PNAS

Climate variability and conflict risk in East Africa, 1990–2009

John O'Loughlin[a,1], Frank D. W. Witmer[a], Andrew M. Linke[a], Arlene Laing[b], Andrew Gettelman[c], and Jimy Dudhia[b]

[a]Institute of Behavioral Science and Department of Geography, University of Colorado, Boulder, CO 80309-0483; [b]Mesoscale and Microscale Meteorology Division, National Center for Atmospheric Research, Boulder, CO 80307-3000; and [c]Climate and Global Dynamics Division, National Center for Atmospheric Research, Boulder, CO 80307-3000

Edited* by B. L. Turner, Arizona State University, Tempe, AZ, and approved September 11, 2012 (received for review March 27, 2012)

Recent studies concerning the possible relationship between climate trends and the risks of violent conflict have yielded contradictory results, partly because of choices of conflict measures and modeling design. In this study, we examine climate–conflict relationships using a geographically disaggregated approach. We consider the effects of climate change to be both local and national in character, and we use a conflict database that contains 16,359 individual geolocated violent events for East Africa from 1990 to 2009. Unlike previous studies that relied exclusively on political and economic controls, we analyze the many geographical factors that have been shown to be important in understanding the distribution and causes of violence while also considering yearly and country fixed effects. For our main climate indicators at gridded 1° resolution (∼100 km), wetter deviations from the precipitation norms decrease the risk of violence, whereas drier and normal periods show no effects. The relationship between temperature and conflict shows that much warmer than normal temperatures raise the risk of violence, whereas average and cooler temperatures have no effect. These precipitation and temperature effects are statistically significant but have modest influence in terms of predictive power in a model with political, economic, and physical geographic predictors. Large variations in the climate–conflict relationships are evident between the nine countries of the study region and across time periods.

social instability | standard precipitation index | generalized additive modeling | negative binomial modeling | disaggregated spatial analysis

The debates in both the academic and policy realms surrounding a possible association between climate change and violent conflict continue without much resolution. The tone of the consensus emerging from politicians and the policy-making community is decidedly gloomy. US President Barack Obama recently declared that climate change represents an "urgent, serious, and growing threat" (1), because the stresses of frequent drought and crop failures "breed hunger and conflict" (2). Government-associated think tanks follow closely to this line, with ecological stress and climate change generating a "range of security problems that will have dire global consequences" (3), according to a Center for Strategic and International Studies report (3). Such claims are predicated on a national security paradigm: the ability of societies in nonindustrialized regions of the world to cope with ecological change can jeopardize the stability of the international system and rebound adversely to wealthy countries. Although they receive significant public and policy attention, such reports are marked by speculation and lack strong empirical support.

Two main bodies of academic research address the climate–conflict nexus. The first body claims a positive link between scarcity and violence (4–8), making the case that shortages—food, water, or crop imports—introduce stress on formal and informal social institutions. In one rendering, these associations purportedly operate through an economic mechanism, where rainfall deficits negatively affect earnings in predominantly agricultural societies (9). Where such changes take place, the gains associated with participation in armed expressions of grievance outweigh the costs. Proponents of this viewpoint have a receptive audience within policy-making communities. A conclusion in this research cluster suggests that both dry (slow onset) and wet (fast onset) precipitation extremes are associated with increased risk of social conflict (10).

Researchers who question any consistent connection between the climate change and violent conflict may be classified into two distinct groups. Relying on quantitative analysis of climate and subnational conflict data, recent work has illustrated either a null (nonsignificant) or negative relationship between scarcity and conflict (11, 12). Considering the specific locations of conflicts, disaggregated analysis moves beyond crude understandings of conflict that follow the country-year unit of analysis common in international relations, where conflict is coded in binary (one or zero) terms for the entire territory of a country and a complete 1 y. The coarse resolution of the country-year approach cannot capture the dramatic location-specific differences that characterize political violence across a country (13, 14); configuring statistical models to include subnational locations has called these country-level findings into question (12).

A second set of studies that questions the climate change–conflict nexus emerges from the political ecology tradition, especially in human geography; it often adopts an ethnographic character, and it is conducted with an emphasis on local-level power dynamics (15–17). In this perspective, individual communities are unique, and place-specific experiences are each rooted in particular historical trajectories that cannot be easily quantified. Power relationships that distort the management of public resources are cited as the true foundation of "resource conflicts" in West Africa's Sahel (18).

Sweeping generalizations have undermined a genuine understanding of any climate–conflict link, whereas cumulative results from the numerous studies of individual communities are difficult to summarize. Our work extends the quantitative approach with close attention to local and temporal differences in climate and conflict by examining nine countries in the Horn and Eastern regions of Africa between 1990 and 2009 (Fig. S1). These countries represent substantial variation across climate regimens, recent conflict experience (Fig. S2), and political systems, and these variations help to support generalization about conflict in sub-Saharan Africa and consideration of regional–local nuances. We recognize that our ability to generalize is limited; across the continent, complexity characterizes the institutional capacity to adapt to social pressures. An example of the type of climate–conflict relationship that we examine is found in our conflict data. On July 3, 2004, over 100 farmers' homes in Tanzania's Arusha District (Themi area) were burned by herders who have been pushing authorities for years to turn the land into grazing area. Such a link between violence and resource availability may be an outcome of climate change on livelihoods in

Author contributions: J.O., F.D.W.W., A.M.L., A.L., A.G., and J.D. designed research; J.O., F.D.W.W., A.M.L., and A.L. analyzed data; J.O., and F.D.W.W., A.M.L., and A.L. wrote the paper.

The authors declare no conflict of interest.

