Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries

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Social and political tensions keep on fueling armed conflicts around the world. Although each conflict is the result of an individual context-specific mixture of interconnected factors, ethnicity appears to play a prominent and almost ubiquitous role in many of them. This overall state of affairs is likely to be exacerbated by anthropogenic climate change and in particular climate-related natural disasters. Ethnic divides might serve as predetermined conflict lines in case of rapidly emerging societal tensions arising from disruptive events like natural disasters. Here, we hypothesize that climate-related disaster occurrence enhances armed-conflict outbreak risk in ethnically fractionalized countries. Using event coincidence analysis, we test this hypothesis based on data on armed-conflict outbreaks and climate-related natural disasters for the period 1980–2010. Globally, we find a coincidence rate of 9% regarding armed-conflict outbreak and disaster occurrence such as heat waves or droughts. Our analysis also reveals that, during the period in question, about 23% of conflict outbreaks in ethnically highly fractionalized countries robustly coincide with climatic calamities. Although we do not report evidence that climate-related disasters act as direct triggers of armed conflicts, the disruptive nature of these events seems to play out in ethnically fractionalized societies in a particularly tragic way. This observation has important implications for future security policies as several of the world's most conflict-prone regions, including North and Central Africa as well as Central Asia, are both exceptionally vulnerable to anthropogenic climate change and characterized by deep ethnic divides.

climate-related natural disasters | ethnic fractionalization | armed conflicts | event coincidence analysis

Climate-related natural disasters are among the most important environmental stressors affecting the development of human societies. Climatic changes—and most prominently the succession of severe natural disasters—have been recognized as an important potential driver for the collapse of complex societies (1). However, not the climatological events per se, but societal vulnerability to its consequences in conjunction with other stressors has led to societal disintegration, armed conflicts, and eventually societal collapse during historic and prehistoric times (2–8). Today, armed conflicts are still among the biggest threats to human societies, and the identification of underlying processes and potential drivers is an area of intense scientific research. Several potential risk enhancement factors for conflict outbreak have been identified, including poverty (9), income inequality (10), weak governance (11), or a preexisting history of conflicts (12). Hypotheses relating to conflict feasibility based on financial assets from natural resource exploitation have also been discussed (13, 14). Additionally, there is a growing body of literature that reports robust indications that ethnic fractionalization is one of the key determinants of armed-conflict outbreak risk (10, 14–17). Although not necessarily rooting in ethnic tension, nearly two-thirds of all civil wars since 1946 have been fought along ethnic lines (18). This prominent role of ethnicity in conflicts might be related to selective access to political power or resources that are often divided along ethnic lines (19), as well as to a high and rapid ethnic mobilization potential (20) arising from geographical clustering of ethnic groups and strong interethnic social ties (21). These two factors may contribute to societal fissures along ethnic boundaries in case of rapidly emerging societal tension stemming from disruptive events such as natural disasters. In addition, it seems plausible that ethnic groups can be impacted very differently by natural disaster occurrence. The prevalent geographic clustering might be reinforced by other factors such as ethnically specific livelihoods (e.g., pastoral or riverine communities) or socioeconomic discrimination resulting in an ethnicity-dependent differential vulnerability to natural disasters (22).

In our analysis, we investigate the hypothesis that climate-related natural disasters (in the following referred to as disasters) enhance the risk of an emergence or violent outbreak of armed conflicts particularly in ethnically fractionalized societies. We explicitly address the impact of such disasters in terms of the resulting economic damage relative to national gross domestic product (GDP), making use of a high-quality database developed for commercial purposes of the reinsurance sector (*Materials and Methods*). Thereby, we explicitly define disasters with respect to their economic impact instead of the associated climatic variables. To test for statistical interrelationships between these damage events and the timing of armed conflicts, we use event coincidence analysis (ECA; see refs. 23 and 24, and Fig. 1 and *Materials and Methods*), a method that is conceptually related to event synchronization (25) and similar approaches that are widely used in the neurosciences for studying neuronal spike trains (26). ECA provides a generally applicable tool for explicitly testing the statistical significance of interdependences between sequences of events and has been proven useful in analyzing relations between

Significance

Ethnic divides play a major role in many armed conflicts around the world and might serve as predetermined conflict lines following rapidly emerging societal tensions arising from disruptive events like natural disasters. We find evidence in global datasets that risk of armed-conflict outbreak is enhanced by climate-related disaster occurrence in ethnically fractionalized countries. Although we find no indications that environmental disasters directly trigger armed conflicts, our results imply that disasters might act as a threat multiplier in several of the world's most conflict-prone regions.

