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Local Warming and Violent Conflict in North and South Sudan

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ABSTRACT

Weather shocks and natural disasters, it has been argued, represent a major threat to national and international security. Our paper contributes to the emerging micro-level strand of the literature on the link between local variations in weather shocks and conflict by focusing on a pixel-level analysis for North and South Sudan at different geographical and time scales between 1997 and 2009. Temperature anomalies are found to strongly affect the risk of conflict. In the future the risk is expected to magnify in a range of 21 to 30 percent under a median scenario, taking into account uncertainties in both the climate projection and the estimate of the response of violence to temperature variations. Extreme temperature shocks are found to strongly affect the likelihood of violence as well, but the predictive power is hindered by substantial uncertainty. Our paper also sheds light on the vulnerability of areas with particular biophysical characteristics or with vulnerable populations.

Keywords: weather shocks, violent conflict, vulnerability, Sudan

1. INTRODUCTION

Climate change and natural disasters, it has been argued, represent a major threat to national and international security by increasing resource scarcity and competition and inducing health problems (Homer-Dixon 1994, 2007; Sachs 2005; Steinbruner, Stern, and Husbands 2012).[1] So far, these claims lack consensual empirical support and would deserve a more careful investigation of the specific channels linking climatic phenomena and conflict events (Salehyan 2008; Scheffran et al. 2012; Steinbruner, Stern, and Husbands 2012). Quantitative assessment of the climate-conflict nexus has largely been initiated by Miguel, Satyanath, and Sergenti (2004), who seminally used rainfall shocks on income growth to assess how the risk of conflict may increase in Africa south of the Sahara (SSA) when the opportunity cost to fight decreases.[2] Since then, Burke et al. (2009) found that temperature variations increase the risk of conflict in SSA and, interestingly, temperature is the only significant climatic variable when included in the model along with rainfall. They suggest that earlier findings, including Miguel, Satyanath, and Sergenti (2004), about increased conflict due to lack of rainfall, might have been partly capturing the effect of higher temperature.[3] The importance of temperature is also in line with the results by Zhang et al. (2007, 2011) showing that temperature variations are correlated with the frequency of wars in Europe and China in the preindustrial period. Offering an alternative approach to the one based on weather variations, Hsiang, Meng, and Cane (2011) further investigated the relationship between climate change and global patterns of civil conflicts. They exploited the dominant interannual mode of the modern climate, the El Niño–Southern Oscillation, to show that conflict is more likely during El Niño years (warmer and dryer in the continental tropics) relative to La Niña years.

A recent paper by Klomp and Bulte (2012) revisits these cross-country analyses through a battery of robustness checks and finds little evidence linking global and local weather shocks and conflict. In line with the general review on the conflict literature by Blattman and Miguel (2010), Klomp and Bulte (2012, 26) call for moving beyond the conventional country-year focus and embracing shorter time intervals and subnational regions. The lack of robustness in previous cross-country findings may indeed result from the inability of country-level variables to capture the dynamics of local conflict events (for a discussion, see Buhaug and Lujala 2005 and Buhaug and Rod 2006). Using subnational units of analysis would allow us to overcome this shortcoming while preserving the robustness of the econometric approach recently advanced by scholars looking at the links between climatic variations and violence in SSA.[4] On the one hand, Harari and La Ferrara (2012) exploit the grid-cell-level (1 degree over 1 degree) annual variation to study the relationship between weather shocks and conflict in Africa. They show that negative weather shocks (proxied by a new drought index), occurring during the growing season of the main crops, significantly increase the incidence of conflict. On the other hand, Raleigh and Kniveton (2012) and O'Loughlin et al. (2012) propose regional analyses focused on East Africa. Based on geo-referenced (2.5 degree) data, Raleigh and Kniveton (2012) assess the link between rainfall anomalies and conflict events in Uganda, Ethiopia, and Kenya and find that the frequency of violent events increases in periods of extreme rainfall variations. O'Loughlin et al. (2012) evaluate the role not only of precipitation, but also of temperature changes at a finer resolution (grid of 1 degree) using similar data and including nine entire countries (Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, Tanzania, and Uganda). They

[1] For example, Homer-Dixon (2007, l. 22) argues that "climate stress may well represent a challenge to international security just as dangerous-and more intractable-than the arms race between the United States and the Soviet Union during the Cold war or the proliferation of nuclear weapons among rogue states today."

[2] The robustness of these results has been discussed mainly in Ciccone (2011) and Miguel and Satyanath (2011).

[3] The results by Burke et al. (2009) have raised a fierce debate between Buhaug (2010) and the same authors (Burke et al. 2010). Such a debate is described in Klomp and Bulte (2012).

[4] A recent special issue of the *Journal of Peace Research* provided mixed evidence based on within-region or within-country analyses or case studies, but the overall assessment by the guest editor (Gleditsch 2012, 3) was that "so far there is not yet much evidence for climate change as an important driver of conflict." Note that such mixed evidence was given also in the special issue of *Political Geography* (Nordas and Gleditsch 2007), which mainly reported qualitative or simple correlation analyses.

show that wetter deviations from the precipitation norms decrease the risk of conflict, whereas warmer than normal temperature raises the risk.

Our paper is complementary to such studies, in particular the above-referenced ones about East Africa, even if they do not specifically include Sudan in their research area. But beyond the exclusive focus on Sudan and the finer grid-cell resolution (0.5 degree)[5], our paper differs by adopting a more restrictive methodological approach. Our main results are estimated using a fixed-effects framework at both pixel and quarterly levels. This framework not only isolates the impact of climatic variations from specific control variables—such as the population, the distance to the nearest urban center (Raleigh and Kniveton 2012), the crop production index, and the infant mortality rate (O'Loughlin et al. 2012)—but also from all the other characteristics that are time constant at the grid-cell level. Although we will discuss the way our results change when a different framework is chosen, we consider an approach based on cell-level fixed effects more likely to reduce estimation bias compared to an approach based on adding a limited number of potentially endogenous control variables (Angrist and Pischke 2009). In this respect, our methodology is closer to Maystadt, Eckers, and Mabiso (2013), who, using monthly and regional variations and focusing on the role of the livestock market as a channel of transmission, found a strong relationship between more frequent and intense temperature-based droughts and the occurrence of violent conflict in Somalia.

Furthermore, our paper contributes to the spatially disaggregated strand of the literature on the links between weather shocks and conflict by assessing the validity of the analysis at different geographical and time scales and by reviewing a series of proxies for weather shocks previously used in the literature in an inconsistent way. More precisely, we estimate the relationship between local warming and violent conflict between 1997 and 2009 in North and South Sudan, controlling for time dummies, grid-cell fixed effects, and area-specific time trends. Following Burke et al. (2012), we then project the changes in violent conflict by 2030 under different climate models and scenarios and show that the uncertainty in the projections increases when the extreme nature of temperature shocks is captured. The available data do not allow us to test the different channels linking weather shocks to conflict, but we assess how some characteristics magnify or reduce the strength of such relationship. Therefore, our discussion about the heterogeneous effects sheds light on the vulnerability of areas with particular biophysical characteristics or with vulnerable populations.

[5] A geographical grid is an agreed, defined, and harmonized grid net for a region or the whole world with standardized location and size of grid-cells. A grid-cell is also called a pixel whose size is the resolution of the grid. The resolution is expressed in degree/minute/second as the longitude and latitude or it can be expressed in length units (e.g. km and meters), treating the earth as a flat surface. For example, 0.5 degree pixel is also commonly referred to 50kmx50km, 5 minute 10kmx10km or 30 second 1kmx1km.

2. BACKGROUND

Sudan is known for having experienced two civil wars after independence in 1956, but it actually has a long-lasting history of repeated conflict events starting well before independence. Like many African conflicts, the Sudan conflict took its roots in the colonization period.[6] Most scholars agree that the divide between the north and the south was fueled by the British colonizers who favored social and economic investment in the north under the so-called Southern Policy implemented between 1920 and 1947 (Ali, Elbadawi, and El-Bathani 2005). After independence, such structural divide was exacerbated by the northern elite that came into power and led to 17 years of civil war (known as the first civil war) between the north and the south. A peace settlement, the Addis Ababa Peace Accord, was reached in 1972, but the then president, Nimeri, aggravated grievances in the south by redesigning the border to include oil-producing areas in the northern territory, by grabbing land through the development of mechanized farming, and by exploiting the divisions between various groups within the south. As a result, the Sudan People's Liberation Army (SPLA) was created in 1983 with external support from Ethiopia. The second Sudanese civil war was then triggered as a continuation of the first civil war and lasted until 2005, when it ended with the signature of the Comprehensive Peace Agreement that paved the way for a referendum in January 2011 and for the independence of South Sudan in July 2011. Although the exact figures are a subject of debate (Duffield 2001), the dramatic history of violence in Sudan resulted in more than 1.9 million civilian deaths between 1983 and 1998 (more than 600,000 since 1993, according to Burr 1998) and about 5 million displaced people (United Nations Environment Programme, UNEP 2007).

Behind this national scene and the description of the civil war as an opposition between the north and the south, local conflict events also multiplied within North and South Sudan (Johnson 2011). The exploitation of resources, once the source of warfare financing, became a warfare objective in itself.[7] At the same time, conflict events evolved from ethnic tensions between the north and the south to local or regional conflicts increasingly reported to be linked to environmental factors. The study by UNEP (2007, 70) was certainly instrumental in maintaining that "competition over declining natural resource was one of the underlying causes of the conflict" and in pointing to four specific conflict-contributing categories of natural resources: "oil and gas reserves, Nile waters, hardwood timbers, rangeland, and rain-fed agricultural land (and associated water points)." In particular, in marginalized areas, conflict was intensified by the expansion of large semimechanized farms and the subsequent loss of access to land for both smallholders and pastoralists (Keen and Lee 2007). Keen and Lee (2007, 17), for example, reported that the area of land taken up by rain-fed semimechanized agriculture increased from about 2 million feddans (that is, about 0.84 million hectares) at the beginning of the 1970s to 14 million feddans (that is, about 6 million hectares) by 2003.

In addition, pastoralist and agropastoralist communities have been increasingly under pressure by the combination of population growth and more frequent and intense droughts. In Sudan, agriculture—that accounted for 30–40 percent of GDP between 1996 and 2010 (Benke 2012)—remains extremely vulnerable to droughts, whereas the climatic conditions appear to have become harsher to cope with. According to UNEP (2007), an estimated 50- to 200-kilometer southward shift of the boundary between desert and semidesert has occurred since the 1930s, and the remaining semidesert and low rainfall land are at considerable risk of further desertification. Thus, the vulnerability of semiarid areas to climatic stresses and shocks is more likely to intensify in the decades to come.

However, the link between resource scarcity and conflict is far from being trivial. Scholars and policymakers have equalized resource scarcity to an incentive for conflict (Homer-Dixon 1994),

[6] Johnson (2011) even points to the establishment by the Turco-Egyptians of an exploitive relationship between the centralizing power of the state and the peripheries (including South Sudan) before the nineteenth century, mainly through the institutions of slavery and slave trading. Such historical factors echo the findings of Nunn (2008) on the legacy of slave trade for contemporaneous economic development.

[7] As quoted by Ali, Elbadawi, and El-Bathani (2005), "the Sudan People's Liberation Army/Movement, instead of being a genuine national liberalization movement, degenerated into an agent of plunder, pillage and destructive conquest."

especially for Sudan and pastoralist communities (UNEP 2007; Hendrickson, Armon, and Mearn 1996), but detrimental weather shocks may also reduce the value of the resources that are fought over. In particular, Butler (2007) and Kevane and Gray (2008) argued that weather patterns only weakly corroborated the claim that climate change caused the Darfur conflict and concluded that the United Nations overestimated the case. Certainly, there is still a need to understand which conditions make the link between resource scarcity and conflict hold in one direction or another. That is the main objective of our empirical analysis.

