

Supplementary Information (SI)

# Common ecology quantifies human insurgency

Juan Camilo Bohorquez, Sean Gourley, Alex Dixon, Michael Spagat and Neil F. Johnson

## Supplementary Notes

All references in this SI refer to references listed at the end of this document, unless otherwise stated. At the very end of the SI, we have included an example selected from the full information in our database, for the casualty data from Iraq. For illustration, we show both the maximum and minimum estimates of casualties per event. Events are labelled using a specific code. In the future, we will make such excerpts available in downloadable form (e.g. Excel) from our website so that interested researchers can check our claims and try their own analyses. To see in detail how events were scrutinized, we refer to the discussion in an online e-print by us, posted in 2005 and freely available at [lanl.arxiv.org/pdf/physics/0506213v1](http://lanl.arxiv.org/pdf/physics/0506213v1) with a more detailed 2006 version at [lanl.arxiv.org/pdf/physics/0605035v1](http://lanl.arxiv.org/pdf/physics/0605035v1). These present a preliminary empirical analysis of the distribution of casualties per encounter in just two conflicts, Iraq and Colombia. The extensive discussion in these e-prints (in particular [lanl.arxiv.org/pdf/physics/0605035v1](http://lanl.arxiv.org/pdf/physics/0605035v1)) concerning how data from individual conflict events was verified, illustrates the examination which was undertaken wherever possible, to avoid double-counting events etc. We also note that at that stage 4 years ago, we had no further accurate data. Instead, the draft represented a pilot study which led us to conjecture that wars might present commonalities, with approximate power-laws in casualties having exponents near 2.5. Since it pre-dated our analysis of other conflicts, the conjecture in these earlier drafts can be viewed as a general prediction which is now borne out by the present results.

Conflict country	Database start date	Database end date	Total number of events	Number of events with >0 deaths	Biggest event (number of deaths)	Total number of deaths	Deaths explained by powerlaw estimate	Average deaths per event (geometric mean)	Number of events with >= xmin	xmin	alpha	error in alpha	DStatistic measuring goodness of fit	statistical significance pvalue
Colombia	01/01/1988	22/01/2005	21,478	11,673	260	38,876	20,637	3	2,251	4	2.90	0.05	0.01	0.74
Iraq	01/01/2003	24/11/2005	3,737	3,678	2,000	22,347	19,184	6	1,186	2	2.03	0.03	0.02	0.41
	01/05/2003	21/07/2007	8,645	8,645	215	31,671	19,262	4	1,435	4	2.32	0.04	0.03	0.65
	01/04/2007	01/09/2008	4,632	4,632	525	15,427	9,834	3	898	3	2.31	0.05	0.02	0.99
Senegal	10/06/1982	04/02/2005	559	305	300	3,313	3,199	11	191	2	1.73	0.05	0.05	0.83
Afghanistan	09/09/2001	29/10/2005	1,225	72	133	5,048	3,655	7	184	8	2.44	0.26	0.05	0.79
Israel-Palestine	01/07/2000	31/07/2002	180	180	40	811	524	5	44	6	2.55	0.17	0.11	0.18
Sierra Leone	13/10/1994	10/01/2003	697	697	550	13,596	9,933	34	83	47	2.41	0.07	0.07	0.89
Peru	01/06/1980	01/12/2002	10,452	5,571	153	17,579	8,452	3	433	8	2.40	0.12	0.05	0.66
Indonesia	18/03/1996	31/12/2001	376	89	57	1,393	998	5	89	5	2.50	0.18	0.04	0.91
N. Ireland	14/07/1969	31/12/2001	2,698	2,698	29	3,523	3,523	1	2,698	1	3.17	0.05	0.00	0.54
<b>TOTALS</b>			<b>54679</b>	<b>38240</b>		<b>153584</b>	<b>99201</b>							

Conflict country	Data sources
Colombia	NGO and media reports: Non-conflict events removed, see CERAC website for details
Iraq	The first Iraq dataset incorporates information from IBC, ITERATE and iCasualties. These three datasets are combined by hand and filtered to identify unique events. The second two use IBC as a starting point, but are filtered in slightly different ways. The three datasets were prepared by three different research teams, and span different time periods. For the periods during which they overlap, their content is mutually consistent – so too are the conclusions from their use. Note that the alpha value moves toward 2.5 as the period of the war is extended (i.e. going from the first to the second dataset), in line with a statement in the main paper.
Senegal	Humphreys dataset (see Refs.): Data collected from the Casamance region
Afghanistan	ADC, DBDC, ITERATE, iCasualties: ADC and DBDC data compiled from media sources by Herold (see Refs.)
Israel-Palestine	CSIS dataset: Individual deaths recorded by Cordesman (see Refs.). Unique events aggregated by hand
Sierra Leone	Humphreys dataset (see Refs.)
Peru	From CERAC, Bogota (J. Restrepo) based on the Truth and Reconciliation report (see Refs.): <a href="http://www.cverdad.org.pe">www.cverdad.org.pe</a>
Indonesia	UNSFIR report: Data from the Separatist conflict (see Refs.)
N. Ireland	Sutton dataset (see Refs.): Data contains individual deaths. Unique events obtained by aggregating single deaths by hand

Supplementary Figure 1: Summary of the datasets used and their corresponding statistical properties for the nine insurgent conflicts.