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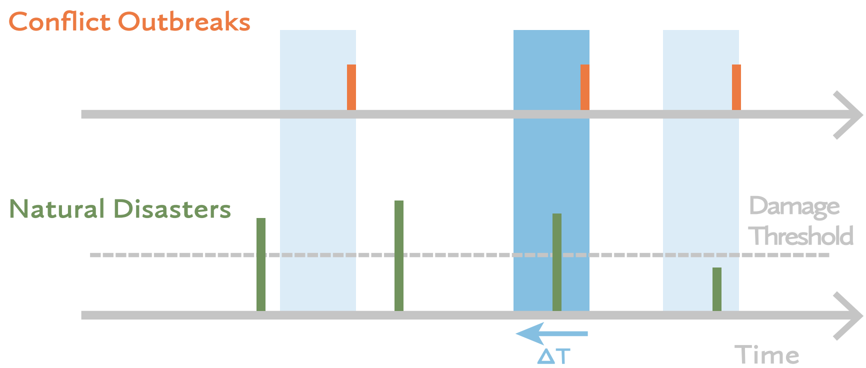

Fig. 1. Illustration of the methodological approach of event coincidence analysis for the risk enhancement test based on armed-conflict occurrence. An armed-conflict outbreak (orange) is counted as coincident with a natural disaster (green), if it co-occurs with or is preceded by such an event exceeding a prescribed damage threshold within a given coincidence interval ΔT.

event time series such as regime shifts in African paleoclimate and the appearance and disappearance of hominin species during the Plio-Pleistocene (23), plant growth response to climatic extremes (27, 28), or the role of flood events as triggers of epidemic outbreaks (24).

ECA allows to quantify the strength and robustness of statistical interrelationships between event series of natural disasters and armed-conflict outbreaks in two complementary ways (*Materials and Methods*): (*i*) the "risk enhancement test" is based on the "aggregated precursor coincidence rate" (24) measuring the fraction of conflicts that co-occurred with or were preceded by at least one disaster exceeding a certain damage level in the same country and that occurred at most at time ΔT before the conflict started (Fig. 1). In this case, a robust coincidence rate would indicate that disaster occurrence is a risk-enhancing factor for armed-conflict outbreak, based on a retrospective analysis with the condition that such an outbreak has occurred. (ii) In turn, the "trigger test" relies on the "aggregated trigger coincidence rate" (24) measuring the fraction of disasters exceeding a prescribed damage level in a country group that co-occurred with or were followed by at least one conflict that occurred at most a time ΔT after the disaster onset in the same country. This analysis allows to assess more explicitly than the risk enhancement test whether disasters may act as a direct trigger to armed-conflict outbreaks in the database under consideration. Statistical significance is tested with respect to an appropriately chosen null model (*Materials and Methods*), and we vary the economic damage threshold for identifying disasters to test for the effect of the event severity on the coincidence rate and significance as well as different disaster types (climatological, meteorological, and hydrological disasters; *SI Appendix*, Table S1).

Besides testing for a global relation between natural disaster occurrence and armed-conflict outbreak, we performed our analysis on a group of 50 countries with the highest ethnic fractionalization (EF) following a well-established ethnic fractionalization index (29) (results for different group sizes are given in *SI Appendix*). Additionally, we grouped countries according to alternative hypotheses such as multiple conflict outbreaks (CONFL, see ref. 12) and income inequality measured by the Gini coefficient (GINI, 50 countries with highest inequality; see Fig. 2 for the country classification). We furthermore analyzed other country groupings such as countries with high religious fractionalization, low levels of overall development, low literacy rates, abundant absolute poverty, high dependency on agricultural production, high corruption levels, or countries markedly affected by the El Niño Southern Oscillation (*SI Appendix*, Table S3). It is important to highlight that such a country grouping approach does not allow for a robust assessment of the relevance of different factors for the risk of armed-conflict outbreak generally, but rather indicates specific vulnerability to climate-related natural disaster impacts.