3. EMPIRICAL ANALYSIS

Methods

We combine climatic and conflict data for each 0.5 degree grid-cell (*i*) of Sudan and for each quarter (*t*) from 1997 until 2009 to examine the relationship between weather shocks ($Weather_{i,t}$) and conflict occurrence ($Conflict_{i,t}$). Accordingly, we estimate the following baseline equation:

$$\text{Conflict}_{i,t} = c + \alpha_i + \varphi_t + t_{i,t} + \eta \text{ Weather}_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \quad (1)$$

The dependent variable, $Conflict_{i,t}$, is given by the quarterly sum of violent conflict events by grid-cell (*i*). Our main variable of interest, $Weather_{i,t}$, seeks to capture weather deviations and extreme events at the grid-cell (*i*) and quarter (*t*) levels. Since there is no consensus, yet, on the best way to assess the impact of weather shocks on socioeconomic outcomes, we propose a series of proxies most likely to capture deviations from normal conditions and the nonlinearity induced by extreme events. First, we apply the anomaly transformation: precipitation and temperature quarterly data are transformed into anomalies, that is, deviations from the long-term quarterly mean, divided by the long-run quarterly standard deviation.[8] Such anomaly transformation has become standard and is frequently adopted in the economic literature (for example, Maccini and Yang 2009; Barrios, Bertinelli, and Strobl 2010; Marchiori, Maystadt, and Schumacher 2012; Dell, Jones, and Olken 2012; Harari and La Ferrara 2012). In addition, we introduce the quadratic term of the weather anomalies as a first indication of nonlinearity. Second, similar to Schlenker, Hanemann, and Fisher (2006); Schlenker and Roberts (2009); and Harari and La Ferrara (2012), we isolate the component of climate variability that is relevant for agriculture interacting the weather variables with an indicator identifying the growing period by state (De-Pauw and Wu 2012).[9] In particular, we try to capture extreme events that could lead to yield losses by defining a dummy for positive and negative deviations happening during the growing period above one (or two) standard deviation(s). Furthermore, we consider also a cell-specific threshold for extreme events and introduce a dummy equal to one for deviations below 15 (or 10 or 5) percent and above 85 (or 90 or 95) percent of the grid-cell-specific distribution in the growing period (as in Brückner 2010 and Burke, Gong, and Jones 2011). Finally, to assess more accurately temperature shocks on agriculture, we follow the approach introduced by Schlenker, Hanemann, and Fisher (2006) that suggests exploiting daily data to compute degree-days transformation. Based on agronomist literature specifically for SSA, Schlenker and Lobell (2010) define a lower threshold at 10 degrees Celsius and a higher threshold at 30 degrees Celsius. The two variables are considered together to capture the nonlinearity of temperature shocks (see also Schlenker and Roberts 2009). The first variable, "moderate degree-days," provides the sum of degree-days above the lower threshold of 10 degrees Celsius and below the upper threshold of 30 degrees Celsius.[10] The second variable, "extreme degree-days," sums the number of degree-days above the upper threshold of 30 degrees Celsius. The two variables are expressed in degree-days per quarter (or the concerned period in the robustness checks) and then transformed into anomalies as in Dillon, Mueller, and Salau (2011). Similar to Schlenker, Hanemann, and Fisher (2006), these variables are interacted with our state-level indicator of the growing period, and a quadratic term is introduced to capture nonlinear effects. As a last robustness check, we follow the approach of Harari and La Ferrara (2012), and we compute for each grid-cell quarter the Standardized Precipitation–Evapotranspiration Index (SPEI), a multiscalar drought index that offers the advantage of being based on both precipitation and temperature.

[8] The quarterly basis for the normal conditions is used to correct for seasonality effects.

[9] We chose this indicator defined by state because, even if it's not disaggregated by crop, it performs better than an indicator based on crop calendars only defined for the whole of Sudan or for macro-regions (FAO crop calendar tool).

[10] In other words, a day with a temperature below 10 degrees results in 0 degree-days, a day with a temperature between 10 and 30 degrees contributes to the number of degree-days above 10, and a day with a temperature at 30 degrees Celsius records 20 degree-days.

We estimate equation (1) with a linear least squares specification because nonlinear models with fixed effects yield inconsistent slope estimates due to the incidental parameter problem (King and Zeng 2001; Greene 2004). To be able to draw causal inferences, we introduce in the equation grid-cell fixed effects (α_i) and time dummies (φ_t). Therefore, we investigate how climate changes (compared to the pixel mean) affect the frequency of conflict events within each grid-cell (compared to the mean). In addition, we augment the specification by introducing a county-specific time trend ($t_{\mathrm{i,t}}$)[11] and the night-lights density ($X_{i,t}$). The former is included to reduce the threat of spurious parallel trends, whereas the latter is used as a proxy to capture changes in economic activities potentially unrelated to climate.[12] However, we cannot reject the hypothesis that county-specific time trends' and night-lights density's get rid of interesting variations in the relationship between weather shocks and violent conflict, and consequently, we will show how our results change when we exclude such variables.[13]

The introduction of grid-cell fixed effects is the main difference from the approach proposed by O'Loughlin et al. (2012), who prefer to introduce highly aggregated country dummies in their main estimations and who present a similar methodology just as a robustness check (O'Loughlin et al. 2012, Supporting Information, 5). Interestingly, when the authors use grid-cell fixed effects in place of country fixed effects (but without replacing yearly dummies by quarterly or monthly ones), precipitation anomalies do not affect the risk of conflict, whereas additional support is found for the role of hotter than usual temperatures in predicting greater conflict. We believe our approach is more likely to control for unobserved (time-constant) characteristics that may bias the estimated relationship between weather shocks and conflict at the grid-cell level. Nevertheless, we acknowledge that the use of fixed effects at a disaggregated level has recently been questioned by some scholars because the effects absorb most of the variation, making the identification rely on slight margins. Dealing with climatic variables, this might lead to the amplification of measurement errors, as Fisher et al. (2012) point out. Thus, we will show that our results are confirmed even when we use the more commonly preferred random-effects estimation with dummies at the state level (suggesting that our findings are not driven by measurement errors).

Moreover, we cluster the standard errors at the county level to reduce potential problems generated by time and spatial dependency within Sudanese counties. In addition, bearing in mind the recent debate on the importance of explicitly modeling such dependency in the process itself (Harari and La Ferrara 2012), we will control for serial and spatial correlation by transforming equation (1) into a simple dynamic model (using the Arellano-Bover/Blundell-Bond estimator) and into a dynamic model with the spatial lags of the independent variables included. This latter model has the advantage of being straightforward since adding the spatial lags does not involve serious econometric problems. The pitfalls of the model are that it does not allow correcting the standard errors for clustering at the county level, it does not take into account the fact that spatial correlation might also be present directly in conflict itself through cross-cell spillovers, and it offers estimates affected by a simultaneity bias. As Harari and La Ferrara (2012, 12) remark, in the typical case of positive covariance of spatial lags and independent variables, we will overestimate the interdependence effect and underestimate the cell-specific effect of weather shocks. Thus, the estimates of such model represent a credible lower bound for the effects of weather shocks on conflict.

[11] There are 117 counties in North and South Sudan.

[12] Several papers have shown that the importance of environmental variables may be downplayed by the inclusion of political and economic variables (Raleigh and Urdal 2007). The use of grid-cell fixed effects and time dummies already reduces the importance of time-constant political or economic factors and of those factors that would affect equally over time the units of observations. Adding night-lights, the best proxy of economic activity at the local level, offers a further robustness check. Nevertheless, we cannot exclude that night-lights are capturing relevant variation or act as a bad control (Angrist and Pischke 2009). We therefore exclude that control (along with the time trend) to provide an upper-bound limit of the effect of extreme weather shocks on conflict and confirm that our findings do not change. The results are also similar when the lagged value of night-lights density is used.

[13] See Results and Robustness Checks section.

Finally, although our empirical strategy relies on quarterly variations in climatic variables to assess their effects on conflict, in section 4, we also exploit time-invariant local characteristics to evaluate the heterogeneous effects of the climate shocks and identify mitigating and exacerbating factors.

Data

Data on conflict events come from the Armed Conflict Location and Event Dataset (ACLED) presented by Raleigh et al. (2010).[14] ACLED is the most recent, detailed, and widely used conflict dataset developed by the International Peace Research Institute of Oslo (PRIO). It specifies the exact location, the date, and other characteristics of conflict events based on news and reports within unstable states. Given its nature, it might be affected by selection in reporting, a drawback common to conflict datasets not based on surveys, but such reporting bias is not likely to be systematically correlated with our weather indicators and should not constitute a major problem for our identification strategy. Another drawback of these data is the lack of information about the number of causalities, but the monthly frequency of violent events should give us a fair approximation of the local intensity of conflict. We focus on violent conflict events, comprising battle, defined as "a violent interaction between two politically organized armed groups at a particular time and location", and violence against civilians (one-sided violence), defined as "deliberate violent acts perpetrated by an organized political group, typically either a rebel or a government force, on an unarmed non-combatant" (ACLED Codebook version 2, 8 and 11). [15] In North and South Sudan, the number of 2,497 violent events represents the overwhelming majority of events (97 percent) reported in the ACLED dataset. Although our results do not depend on that restriction (results available on request), we exclude nonviolent events (establishment of rebel headquarters, nonviolent rebel presence, changes of territorial control without violence, and protests and riots) as they are not directly related to resource-based conflicts.

Weather data are mainly generated from the University of East Anglia's (UEA) Climatic Research Unit (CRU) Time Series (TS) dataset, version 3.1. This dataset provides monthly mean temperature and precipitation from January 1901 at 0.5 degree grid resolution (equivalent a 50-kilometer grid resolution). However, the accuracy of these data has been questioned. As explained in Mitchell and Jones (2005, 702), values at the station level "were interpolated onto a continuous surface from which a regular grid of boxes of 0.5 degree was derived and, in order to ensure that the interpolated surface did not extrapolate station information to unwarranted distances, 'dummy' stations with zero anomalies were inserted in regions where there were no stations." Thus, if the closest weather station with available data is too far, a long-term average value is used. The issue seems to be particularly important for precipitation data.[16] For North and South Sudan, Figures A.1.a and A.1.b illustrate the bias it introduces in the shape of the precipitation distribution. In spite of the critics,[17] most studies on the climate-conflict nexus use this dataset, not only at the cross-country level (Miguel, Satyanath, and Sergenti 2004; Burke et al. 2009; Harari and La Ferrara 2012) but also at the regional level (Kevane and Gray 2008; Raleigh and Kniveton 2012; O'Loughlin et al. 2012) and the national level (Theisen 2012; Maystadt, Eckers, and Mabiso 2013). The CRU dataset is so widely used because it has the advantage of providing precipitation and temperature data from 1901 and, consequently, allows correcting for deviations from long-term normal conditions. Given the consensus confirming that data from 1901 to about 1950 are not accurate for SSA,

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[14] See www.acleddata.com, downloaded in October 2012.

[15] See http://strausscenter.org/codebooks/ACLED%202.0%20Codebook.pdf.

[16] In our sample, out of 75,012 observations, there are only 18 observations with zero anomalies for mean temperatures, but there are, depending on the quarter, between 357 and 5,586 observations with zero anomalies for precipitations.

