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_{it}^0, and the predicted conflict under future climate, x_{it}^1, $f(x^1) - f(x^0)$. 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)
$\text{Temp}_{(t-1)}$		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)	
$\text{Precip}_{(t-1)}$					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$_{(year\ t)}$					
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$Temp_t$	0.0430*	0.0448*				
	(0.0217)	(0.0241)				
$Temp_{(t-1)}$	0.0132	0.0128				
	(0.0233)	(0.0248)				
$Precip_t$	−0.0230	0.0127				
	(0.0519)	(0.0742)				
$Precip_{(t-1)}$	0.0250	0.0274				
	(0.0489)	(0.0748)				
Temp $diff_t$			0.0274	0.0279		
			(0.0174)	(0.0175)		
Temp $diff_{(t-1)}$			0.0250	0.0254		
			(0.0172)	(0.0163)		
Precip $diff_t$			−0.00370	0.0144		
			(0.0427)	(0.0428)		
Precip $diff_{(t-1)}$			0.0405	0.0476		
			(0.0465)	(0.0443)		
Temp dev $trend_t$					0.0430*	0.0409*
					(0.0217)	(0.0213)
Temp dev $trend_{(t-1)}$					0.0132	0.0102
					(0.0233)	(0.0245)
Precip dev $trend_t$					−0.0230	−0.00682
					(0.0519)	(0.0500)
Precip dev $trend_{(t-1)}$					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$_{(year\ t)}$					
	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$_{(\text{year } t)}$			
	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: ***, $P < .01$; **, $P < .05$; *, $P < .10$.