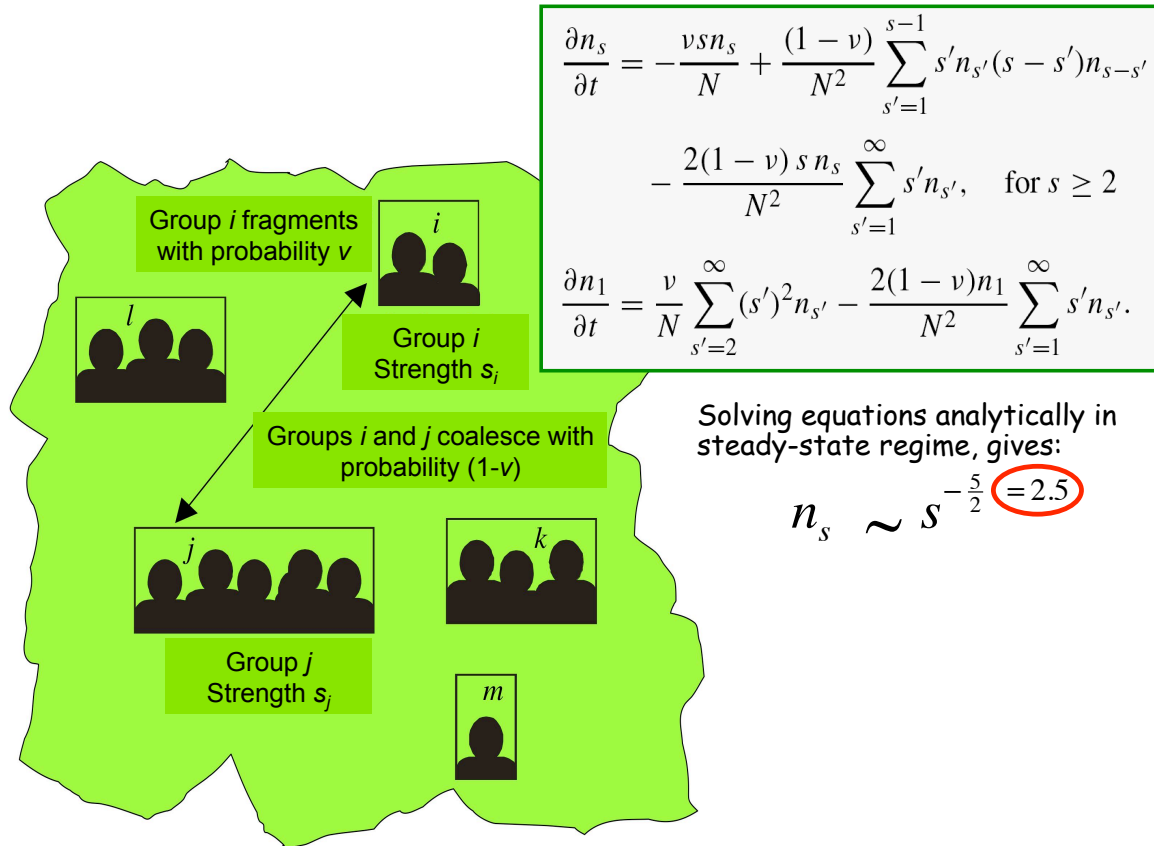
# 1 Details of the datasets

We rely on data collection by a wide range of organizations and scholars who all determine their own methods. However, to the extent possible we try to enforce a common-sense definition of an ‘event’ in a conflict, as an occurrence of an action involving a group of armed actors that (1) cannot be partitioned into any smaller set of actions, (2) can be distinguished from other such events, (3) is carried out by at least one recognized group in a conflict, (4) involves a number of casualties being reported, and (5) there is some broad strategic description that can be given, i.e. weapons used, or military objective, or general identity of units involved. Sources may use subtly different definitions of an event, differ in their coverage or make mistakes in reporting, hence we use multiple source types for the same conflict wherever possible. For example, for the Afghanistan conflict we used a dataset integrating data provided by Marc Herold of the University of New Hampshire (<http://pubpages.unh.edu/~mwherold/>) with data from [icasualties.org](http://www.icasualties.org/) (<http://www.icasualties.org/>) and the ITERATE (<http://www.ciser.cornell.edu>) terrorism database. The approach to integrating the Afghanistan data is similar to how the Iraq data was built which we now describe in some detail since this discussion gives good insight into the nature of the data we are using.

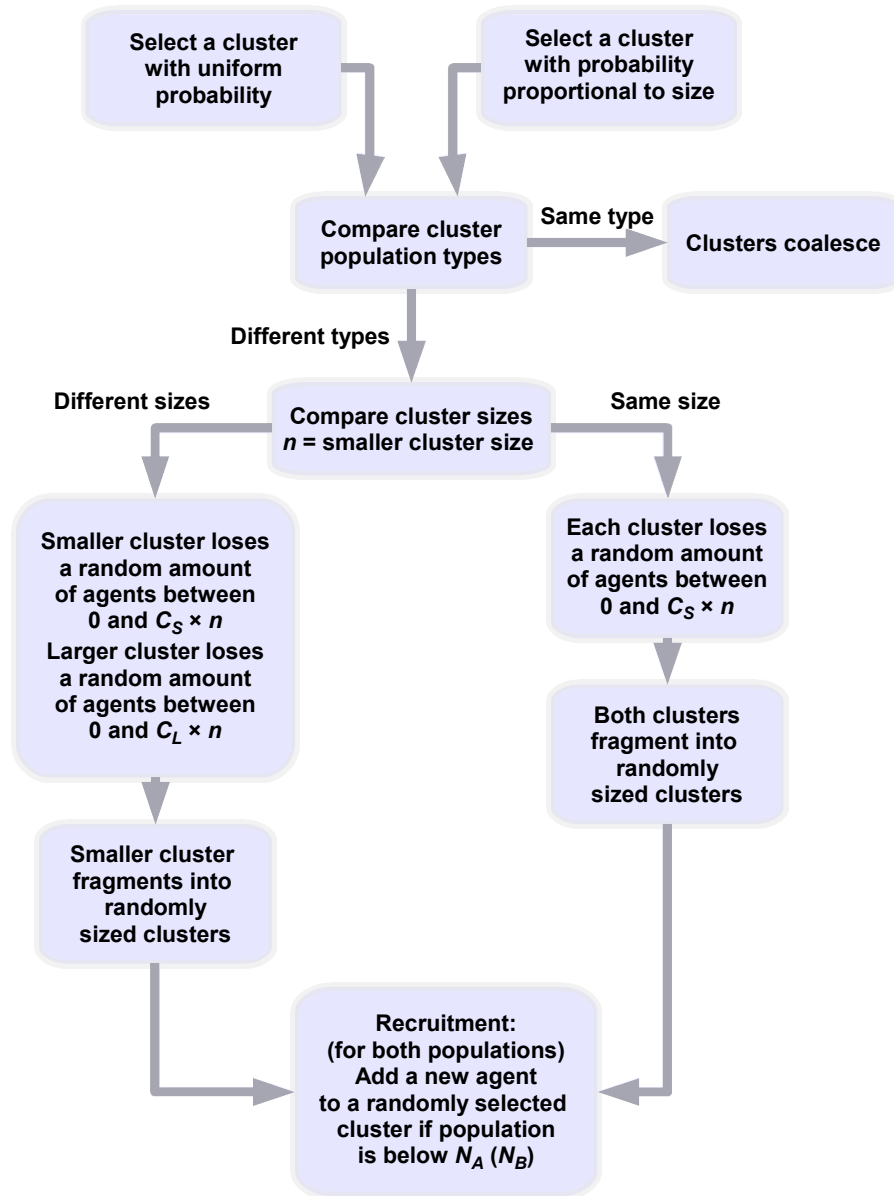
The Iraq data, like the Afghanistan data, is an amalgamation of three separate data sets that record violent events in Iraq. These data-sets are Iraq Body Count (IBC, <http://www.iraqbodycount.org/>), [icasualties.org](http://www.icasualties.org/) and ITERATE. The IBC project monitors a large number of respected online news sources for reports/stories of violent events in Iraq. An event is recorded in the IBC database if at least one civilian is killed. IBC records whenever possible a number of pieces of information on each event including the date, estimates of the minimum and maximum number of civilians killed and the sources that report the event. We have checked that our conclusions are robust to the use of either minimum or maximum numbers. [icasualties.org](http://www.icasualties.org/) monitors coalition deaths from online news reports. ITERATE is a database that monitors terrorist attacks from all over the world, including in Iraq. We note that for Iraq, the events in the IBC database often have an end date one day after the start date – but this rarely means that these are actually two day events. Instead, an event might appear on the news Thursday morning written in such a way as to make it impossible to determine whether it actually happened on Wednesday or Thursday. Hence the two-day listing reflects the uncertainty over dates, rather than the events being prolonged. This highlights the importance of our methodological approach of consulting multiple sources, wherever possible, in order to construct reliable conflict event databases. We also update and check the robustness of our results by using two IBC-only datasets that were cleaned separately to satisfy our event definition, finding very similar results for the periods of overlap between the three datasets. For Iraq we were able to repeat our analysis for both upper and lower fatality counts to check the robustness of our conclusions.

