Effects of temperature and precipitation variability on the risk of violence in sub-Saharan Africa, 1980–2012

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Ongoing debates in the academic community and in the public policy arena continue without clear resolution about the significance of global climate change for the risk of increased conflict. Sub-Saharan Africa is generally agreed to be the region most vulnerable to such climate impacts. Using a large database of conflict events and detailed climatological data covering the period 1980–2012, we apply a multilevel modeling technique that allows for a more nuanced understanding of a climate–conflict link than has been seen heretofore. In the aggregate, high temperature extremes are associated with more conflict; however, different types of conflict and different subregions do not show consistent relationship with temperature deviations. Precipitation deviations, both high and low, are generally not significant. The location and timing of violence are influenced less by climate anomalies (temperature or precipitation variations from normal) than by key political, economic, and geographic factors. We find important distinctions in the relationship between temperature extremes and conflict by using multiple methods of analysis and by exploiting our time-series cross-sectional dataset for disaggregated analyses.

climate variability | multilevel modeling | disaggregated spatial analysis | regional contexts | types of violence indicators

Continued public and academic interest in the topic of global climate change consequences for political instability and the risk of conflict has generated a growing but inconclusive literature, especially about the effects in sub-Saharan Africa. Claims that climate change contributes to conflict have been plentiful since Miguel et al. (1) found that negative deviations of annual precipitation in sub-Saharan African countries reduce national economic growth, and thus indirectly lead to higher risk of civil war. The recent fifth assessment of the Intergovernmental Panel on Climate Change highlights the severely damaging effects of predicted climatic disturbances for vulnerable societies around the world (2). Multiple recent analyses provide support for the general position that climate change has "strong causal" influences on conflict (3, 4), although the authors do not elaborate on nor test the causal mechanisms (also refs. 5 and 6).

Many existing statistical studies are based on data aggregated to large geographic units such as countries, using crude climate indicators and generalized high-level conflict measures. Some studies indicate positive relationships between climate extremes and violence at the large scale (7–9), whereas contrasting work reports a lack of significant effects (10–12). Using fine-resolution spatial scales, other researchers find weak or no climate–conflict association; they conclude that the relationship is complex and depends on the social characteristics of the regional settings (13–15), or that the relationship is nonlinear across multiple regions and livelihood zones (16). In direct contrast to the scarcity narrative, some research suggests that an abundance of water is associated with conflict across the globe (17).

Scholarly debates about methods and measurement (18, 19) and the theoretical framings on this topic (20) are lively. Most researchers accept that conflict is not expected to be a direct result of higher temperatures and/or decreased rainfall, but instead, believe that these climate anomalies lead to resource scarcities that are, in turn, predicated on a complex interplay of social, political, and economic conditions in specific countries whose response capacities are limited (21). Competition over essential water supplies—for grass, grain, or livestock—will be intensified when communities have difficulty raising cattle or staple crops on their own. These intermediate effects are typically expected to increase popular grievances, undermining government legitimacy, and generating protests and demands for grievance redress (22, 23). Government responses to these environmental stresses play a large role in determining the magnitude and geographic distribution of resulting violence.

Despite the ethnographic confirmations of the value of nonclimatic explanations for conflict in specific social and political contexts, much of the statistical research in climate–conflict studies does not report empirical estimates for the influence of such factors (e.g., ref. 4). In contrast, analyses that formally consider nonclimatic explanations find political, ethnic, and economic grievances to be important factors in explaining African conflicts, in line with the dominant literature in international relations and conflict/peace studies (24–27). There are, however, notable exceptions to the dearth of explanatory mechanisms for a climate–conflict link. Maystadt and Ecker (28), for example, find that deviations in Somali cattle market prices provide the mechanism by which weather extremes translate into political instability. Key climate–conflict connections emerge in zones of ethnic exclusion and political marginalization (29, 30). Greiner (31), in studying cattle raiding activity in northern Kenya, has

Significance

A robust debate about the effects of climate change on conflict occurrences has attained wide public and policy attention, with sub-Saharan Africa generally viewed as most susceptible to increased conflict risk. Using a new disaggregated dataset of violence and climate anomaly measures (temperature and precipitation variations from normal) for sub-Saharan Africa 1980–2012, we consider political, economic, and geographic factors, not only climate metrics, in assessing the chances of increased violence. The location and timing of violence are influenced less by climate anomalies than by key political, economic, and geographic factors. Overall, the temperature effect is statistically significant, but important inconsistencies in the relationship between temperature extremes and conflict are evident in more nuanced relationships than have been previously identified.