*This Direct Submission article had a prearranged editor.

Freely available online through the PNAS open access option.

Data deposition: The replication data and files reported in this paper are available on the University of Colorado website (www.colorado.edu/ibs/climateconflict/PNAS).

[1]To whom correspondence should be addressed. E-mail: johno@colorado.edu.

This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1205130109/-/DCSupplemental.

sub-Saharan Africa, but the event must be analyzed in the context of political, social, economic, and geographic considerations, variables that are often ignored as key controls. By doing so, we address a common complaint leveled by social scientists against the existing conflict–climate literature that finds associations but does not consider other explanations.

Using a 1° gridded analysis (402 grids), we estimate the influence of 6-mo deviations in rainfall [standard precipitation index (SPI6)] and temperatures [temperature index (TI6)] from long-term averages (Figs. S3 and S4) on levels of violence. We use the Armed Conflict Location and Event Dataset (ACLED) (19) to capture the nuances of violence beyond the confines of a civil war (rebel vs. government logic), and we use multiple measures of violence beyond the often used binary measure that indicates simplistically whether a country suffers violence. Our estimation procedure accommodates both the known spatial interdependence of observations and the possible nonlinear relationship between climate measures and conflict. Through myriad robustness checks, including the use of a more conservative definition of violence (20) and multiple climate indicators (*SI Text*), our findings question the most simplistic climate–conflict narratives. The relationships between rainfall and temperature variability and violence are complex and warrant careful interpretation.

Results

For East Africa from 1991 to 2009, a simple generalized linear model (GLM) shows no statistically significant relationship between precipitation anomalies and conflict after controlling for socioeconomic and physiographic factors (Table S1) and country and year fixed effects (Table 1, column a). All of the statistically significant nonclimate variables match our expectations for predicting violence. (Because we lag some variables, data for 1990 are not modeled.) We also explore the climate anomaly effects by creating binary versions of SPI6 and TI6 using a threshold of $\pm 1\sigma$. Results for SPI6 (Table 1, columns b and c) show only a statistically significant effect for unusually wet periods; when rainfall is higher by more than 1σ of the historical average for the same months, we find a reduction in the risk of conflict ($e^{-0.205} = 0.815$ relative risk ratio) after controlling for influential social, geographic, and political factors (Table 1, column c). Although we have a regional (rather than global or continental) focus, this finding about rainfall stands in contrast to the thrust of some existing research (10, 21).

Our initial results for temperature deviations in the GLM model also do not conform to findings that hold that warming increases conflict (6). TI6 results (Table 1, columns d and e) are not statistically significant in the basic GLM binary model. To capture any possible coefficient variations over the variable range, we allow the estimates to vary in a generalized additive model (GAM). Both climate anomaly variables significantly affect the risk of conflict in this functional form (Table 1, column f) but to a varying degree depending on the severity of the anomaly (Fig. 1).

Fig. 1 shows the coefficient estimates for a given weather condition; thus, for periods wetter than usual (SPI6 = +2), the coefficient estimate predicts less violent conflict by about −0.3 logged events, which corresponds to a relative risk ratio of 0.74

Table 1. Negative binomial regression models for total number of violent events per grid cell, 1991–2009

	a) GLM socioeconomic, physical, and climate		b) SPI6 binary dry (≤−1 σ)		c) SPI6 binary wet (≥1 σ)		d) TI6 binary hot (≥1 σ)		e) TI6 binary cold (≤−1 σ)		f) GAM splines	
	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value	Estimate	*z* value
Intercept	−8.196	−5.995*	−8.173	−5.982*	−8.235	−6.017*	−8.216	−6.011*	−8.228	−6.031*	−8.292	−6.029*
Space–time lag	0.524	14.917*	0.525	14.993*	0.526	14.961*	0.530	14.857*	0.532	14.822*	0.512	14.789*
Precipitation (SPI6)	−0.048	−1.558					−0.053	−1.730	−0.057	−1.832		
SPI6 dry			−0.044	−0.566								
SPI6 wet					−0.205	−2.231†						
Spline (SPI6)											*P* value	0.000*
Temperature (TI6)	0.078	1.545	0.089	1.779	0.081	1.613						
TI6 hot							0.061	0.873				
TI6 cold									0.021	0.113		
Spline (TI6)											*P* value	0.000*
Ethnic leadership	−0.334	−1.583	−0.340	−1.604	−0.337	−1.599	−0.323	−1.541	−0.314	−1.492	−0.332	−1.572
Distance to border (ln)	−0.420	−4.906*	−0.419	−4.888*	−0.419	−4.880*	−0.422	−4.923*	−0.424	−4.938*	−0.417	−4.843*
Capital city grid cell	1.636	5.666*	1.634	5.652*	1.627	5.651*	1.635	5.676*	1.632	5.672*	1.625	5.655*
Population (ln)	0.495	7.457*	0.498	7.490*	0.499	7.509*	0.494	7.453*	0.494	7.448*	0.502	7.551*
Wellbeing (IMR lag)	0.010	1.604	0.010	1.554	0.010	1.568	0.010	1.647	0.010	1.670	0.010	1.600
Political rights (lag)	0.087	1.766	0.085	1.731	0.091	1.858	0.089	1.810	0.090	1.833	0.092	1.896
Presidential election buffer	0.303	2.541†	0.287	2.414†	0.306	2.560†	0.308	2.619*	0.310	2.653*	0.325	2.715*
Grassland (%)	0.020	4.131*	0.020	4.126*	0.020	4.112*	0.020	4.148*	0.020	4.157*	0.020	4.088*
Distance to road (ln)	−0.400	−3.151*	−0.400	−3.146*	−0.400	−3.141*	−0.401	−3.150*	−0.401	−3.156*	−0.388	−3.084*
Crop production index (pct. Δ)	−0.004	−1.447	−0.004	−1.551	−0.004	−1.507	−0.004	−1.476	−0.004	−1.473	−0.004	−1.601
VCI (lag)	−0.002	−0.956	−0.002	−0.971	−0.001	−0.909	−0.001	−0.893	−0.001	−0.877	−0.002	−0.955
Log-likelihood	−25,150.6		−25,153.0		−25,146.1		−25,153.9		−25,155.0		−25,112.0	
AIC	50,395.1		50,399.9		50,386.3		50,401.9		50,404.0		50,331.7	
AUC	0.849		0.849		0.849		0.849		0.849		0.850	