Ultimately, all the data comes from multiple sources which can be grouped into three broad categories; real-time media databases, official (government and nongovernmental organization (NGO)) reports, and academic studies. Some sources use real-time media monitoring of a the stream of information/stories about violent events from newspapers, web-sites and television. These databases typically monitor a range of media channels and employ filters to cross-check different stories for accuracy. As both the global coverage and access to this type of information increases, these types of databases are becoming increasingly important for the analysis of conflict. Governmental and NGO reports are generally produced well after events have occurred. They also tend to rely on media reports of violence but a utilize information from other sources as well such as government monitoring programmes, hospital and coroner reports and witness testimonies, this latter source being crucial for our Peru data. The Colombia data (<http://www.cerac.org.co/>) is based primarily on periodic reports of a Catholic NGO (CINEP). For older data on the American and Spanish civil wars we use the academic work of Ron Francisco of the University of Kansas who, in turn, relies on historians accounts (<http://web.ku.edu/~ronfran/data/civilwars/index.html>).

For the Peruvian conflict the data is built from the report published by the Truth and Reconciliation Committee (TRC)[37]. Data on the Indonesian separatist conflict was developed with the support of the United Nations Support Facility for Indonesian Recovery (UNSFIR)[38]. The data for the Israel-Palestine conflict is derived from the event chronology published in a report produced by CSIS[34]. The data for Sierra Leone and Senegal comes from the academic work of Macartan Humphrey of Colombia University[35]. The data source for the Northern Ireland conflict is the research of Malcolm Sutton[36] using a large number of sources.



Supplementary Figure 2: The simplest possible incarnation of our model, discussed in the main paper in connection with Figure 1. It reproduces [32] the observation of a power-law with exponent value of approximately 2.5. For illustration purposes in this figure, we show  $\nu_{\text{frag}} = \nu$  and  $\nu_{\text{coal}} = (1-\nu)$ , but we note that  $\nu_{\text{frag}}$  and  $\nu_{\text{coal}}$  do not have to satisfy such a relationship for the 2.5 value result to emerge. Indeed, the 2.5 analytic result [32] is remarkably robust to additional generalizations (e.g. multiple groups coalescing, fluctuating  $N$ , and even the addition of an internal character (i.e. hidden variable) in the model: see B. Rusczycki et al. physics/0808.0032 at LANL arXiv which is referenced in the main paper). The inset shows the master equations for the model, which yield analytically the 2.5 result[32]. Note that the term ‘group’ is equivalent to a ‘cluster’. Clusters (and cluster master equations) are terms which are likely to be more familiar to readers from the physical or chemical sciences.



Supplementary Figure 3: Schematic of the more sophisticated incarnation of our one-population version from Supplementary Figure 2, where we now explicitly account for the opposing population (as explained in the main paper) yielding a two-population model. For simplicity, the strength of a group is now referred to equivalently as its size. As also noted in the caption for Supplementary Figure 2, the term ‘cluster’ is equivalent to ‘group’, but we use ‘cluster’ in this flow-chart for the benefit of physical and chemical scientists who may be more used to dealing with this terminology. This model produces the green curves in Figure 2 of the main paper. Because it moves beyond the simple one-population power-law model, the green curves show significant features *beyond* power-law.

## 2 Additional details about our model in Figure 4.

### 2.1 Grouping Mechanism

Supplementary Figure 2 shows the schematic of the simplest possible incarnation of our model, with one population and fragmentation and coalescence determined by probabilities.

The model consists of a population of agents. In this context the agents are taken to be ‘casualty causing units’; in the simplest case just single fighters, but this definition also covers equipment such as explosives, or even information. The agents tend to join together to form groups (which can equivalently be referred to as ‘clusters’), which can then merge with other groups to form larger groups or fragment into single agents. The ‘strength’ of the group dictates the average number of people who would be killed or injured as a result of an event involving that group. Each agent is taken to have a strength of 1, so that a group of size  $s$  has a strength of  $s$ . The number of groups with a given strength is denoted by  $n_s$ , and the total strength of the population (which is equal to the total number of agents in it) is taken to be a constant,  $N = \sum sn_s$ .

On each timestep in the model a group (this term includes single agents) is selected with probability proportional to its size ( $s$ ), so the probability of a given group size being selected is  $P(s) = \frac{sn_s}{N}$ . With a probability  $\nu$  the group selected fragments into single agents. Otherwise, with a probability  $(1-\nu)$ , a second group is selected with probability proportional to its size and the two groups coalesce into a single group. The size of this new group is equal to the size of the two constituent groups. (For illustration purposes in Supplementary Figure 2, we show  $\nu_{\text{frag}} = \nu$  and  $\nu_{\text{coal}} = (1-\nu)$ , but we note that  $\nu_{\text{frag}}$  and  $\nu_{\text{coal}}$  do not have to satisfy such a relationship for the same 2.5 result to emerge). The continuous fragmentation and coalescence process results in a dynamic equilibrium, with a steady state distribution of group sizes which has been found both by numerical simulation and by analytic methods [31, 32, 33]. The distribution is a power law with an exponential cut off,

$$n_s \approx N \left( \frac{4(1-\nu)}{(2-\nu)^2} \right)^s s^{-5/2}$$

for small values of the fragmentation probability  $\nu$  the dominant  $s$  dependence is the power law.

This simple one-population form enables a straightforward explanation of the results in Figure 1 of the main paper, which records the approximate power-law behaviour observed in each of the conflicts that we have studied (see Figure 2 for four examples). For a quantitative explanation of the detailed behaviours within each conflict – in particular, the details beyond power-law – a more detailed model is required. Supplementary Figure 3 shows the more sophisticated model incarnation which explicitly features two opposing populations (insurgents and state army) and generates the model results shown as green lines in Figure 2. The two separate populations of agents are of total size  $N_A$  and  $N_B$ . Each population is distributed in groups of various sizes, with the number of groups of size  $s$  at any time given by  $n_s^A$  for population A and  $n_s^B$  for population B. On each timestep an agent is selected at random out of the combined A and B population. This is equivalent to selecting a group with probability proportional to its size. The group this agent is a member of then interacts with a second group selected at random (with uniform probability, i.e. not proportional to its size) from the combined population. If the two groups are of the same population type they join together to form a larger group. If however the two groups are from separate populations, the smaller group takes a random number of casualties up to parameter  $C_S$  times its size, and the larger group takes a random number of casualties up to parameter  $C_L$  times the smaller groups size. The smaller group then fragments into randomly sized groups. If either population is below its target size ( $N_A$  or  $N_B$ ) an agent is added to a randomly selected group in that population. The model develops into a steady state and the number of casualties occurring in each interaction is recorded. This is averaged over 100,000 simulations to generate the mean distributions shown in Figure 2. The initial conditions of the model do not effect the steady state result, which depends only on  $N_A$ ,  $N_B$ ,  $C_S$  and  $C_L$ . The parameters used for each of the conflicts modeled in Figure 2 are shown in Supplementary Table 1, with A and B representing the insurgency and state army respectively.

