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Explaining conflict violence in terms of conflict actor dynamics

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We study the severity of conflict-related violence in Colombia at an unprecedented granular scale in space and across time. Splitting the data into different geographical regions and different historically-relevant periods, we uncover variations in the patterns of conflict severity which we then explain in terms of local conflict actors' different collective behaviors and/or conditions using a simple mathematical model of conflict actors' grouping dynamics (coalescence and fragmentation). Specifically, variations in the approximate scaling values of the distributions of event lethalities can be explained by the changing strength ratio of the local conflict actors for distinct conflict eras and organizational regions. In this way, our findings open the door to a new granular spectroscopy of human conflicts in terms of local conflict actor strength ratios for any armed conflict.

Since Richardson demonstrated that the distribution of the severity (size) of wars follows an approximate power-law[1,2], other researchers have identified a similar result in phenomena such as protests[3], modern wars[4], insurgencies[5,6], and terrorism[7,8]. Those studies mostly focus on the existence of this distribution across such violent scenarios. However, our knowledge and understanding of the variation of the severity distribution in time and space *within* a given conflict is very limited—and so too is what that knowledge might then tell us about human behavior within a conflict.

Our aim in this paper is to contribute to this literature by exploring the severity of conflict events within the armed conflict in Colombia at an unprecedented granular scale in space and across time. Moreover, we split the conflict into specific segments that all have historical and/or organizational meaning, i.e. smaller geographical units and three periods that represent distinct eras of the conflict[9]. We then test the fitting of event severity data within these separate space–time sections of the armed conflict, to a power-law (i.e. scale-free) distribution. Combining this with a previously published mathematical model of conflict actor group behavior[5], this allows us to interpret the evolution of the conflict across time and space. Specifically, because of this unique granular focus, we are able to interpret the patterns in this important but complex conflict in terms of a spatial–temporal decomposition guided by an established multi-actor conflict framework[9] where the conflict is best understood as a set of interrelated but approximately separable subconflicts.

As background, we note that a power-law distribution describes the frequency of conflict events of a size x, as $p(x) = x^{-\alpha}/\zeta(\alpha, x_{min})$, where α is a scaling exponent and $\zeta(\alpha, x_{min})$ is a Hurwitz zeta function for discrete power-laws which is more appropriate for our type of data[8,10,11]. When plotted on a log–log plot where the x-axis is the logarithm of the event size and the y-axis is the logarithm of the cumulative probability $P(x)$ of that event being at least size x, the data produce a straight line with a slope $\alpha - 1$[12] (N.B. all figures show $P(x)$). A power-law distribution is also often called scale-free. This means that increasing the scale or changing the unit in which x is measured does not result in any change in the shape of the distribution[13,14]. This characteristic implies that there is no fundamental difference, from a statistical perspective, between large and small events in a conflict[8].

Various mathematical mechanisms produce power-law distributions in physics, biology, and social systems [14]. For instance, forest fires[15], wars[4] and protests[3], and the collapse of civilizations[16] are modeled according to self-organized criticality (SOC) suggesting that large composite systems tend to reach a critical state in which even small events can cause a catastrophe, such as a landslide or a volcano eruption[17]. Although widely used, SOC does not consider the interaction between two or more actors. Thus, to explain the existence of power-law distributions, we rely on a published coalescence-fragmentation model for conflict actor grouping dynamics[18] that allows us to include armed groups as dynamically evolving clusters of populations that can lose or gain their members over time, i.e., fragment or coalesce. The coalescence-fragmentation model was further developed to account for two or more opposing sides of conflict[5]. This model suggests a possible range of α, the scaling

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exponent for the power-law distribution, conditioned by the varying strength ratio of conflict actors. It means that interactions of conflict actors yield distinct values of α in the individual regions that give insights into the power ratio between relevant actors.

To give an overview of how this coalescence-fragmentation model behaves, we focus on a hypothetical situation with two conflict actors: government and insurgents. The conflict actors have a total strength that consists of the combined populations of N_a (government) and N_b (insurgents). Both populations consist of fighters (agents) who form armed groups (clusters) via the coalescence and fragmentation processes that operate as follows. First, two agents are selected from the combined populations N_a and N_b. If they are from the same side of the conflict, for instance, both agents belong to the state forces, the clusters of which they are members coalesce, i.e. the two armed groups join forces. If the selected agents are from opposing sides, they fight, resulting in casualties on both sides. Scales for smaller and larger groups engaged in the violent encounter, denoted as C_S and C_L, respectively, determine the number of losses. These scales function similarly to the attrition coefficient in Lanchester's equations[19,20]. Hence, the smaller armed group fragments into even smaller groups of fighters after the battle. The frequency of events and their size, defined as combined losses of groups engagement in battle, yield approximate power-law distribution with scaling exponent $\alpha = 2.5$. The obtained value of α is in line with other research fitting data from various conflicts involving insurgencies in the power-law distribution and solving the coalescence-fragmentation model analytically[5].

The ratio between the strength of the conflict sides affects the value of the scaling exponent α [5]. Weaker sides tend to create smaller groups on average than the stronger side due to the larger number of opposing agents within the population. Assuming the weaker side suffers higher losses than the stronger side, the greater difference between the strength of the two enemy populations leads to the steeper slope of the exponent α, meaning a decreasing probability of large battles. Thus the exponent α can serve as a proxy for the strength ratio between conflict sides. By studying the values of α, we can better understand the strength ratio between conflict actors and thereby provide important insights into a given conflict's dynamics.

Here we examine the within-conflict variation in α for the case of the Colombian armed conflict in which violence has fluctuated over time and across space. The conflict began with an episode of violence, "La Violencia", in the late 1940s and turned into a civil war between leftist guerrillas, including the then largest non-state armed actor, the Revolutionary Armed Forces of Colombia (FARC), founded in 1964, and the government. Soon paramilitary groups formed to fight the guerrillas and protect large landowners. With the rise of cocaine production in the 1970s and 1980s in the country, drug cartels and other criminal actors became involved in the conflict. After the FARC's demobilization in 2017, multiple violent non-state actors continued to engage in violence[9,21].

The Colombian armed conflict manifests remarkable changes over its long and violent history; therefore, it represents an ideal case for our study. The intensity and frequency of violence has been fluctuating over time and across space, especially, during the demobilization of the paramilitaries between 2003 and 2006, following the peace agreement with the largest non-state armed actor FARC in 2016, and in the run-up to most of the recent presidential elections, which often introduced changes in the course of governmental strategies to tackle insurgent groups.

Measuring these variations within a given conflict is important because it highlights the interdependent and interconnected character of conflict actors across different subconflicts that together form a larger conflict. It is possible, for example, that in a large conflict the measurements of local events in that conflict share the same features as the conflict as a whole (an expectation that would come from the scale-free nature of conflict statistics). This has implications for strategic and policy decisions on how to understand the overall conflict, and how to prioritize solutions to it. Our work offers a first glimpse into these different scenarios.

Results
Identifying the conflict segments

We conceptualize the armed conflict in Colombia as a multi-actor conflict with the involvement of the following actors in the period 1989–2018: state forces, left-wing guerrillas, paramilitaries, and criminal groups involved in conflict-related violence[9]. We split the conflict into three periods, each featuring a distinct government strategy toward the conflict actors reflecting the change in the strength of the main actors. In addition, we identify the distinct regions within the Colombian armed conflict based on organizational structure and mutual interactions of the main conflict actors. Through this approach we obtain regions that allow us to estimate the strength ratio of the regional branches or sections of the main conflict actors.

The first period (1989–1999) comprises various presidencies characterized by peace negotiations with various guerrilla groups. The peace process initiated by former President Samper failed and left FARC rebels strengthened[22,23]. The second period (2000–2009) represents former President Uribe's administration. His hard-line Democratic Security Policy sought to weaken the FARC through the counternarcotics and counterinsurgency strategy "Plan Colombia" that was supported by the United States. The third one (2010–2018) covers 2010 when President Santos took office. He later initiated peace talks with the FARC, followed by signing the peace deal between the government and these rebels in 2016 and the FARC's subsequent demobilization in 2017[24].

