Warming increases the risk of civil war in Africa

Marshall B. Burke[a,b,1], Edward Miguel[c], Shanker Satyanath[d], John A. Dykema[e], and David B. Lobell[b]

[a]Department of Agricultural and Resource Economics and [c]Department of Economics, University of California Berkeley, Berkeley CA 94720; [d]Department of Politics, New York University, New York, NY 10012; [e]School of Engineering and Applied Sciences, Harvard University, Cambridge MA 02138; and [b]Program on Food Security and the Environment, Stanford University, Stanford CA 94305

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Armed conflict within nations has had disastrous humanitarian consequences throughout much of the world. Here we undertake the first comprehensive examination of the potential impact of global climate change on armed conflict in sub-Saharan Africa. We find strong historical linkages between civil war and temperature in Africa, with warmer years leading to significant increases in the likelihood of war. When combined with climate model projections of future temperature trends, this historical response to temperature suggests a roughly 54% increase in armed conflict incidence by 2030, or an additional 393,000 battle deaths if future wars are as deadly as recent wars. Our results suggest an urgent need to reform African governments' and foreign aid donors' policies to deal with rising temperatures.

civil conflict | climate change

More than two-thirds of the countries in sub-Saharan Africa ("Africa" hereinafter) have experienced civil conflict since 1960 (1), resulting in millions of deaths and monumental human suffering. Understanding the causes and consequences of this conflict has been a major focus of social science research, with recent empirical work highlighting the role of economic fluctuations in shaping conflict risk (2). Combined with accumulating evidence on the potentially disruptive effects of climate change on human enterprise, such as through possible declines in global food production (3) and significant sea level rise (4), such findings have encouraged claims that climate change will worsen instability in already volatile regions (5–7).

Despite a growing research effort, however, linkages between climate change and conflict remain uncertain, however. Most existing studies linking the 2 variables have focused on the role of precipitation in explaining conflict incidence, finding past conflict in Africa more likely in drier years (2, 7). Given that African countries remain highly dependent on rain-fed agriculture for both employment and economic production, with agriculture accounting for more than 50% of gross domestic product and up to 90% of employment across much of the continent (8), this focus on precipitation is understandable. But such a focus bears uncertain implications for changes in conflict risk under global climate change, as climate models disagree on both the sign and magnitude of future precipitation change over most of the African continent (9). This uncertainty confuses efforts aimed at building a more comprehensive understanding of the human costs of climate change, and planning appropriate policy responses.

While global climate model predictions of future precipitation vary widely, predictions of future temperatures are more uniform, particularly over the next few decades. With recent studies emphasizing the particular role of temperature in explaining past spatial and temporal variation in agricultural yields and economic output in Africa (10, 11), it thus appears plausible that temperature fluctuations could affect past and future conflict risk, but few studies have explicitly considered the role of temperature. An analysis of historical climate proxies since 1400 C.E. finds that long-term fluctuations of war frequency follow cycles of temperature change (12); however, the relevance of this to modern-day Africa is uncertain.

We provide quantitative evidence linking past internal armed conflict incidence to variations in temperature, finding substantial increases in conflict during warmer years, and we use this relationship to build projections of the potential effect of climate change on future conflict risk in Africa. To explore the direct role of climate in explaining the historical risk of conflict, we use a panel regression of climate variation and conflict events between 1981 and 2002 (see *Methods*). Our model relates country-level fluctuations in temperature and precipitation to the incidence of African civil war, defined as the use of armed force between 2 parties, one of which is the government of a state, resulting in at least 1,000 battle-related deaths (13). Consistent with previous studies (2, 7), and to capture the potentially delayed response of conflict to climate-induced economic shocks (due to, e.g., the elapsed time between climate events and the harvest period), we allow both contemporaneous and lagged climate variables to affect conflict risk.

Results

Temperature variables are strongly related to conflict incidence over our historical panel, with a 1 °C increase in temperature in our preferred specification leading to a 4.5% increase in civil war in the same year and a 0.9% increase in conflict incidence in the next year (model 1 in Table 1). Relative to the 11.0% of country-years that historically experience conflict in our panel, such a 1 °C warming represents a remarkable 49% relative increase in the incidence of civil war.

Despite the prominence of precipitation in past conflict studies, this temperature effect on conflict is robust to the inclusion of precipitation in the regression (model 2 in Table 1) and also robust to explicit controls for country-level measures of per capita income and democracy over the sample period (model 3 in Table 1)—factors highlighted by previous studies as potentially important in explaining conflict risk (1, 14–16). We also find the effect of temperature is robust to various alternative model specifications, including models with and without lags (Table S1); specifications using alternative transformations of climate variables, such as first differences or deviations from country trend (Table S2); the use of alternative climate data sets (Table S3); models including climate leads as well as lags (Table S4); models using conflict onset rather than incidence as the dependent variable (Table S5); and alternate specifications using the income and democracy controls (Table S6). Following the agricultural impact literature (3, 11), we also explore whether climate variables averaged over agricultural areas and during growing-season months provide a better signal, finding mixed results (Table S7). Finally, we find little evidence of nonlinear effects of climate variables on conflict incidence (Table S8).

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[1]To whom correspondence should be addressed. E-mail: marshall.burke@berkeley.edu.

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Table 1. Regression coefficients on climate variables, with civil war as a dependent variable

Variable	Model 1		Model 2		Model 3	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Temperature	0.0447**	(0.0218)	0.0430*	(0.0217)	0.0489*	(0.0275)
Temperature lagged 1 year	0.00873	(0.0210)	0.0132	(0.0233)	0.0206	(0.0298)
Precipitation			−0.0230	(0.0519)	0.0165	(0.0848)
Precipitation lagged 1 year			0.0250	(0.0489)	0.0278	(0.0811)
Per capita income lagged 1 year					−0.0266	(0.0258)
Political regime type lagged 1 year					−0.000538	(0.00576)
Constant	−1.514	(0.923)	−1.581*	(0.854)	−1.872	(1.254)
Observations	889		889		815	
R^2	0.657		0.657		0.389	
RMSE	0.193		0.193		0.241	

Coefficients represent effect of temperature (°C) and precipitation (m) on civil war in Africa, 1981–2002. All regressions include country fixed effects to control for time-invariant country characteristics; Models 1 and 2 include country time trends to control for time-varying country characteristics. Model 3 includes lagged income ($1,000) and political regime type [score from least democratic (−10) to most democratic (+10)] as controls, and includes a common time trend. Standard errors are robust and clustered at the country level. Asterisks indicate coefficient significance level (2-tailed): ***, $P < .01$; **, $P < .05$; *, $P < .10$.

