Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand 2002. "Armed Conflict 1946–2001: A New Dataset", *Journal of Peace Research* **39**(5): 615-637.

Gleditsch, Kristian Skrede & Kyle Beardsley, 2010. "Core Issues in International Data Collection" in Paul F. Diehl & James D. Morrow, eds, *International Studies Encyclopedia, Volume on Scientific Study of International Processes*. New York.

Hazlewood, Leo A., and Gerald T. West 1974. "Bivariate Associations, Factor Structures, and Substantive Impact: The Source Coverage Problem Revisited." *International Studies Quarterly* **18**(3):317-337.

Hocke, Peter 1995. Determining the Selection Bias in Local and National Newspaper Reports on Protest Events. Paper presented at the *Workshop on Protest Event Analysis*, Social Science Research Center Berlin.

Hug, Simon, and Dominique Wisler 1998. "Correcting for Selection Bias in Social Movement Research." *Mobilization: An International Journal* **3**(2):141-161.

Jackman, Robert W., and William A. Boyd 1979. "The Workshop: Multiple Sources in the

Collection of Data on Political Conflict." *American Journal of Political Science* **23**(2):343-458.

King, Gary, and Will Lowe 2003. "An automated information extraction tool for international conflict data with performance as good as human coders: A rare events evaluation design." *International Organization* **57**:617-642.

Laver, Michael, Kenneth Benoit, and John Garry 2003. "Extracting policy positions from political texts using words as data." *American Political Science Review* **97**(2):311-331.

Lebow, Richard N. 2000. "Contingency, Catalysts, and International System Change." *Political Science Quarterly* **15**(4):591-616.

McClelland, Charles A. 1976. "World Event/Interaction Survey Codebook." Ann Arbor: Inter-University Consortium for Political and Social Research.

Melander, Erik, and Ralph Sundberg 2011. Climate Change, Environmental Stress, and Violent Conflict - Tests introducing the UCDP Georeferenced Event Dataset. Presented at the *International Studies Association* Annual Conference.

Mueller, Carol 1997. "Media Measurement Models of Protest Event Data." *Mobilization: An International Journal* **2**(2):165-184.

Nardulli, Peter F., Kalev H. Leetaru, and Matthew Hayes 2011. "Event data, civil unrest and the speed project." *Proceedings of the International Studies Association* Annual Convention, 2011.

National Geospatial-Intelligence Agency (NGA) 2011. GEOnet Names Server (GNS). Document last modified April 15, 2011. <http://earth-info.nga.mil/gns/html/index.html> (2011, April 18).

Öberg, Magnus, and Margareta Sollenberg 2011. "Gathering Conflict Information Using News Resources." *Understanding Peace Research: Methods and Challenges,* eds. Kristine

Hoglund and Magnus Öberg. Abingdon, New York: Routledge.

O'Loughlin, John, Frank D. W. Witmer, Andrew M. Linke, and Nancy Thorwardson 2010. "Peering into the Fog of War: The Geography of the WikiLeaks Afghanistan War Logs, 2004–2009." *Eurasian Geography and Economics* **51**(4):472-495.

Ortiz, David G., Daniel J. Myers, Eugene N. Walls, and Maria-Elena D. Diaz 2005. "Where Do We Stand With Newspaper Data?" *Mobilization: An International Journal* **10**(3):397-419.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joachim Carlsen 2009. Armed Conflict Location and Event Dataset (ACLED) Codebook 2009. Centre for the Study of Civil War, International Peace Research Institute, Oslo (PRIO).

Raleigh, Clionadh, Andrew Linke, Håvard Hegre, and Joachim Carlsen 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset: Special Data Feature." *Journal of Peace Research* **47**(5):651-660.

Rothman, Steven B. 2007. "Understanding data quality through reliability: A comparison of data reliability assessment in three international relations datasets." *International Studies Review* **9**(3):437-456.