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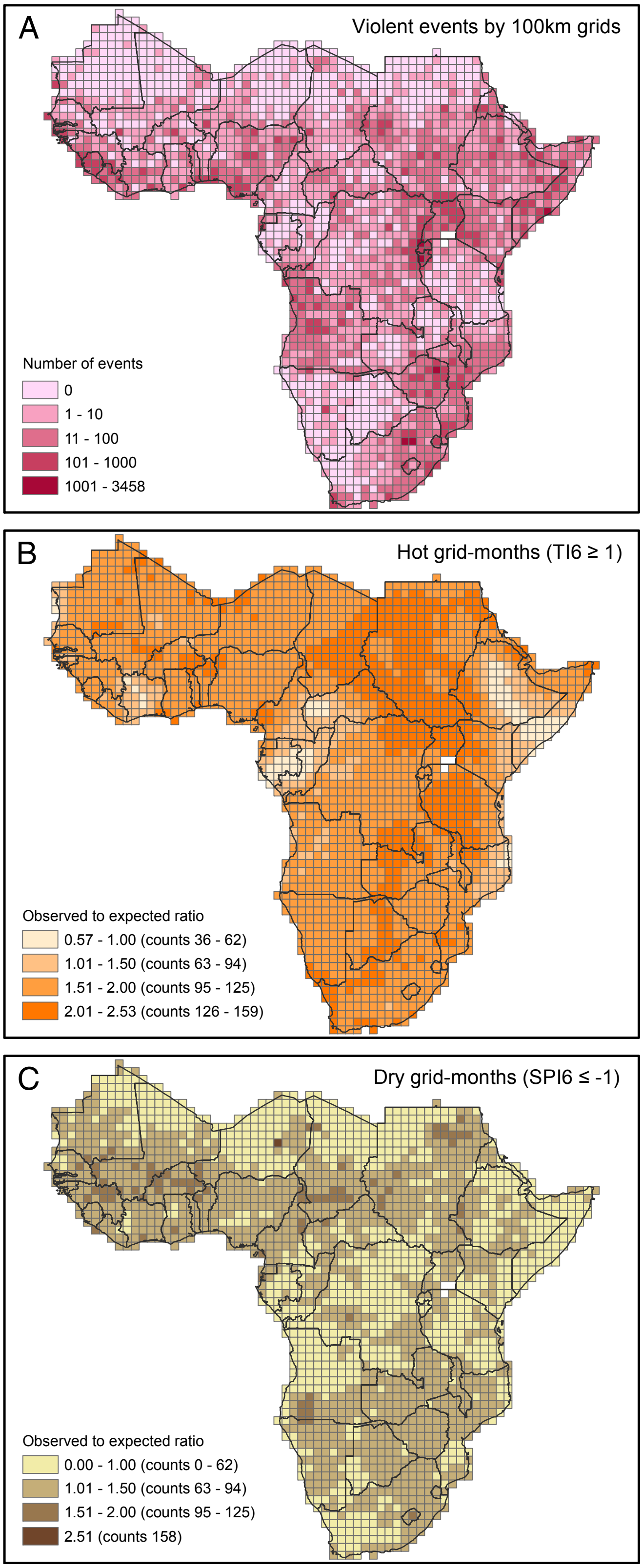


Fig. 1. Descriptive maps of (*A*) ACLED violent events, (*B*) hot temperature anomalies, and (*C*) dry precipitation anomalies, 1980–2012. For temperature (TI6) and precipitation (SPI6) data, the number of observed grid-months beyond 1 SD is compared with the expected number from a standard normal distribution. Distribution plots of the TI6 and SPI6 values and the grid means are shown in Figs. S1 and S2.

illustrated complex linkages between political marginalization, government policing, and even criminal networks that determine conflict risk—in addition to evident weather anomalies. By using a statistical multilevel modeling technique that identifies observable differences within sub-Saharan African countries, we investigate in this article how trends in climate variability operate along with other social conditions to shape temporal and geographic patterns of conflict. We recognize and model the discrepancies in contextual conditions of conflict, simultaneously between grid cells and also within a grid cell over time.