Historically, and to a great extent influenced by geography, Colombia's economic, social, and political dynamics have significantly varied across regions, reflected in distinct cultures and identities and influential regional elites[25]. Similarly, the armed conflict patterns exhibit regional diversity[26]. Many conflict actors' organizational structures are adjusted to the primary geographical location in which they are active; these locations coincide across key conflict actors, including the Colombian National Police, the National Army, and the FARC. For instance, the 1st division of the National Army covers approximately the same area as region 8 of the National Police and FARC's Caribbean Bloc. Given the geographical proximity, we assume that the 1st division and police units from region 8 are more likely to interact with the Caribbean Bloc than other FARC blocs and vice versa.

Hence, we assume that there are more interactions between these three than Army divisions, police regions, and blocs active in other parts of Colombia and that the interactions between the 1st division, police units from region 8, and the Caribbean Bloc are to some extent independent from the other divisions, police regions, and FARC blocs.

Given that over 75% of the interactions in our data are between the FARC and the state forces (see Table 1), we construct the spatial split of the Colombian armed conflict based on the geographical overlap of the institutional structure of the National Police, the National Army, and the FARC. Although we do not use the structures of other conflict actors to construct the conflict segments, we include them when analyzing the conflict events. In this way, we can isolate the local strength ratio of the actors.

We proceed by first determining the overlap between the eight National Police regions and the National Army divisions and form seven resulting regions. Both organizations mirror each other's spatial organization with two exceptions. The 3rd division of the National Army covers an area of regions 3 and 4 of the National Police. Similarly, combining the 4th and 8th National Army divisions, we cover the area of region 7 of the National Police. Second, we identify the primary locations where the FARC blocs are active and overlay them with the regions identified in the previous step. Although the FARC blocs are to some extent mobile and do not fully spatially coincide with the state forces, their geographical overlap still represents a reasonable approximation to identify the resulting regions. To match the National Police and National Army organizational structure across Colombia, we split FARC's North Western Bloc into regions 2 and 3.

Similarly, while region 5 comprises mainly FARC's Central Bloc, we also added parts of the Eastern Bloc and the Southern Bloc. In both cases, our decision to split some FARC Blocs was also driven by the natural geographical features, including elevation and terrain type forming, in the case of Colombia, prominent boundaries of the armed conflict on its own (see Fig. 1). To compile the regions based on the organizational structure of the main conflict actors, we consulted several sources[27–33].

Colombia's Constitution of 1991 (article 287)[34] decentralized the country, granting departments some autonomy to govern themselves and administer and use the resources they are allocated[35]. Conflict dynamics vary across departments and regions—the departments' administrative autonomy and the somewhat decentralized nature of the police forces contribute to this diversity. During former President Uribe's administration, for example, the national government considered the FARC a terrorist group and acted accordingly, including refusing to engage in talks with the FARC, whereas the (regional) government of the Nariño department engaged in peacebuilding activities open to dialogue[36]. We, therefore, include the analysis of the individual departments in addition to the regions described above.

Data

We obtain data from the Uppsala Conflict Data Programme Georeferenced Event Dataset version 19.1 (UCDP GED)[37,38] that provides information on geo-referenced conflict events and is widely used by conflict researchers[39–41].

Following the conflict conceptualization as a "dynamic multi-actor setting of organized violence with one or more contested issues between two or more conflict actors resulting in deaths"[42], we identify the relevant conflict actors and conflict events for our analysis. Accordingly, the actors selected from the UCDP GED data are the Colombian government (forces representing the Colombian government, including the National Police and the National Army), the FARC, FARC dissidents, the National Liberation Army (ELN), the Popular Liberation Army (EPL), EPL—Megateo, the United Self-Defences of Colombia (AUC), the Central Bolivar Bloc, the "Persecuted by Pablo Escobar" (PEPES), the Cali cartel, and the Medellin cartel. We include conflict events involving the selected conflict actors that resulted in at least one battle-related death. Conflict events that cannot be assigned to specific departments due to their low geo-precision are excluded from our analysis. Based on these selection criteria, we obtained 3303 events for 1989–2018. We split data according to the event's location and date to obtain data for the individual segments of the conflict.

Conflict actor	Conflict events involvement (N)
Government of Colombia (the National Police and the National Army combined)	3164
FARC	2595
ELN	625
AUC	130
EPL—Megateo	36
FARC dissidents	28
EPL	10
Medellin Cartel	8
Cali Cartel	4
PEPES	4
Bloque Central Bolivar	1
ELN, FARC	1

Table 1. Number of conflict events per actor for the period 1989–2018. Data obtained from the UCDP GED.

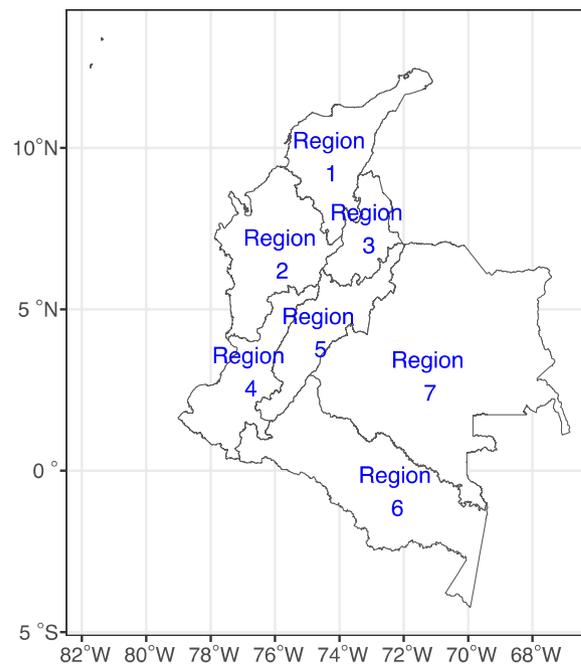| Region	National Army	National Police	FARC Blocs	Departments/administrative units
Region 1	1st Division	Region 8	Caribbean Bloc	La Guajira, Cesar, Magdalena, Atlántico, Bolivar, Sucre
Region 2	7th Division	Region 6	North Western Bloc	Córdoba, Antioquia, Chocó
Region 3	2nd Division	Region 5	North Western Bloc	Norte Santander, Santander
Region 4	3rd Division	Region 3 and 4	Western Bloc	Nariño, Cauca, Valle de Cauca, Risaralda, Caldas, Quindio
Region 5	5th Division	Region 1	Part of the Eastern Bloc, Central Bloc and part of the Southern Bloc	Cundinamarca, Boyacá, Tolima, Huila, Bogota
Region 6	6th Division	Region 2	Southern Bloc	Caquetá, Putumayo, Amazonas
Region 7	4th and 8th Divisions	Region 7	Eastern Bloc	Arauca, Casanare, Meta, Vichada, Guainia, Guaviare, Vaupes

Figure 1. Regions compiled by overlaying the organizational structure of the National Police, the National Army and the FARC Blocs. Top: Table listing the National Army divisions, the National Police regions, the FARC blocs and departments for each compiled region. Bottom: Map showing the geographical distribution of the compiled regions.

Findings

This section describes the results obtained after attempting to fit our data for the individual segments of the armed conflict in Colombia to the power-law distribution. We proceed as follows to test whether our data have power-law distributions. First, we estimate α and x_{min} from our data to draw ideal power-law distribution based on these parameters. Second, we calculate the Kolmogorov–Smirnov goodness of fit test and obtain the P-value via the bootstrap procedure with 5000 iterations. We accept that data follow an approximate power-law distribution if the resulting P-value is equal to or greater than 0.1[10].

The value of x_{min} sets the threshold for the minimum size events, in our case number of fatalities, for the power-law to apply. In other words, conflict events with a number of fatalities smaller than x_{min} are not part of the data forming the power-law distribution. The estimated value of the exponent α suggests a possible level of imbalance between the strength of the conflict actors. Based on the coalescence-fragmentation model[5], a higher value of α means that larger battles are less frequent; therefore, the strength of the conflict actors is more asymmetric. While the scaling exponent describes violence patterns across sections of conflicts (regions and departments in different periods), the P-value confirms the presence of the power-law distribution.