To predict changes in the incidence of civil war under future climate change, we combine our estimated historical response of conflict to climate with climate projections from 20 general circulation models that have contributed to the World Climate Research Program's Coupled Model Intercomparison Project phase 3 (WCRP CMIP3). We focus on climate changes and associated changes in conflict risk to the year 2030, both because the host of factors beyond climate that contribute to conflict risk (e.g., economic performance, political institutions) are more likely to remain near-constant over the next few decades relative to mid-century or end of century, and because climate projections themselves are relatively insensitive to alternate greenhouse gas emissions scenarios to 2030.

The left panel of Fig. 1 shows the range of climate model projected changes in growing season precipitation and temperature for 5 African regions and the continent as a whole for 2020–2039 relative to 1980–1999, for the 18 climate models running the A1B emissions scenario. Projections of temperature change for the continent average around +1 °C, with some models projecting as much as +1.6 °C and some as little as +0.7 °C. Precipitation projections are more variable, with climate models disagreeing on both the sign and magnitude of

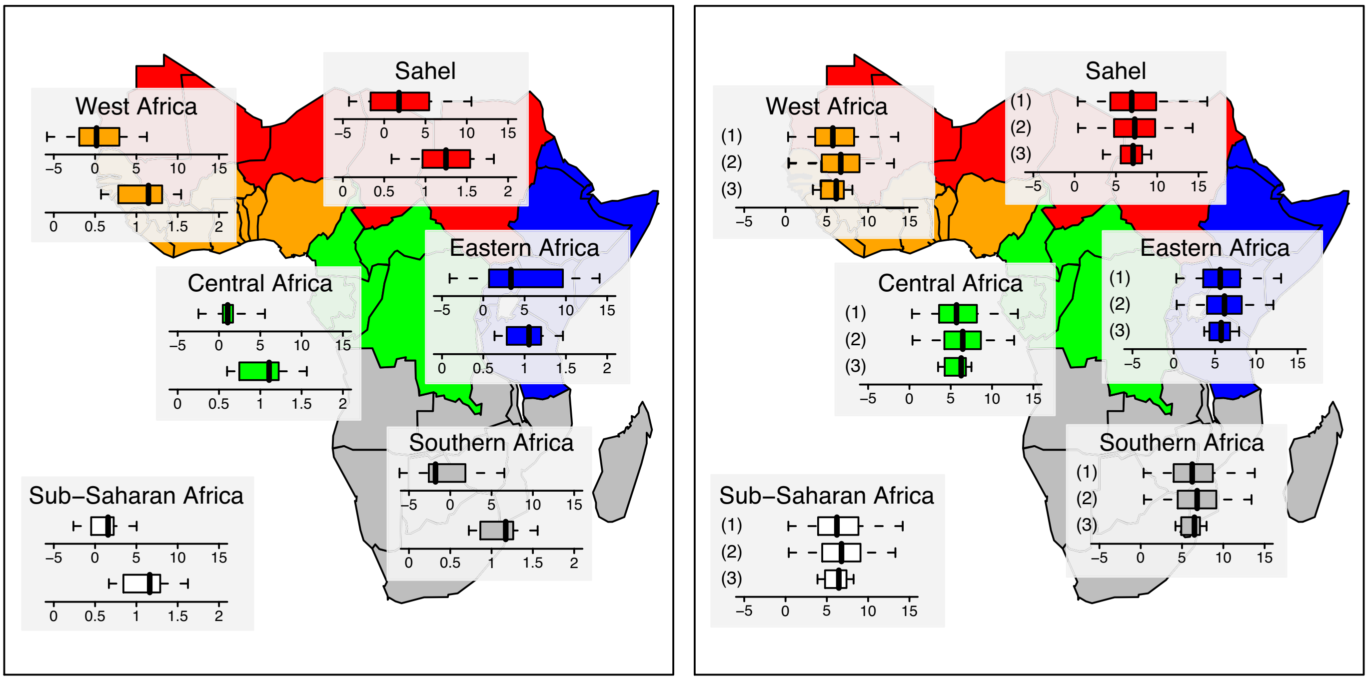

Fig. 1. Projected changes in climate and conflict to 2030. (*Left*) Projected changes in climate to 2030 for 5 sub-Saharan Africa subregions and the region as a whole. Boxplots show the range of model ensemble projected changes for precipitation (% change, *Top*) and temperature (°C, *Bottom*), for 2020–2039 minus 1980–1999, based on the 18 models running the A1B scenario, with the dark vertical line representing the median, the colored boxes showing the interquartile range, and the whiskers indicating the extremes. (*Right*) Projected percentage point change in the incidence of civil war for the same period and regions, based the same climate model projections and a 10,000-run bootstrap of model 1 in Table 1. For each region, boxplot 1 represents projections including uncertainty in both climate model projections and in conflict response to climate, boxplot 2 represents uncertainty only in conflict response to climate, and boxplot 3 represents uncertainty only in climate projections. Dark vertical lines represent median projection, colored boxes show the interquartile range, and whiskers indicate the 5th–95th percentile of projections.

Table 2. Projected changes in African civil war incidence to 2030, by emissions scenario

	Median % change	% increase in civil war relative to baseline	5th–95th percentile observations of projected % increase	% of observations < 0
A1B				
Model 1	5.9	53.7	6.2–119.4	3.0
Model 2	6.1	55.8	2.7–128.8	4.1
A2				
Model 1	5.2	47.4	5.4–101.8	3.0
Model 2	5.4	49.2	2.3–109.8	4.2
B1				
Model 1	4.8	43.4	5.0–99.4	3.0
Model 2	5.0	45.1	2.0–107.1	4.2

Projections are for all of sub-Saharan Africa for 3 emissions scenarios, based on 10,000-run bootstrap of models 1 and 2 in Table 1, which combine uncertainty in climate model projections and in the responsiveness of conflict to climate. Eleven percent of the country-years in the 1981–2002 baseline experienced civil war.

future changes, with the median projected precipitation change near 0.

The right panel of Fig. 1 shows projections of changes in African civil war incidence to 2030, accounting for uncertainty in both climate projections and conflict response to climate. The projections are built from model 1 in Table 1, with the uncertainty of conflict response to climate derived from 10,000 bootstrap runs of the model, and climate uncertainty determined by evaluating the set of bootstrap runs across each of the 18 individual climate models running the A1B scenario, giving each model equal weight (17) (see *SI Text*). Thus, the resulting distributions represent 180,000 predicted impacts, of which the 5th–95th percentiles are displayed.