Ruggeri, Andrea, Ismene Gizelis, and Han Dorussen 2009. If You Don't Succeed the First Time, Try and Try Again – Event Data and Inter-Coder Reliability. Paper presented at the International Studies Association Annual Conference *Exploring the Past, Anticipating the Future*, New York, Feb 15, 2009.

Schrodt, Philip A. and Omur Yilmaz 2007. "CAMEO: Conflict and Mediation Event Observations Codebook." Lawrence: University of Kansas.

Schrodt, Philip A. 2008. "TABARI: Textual Analysis by Augmented Replacement Instructions, Version 0.6." Lawrence: University of Kansas.

Sundberg, Ralph, Mathilda Lindgren and Ausra Padskocimaite 2010. "UCDP GED Codebook version 1.0-2011." Uppsala: Department of Peace and Conflict Research, Uppsala University.

Taylor, Charles L., and Michael C. Hudson 1972. *World Handbook of Political and Social Indicators,* 2nd ed. New Haven: Yale University Press.

Thion-Goasdoué, Virginie, Sylvaine Nugier, Dominique Duquennoy, and Brigitte Laboisse 2007. "An evaluation framework for data quality tools." *Proceedings of International Conference for Information Quality (ICIQ)* 2007:280-294.

Weidmann, Nils. B., and Michael D. Ward 2010. "Predicting Conflict in Space and Time." *Journal of Conflict Resolution* **54**(6):883-901.

Wiesel, John and Christian Ickler 2012. "I, Coder: Examining the Impact of Artificial Intelligence on Event Data Coding." *Proceedings of the 53rd International Studies Association* Annual Convention, Forthcoming.

Woolley, John T. 2000. "Using Media-Based Data in Studies of Politics." *American Journal of Political Science* **44**(1):156-173.

Wu, Jianguo, and Richard J. Hobbs 2007. "Key topics in landscape ecology", Cambridge.

FIGURE 1 Challenges to Conflict Event Data.

	Data	Process
Event	News reports • Selection bias • Description bias	Transformation • Misinterpretation • Oversights
Auxiliary	Settlement data • Spatial precision • Temporal accuracy Information on actors • Synonyms • Misspellings	Contextualization • Event localization • Spatiotemporal comparability • Actor identification

→ Event data

FIGURE 2 EDACS, ACLED[15] and UCDP-GED[16] Monthly Event Counts Somalia 1997-2009 –Locally-weighted Polynomial Regression Smoothing with a 10 percent Window (see Cleveland 1981).