[17] Kudamatsu et al. (2012, 6), among other scholars, stated that such an interpolation method is problematic for exploiting variation within location over time since weather stations with consistent time-series observations in most African countries are few and far between. For example, Kevane and Gray (2008), investigating the relationship between rainfall shocks and conflict in Darfur, noticed that rainfall station data for Darfur had been collected since the early 1990s only in three or four main towns. Similarly, some climatologists claim that only data based on satellite estimates can really cover the entire African continent at a suitably detailed resolution. Others, such as Lobell (2013), stress that the measurement errors resulting from the interpolation method may be particularly problematic for data on precipitation.

anomalies have been computed based on a long-term reference period starting in 1949 as in O'Loughlin et al. (2012). In addition, considering the criticism expressed about data based on weather stations, we test the robustness of our analysis with an alternative satellite-based dataset covering the period from 1997 to 2009 and provided by the POWER project of the National Aeronautics and Space Administration (NASA) of the United States.[18] Beyond offering a robustness check on the quality of the East Anglia data, these data also offer us the possibility to compute the degree-days variables based on daily data. Moreover, such data are based on a larger pixel size and thus allow us to show that our results are not affected by the so-called modifiable areal unit problem and, in particular, by the scale problem, "which is the variation in numerical results occurring due to the number of zones used in the analysis, and hence the possibility of obtaining different results for different resolutions" (Harari and La Ferrara 2012, 27). Finally, SPEI comes from SPEIbase, version 2.0, a global dataset with a spatial resolution of 0.5 degree latitude/longitude and temporal coverage between 1901 and 2009, based on the routine programmed by Vicente-Serrano et al. (2010).[19] Compared to other multiscalar drought indexes, SPEI has the advantage of taking into account the joint effects of precipitation, potential evaporation, and temperature and therefore offers a more accurate measure of "effective" rainfall. Table A.1 summarizes the names, the construction, and the sources of all the weather variables used.

Furthermore, we collect geo-referenced data on various geographical, economic, and social time-invariant characteristics. Geographical data are similar to the variables employed by Dorosh et al. (2012), who explained to a greater extent the algorithms used for the estimations. Data on agroecological zones are based on the calculations of the FAO and the International Institute for Applied Systems Analysis, which combine data on land resources (climate, soil, and terrain) with a mathematical model for the estimation of potential biomass (Fischer et al. 2001). Crop-type data are drawn from the Spatial Production Allocation Model (2000, version 3, release 6) of the IFPRI. The IFPRI Spatial Production Allocation Model (You, Wood, and Wood-Sichra 2009) generates highly disaggregated, crop-specific production data by a triangulation of any and all relevant background and partial information. This includes national or subnational crop production statistics, satellite data on land cover, maps of irrigated areas, biophysical crop suitability assessments, population density, secondary data on irrigation and rainfed production systems, cropping intensity, and crop prices. This information is compiled and integrated to generate "prior" estimates of the spatial distribution of individual crops. Priors are then submitted to an optimization model that uses cross-entropy principles and area and production accounting constraints to simultaneously allocate crops into the individual pixels of a Geographic Information System database. The result for each pixel (notionally of any size, but typically from 1 to 100 square kilometers) is the area and production of each crop produced, split by the shares grown under irrigated, high-input rainfed, and low-input rainfed conditions (each with distinct yield levels). Data on road infrastructure are largely based on UNEP (2005) data,[20] urban centers are identified using the Global Rural-Urban Mapping Project (2000) data from the Center for International Earth Science Information Network (CIESIN),[21] and travel times are estimated based on an algorithm taking into account road quality, slope, biophysical characteristics of the land, and other factors (Thomas 2007). Data on population come from the fourth version of the African Population Database (UNEP/CIESIN 2004);[22] in particular, we use the population from 1990, which is based on intercensual 1983 through 1993 growth rates at the county level (or at the state level for the areas not enumerated).[23] Geo-referenced yearly

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[18] These data were obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center POWER Project funded through the NASA Earth Science Directorate Applied Science Program. See http://power.larc.nasa.gov/index.php, downloaded in October 2012.

[19] See http://sac.csic.es/spei/spei_index.html, downloaded in October 2012.

[20] See the Global Environment Outlook Data Portal: http://geodata.grid.unep.ch.

[21] See http://sedac.ciesin.columbia.edu/data/collection/grump-v1.

[22] See the African Population Database 1960–2000, version 4: http://na.unep.net/siouxfalls/globalpop/africa/Africa_index.html.

[23] Thus, such data are based on the following two census datasets: (1) Population Studies Center, "Population of Sudan and Its Regions, 1983 Census: Total Populations by Region, Province and District" (Wad Medani, Sudan: University of Gezira jointly with Department of Statistics, Census Office, 1983); and (2) Central Bureau of Statistics, "Population Census of Sudan 1993"

information on night-lights density comes from the database presented by Henderson, Storeygard, and Weil (2012), and data on livestock density (head/square km, 2005) are drawn from the Gridded Livestock of the World (Wint and Robinson 2007). Information on the location of ethnic groups is based on the University of Zurich's Geo-referencing of Ethnic Groups dataset that relies on maps from the classical Soviet Atlas Narodov Mira.[24] More specifically, we use anthropological studies to classify the different ethnic groups according to their main type of livelihood: pastoral (including nomad and seminomad groups), agropastoral, or mostly based on agriculture.[25] Information about the distance to a major river or a lake comes from the Yale Geographically Based Economic Dataset (G-Econ, version 4.0) introduced by Nordhaus et al. (2006).[26]

The descriptive statistics of the conflict- and weather-based variables are given in Table A.2. Figure A.2.a shows the time variation for the whole sample of the conflict data, along with the time variations of the first two climatic variables, that is, temperature anomalies and temperature shocks greater than one standard deviation, happening during the growing period. The time variation in the occurrence of conflict events is a case in point with major peaks corresponding to the main events reported by Johnson (2011).[27] Figure A.2.b presents the maps illustrating the location of violent events and the geographical variation of the aggregated values of the two climatic variables, chosen for presentation purposes.[28] These figures constitute a first indication of a time and spatial correlation between temperature-related shocks and the frequency of conflict. However, on this basis, we cannot infer a causal relationship. The cross-country literature warns us about potential bias due to unobserved heterogeneity. Favorable climatic conditions (for example, moderate temperature) have been associated with better institutions (Acemoglu, Johnson, and Robinson 2002; Easterly and Levine 2003; Rodrik, Subramanian, and Trebbi 2004), faster transition out of agriculture (Diamond 1997; Masters and McMillan 2001), and hence, stronger economic growth (Sachs and Warner 1997; Nordhaus 2006; Dell, Jones, and Olken 2012). Although certainly reduced, the same concern applies within a country. For example, the preference for a more temperate climate by colonizers and its impact on institutions may well explain the differences in local governance between locations of North and South Sudan. Similarly, we cannot exclude that the time correlation is driven by common factors generating spurious correlations between weather shocks and conflict. The introduction of grid-cell fixed effects, time dummies, and county-specific parallel trends in the regression analysis should drastically reduce these threats to causal inference.

(Khartoum, Sudan: Census Office, 1993).

[24] See http://www.icr.ethz.ch/data/other/greg, downloaded in October 2012.

[25] Pastoral groups include nomad (Baggara/Shoa Arabs) and seminomad (Karamojo, Teso, Zagawa, and Tubu) groups. Agropastoral groups include Hamitic (Lotuko, Bari, and Murle) and Nuba (Dago, Kadugli-Krongo, Koalib-Tagoi, and Temaini) tribes. The other groups are considered mainly reliant on agriculture.

[26] See http://gecon.yale.edu/data-and-documentation-g-econ-project, downloaded in October 2012.

[27] For example, the five major peaks correspond to particularly conflictive times in North and South Sudan. The first peak in 1997 (quarter 1) corresponds to operations conducted by the Ethiopian army in collaboration with SPLA and the operation launched in Central Equatoria; in 1999 (quarter 2), the resurgence of violence between the government of Sudan (GOS) and SPLA followed the agreement between GOS and Eritrea not to support each other's rebel movement; in 2002 (quarter 2), the number of violent events surged as a result of the agreement by the GOS to allow the Ugandan army to pursue the Lord's Resistance Army in Sudan and the intensification of fighting (including bombing) in Bhar al-Ghazal and Upper Nile as well as in the south; in 2008 (quarter 2) and 2009 (quarter 1), fighting between SPLA and government militias intensified along the Kordofan–northern Bahr al-Ghazal border as well as in Unity State and around the town of Malakal (in Upper Nile).

[28] Violence frequently occurred in Darfur (around the three major cities of Nyala, El Fasher, and Geneina); in the bordering state with Uganda (Eastern Equatoria) given the recurrent involvement of the Lord's Resistance Army in South Sudanese conflicts; in South Kordofan, Upper Nile, and Jonglei provinces (around the oil fields close to the town of Bentio); and in the Eastern part of North Sudan (Blue Nile and Kassala).

Results and Robustness Checks

Table A.3 summarizes the results of estimating equation (1) including only temperature indicators. Based on these results, a change in temperature anomalies of one standard deviation increases the frequency of violent conflict by 31 percent (partial effect expressed as a share of the mean value of violent conflict). In addition, a change of one standard deviation in moderate temperature shocks during the growing period increases conflict by about 21 percent (for the variables "Temp> 1 s.d.," "Heat Shock> 1 s.d.," or "Heat Shock Pctile85"). A change of one standard deviation in extreme temperature shocks during the growing period increases conflict by 27 percent (for "Temp> 2 s.d." or "Heat Shock> 2 s.d.") or by 31 percent (for "Heat Shock Pctile90"). These partial effects (obtained based on regressions 1 to 9 of Table A.3) reveal an interesting pattern according to which the impact of weather shocks, happening during the growing period, increases when our proxies capture more extreme events. This pattern is also confirmed when moderate and extreme events are distinguished with the use of degree-days thresholds. Introducing the quadratic terms, moderate temperature shocks reduce conflict by about 12 percent, whereas extreme temperature shocks exacerbate violence by about 4 percent (see regressions 10 and 11 of Table A.3). This result also confirms that the choice of scale for the units of analysis does not drive our findings, given that the pixel size used in the NASA POWER dataset is much larger. All the partial effects relative to Table A.3 are summarized in Table 3.1, column 2.

When estimated without time trends and night-lights density, the effects remain essentially unchanged (see Table A.4 and column 4 of Table 3.1). Adding rainfall-related variables indicates that precipitation variations do not affect the frequency of conflict and do not alter the coefficients of the temperature-related variables (see Table A.5) or the relative partial effects (see column 6 of Table 3.1). These results clearly point to the role of temperature shocks in explaining variations in violence in North and South Sudan and are in line with recent evidence on the impact of temperature shocks on agricultural income in both developed (Schlenker and Roberts 2009; Lobell et al. 2013) and developing countries (Schlenkler and Lobell 2010; Lobell et al. 2011). However, they may still be sensitive to the choice of the specification adopted to estimate equation (1).

Therefore, we investigate the robustness of our results (1) to other proxies, functional forms, and data sources for precipitation shocks; (2) to other modeling choices, including the use of state fixed effects and state-level controls similar to that of O'Loughlin et al. (2012) or Raleigh and Kniveton (2012); (3) to other levels of aggregation, that is, monthly and yearly levels; and (4) to explicitly modeling time and spatial dependency.

Table 3.1—Partial effects for the number of violent events

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Table A.3 Baseline model		Table A.4 Model without time-trends & night lights		Table A.5 Model including precipitation indicators		Table A.18 Dynamic model		Table A.19 Dynamic model with spatial lags	
	β / s.d	part. eff.	β / s.d.	part. eff.	β / s.d.	part. eff.	β / s.d.	part. eff.	β / s.d.	part. eff.
Temp Anom	0.017	30.75	0.021	38.72	0.017	31.89	0.017	32.03	0.016	29.18
Temp Anom + Temp Anom Sq	0.021	39.3	0.022	41.14	0.021	39.3	0.013	24.13	0.014	26.33
Temp Shock > 1 s.d. Grow. Per.	0.011	21.24	0.01	18.26	0.011	20.48	0.013	23.33	0.011	20.13
Temp Shock > 2 s.d. Grow. Per.	0.014	26.68	0.016	29.37	0.014	26.44	0.014	26.19	0.012	21.74
Heat Shock > 1 s.d. Grow. Per.	0.011	21.32	0.01	19.08	0.011	20.77	0.013	24.43	0.009	16.98
Heat Shock > 2 s.d. Grow. Per.	0.014	26.91	0.016	29.6	0.014	26.67	0.014	26.26	0.012	22.03
Heat Shock Pctile85 Grow. Per.	0.012	21.84	0.011	20.63	0.012	21.52	0.013	24.38	0.009	17.44
Heat Shock Pctile90 Grow. Per.	0.017	31.32	0.017	32.41	0.017	30.93	0.016	30.38	0.013	23.47
Heat Shock Pctile95 Grow. Per.	0.016	30.06	0.018	33.18	0.016	29.77	0.016	30.14	0.013	24.4
Moderate DD Anom Grow. Per.	-0.022	-11.14	-0.034	-16.96	-0.022	-11.14				
Mod DD An GP + M DD An Sq GP	-0.024	-11.85	-0.034	-17.29	-0.024	-11.85				
Ext DD An GP + E DD An Sq GP	0.021-0.013	3.99	0.016	8.11	0.021-0.013	4.04	0.03-0.023	3.57	0.028	14.29

Source: Authors' estimation based on ACLED, UEA CRU-TS and NASA POWER.