Results

In the following, we present the results of ECA of armed-conflict outbreaks listed in the UCDP/PRIO conflict dataset (30, 31) with natural disasters based on the NatCatSERVICE database from Munich Re over the period from 1980 to 2010 (32). We find no statistically significant precursor coincidence rates for the risk enhancement test at the global scale and all disaster types, except for the most devastating disasters that caused damage above 10% of annual country GDP (compare Fig. 3). As the database contains only about 40 events of this damage class globally (*SI Appendix*,

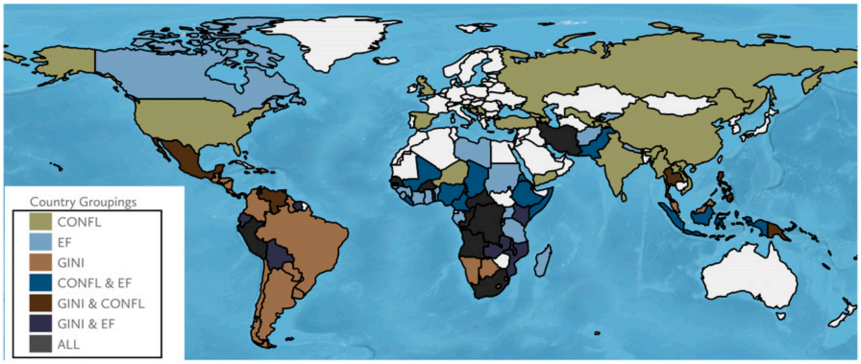

Fig. 2. Mapping of countries according to different analysis criteria including countries with more than one conflict (CONFL), the 50 countries with the highest Gini coefficient (GINI), as well as the 50 countries with the highest ethnic fractionalization (EF).

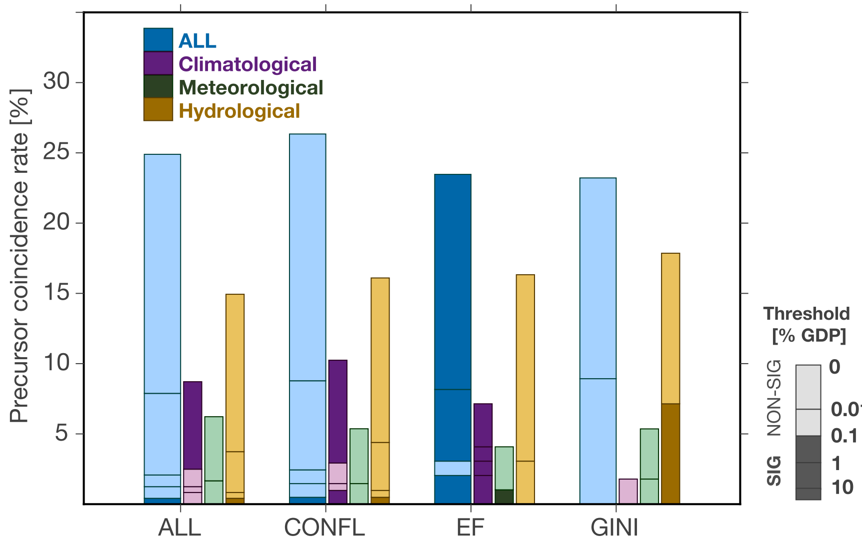

Fig. 3. Results of ECA for the risk enhancement test: the percentage of armed-conflict outbreaks that coincide with a climate-related natural disaster within the same month (*Materials and Methods*). We resolve different country groupings, disaster types (color coding), and disaster damage levels. Damage levels are indicated by segments of the individual bars and are assessed relative to the country's GDP in the year of the event. Segmenting starts with zero threshold from the top and the number of segments with nonzero coincidences can differ between country groupings and disaster types. Filled segments indicate coincidence rates that are significant at the 95% level. Results shown are for coincidences between events occurring within the same month (see *SI Appendix*, Fig. S3 for results for coincidence intervals of up to 12 months).