A civilian population can also be added to the model, as shown in Supplementary Figure 4, without altering the distribution. Note that to make the flow-chart easier to read, we have reverted to a subscript form that has A for state army, B for the insurgents, and C for civilians. Just as in many modern insurgent conflicts, it turns out within this model that for an asymmetric war with  $N_A \gg N_B$ , then the majority of encounters involve population B (i.e. insurgents) being the smaller group. Hence the majority of casualties are in population B (i.e. insurgents). This number could be used as the casualty figure, but equally – since insurgents are often indistinguishable from civilians physically in terms of dress – it makes sense to introduce a third ‘civilian’ population, as shown in Supplementary Figure 4. This population (type C) can only be selected in the second selection step, since it does not itself initiate a fight, and is selected in this step with probability proportional to its size, the same as for the A or B population. Since the C population can only be selected second, it

Supplementary Table 1: Parameters used in the model for event size distributions shown in Figure 2 of the main paper. Here we have chosen the labels  $A$  and  $B$  to represent the insurgency and state army respectively

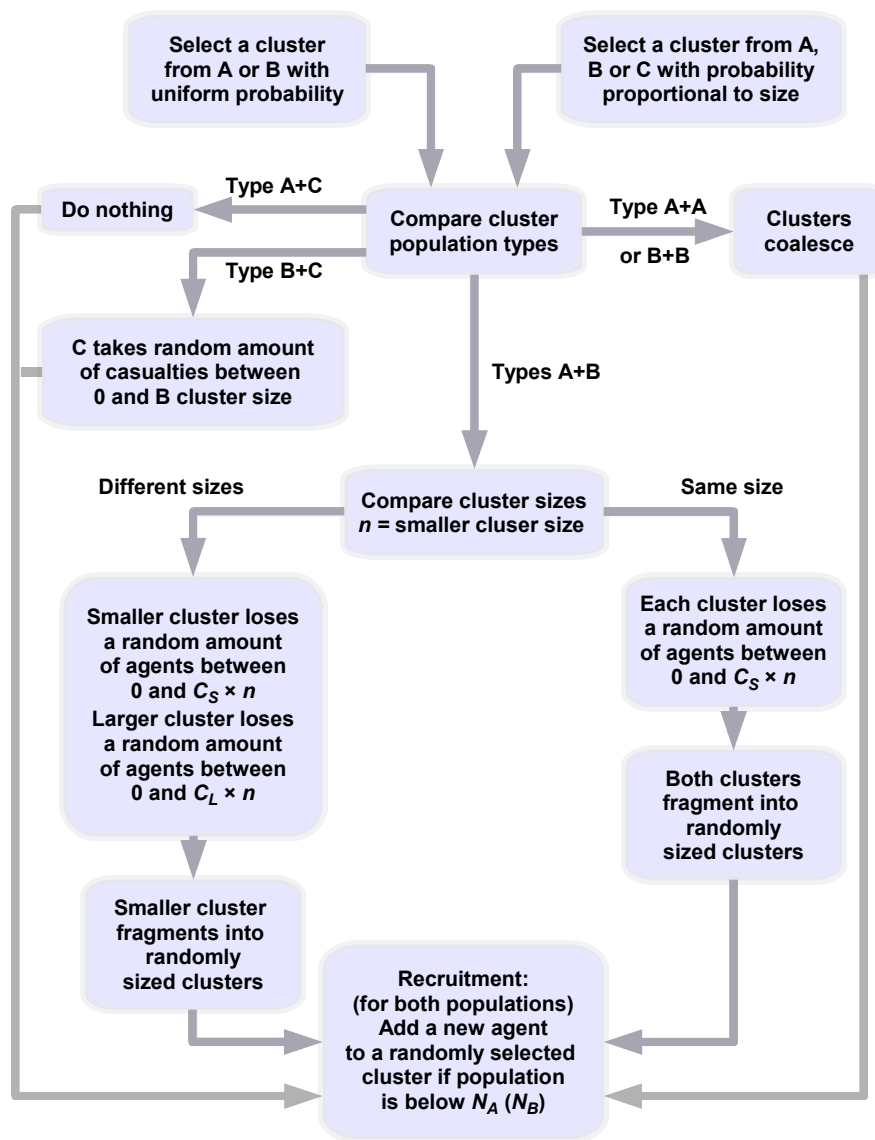
Conflict	$N_A$	$N_B$	$C_L$	$C_S$
Afghanistan	440	660	0.1	1
Iraq	25332	48000	0.15	0.7
Colombia	3000	9750	0.15	1
Peru	460	900	0.1	0.66

therefore cannot interact with itself – nor does the main population A (i.e. state army) have any effect. By contrast, picking a B (i.e. insurgent) and a C (i.e. civilian) group corresponds to the situation of insurgents attacking civilians. If such an interaction happens, then the C population takes a number of casualties between 0 and the group size of B. Hence we do *not* need to assume that casualties are proportional to the strength. The size of the damage, and the population which inflicted it, is recorded as the size of that event (i.e. severity). Since the C population has no effect on A or B populations, it has no effect on the behavior of the model. Instead, the distribution of event sizes (i.e. casualties) reflects, in the steady state, the distribution of the B (i.e. insurgent) population which is causing the damage. The size of the C population scales the overall event distribution, but otherwise has no effect. Therefore provided that the C population is large enough so it cannot be wiped out (which is realistic, given that civilian populations are tens of millions while insurgent forces tend to be tens of thousands) then it makes no difference to the model if C agents are destroyed in interactions. This model therefore relaxes the assumptions of strict proportionality between  $s$  and  $x$ , and the involvement of groups with probability strictly proportional to  $s$ . We stress that *many further variations of the model details (e.g. rules-of-engagement) are possible without changing the main conclusions in the paper.*

## 2.2 Timing Mechanism

We now turn to our analysis of event timings as shown in Figure 3 of the main paper. In an insurgent conflict, setting aside occasional offensives by the state army, most violent events are initiated by the insurgency. Hence we introduce a decision-making model for insurgent attacks where we use this word ‘attack’ in a broad sense. For high profile attacks such as car bombs, the time-stamp associated with the event has a high temporal resolution often on the scale of minutes. For lower profile attacks, the resolution may be reduced with the time-stamp simply recording the day of the attack. For the type of analysis that we wish to undertake, a resolution on the scale of days is sufficient. Thus for each event we define the time-stamp to be the date that the attack occurred. For multi-day attacks we take the time-stamp to be the day that the attack started. In Figure 3, the first three months of the Iraq conflict are associated with the invasion phase of the war and the majority of the attacks in this period are a result of battles between two conventional forces. The 1<sup>st</sup> of May 2003 is thought to be a good approximation to the start of the insurgent group (i.e. guerilla-like) phase of the war and it is from this date that we start our analysis. For labelling purposes we denote the 1<sup>st</sup> of May 2003 to be day 0 of the time-series.

To determine if there is indeed significant clustering of events within the time-series, we compare the real data from the Iraq war with that of a ‘random’ war in which the numbers of attacks on consecutive days are (by construction) unrelated. This can be simply achieved by randomly shuffling the dates such that each attack is assigned to a randomly chosen date within the same database, thereby creating a list of attacks for a ‘random’ war. However, we first need to remove any long-term trends in the real war, since such trends will create an almost guaranteed, but trivial, difference between the real war and the randomly constructed war (‘random’ war). This is achieved using the following algorithm: (1) Take time-stamp of each attack. (2) Plot number of attacks on each day of the conflict. This is the time-series for the real war. (3) Split the time-series for the real war into smaller intervals of time (which we refer to as ‘epochs’) with a particular time-window duration. We then repeat this exercise for a range of choices of epoch time-window, to (i) test that we have indeed removed longer term trends, and yet (ii) make sure that the results are not sensitive to the precise choice of a epoch time-window. We are satisfied that our choices of time-window in Figure 3 of the main paper do indeed satisfy both criteria. In terms of the results of Figure 3 in the main paper, we note that we did not detect any such long-term trends within the range of the datasets that we have for Afghanistan and Peru – any that do exist, are so subtle that they do not affect our main results or conclusions. (4) Collect all events from within a given epoch (i.e. within each time-window in turn, repeating this throughout the database) and then randomly reassign the events to new days within this same epoch (i.e. within the