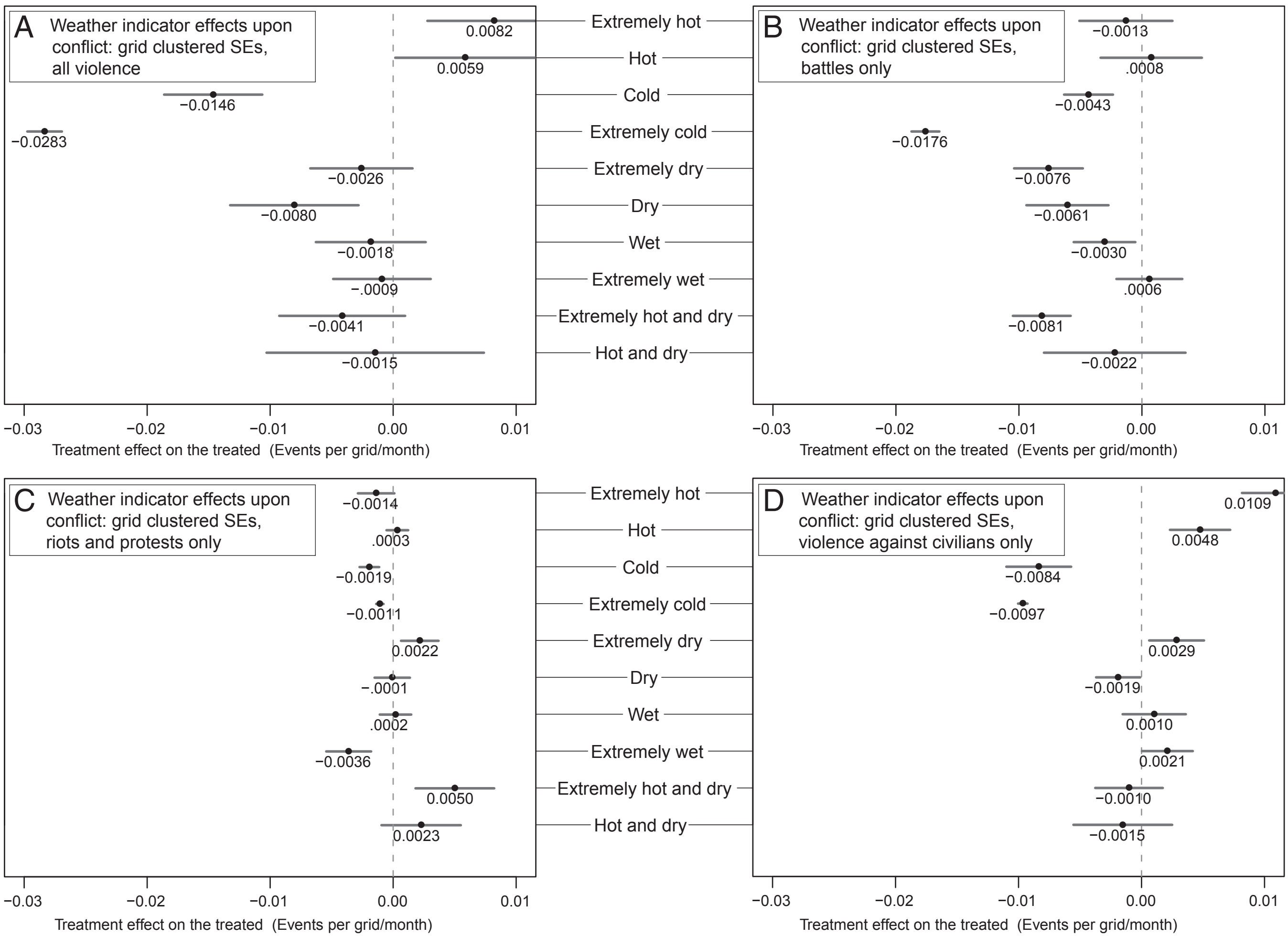
In the following section, we report our findings in three analytical sections, using a quasiexperimental approach, a within–between effects multilevel model, and a comparative method to gauge the improvement that each predictor makes in our ability to predict the location and timing of violent events in Africa. Data sources and robustness checks are presented in *SI Text*.

Results

In Fig. 1, we map the spatial distribution of key violence data together with temperature anomalies [6-mo temperature index (TI6)] and 6-mo precipitation anomalies [standard precipitation index (SPI6)] for the study area. The sum of violent events by grid over the 33-y study period, 1980–2012, is shown in Fig. 1*A* with the increasing size of the cartographic breaks reflecting the highly skewed distribution of these data. We use the Armed Conflict Location and Event Dataset (ACLED), based on media reports (32), for our analysis. In *SI Text*, we also compare our results in a robustness check to the Uppsala Conflict Data Program Georeferenced Event Data (33) for the limited period (1989–2010) where these data are available. Fig. 1 *B* and *C* show the spatial distribution of hot and dry grid-months using a value of 1 SD to define these thresholds. Our climatological data are from the University of East Anglia Climate Research Unit (34). Assuming a normal data distribution, we normalize these observed counts by the expected number of dry and hot grid-months. Thus, grids with an observed-to-expected ratio of 2 had twice as many hot or dry months than expected. The maps clearly show that, during the last 33 y, most of sub-Saharan Africa has been much warmer than expected compared with long-term trends (Fig. 1*B*) and many parts (e.g., the Sahel and southern Africa) have been dryer than usual (Fig. 1*C*).

To isolate and comparatively assess the effects of climate variability on violence, all of our models incorporate important social, political, and economic indicators that have been associated with violence in previous conflict studies research (see Table S1 for data sources, spatial and temporal resolutions, and aggregation rules; see Table S2 for summary statistics). All data are measured with a temporal lag so that the reported results are not biased by endogeneity between key indicators and conflict as an outcome.

Using a quasiexperimental matching analysis, we examine temperature and rainfall anomalies in relation to the specific political–economic settings and we can determine whether climate conditions are associated with variation in the level of violence observed across the continent. We use coarsened exact matching (CEM) (35) to drop outlying observations for key social indicators in the quasiexperimental analysis data. Our goal is to evaluate a treatment effect (TE) of climate variability after controlling for alternative economic and political explanations of conflict occurrence. We also present the simple differences in the average conflict event counts for each treatment condition (Table S3). In Fig. 2, we report the TE estimates and balance improvement statistics (*E*, *Bottom*). For each temperature and precipitation TE estimate, we control for the possible influences of the other climate indicator (e.g., the extremely dry precipitation TE is measured after controlling for temperature). We define extreme values as ±2 SD of the long-term values (Fig. S3 shows the maps for extremely dry, SPI6 ≤ -2, and extremely hot