Table S2), however, no robust conclusions can be drawn for this category. To the contrary, our analysis reveals robust precursor coincidence within the same month for EF largely independent of the damage threshold resulting in a maximum coincidence rate of about 23% for all disaster types, which corresponds to 23 conflict outbreaks in total (see *SI Appendix*, Table S4, for an overview of the number of conflict outbreaks per country grouping). This finding is largely robust with regard to the arbitrarily chosen size of the country grouping (*SI Appendix*, Fig. S1). The results for the GINI, CONFL, as well as alternative country groupings (*SI Appendix*, Fig. S2) do not differ substantially from the global assessment. Despite existing linkages between some of the aforementioned factors and EF (compare Fig. 2), none of these country groupings yields results of similar robustness. In addition, we analyzed immediate and longer-term responses to disaster impacts (*SI Appendix*, Fig. S3). Although we find significant precursor coincidence rates for an extended coincidence interval of up to 3 months before the conflict outbreak, our analysis does not reveal significant effects for longer intervals.

A different picture emerges when different types of disasters are treated separately (see *SI Appendix*, Table S1, for further details on the event type classification). About 9% of all global armed-conflict outbreaks (21 in total) significantly coincide with a climatological disaster (drought or heat wave) in the same country even without applying a disaster damage threshold (7% for the EF country grouping). For hydrological events, only those with strongest impact yield statistically significant results, albeit at a low precursor coincidence rate. Also, we only find significant precursor coincidence for meteorological disasters for EF with a low coincidence rate.

The same analysis has been performed for the trigger test quantifying to what degree armed-conflict outbreaks coincide with or follow disasters (Fig. 4). Again, we find the signal for coincidences within the same month and climatological disasters to be most robust with the largest statistically significant coincidence rate for the EF country group. However, trigger coincidences have only been identified for 2.5% of all climatological events and about 2% of all disasters above a 1% relative GDP threshold for the EF country grouping and are not robust at the global scale.

Discussion

The question whether or not climate-related factors have significantly contributed to recent armed-conflict outbreaks has been heavily disputed in the scientific literature (33–38). Although a sequence of studies has suggested that a large number of outbreaks of armed conflicts in modern as well as premodern times have been associated with climatic variability (33, 36, 37, 39–41), the robustness of these findings and underlying mechanisms are controversially discussed (10, 37, 42, 43). Other literature that assessed the influence of climate signals on armed-conflict outbreak risk did not report a robust connection (9, 44, 45).

A clear shortcoming of most studies investigating the relation between climate change and armed conflicts is that they focus solely on meteorological indices such as temperature or precipitation time series (9, 39–42, 46), thereby neglecting the crucial importance of vulnerability and exposure for the impacts of climate hazards (35, 47). This might be one reason for the substantial disagreement on the matter in the literature. Moving beyond purely meteorological indices toward the development of composite indices accounting for vulnerability and exposure to climate change, as well as conflict risk provides a promising way forward to reconcile this debate (48, 49).

Our ECA approach, based on disaster occurrence characterized by the economic impact of a climate-related event instead of a meteorological index, accounts to some extent for the effects of vulnerability and exposure. However, some potential caveats need to be considered. Economic losses as measured relative to GDP are of limited relevance in assessing disaster impacts in the most vulnerable countries, as disaster-related losses are difficult to quantify and loss of lives and livelihoods may substantially outweigh economic losses. At the same time, damages by disasters that are not directly affecting economic assets but rather living conditions and subsistence agriculture, such as droughts, are difficult to quantify in economic terms (32). These shortcomings of the economic indicators may explain why we find robust significant relationships down to low damage threshold levels as well as the apparent insensitivity to the threshold level for climatological events (compare Fig. 3). A second shortcoming is associated with the country-level resolution of our study that can impede the assessment of potential relations