Notes: Columns 1, 3, 5, 7, and 9 report only the coefficients that were statistically significant in the models' equations. Descriptions of the weather variables are given in Table A.1. s.d. = standard deviation; part. eff. = partial effects.

First, we may wonder whether the fact that variations in precipitation do not affect violence is related to the lack of accuracy of the adopted proxies for precipitation shocks. In line with Harari and La Ferrara (2012), precipitation shocks may be better captured by variations in SPEI. Our results suggest that it is not the case for North and South Sudan, without altering the impact of temperature shocks (see Table A.6). We also exclude the possibility that the lack of impact of precipitation shocks may be driven by the absence of a time-lagging effect since including the time lags does not alter the coefficients of the temperature indicators and changes only slightly the partial effects (see Table A.7).[29] Still, the explanatory dominance of temperature shocks in contrast to rainfall shocks might just be due to larger errors in measuring precipitation. For example, Lobell (2013) shows that the interpolation method used in the UEA CRU-TS dataset substantially underestimates the impact of precipitation on crop yields. Therefore, we collected information regarding the exact location of the weather stations employed by the University of East Anglia for its Sudan database to check that the interaction terms between the weather indicators and the distance from the nearest weather station were indeed not significant.[30] This is a first indication that such measurement errors do not play much of a role in driving our results. In addition, we test the importance of precipitation shocks using the alternative NASA POWER dataset, and even in this case, we confirm the superiority of temperature shocks in explaining variations in violent conflict (see Table A.8). All the partial effects related to Tables A.6, A.7, and A.8 can be found in Table A.9.

Second, we test the robustness of our results to the use of fixed effects at the highest level of aggregation (26 states in North and South Sudan), similar to O'Loughlin et al. (2012) and Raleigh and Kniveton (2012). Our results remain robust to such a modeling choice (see Table A.10); the coefficients of interest have the same direction and significance but are larger in magnitude, pointing to a possible upward bias. Adding the population by grid-cell (transformed into logarithm), an urban dummy, and the distance to roads and to international borders (transformed into logarithm) as control variables, like O'Loughlin et al. (2012), provides the expected signs without altering our main results (see Table A.11). Although introducing potential selection bias and changing the external validity of the results, we also implement a model with state fixed effects excluding the cells that never experienced violent conflict, similar to Raleigh and Kniveton (2012). Our results remain unaltered and the control variables proposed by the authors have the expected signs (see Table A.12). All the partial effects based on Tables A.10, A.11, and A.12 are summarized in Table A.13.

Third, we confirm the validity of our findings using alternative time aggregations. When we estimate equation (1) at the monthly level, our results maintain the same signs (see Table A.14) and offer conclusions similar to the ones based on the estimates at the quarterly level, with the main difference that the introduction of two lags is needed to obtain effects of comparable magnitudes (see Table A.15)—as expected. At the yearly level, our results are equally confirmed (see Table A.16). Table A.17 shows all the partial effects related to Tables A.14, A.15, and A.16.

Fourth, our results are robust to taking into account possible serial and spatial correlations. Table A.18 and column 8 of Table 3.1 present the estimates and the partial effects of the dynamic panel model, whereas Table A.19 shows that even adding the spatial lags of the variables of interest does not change the previous findings. These spatial lags are obtained by multiplying the vector of observations by the matrix W, a normalized spatial matrix of order 1 (but the results appeared to be robust also to the choice of a matrix of order 2). There are spatial spillovers for temperature shocks, but they are sufficiently close to zero and do not alter the partial effects (see column 10 of Table 3.1).

Therefore, the estimation of equation (1) indicates that extreme temperature shocks increase the frequency of conflict in North and South Sudan. Such impact appears to be robust to other proxies, functional forms, and data sources for precipitation shocks; to other modeling choices; to other levels of

[29] In Table A.7, column 6, we even find an unexpected negative sign for the lag of the precipitation deviation below two standard deviations, but this impact is not sufficiently robust to other specifications to deserve interpretation.

[30] Data on the location of the weather stations were provided by Dr. D. Lister, senior associate of the University of East Anglia's Climatic Research Unit, and by the help desk of the U.K. Centre for Environmental Data Archival.

aggregation; and to explicitly modeling time and spatial dependency. With a view to our projection exercise, the most reduced-form set of estimations whose partial effects are given in column 4 of Table 3.1 (excluding night-lights and time trends) can be considered an upper-bound limit of the effect of extreme weather shocks on conflict. On the contrary, the most structured set of models, that is, the dynamic model with spatial lags, represents the lower-bound limit of such an impact.

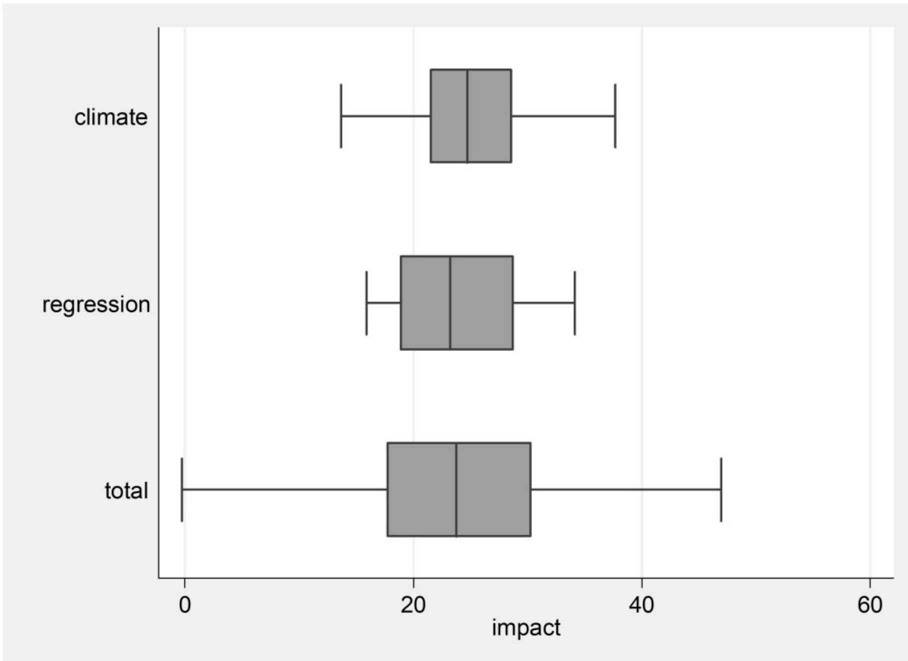
Projections

Projecting changes in the incidence of violent events under future climate change is far from trivial. Previous research has tended to rely on selected climate models and to overlook climate uncertainty in future temperature (and rainfall) changes. To incorporate that uncertainty into our projections, we follow the approach recommended by Burke et al. (2012) and applied in their study on conflict in SSA (Burke et al. 2009). Thus, we incorporate our estimated responses of conflict to climate (see Table 3.1) with climate projections for the corresponding SSA subregion (Sahel) from 20 climate models and three scenarios resulting from the World Climate Research Project Program's (WCRP) Coupled Model Inter-comparison Project phase 3 (CMIP3).[31] Such models provide the expected change in temperature between 2030 and 1980–1999, expressed in degrees Celsius, for each model and scenario. To calculate the expected temperature in 2030 we summed the expected change at the quarter level and the average quarterly temperature for the period 1980–1999. Temperature anomalies in 2030 are then estimated considering the same long-term mean and standard deviation described in the previous section. A major assumption is that no adaptation behaviors or policies in addition to the ones already incorporated in our estimates will take place by 2030. Given the relatively short timeframe, the assumption seems reasonable.

We apply the same method used by Burke et al. (2012) by distinguishing between climate and regression uncertainties. Climate uncertainty results from the difference in the various predictions for the expected change in monthly temperatures given by three possible scenarios and 20 possible climate models for each scenario. The expected impact on violent conflict is calculated by multiplying the expected percentage change in temperature anomalies by the coefficient showed in Table A.3. Regression uncertainty results from taking into account the variability given by the standard errors of the estimated coefficient. To quantify that uncertainty, we bootstrap 10,000 times the specification regressing temperature anomalies on violent conflict and we multiply the percentage change in temperature anomalies given by the median of the three scenarios by the coefficients obtained by bootstrapping. Total uncertainty results from taking into account both climate and regression uncertainty. According to Figure 3.1, all models predict more frequent violence as a result of projected temperature anomalies, with a 23.8 percent median projected increase by 2030. Such predictions are based on the partial effects obtained in our baseline model. Such additional increase would vary in a range between 21 and 30 percent for the lower-bound (dynamic model with spatial lags) and upper-bound estimates (model excluding night-lights and time trends). Similar to Burke et al. (2012), climate uncertainty is a larger concern than regression uncertainty in predicting the changes in violence by 2030. Taking the ratio of the difference between the 95th and 5th percentiles for the climate-uncertainty-only projections and the regression-uncertainty-only projections, we find that climate uncertainty is about 1.4 times larger than regression uncertainty.

[31] We thank Marhsall Burke for sharing the data for the 20 following models — BCCR, CCCMA.T63, CCSM, CNRM, CSIRO, ECHAM, GFDL0, GFDL1, GISS.Aom, GISS.Eh, GISS.Er, HADCM3, HADGEM1, IAP, INMCM3, IPSL, MIROC.Hires, MIROC.Medres, MRI, and PCM—and the three following scenarios—B1, A1B, and A2.

Figure 3.1—Importance of climate versus regression uncertainty in the projection of climate impacts on number of violent events in 2030, considering only temperature anomalies



Source: Authors' calculation based on WCRP CMIP3, UEA CRU-TS, and ACLED.

We also perform similar projections using proxies for more extreme temperature shocks.[32] As summarized in Table 3.2, the median projected impact is 10.2 percent when the shock is defined as a temperature deviation above one standard deviation, whereas the expected impact increases to 39.6 and 75.9 percent for more extreme shocks (above two standard deviations and above 95 percent of the pixel-specific distribution, respectively). However, the level of both climate and regression uncertainties does not allow us to give much interpretation to the projected changes in conflict due to changes in other proxies than temperature anomalies. Such a limit in our analysis confirms the difficulty of projecting how expected increases in temperature will translate into more frequent and more intense extreme events (Hansen, Sato, and Ruedy 2012; Rhines and Huybers 2013), hence the challenge to make predictions on the socioeconomic consequences of future extreme events.

Table 3.2—Projected impacts on number of violent events in 2030, by weather variable

Variable	Median percentage impact under total uncertainty	5th and 95th percentiles for percentage impact under total uncertainty	Ratio of climate over regression uncertainty
Tmp Anom	23.8	12.3, 41.5	1.4
Heat Shock > 1 s.d. Grow. Per.	10.2	5.3, 17.9	0.8
Heat Shock > 2 s.d. Grow. Per.	39.6	–10.6, 362.9	2.8
Heat Shock Pctile95 Grow. Per.	75.9	–3.3, 238.1	1.4

Source: Authors' calculation based on WCRP CMIP3, UEA CRU-TS, and ACLED.
Note: Variables are defined in Table A.1.