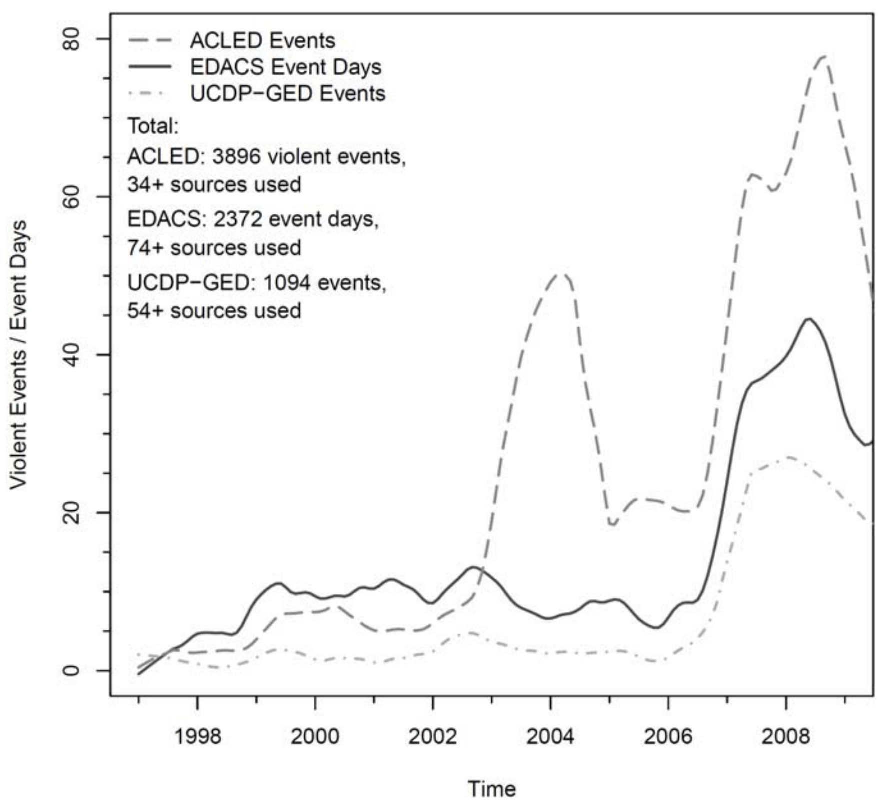


FIGURE 3 EDACS, ACLED and UCDP-GED Monthly Event Counts Sierra Leone 1997-2003 – Locally-weighted Polynomial Regression Smoothing with a 10 percent Window.