Carrying out this power-law fitting procedure for all of our data over all the studied periods of the Colombian conflict (1989–2018), we obtain an α exponent with a value of 2.54 and P value of the Kolmogorov–Smirnov goodness of fit test greater than 0.1. This confirms existing research that found a power-law distribution with α near 2.5 for modern insurgencies[5] and it confirms that the conflict as a whole follows such a power-law distribution. Figure 2 shows how the size (severity) distribution of conflict events indeed forms an approximate straight line when displayed on a log–log plot where the horizontal axis is the event size, and the vertical axis is the probability distribution of that event being at least that size. The mean size of conflict events during the studied period is 6.34.

Segments of armed conflict: Regions
The results for the regions formed by overlaying the institutional structure of the National Police, the National Army, and FARC show that splitting the data into smaller segments based on the predominant mutual interaction of the main actors also follow approximate power-law distributions. The Kolmogorov–Smirnov goodness of fit test yields *P*-values greater or equal to 0.1 for most of the regions (see complete results in Table 2). Since the data is now being split, there are less data points within a given region than overall, hence the data can appear more noisy, i.e. there is generally more scatter around the straight line.

Figure 3 shows that conflict event data for the individual regions mostly follow an approximate power-law distribution except for region 1 in 1989–1999 and regions 2 and 5 in 2010–2018. Notably, all regions in 2000–2009, the most intensive period of the conflict with regard to the number of conflict events, reached the P-value above 0.1. This suggests that the small number of observations might be driving some P-values below the 0.1 thresholds. For example, region 5 in 2010–2018 contains only 28 data points.

The variation of the exponent α provides insights into the patterns of conflict-related violence across time and space. In 1989–1999, α tends to oscillate around 2.5, suggesting a similar pattern of the events' occurrence conditioned by their size in most parts of Colombia, except from regions 4, 5 and 7. During this period, neighbouring regions 4 and 5 in central and west Colombia, with exponents $\alpha = 3.0$ and $\alpha = 3.3$, respectively, experienced large events less often than region 7 in South-East Colombia, with exponent $\alpha = 1.9$. In the second period, 2000–2009, the α values decrease and drop below 2.5 except for region 6 in southern Colombia. Thus, we observe relatively larger events more often across most parts of Colombia compared to the previous period. Results for the period 2010–2018 point to more significant variation in the conflict dynamics across the regions. For example, region 6, located in central Colombia with exponent $\alpha = 5.3$, experienced predominantly small events. Similarly, regions 7 and 3, located in eastern Colombia at the border with Venezuela, had relatively small events. Compared to other regions, larger events were more frequent in region 4 situated at the borders with Ecuador, as its exponent α is 2.4.

According to the coalescence-fragmentation model[5], the exponent α variation is based on the strength ratio of the conflict actors engaged in fighting. Thus the results described above can provide insights into conflict dynamics that go beyond the frequency of conflict events conditioned by their size. Relatively small differences in the exponent α across most of Colombia in 1989–1999 suggest a similar strength ratio of conflict actors across Colombia. At that time, the guerrillas and other non-state conflict actors profited greatly from the illegal
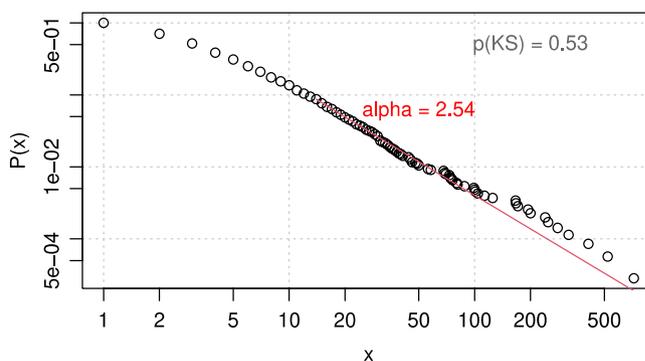
Figure 2. Frequency-size distribution of conflict events in the armed conflict in Colombia, 1989–2018.

Region	Period	Total N of events	N of events in tail	X(min)	Alpha	P-value (KS)
Region 1	All years	429	258	2	2.07	0.07
Region 1	1989–1999	91	38	5	2.43	0.06
Region 1	2000–2009	328	174	2	2.17	0.77
Region 1	2010–2018	10	8	2	2.45	0.81
Region 2	All years	677	350	3	2.00	0.00
Region 2	1989–1999	177	34	13	2.80	0.54
Region 2	2000–2009	447	199	3	2.04	0.28
Region 2	2010–2018	53	53	1	1.79	0.04
Region 3	All years	305	154	3	2.37	0.08
Region 3	1989–1999	98	69	3	2.36	0.18
Region 3	2000–2009	179	122	2	2.27	0.23
Region 3	2010–2018	28	9	5	3.25	0.13
Region 4	All years	564	97	7	2.67	0.26
Region 4	1989–1999	78	23	7	3.03	0.67
Region 4	2000–2009	401	99	5	2.46	0.86
Region 4	2010–2018	85	42	3	2.35	0.27
Region 5	All years	537	115	6	2.75	0.21
Region 5	1989–1999	144	47	6	3.28	0.24
Region 5	2000–2009	365	163	3	2.29	0.49
Region 5	2010–2018	28	19	2	2.35	0.01
Region 6	All years	302	120	4	2.29	0.14
Region 6	1989–1999	49	16	9	2.51	0.59
Region 6	2000–2009	224	56	5	2.61	0.53
Region 6	2010–2018	29	9	9	5.34	0.79
Region 7	All years	483	38	20	3.18	0.81
Region 7	1989–1999	139	98	3	1.92	0.46
Region 7	2000–2009	271	97	5	2.39	0.25
Region 7	2010–2018	73	20	9	3.16	0.93

Table 2. Results obtained from the bootstrapping procedure for regions.

drug trade. The FARC, for example, who controlled land for coca cultivation, required drug traffickers to pay for establishing laboratories to process coca into cocaine. The FARC's large income, hierarchically centralized structure, and ability to govern territory and its inhabitants[43] explain the weak position of the Colombian state relative to FARC and the lack of variation in strength ratio between those two actors across most of Colombian territory. The state offensive after 2000 led to intensified violence, forced the guerrillas to Colombia's geographical margins, and gradually weakened them. Smaller values of the exponent α in most regions hint at the lesser strength disparity and a higher frequency of large events compared to the previous period. During 2000–2009, the Colombian government increased its military expenditure from $2.6 billion in 2001 to $11 billion in 2010. The pressure from the Colombian government led to more strength parity as the FARC weakened. The government grew stronger[43] and matched the power of many non-state conflict actors benefiting from the illegal drug trade. The period 2010–2018 saw a de-escalating trend. The weakened FARC lost territory across Colombia, resulting in a power vacuum filled by other non-state conflict actors. However, none of these non-state actors managed to attain as strong a presence across most regions as the FARC did in previous periods. As our results suggest, the strength ratio between the government and non-state actors varied across Colombia after 2010.

Segments of armed conflict: departments
Figure 4 shows the results obtained when we divided the data into even smaller sections of armed conflict. As explained above, Colombian departments possess some level of autonomy that can manifest in their approach to non-state actors. Thus it is reasonable to assume that fitting the conflict event data for the individual departments might provide further insights into the conflict dynamics. The P-value obtained by carrying out the Kolmogorov–Smirnov goodness of fit is mostly above the 0.1 threshold (see complete results in Table 3), justifying our decision to analyze also the smaller segments of armed conflict. Focusing on the smaller conflict segments allows us to better interpret our results in the context of the local conflict dynamics.

A large number of diverse conflict actors in Colombia might affect the scaling exponents for individual departments. Assuming that the presence of more actors leads to fragmentation of resources and greater competition for local support and recruits, we expect departments with more actors to have a larger imbalance of strength as the populations from which armed actors can form their fighting units are smaller relative to the governmental forces due to the more intense competition for support from civilians. Therefore, larger events occur less often.