E

Extremely hot: N = 336573; L1 = 0.991; LCS = 0.626
Hot: N = 642312; L1 = 0.959; LCS = 2.558
Cold: N = 357841; L1 = 0.991; LCS = 0.676
Extremely cold: N = 85066; L1 = 0.999; LCS = 0.072
Extremely dry: N = 324838; L1 = 0.994; LCS = 0.539
Dry: N = 574333; L1 = 0.968; LCS = 2.539
Wet: N = 529956; L1 = 0.979; LCS = 1.804
Extremely wet: N = 223112; L1 = 0.997; LCS = 0.299
Extremely hot and dry: N = 155554; L1 = 0.992; LCS = 0.476
Hot and dry: N = 618948; L1 = 0.847; LCS = 10.110

Fig. 2. Coarsened exact matching treatment effects (CEM TE) results for the effect of climate variability on conflict in sub-Saharan Africa, 1980–2012. See Table S1 for listing of controls and maps (Fig. S3) of binary climatological conditions. The relationship is only statistically significant when the 95% confidence interval (gray horizontal line) does not overlap the vertical dashed line representing no effect. (*A*) Climate variability effects for all types of violence. (*B*–*D*) Effects for the subsets of violence, battles, riots and protests, and violence against civilians, respectively.

grid months, TI6 ≥ 2), but we also report smaller extremes with the effects for ± 1 SD indicated.

The TE estimates indicate that extremely high temperatures increase the level of conflict. TE is interpreted as the change in number of events per grid-month that can be attributed to the corresponding climate indicator (for extremely high temperatures, the value is 0.008 greater events). Colder anomalies are associated with dramatically reduced levels of conflict (0.028 fewer events). Our precipitation result suggests that dry conditions reduce the level of conflict (0.008 fewer events). In Fig. 2 *B*–*D*, we compare the effects of these indicators across different types of conflict because climate anomalies are not expected to influence all forms of violence equally. The additional models show that the main high temperature result (Fig. 2*A*) is driven primarily by the effect for violence against civilians (Fig. 2*D*), and the relationship does not emerge for any of the other forms of violence in our database. This is a noteworthy result considering that existing studies [e.g., Hsiang et al. (3)] have been based on a problematic conflation of dramatically varying forms of violence. Violence against civilians may drive the high temperature effect because, at the fine spatial and temporal resolution that we use, responses to weather stress are likely to be immediate rather than long term in their scope. Such conflict would be characterized by loose organizational structure (not interactions between two armed actors, or "battles") and may involve land seizures or cattle-raiding activity rather than cohesive (e.g., rebel group) actor formation and organized warfare (e.g., against a government), qualities that characterize civil-war definitions of conflict used in other studies (as in ref. 7).

Dry precipitation anomalies have the effect of reducing the number of violent events between two armed actors (Fig. 2*B*) and in the main model (Fig. 2*A*), but extremely dry conditions increase the observed level of rioting (Fig. 2*C*) and violence against civilians (Fig. 2*D*). In a similarly inconsistent conclusion that further illustrates the importance of disaggregating violence, the combined effect of extremely dry and extremely hot conditions reduces the number of observed battle events (Fig. 2*B*) but elevates the prevalence of rioting and protesting (Fig. 2*C*).

Table 1. Poisson within–between multilevel model–random effects (MLM-RE) of the influences of violence in sub-Saharan Africa, 1980–2012

	(*i*) Null model		(*ii*) With predictors		
	Estimate	SE	Estimate	SE	
Fixed part					
Constant	−2.597	0.208**	−13.262	1.922	**
Events space–time lag			0.184	0.052	**
Precipitation (SPI6), B			2.099	1.648	
Precipitation (SPI6), W			0.025	0.026	
Temperature (TI6), B			−0.344	1.365	
Temperature (TI6), W			0.102	0.042	*
Population (ln), B			0.708	0.121	**
Population (ln), W			0.760	0.135	**
Well-being (IMR lag), B			0.310	0.195	
Well-being (IMR lag), W			0.255	0.133	
Political rights (lag), B			0.101	0.163	
Political rights (lag), W			0.302	0.115	**
Ethnic leadership			0.069	0.190	
Presidential election buffer			0.112	0.113	
Capital city grid cell			1.110	0.376	**
Distance to border (ln)			−0.128	0.119	
Distance to road (ln)			−0.112	0.117	
Nonviolence media trend (ln)			0.342	0.077	**
Random part					
Country level σ^2	2.011		0.699		
Model diagnostic					
AUC	0.738		0.852		

Poisson models are used for the discrete event data counts; *SI Text* reports simple linear estimates. Number of observations (grid-months) = 814,490. Random-effect intercepts are not reported for 42 countries. AUC, area under the receiver operator characteristic curve; SE, bootstrap SEs with 100 hierarchical resamples. $^{**}P < 0.01$, $^{*}P < 0.05$. B, between grids; W, within grid. σ^2 is variance.

We also aim to advance the current understanding of how climate and conflict operate alongside other characteristics of social settings by following the multilevel modeling approach (MLM) recently published by Bell and Jones (36). For time-variant explanatory variables, this approach separates out within-unit and between-unit variance to allow a more nuanced explanation of the predictor's effect. For instance, in considering the effect of temperature anomalies on violence, we would like to know if there is a relationship due to a grid cell being consistently hotter than other cells (1980–2012 grid mean compared with its climatological mean, 1949–2012, the between effect), and/or if the effect is due to increasing temperatures within that grid cell (the within effect). For each time-variant indicator, we calculate a grid mean to extract the between-unit variance and then subtract this mean from the original value to generate the demeaned (within) variance. Although researchers often prefer observation unit fixed effects in statistical analysis (controlling away all unknown influences upon the outcome of interest), we select a multilevel model that retains all variables of interest.