[32] Boxplots are available on request.

4. DISCUSSION

Our empirical analysis clearly points to the negative role of extreme temperature shocks in North and South Sudan, but due to limited data availability, it cannot describe the channels through which such shocks affect conflict. To partially cover this gap, we exploit the heterogeneity in the impact of weather variables and identify mitigating and exacerbating factors of the relationship between weather shocks and violence.[33]

The worst detrimental effect of climate change on African economies usually relates to decreased crop yields, in particular for maize, sorghum, millet, groundnut, and cassava (Jones and Thornton 2003; Lobell et al. 2008; Lobell and Burke 2010; Schlenker and Lobell 2010; Blanc 2012). The literature links this detrimental impact to a robust predictor of conflict: the relative change in income and, consequently, in the opportunity cost to participate in violence (Miguel, Satyanath, and Sergenti 2004; Burke et al. 2009; Blattman and Miguel 2010). However, in North and South Sudan, the presence of these crops is not a significant exacerbating factor (see Tables A.20.a through A.20.e). On the contrary, as summarized in Table 4.1, we find a mitigating impact when weather shocks occur in areas with a large share of land occupied by millet production (see Table A.20.c). This impact can be explained by the low sensitivity of the crop to temperature variations (thanks to its high threshold temperature, set in the agronomy literature at 35 degrees Celsius). Moreover, it produces a low but steady yield with little fertilizer input,[34] and it grows well in arid and semiarid environments, requiring less water compared to other grains.[35] Table 4.1 and, in more detail, Tables A.20.a through A.20.e indicate that with the exception of millet, the presence of particular crops does not affect the relationship between weather shocks and conflict in Sudan—in line with the low percentage of national income that is on average derived from crops.

In accordance with the importance of livestock for livelihoods in North and South Sudan, our analysis points to three main significant factors. All partial effects are summarized in Table 4.1. First, Tables A.21.a and A.21.b indicate that the interaction terms with the proxies for the presence of pastoralist livelihoods (using goat densities or the presence of pastoral and agropastoral ethnic groups) constitute exacerbating factors and confirm the vulnerability of livestock to temperature shocks (Thornton et al. 2009). Second, mitigating roles are found in Tables A.21.c and A.21.d for water availability and irrigation systems (when we interact our proxies of weather shocks with a dummy for grid-cells near a major river[36] and with the share of irrigated land). The importance of water availability is not surprising, in particular in lowland areas where shocks on the limited amount of water have been reported to generate conflict about property rights and competition between pastoralists and other farmers. Interpretation about the role of irrigation systems is less obvious. The mitigating role of irrigation may point to a social benefit associated with the private benefits found for such investments (Lipton, Litchfield, and Faurèsc 2003; Smith 2004). However, our results should be taken with caution since we do not shed light on the potential of new investments that, it has been argued, are relatively limited in pastoralist areas (You et al. 2011; Headey, Taffesse, and You 2013). Third, Table A.21.e shows that the impact of weather shocks on conflict is largely mitigated by road and market accessibility (being within two hours' reach from the nearest human settlement of 50,000 or greater population). Such result can be explained by market access's facilitating destocking and restocking process and thus helping herders to smooth the detrimental impact of extreme weather shocks.

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[33] As pointed by Gleditsch (2012, 6), "one of the lessons that the large N-community could learn from proponents of case studies is the emphasis on interaction terms." Nevertheless, we cannot rule out that these interaction terms may be endogenous to conflict. We therefore consider this exercise primarily interpretative.

[34] El-Dukheri, Damous, and Khojali (2004, 56) reported that between 1992 and 2004 millet had a mean yield of 99 kilograms/feddans, with standard deviation equal to 17, while sorghum had a mean yield of 201 kilograms/feddans, with standard deviation equal to 45 (data from the Sudan Statistics Department, General Administration of Planning and Agricultural Economics).

[35] In particular, in Sudan, millet can grow in sandy soil (Goz land), whereas the other crops need to be cultivated in clay soil or near watercourses (Wadis land). These sandy areas (mostly in Darfur and Kordofan) are classified as marginal lands, unsuitable to and unfavorable for the cultivation of other crops. In case of shocks or of a negative yield-per-feddan trend, it's easier to increase the cultivated area of millet and therefore to keep the same total production amount.

[36] A grid-cell is classified as "near to major river" if its distance to a major river is lower than the 25th percentile. Similar results are obtained using a dummy for grid-cells near a lake.

Table 4.1—Mitigating and exacerbating factors of the climate-conflict nexus

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Table A20.c. 'Main Crop is Millet'				Table A21.a. 'Goat Density'				Table A21.b. 'Pastoral and Agropastoral Groups'			
	weather vars		interaction term		weather vars		interaction term		weather vars		interaction term	
	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.
Temp Anom					0.02	37.86			0.015	27.33	0.048	33.16
Temp Shock > 1 s.d. Grow. Per.	0.014	26.59	-0.017	-46.86			0.0003	0.16			0.029	19.8
Temp Shock > 2 s.d. Grow. Per.	0.014	26.53	-0.016	-46.19							0.03	21.61
Heat Shock > 1 s.d. Grow. Per.	0.021	38.7	-0.016	-43.85			0.0004	0.19	0.008	15.38		
Heat Shock > 2 s.d. Grow. Per.	0.021	38.89	-0.016	-44.22			0.0004	0.2	0.008	15.59		
Heat Shock Pctile85 Grow. Per.	0.015	28.59	-0.02	-56.31							0.035	23.98
Heat Shock Pctile90 Grow. Per.	0.023	42.78	-0.021	-58.66	0.01	19.47			0.01	18.54	0.046	31.42
Heat Shock Pctile95 Grow. Per.	0.024	43.71	-0.019	-54.03			0.0004	0.22	0.008	15.44	0.058	39.81
	Table A21.c. 'Near to Major River'				Table A21.d. 'Share of Irrigated Land'				Table A21.e. 'Market Accessibility'			
	weather vars		interaction term		weather vars		interaction term		weather vars		interaction term	
	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.	β / s.d	part. eff.
Temp Anom	0.108	54.04	-0.099	-72.56	0.022	41.28	-5E-04	-0.94	0.023	41.85		
Temp Shock > 1 s.d. Grow. Per.	0.063	31.62	-0.084	-61.97	0.01	18.95	-0.001	-1.47	0.01	18.75	-0.02	-41.9
Temp Shock > 2 s.d. Grow. Per.	0.068	34.18	-0.089	-64.97	0.011	19.76	-0.001	-1.59	0.01	19.49	-0.018	-37.76
Heat Shock > 1 s.d. Grow. Per.	0.082	40.98	-0.057	-42.19	0.016	29.86	-0.001	-1.12	0.016	29.79	-0.022	-46.97
Heat Shock > 2 s.d. Grow. Per.	0.082	40.91	-0.056	-41.11	0.016	30.08	-0.001	-1.12	0.016	29.91	-0.018	-38.61
Heat Shock Pctile85 Grow. Per.	0.073	36.8	-0.09	-65.96	0.011	21.2	-0.001	-1.55	0.011	20.95	-0.017	-36.26
Heat Shock Pctile90 Grow. Per.	0.105	52.8	-0.095	-70.17	0.018	33.18	-0.001	-1.68	0.018	32.8	-0.017	-36.95
Heat Shock Pctile95 Grow. Per.	0.095	47.77			0.018	33.89	-0.001	-1.52	0.018	33.6	-0.019	-40.86

Source: Authors' estimation based on ACLED and UEA CRU-TS. The sources for the interaction terms are detailed in the Data part of Section 3.

Notes: Table 4.1 reports only the coefficients that were statistically significant in the models' equations. The values of the interaction terms "Main Crop is Millet," "Pastoral and Agropastoral Groups," "Near to Major River," and "Market Accessibility" are calculated for the dummy = 1. The values of the interaction terms "Goat Density" and "Share of Irrigated Land" are calculated for the median value. A description of the weather variables is given in Table A.1. vars = variables; s.d = standard deviation; part. eff. = partial effects.

Last, we want to point to recent evidence suggesting that the coping strategies that had traditionally been adopted in arid and semi-arid areas of the Horn of Africa are progressively breaking down due to different mutually reinforcing factors, such as population growth, spread of pests (for example, prosopis julifora), limited mobility, and fragmentation of grazing land (Lybbert et al. 2004; Devereux 2006; McPeak, Little, and Doss 2011). Our results on the security consequences of the vulnerability of these areas make action even more urgent. As critically reviewed by Headey, Taffesse, and You (2013), the existing literature in the field suggests not only improving the resilience of the livestock sector through improved veterinary services, access to credit, provision of emergency feed, and better access to water but also supporting income diversification, in particular through education investments.

5. CONCLUSIONS

Our analysis sheds light on the importance of enhancing resilience to weather shocks in North and South Sudan, in particular in arid and semiarid lowland areas, and therefore calls for more decisive and coordinated action to help herders better cope with shocks. Initiatives aimed at reducing vulnerability in the Horn of Africa should include support in destocking and restocking processes at times of drought through improved access to markets; development of insurance and credit markets, especially weather insurance schemes; and supply of income diversification opportunities through investment in irrigation (when profitable) and in education services adapted to a mobile population. Nevertheless, our analysis is limited in drawing clear policy recommendations. Understanding the returns on investment, also for conflict resilience, is certainly a path for further research.

APPENDIX: SUPPORTING INFORMATION

Figure A.1.a—Distribution of precipitation anomalies based on the University of East Anglia's Climatic Research Unit Time Series dataset

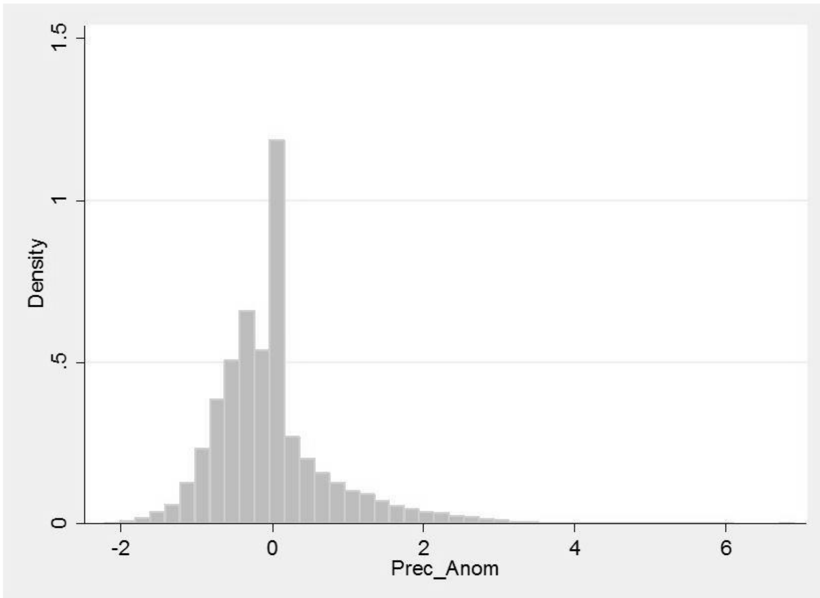
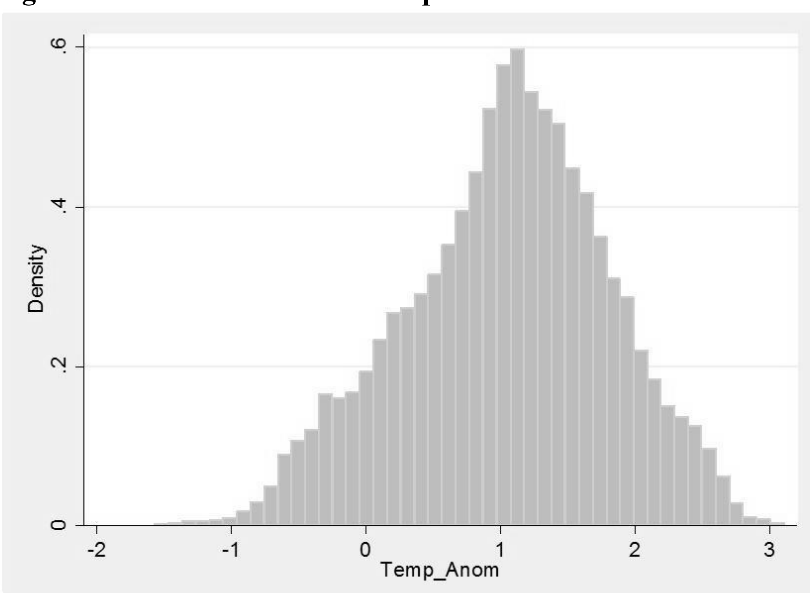


Figure A.1.b—Distribution of temperature anomalies



Source: Authors' calculation based on University of East Anglia's Climatic Research Unit Time Series dataset.
Note: Prec_Anom = precipitation anomalies; Temp_Anom = temperature anomalies.