Number of observations for all models is 91,656 grid months. Binary models b–d use precipitation and temperature anomalies of beyond 1 SD (σ) of the long-term mean to define binary variable. All models are estimated with year and country fixed effects (not shown). AIC, Akaike information criterion; IMR, infant mortality rate; VCI, vegetation condition index.

**P* < 0.01 using grid-clustered SEs.

†*P* < 0.05 using grid-clustered SEs.

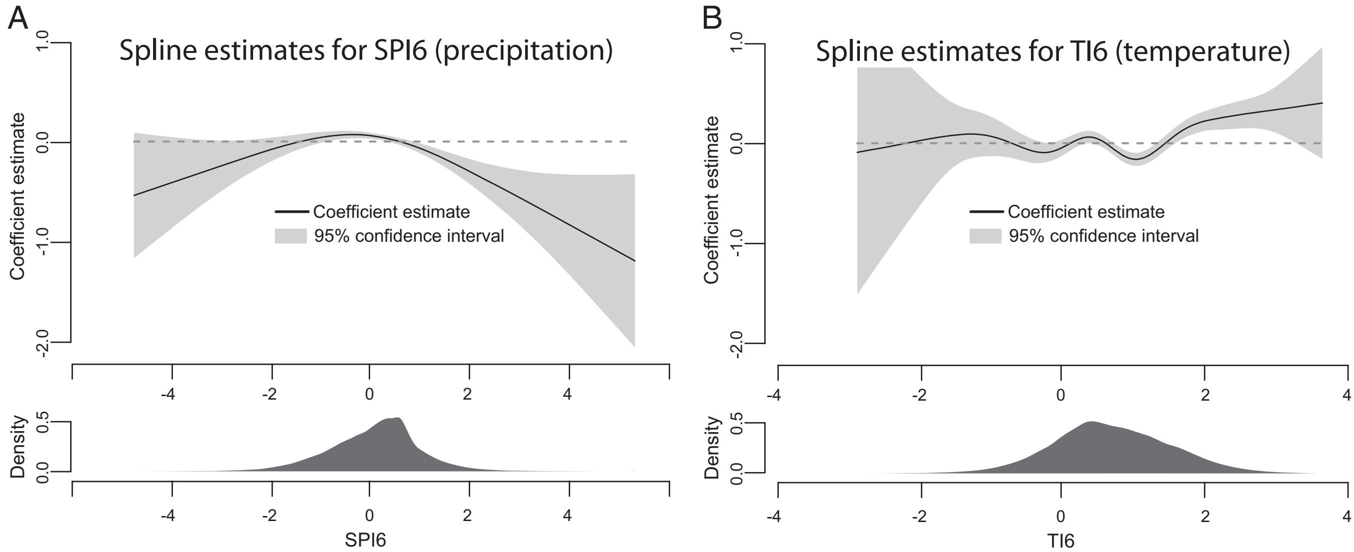

Fig. 1. These plots show the coefficient estimate and 95% confidence interval over the range of SPI6 (*A*) and TI6 (*B*) for the model in Table 1, column f. Nonoverlap between the confidence interval and dashed zero line indicates a statistically significant effect. The lower dark gray plots show the density distributions of the variable—both SPI6 and TI6 are centered right of zero, indicating that our study period is wetter and warmer than the 60-y comparison period.

(values > 1 indicate increase, and values < 1 indicate decrease). The broad effect of SPI6 on conflict forms an inverse U relationship, but the effect is only significant for unusually wet periods (Fig. 1*A*). We are particularly interested in the impact of unusually wet and dry periods on conflict compared with normal conditions. Table 2 presents the relative risk ratios with zero (normal climate conditions) as the starting point. Compared with normal conditions, the model predicts a 30.3% decrease in violent events when recent precipitation is 2σ above the long-term mean (difference for SPI6 changing from zero to two with all other factors constant).

For the temperature–conflict relationship, colder temperatures have no effect on the risk of conflict, whereas moderate increases in temperature (TI6 = 1) reduce the risk of conflict (12% decrease). Very hot temperatures increase the risk; for TI6 = 2, there is a 29.6% increase in predicted violent events compared with normal temperature conditions.

Given the very large N (91,656) of our study and despite using grid-clustered SEs, we are hesitant to rely too much on the statistical significance of our model estimates. As an alternative measure of significance, we calculate the predictive power for each variable based on the effect that each variable has on the overall prediction accuracy of the model. This area under the curve (AUC) metric is calculated based on true and false-positive prediction rates for thresholds from 0.0 to 1.0. The AUC is more commonly used for logit models (22), but we apply it to our count models by truncating predicted values above one. Fig. 2 shows the change in predictive power contributed by each variable. Population size and the space–time lag for violence stand out as contributing most to the predictive power of our model. Two variables, infant mortality and crop production, slightly reduce the model's predictive power. Because the SPI6 and TI6 climate measures have no single z value, their predictive power is plotted as a dashed line for a range of possible z values. TI6 improves the predictive power slightly (ranked seventh overall in contribution to the AUC change), whereas SPI6 is closer to zero. A key conclusion of our research is that, despite the significant relationships found in Fig. 1*A*, the actual contribution of SPI6 and TI6 to predicting violence in the study area is modest when combined with other factors.