While the grid means for the temperature and precipitation anomalies are close to zero in our data, there is sufficient variation to warrant their inclusion in the model (see maps and distributions in Figs. S1 and S2). With the geographic cells as the first level, the second level for our MLM–random effects (MLM-RE) model is the country. To improve ease of model estimation, the infant mortality rates were rescaled to mean 0 and SD 1.

Our overall conclusion from the MLM-RE analysis is that climate variability effects are either absent or are quite specific to higher temperatures over time in an area (within effects) (Table 1). No between grids effect is significant but hotter periods for a given geographic cell are associated with a higher risk of violence. For every 1 SD increase in temperature, we expect an increase of 0.102 violent events, corresponding to a 10.7% increase in the level of violence. We find no statistically significant influence of SPI6 (precipitation measure) upon conflict, either as a between or within effect. Stated another way, cells that are wetter or drier than their long-term means are neither more or less likely to experience a greater number of violent events, and dry and wet periods within a grid cell are also not associated with a change in violence risk. Recent nearby political violence (space–time lag) is a strong indicator of violence in a given cell location, predicting 0.184 more violent events in an area (for each unit increase in neighboring violence in the previous month, a 20.2% increase in violence is predicted). Similarly, those areas in less democratic states (higher value for political rights indicator) experience more violence. Cells that include national capitals experience a greater risk of violence than other regions of the country. Table 1 also reports the null model, with no predictors, to show how much the country-level variance is reduced after adding the explanatory variables to the model.

We explore the robustness of these results by using a linear functional form (Fig. S4 and Table S4), by testing ACLED violent event subsets (i.e., riots/protest, violence against civilians, and battles; Table S5, models *i–iii*), and by testing with the independently coded Uppsala Conflict Data Program Georeferenced Event Data (UCDP-GED) violent event dataset (Table S5, models *iv* and *v*). These checks reveal that the temperature effect is not consistently robust to the alternate ACLED data specifications. To see whether any particular region is driving the relationships we observe, we divide sub-Saharan Africa into geographical regions (Fig. S5) and find that of the five regional subdivisions, the temperature effect is statistically significant only for the Sahel region (Table S6). This result suggests that temperature anomalies in the Sahel region are driving the overall continent-wide relationship. We also test an alternate governance indicator [Polity (37)] and nonlinear governance effects, with little impact to the model (Table S7).

Predictive power analysis allows us to present improvements in the in-sample predictive power of the model as we systematically exclude each indicator in turn (38). Instead of using SEs (the usual metric) to judge the importance of a given predictor, this approach shows the relative predictive capability of each variable to explain violence. We plot the level of significance (absolute *z* value) of each indicator on the horizontal axis against the effect that the indicator has on the ability of our model to accurately predict conflict events on the vertical axis. Indicators near the zero dashed line have little influence on our ability to predict the timing and location of violence, whereas variables above the line improve the accuracy of conflict predictions.

From Fig. 3, we conclude that existing conflict in neighboring areas (time–space lag), socioeconomic well-being (within cell effect), distance to national borders, capital city location, and political rights (within-cell effect) are all better predictors of observed conflict levels than either of the climate variability measures, temperature or precipitation. Although changing temperature (TI6, within-cell effect) has a larger *z* score than roughly one-half of the other variables, it lies very near the zero line, indicating that it provides little improvement in the predictive power of the model.

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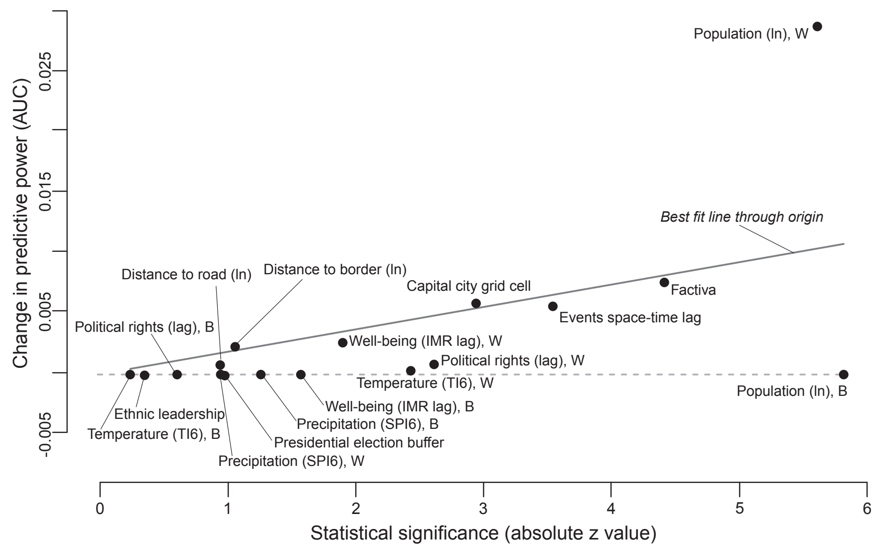

Fig. 3. In-sample predictive power plot of the violent event count Poisson MLM-RE model for sub-Saharan Africa, 1980–2012. The predictive contribution of each variable is quantified using the area under the (receiver operator characteristic) curve (AUC) metric, which plots the false-positive rate against the true-positive predictions of conflict for thresholds from 0.0 to 1.0, modified for our count data by truncating predicted values above 1. Figure contains the same predictors as the full model in Table 1. B, between grids; W, within grid.