The Arauca department experienced larger battles more often than many other departments in the 1990s, suggesting that the strength of the main conflict actors, namely the Colombian government, the FARC, and the
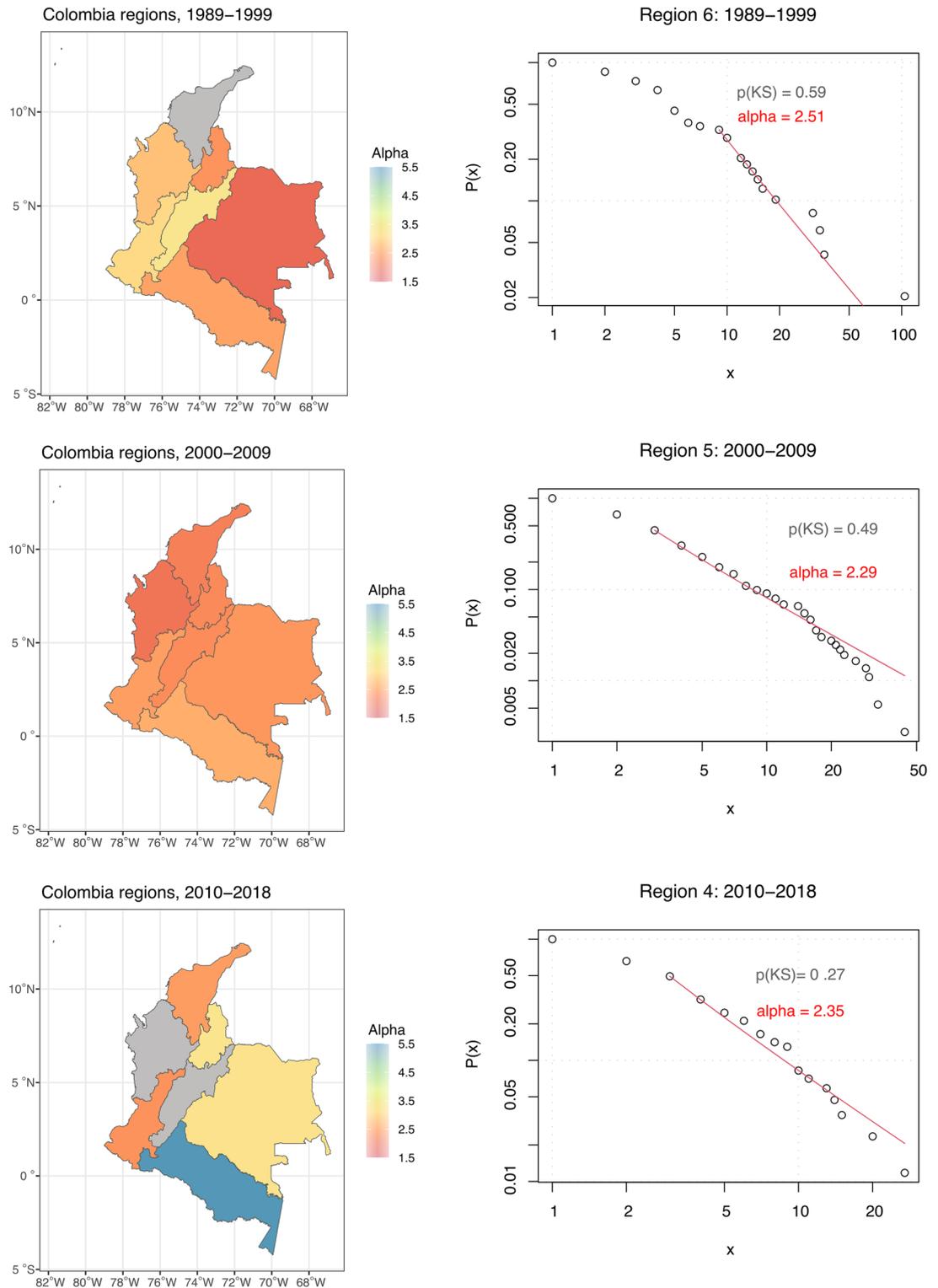
Figure 3. Results for the regions in Colombia obtained by fitting the data in the power-law distribution and calculating the Kolmogorov–Smirnov goodness of fit test. Left: Geographical distribution of exponent alpha, regions with *P*-value <0.1 in grey. Right: CCDF for the selected regions.

ELN, in this department, was more balanced. This changed in the second period starting in 2000 when paramilitaries joined the fight against the guerrillas resulting in less frequent large battles. The trend continued in the third period beginning in 2010, when the scaling exponent reached the value of 3.81, suggesting that non-state actors became weaker relative to the state forces. Certainly, the demobilization of the paramilitaries and later the FARC played a role as strong conflict actors were replaced by smaller conflict actors such as FARC dissidents. We observe a similar trend in the Casanare department, where larger battles became less frequent over time.
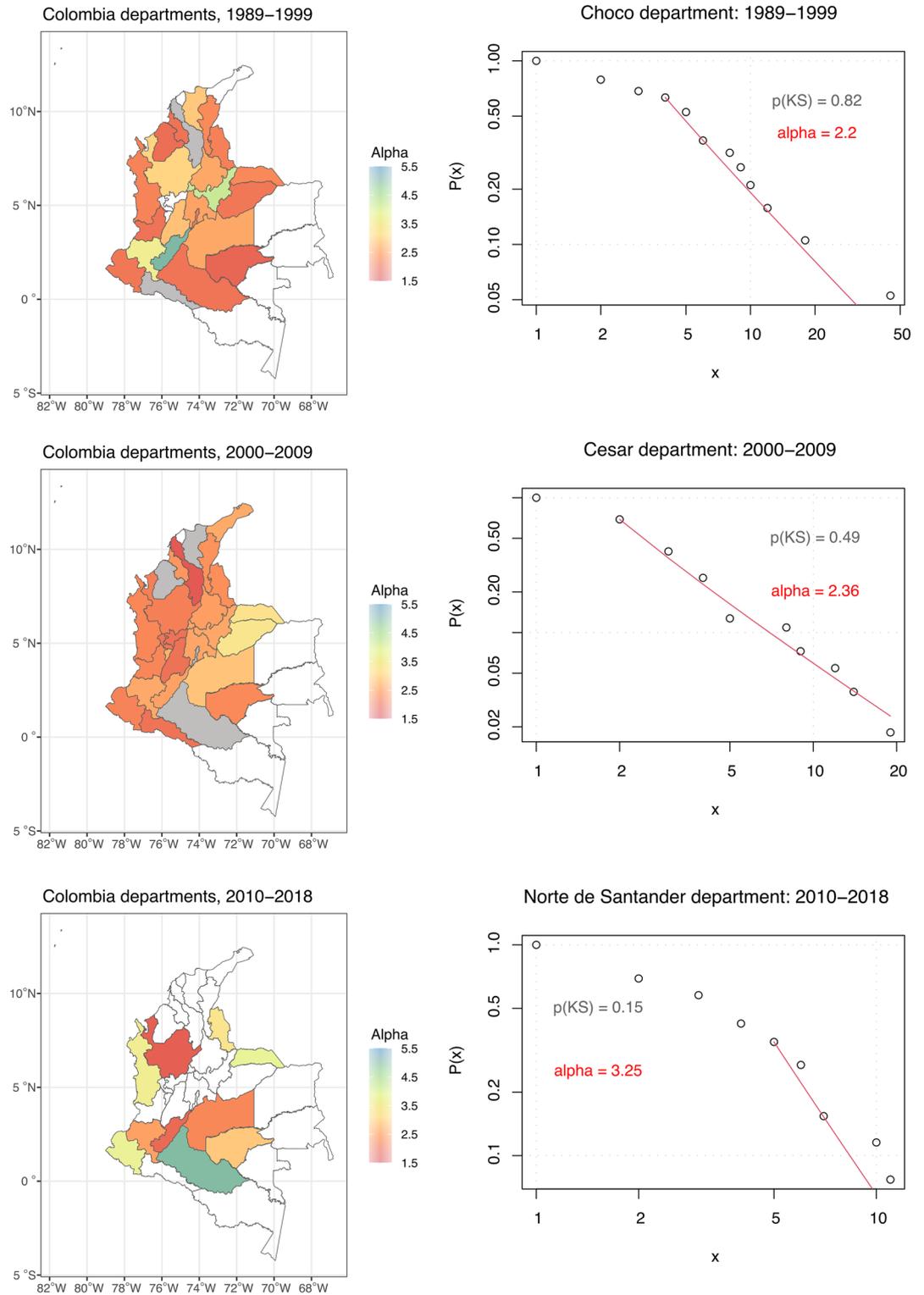
Figure 4. Results for the departments in Colombia obtained by fitting the data in the power-law distribution and calculating the Kolmogorov–Smirnov goodness of fit test. Left: Geographical distribution of exponent alpha, departments with *P*-value < 0.1 in grey, departments with no data in white. Right: CCDF for the selected departments.