Supplementary Figure 4: Schematic of the more sophisticated incarnation of our one-population version, as shown in Supplementary Figure 3 but with the civilian population explicitly included. Note that for simplicity in drawing the flow-chart, we use A for the state army, B for the insurgents, and C for civilians. Most importantly, the conclusions in the main paper are unaffected whether we measure the casualties of civilians alone, civilians plus insurgents, or just insurgents, since civilian casualty distribution just mimics distribution of insurgent groups which create these civilian casualties. It also mimics distribution of insurgent casualties themselves since they in turn reflect distribution of insurgent groups. Note also that that the term ‘cluster’ is equivalent to ‘group’, but we use ‘cluster’ in this flow-chart for the benefit of physical and chemical scientists who may be more used to dealing with this terminology.

same time-window). (5) Plot the new number of attacks on each day to create one realization of the ‘random’ war. By its construction, this algorithm creates a random war that has the same total number of attacks within each epoch and hence throughout the entire database, and also the same distribution of casualties for the entire database. It also preserves the identity and time-ordering of the different epochs found in the real war data. We then repeat this shuffling process to produce a large collection of realizations of such random war datasets. We can then compare (as in Figure 3) the distribution of the number of days with  $n$  attacks for the purely random war and the real war, to determine if there are any deviations for a given epoch. In particular, the large collection of realizations for the random war can be used to produce an average value for the random war distribution at each  $n$ , plus a standard deviation.

For example, the data displayed in the first panel for Iraq in Figure 3 of the main paper, is for the epoch we identified from day 540 (25/10/2004) through to day 1032, by which time the conflict had reached an approximate steady state. We stress that our results are, however, insensitive to the precise choice of epoch. (Indeed, we stress that the reason for breaking each dataset into epochs at all, is to reduce the possibility that any observed variations between real and random wars are simply arising because of an expected long-term crescendo within a given conflict). The random war data is calculated by taking the mean of 10,000 random versions of the Iraq war generated using the algorithm discussed above and the error bars represent  $\pm$  one standard deviation from the mean. At first sight, a simple explanation for the existence of this burstiness might come from variations in violence as a function of the day of the week. To investigate, and finally eliminate, this as a possible explanation, we did the following: We first identified that for Iraq, Fridays had 15% less attacks than would be expected from a purely random distribution of events. This decrease in violence is associated with the holy day in the Muslim week. We then took this Friday effect into account by eliminating Fridays from the dataset – and then later taking other subsets of days – and repeating the exercise of obtaining Figure 3. We found that the impacts on the general patterns in Figure 3 was negligible, and hence that the bursty signature in Figure 3 is not simply a result of day-of-the-week effects. There may be other possible explanations for the burstiness of the signal (see in particular, Refs. [39] and [40]). We have tried implementing some of these – however the quality of the data, while state-of-the-art in our opinion – prevents us from obtaining clear results from more subtle correlation measures. The bars in the distributions in Figure 3 measure  $\Delta(n)$ , which we define to be the difference between the real war data and the random war data expressed in terms of the number of standard deviations from the mean:

$$\Delta(n) = \frac{p_{\text{real}}(n) - p_{\text{random}}(n)}{\sigma_{\text{random}}(n)}.$$

This non-random, bursty distribution in Figure 3 of the main paper, suggests a possible degree of coordination between the various insurgent groups. Direct communication between groups over large distances is possible in a conflict, thanks to modern communications (e.g. mobile phone) over arbitrarily far distances, and hence our coalescence mechanism in the simpler one-population model version – however, such communication will likely be infrequent. Hence it is unlikely to give the significant level of event clustering observed [41] [42] [43] [44]. The dominant force driving the clustering is more likely to be coordination by proxy using a global signal – hence our model in Figure 4.

Although all members of the insurgency want the insurgency as a whole to have maximum media exposure everyday, they know that there is some finite daily media capacity above which they will have wasted their time and resources if they initiate an attack. Funding, resources and the ability to attract new recruits will all depend on a group’s profile, hence it is in the interests of a given group to create an event which makes it into the media [44]. If they attack on a day where the media capacity is not exceeded and hence their attack makes it into the media, or they hold back on a day where the media capacity is exceeded, they will ‘win’ in terms of rewards within the insurgency and/or wise use of their own group’s resources. If they hold back on a day where the media capacity is under-used, or they attack on a day where the media capacity is exceeded, they will ‘lose’. This setup is very similar to the El Farol problem of Brian Arthur, which is used in association with financial markets to understand the effect of competition for limited resources within a heterogeneous population with adaptive capabilities and access to limited public information (see Ref. [33] for full details of this and related models in the context of financial markets). Here each group plays the role of a single ‘agent’. The key parameters of (Figure 4) are therefore: (1)  $L$ , the capacity level of media attention (taken as a proxy for airtime, or column inches) that the insurgency would like to fill. We stress that an entirely equivalent setup can be obtained using a variant of this story, in which the insurgency as a whole has its own desired level of attacks  $L$ . If a given group attacks on a day which is below  $L$ , or holds back on a day which is above  $L$ , it will think it has ‘won’ since it used its own finite resources wisely. Likewise, if it attacks on a day which is above  $L$ , or holds back on a day which is below  $L$ , it will think it has ‘lost’ since it did not use its own finite resources wisely. (2)  $C$ , the confidence threshold required for an insurgent group to be able to launch an attack. The insurgent groups each have an individual confidence level  $c_i$ , this measures their ability to predict the actions of other groups involved in the conflict. A high individual confidence level  $c_i$  means that group  $i$  knows how other groups will react to specific global signals. In order for group  $i$  to launch an attack,  $c_i \geq C$ . Thus the confidence

threshold  $C$  determines the level of knowledge required for an attack to be launched and can best be thought of as a barrier to entry. (3)  $N_g$ , where this parameter denotes the average number of autonomous insurgent groups that are involved in the conflict during that period in time. This average number of groups can in principle always be extracted from the event size part of the model framework, as discussed earlier. (4)  $p_r$ , which is a measure of the probability that other groups in the conflict will react in the same way to the global signal as they did last time the system was in this state. The parameter  $p_r$  can take a value from 0 to 1 and is randomly assigned to each group. Depending on the desired level of accuracy (i.e. closeness-of-fit to the data) other parameters can be included, each of which adds a plausible detail from the real-world but which then makes the model more complex. These parameters are not essential for burstiness, and burstiness phenomena are still produced using the more basic version of the model. These parameters are:  $m$ , the number of previous time-steps that are used to make a decision;  $d$ , the rate that unsuccessful strategies/groups are updated/replaced;  $h$  the size of the window used to calculate the confidence and success thresholds.