We performed a variety of robustness tests that are reported in *SI Text*. Examination of the grid months data by the nine countries in the region and across 5-y periods shows dissimilarities in the significance of both the control and the climate variables (Figs. S5, S6, S7, and S8 and Tables S2 and S3). Both the precipitation and temperature spline plots display considerable variation in predicting violence, suggesting that the effects of these predictors are mediated by location and time period. Recognizing that we are emphasizing local climatic conditions in our models, we also examine whether larger-scale effects in the form of the El Niño–Southern Oscillation (ENSO) and Indian Ocean surface temperatures influences modify our overall conclusions. The results (Figs. S7 *G* and *H* and S8 *G* and *H* and Table S3, columns g and h) indicate that including Indian Ocean temperatures has little impact on the model; subsetting the model based on ENSO months results in less confidence in the SPI6 spline plots and a more linear TI6 relationship, with cooler than usual temperatures associated with less violence.

We also test two alternative measures of violence and a logistic regression model functional form. We subset the ACLED events classified as riots/protests and violence against civilians as a measure of lesser violence; there are some differences in coefficient SEs but little change to the climate spline plots (Figs. S9*A* and S10*A* and Table S4, column a). The ACLED logit model uses the full database with violent event counts truncated to one and yields largely similar results (Figs. S9*B* and S10*B* and Table S4, column b) to the main model.

A recently released conflict dataset from the Uppsala Conflict Data Program (20) that has independently geolocated African violence allows a helpful check on our results, although the definition of conflict is much more conservative than our definition. Using these data and both negative binomial and logit functional forms,

Table 2. Relative risk ratios for climate anomalies for Table 1, column f model

SPI6	From	To	Relative risk ratio	TI6	From	To	Relative risk ratio
Drier	0	−1	0.980	Colder	0	−1	1.100
	0	−2	0.867		0	−2	1.063
	0	−3	0.736		0	−3	0.932
	0	−4	0.621				
Wetter	0	1	0.881*	Hotter	0	1	0.880*
	0	2	0.697*		0	2	1.296*
	0	3	0.536*		0	3	1.448*
	0	4	0.408*		0	4	1.602

Values are for SPI6 and TI6 values.
*Significantly different from zero based on a 95% confidence interval (Fig. 1).

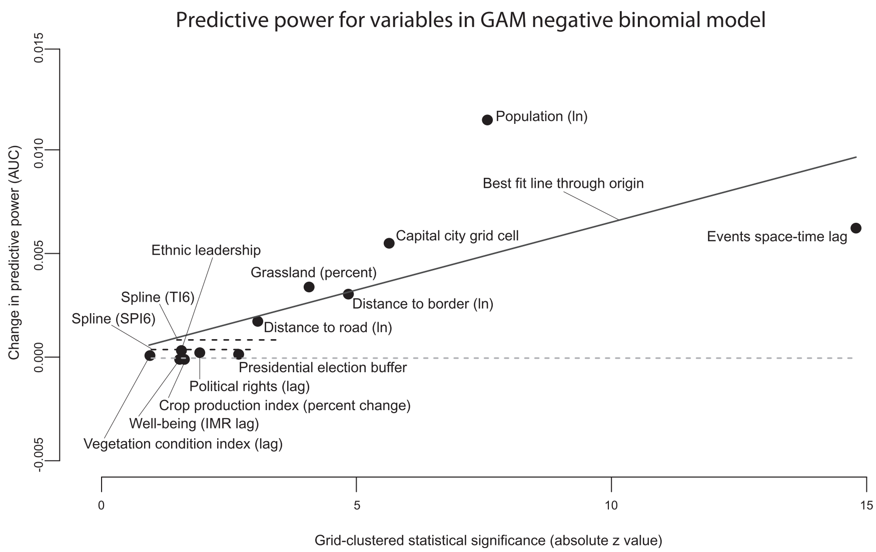

Fig. 2. Change in predictive power vs. statistical significance for the model in Table 1, column f. The positions of the predictors on the graph clearly indicate the modest contribution of the climate predictors to the model. Geographic variables (cell populations, space–time clustering effect, capital city locations, distance to international borders, grassland ratio, and distance to road) are more important in predictive power than the climate or political measures.

the temperature and precipitation variable splines retain statistical significance (Table S4, columns c and d). Fig. S9 *C and D* shows few differences for the estimation of precipitation using these data, but the effect of temperature differs substantially (Fig. S10 *C and D*), with less violence predicted for warmer temperature anomalies and more violence predicted for cooler anomalies (although this result is only statistically significant for the negative binomial version).

As another robustness check of our climate variables, we drop all control variables (Table S4, column e). The spline plot estimates for our climate coefficients change little (Figs. S9*E* and S10*E*), providing evidence that they are exogenous. Separately, we drop the space–time lag variable to little effect (Figs. S9*F* and S10*F* and Table S4, column f).

Conceptually, we might expect that the effect of climate variability on conflict may be greatest during growing seasons, but inclusion of a growing season control has little effect (Figs. S9*G* and S10*G* and Table S4, column g).

We also estimate several models with interaction terms added for political rights and ethnic leadership with both climate variables (Table S5, columns a–d). None of the interaction terms are significant or affect the climate variable spline plots (Figs. S11 *A–D* and S12 *A–D*). These results indicate that climate effects on conflict are independent of regime type and ethnic leadership as we have measured them.