All models predict increased conflict incidence across all regions for this 5th–95th percentile range, with a 5.9% median projected increase across the continent. Again given the 11% of country-years in our panel that experience conflict, this increase corresponds to a 54% rise in the average likelihood of conflict across the continent (Table 2). If future conflicts are on average as deadly as conflicts during our study period, and assuming linear increases in temperature to 2030, this warming-induced increase in conflict risk would result in a cumulative additional 393,000 battle deaths by 2030 (see *Methods*). Given that total loss of life related to conflict events can be many times higher than direct battle deaths (18), the human costs of this conflict increase likely would be much higher.

Because uncertainty in projections of conflict incidence appear driven more by the uncertainty in the climate–conflict relationship than by climate model projections (Fig. 1, *Right*), we reran the all-Africa projections for various alternative specifications of model 1. Estimates of the median and range of projected increases in conflict remain remarkably consistent across specifications of how civil war responds to climate (Fig. 2, *Top*), including whether war is assumed to respond to levels of climate variables or year-to-year changes in those variables, whether or not potential response to precipitation in addition to temperature is included, and the use of alternative climate data sets. Alternative emissions scenarios (A2 and B1) also give very similar projections of the median and range of increases in conflict risk (Table 2).

In addition, because nonclimate factors that affect conflict risk also could change over time, we include 2 projections of 2030 civil war incidence taking into account the combined effects of projected changes in climate, economic growth, and democratization (Fig. 2, *Bottom*). Using a 10,000-run bootstrap of model 3 in Table 1, we evaluate 2 scenarios: (i) a "linear extrapolation," in which future per capita economic growth and democratization are assumed to proceed at the same rate as in 1981–2002 (using the average over our African sample countries), and (ii) an "optimistic scenario," in which the annual per capita economic growth rate is 2% and the increase in democracy is the same as during 1981–2002, a period of substantial democratic reform in Africa (see *Methods*). We find that neither is able to overcome the large effects of temperature increase on civil war incidence, although the optimistic scenario reduces the risk of civil war by roughly 2% relative to the linear extrapolation, corresponding to a 20% relative decline in conflict (Fig. 2, *Bottom*).

Discussion

The large effect of temperature relative to precipitation is perhaps surprising given the important role that precipitation plays in rural African livelihoods and previous work emphasizing the impact of falling precipitation on conflict risk (2). In fact, precipitation and temperature fluctuations are negatively correlated ($r = -0.34$) over our study period, suggesting that earlier findings of increased conflict during drier years might have been partly capturing the effect of hotter years. The inferred precipitation effect is stronger in the current study when using the same precipitation dataset as in ref. 2 (Table S3), suggesting that the role of precipitation remains empirically ambiguous, perhaps because the high spatial variability of precipitation is less well captured than temperature variability by the relatively coarse climate data. Nevertheless, the temperature signal is robust across datasets and is consistent with a growing body of evidence demonstrating the direct negative effects of higher temperatures on agricultural productivity and the importance of these fluctuations for economic performance (10, 11, 19).

Temperature can affect agricultural yields both through increases in crop evapotranspiration (and hence heightened water stress in the absence of irrigation) and through accelerated crop development, with the combined effect of these 2 mechanisms often reducing African staple crop yields by 10%–30% per °C of warming (3, 11, 20). Because the vast majority of poor African households are rural, and because the poorest of these typically derive between 60% and 100% of their income from agricultural activities (21), such temperature-related yield declines can have serious economic consequences for both agricultural households and entire societies that depend heavily on agriculture (10). Finally, because economic welfare is the single factor most consistently associated with conflict incidence in both cross-country and within-country studies (1, 2, 14–16), it appears likely that the variation in agricultural performance is the central mechanism linking warming to conflict in Africa. Yet because our study cannot definitively rule out other plausible contributing factors—for instance, violent crime, which has been found to increase with higher temperatures (22), and nonfarm labor