After receiving the global signal, each group (i.e. agent) uses this information to decide whether or not to launch an attack at this time-step. To make this decision the groups are assigned a specific  $p_r$  value that acts like a strategy to determine the group's actions. The parameter  $p_r$  represents the likelihood that the various groups in the conflict will react to the global information in the same way they did last time the system was in this state. Thus the  $p_r$  values can be thought of as a measure of the repeatability of system. Using this parameter  $p_r$ , some groups will determine that the global signal means that they should launch an attack, whilst other groups will interpret the signal as meaning that today is not a good day to launch an attack. Before implementing their decision each group first determines whether their confidence level is above a critical threshold  $C$ . The group's confidence level is determined by their past ability to make correct decisions about when to launch an attack. If their current strategy, as determined by their  $p_r$  value, has been successful in the past then the group will implement their decision. If the strategy is not successful, then the group will not act and will instead wait until their confidence is above the critical threshold  $C$ . At the next step in the cycle the total number of attacks is determined by summing over the actions of all the groups involved. The total number of attacks of all sizes is given by  $\sum_x N_x(t)$  and this number is compared against the level  $L$ . If this attack level is below  $L$  then the correct decision was to have launched an attack as it would have increased the insurgency's exposure that day. If on the other hand the number of attacks was above  $L$ , then the best decision was not to launch an attack as there is already a sufficient number of attacks and further attacks would see a diminishing return in terms of exposure. The groups that made the correct decision become more confident, attract more resources and continue to survive. Following this, in the fourth phase of the cycle (survive/adapt/dissolve) the groups that continually make the wrong decision about when to attack are forced to adapt and update their strategies or are replaced by new groups with different strategies. When the cycle is complete the global signal of daily attacks, troop movement etc is broadcast and the cycle of violence is repeated with agents using their success on previous iterations to update their future behaviour. *Though this model is possibly unfamiliar to many readers, we stress that it is simply a modified version of the well-known and well-studied El Farol problem of Brian Arthur in which potential bar-goers compete for space in a crowded bar on successive days, making decisions about whether to act (i.e. attend the bar) or not based on common limited knowledge about the past* (see Ref. [33] for details).

We use this timing model as the basis of our numerical simulation, and from the simulation we generate a time-series of attacks for each war that we want to analyse. The simulation is run over the same number of days as the war, and we assume that each insurgent group is capable of an average of one attack per timestep. Given the resolution of the data, and the relative sparsity of attacks, we can simply take one timestep as one day. (In the future, when data becomes more reliable intra-day as to precise time-of-the-day, and more intense wars break out with individual groups regularly initiating multiple attacks within the same day, we can simply set the definition of a timestep equal to the minimum timescale separating any two consecutive attacks by a given group). From the resulting time-series of attacks we then calculate the distribution of the number of attacks per day, as in Figure 3. We run the simulation 10,000 times for each war. In determining the distribution in Figure 3, the mean and standard deviation is calculated from the set of all runs. The same model is used for all the conflicts that we have studied. The output from the model is shown in Figure 3 of the main paper, and is denoted by the solid line within each panel. The standard deviation is not shown on this figure due to the lack of space, however all of the empirical data from the actual conflicts lie within one standard deviation of the model's output. From this set of results, we can see that the output from the model is in excellent agreement with the empirical data and this holds across different wars. The quality of the fit suggests that the timing model captures many of the key features of both the decision-making and strategy processes employed by insurgent groups. The precise values used for the simulation are shown in the Supplementary Table 2. The parameters  $d$  and  $m$  were fixed for all the simulations and the remaining three parameters were calculated using a least-squares fitting algorithm (discussed below) to minimise the difference between the real war data and model output.

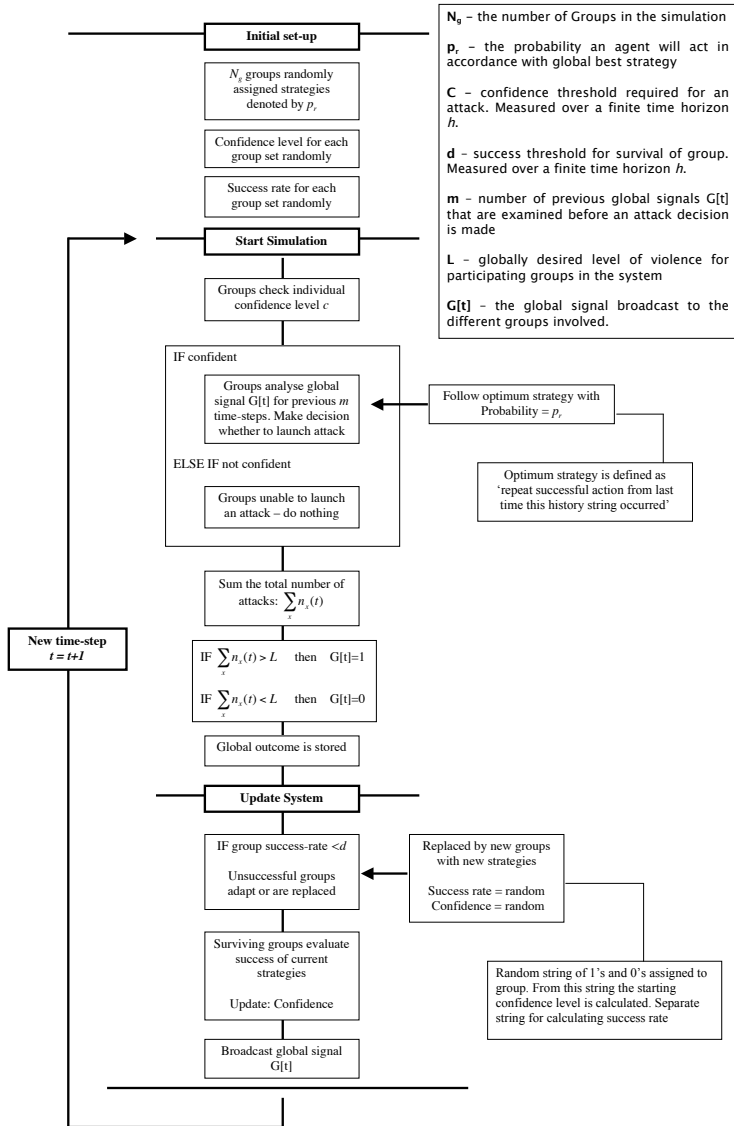
Supplementary Table 2: Parameters in our model for attack timing, that we varied to obtain the model curve in Figure 3

Conflict	Period (days)	$N_g$	$C$	$L$	$d$	$m$
Iraq	0-180	25	0.85	1	0.5	2
	180-360	65	0.83	2	0.5	2
	360-540	86	0.77	2	0.5	2
	540+	116	0.75	2	0.5	2
Colombia	0-500	147	0.75	2	0.5	2
	500+	85	0.71	5	0.5	2
Afghanistan	500+	42	0.78	2	0.5	2
Peru	1000-5000	26	0.74	1	0.5	2

Looking first at the data for the Iraq conflict we see that during the first phase of the war, the model estimates that there are 25 autonomous groups within the insurgency. As the war evolves the number of groups increases to an estimated 116 groups for the period between day 540 and 1032. Using the empirical data the model shows that the number of autonomous groups, that are able to launch an attack that can kill at least 1 person, has increased 5-fold since the start of the war. This result is consistent with a more fragmented group structure – in particular, it is consistent with some results that we have obtained (not shown) that find the estimated  $\alpha$  from successive time-windows during the war, increases over this same period of the war. Coupled with this increase in group numbers is a decrease in the confidence threshold ( $C$ ) from 0.85 to 0.75. This change in  $C$  can be interpreted as implying that as the war progresses, the various insurgent groups do not need to be as successful with their past predictions in order to be confident enough to launch a future attack. For Colombia we observe a similar decrease in the confidence threshold from  $C = 0.75$  to  $C = 0.71$  as the war evolves. However, unlike Iraq, this reduction in  $C$  is not accompanied by an increase in  $N_g$ . Here the number of autonomous groups in Colombia decreases as the war evolves from  $\sim 147$  at the start of the war to  $\sim 85$  during the final phase. This decrease in  $N_g$  is also consistent with the increased coalescence that we believe accompanies the decrease in  $\alpha$  over time (not shown). For Afghanistan the model predicts the involvement of  $\sim 42$  groups within the insurgency, with a confidence threshold approximately the same as for Iraq at day 360. In Peru there is only a small number of groups within the insurgency  $N_g = 26$  and there is also a low confidence threshold. For all the wars  $L$  is small at around 2, while  $d$ , the rate of replacement of unsuccessful strategies/groups stays constant at  $d = 0.5$ .