The landlocked Antioquia department experienced the opposite trend. In the 1990s, this department was fragmented with predominantly smaller battles and many actors, including the Colombian government, the FARC,

Department/political unit	Period	Total N of events	N of events in tail	X(min)	Alpha	P-value (KS)
Antioquia department	All years	564	280	3	2.06	0.03
Antioquia department	1989–1999	147	28	13	2.98	0.77
Antioquia department	2000–2009	379	159	3	2.16	0.36
Antioquia department	2010–2018	38	38	1	1.82	0.34
Arauca department	All years	146	36	7	2.60	0.44
Arauca department	1989–1999	35	22	4	2.26	0.21
Arauca department	2000–2009	78	21	5	3.15	0.91
Arauca department	2010–2018	33	11	10	3.81	0.97
Bogotá	All years	53	14	5	2.92	0.77
Bogotá	1989–1999	24	16	2	2.20	0.12
Bogotá	2000–2009	25	25	1	1.72	0.05
Bolívar department	All years	129	83	2	1.86	0.12
Bolívar department	1989–1999	31	28	2	1.76	0.01
Bolívar department	2000–2009	92	92	1	1.76	0.18
Boyacá department	All years	74	55	2	1.99	0.07
Boyacá department	1989–1999	21	8	8	4.19	0.14
Boyacá department	2000–2009	51	24	3	2.55	0.12
Córdoba department	All years	35	35	1	1.52	0.39
Córdoba department	1989–1999	11	7	6	1.97	0.33
Córdoba department	2000–2009	22	22	1	1.64	0.07
Caldas department	All years	53	53	1	1.94	0.02
Caldas department	2000–2009	46	46	1	2.01	0.22
Caquetá department	All years	211	63	5	2.56	0.45
Caquetá department	1989–1999	28	19	3	2.03	0.18
Caquetá department	2000–2009	160	41	5	2.86	0.05
Caquetá department	2010–2018	23	8	9	4.95	0.86
Casanare department	All years	61	30	3	2.34	0.77
Casanare department	1989–1999	27	15	3	2.07	0.59
Casanare department	2000–2009	29	10	4	3.29	0.94
Cauca department	All years	213	38	7	2.79	0.90
Cauca department	1989–1999	29	9	7	3.58	0.70
Cauca department	2000–2009	133	29	6	2.56	0.64
Cauca department	2010–2018	51	22	3	2.49	0.81
Cesar department	All years	86	63	2	2.33	0.19
Cesar department	1989–1999	29	24	2	2.26	0.37
Cesar department	2000–2009	55	38	2	2.36	0.49
Chocó department	All years	78	51	3	1.90	0.02
Chocó department	1989–1999	19	12	4	2.20	0.82
Chocó department	2000–2009	46	18	8	2.23	0.49
Chocó department	2010–2018	13	5	4	3.59	0.58
Cundinamarca department	All years	115	36	5	2.62	0.66
Cundinamarca department	1989–1999	48	19	5	2.51	0.27
Cundinamarca department	2000–2009	66	37	3	2.53	0.65
Guaviare department	All years	50	35	3	2.06	0.68
Guaviare department	1989–1999	15	11	3	1.88	0.61
Guaviare department	2000–2009	24	15	4	2.27	0.56
Guaviare department	2010–2018	11	6	3	2.86	0.33
Huila department	All years	126	26	6	3.38	0.48
Huila department	1989–1999	30	12	6	4.99	0.47
Huila department	2000–2009	84	38	3	2.49	0.85
Huila department	2010–2018	12	12	1	1.92	0.11
La Guajira department	All years	34	16	3	2.29	0.47
La Guajira department	2000–2009	30	11	4	2.58	0.94
Magdalena department	All years	105	105	1	2.12	0.05
Magdalena department	1989–1999	11	6	4	2.86	0.91
Magdalena department	2000–2009	94	94	1	2.25	0.04
Continued						

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Department/political unit	Period	Total N of events	N of events in tail	X(min)	Alpha	P-value (KS)
Meta department	All years	199	22	17	3.18	0.84
Meta department	1989–1999	53	19	7	2.55	0.72
Meta department	2000–2009	123	22	12	2.82	0.60
Meta department	2010–2018	23	12	5	2.24	0.44
Nariño department	All years	131	100	2	2.09	0.05
Nariño department	1989–1999	13	10	3	2.07	0.19
Nariño department	2000–2009	93	68	2	2.19	0.63
Nariño department	2010–2018	25	5	9	3.76	0.57
Norte de Santander department	All years	180	21	9	3.41	0.89
Norte de Santander department	1989–1999	46	30	3	2.17	0.14
Norte de Santander department	2000–2009	108	74	2	2.32	0.15
Norte de Santander department	2010–2018	26	9	5	3.25	0.15
Putumayo department	All years	89	68	2	1.88	0.21
Putumayo department	1989–1999	21	17	3	1.81	0.09
Putumayo department	2000–2009	63	44	2	2.03	0.68
Quindío department	All years	11	7	3	2.56	0.30
Quindío department	2000–2009	10	6	3	2.65	0.34
Risaralda department	All years	35	35	1	1.94	0.72
Risaralda department	2000–2009	31	31	1	2.05	0.37
Santander department	All years	125	70	3	2.51	0.43
Santander department	1989–1999	52	39	3	2.55	0.75
Santander department	2000–2009	71	31	3	2.46	0.72
Sucre department	All years	69	32	3	2.39	0.78
Sucre department	1989–1999	15	12	3	2.02	0.51
Sucre department	2000–2009	54	33	2	2.39	0.10
Tolima department	All years	169	76	3	2.22	0.14
Tolima department	1989–1999	21	14	3	2.80	0.77
Tolima department	2000–2009	139	85	2	2.00	0.27
Valle del Cauca department	All years	121	72	3	2.14	0.24
Valle del Cauca department	1989–1999	24	22	2	2.02	0.95
Valle del Cauca department	2000–2009	88	38	4	2.23	0.73
Vichada department	All years	14	4	20	5.88	0.66

Table 3. Results obtained from the bootstrapping procedure for departments.

the ELN, the EPL, the paramilitaries, and the Medellin and Cali cartels. The change started in the second period when the number of actors was reduced to the FARC, the ELN, the paramilitaries, and the Colombian government, and large battles became more frequent. This trend continued in the third period. The Cauca department went through similar changes in the frequency of large battles.

This brief description demonstrates how the variation of the patterns of conflict-related violence is associated with the changes in the actor constellations, including the number of actors involved and their relative strength. Such dynamics are often overlooked when only studying the number of conflict events or battles-related deaths. By dividing the armed conflict into three distinct periods and geographically defined segments of conflict, the analysis demonstrates the importance of understanding armed conflicts as fluid, constantly evolving rather than static phenomena. For instance, the change in Casanare from conflict with frequent large battles in the period 1989–1999 to conflict with predominantly small battles in the period 2000–2009 would be missed as both periods experienced a similar number of battles (27 and 29, respectively). Similarly, data on the number of fatalities in Cauca in the second and third periods shows a significant drop from 615 to 174 and, therefore, a decrease in the intensity of violence. Yet, the structure of the conflict events conditioned by their size remained the same, suggesting an unchanged strength ratio of the actors involved.