Table A.1—Description of the weather variables

Variables	Definition	Source
Temp (or Prec) Anom	Temperature (or Precipitation) anomalies	University of East Anglia
Temp (or Prec) Anom Sq	Squared term of temperature (or precipitation) anomalies	University of East Anglia
Growing Period	Indicator defining the growing period by state	De-Pauw and Wu (2012)
Temp (or Prec) Shock > 1 s.d. Growing Period	Dummy =1 for positive and negative temperature (or precipitation) anomalies, during the growing period, above one standard deviation	University of East Anglia
Temp (or Prec) Shock > 2 s.d. Growing Period	Dummy =1 for positive and negative temperature (or precipitation) anomalies, during the growing period, above two standard deviations	University of East Anglia
Heat (or Wet) Shock > 1 s.d. Growing Period	Dummy =1 for positive temperature (or precipitation) anomalies, happening during the growing period, above one standard deviation	University of East Anglia
Cold (or Dry) Shock > 1 s.d. Growing Period	Dummy =1 for negative temperature (or precipitation) anomalies, happening during the growing period, above one standard deviation	University of East Anglia
Heat (or Wet) Shock > 2 s.d. Growing Period	Dummy =1 for positive temperature (or precipitation) anomalies, happening during the growing period, above two standard deviations	University of East Anglia
Cold (or Dry) Shock > 2 s.d. Growing Period	Dummy =1 for negative temperature (or precipitation) anomalies, happening during the growing period, above two standard deviations	University of East Anglia
Heat (or Wet) Shock Pctile85 Growing Period	Dummy =1 for temperature (or precipitation) anomalies, happening during the growing period, above the 85 percentile	University of East Anglia
Cold (or Dry) Shock Pctile15 Growing Period	Dummy =1 for temperature (or precipitation) anomalies, happening during the growing period, below the 15 percentile	University of East Anglia
Heat (or Wet) Shock Pctile90 Growing Period	Dummy =1 for temperature (or precipitation) anomalies, happening during the growing period, above the 90 percentile	University of East Anglia
Cold (or Dry) Shock Pctile10 Growing Period	Dummy =1 for temperature (or precipitation) anomalies, happening during the growing period, below the 10 percentile	University of East Anglia
Heat (or Wet) Shock Pctile95 Growing Period	Dummy =1 for temperature (or precipitation) anomalies, happening during the growing period, above the 95 percentile	University of East Anglia
Cold (or Dry) Shock Pctile5 Growing Period	Dummy =1 for temperature (or precipitation) anomalies, happening during the growing period, below the 5 percentile	University of East Anglia
Moderate DD Anom Growing Period	Moderate degree-days anomalies (10-30°C) happening during the growing period	NASA POWER
Extreme DD Anom Growing Period	Extreme degree-days anomalies (30°C) happening during the growing period	NASA POWER
Moderate DD Anom Sq Growing Period	Squared term of the moderate degree-days anomalies (10-30°C) happening during the growing period	NASA POWER
Extreme DD Anom Sq Growing Period	Squared term of the extreme degree-days anomalies (30°C) happening during the growing period	NASA POWER
Prec Anom (97-09)	Precipitation anomalies	NASA POWER
SPEI	Standardized Precipitation-Evapotranspiration Index	SPEIbase

Source: Author's compilation.

Note: NASA POWER = POWER project of the National Aeronautics and Space Administration; SPEIbase = Standardized Precipitation–Evapotranspiration Index dataset.

Table A.2.a—Descriptive statistics of the weather variables

Variables	Obs	Mean	S.d.	Min	Max
Number of Violent Events (ACLED)	46,436	0.054	0.535	0	34
Temp Anom	46,436	1.046	0.765	-1.569	3.11
Temp Anom Sq	46,436	1.679	1.65	0	9.672
Temp Shock > 1 s.d. Growing Period	46,436	0.1673	0.373	0	1
Temp Shock > 2 s.d. Growing Period	46,436	0.036	0.186	0	1
Heat Shock > 1 s.d. Growing Period	46,436	0.157	0.364	0	1
Cold Shock > 1 s.d. Growing Period	46,436	0.01	0.101	0	1
Heat Shock > 2 s.d. Growing Period	46,436	0.036	0.185	0	1
Cold Shock > 2 s.d. Growing Period	46,436	0.0003	0.017	0	1
Heat Shock Pctile85 Growing Period	46,436	0.136	0.342	0	1
Cold Shock Pctile15 Growing Period	46,436	0.01	0.099	0	1
Heat Shock Pctile90 Growing Period	46,436	0.096	0.294	0	1
Cold Shock Pctile10 Growing Period	46,436	0.005	0.068	0	1
Heat Shock Pctile95 Growing Period	46,436	0.053	0.224	0	1
Cold Shock Pctile5 Growing Period	46,436	0.001	0.037	0	1
Prec Anom	46,436	-0.002	0.813	-2.212	6.893
Prec Anom Sq	46,436	0.661	1.734	0	47.519
Prec Shock > 1 s.d. Growing Period	46,436	0.042	0.2	0	1
Prec Shock > 2 s.d. Growing Period	46,436	0.006	0.075	0	1
Dry Shock > 1 s.d. Growing Period	46,436	0.019	0.136	0	1
Wet Shock > 1 s.d. Growing Period	46,436	0.023	0.15	0	1
Dry Shock > 2 s.d. Growing Period	46,436	0.0002	0.013	0	1
Wet Shock > 2 s.d. Growing Period	46,436	0.006	0.074	0	1
Dry Shock Pctile15 Growing Period	46,436	0.019	0.138	0	1
Wet Shock Pctile85 Growing Period	46,436	0.023	0.151	0	1
Dry Shock Pctile10 Growing Period	46,436	0.012	0.108	0	1
Wet Shock Pctile90 Growing Period	46,436	0.014	0.119	0	1
Dry Shock Pctile5 Growing Period	46,436	0.006	0.076	0	1
Wet Shock Pctile95 Growing Period	46,436	0.007	0.082	0	1
SPEI	46,428	-0.722	1.053	-7.001	6.96

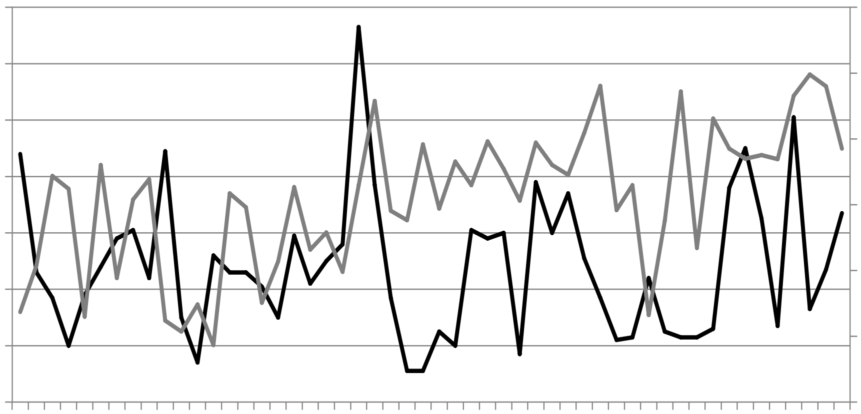
Table A.2.b—NASA POWER dataset

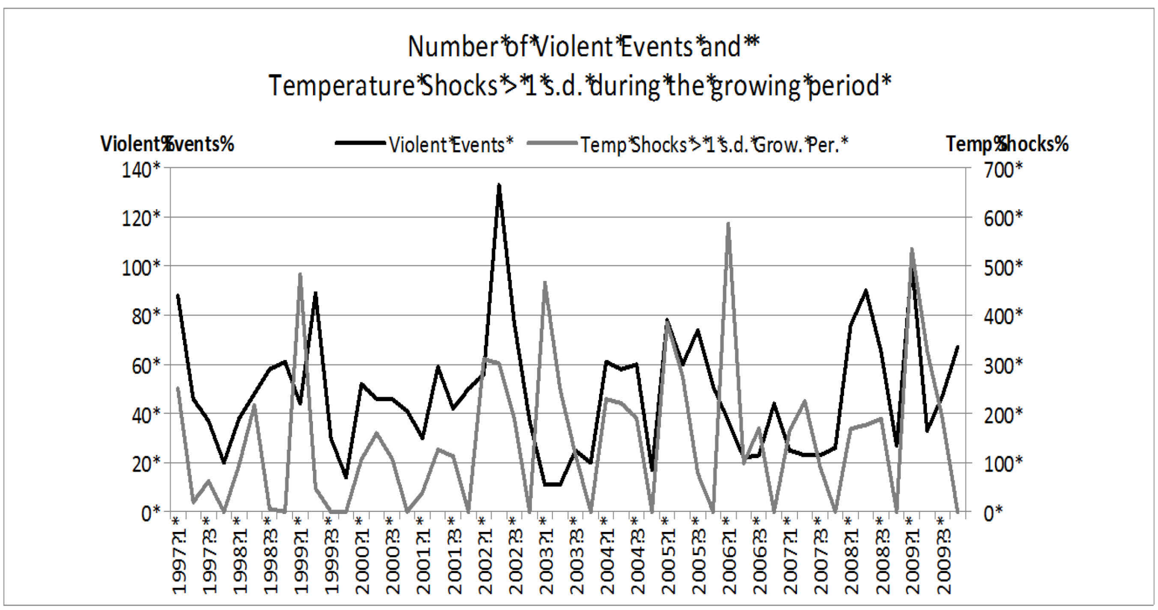
Variables	Obs	Mean	S.d.	Min	Max
Number of Violent Events (ACLED)	12,532	0.199	1.117	0	39
Moderate DD Anom Growing Period	12,532	-0.002	0.589	-3.817	3.067
Extreme DD Anom Growing Period	12,532	-0.006	0.266	-2.656	4.364
Moderate DD Anom Sq Growing Period	12,532	0.347	1.05	0	14.566
Extreme DD Anom Sq Growing Period	12,532	0.07	0.675	0	19.048
Prec Anom (97-09)	12,532	-0.0	0.961	-2.759	3.307

Source: Authors' calculation based on ACLED, UEA CRU-TS, SPEIbase, and NASA POWER.

Note: NASA POWER = POWER project of the National Aeronautics and Space Administration. Obs = number of observations; S.d. = standard deviation; Min = minimum; Max = maximum.