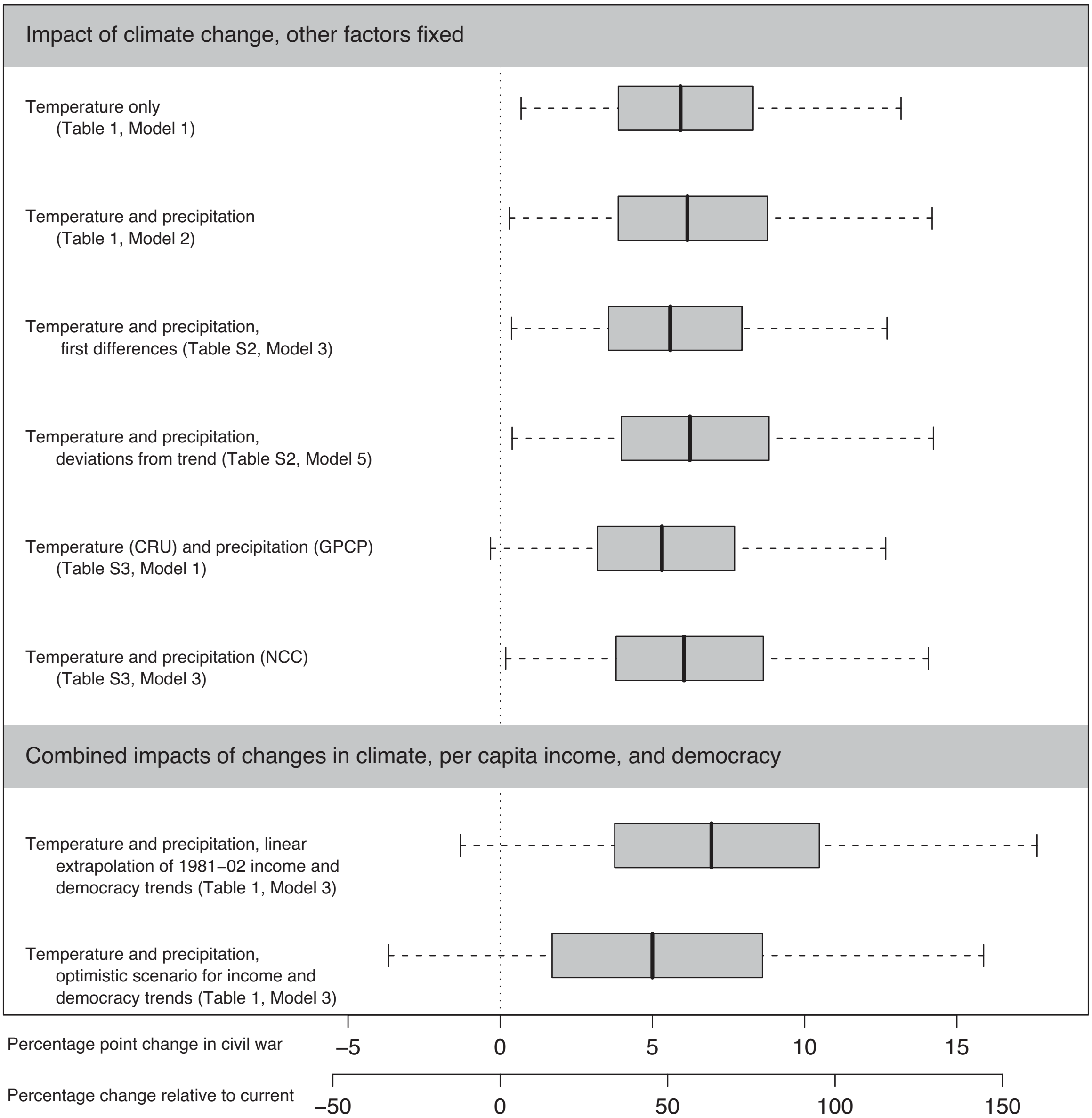

Fig. 2. Projected percent changes in the incidence of civil war for all of sub-Saharan Africa, including both climate and conflict uncertainty as calculated as in Fig. 1. (*Top*) Projections based on alternative specifications of the relationship between climate and conflict, with other factors fixed. (*Bottom*) Projected combined effects of changes in climate, per capita income, and democracy. Dark vertical lines represent the median projection, colored boxes show the interquartile range, and whiskers indicate the 5th–95th percentile of projections, using climate projections from all climate models for the A1B scenario, such that each boxplot represents 180,000 projections. Each specification includes the variables listed on the left (contemporaneous and lagged for the climate variables) in addition to country time trends and country fixed effects.

productivity, which can decline with higher temperatures (23)—further elucidating the relative contributions of these factors remains a critical area for future research.

Nevertheless, the robustness of the reduced-form relationship between temperature and conflict across many alternative model specifications argues for a large direct role of temperature in shaping conflict risk. When combined with the unanimous projections of near-term warming across climate models and climate scenarios, this temperature effect provides a coherent and alarming picture of increases in conflict risk under climate change over the next 2 decades in Africa. Furthermore, the adverse impact of warming on conflict by 2030 appears likely to outweigh any potentially offsetting effects of strong economic growth and continued democratization. We view this final result with some caution, however, because economic and political variables are clearly endogenous to conflict; for example, conflict may both respond to and cause variation in economic performance (2) or democratization. Consequently, credibly identifying past or future contributions of economic growth or democratization to civil war risk is difficult. We interpret our result as evidence of the strength of the temperature effect rather than as documentation of the precise future contribution of economic progress or democratization to conflict risk. Similarly, we do not explicitly account for any adaptations that might occur within or outside agriculture that could lessen these countries' sensitivities to high temperatures, and thus our 2030 results should be viewed as projections rather than predictions.

The possibility of large warming-induced increases in the incidence of civil war has a number of public policy implications. First, if temperature is primarily affecting conflict via shocks to

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economic productivity, then, given the current and expected future importance of agriculture in African livelihoods (24), governments and aid donors could help reduce conflict risk in Africa by improving the ability of African agriculture to deal with extreme heat. Such efforts could include developing better-adapted crop varieties, giving farmers the knowledge and incentives to use them, and expanding irrigation infrastructure where feasible (25).

Second, implementing insurance schemes to protect poor societies from adverse climate shocks also could help reduce the risk of civil war in Africa. One possibility is the expansion of weather-indexed crop insurance, which has shown promise in many less-developed countries (26). Another variant would be making the provision of foreign aid contingent on climate risk indicators—"rapid conflict prevention support" (27)—to bolster local economic conditions when the risk of violence is high. Our findings suggest that the need for such mechanisms in Africa will become increasingly urgent as global temperatures continue to rise.

Methods

Climate variables represent time series of temperature and precipitation from the Climatic Research Unit (CRU) of the University of East Anglia (28), averaged (for temperature) or summed (for precipitation) over all months at a given grid cell (0.5 $\times$ 0.5 degree in these data, or about 50 km at the equator), and then averaged over all cells in a given country. Our dependent variable is country- and year-specific civil war incidence (13), where $war_{it} = 1$ if there was a conflict resulting in $>$1,000 deaths in country i in year t and 0 otherwise.

Our regression equation links civil war to various measures of historical climate, x_{it}, conditional on country fixed effects and time trends,

$$war_{it} = f(x_{it}) + c_i + d_i year_t + \varepsilon_{it},$$

where c_i represents country fixed effects accounting for time-invariant country-specific characteristics (such as institutional capacity) that might explain differences in baseline level of conflict risk, and $d_i year_i$ represents country-specific time trends to control for variables that could be evolving over time (such as economic performance or political institutions) and altering conflict risk. In our baseline specification (model 1 in Table 1), climate is represented by levels of country-average temperature h in the current and previous year (29), such that $x_{it} = \beta_1 h_{it} + \beta_2 h_{it-1}$. Alternative panel specifications shown in Fig. 2 model x_{it} with contemporaneous and lagged precipitation included, with different transformations of climate (such as deviations from trend or first differences), with explicit controls for trends in country per capita income or democratization, or using alternative climate data sets (Tables S1–S8).

Per capita incomes are lagged annual values (in purchasing power parity, 1985 dollars), and political regime type is represented by the common Polity2 measure, where countries receive a yearly score between -10 (least democratic) and $+10$ (most democratic) (30) (see *SI Text*). These variables are lagged 1 year because both political regime type and economic growth are potentially endogenous to conflict (2), and using predetermined values reduces the most immediate endogeneity concerns. Projections of these variables to 2030 are based either on linear extrapolation of median 1981–2002 trends across sample countries (equal to $+0.1\%$ annual per capita income growth and a $+7$-point increase in the Polity2 score) or on an optimistic scenario [equal to the same large increase in the Polity2 score and a $+2.0\%$ annual increase in per capita incomes, which is similar to the average African performance between 2000 and 2008 (31)].

Additional battle deaths related to warming are calculated using historical battle death data (32), and assume a linear increase in the conflict risk related to warming beginning in 1990 (corresponding to historical risk levels in our panel) and ending in 2030 (a 54% increase in risk). Cumulative additional battle deaths are then summed from the first year after the end of our panel (2003) through 2030, assuming a baseline annual battle death total equal to the average during our 1981–2002 study period (39,455 deaths/year).