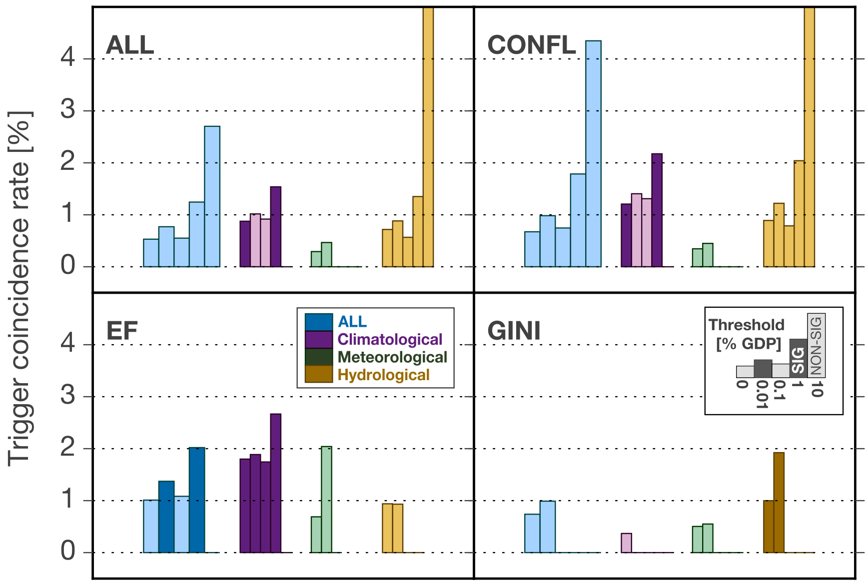

Fig. 4. Results of ECA for the trigger test based on the occurrence of disasters that coincide with an armed-conflict outbreak within the same month (*Materials and Methods*). Results for four different country groupings are resolved in four individual panels, whereas results for different disaster types are indicated by the color coding. Coincidence rates are displayed for different damage threshold levels by individual bars with increasing damage threshold from left to right. For some threshold levels, the trigger coincidence rate is zero. Filled segments indicate coincidence rates that are significant at the 95% level. Note that the coincidence rates are one order of magnitude smaller than for the risk enhancement test depicted in Fig. 3.

between disasters and armed-conflict outbreaks happening in different parts of the country. Although a higher resolution would indeed improve our analysis, the current country aggregation does not undermine the validity of our test as a larger number of possibly disconnected disasters and armed-conflict outbreaks on a country level will only lead to higher significance thresholds (*Materials and Methods*) and, consequently, to a more conservative test.

The results for the different country groupings depend not only on the ad hoc selection of group sizes (although our findings for EF are largely robust for different group sizes; compare *SI Appendix*, Fig. S1) but also on the index chosen. Although widely used, the classification following general indicators such as GINI or EF has led to inconsistent results in the conflict literature and it has been shown that theoretically informed country profiles combining multiple factors and relating them to dimensions of power sharing are much better predictors of armed-conflict outbreaks (10). Specifically, discriminatory political and power-sharing systems along ethnic boundaries have been found to be of key relevance (10). Thereby, a refinement of our analysis based on indices reflecting ethnic inclusiveness in power sharing might be promising for further research.

Commonly, high ethnic separation on a country level coincides with other potential sources of conflict such as economic inequality or poverty, which makes it difficult to disentangle their specific effects (50). However, the results for alternative groupings (e.g., for inequality, poverty, and conflict proneness) are much less robust than those for EF, despite a substantial overlap in the actual country groupings (compare Fig. 2). Although the country grouping approach as applied here does not allow for a direct quantification of the driver's importance, our results imply that the mechanisms specific to EF and conflict outbreak discussed above may play a significant role for armed-conflict outbreak following a natural disaster (18). Thereby, it is not the domain-specific factors, EF, or natural disasters occurrence alone, but their interplay that results in enhanced risk of armed-conflict outbreak. Besides our robust findings of risk enhancement, we report no further indications that natural disasters are causing armed-conflict outbreaks in a more direct manner (based on the trigger test). Thereby, our results do not support attempts of single-factor attribution of conflict outbreaks to disaster occurrence.

Unlike development-related factors such as poverty and inequality, ethnic fractionalization of societies cannot be overcome via economic development alone. As a consequence, country-specific risks may prevail over the next decades independently of the countries' state of development, if no robust progress in ethnic inclusiveness regarding power sharing is achieved (10). Among the most fractionalized countries are many African as well as Central Asian nations (compare Fig. 2), which makes these regions potential hot spots of armed-conflict outbreak risk enhancement due to climate-related natural disasters. Climate projections indicate a substantial increase in extreme event hazards in these regions and most of the affected countries are also characterized by high vulnerability and low adaptive capacity, which renders them particularly susceptible to high-impact climate-related natural disasters (51, 52). Projections of overall conflict risk up to 2050 based on a multifactorial analysis also find these regions to be particularly endangered (12), which highlights the relevance of our findings in the wider context of conflict prevention and development.