To produce the theoretical curves in Figure 3 in the main paper we employed a well-known, standard least squares minimization technique [45]. Although the precise fitting mechanism of least squares minimization would in theory depend on how the weighting is assigned, in practice we found consistency when we checked using several standard choices such as unweighted and also density-dependent weighting methods. The details of the technique are as follows. We first searched the parameter space to identify the variables to which the model is most sensitive. We found that although there are several parameters in the model, in practice only a few had a significant effect on the results. This result is entirely consistent with the findings for the El Farol Bar Problem upon which our model is based, as discussed in Ref. [26] of the main paper. Specifically, in the model the most sensitive parameters are  $N_g$ ,  $L$  and  $C$ . By contrast, the model was not found to be sensitive to  $m$  and  $d$  and these variables were selected to be constant for simplicity. We chose  $m = 2$  and  $d = 0.5$  since it is reasonable to expect decisions based on short memory length (i.e. small  $m$ ), while a value of  $d = 0.5$  makes sense since this implies that a group changes strategies/dissolve if they are wrong more times than they are right. A summary of the parameter values is given in Supplementary Table 2, and they are shown in the flow-chart of Supplementary Figure 5.

Finally, we give some further details of our standard fitting procedure based on least squares minimization [45]. A grid-like search was conducted across the parameter space to find the parameters that minimized the sum of the square of the differences between the empirical data and the model.  $L$  was fixed for values 1 to 10, and then for 10 to 50 in increments of +5, and for 50 to 100 in increments of +10. With  $L$  fixed for each run,  $N_g$  and  $C$  were then varied to explore the parameter space for these two variables.  $N_g$  was tested from 1 to 1000 using step sizes that changed in proportion to the size of  $N_g$ , and  $C$  was varied from 0 to 1 in decimal increments. A standard library least squares fitting process was used to determine the best fit for each value of  $L$  and then  $N_g$  and  $C$  were recorded. The  $L$  with the lowest least squares difference was then chosen. For the least square fitting process, we tried several variants, e.g. equal weighting for each of the empirical data points, and a density-dependent version where more weight was placed on empirical values that had more data points.



Supplementary Figure 5: Flow chart for the timings model, with which the results in Figure 3 are obtained. See Supplementary Notes for a full discussion.

These variants did not produce significantly different results, giving us confidence that our procedure was unbiased and robust. The parameters given in Supplementary Table 2 are for the unweighted least squares fitting method.

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# Supplementary Data

An example of 3000 events for the casualty data from Iraq for the period 2003 to 2005. For illustration purposes, this excerpt shows both the maximum (KMAX) and minimum (KMIN) estimates of casualties per event. Each event is marked with a unique key (ID) and the day of the event (DAY). The first day in this sample was randomly picked. The Iraq data, like the Afghanistan data, is an amalgamation of three separate data sets that record violent events in Iraq. These data-sets are Iraq Body Count (IBC, <http://www.iraqbodycount.org/>), icasualties.org and ITERATE. For more information regarding the data, please refer to the Supplementary Notes.