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Supporting Information

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SI Text

Conflict Data. Our dependent variable, the incidence of civil war, comes from the Armed Conflict Data database developed by the International Peace Research Institute of Oslo, Norway, and the University of Uppsala, Sweden (referred to as PRIO/Uppsala), version 4–2008 (1).* Civil war is defined in the PRIO/Uppsala database as "a contested incompatibility which concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 1000 battle-related deaths."

We denote civil war in country i in year t as war_{it}. All country-year observations with a civil war in progress are coded as 1s, and other observations are coded as 0s. The PRIO data extend from 1946 to 2006, but because of the limited temporal availability of some climate data products (discussed below), and because the political processes underlying conflict were likely changing rapidly before 1980 as increasing numbers of African countries gained independence, we focus our analysis on the 1981–2002 period. During this period, 11.0% of country-years in sub-Saharan Africa experienced civil war.

Climate Data. Our historical climate data are derived from 3 sources. Our main source is the CRU of the University of East Anglia, which provides monthly minimum and maximum temperature and precipitation on a 0.5 × 0.5-degree grid for the period 1901–2002. We use version 2.1 of these data (2).† A second source is the National Center for Environmental Prediction/National Center for Atmospheric Research (NCC), which is available on a 6-hourly time step and a 1 × 1-degree grid for 1948–2000 (3).‡ We construct the daily minimum and maximum as the minimum and maximum of the 4 daily observations. Our third source of precipitation data is the Global Precipitation Climatology Project (GPCP) of NASA's Goddard Space Center (4), a monthly product on a 1 × 1-degree grid available for 1979–2008.§

From these data, we construct country-level time series of average temperature and precipitation, using 2 different spatial and temporal averages: (i) averaging climate over all grid cells in a country, for a given year; that is, temperature (precipitation) is averaged over all cells, and then averaged (summed) over all of the months in a year; and (ii) averaging climate data over the areas and months in which crops are grown. Leff et al. (5) provided 0.5 × 0.5-degree gridded estimates of the percentage of land area sown to a given crop, which we use to weight the climate cells in a given country to build a monthly time series of country-specific crop climate (0.5 degree is roughly 50 km at the equator). Following Lobell et al. (6), we then average (for temperature) or sum (for precipitation) over estimates of the primary maize growing season in each country to construct annual time series. We develop separate weighted averages for maize (the primary African cereal) and for all crop areas.

Control Data. Because changes in economic and political variables over time could influence conflict risk in our countries, we use 2 types of data to control explicitly for economic and political performance (in addition to our use of country-specific time trends, described below).

Income Data. We control for economic performance using levels of annual per capita income (in 1985 dollars), lagged 1 year, which we derive from the World Development Indicators and the Penn World Tables (7, 8). Although common in the conflict literature, the direct use of income measures to explain conflict risk is subject to problems of endogeneity—that is, fluctuations in economic performance both cause and result from civil conflict. But even using lagged income measures to explain subsequent conflict risk is unlikely to solve the endogeneity problem, because current investment levels can be affected by the risk of future political instability. Nevertheless, we use these measures as a robustness test in a subset of our specifications, described below.

Political Regime–Type Data. To capture the possible role that the development of democratic institutions could play in reducing conflict risk, we use the Polity2 measure from the Polity IV data set¶ to describe the extent to which countries are democratic. Scores are reported annually on the country level and range between −10 (full autocracy) and +10 (full democracy), and this variable is lagged by 1 year. As with income measures, democratization also is likely endogenous to conflict, and caution should be exercised in evaluating its effects on conflict.

Modeling Climate Effects on Conflict, and Robustness Checks

Baseline Specification. Our regression equation links civil war in country i in year t (war_{it}) to various measures of historical climate, x_{it}, conditional on country fixed effects and country time trends,

$$war_{it} = f(x_{it}) + c_i + d_i year_t + \varepsilon_{it},$$

where c_i represents country fixed effects that account for time-invariant country-specific characteristics (such as institutional capacity) that might explain differences in baseline level of conflict risk, and $d_i year_t$ represents country time trends to control for country-specific variables that could be evolving over time (such as economic performance or political institutions) and altering conflict risk. In our baseline specification (model 1 in Table 1), climate is represented by country-average temperature h in the current and previous year using the CRU data, such that $x_{it} = \beta_1 h_{it} + \beta_2 h_{it-1}$. We include both contemporaneous and lagged climate variables in the model, because conflict could respond slowly to climate fluctuations—for instance, due to elapsed time between climate events and the harvest period, or because 1,000 battle deaths might not accumulate until the year after the climate shock.

Robustness Tests. To test the robustness of our baseline specification, we explore the sensitivity of our results to alternative specifications of both conflict and climate, outlined in turn below.

Modeling climate as precipitation as well as temperature. Given that earlier work found a strong relationship between historical precipitation fluctuations and conflict risk (9), and that precipitation and temperature fluctuations are negatively correlated across our study period ($r = -0.34$ for the correlation between precipitation and temperature differences), one concern is that

*Available at http://www.prio.no/CSCW/Datasets/Armed-Conflict/.

†Available at http://www.cru.uea.ac.uk/cru/data/.

‡Available at http://thanh.ngoduc.free.fr/wiki/index.php/Main/NCCDataset.

§Available at http://precip.gsfc.nasa.gov/.

¶Data available at: http://www.systemicpeace.org/polity/polity4.htm.

omitted variables (in this case precipitation) could bias our temperature parameter estimates. Table S1 explores this possibility with the CRU data, with country annual precipitation represented by p, and in our most complete model (model 7) with $x_{it} = \beta_1 h_{it} + \beta_2 h_{it-1} + \beta_3 p_{it} + \beta_4 p_{it-1}$. We find that our baseline estimate of the effect of temperature remains undiminished by the inclusion of precipitation.

Modeling climate using alternative transformations of climate variables, with additional country and year controls. Our baseline specification focuses on levels of climate variables, but conflict plausibly could depend more on fluctuations in climate—represented either as deviations from local trends in climate or as changes in climate from the year before. Table S2 explores this possibility, finding similar parameter estimates on temperature between our baseline levels specification (model 1) and the corresponding specifications with differences (model 3) and deviations from trend (model 5). We also test whether results in these specifications are sensitive to including only a common time trend rather than a country-specific time trend (models 2, 4, and 6). Our results are broadly similar across these specifications, with the summed effect of a 1 °C warming resulting in a roughly 5% increase in conflict in all specifications, albeit with larger standard errors in the models with fluctuations.