The robust finding of armed-conflict outbreak risk enhancement for climatological events globally points towards increased risks due to a projected drying trend in already drought-prone regions such as Northern Africa and the Levant (53). Recent analyses of the societal consequences of droughts in Syria and Somalia indicate that such climatological events may have already contributed to armed-conflict outbreaks or sustained conflicts in both countries (54–57). Similarly, a prolonged drought might have contributed negatively to the ongoing conflicts in Afghanistan (58). Further destabilization of Northern Africa and the Levant may have widespread effects by triggering migration flows to neighboring countries and remote migrant destinations such as the European Union. Although not highly ethnically fractionalized following the ad hoc threshold classification applied here, ethnic identities also appear to play a prominent role in the ongoing civil wars in Syria and Iraq (18). It is clear that the roots of these conflicts, as for armed conflicts in general, are case specific and not directly associated with climate-related natural disasters. Nevertheless, such disruptive events have the potential to amplify already existing societal tensions and stressors and thus to further destabilize several of the world's most conflict-prone regions (12, 31).

Materials and Methods

Data Sources.

Natural disaster database. The analysis of disaster damages is based on the NatCatSERVICE database from Munich Re (32) developed for the private sector, which is available upon request from the Munich Re NatCatSERVICE. This database provides state-of-the-art estimates of economic damages connected to natural hazards. The database comprises the 1980–2010 period and gives estimates for total economic damages based on internal estimates and third-party sources. It contains about 18,000 climate-related events for that period. Damage events are classified according to the nature of the underlying natural hazard and include also geophysical events such as earthquakes, which are excluded from our analysis (see *SI Appendix*, Table S1 for an overview on the climate-related natural hazards and their classification). To account for country-specific economic conditions, the absolute damages are considered relative to the countries' annual GDP (International Monetary Fund database; https://www.imf.org/external/data.htm), which allows for the analysis of climate-related natural hazards dependent on their destructiveness in economic terms. All damages are deflated to 2010 US dollars.

Armed-conflict database. Data on armed conflicts are taken from the openly available UCDP/PRIO Armed Conflict Dataset (30, 31) (www.pcr.uu.se/research/ucdp/datasets/ucdp_prio_armed_conflict_dataset/). This dataset counts all incidences with more than 25 battle-related deaths globally, both interstate and intrastate conflicts. Conflict outbreaks are counted on a yearly basis, for each dyad of conflicting parties (either interstate or intrastate). For ongoing conflicts, each new outbreak is included when preceded by at least 24 months of nonconflict. Interstate conflicts are treated separately and coincidences are counted if at least one of the countries has been hit by a disaster within the coincidence interval and above the damage threshold. Conflicts involving multiple countries (such as US-led coalitions in Afghanistan and Iraq in the 2000s) are excluded. The dataset includes 241 conflict outbreaks over the 1980–2010 period for both interstate and intrastate conflicts globally.

Country classification. The country classification in terms of ethnic as well as religious fractionalization is based on indices developed by Alesina et al. (29) and the Gini coefficient is based on World Bank data and averaged over the 1980–2010 period (World Bank database; data.worldbank.org/indicator/). For both indices, the 50 countries with the highest values are used. For further country classifications, see *SI Appendix*, Table S3.

Method Description: ECA. ECA is a method tailored for quantifying and testing statistical interrelationships between event series while allowing to specify explicitly the coincidence interval, lag, and directionality (in terms of precursor and trigger coincidences) of these interrelationships (24). In this study, we perform two coincidence tests: (*i*) the risk enhancement test, which is based on armed-conflict outbreak and tests for coincidences of natural disasters co-occurring with or preceding conflict events, and (*ii*) the trigger test based on climate-related natural disaster occurrence, which tests for coincidences with armed-conflict outbreaks following or co-occurring with a disaster event (24). Both tests differ with regard to the considered set of countries and the definition of the coincidence interval, but otherwise the same methodology is applied. We analyze countrywise coincidences between armed-conflict outbreaks at times $t_i^{c,k}$ ($i=1,\ldots,N_{c,k}$) and disaster events at times $t_j^{d,k}(\varepsilon)$ ($j=1,\ldots,N_{d,k}(\varepsilon)$) within a coincidence interval ΔT (Fig. 1) for a group of countries G, where $k\in G$ is a country index. $N_{c,k}$ and $N_{d,k}(\varepsilon)$ denote the numbers of armed conflicts and disasters for a given country k, respectively. The disaster events are filtered by a damage threshold ε measured in units relative to annual GDP.