We estimate models using grid fixed effects in place of country fixed effects and find few differences for the climate anomaly variables for the negative binomial fit of the models (Figs. S11 *E* and *F* and S12 *E* and *F* and Table S5, columns e and f). We also revise Table 1 using this same grid fixed effects replacement and ordinary least squares estimation (Table S6). These results challenge the effects of precipitation anomalies in predicting conflict identified in earlier models, but they provide additional support for the role of hotter than usual temperatures in predicting greater conflict (Figs. S11*G* and S12*G*). As a confirmation of the effect of very hot temperature anomalies in Fig. 1*B*, we estimate a GLM model with a very hot binary temperature variable (Table S5, column g; similar to Table 1, column d but with TI6 $\geq 2\sigma$). The relative risk ratios reported for this model (compare to Table 2) shows that the predicted increase in violence during very hot periods is similar to violence associated with presidential election periods; both yield a 30–35% increase in violence.

Discussion

Anecdotal climate–conflict narratives often focus on cattle raiding. In our study area, however, a minority of the population practices pure livestock husbandry. There are, therefore, two livelihood systems to consider for our findings, pastoralist and nonpastoralist agricultural. In the pastoralist sector, positive rainfall deviations can be associated with lower conflict risk, because during rainier periods, households are spread far from opposing groups and dispersed, aggregating in temporary homes nearer water during drier times (23). Our empirical data correspond with this model for wetter periods but do not support the inverse (that lack of rain would raise conflict risk). For pastoralists, temperature extremes have been associated with stock losses, increasing incentives to replenish the herd by raiding: 2.5 °C and 5 °C increases represent a 32% and 70% net income deficit, respectively (24). For the nonpastoral sector, the positive association between instability and temperature may result from the harmful effects of high temperatures on food products such as maize (25). Our vegetation condition index measure is not restricted to crops for human consumption. Greater than average precipitation increases agricultural productivity, which improves the availability of food and also raises incomes for households reliant on earnings from farming.

Although decades of research on the distribution and correlates of war have greatly increased understanding of its social, political, and economic dimensions, more recent work in this genre has tackled the highly variegated nature of violence across the localities of countries experiencing war. Our study and other studies (11, 26, 27) question the evidence that climatic variability is uniformly driving up the risk of conflict in sub-Saharan Africa, which is the world region generally recognized as most vulnerable to such new hazards. However, unlike previous skeptical studies of the climate–conflict nexus, our study of East Africa over the past two decades is more nuanced in two respects. First, we have shown that higher temperatures increase the risk of conflict in East Africa (even when precipitation trends are considered), a wide range of geographic and socioeconomic–political controls are used, and yearly and country fixed effects are included. Previous work (6) had attributed more influence in raising violence to temperature increases than to precipitation deviations across Africa, and our study can be seen as partially vindicating this finding for East Africa. Wet precipitation deviations from the long-term trends seem to dampen conflict, and drier than normal conditions have no effect, a result that questions existing accounts (10, 21). Alongside the results in Table 2 (including a 29.6% increase in predicted conflict when temperatures are 2 SDs warmer than usual), Fig. 2 shows how modest the contribution of temperature and especially, precipitation are in predicting conflict relative to other factors. Second, we have identified dramatic differences between countries and between 5-y time periods in the model fit and the important precipitation and temperature coefficient splines. We provide these checks as a cautionary notice to the policy community of the instability of the climate–conflict relationship, and we suggest that estimating a model without consideration of specific locations of violence across a large region and over a long time period hides a myriad of contextual conditions.

Methods

We aggregate all data to a common 1° grid (∼110 × 110 km). Grid cells for the study area include a 100-km buffer inland to incorporate conflict spillover effects with neighboring countries, resulting in a total of 402 cells (after excluding grid cells over Lake Victoria, cells with missing climate data, and coastal cells with <20% land area and no violence). The count distribution of grid month violence is heavily overdispersed; of the 91,656 grid month units (402 grids over 19 y, because a 1-y lag for several variables requires excluding 1990 data), 5.9% of the observations are nonzero ($\mu = 0.18$, $\sigma = 1.28$) (Table S1). We use a negative binomial GLM to retain the full distribution of the data, preferring it over the logit model often used in conflict study, which truncates count values greater than one (Table S4 has logit versions in a robustness test). For SPI6 and TI6 indicators, initial model estimates for extreme conditions ($\geq 1\sigma$ and $\leq 1\sigma$) (Table 1, columns b–e) varied sufficiently to suggest that a more flexible model (with nonlinear parameters) was required.

To address this nonlinearity, we estimate a GAM (28) using the R package *mgcv* and a thin-plate spline for SPI6 and TI6 (Table 1, column f). This specification allows SPI6 and TI6 coefficients to vary over the values within their distributions, and it enables us to explore the nuances of the relationship between our climate measurements and conflict across our study area. Because there is no single coefficient estimate for these splined variables, we present these coefficients graphically (Fig. 1).

For both the GLM and GAM versions of the models, we control for residual unmeasured country-scale variables by estimating country-level effects. These country-level effects are included as fixed instead of random effects, because several of the predictor variables are reported at the country level; therefore, they are correlated at that spatial scale. Such country-level fixed effects are common in studies of violence (6, 11). We also include year fixed effects to account for unexplained variation over time and the possibility that media coverage of conflict in earlier years of our study period is sparse relative to later periods. The negative binomial dispersion parameter, θ in R, is estimated using maximum likelihood for both the GLM and GAM versions of the model.