Modeling climate with alternative climate products. We also test robustness to the different climate products listed above (Table S3). These include substituting estimates of precipitation from the GPCP into our baseline levels and difference specifications (models 1 and 2), and using temperature and precipitation data from the NCC, which are taken from Schlenker and Lobell (10) and represent climate averaged over maize area, as explained above (model 3). Our parameter estimates on the temperature variables again remain similar in magnitude to our baseline specification, albeit with somewhat higher SEs in the case of the GPCP models.

Modeling civil war onset rather than incidence. Explaining why wars start, rather than explaining whether they continue to occur, is also of paramount interest to policy makers, and war onset plausibly could respond to climate in distinct ways from conflict incidence. To test the responsiveness of civil war onset to climate, we denote war onset in country i in year t as on_{it}, with all country-year observations with a civil war starting in that year coded as 1s and other observations coded as 0s. Table S4 explores the responsiveness of onset to our baseline level specifications (models 1 and 2) and to first differences specifications (models 3 and 4). We find that onset responds similarly to incidence across all specifications, with a 1 °C warming leading from a 3.5%–5.5% increase in the likelihood that a civil war will start, depending on specification.

Modeling climate with leads as well as lags. As an econometric identification check, we run our baseline specifications with climate leads as well as lags in Table S5, such that in model 1, $x_{it} = \beta_1 h_{it} + \beta_2 h_{it-1} + \beta_3 h_{it+1}$. We expect that future climate should have no effect on current conflict, and indeed our β_3 estimates are close to 0.

Modeling the effect of climate, controlling explicitly for per capita income and level of democracy. Instead of controlling for time-varying country characteristics with country time trends, we also control specifically for the evolution over time of per capita income and democracy. Table S6 explores the effects of warming on conflict, controlling for these 2 variables individually and together, with and without precipitation included. The temperature coefficients remain at roughly the same magnitude and significant with at least 90% confidence in all specifications. Coefficients on per capita income and democracy variables are of the expected sign (with higher incomes and improvements in democracy both conflict-reducing), but neither is significant at conventional confidence levels.

Modeling climate over agricultural areas. If climate effects conflict through economic shocks, and if these shocks occur primarily through fluctuations in agricultural productivity, then one might expect that agriculture-weighted climate variables—that is, averaged of crop areas and during the months when crops are grown—would be more closely related to conflict. To test this, we average climate over agricultural areas and growing seasons as explained above, and repeat the levels and differences specifications using the CRU data (Table S7). Overall, we find that the unweighted climate variables perform somewhat better than the agriculture-weighted variables, although the point estimates of change in conflict in the difference specifications are roughly similar. Furthermore, the projections for future climate (described below) using agricultural climate overlap considerably with projections without climate weighting, suggesting no significant difference between the 2 measures (results not shown).

Modeling quadratic climate terms. Finally, we test for nonlinear effects of temperature and precipitation on conflict by adding quadratic temperature and precipitation terms to our baseline specification (Table S8). The coefficients on the quadratic terms for current and lagged climate variables are not near conventional significance levels, so we conclude that there is no evidence for strong nonlinearities in the climate–conflict relationship, at least in the historical data.

Projections for Future Climate

Climate Models. Changes in the incidence of civil war due to climate change are derived by combining the historical response of conflict to climate, modeled above, with climate projections from 20 general circulation models that have contributed to WCRP CMIP3. Our main projections use the A1B scenario, reported by 18 climate models in the CMIP3 database: CCMA, CNRM, CSIRO, GFDL0, GFDL1, GISS.AOM, GISS.EH, GISS.ER, IAP, INMCM3, IPSL, MIROC.HIRES, MIROC.MEDRES, ECHAM, MRI, CCSM, PCM, and HADCM3. (See ref. 11 for a complete treatment of climate models.)

We derive estimates of the year 2030 African climate by calculating model-projected changes in temperature (°C) and precipitation (%) between 2020–2039 and 1980–1999, and then adding (for temperature) or multiplying (for precipitation) these changes to the observed record.

Projecting Future Impacts. We calculate the predicted change in conflict as the change between predicted baseline conflict under historical climate, x^0_{it}, and the predicted conflict under future climate, $x^1_{it}, f(x^1) - f(x^0)$. To obtain confidence intervals for these projected changes, we bootstrap the data (10,000 random draws with replacement from the original panel) and reestimate the model. Full confidence intervals on projected changes are obtained by combining these bootstrap reestimates with the range of projected changes in precipitation and temperature from each climate model. With 18 climate models running the A1B scenario, we obtain 180,000 projections of future change in conflict, summarized in Fig. 1 and Table 2 for our baseline specification, with summaries for alternative specifications summarized in Fig. 2.

Finally, in Table 2 we explore sensitivity of results to alternative greenhouse gas emissions scenarios A2 and B1 in 2030. Results are qualitatively similar, if slightly lower, than projections using the A1B scenario, primarily because the A1B scenario features higher initial greenhouse gas emissions, and thus slightly more initial warming, than the A2 and B1 scenarios.

Projections of Economic and Political Variables. Because conflict risk clearly depends on nonclimate variables as well as on climate variables, and because changes in these variables to the year 2030 could affect conflict risk beyond the effects of temperature, we combine historical estimates of the contribution of temperature, income, and political regime type (model 3 in Table 1) with various scenarios of how future incomes and political regimes might change by 2030. We examine 2 scenarios: (i) a linear extrapolation, in which incomes and political regime types change at the same pace as during our 1981–2002 sample period (corresponding to 0.1% yearly per capita income growth and a median 7-point improvement in Polity2 score), and (ii) an "optimistic" scenario, corresponding to a 2% annual per capita income growth (similar to what sub-Saharan Africa achieved between 2000 and 2008) and the same large improvement in democratic institutions as in the linear extrapolation scenario. We retain the same improvement in the Polity score, because we believe that it is highly optimistic to anticipate another wave of democratization to occur over the next few decades in sub-Saharan Africa on the scale of what occurred between 1981 and 2002.

Such projections are subject to an important caveat, mentioned above—that it is difficult to identify the historical impact of economic fluctuations or changes in institutions on conflict risk because economic and political variables are endogenous to conflict. For instance, fluctuations in economic performance both cause and result from civil conflict. Even using lagged economic and political variables in conflict regressions is unlikely to solve the endogeneity problem, because current investment levels can be affected by the risk of future political instability. As a result, absent an explicit attempt to instrument for economic or political changes (such as in ref. 9), direct estimates of the effects of these variables on conflict should be interpreted with caution, as should forward-looking projections that depend on them.