Discussion

We have shown that the data on conflict events for the armed conflict in Colombia and the individual segments of the conflict follow an approximate power-law distribution for conflict event severities with an exponent α varying broadly around the value 2.5. To the best of our knowledge, this is the first attempt to confirm the presence of the power-law distribution in armed conflict on such a fine-grained scale. While some of the spatial variation in the power-law exponent might be related to the random subsampling variation, we are confident that the further variation that we detect is not random and instead corresponds with the actor constellations within

the individual conflict segments. This is validated by the results of our resampling analysis. Further details are provided in the Methods section.

The existence of such a robust pattern has several important consequences for the future analysis of armed conflict dynamics. First, our results show that detailed conflict analysis is a useful tool to understand how interconnected subconflicts form a larger conflict.

Second, the power-law distribution is a scale-free distribution meaning that conflict events are the results of the same generative process[8] and imply that there is a potential to have one theory explaining conflict events occurrences without distinguishing between large and small events.

Third, knowing that the underlying distribution of conflict events frequency and size fit power-law distribution allows for the inference of the missing fatalities in the data. This is particularly useful for conflict research as we know that conflict events, especially in remote areas, tend to be underreported. Bayesian modeling of different types of errors, for example, erroneous counting of fatalities or the use of rounding in official data, was successfully used to fill the gaps in the data on overall fatalities numbers in the American Indian War[44].

Fourth, the presence of the power-law distribution across different segments of the armed conflict in Colombia suggests the possibility of predicting the occurrence and the size of future conflict events simultaneously[6]. This is crucial from the practitioners' perspective as the impact of large events is distinctive from the small ones. Being able to anticipate a large conflict event in a specific region of Colombia can enable practitioners to better plan and, thus, more efficiently mitigate the impact of armed conflict on civilians.

Finally, we show that the fluctuations in the scaling exponent α correspond with changes in the actor constellations in line with the conflict actor fragmentation-coalescence model. The increase in the magnitude of the exponent, meaning fewer large conflict events, is associated with an increasing number of actors or a skewed strength ratio between the actors. Similarly, the decrease in the magnitude of the exponent depicts a higher frequency of large conflict events, which corresponds with a more balanced strength ratio. Future research should explore the possibility of using the α exponent as a proxy for the strength ratio of conflict actors more systematically and across the universe of armed conflicts.

Methods

Data

We obtain information on conflict events, their location, date, actors involved and the number of fatalities from the Uppsala Conflict Data Programme Georeferenced Event Dataset version 19.1 (UCDP GED)[37,38]. UCDP defines a conflict event as '[a]n incident where armed force was used by an organized actor against another organized [sic] actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date'[45].

For our analysis, we select only conflict events that have accurate enough location information available that events can be assigned to a specific department. This enables us to assign these events to specific departments. To achieve this, we rely on the UCDP variable called "where_prec" and include only events with values equal to or smaller than four. This eliminates 214 out of 3517 conflict events.

Analysis

A power-law distribution describes the frequency of conflict events of a size x, as $p(x) = x^{-\alpha}/\zeta(\alpha, x_{min})$, where α is a scaling exponent, and $\zeta(\alpha, x_{min})$ is a Hurwitz zeta function for discrete power-laws which is more appropriate for our type of data[8]. When plotted on a log–log plot where the x-axis is the logarithm of the event size and the y-axis is the cumulative probability $P(x)$ of that event being at least x, the data produce a straight line with a slope α-1[12] (N.B. all figures show $P(x)$). A power-law distribution is also often called scale-free. This means that increasing the scale or changing the unit in which x is measured does not result in any change in the shape of the distribution[13,14].

We used the following procedure to fit our data to the power-law distribution. First, we estimated α and x_{min} from our data to draw the ideal power-law distribution based on these parameters. Second, we calculated the Kolmogorov–Smirnov goodness of fit test and obtained the P-value via the bootstrap procedure with 5000 iterations. We accept that data follow approximate power-law distribution if the resulting P-value is equal to or greater than 0.1[10]. The complete results are reported in Tables 2, 3.

Random sub-sampling

To ensure that the variation in the estimated value of the exponent α across the conflict segments has some meaning and does not arise entirely by chance, we draw random subsamples, estimate the exponent α for them and compare those estimates with the exponent values obtained for the individual conflict segments. More specifically, each conflict period j has N_j total events across Colombia, consisting of n_{ij} events in each region i. We sample 50 times n_{ij} points from N_j to simulate the alternative composition of region i in each period. Afterwards, we fit each simulated region into the power-law distribution and below we report the values of the scaling exponent α. We performed the Kolmogorov–Smirnov goodness of fit test to obtain the P-value via bootstrapping with 5000 iterations. We repeat that same process for all departments.

We include in our results presented below, only those values of α that have their corresponding P-values equal to or greater than 0.1. Results comprising all values of α, including those with lower P-values, follow similar patterns. This applies to both regions and departments.

Figure 5 depicts how the values of α for the simulated alternative regions in the periods 1989–1999 and 2010–2018 remained relatively stable in comparison to the values of α estimated for the actual regions. The median values of the exponent for simulated regions during the period 2000–2009 tend to oscillate more than the other periods, but the variation in α is still lower compared to the estimated values for the actual regions in the same period. Table 4 further demonstrates that the simulated alternative regions have a lower level of variation
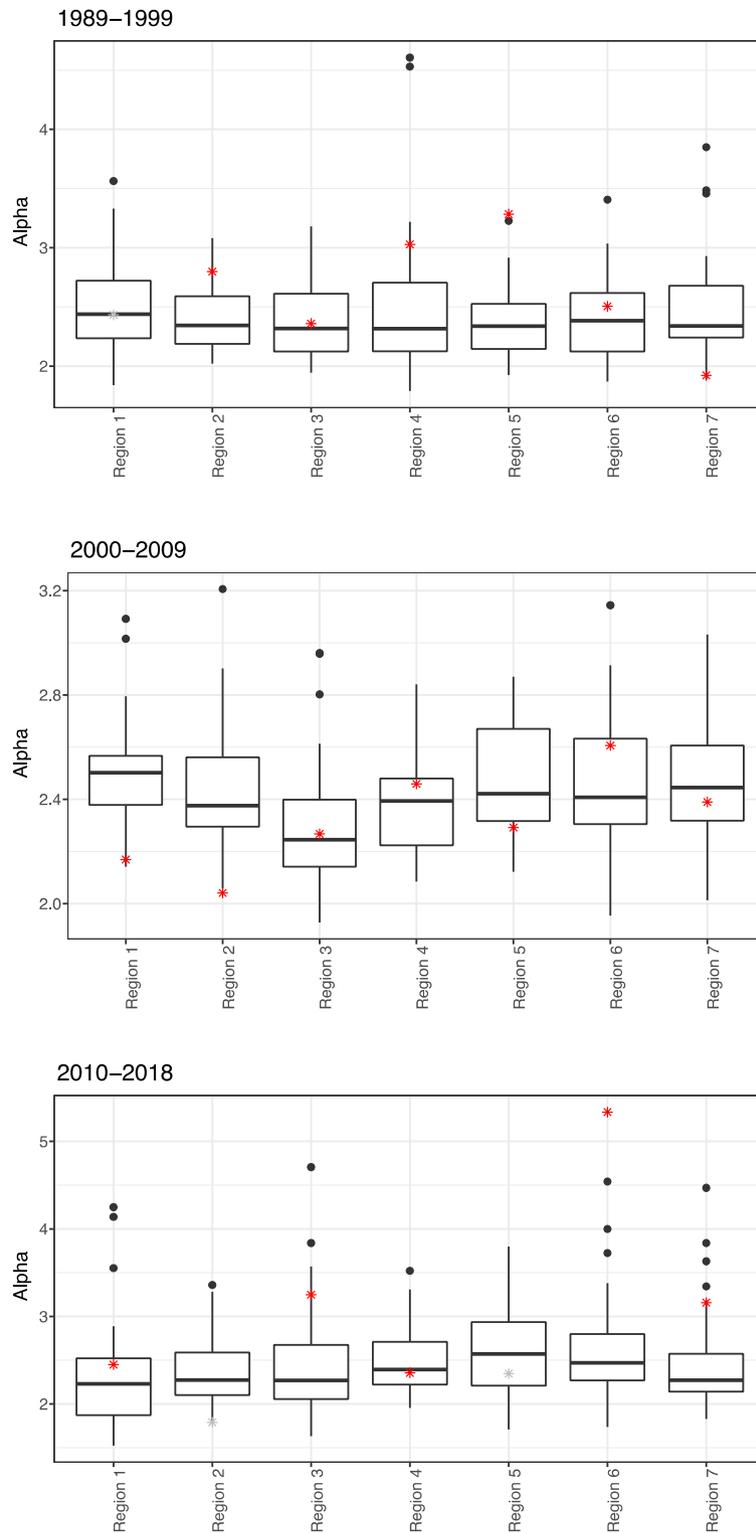
Figure 5. Results obtained from the bootstrapping procedure by simulating alternative regions for each of the studied periods. The boxplot displays the median, 25th and 75th quantiles of the alpha values for the simulated regions. The alpha values estimated for the actual regions are depicted by stars, with corresponding *P*-value ≥ 0.1 in red, otherwise in grey.