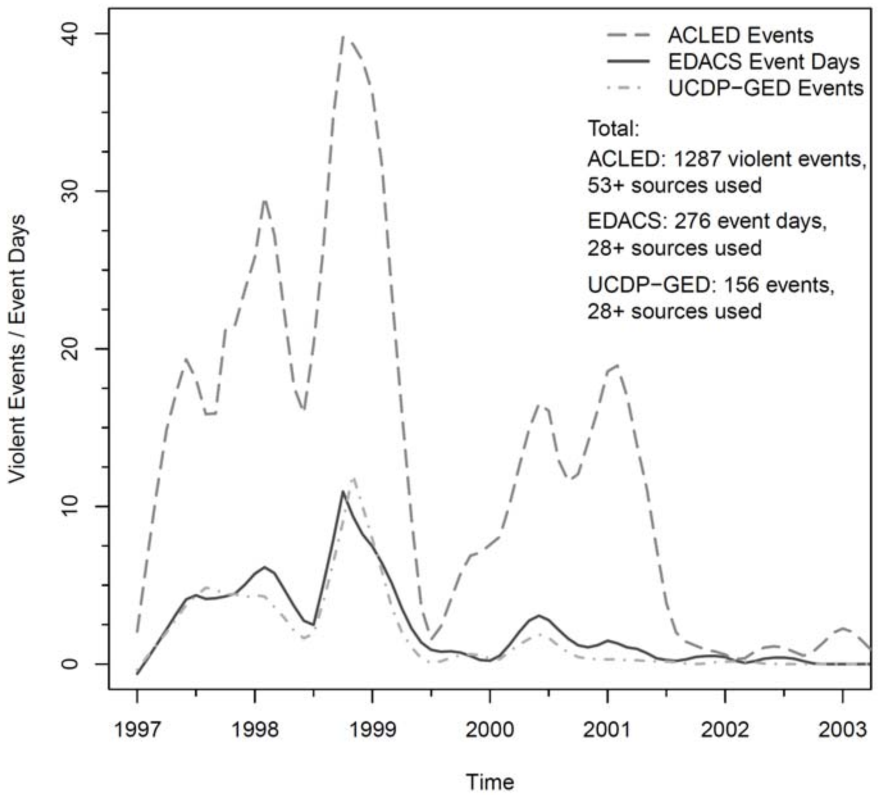
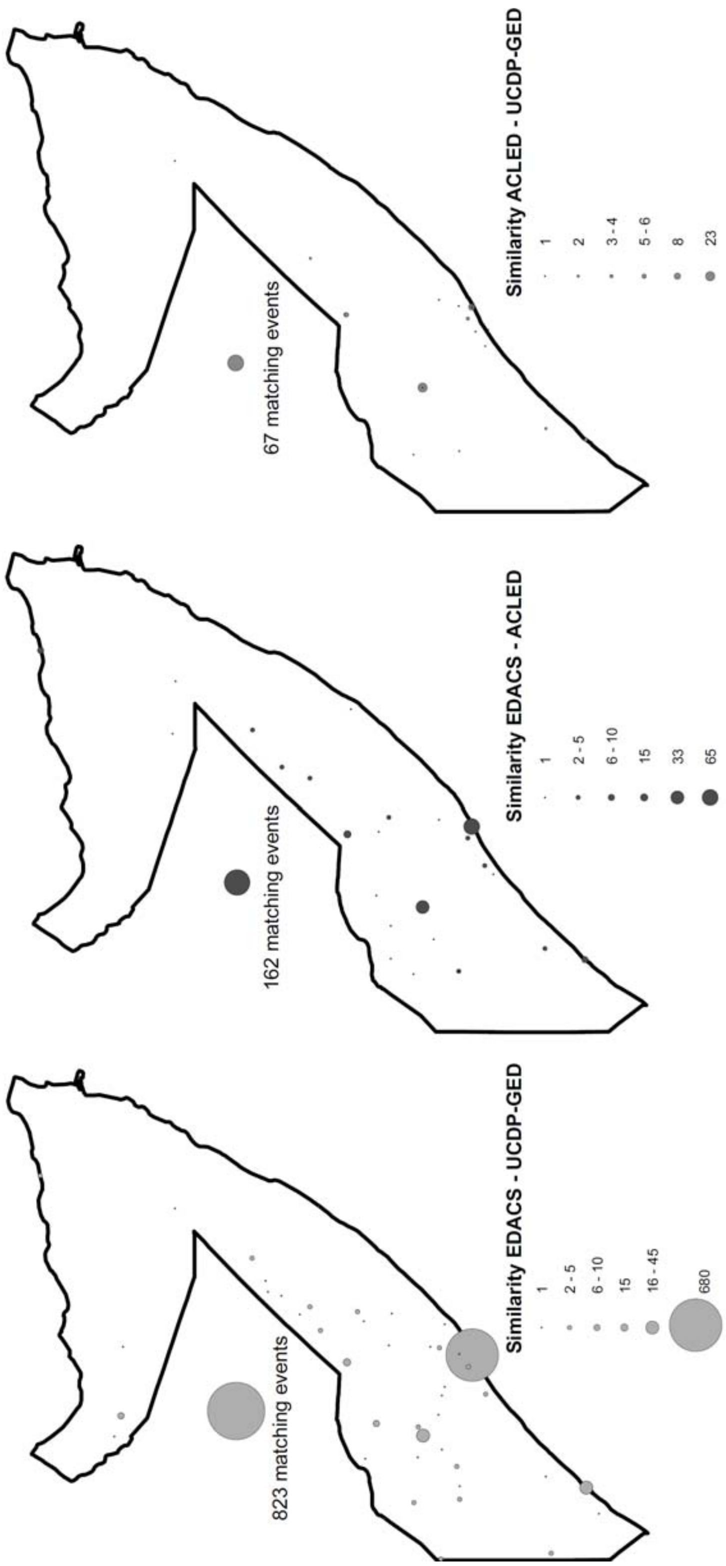


TABLE 1 Mean EDACS Event Buffering, Median of ACLED Geoprecision Level, Range of Event Buffering/Geoprecision, Median UCDP-GED Geoprecision Level, and Share of Event Time Estimates for Somalia and Sierra Leone.