Calculating Additional Battle Deaths. Additional battle deaths related to warming are calculated using historical battle death data (12), and assuming a linear increase in the conflict risk related to warming beginning in 1990 (the middle of our baseline for projecting changes in climate variables, corresponding to a zero increase in risk) and ending in 2030 (a 54% increase in risk). Cumulative additional battle deaths are then summed from the end of our panel (2003) through 2030, assuming a baseline annual battle death total equal to the average during our 1981–2002 study period (39,455 deaths/year).

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Table S1. Individual and combined effects of temperature and precipitation on conflict in Africa, 1981–2002

	Incidence of civil war$_{(\text{year } t)}$							Residuals from model 6
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Temp$_t$	0.0446**		0.0447**				0.0430*	0.0411*
	(0.0216)		(0.0218)				(0.0217)	(0.0218)
Temp$_{(t-1)}$		0.00801	0.00873				0.0132	0.0108
		(0.0210)	(0.0210)				(0.0233)	(0.0210)
Precip$_t$				−0.0490		−0.0492	−0.0230	
				(0.0463)		(0.0460)	(0.0519)	
Precip$_{(t-1)}$					0.00436	0.00566	0.0250	
					(0.0492)	(0.0484)	(0.0489)	
Constant	−1.262**	−0.228	−1.514	−0.00890	−0.133	−0.0219	−1.581*	−1.590*
	(0.612)	(0.597)	(0.923)	(0.107)	(0.116)	(0.174)	(0.854)	(0.927)
Observations	889	889	889	889	889	889	889	889
R^2	0.657	0.655	0.657	0.656	0.655	0.656	0.657	0.656
RMSE	0.193	0.193	0.193	0.193	0.193	0.193	0.193	0.193

Climate variables represent contemporaneous and lagged country-level temperature (°C) and precipitation (m), using data from CRU. Model 8 regresses temperature on the residuals from model 6 to further isolate the effect of temperature. All models include country fixed effects and country time trends. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***$P < .01$; **$P < .05$; *$P < .1$.

Table S2. Climate on conflict for various specifications with the CRU data: Climate levels (models 1 and 2), differences (models 3 and 4), and deviations from trend (models 5 and 6).

	Incidence of civil war$_{(\text{year } t)}$					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Temp_t	0.0430*	0.0448*				
	(0.0217)	(0.0241)				
$\text{Temp}_{(t-1)}$	0.0132	0.0128				
	(0.0233)	(0.0248)				
Precip_t	−0.0230	0.0127				
	(0.0519)	(0.0742)				
$\text{Precip}_{(t-1)}$	0.0250	0.0274				
	(0.0489)	(0.0748)				
Temp diff_t			0.0274	0.0279		
			(0.0174)	(0.0175)		
Temp $\text{diff}_{(t-1)}$			0.0250	0.0254		
			(0.0172)	(0.0163)		
Precip diff_t			−0.00370	0.0144		
			(0.0427)	(0.0428)		
Precip $\text{diff}_{(t-1)}$			0.0405	0.0476		
			(0.0465)	(0.0443)		
Temp dev trend_t					0.0430*	0.0409*
					(0.0217)	(0.0213)
Temp dev $\text{trend}_{(t-1)}$					0.0132	0.0102
					(0.0233)	(0.0245)
Precip dev trend_t					−0.0230	−0.00682
					(0.0519)	(0.0500)
Precip dev $\text{trend}_{(t-1)}$					0.0250	0.00824
					(0.0489)	(0.0563)
Constant	−1.581*	−1.562	1.168***	0.933***	1.172***	0.932***
	(0.854)	(1.042)	(0.00215)	(0.0428)	(0.00269)	(0.0428)
Country-specific time trends	Yes	No	Yes	No	Yes	No
Common time trend	No	Yes	No	Yes	No	Yes
Observations	889	889	889	889	889	889
R^2	0.657	0.466	0.657	0.465	0.657	0.466
RMSE	0.193	0.235	0.193	0.235	0.193	0.235

For each, specifications are run with country fixed effects and country specific time trends (first model in set), or with country fixed effects and a common time trend (second model). Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***, $P < .01$; **, $P < .05$; *, $P < .10$.

Table S3. Effects of climate on conflict using different climate products: Levels of precipitation from GPCP and temperature from CRU (model 1), same but using first differences (model 2), and levels of maize temperature and precipitation with the NCC data (model 3)

	Incidence of civil war$_{(\text{year } t)}$		
Variable	Model 1	Model 2	Model 3
Temp_t	0.0318		
	(0.0234)		
$\text{Temp}_{(t-1)}$	0.0155		
	(0.0238)		
Precip_t (GPCP)	−0.106**		
	(0.0522)		
$\text{Precip}_{(t-1)}$ (GPCP)	0.00774		
	(0.0585)		
Temp diff_t		0.0212	
		(0.0161)	
Temp $\text{diff}_{(t-1)}$		0.0221	
		(0.0157)	
Precip diff_t (GPCP)		−0.0518	
		(0.0390)	
Precip $\text{diff}_{(t-1)}$ (GPCP)		−0.0198	
		(0.0447)	
Maize temp_t (NCC)			0.0284**
			(0.0128)
Maize $\text{temp}_{(t-1)}$ (NCC)			0.0264
			(0.0193)
Maize precip_t (NCC)			−0.0491
			(0.0749)
Maize $\text{precip}_{(t-1)}$ (NCC)			0.0952
			(0.0743)
Constant	−1.085	−0.0275*	−1.688**
	(1.051)	(0.0148)	(0.778)
Observations	889	889	809
R^2	0.659	0.662	0.670
RMSE	0.192	0.194	0.194

The stronger precipitation response with the GPCP data is consistent with results in Miguel et al. (9). All regressions include country fixed effects and country-specific time trends. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***, $P < .01$; **, $P < .05$; *, $P < .10$.

Table S4. Effect of temperature and precipitation on conflict onset in Africa, 1981–2002

	Civil war onset$_{(year\ t)}$			
	Model 1	Model 2	Model 3	Model 4
$Temp_t$	0.0432*	0.0385*		
	(0.0215)	(0.0206)		
$Temp_{(t-1)}$	−0.00786	−0.00311		
	(0.0160)	(0.0195)		
$Precip_t$		−0.0459		
		(0.0551)		
$Precip_{(t-1)}$		0.0168		
		(0.0450)		
Temp $diff_t$			0.0324**	0.0325**
			(0.0155)	(0.0153)
Temp $diff_{(t-1)}$			0.0162	0.0224
			(0.0141)	(0.0167)
Precip $diff_t$				−0.0161
				(0.0432)
Precip $diff_{(t-1)}$				0.0354
				(0.0334)
Constant	−9.705***	−9.754***	−8.985***	−8.917***
	(0.538)	(0.615)	(0.152)	(0.174)
Observations	817	817	817	817
R^2	0.256	0.257	0.255	0.257
RMSE	0.151	0.151	0.151	0.151

Climate variables represent contemporaneous and lagged climate averaged over the entire country and year, using either levels (models 1 and 2) or first differences (models 3 and 4) with the CRU data. All regressions include time trends and country fixed effects. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***, $P < .01$; **, $P < .05$; *, $P < .10$.