Period	Region	Simulated results for alternative regions				Results for regions		Comparison	
		Alpha mean	Alpha SD	Alpha 25th percentile	Alpha 75th percentile	Alpha	P-value (KS)	Within 25th–75th percentile	Within 1 SD
1989–1999	Region 1	2.49	0.37	2.23	2.72	2.43	0.06	TRUE	TRUE
	Region 3	2.39	0.33	2.12	2.61	2.36	0.18	TRUE	TRUE
	Region 4	2.5	0.59	2.12	2.71	3.03	0.67	FALSE	TRUE
	Region 5	2.39	0.3	2.14	2.53	3.28	0.24	FALSE	FALSE
	Region 6	2.42	0.36	2.12	2.62	2.51	0.59	TRUE	TRUE
	Region 2	2.41	0.27	2.19	2.59	2.8	0.54	FALSE	FALSE
	Region 7	2.47	0.41	2.24	2.68	1.92	0.46	FALSE	FALSE
	Range of alpha	2.39–2.50				1.92–3.28			
2000–2009	Region 1	2.49	0.2	2.38	2.57	2.17	0.77	FALSE	FALSE
	Region 2	2.45	0.24	2.3	2.56	2.04	0.28	FALSE	FALSE
	Region 3	2.29	0.23	2.14	2.4	2.27	0.22	TRUE	TRUE
	Region 4	2.39	0.2	2.22	2.48	2.46	0.86	TRUE	TRUE
	Region 5	2.47	0.22	2.32	2.67	2.29	0.49	FALSE	TRUE
	Region 6	2.47	0.25	2.3	2.63	2.61	0.53	TRUE	TRUE
	Region 7	2.48	0.22	2.32	2.61	2.39	0.25	TRUE	TRUE
	Range of alpha	2.29–2.49				2.04–2.61			
2010–2018	Region 1	2.28	0.58	1.87	2.52	2.45	0.81	TRUE	TRUE
	Region 2	2.39	0.39	2.1	2.59	1.79	0.04	FALSE	FALSE
	Region 4	2.5	0.41	2.22	2.71	2.35	0.27	TRUE	TRUE
	Region 5	2.62	0.59	2.21	2.93	2.35	0.01	TRUE	TRUE
	Region 6	2.57	0.58	2.27	2.8	5.34	0.79	FALSE	FALSE
	Region 7	2.46	0.55	2.14	2.57	3.16	0.93	FALSE	FALSE
	Region 3	2.47	0.64	2.06	2.68	3.25	0.13	FALSE	FALSE
	Range of alpha	2.28–2.62				1.79–5.34			

Table 4. Comparison of the results obtained from the bootstrapping procedure by simulating alternative regions for each of the studied periods. The last two columns on the right side of the table compare the values of actual alpha to the simulated results.

in α compared to the actual data. The range of mean values for the simulated regions is smaller for each period than the range of actual values. Moreover, only some values of α fall within the range of 25th and 75th percentile or ± 1 standard deviations from the mean of the simulated regions for each studied period.

Figure 6 and Table 5 show that the conflict segments based on departments exhibit similar patterns. The mean and median values for the simulated alternative departments tend to vary within a narrower range compared to the estimated values for the actual departments. As in the case of regions, some of the values of α estimated for the actual departments fall outside the 15th and 75th percentile and are greater or smaller than the mean of the simulated departments ± 1 standard deviations. This supports our claim that the α value for an actual department does generally contain information about its specific conflict dynamics. Such information is not present in a randomized version. Hence the α values that we report for the conflict on the fine-grained scale, are meaningful.
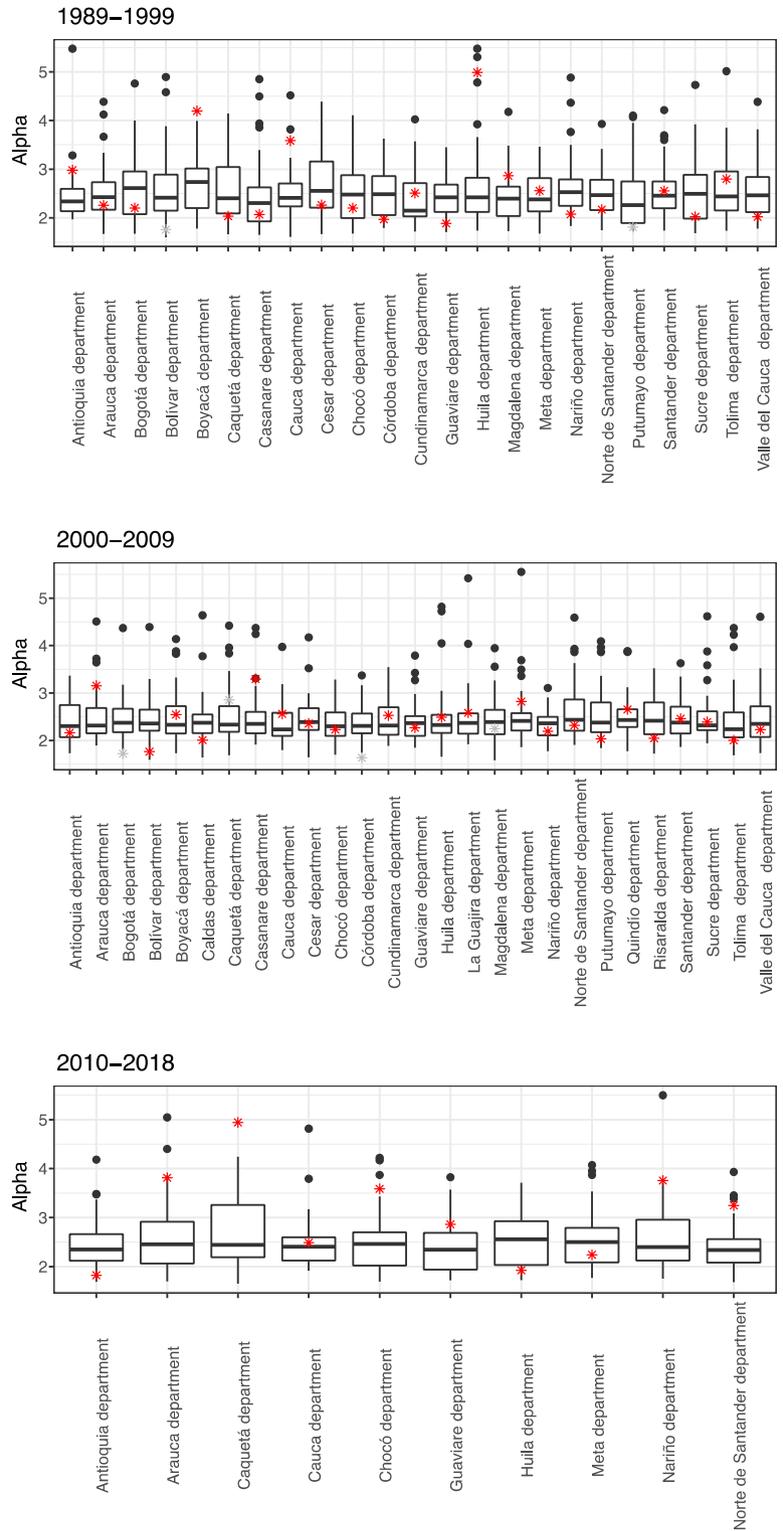
Figure 6. Results obtained from the bootstrapping procedure by simulating alternative departments for each of the studied periods. The boxplot displays the median, 25th and 75th quantiles of the alpha values for the simulated departments. The alpha values estimated for the actual departments are depicted by stars, with corresponding *P*-value ≥ 0.1 in red, otherwise in grey.