The GAM version of the model has the following functional form (Eq. **1**):

$$\mathrm{Y}_{it} = \mathrm{WY}_{i,t-1} + \mathrm{X}_{it}\beta + f_1(\mathrm{SPI6}_{it}) + f_2(\mathrm{TI6}_{it}) + \mathrm{Country}_{it} + \mathrm{Year}_{it} + \varepsilon_{it,} \qquad [1]$$

where i = grid, t = time (month), W is the first-order contiguity spatial weights matrix used to calculate the violent events space–time lag, β is a vector of coefficients associated with the matrix of independent variables X, f_1 and f_2 are thin-plate spline functions, Country and Year are fixed effect terms, and ε is the grid month error term. Because the data for some variables are duplicated over time, we use grid-clustered SEs for all models to assess statistical significance.

Data

Precipitation. We use SPI6 to compare the moving 6-mo precipitation record with the long-term (since 1949) distribution for the same 6-mo period. The primary data are monthly mean gridded land surface precipitation and temperature values obtained from the Climate Research Unit of the University of East Anglia. These data are the Climate Research Unit TS3.10 global data on 0.5° × 0.5° grids for the period 1949–2009, which are resampled to 1° × 1° grids, thereby facilitating regression with environmental and socioeconomic variables. The SPI measures the number of SDs that the observed cumulative precipitation departs from the long-term mean. It can be compared across markedly different climates, and it is calculated for each grid cell. Negative deviation in rainfall is said to be one of the primary observable effects of climate change, and it is one effect that increases the risk of civil war (29) and the likelihood of other low-intensity forms of conflict (10); other research finds an association between conflict and positive vegetation growth (30). Related measures reach similar conclusions, such as greater freshwater availability reducing the risk of civil war onset (31).

Temperature. We use a 6-mo TI6 to measure the deviation from the corresponding long-term monthly mean temperature (since 1949). The temperature index expresses the monthly anomaly departure as a multiple of the SD, thus helping to identify anomalous warm or cold periods. Although higher than normal temperatures have been linked to civil war (6), others have questioned this claim, believing that the work by Burke et al. (6) used a poorly specified model and only a generic national-level conflict measure (11). Temperature variability has important effects on evapotranspiration; the work by Hsiang et al. (7) uses both climate metrics as part of their classification of areas affected by ENSO cycles (Table S3, column g shows a test of this effect in our study region). In contrast to the claim that rising temperatures will cause violence, global (8) and regional (32) studies have uncovered an association between human insecurity and colder temperatures. In the studies with competing conclusions, however, the mechanism remains the same: colder temperatures in temperate climates resulted in crop failure just as warmer deviations introduced agricultural stress in warmer climates.

Violent Events. The human-coded and media-based conflict data are from ACLED (19). Much of the existing research relies on country-level data (6), which can be problematic, because conflict processes do not unfold uniformly within a country. ACLED data are georeferenced with latitude and longitude coordinates, allowing for the localized study of conflict within a country's borders: the database also distinguishes between various types of violence (civil war, riots/protests, and attacks on civilians), thus allowing robustness checks with different conflict measures. For Somalia, we have excluded the data in the file that are not based on the standard media sources. To assign large countries (e.g., Ethiopia or Tanzania) a single binary measure of war or peace for a given year is clearly ignoring the dynamic geographic and temporal differences evident in violence, which is indicated in Fig. S1 for our nine countries of study.

Space–time Lag. At an international (33) and local level (34, 35), conflict exhibits qualities that might be described as contagion, diffusion, and clustering patterns. We account for these kinds of dependencies by including a space–time lagged dependent variable. Failure to account for geographic clustering may have biased the results of previous research on the climate change–conflict relationship, although previous studies may have controlled for temporal trends. In our models, the space–time effect is the second most influential predictor.

Population. Within a country, conflict risk is associated with greater population densities (12) and rates of population growth (36). We use the Gridded Population of the World (v3) data from the Center for International Earth Science Information Network and Socio-Economic Data and Applications Center of Columbia University (37) to derive yearly populations for the 1° cells. Population is the most important predictor of the number of violent events in an area.

Wellbeing (Infant Mortality Rate). Cross-national studies have illustrated a link between low socioeconomic status and conflict at the country (38). We use the yearly infant mortality rate (39) instead of gross domestic product per capita, because it serves as a broader measure of social wellbeing.

Political Rights. In authoritarian political climates, violent social unrest can develop, because citizens have a limited ability to express their interests through formal governmental avenues (40). We use the yearly political rights score from Freedom in the World (41) to measure the extent to which a country's government is autocratic or democratic in character.

Presidential Election. Violence may rise during campaigning or as a reaction to the outcome of an election (42), when ethnic conflict is especially likely to occur. To isolate the influence of this factor, we include a binary variable for every country coded as one if a presidential election occurred in a ±3-mo period.

Ethnic Leadership. Clientelism or private rule is a known characteristic of political regimes in sub-Saharan Africa (43). Patron–client ties can result in the (usually ethnic) exclusion of certain populations from government representation and services (44). We control for the fact that certain territories within states may benefit from central government patronage ties by coding cells (excluded group or not) in a geographic representation of political leadership information from Archigos data (45) using Ethnologue spatial boundaries (46).

Crop Production Index. There is a risk that social unrest will follow rising food prices because of impacts on family budgets (47); also, crop shortages represent a threat to central government coffers and disbursement options (48). As a surrogate for fluctuating food prices, we include the crop production index (annual percentage change) from the Food and Agriculture Organization and the World Bank (49).