Table S5. Effect of temperature and precipitation on conflict in Africa, 1981–2002, as in Table 1 but adding climate leads in addition to lags

	Incidence of civil war$_{(year\ t)}$	
Variable	Model 1	Model 2
Temperature$_t$	0.0513**	0.0447**
	(0.0230)	(0.0207)
Temperature$_{(t-1)}$	0.0133	0.0180
	(0.0220)	(0.0238)
Temperature$_{(t+1)}$	−0.00102	0.00525
	(0.0188)	(0.0205)
Precipitation$_t$		−0.0295
		(0.0600)
Precipitation$_{(t-1)}$		0.0356
		(0.0529)
Precipitation$_{(t+1)}$		0.0679
		(0.0465)
Constant	−0.778	−0.882
	(0.571)	(0.568)
Observations	849	849
R^2	0.662	0.663
RMSE	0.194	0.194

All regressions include country fixed effects and country time trends. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***, $P < .01$; **, $P < .05$; *, $P < .10$.

Table S6. Effects of season temperature and precipitation on conflict in Africa, 1981–2002, controlling for per capita income and political regime type

	Incidence of civil war$_{(year\ t)}$				
	Model 1	Model 2	Model 3	Model 4	Model 5
$Temp_t$	0.0447**	0.0469*	0.0423*	0.0463*	0.0489*
	(0.0218)	(0.0255)	(0.0229)	(0.0256)	(0.0275)
$Temp_{(t-1)}$	0.00873	0.0193	0.0102	0.0186	0.0206
	(0.0210)	(0.0228)	(0.0256)	(0.0263)	(0.0298)
$Precip_t$					0.0165
					(0.0848)
$Precip_{(t-1)}$					0.0278
					(0.0811)
Per capita $GDP_{(t-1)}$		−0.0259		−0.0266	−0.0266
		(0.0265)		(0.0258)	(0.0258)
Political $regime_{(t-1)}$			−0.000325	−0.000612	−0.000538
			(0.00528)	(0.00566)	(0.00576)
Constant	−1.514	−1.822*	−1.452	−1.789	−1.872
	(0.923)	(1.069)	(1.086)	(1.169)	(1.254)
Observations	889	815	889	815	815
R^2	0.657	0.388	0.466	0.388	0.389
RMSE	0.193	0.240	0.235	0.240	0.241

All specifications include country fixed effects. Model 1 includes country time trends; models 2–5 include common time trends. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: $***P < .01$; $**P < .05$; $*P < .10$.

Table S7. Effect of temperature and precipitation on conflict in Africa, 1981–2002, using unweighted or agriculture-weighted climate variables with the CRU data, either in levels (models 1–3) or first differences (models 4–6)

	Civil war incidence$_{(\text{year } t)}$					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Temp$_t$	0.0430*			0.0274		
	(0.0217)			(0.0174)		
Temp$_{(t-1)}$	0.0132			0.0250		
	(0.0233)			(0.0172)		
Precip$_t$	−0.0230			−0.00370		
	(0.0519)			(0.0427)		
Precip$_{(t-1)}$	0.0250			0.0405		
	(0.0489)			(0.0465)		
Temp all-crop$_t$		0.0195			0.0135	
		(0.0182)			(0.0139)	
Temp all-crop$_{(t-1)}$		0.0189			0.0283**	
		(0.0178)			(0.0139)	
Precip all-crop$_t$		−0.0776			−0.0541	
		(0.0517)			(0.0396)	
Precip all-crop$_{(t-1)}$		0.0560			0.0343	
		(0.0566)			(0.0513)	
Temp maize$_t$			0.0203			0.0160
			(0.0188)			(0.0139)
Temp maize$_{(t-1)}$			0.0154			0.0298**
			(0.0170)			(0.0139)
Precip maize$_t$			−0.0751			−0.0526
			(0.0508)			(0.0382)
Precip maize$_{(t-1)}$			0.0518			0.0317
			(0.0574)			(0.0508)
Constant	−1.581*	−1.134	−1.050	1.168***	1.167***	1.167***
	(0.854)	(0.836)	(0.828)	(0.00215)	(0.00219)	(0.00224)
Observations	889	889	889	889	889	889
R^2	0.657	0.657	0.657	0.657	0.658	0.658
RMSE	0.193	0.193	0.193	0.193	0.193	0.193

Models 1 and 4 average climate over the entire country and year, models 2 and 5 average over the area and season in which all primary crops are grown, and models 3 and 6 average over maize area and growing season. All regressions include country time trends and country fixed effects. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***$P < .01$; **$P < .05$; *$P < .10$.

Table S8. Effect of current and lagged temperature and precipitation on civil war in Africa, 1981–2002, including quadratic climate terms

	Incidence of civil war$_{(year\ t)}$			
	Model 1	Model 2	Model 3	Model 4
$Temp_t$	0.0447**	−0.0807	−0.0749	−0.106
	(0.0218)	(0.0832)	(0.0815)	(0.0877)
$Temp_{t2}$		0.00259	0.00247	0.00301
		(0.00200)	(0.00197)	(0.00207)
$Temp_{(t-1)}$	0.00873	0.0204		0.0450
	(0.0210)	(0.0770)		(0.0704)
$Temp_{(t-1)2}$		−0.000210		−0.000503
		(0.00179)		(0.00169)
$Precip_t$				−0.152
				(0.155)
$Precip_{t2}$				0.0498
				(0.0681)
$Precip_{(t-1)}$				0.150
				(0.127)
$Precip_{(t-1)2}$				−0.0483
				(0.0493)
Constant	−1.514	−0.203	0.141	−0.282
	(0.923)	(1.078)	(0.816)	(1.044)
Observations	889	889	889	889
R^2	0.657	0.658	0.657	0.658
RMSE	0.193	0.193	0.193	0.193

All models include country fixed effects and country specific time trends. Robust SEs are in parentheses, clustered at the country level. Asterisks indicate coefficient significance level: ***, $P < .01$; **, $P < .05$; *, $P < .10$.