Figure A.2.a—Graphs of the time series



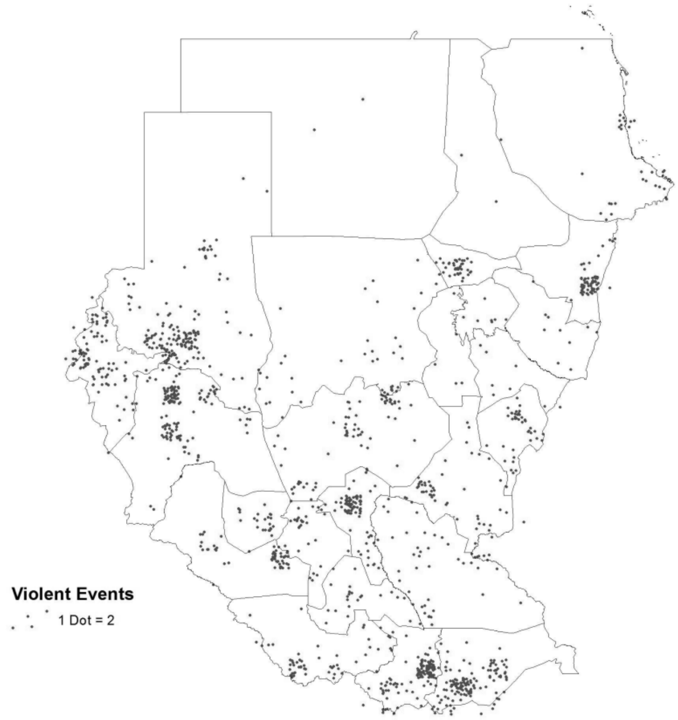


Source: Authors' calculation based on ACLED and UEA CRU-TS.

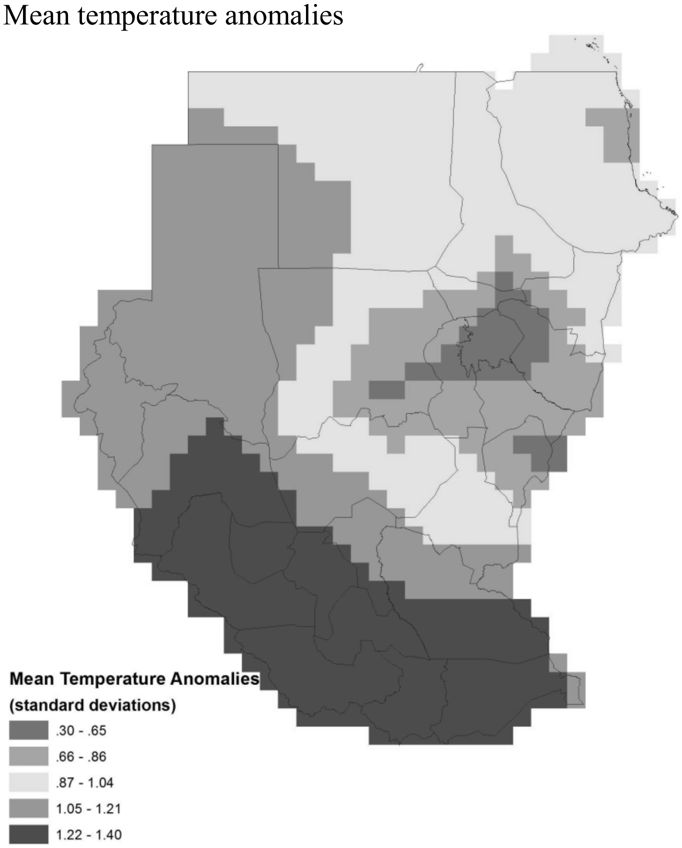
Note: Temp Anom = temperature anomalies; s.d. = standard deviation; Grow. Per. = growing period; Temp Shocks = temperature shocks.

Figure A.2.b—Location of violent events

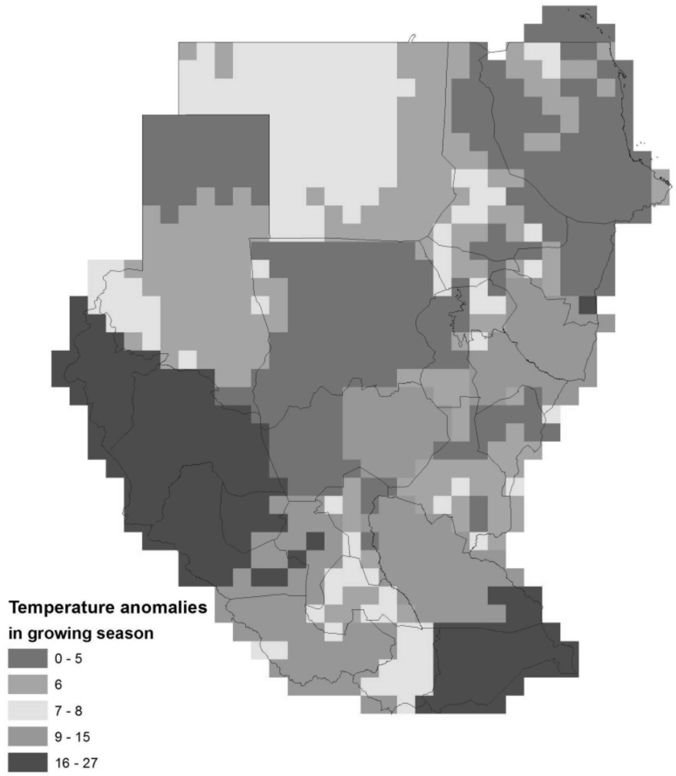
Armed Conflict Location and Event Dataset



Mean temperature anomalies



Number of temperature shocks greater than 1 standard deviation during the growing period



Source: Authors’ calculation based on ACLED and UEA CRU-TS.

Table A.3—Effects of temperature shocks on violent conflict, model at the quarterly level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.022***	-0.003	0.019***	0.017***	0.019***	0.017***	0.018***	0.016**	0.016**		
	(0.007)	(0.012)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)		
Temp Anom Sq		0.013*									
		(0.007)									
Temp Shock > 1 s.d. Growing Period			0.031**								
			(0.014)								
Temp Shock > 2 s.d. Growing Period				0.077**							
				(0.034)							
Heat Shock > 1 s.d. Growing Period					0.032**						
					(0.015)						
Cold Shock > 1 s.d. Growing Period					0.023						
					(0.023)						
Heat Shock > 2 s.d. Growing Period						0.078**					
						(0.035)					
Cold Shock > 2 s.d. Growing Period						-0.007					
						(0.034)					
Heat Shock Pctile85 Growing Period							0.034**				
							(0.017)				
Cold Shock Pctile15 Growing Period							-0.012				
							(0.017)				
Heat Shock Pctile90 Growing Period								0.057**			
								(0.023)			
Cold Shock Pctile10 Growing Period								0.008			
								(0.022)			
Heat Shock Pctile95 Growing Period									0.072**		
									(0.033)		
Cold Shock Pctile5 Growing Period									-0.007		
									(0.032)		
Moderate DD Anom Growing Period										-0.038**	-0.04**
										(0.016)	(0.015)
Extreme DD Anom Growing Period										0.048	0.08**
										(0.033)	(0.034)
Moderate DD Anom Sq Growing Period											0.009
											(0.015)
Extreme DD Anom Sq Growing Period											-0.02*
											(0.012)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	12,532	12,532
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.03	0.09	0.09

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset. **p* < .1. ***p* < .05. ****p* < .01.

Table A.4—Effects of temperature shocks on violent conflict, model at the quarterly level without time-trend effects and night-lights density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.027***	0.001	0.025***	0.022***	0.025***	0.022***	0.023***	0.021***	0.021***		
	(0.009)	(0.012)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)		
Temp Anom Sq		0.013**									
		(0.006)									
Temp Shock > 1 s.d. Growing Period			0.026**								
			(0.013)								
Temp Shock > 2 s.d. Growing Period				0.085***							
				(0.03)							
Heat Shock > 1 s.d. Growing Period					0.028**						
					(0.014)						
Cold Shock > 1 s.d. Growing Period					0.01						
					(0.026)						
Heat Shock > 2 s.d. Growing Period						0.086***					
						(0.03)					
Cold Shock > 2 s.d. Growing Period						-0.002					
						(0.035)					
Heat Shock Pctile85 Growing Period							0.0324*				
							(0.0164)				
Cold Shock Pctile15 Growing Period							-0.0245				
							(0.0168)				
Heat Shock Pctile90 Growing Period								0.059***			
								(0.022)			
Cold Shock Pctile10 Growing Period								-0.011			
								(0.026)			
Heat Shock Pctile95 Growing Period									0.08**		
									(0.032)		
Cold Shock Pctile5 Growing Period									-0.031		
									(0.046)		
Moderate DD Anom Growing Period										-0.057**	-0.059**
										(0.023)	(0.022)
Extreme DD Anom Growing Period										0.046	0.061**
										(0.036)	(0.028)
Moderate DD Anom Sq Growing Period											0.005
											(0.015)
Extreme DD Anom Sq Growing Period											-0.009
											(0.013)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	12,532	12,532
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.004	0.004	0.004	0.005	0.004	0.005	0.004	0.005	0.005	0.011	0.011

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed and time-fixed effects and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset. **p* < .1. ***p* < .05. ****p* < .01.

Table A.5—Effects of weather shocks on violent conflict, model at the quarterly level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Prec Anom	0.005	0.002	0.004	0.006	0.004	0.006	0.003	0.003	0.006		
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)		
Temp Anom	0.022***	-0.002	0.02***	0.018***	0.02***	0.018***	0.019***	0.017**	0.017***		
	(0.007)	(0.011)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)		
Prec Anom Sq		0.002									
		(0.003)									
Temp Anom Sq		0.013*									
		(0.007)									
Prec Shock > 1 s.d.			0.013								
Growing Period			(0.017)								
Temp Shock > 1 s.d.			0.03**								
Growing Period			(0.013)								
Prec Shock > 2 s.d.				-0.045							
Growing Period				(0.033)							
Temp Shock > 2 s.d.				0.077**							
Growing Period				(0.034)							
Dry Shock > 1 s.d.					0.007						
Growing Period					(0.024)						
Wet Shock > 1 s.d.					0.017						
Growing Period					(0.033)						
Heat Shock > 1 s.d.					0.031**						
Growing Period					(0.015)						
Cold Shock > 1 s.d.					0.021						
Growing Period					(0.023)						
Dry Shock > 2 s.d.						-0.024					
Growing Period						(0.028)					
Wet Shock > 2 s.d.						-0.046					
Growing Period						(0.034)					
Heat Shock > 2 s.d.						0.078**					
Growing Period						(0.035)					
Cold Shock > 2 s.d.						-0.005					
Growing Period						(0.035)					
Dry Shock Pctile15							-0.006				
Growing Period							(0.027)				
Wet Shock Pctile85							0.022				
Growing Period							(0.033)				
Heat Shock Pctile85							0.034**				
Growing Period							(0.017)				
Cold Shock Pctile15							-0.013				
Growing Period							(0.016)				

Table A.5—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Dry Shock Pctile10 Growing Period								-0.004			
								(0.03)			
Wet Shock Pctile90 Growing Period								0.022			
								(0.05)			
Heat Shock Pctile90 Growing Period								0.056**			
								(0.022)			
Cold Shock Pctile10 Growing Period								0.006			
								(0.022)			
Dry Shock Pctile5 Growing Period									0.027		
									(0.049)		
Wet Shock Pctile95 Growing Period									-0.03		
									(0.03)		
Heat Shock Pctile95 Growing Period									0.072**		
									(0.032)		
Cold Shock Pctile5 Growing Period									-0.006		
									(0.032)		
Prec Anom (97-09)										0.005	0.005
										(0.011)	(0.011)
Moderate DD Anom Growing Period										-0.038**	-0.04**
										(0.016)	(0.015)
Extreme DD Anom Growing Period										0.048	0.081**
										(0.033)	(0.034)
Moderate DD Anom Sq Growing Period											0.009
											(0.015)
Extreme DD Anom Sq Growing Period											-0.02*
											(0.012)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	12,532	12,532
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.029	0.029	0.029	0.03	0.029	0.03	0.029	0.03	0.03	0.09	0.09

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

*p < .1. **p < .05. ***p < .01.