Capital City. The capital city can be an important site of contention during certain conflicts because of its symbolic importance (claiming control of the seat of government of a state in civil war) (50). Lower-level skirmishes (riots and protests) may also concentrate in a capital city, because it is the seat of government. We use a binary measure of whether a grid cell includes the capital city of a country.

Distance to Borders. Because armed actors can use neighboring territory as a sanctuary, borders represent transmission points of conflict; a substantial body of work on the geography of conflict shows the importance of border regions in conflict diffusion (35). We calculate the mean distance to the border from the centroid of each grid cell.

Distance to Roads. As routes for transporting people and supplies, roads are often key targets for military activity (51), although they may also serve as a tool for a central government to secure control over a country's territory (52). We judge the road network data from the Digital Chart of the World (53) to be the most spatially consistent, and we calculate the average distance to primary and secondary roads for each grid cell.

Grassland. Pastoralist cattle raiding activity can be a livelihood strategy in regions of our study area, such as northern Kenya (54). We account for the influence of this social dynamic by including a measurement of the percentage of a grid cell that is grassland in the History Database of the Global Environment (55).

Vegetation. We include a vegetation condition index to control for variation in vegetation health over time. This weekly metric is derived from the National Oceanic and Atmospheric Administration's advanced very high-resolution radiometer sensor and captures changes in the normalized vegetation difference index compared with its historical range for each pixel (56). We elaborate on the data sources and specific metrics in Table S1.

Growing Season. A binary variable is used to designate each grid month as part of the growing season. Growing seasons were calculated based on average daily temperatures above 6 °C and a ratio of actual to potential evapotranspiration exceeding 0.35 (57).

Replication codes and data are available at www.colorado.edu/ibs/climateconflict/PNAS.

ACKNOWLEDGMENTS. We thank Clionadh Raleigh (Trinity College, Dublin) for providing much of the ACLED (Armed Conflict Location and Event Dataset) conflict data, students at the University of Colorado at Boulder who coded the thousands of violent events pre-1997, and Nancy Thorwardson (Institute of Behavioral Science, University of Colorado, Boulder, CO) for converting our graphics into publication-ready format. Audiences at Ohio State University, University of Illinois, Arizona State University, and University of Colorado at Boulder offered valuable suggestions for analytical improvements and posed challenging questions. We also thank the anonymous reviewers for their valuable suggestions. This work was supported by US National Science Foundation Grants 0964687 and 0964515. The National Center for Atmospheric Research is sponsored by the National Science Foundation.