	Total N	Mean buffer/ Median level	Range geo[1]	Share of buffered events in % of total	Share of time estimated events in % of total[2]
EDACS Somalia	3027	14.51	0 – 930	18.33	21.01
(split by day)		1.091	5 – 103		
EDACS Sierra Leone	499	63.40	1 – 220	48.89	41.68
(split by day)		1.43	0 – 87		
ACLED Somalia	3899	1	0 – 3	50.30	4.13
ACLED Sierra Leone	1290	1	1 – 3	8.06	5.96
UCDP-GED Somalia	1829	1	1 – 6	18.86	21.43
UCDP-GED Sierra Leone	420	1	1 – 6	47.62	41.43

Notes: [1] EDACS buffer types: Geo-Location, Event-Location in km; ACLED geo-precision level: 1 – 3; UCDP-GED geo-precision level: 1 – 7; [2] EDACS time estimate and ACLED time-precision level: 1-3; UCDP-GED time-precision level: 1-5.

FIGURE 4 Matching events of ACLED, EDACS, and UCDP-GED: Similarity of EDACS and UCDP-GED (left), EDACS and ACLED (middle) and UCDP-GED and ACLED (right) in Somalia, 1997 to 2009.



NOTES

[1] This research has received financial support from the German Research Foundation (DFG).

[2] This was the conclusion from a comparison of war data sets. Eberwein and Chojnacki's key finding was that the data-gathering projects in the study showed different 'worlds' of violence irrespective of whether they were based on qualitative or quantitative operational criteria.

[3] Many issues discussed here are relevant for media-based event datasets in general. Nevertheless, non-georeferenced event datasets such as the Conflict and Mediation Event Observations (CAMEO) of the Kansas Event Data System (KEDS) project (Schrodt and Yilmaz 2007) or the World Event/Interaction Survey (WEIS – McClelland 1978) are not the focus of this paper.

[4] Other geo-referenced conflict event datasets are either not (yet) publicly available (e.g. Nardulli et al. 2011) or cover different regions or time series (e.g. Dulic 2010; O'Loughlin et al. 2010).

[5] See www.conflict-data.org.

[6] UCDP-GED appears to follow a similar approach by coding data from five different news wires (BBC Monitoring, Reuters News, Agence France Presse, Dow Jones International News, and Xinhua News Agency) (Eck and Hultman 2007), although no detailed documentation on how sources are searched is available. ACLED, in contrast, does not apply a standardized search but arbitrarily selects different sources for different countries and periods of observation.

[7] A comparison of the datasets is limited to this time period, since ACLED is available for the years 1997-2010, UCDP-GED for 1989-2010, and EDACS for 1990-2009.

[8] ACLED also comprises non-violent event types that are excluded from this comparison (see Raleigh et al. 2010).

[9] EDACS collects start and end dates, since events can last for more than one day. To make our data comparable to ACLED events that have a single date only, we split events by days (see the sub-section Problems of Temporal Inaccuracy).

[10] See www.conflict-data.org.

[11] UCDP-GED follows a similar approach by providing three different fatality estimate categories (low, high, and best estimates) (see Sundberg et al. 2010).

[12] i.e. EDACS events without buffer and estimated start date, UCDP-GED events without summary events, events lasting more than 1 day (continuous events have been split), and ACLED violent events with precision variables = 1.

[13] One approach we currently follow is to contextualize actors within their spatiotemporal areas of operation. In a second step, this can help to identify, to a certain probability, generic and unspecified actors.

[14] Other recently available sources and techniques that have the potential to generate event data are based on information provided by Cablegate (wikileaks.org) or crowd-sourcing and crowd-seeding approaches, such as Voix Des Kivu, conducted by staff of the Columbia University in Eastern Congo. See http://cu-csds.org/wp-content/uploads/2009/10/Voix-des-Kivus-Leaflet.pdf.

[15] Only "violent" ACLED events are counted here, i.e. the event types "battle" and "violence against civilians". The ACLED event types "headquarters or base establishment", "non-violent rebel presence",

“rioting/protesting”, and “non-violent transfer of location control” cannot be compared with EDACS data.

[16] UCDP-GED event type 2 (summary events) and Events with a temporal precision 0 and 5 (summary event and year) are excluded here.