Whether or not an area experienced precipitation anomalies (SPI6) has little value for understanding where and when conflict takes place compared with other alternative explanations of conflict. These general findings are confirmed for a linear functional form of the relationships (Table S4 and Fig. S4).

Discussion

Our analysis supports a link between temperature extremes and conflict in sub-Saharan Africa between 1980 and 2012. We find that higher temperatures have the effect of increasing the level of observed conflict in a quasiexperimental research design. Our hierarchical model also provides evidence of a temperature effect for localities over time. However, in our predictive power analysis, higher temperature deviations from long-term means do not contribute much to our understanding of elevated conflict risk across space and time compared with some socioeconomic and political considerations.

Each of these conclusions comes with important caveats. Compared with other world regions, sub-Saharan Africa has low standards of living, poor governance, and enduring legacies of severe large-scale violence. Generalizing from our work (which examines a vulnerable region) to more stable regions may reveal even weaker climate variability effects, as was already noted in Asia (15). Our treatment effect estimates of temperature are also not consistent across different forms of political violence; for example, a high temperature change will not affect confrontations between two armed actors (e.g., military and rebel forces) in the same way that it will affect violence in the form of rioting and protesting. Our regression analysis estimates indicating that high temperature anomalies raise the risk of violence are also inconsistent among geographic regions of Africa, holding only for the Sahel region. Finally, although our knowledge of temperature variability may improve predictions of when and where conflict risk is raised, other social, political, and economic forces help us predict conflict occurrences much more effectively.

Methods

We prefer the CEM procedure among matching analysis options because imbalance between treatment and control groups of observations is optimized without the need to check a diagnostic statistic of the matched dataset balance (35). We assign observations to treatment and control groups using the values for each of the key social and political indicators that may influence conflict. Details of the CEM algorithm are provided by Iacus et al. (35). After matching, we estimate sample average treatment effect on the treated (SATT) (TE above) to see how key climate anomalies influence conflict levels. For SPI6 and TI6, binary treatment designations are −2, −1, +1, and +2 SDs. SATT is estimated as a linear model of violent event counts/month. Outcome $Y_i = T_i Y_i(1) + (1 - T_i) Y_i(0)$, where $Y_i(0)$ is the potential outcome for control observation *i*, $Y_i(1)$ is the potential outcome if the same unit (*i*) were treated, and T_i is the treatment status of an observation. We cannot observe $Y_i(0)$ with treatment for *i*, and similarly, $Y_i(1)$ is not known if *i* is not treated. The final estimate of $TE_i = Y_i(1) - Y_i(0)$, which across observations is $SATT = (1/n_T)\sum_{i \in \{T_i = 1\}} TE_i$. We report the SATT point estimate and each associated *P* value. We cluster SEs in the SATT estimation at the grid level.

We use maximum-likelihood estimation to fit a generalized linear MLM using a Poisson functional form and log link. The model uses a within–between formulation: $Y_{ij} = \beta_0 + \beta_1(x_{ij} - \overline{x}_j) + \beta_2 \overline{x}_j + \beta_3 z_{ij} + \alpha_s + \varepsilon_{ij}$, where β_0 is the constant, β_1 are the within effect coefficients for the demeaned variables, β_2 are the between effects of x_{ij}, and β_3 are the coefficients for the time-invariant predictors z_{ij} (36). The term α_s allows for differential country-level intercepts with the remaining unexplained error captured by ε_{ij}. Given the large *N* of our models, the usual SEs are underestimated. Because robust clustered SEs are typically not used with multilevel models, we instead rely on bootstrapped SEs. The multilevel structure of our data calls for a hierarchical resampling approach that mimics the data-generating process as closely as possible (39). We achieve this by sampling with replacement for the country level first, then grid cell level, and then monthly level.

Data

Table S1 describes predictors and outcomes and indicates their source material. Descriptive statistics for the data are presented in Table S2. Our 0.5° × 0.5° monthly climatological measures are Climate Research Unit TS3.10 data from the University of East Anglia Climate Research Unit (34). We convert these precipitation and temperature data to anomaly indices for each 1° grid-month by comparing the most recent 6 mo to the long-term record (1949–2012) for those same 6 mo and grid location. For rainfall, this metric is the SPI6, where an SPI6 value of −1 indicates the past 6 mo are 1 SD drier than usual. Regions are considered to be in drought when values fall below −1, and are considered severely dry below −1.5, and extremely dry below −2. The SPI6 value is transformed using an incomplete γ distribution such that the SPI6 values can be interpreted as SDs from the mean (40). The TI6 is calculated in a similar manner to SPI6, but relies on the standard normal distribution because temperature distributions are not skewed in the same way as precipitation values. Normalizing the data in this way allows us to directly compare temperature and precipitation anomalies for regions characterized by starkly different climates and ecosystems.