1. Obama B (2009) *Remarks at United Nations Climate Change Summit* (United Nations, New York).
2. US Department of State (2010) *National Security Strategy of the United States* (Office of the President of the United States, Washington, DC).
3. Center for Strategic and International Studies (2007) *The Age of Consequences: The Foreign Policy and National Security Implications of Global Climate Change* (Center for Strategic and International Studies, Washington, DC).
4. Homer-Dixon T (1999) *Environment, Scarcity and Violence* (Princeton Univ Press, Princeton).
5. Kahl C (2006) *States, Scarcity and Civil Strife* (Princeton Univ Press, Princeton).
6. 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.
7. Hsiang SM, Meng KC, Cane MA (2011) Civil conflicts are associated with the global climate. *Nature* 476(7361):438–441.
8. Zhang DD, et al. (2011) The causality analysis of climate change and large-scale human crisis. *Proc Natl Acad Sci USA* 108(42):17296–17301.
9. Miguel E, Satyanath S, Sergenti E (2004) Economic shocks and civil conflict: An instrumental variables approach. *J Polit Econ* 112:725–753.
10. Hendrix C, Salehyan I (2010) Climate change, rainfall, and social conflict in Africa. *J Peace Res* 49:45–50.
11. Buhaug H (2010) Climate not to blame for African civil wars. *Proc Natl Acad Sci USA* 107(38):16477–16482.
12. Theisen OM, Holterman H, Buhaug H (Winter 2011–2012) Drought, political exclusion, and civil war. *Int Secur* 36:79–106.
13. O'Loughlin J, Witmer F (2011) The localized geographies of violence in the North Caucasus of Russia, 1999–2007. *Ann Assoc Am Geogr* 101:178–201.
14. Kalyvas S (2006) *The Logic of Violence in Civil War* (Cambridge Univ Press, New York).
15. Peluso NL, Watts M, eds (2001) *Violent Environments* (Cornell Univ Press, Ithaca, NY).
16. Benjaminsen TA, Alinon K, Buhaug H, Buseth JT (2012) Does climate change drive land-use conflicts in the Sahel? *J Peace Res* 49:97–111.
17. Bassett TJ (1998) The political ecology of peasant-herder conflicts in the northern Ivory Coast. *Ann Assoc Am Geogr* 78:433–472.
18. Turner M (2004) Political ecology and the moral dimensions of "resource conflicts": The case of farmer-herder conflicts in the Sahel. *Polit Geogr* 23:863–889.
19. Raleigh C, Linke A, Hegre H, Karlsen J (2010) Introducing ACLED: An armed conflict location and event dataset. *J Peace Res* 47:651–660.
20. Uppsala Conflict Data Program (UCDP) (2011) *Georeferenced Event Dataset*. Available at http://www.pcr.uu.se/research/ucdp/datasets/. Accessed December 11, 2011.
21. Fjelde H, von Uexkull N (2013) Climate triggers: Rainfall anomalies, vulnerability and communal conflict in sub-Saharan Africa. *Polit Geogr*, in press.
22. Ward MD, Greenhill BD, Bakke KM (2010) The perils of policy by p-value: Predicting civil conflicts. *J Peace Res* 47:363–375.
23. Mathew S, Boyd R (2011) Punishment sustains large-scale cooperation in prestate warfare. *Proc Natl Acad Sci USA* 108(28):11375–11380.
24. Seo SN, Mendelsohn R (2007) *The impact of climate change on livestock management in Africa: A structural Ricardian analysis. World Bank Policy Research Working Paper 4279*. Avaialable at http://elibrary.worldbank.org/content/workingpaper/10.1596/1813-9450-4279. Accessed August 22, 2012.
25. Lobell DB, Banziger M, Magorokosho C, Vivek B (2011) Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nat Clim Change* 13:42–45.
26. Raleigh C, Kniveton D (2012) Come rain or shine: An analysis of conflict and climate variability in East Africa. *J Peace Res* 49:51–64.
27. Theisen OM (2012) Climate clashes? Weather variability, land pressure, and organized violence in Kenya, 1989–2004. *J Peace Res* 49:81–96.
28. Wood SN (2006) *Generalized Additive Models: An Introduction with R* (Chapman & Hall/CRC, Boca Raton, FL).
29. Hendrix C, Glaser S (2007) Trends and triggers: Climate, climate change, and civil conflict in sub-Saharan Africa. *Polit Geogr* 26:695–715.
30. Meier P, Bond D, Bond J (2007) Environmental influences on pastoralist conflict in the Horn of Africa. *Polit Geogr* 26:716–735.
31. Raleigh C, Urdal H (2007) Climate change, environmental degradation, and armed conflict. *Polit Geogr* 26:674–694.
32. Tol RSJ, Wagner S (2010) Climate change and violent conflict in Europe over the last millennium. *Clim Change* 99:65–79.
33. Ward MD, Gleditch KS (2002) Location, location, location: An MCMC approach to modeling the spatial context of war and peace. *Polit Anal* 10:244–260.
34. Schutte S, Weidmann NB (2011) Diffusion patterns of violence in civil wars. *Polit Geogr* 30:143–152.
35. O'Loughlin J, Witmer F, Linke A (2010) The Afghanistan-Pakistan wars 2008–2009: Micro-geographies, conflict diffusion and clusters of violence. *Eurasian Geogr Econ* 51:437–471.
36. Urdal H (2008) Population, resources and political violence: A sub-national study of India 1956–2002. *J Conflict Resolut* 52:590–617.
37. Center for International Earth Science Information Network (CIESIN) (2011) *Gridded Population of the World*. Available at http://sedac.ciesin.columbia.edu/gpw/index.jsp. Accessed October 25, 2011.
38. Collier P, Hoeffler A (2004) Greed and grievance in civil war. *Oxf Econ Pap* 56:563–595.
39. Interagency Group for Child Mortality Estimation (2011) *Infant Mortality Rate*. Available at http://childmortality.org. Accessed January 6, 2011.
40. Fearon JD, Laitin DD (2003) Ethnicity, insurgency, and civil war. *Am Polit Sci Rev* 97:75–90.
41. Freedom House (2010) *Freedom in the World*. Available at http://freedomhouse.org. Accessed December 10, 2010.
42. Lindberg S (2006) *Democracy and Elections in Africa* (Johns Hopkins Univ Press, Baltimore).
43. Clapham C (1982) *Private Patronage and Public Power: Political Clientelism in the Modern State*, ed Clapham C (St. Martin's Press, New York), pp 1–35.
44. Buhaug H, Cederman L-E, Rod JK (2008) Disaggregating ethno-nationalist civil wars: A dyadic test of exclusion theory. *Int Organ* 62:531–551.
45. Goemans HE, Gleditsch KS, Chiozza G (2009) Introducing Archigos: A dataset of political leaders. *J Peace Res* 46:269–283. Available at http://rochester.edu/college/faculty/hgoemans/data.htm. Accessed January 3, 2011.
46. World Language Mapping System (2010) *Ethnologue Global Spatial Representation of Ethnic Groups*. Available at http://worldgeodatasets.com/language/. Accessed May 29, 2010.
47. Johnstone S, Mazo J (2011) Global warming and the Arab Spring. *Survival* 53:11–17.
48. Bates R (1989) *Beyond the Miracle of the Market: The Political Economy of Agrarian Development in Kenya* (Cambridge Univ Press, New York).
49. World Bank (2011) *Crop Production Index*. Available at http://data.worldbank.org/indicator/AG.PRD.CROP.XD. Accessed June 7, 2011.
50. Buhaug H, Gates S (2002) The geography of civil war. *J Peace Res* 39:417–433.
51. Zhukov Y (2012) Roads and the diffusion of insurgent violence: The logistics of conflict in Russia's North Caucasus. *Polit Geogr* 31:144–156.
52. Herbst J (2000) *States and Power in Africa: Comparative Lessons in Authority and Control* (Princeton Univ Press, Princeton).
53. Danko DM (1992) The digital chart of the world project. *Photogramm Eng Remote Sensing* 58:1125–1128.
54. McCabe T (2004) *Cattle Bring Us to Our Enemies* (Univ of Michigan Press, Ann Arbor, MI).
55. Goldewijk KK, Beusen A, de Vos M, van Drecht G (2011) The HYDE 3.1 spatially explicit database of human induced land use change over the past 12,000 years. *Glob Ecol Biogeog* 20:73–86.
56. National Oceanic and Atmospheric Administration (2011) *Vegetation Health Indices*. Available at http://www.star.nesdis.noaa.gov/smcd/emb/vci/VH/vh_ftp.php. Accessed June 8, 2011.
57. Jones PG, Thornton PK (2009) Croppers to livestock keepers: Livelihood transitions to 2050 in Africa due to climate change. *Environ Sci Policy* 12:427–437.