Period	Department	Simulated results for alternative departments				Results for departments			Comparison
		Alpha mean	Alpha SD	Alpha 25th percentile	Alpha 75th percentile	Alpha	P-value (KS)	Within 25th-75th percentile	Within 1 SD
1989–1999	Antioquia department	2.47	0.6	2.14	2.59	2.98	0.77	FALSE	TRUE
	Arauca department	2.52	0.54	2.16	2.73	2.26	0.21	TRUE	TRUE
	Bogota department	2.65	0.68	2.07	2.95	2.2	0.12	TRUE	TRUE
	Boyaca department	2.69	0.55	2.2	3.01	4.19	0.14	FALSE	FALSE
	Cordoba department	2.53	0.52	2.06	2.86	1.97	0.33	FALSE	FALSE
	Caqueta department	2.58	0.63	2.09	3.04	2.03	0.18	FALSE	TRUE
	Cauca department	2.53	0.51	2.23	2.71	3.58	0.7	FALSE	FALSE
	Cesar department	2.76	0.75	2.21	3.16	2.26	0.37	TRUE	TRUE
	Choco department	2.5	0.6	2	2.88	2.2	0.82	TRUE	TRUE
	Cundinamarca d	2.38	0.53	2.03	2.71	2.51	0.27	TRUE	TRUE
	Guaviare department	2.41	0.41	2.12	2.68	1.88	0.61	FALSE	FALSE
	Huila department	2.7	0.86	2.12	2.82	4.99	0.47	FALSE	FALSE
	Magdalena d	2.41	0.49	2.04	2.64	2.86	0.91	FALSE	TRUE
	Meta department	2.46	0.46	2.13	2.82	2.55	0.72	TRUE	TRUE
	Narino department	2.65	0.63	2.25	2.79	2.07	0.19	FALSE	TRUE
	Norte de Santander d	2.51	0.44	2.16	2.78	2.17	0.14	TRUE	TRUE
	Sucre department	2.61	0.71	1.98	2.88	2.02	0.51	TRUE	TRUE
	Tolima department	2.56	0.64	2.15	2.95	2.8	0.77	TRUE	TRUE
	Valle del Cauca d	2.56	0.62	2.11	2.84	2.02	0.95	FALSE	TRUE
	Bolivar department	2.62	0.72	2.15	2.89	1.76	0.01	FALSE	FALSE
	Casanare department	2.46	0.76	1.93	2.62	2.07	0.59	TRUE	TRUE
	Putumayo department	2.43	0.64	1.89	2.75	1.81	0.09	FALSE	TRUE
	Santander department	2.57	0.57	2.19	2.75	2.55	0.75	TRUE	TRUE
	Range of alpha	2.38–2.76				1.76–4.99			
2000–2009	Antioquia department	2.46	0.23	2.33	2.61	2.16	0.36	FALSE	FALSE
	Arauca department	2.43	0.47	2.08	2.62	3.15	0.91	FALSE	FALSE
	Bogota department	2.56	0.71	2.04	2.86	1.72	0.05	FALSE	FALSE
	Bolivar department	2.46	0.36	2.17	2.69	1.76	0.18	FALSE	FALSE
	Boyaca department	2.56	0.66	2.12	2.77	2.55	0.12	TRUE	TRUE
	Cordoba department	2.32	0.49	1.97	2.65	1.64	0.07	FALSE	FALSE
	Caldas department	2.37	0.45	2.05	2.52	2.01	0.22	FALSE	TRUE
	Caqueta department	2.36	0.28	2.18	2.43	2.86	0.05	FALSE	FALSE
	Casanare department	2.63	0.73	2.15	2.69	3.29	0.94	FALSE	TRUE
	Cauca department	2.46	0.43	2.18	2.61	2.56	0.64	TRUE	TRUE
	Cesar department	2.48	0.55	2.1	2.67	2.36	0.49	TRUE	TRUE
	Choco department	2.43	0.49	2.12	2.66	2.23	0.49	TRUE	TRUE
	Cundinamarca d	2.42	0.44	2.09	2.65	2.53	0.65	TRUE	TRUE
	Guaviare department	2.46	0.5	2.16	2.67	2.27	0.56	TRUE	TRUE
	Huila department	2.46	0.51	2.16	2.55	2.49	0.85	TRUE	TRUE
	Magdalena d	2.45	0.42	2.18	2.63	2.25	0.04	TRUE	TRUE
	Meta department	2.42	0.27	2.26	2.59	2.82	0.6	FALSE	FALSE
	Narino department	2.42	0.41	2.14	2.55	2.19	0.63	TRUE	TRUE
	Norte de Santander d	2.43	0.43	2.17	2.57	2.32	0.15	TRUE	TRUE
	Putumayo department	2.45	0.59	2.12	2.67	2.03	0.68	FALSE	TRUE
	Quindio department	2.42	0.58	1.99	2.81	2.65	0.34	TRUE	TRUE
	Risaralda department	2.5	0.49	2.07	2.87	2.05	0.37	FALSE	TRUE
	Santander department	2.44	0.44	2.14	2.63	2.46	0.72	TRUE	TRUE
	Sucre department	2.57	0.69	2.13	2.67	2.39	0.1	TRUE	TRUE
	Tolima department	2.4	0.33	2.17	2.61	2	0.27	FALSE	FALSE
Continued									

Period	Department	Simulated results for alternative departments				Results for departments			Comparison
		Alpha mean	Alpha SD	Alpha 25th percentile	Alpha 75th percentile	Alpha	P-value (KS)	Within 25th-75th percentile	Within 1 SD
	Valle del Cauca d	2.34	0.25	2.17	2.45	2.23	0.73	TRUE	TRUE
	La Guajira d	2.77	0.72	2.22	3.18	2.58	0.94	TRUE	TRUE
	Range of alpha	2.32–2.77				1.64–3.29			
2010–2018	Antioquia department	2.45	0.53	2.12	2.66	2.16	0.36	TRUE	TRUE
	Arauca department	2.59	0.7	2.06	2.92	3.15	0.91	FALSE	TRUE
	Cauca department	2.5	0.53	2.12	2.6	2.56	0.64	TRUE	TRUE
	Choco department	2.51	0.63	2.02	2.7	2.23	0.49	TRUE	TRUE
	Guaviare department	2.36	0.48	1.94	2.69	2.27	0.56	TRUE	TRUE
	Huila department	2.54	0.56	2.03	2.93	2.49	0.85	TRUE	TRUE
	Meta department	2.56	0.59	2.09	2.79	2.82	0.6	FALSE	TRUE
	Narino department	2.62	0.71	2.12	2.96	2.19	0.63	TRUE	TRUE
	Norte de Santander d	2.4	0.49	2.08	2.56	2.32	0.15	TRUE	TRUE
	Caqueta department	2.66	0.66	2.19	3.26	2.86	0.05	TRUE	TRUE
	Range of alpha	2.36–2.66				2.16–3.15			

Table 5. Comparison of the results obtained from the bootstrapping procedure by simulating alternative departments for each of the studied periods. The last two columns on the right side of the table compare the values of actual alpha to the simulated results.

Supplementary materials

All data used, generated, or analyzed during this study are included in this article or supplementary files. Data and R scripts are also available at: https://zenodo.org/records/10159421.

Data availability

Data and R scripts are available at: https://zenodo.org/records/10159421. We carried out all calculations using R version 4.3.1 ("Beagle Scouts") and R package poweRlaw 0.70.6[46].

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Author contributions

KT, AI, NJ, and EL conceived and designed the experiments and wrote the paper. KT and AI contributed materials/analysis tools. KT performed the experiments and analyzed the data.

Competing interests

The authors declare no competing interests.

Additional information

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