Violent events are from a version of the ACLED project (32) extended backward from 1997 to 1980. Each event is recorded with location coordinates, date, and actors involved, as well as the type of incident (e.g., violence against unarmed civilians or rioting). Our analysis is based on 72,451 conflict events across the 42 countries of sub-Saharan Africa. Note that Eritrea is coded as an independent country starting in June 1993, and South Sudan is marked as independent starting July 2011. Some of the locational trends in violence are expected (Fig. 1), including the clustering of violence in Rwanda and Burundi (genocide and civil war, respectively), West Africa (civil and regional wars in the early and mid-1990s), northern Uganda (Lord's Resistance Army violence), and Somalia (a major rise in conflict after 2007). We compared our results in a robustness check to the UCDP-GED (33) for the more limited period (1989–2010) for which the UCDP-GED data are available.

Our population data are derived from the Center for International Earth Science Information Network GPWv3 database and interpolated yearly from the given 5-y interval data (41). We account for accessibility-related influences on conflict (main roads are often the target of rebel activity) by measuring the average distance of 10-km grid cells (aggregated to our 1° unit of analysis) to primary and secondary roads (42). Because the capital city of a country is typically the center of political activity, including protests against the government, we account for this factor by coding grid cells that include capital cities. Violent conflict is known to exhibit spatial dependency (nearby units of analysis have similar values) within and across borders. To account for prior and nearby conflict, we include the mean number of events within a first-order queen contiguity matrix, lagged 1 mo. During electoral campaigns in African countries, the political climate of a country is likely to become tense as unrest often emerges during these periods. We use a binary indicator for all cells in a country if a national presidential election took place within a 3-mo window before and after the election (coded as 1) to see whether it is associated with a possible increased risk of violence. As a surrogate for socioeconomic well-being, we use the infant mortality rate (IMR) (infant deaths under 1 y old per 1,000 live births) at the country level, lagged 1 y (43). Regime type (accounting for the kind of institutional response that a government is likely to use) may play an important role in conflict dynamics, and we use data from Freedom House to capture the effects of formal political institutions, lagged 1 y (44). We also use an alternative measure of governance from Polity (37). We measure distance to national borders for every 1° grid cell by calculating grid means from a 10-km subgrid of distance to the closest international boundary. This metric captures the greater level of violence seen in border areas of sub-Saharan Africa compared with other regions.

We combine two data sources to determine whether an area (grid cell) can be considered excluded from power within a system of ethnic patronage, a political style that dominates African politics. We match Archigos for leadership of countries over time, coded by the ethnicity of the leader (45), with Ethnologue (46) for a spatial representation of language/ethnic groups across the continent that are assigned to the grid cells. Finally, because we know that the availability of media reporting of African events has increased over time due to the greater use of electronic information gathering, we add a country-specific media coverage index for each year. This variable is generated using aggregated counts of all documents returned in Factiva searches for non–conflict-related events (details in *SI Text*).