The risk enhancement test is based on the aggregated precursor coincidence rate $r_p^G(\Delta T,\varepsilon)$ (24) measuring the fraction of conflicts in country group G that were preceded by at least one disaster of the strength of at least ε in the same country and that occurred at most at time ΔT before the conflict started:

$$r_p^G(\Delta T,\varepsilon)=\frac{\sum_{k\in G}\sum_{i=1}^{N_{c,k}}\Theta\left[\sum_{j=1}^{N_{d,k}(\varepsilon)}1_{[0,\Delta T]}\left(t_i^{c,k}-t_j^{d,k}(\varepsilon)\right)\right]}{\sum_{k\in G}N_{c,k}},\qquad [1]$$

where $\Theta(\cdot)$ is the Heaviside function [here defined as $\Theta(x)=0$ for $x\le 0$ and $\Theta(x)=1$ otherwise] and $1_I(\cdot)$, the indicator function of the interval I [defined as $1_I(x)=1$ for $x\in I$ and $1_I(x)=0$ otherwise]. Note that, according to this definition, multiple disasters preceding a given conflict within the coincidence interval are counted only once. In turn, the trigger test is based on computing aggregated trigger coincidence rates (24):

$$r_t^G(\Delta T,\varepsilon)=\frac{\sum_{k\in G}\sum_{j=1}^{N_{d,k}(\varepsilon)}\Theta\left[\sum_{i=1}^{N_{c,k}}1_{[0,\Delta T]}\left(t_i^{c,k}-t_j^{d,k}(\varepsilon)\right)\right]}{\sum_{k\in G}N_{d,k}(\varepsilon)},\qquad [2]$$

measuring the fraction of disasters of a strength of at least ε in country group G that were followed by at least one conflict that occurred at most a time ΔT after the disaster onset in the same country.

The temporal resolution of the analysis is limited to monthly values, which accounts for both dating uncertainties in the conflict database as well as in disaster onsets (as in, e.g., droughts). For temporally extended disaster events, the start date is used. Although certain events such as heat waves and in particular droughts can last for several months, an analysis using the end dates of such temporally extended disasters (not shown) does not exhibit significant coincidence rates. To assess the statistical robustness of our findings, independent Poisson processes are assumed for both the disaster as well as the conflict outbreak event series at the individual country level, conserving the event rates $N_{c,k}/T$ and $N_{d,k}(\varepsilon)/T$, respectively (23). Here, T denotes the total time span covered by both event series. The corresponding null hypothesis (NH) to be tested is that the observed coincidence rates for a group of countries G occur due to chance alone. To perform this test, Monte Carlo simulation is applied for generating M pairs of surrogate event series. Event rates for each country $k\in G$ are conserved by uniformly and independently drawing $N_{c,k}$, $N_{d,k}(\varepsilon)$ event timings from the considered period 1980–2010 to compute a test distribution of coincidence rates $p(r^G)$ using Eqs. 1 and 2. For each considered country grouping, $M=1{,}000$ ensemble members are generated and a 95% significance level is applied for the rejection of the NH of coincidence rates arising due to chance alone. No significance assessments are made, if the absolute number of coincidences counted is smaller than 2.

A variety of approaches related to ECA is applied in the neurosciences for investigating statistical interrelationships between neuronal spike trains (26). Among others, event synchronization (25) has been widely used for studying climatological extreme events in various contexts (60, 61). Donges et al. (24) provide a more detailed discussion of ECA in comparison with related approaches.

It should be noted that the statistically significant coincidence rates observed in this study could in principle be due to a hidden common cause that affects the timing of both climate-related disasters and armed-conflict outbreaks. Although the existence of such a root cause cannot be ruled out a priori, there is no obvious hypothesis available on what a hidden common cause or common driver could be in the setting of our study. If event or other data on candidate processes is available, extensions of ECA such as conditional ECA could be applied to study common driver effects (62). Alternatively, recurrence-based methods proposed for discovering hidden common causes in the case of bivariate standard time series (63) could be adapted for event time series in future research.

The software (Python scripts) and openly available data used for performing the analysis presented in this paper have been made available at www.pik-potsdam.de/research/publications/pnas/Schleussner_et_al_2016_PNAS_scripts.zip.

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