ID	DAY	KMIN	KMAX	ID	DAY	KMIN	KMAX	ID	DAY	KMIN	KMAX	ID	DAY	KMIN	KMAX	ID	DAY	KMIN	KMAX
IQ0001	0	1	1	IQ0051	286	3	3	IQ0101	421	1	1	IQ0151	529	1	1	IQ0201	622	2	2
IQ0002	2	1	1	IQ0052	286	1	1	IQ0102	421	2	2	IQ0152	529	2	2	IQ0202	622	2	2
IQ0003	4	38	38	IQ0053	286	4	4	IQ0103	421	9	9	IQ0153	529	21	22	IQ0203	622	21	24
IQ0004	4	1	2	IQ0054	286	2	2	IQ0104	421	3	3	IQ0154	530	2	3	IQ0204	622	21	21
IQ0005	5	2	2	IQ0055	286	1	1	IQ0105	421	2	2	IQ0155	530	12	15	IQ0205	622	1	1
IQ0006	6	1	1	IQ0056	287	2	2	IQ0106	421	2	2	IQ0156	530	6	13	IQ0206	622	3	3
IQ0007	8	1	1	IQ0057	287	1	1	IQ0107	421	5	5	IQ0157	530	3	3	IQ0207	622	2	2
IQ0008	9	1	1	IQ0058	287	2	2	IQ0108	422	1	1	IQ0158	530	2	2	IQ0208	622	4	4
IQ0009	10	1	1	IQ0059	287	1	1	IQ0109	422	0	0	IQ0159	530	4	4	IQ0209	623	3	3
IQ0010	11	1	1	IQ0060	287	2	2	IQ0110	422	2	2	IQ0160	530	2	2	IQ0210	623	2	2
IQ0011	11	3	4	IQ0061	288	1	1	IQ0111	422	2	2	IQ0161	530	1	1	IQ0211	623	4	4
IQ0012	11	1	1	IQ0062	288	2	2	IQ0112	423	1	1	IQ0162	530	1	1	IQ0212	623	1	1
IQ0013	12	3	3	IQ0063	288	1	1	IQ0113	423	1	1	IQ0163	530	581	670	IQ0213	623	1	1
IQ0014	13	1	1	IQ0064	288	2	2	IQ0114	424	2	2	IQ0164	531	2	2	IQ0214	624	1	1
IQ0015	15	5	5	IQ0065	289	1	1	IQ0115	424	1	1	IQ0165	531	1	1	IQ0215	624	2	2
IQ0016	16	1	1	IQ0066	290	1	1	IQ0116	424	2	2	IQ0166	531	2	3	IQ0216	624	1	1
IQ0017	19	2	2	IQ0067	290	5	6	IQ0117	424	3	3	IQ0167	531	1	1	IQ0217	624	2	4
IQ0018	19	1	1	IQ0068	290	3	3	IQ0118	424	1	1	IQ0168	531	1	1	IQ0218	624	10	14
IQ0019	20	1	1	IQ0069	290	2	2	IQ0119	425	3	3	IQ0169	531	2	2	IQ0219	624	1	1
IQ0020	21	1	1	IQ0070	291	2	2	IQ0120	425	1	1	IQ0170	531	1	1	IQ0220	625	4	4
IQ0021	21	2	2	IQ0071	291	1	1	IQ0121	425	0	0	IQ0171	531	59	59	IQ0221	625	6	6
IQ0022	21	1	1	IQ0072	292	2	2	IQ0122	425	2	2	IQ0172	531	10	10	IQ0222	625	2	2
IQ0023	22	1	1	IQ0073	292	4	4	IQ0123	425	3	3	IQ0173	532	7	10	IQ0223	625	9	11
IQ0024	23	3	3	IQ0074	293	2	2	IQ0124	426	1	1	IQ0174	532	10	10	IQ0224	625	9	9
IQ0025	25	1	1	IQ0075	293	4	4	IQ0125	426	1	1	IQ0175	532	1	1	IQ0225	625	1	1
IQ0026	26	2	2	IQ0076	293	1	1	IQ0126	426	1	1	IQ0176	532	1	1	IQ0226	625	2	2
IQ0027	27	4	6	IQ0077	293	3	3	IQ0127	427	1	1	IQ0177	532	2	2	IQ0227	626	1	1
IQ0028	28	1	1	IQ0078	293	1	1	IQ0128	427	1	1	IQ0178	532	3	3	IQ0228	626	3	3
IQ0029	28	2	2	IQ0079	294	1	1	IQ0129	427	0	0	IQ0179	532	1	1	IQ0229	626	3	3
IQ0030	29	1	2	IQ0080	294	6	7	IQ0130	427	4	4	IQ0180	532	6	6	IQ0230	626	1	1
IQ0031	29	1	1	IQ0081	294	1	1	IQ0131	427	1	1	IQ0181	533	1	1	IQ0231	626	5	5
IQ0032	30	1	1	IQ0082	295	2	2	IQ0132	427	1	1	IQ0182	533	17	19	IQ0232	626	6	6
IQ0033	30	1	1	IQ0083	295	2	2	IQ0133	427	70	70	IQ0183	533	3	3	IQ0233	626	1	1
IQ0034	31	1	1	IQ0084	295	3	3	IQ0134	427	2	2	IQ0184	533	1	1	IQ0234	626	1	1
IQ0035	31	25	30	IQ0085	295	3	3	IQ0135	427	1	1	IQ0185	533	2	2	IQ0235	626	1	1
IQ0036	31	1	1	IQ0086	295	1	1	IQ0136	428	0	0	IQ0186	533	1	1	IQ0236	626	2	2
IQ0037	32	1	1	IQ0087	295	2	2	IQ0137	428	0	0	IQ0187	533	1	1	IQ0237	626	16	18
IQ0038	32	1	1	IQ0088	296	1	1	IQ0138	428	8	10	IQ0188	534	4	4	IQ0238	627	1	1
IQ0039	32	3	3	IQ0089	297	1	1	IQ0139	428	1	1	IQ0189	534	1	1	IQ0239	627	3	3
IQ0040	33	7	10	IQ0090	297	1	1	IQ0140	428	1	1	IQ0190	534	1	1	IQ0240	627	2	2
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IQ0043	34	2	2	IQ0093	298	1	1	IQ0143	429	0	0	IQ0193	534	1	1	IQ0243	627	2	2
IQ0044	36	0	1	IQ0094	298	1	1	IQ0144	430	2	2	IQ0194	535	2	2	IQ0244	627	7	7
IQ0045	36	1	1	IQ0095	298	1	1	IQ0145	430	3	3	IQ0195	535	6	6	IQ0245	627	1	1
IQ0046	36	2	2	IQ0096	298	1	1	IQ0146	431	3	3	IQ0196	536	1	1	IQ0246	627	1	1
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IQ0048	39	1	2	IQ0098	298	1	1	IQ0148	431	1	1	IQ0198	536	2	2	IQ0248	628	2	2
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IQ0050	40	1	1	IQ0100	299	1	1	IQ0150	431	1	2	IQ0200	536	3	3	IQ0250	628	1	1
IQ0051	41	3	3	IQ0101	299	1	1	IQ0151	431	10	12	IQ0201	537	1	1	IQ0251	628	4	4
IQ0052	42	1	1	IQ0102	299	1	1	IQ0152	431	4	5	IQ0202	537	7	7	IQ0252	629	1	1
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IQ0054	42	1	1	IQ0104	300	2	2	IQ0154	432	1	1	IQ0204	537	2	2	IQ0254	629	1	1
IQ0055	46	2	2	IQ0105	300	9	9	IQ0155	432	1	1	IQ0205	537	2	2	IQ0255	630	1	1
IQ0056	47	1	1	IQ0106	300	3	3	IQ0156	432	2	2	IQ0206	537	2	2	IQ0256	630	1	1
IQ0057	49	1	1	IQ0107	300	2	2	IQ0157	432	1	1	IQ0207	537	6	6	IQ0257	630	1	1
IQ0058	49	1	1	IQ0108	301	1	1	IQ0158	433	1	2	IQ0208	537	7	7	IQ0258	630	2	2
IQ0059	51	1	1	IQ0109	301	1	1	IQ0159	433	1	1	IQ0209	538	1	1	IQ0259	630	1	1
IQ0060	52	1	1	IQ0110	301	3	3	IQ0160	433	1	1	IQ0210	538	1	1	IQ0260	630	1	1
IQ0061	52	1	1	IQ0111	301	1	1	IQ0161	434	4	14	IQ0211	538	3	3	IQ0261	630	1	1
IQ0062	53	1	1	IQ0112	302	1	1	IQ0162	434	2	2	IQ0212	538	2	2	IQ0262	630	1	1
IQ0063	53	2	2	IQ0113	302	1	1	IQ0163	435	1	1	IQ0213	538	2	2	IQ0263	631	1	1
IQ0064	54	1	1	IQ0114	303	1	1	IQ0164	435	0	0	IQ0214	538	1	1	IQ0264	631	2	2
IQ0065	54	1	1	IQ0115	303	1	1	IQ0165	435	4	6	IQ0215	539	3	3	IQ0265	631	1	1
IQ0066	54	1	1	IQ0116	303	4	4	IQ0166	435	7	9	IQ0216	539	1	1	IQ0266	631	3	3
IQ0067	55	1	1	IQ0117	303	1	1	IQ0167	435	1	1	IQ0217	539	9	15	IQ0267	631	1	1
IQ0068	55	1	1	IQ0118	303	4	4	IQ0168	435	1	1	IQ0218	539	1	1	IQ0268	632	4	4
IQ0069	55	1	1	IQ0119	303	9	15	IQ0169	435	2	2	IQ0219	540	1	1	IQ0269	632	6	6
IQ0070	55	1	1	IQ0120	303	1	1	IQ0170	435	1	1	IQ0220	540	4	4	IQ0270	632	3	3
IQ0071	56	1	1	IQ0121	304	1	1	IQ0171	435	1	1	IQ0221	540	2	2	IQ0271	632	3	3
IQ0072	56	1	1	IQ0122	304	4	4	IQ0172	436	7	7	IQ0222	540	2	2	IQ0272	632	7	7
IQ0073	57	0	2	IQ0123	305	2	2	IQ0173	436	2	2	IQ0223	540	3	3	IQ0273	632	14	15
IQ0074	57	3	3	IQ0124	305	2	2	IQ0174	436	2	2	IQ0224	540	2	2	IQ0274	632	1	1
IQ0075	59	2	2	IQ0125	306	2	2	IQ0175	436	1	1	IQ0225	540	4	4	IQ0275	633	2	2
IQ0076	59	3	3	IQ0126	306	1	1	IQ0176	437	3	3	IQ0226	541	2	4	IQ0276	633	2	2
IQ0077	59	1	1	IQ0127	306	1	1	IQ0177	437	1	2	IQ0227	541	2	2	IQ0277	633	1	1
IQ0078	60	5	5	IQ0128	307	1	1	IQ0178</											

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