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1. Miguel E, Satyanath S, Sergenti E (2004) Economic shocks and civil conflict: An instrumental variables approach. *J Polit Econ* 112(4):725–753.
2. Field CB, et al., eds (2014) *Climate Change 2014: Impacts, Adaptation, and Vulnerability* (Cambridge Univ Press, New York).
3. Hsiang SM, Burke M, Miguel E (2013) Quantifying the influence of climate on human conflict. *Science* 341(6151):1235367.
4. Hsiang SM, Burke M (2013) Climate, conflict and social stability: What does the evidence say? *Clim Change* 123(1):39–55.
5. Hsiang SM, Meng KC, Cane MA (2011) Civil conflicts are associated with the global climate. *Nature* 476(7361):438–441.
6. Hendrix CS, Glaser SM (2007) Trends and triggers: Climate change and civil conflict in Sub-Saharan Africa. *Polit Geogr* 26(6):695–715.
7. Burke MB, Miguel E, Satyanath S, Dykema JA, Lobell DB (2009) Warming increases the risk of civil war in Africa. *Proc Natl Acad Sci USA* 106(49):20670–20674.
8. Hendrix CS, Saleyhan I (2012) Climate change, rainfall, and social conflict in Africa. *J Peace Res* 49(1):35–50.
9. Landis ST (2014) Temperature seasonality and violent conflict: The inconsistencies of a warming planet. *J Peace Res* 51(5):603–618.
10. Buhaug H (2010) Climate not to blame for African civil wars. *Proc Natl Acad Sci USA* 107(38):16477–16482.
11. Koubi V, Bernauer T, Kalbhenn A, Spilker G (2012) Climate variability, economic growth, and civil conflict. *J Peace Res* 49(1):113–127.
12. Bergholt D, Lujala P (2012) Climate-related natural disasters, economic growth, and armed civil conflict. *J Peace Res* 49(1):147–162.
13. O'Loughlin J, et al. (2012) Climate variability and conflict risk in East Africa, 1990–2009. *Proc Natl Acad Sci USA* 109(45):18344–18349.
14. Raleigh C, Kniveton D (2012) Come rain or shine: An analysis of conflict and climate variability in East Africa. *J Peace Res* 49(1):51–64.
15. Wischnath G, Buhaug H (2014) On climate variability and civil war in Asia. *Clim Change* 122(4):709–721.
16. Sterzel T, et al. (2014) Armed conflict distribution in global drylands through the lens of a typology of socio-ecological vulnerability. *Reg Environ Change* 14(4):1419–1435.
17. Salehyan I, Hendrix CS (2014) Climate shocks and political violence. *Glob Environ Change* 28:239–240.
18. Buhaug H, et al. (2014) One effect to rule them all? A comment on climate and conflict. *Clim Change,* 10.1007/s10584-014-1266-1.
19. O'Loughlin J, Linke AM, Witmer FD (2014) Modeling and data choices sway conclusions about climate-conflict links. *Proc Natl Acad Sci USA* 111(6):2054–2055.
20. Raleigh C, Linke AM, O'Loughlin J (2014) Extreme temperatures and violence. *Nat Clim Chang* 4(2):76–77.
21. O'Brien K, Eriksen S, Nygaard LP, Schjolden A (2007) Why different interpretations of vulnerability matter in climate change discourses. *Clim Policy* 7(1):73–88.
22. Homer-Dixon T (1999) *Environment, Scarcity, and Violence* (Princeton Univ Press, Princeton).
23. Kahl C (2006) *States, Scarcity, and Civil Strife in the Developing World* (Princeton Univ Press, Princeton).
24. Turner M (2004) Political ecology and the moral dimensions of "resource conflicts": The case of farmer-herder conflicts in the Sahel. *Polit Geogr* 23(7):863–889.
25. Benjaminsen TA, Alinon K, Buhaug H, Buseth JT (2012) Does climate change drive land-use conflicts in the Sahel? *J Peace Res* 49(1):97–111.
26. Adano WR, Deitz T, Witsenburg K, Zaal AFM (2012) Climate change, violent conflict and local institutions in Kenya's drylands. *J Peace Res* 49(1):65–80.
27. Witsenburg KM, Zaal AFM (2012) *Spaces of Insecurity: Human Agency in Violent Conflicts in Kenya* (African Studies Centre, Leiden, The Netherlands).
28. Maystadt J-F, Ecker O (2014) Extreme weather and civil war: Does drought fuel conflict in Somalia through livestock price shocks?. *Am J Agr Econ* 96(4):1157–1182.
29. Theisen OM, Holtermann H, Buhaug H (2012) Climate wars? Assessing the claim that drought breeds conflict. *Int Secur* 36(3):79–106.
30. Fjelde H, von Uexkull N (2012) Climate triggers: Rainfall anomalies, vulnerability and communal conflict in sub-Saharan Africa. *Polit Geogr* 31(7):444–453.
31. Greiner C (2013) Guns, land, and votes: Cattle rustling and the politics of boundary-re(making) in northern Kenya. *Afr Aff (Lond)* 112(447):216–237.
32. Raleigh C, Linke AM, Hegre H, Karleson J (2010) Introducing ACLED: An armed conflict location and event dataset. *J Peace Res* 47(5):651–660.
33. Sundberg R, Melander E (2013) Introducing the UCDP georeferenced event dataset. *J Peace Res* 50(4):523–532.
34. Harris I, Jones PD, Osborn TJ, Lister DH (2014) Updated high-resolution grids of monthly climate observations—the CRU TS3.10 dataset. *Int J Climatol* 34(3):623–642.
35. Iacus SM, King G, Porro G (2012) Causal inference without balance checking: Coarsened exact matching. *Polit Anal* 20(1):1–24.
36. Bell A, Jones K (2015) Explaining fixed effects: Random effects modelling of time-series cross-sectional and panel data. *Polit Sci Res Methods*, 10.1017/psrm.2014.7.
37. Polity IV Project (2010) Polity IV dataset and codebook. Available at www.systemicpeace.org/. Accessed September 12, 2014.
38. Ward M, Greenhill B, Bakke K (2010) The perils of policy by p-value: Predicting civil conflicts. *J Peace Res* 47(4):363–375.
39. Davison AC, Hinkley DV (1997) *Bootstrap Methods and their Application* (Cambridge Univ Press, Cambridge, UK).
40. McKee TB, Doesken NJ, Kliest J (1993) The relationship of drought frequency and duration to time scales. *Proceedings of the Eighth Conference of Applied Climatology* (American Meteorological Society, Boston), pp 179–184.
41. Center for International Earth Science Information Network (2013) *Gridded Population of the World*. Available at sedac.ciesin.columbia.edu/gpw/index.jsp. Accessed September 23, 2013.
42. Danko D (1992) The digital chart of the world project. *Photogramm Eng Remote Sensing* 58(8):1125–1128.
43. United Nations (2013) *World Population Prospects: The 2012 Revision* (United Nations, Department of Economic and Social Affairs, Population Division, New York).
44. Freedom House (2013) *Freedom in the World.* Available at freedomhouse.org. Accessed October 30, 2013.
45. Goemans HE, Gleditsch KS, Chiozza G (2009) Introducing Archigos: A dataset of political leaders. *J Peace Res* 46(2):269–283.
46. WLMS (2010) *World Language Mapping System. Ethnologue Global Spatial Representation of Ethnic Groups.* Available at worldgeodatasets.com/language/. Accessed May 29, 2010.