Table A.6—Effects of weather shocks on violent conflict, model at the quarterly level with the Standardized Precipitation–Evapotranspiration Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Number of Violent Events (ACLED)								
SPEI	0.003	0.0	0.002	0.003	0.002	0.003	0.003	0.002	0.003
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Temp Anom	0.023***	-0.003	0.02**	0.018**	0.02**	0.018**	0.019**	0.017**	0.017**
	(0.008)	(0.012)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
Temp Anom Sq		0.013*							
		(0.007)							
Temp Shock > 1 s.d.			0.03**						
Growing Period			(0.014)						
Temp Shock > 2 s.d.				0.077**					
Growing Period				(0.034)					
Heat Shock > 1 s.d.					0.031**				
Growing Period					(0.015)				
Cold Shock > 1 s.d.					0.022				
Growing Period					(0.023)				
Heat Shock > 2 s.d.						0.078**			
Growing Period						(0.034)			
Cold Shock > 2 s.d.						-0.009			
Growing Period						(0.036)			
Heat Shock Pctile85							0.034**		
Growing Period							(0.017)		
Cold Shock Pctile15							-0.013		
Growing Period							(0.017)		
Heat Shock Pctile90								0.057**	
Growing Period								(0.023)	
Cold Shock Pctile10								0.007	
Growing Period								(0.022)	
Heat Shock Pctile95									0.072**
Growing Period									(0.032)
Cold Shock Pctile5									-0.008
Growing Period									(0.032)
Observations	46,428	46,428	46,428	46,428	46,428	46,428	46,428	46,428	46,428
Grid-cells	893	893	893	893	893	893	893	893	893
R-squared	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.03	0.03

Source: Authors' estimation based on ACLED, UEA CRU-TS, and SPEIbase.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

**p* < .1. ***p* < .05. ****p* < .01.

Table A.7—Effects of weather shocks on violent conflict, model at the quarterly level with the time lags of the weather variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Prec Anom	0.005	0.001	0.004	0.005	0.003	0.005	0.002	0.002	0.005		
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)		
Prec Anom (t-1)	-0.001	0.004	-0.001	-0.002	-0.002	-0.002	-0.002	-0.003	-0.001		
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)		
Temp Anom	0.021***	-0.006	0.019***	0.016***	0.019***	0.015***	0.017***	0.015**	0.015**		
	(0.006)	(0.012)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)		
Temp Anom (t-1)	0.005	-0.029**	0.003	0.001	0.002	0.001	0.001	-0.0	0.001		
	(0.008)	(0.011)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)		
Prec Anom Sq		0.002									
		(0.003)									
Prec Anom Sq (t-1)		-0.003									
		(0.003)									
Temp Anom Sq		0.013**									
		(0.007)									
Temp Anom Sq (t-1)		0.018***									
		(0.006)									
Prec Shock > 1 s.d.			0.014								
Growing Period			(0.018)								
Prec Shock > 1 s.d.			-0.005								
Growing Period (t-1)			(0.014)								
Temp Shock > 1 s.d.			0.03**								
Growing Period			(0.013)								
Temp Shock > 1 s.d.			0.012								
Growing Period (t-1)			(0.008)								
Prec Shock > 2 s.d.				-0.039							
Growing Period				(0.035)							
Prec Shock > 2 s.d.				0.064							
Growing Period (t-1)				(0.04)							
Temp Shock > 2 s.d.				0.081**							
Growing Period				(0.036)							
Temp Shock > 2 s.d.				0.069							
Growing Period (t-1)				(0.046)							
Dry Shock > 1 s.d.					0.008						
Growing Period					(0.023)						
Dry Shock > 1 s.d.					-0.036						
Growing Period (t-1)					(0.026)						
Wet Shock > 1 s.d.					0.018						
Growing Period					(0.034)						
Wet Shock > 1 s.d.					0.019						
Growing Period (t-1)					(0.023)						

Table A.7—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
					Number of Violent Events (ACLED)						
Heat Shock > 1 s.d.					0.03**						
Growing Period					(0.014)						
Heat Shock > 1 s.d.					0.015						
Growing Period (t-1)					(0.01)						
Cold Shock > 1 s.d.					0.021						
Growing Period					(0.022)						
Cold Shock > 1 s.d.					-0.017						
Growing Period (t-1)					(0.026)						
Dry Shock > 2 s.d.						-0.025					
Growing Period						(0.031)					
Dry Shock > 2 s.d.						-0.058*					
Growing Period (t-1)						(0.033)					
Wet Shock > 2 s.d.						-0.04					
Growing Period						(0.036)					
Wet Shock > 2 s.d.						0.068*					
Growing Period (t-1)						(0.041)					
Heat Shock > 2 s.d.						0.082**					
Growing Period						(0.037)					
Heat Shock > 2 s.d.						0.069					
Growing Period (t-1)						(0.046)					
Cold Shock > 2 s.d.						-0.01					
Growing Period						(0.034)					
Cold Shock > 2 s.d.						0.06**					
Growing Period (t-1)						(0.028)					
Dry Shock Pctile15							-0.006				
Growing Period							(0.026)				
Dry Shock Pctile15							-0.039				
Growing Period (t-1)							(0.026)				
Wet Shock Pctile85							0.023				
Growing Period							(0.034)				
Wet Shock Pctile85							0.003				
Growing Period (t-1)							(0.021)				
Heat Shock Pctile85							0.034**				
Growing Period							(0.016)				
Heat Shock Pctile85							0.021*				
Growing Period (t-1)							(0.012)				
Cold Shock Pctile15							-0.014				
Growing Period							(0.017)				
Cold Shock Pctile15							-0.036				
Growing Period (t-1)							(0.031)				
Dry Shock Pctile10								-0.002			
Growing Period								(0.03)			

Table A.7—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
					Number of Violent Events (ACLED)						
Dry Shock Pctile10								-0.022			
Growing Period (t-1)								(0.035)			
Wet Shock Pctile90								0.025			
Growing Period								(0.051)			
Wet Shock Pctile90								0.025			
Growing Period (t-1)								(0.03)			
Heat Shock Pctile90								0.056**			
Growing Period								(0.022)			
Heat Shock Pctile90								0.038**			
Growing Period (t-1)								(0.017)			
Cold Shock Pctile10								0.005			
Growing Period								(0.022)			
Cold Shock Pctile10								-0.005			
Growing Period (t-1)								(0.033)			
Dry Shock Pctile5									0.033		
Growing Period									(0.049)		
Dry Shock Pctile5									0.046		
Growing Period (t-1)									(0.06)		
Wet Shock Pctile95									-0.026		
Growing Period									(0.031)		
Wet Shock Pctile95									0.039		
Growing Period (t-1)									(0.034)		
Heat Shock Pctile95									0.072**		
Growing Period									(0.032)		
Heat Shock Pctile95									0.057*		
Growing Period (t-1)									(0.032)		
Cold Shock Pctile5									-0.008		
Growing Period									(0.032)		
Cold Shock Pctile5									0.063		
Growing Period (t-1)									(0.078)		
Prec Anom (97-09)										0.012	0.013
										(0.008)	(0.008)
Prec Anom (97-09) (t-1)										0.01	0.009
										(0.011)	(0.011)
Moderate DD Anom										-0.034**	-0.037***
Growing Period										(0.014)	(0.014)
Moderate DD Anom										-0.056*	-0.057*
Growing Period (t-1)										(0.031)	(0.031)
Extreme DD Anom										0.055*	0.088***
Growing Period										(0.031)	(0.033)
Extreme DD Anom										0.017	0.025
Growing Period (t-1)										(0.022)	(0.037)

Table A.7—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Moderate DD Anom Sq Growing Period											0.007 (0.015)
Moderate DD Anom Sq Growing Period (t-1)											0.001 (0.008)
Extreme DD Anom Sq Growing Period											-0.02 (0.012)
Extreme DD Anom Sq Growing Period (t-1)											-0.006 (0.016)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	12,291	12,291
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.029	0.030	0.029	0.030	0.029	0.030	0.029	0.030	0.030	0.094	0.094

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). The description of the weather variables is given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.
*$p < .1$. **$p < .05$. ***$p < .01$.

Table A.8—Effects of weather shocks on violent conflict, model at the quarterly level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Number of Violent Events (ACLED)								
Prec Anom (97-09)	0.002	0.00	0.002	0.002	0.002	0.002	0.002	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Temp Anom	0.022***	-0.002	0.019***	0.018***	0.019***	0.017***	0.018***	0.016**	0.017**
	(0.007)	(0.012)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)
Temp Anom Sq		0.013*							
		(0.007)							
Temp Shock > 1 s.d. Growing Period			0.031**						
			(0.014)						
Temp Shock > 2 s.d. Growing Period				0.077**					
				(0.034)					
Heat Shock > 1 s.d. Growing Period					0.032**				
					(0.015)				
Cold Shock > 1 s.d. Growing Period					0.023				
					(0.023)				
Heat Shock > 2 s.d. Growing Period						0.078**			
						(0.035)			
Cold Shock > 2 s.d. Growing Period						-0.009			
						(0.034)			
Heat Shock Pctile85 Growing Period							0.035**		
							(0.017)		
Cold Shock Pctile15 Growing Period							-0.011		
							(0.016)		
Heat Shock Pctile90 Growing Period								0.058**	
								(0.023)	
Cold Shock Pctile10 Growing Period								0.008	
								(0.022)	
Heat Shock Pctile95 Growing Period									0.073**
									(0.032)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436
Grid-cells	893	893	893	893	893	893	893	893	893
R-squared	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.03	0.03

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset. *$p < .1$. **$p < .05$. ***$p < .01$.

Table A.9—Partial effects for the number of violent events

	(1)	(2)	(3)	(4)	(5)	(6)
	Table A6. Model with the SPEI		Table A7. Model with the time lags		Table A8. Model based on NASA-POWER	
	β / s.d	part. eff.	β / s.d.	part. eff.	β / s.d.	part. eff.
Temp Anom	0.017	32.46	0.016	30.46	0.017	31.03
Temp Anom + Temp Anom Sq	0.021	39.3	0.022	40.83	0.021	38.99
Temp Shock > 1 s.d. Grow. Per.	0.011	21.11	0.011	20.9	0.012	21.45
Temp Shock > 2 s.d. Grow. Per.	0.011	21.25	0.011	20.5	0.012	21.52
Heat Shock > 1 s.d. Grow. Per.	0.014	26.61	0.015	28.06	0.014	26.68
Heat Shock > 2 s.d. Grow. Per.	0.014	26.85	0.015	28.29	0.014	26.95
Heat Shock Pctile85 Grow. Per.	0.012	21.77	0.012	21.52	0.012	22.09
Heat Shock Pctile90 Grow. Per.	0.017	31.26	0.017	30.93	0.017	31.54
Heat Shock Pctile95 Grow. Per.	0.016	30.02	0.016	30.14	0.016	30.22
Moderate DD Anom Grow. Per.			-0.02	-10.11		
Extreme DD Anom Grow. Per.			0.015	7.37		
Mod DD An GP + M DD An Sq GP			-0.022	-10.87		
Ext DD An GP + E DD An Sq GP			0.023	11.7		

Source: Authors' estimation based on ACLED, UEA CRU-TS, SPEIbase, and NASA POWER.

Notes: Columns 1, 3, 5, 7, and 9 report only the coefficients that were statistically significant in the models' equations. Degree-days variables are not included in Tables A.6 and A.8 and thus in columns 1, 2, 5, and 6. Descriptions of the weather variables are given in Table A.1. NASA-POWER = National Aeronautics and Space Administration POWER project; s.d. = standard deviation; part. eff. = partial effects.

Table A.10—Effects of temperature shocks on violent conflict, model at the quarterly level without cell-fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.014 (0.009)	-0.015 (0.015)	0.012 (0.008)	0.01 (0.007)	0.012 (0.008)	0.01 (0.008)	0.011 (0.008)	0.009 (0.007)	0.009 (0.008)		
Temp Anom Sq		0.015* (0.008)									
Temp Shock > 1 s.d. Growing Period			0.027* (0.015)								
Temp Shock > 2 s.d. Growing Period				0.082** (0.036)							
Heat Shock > 1 s.d. Growing Period					0.028* (0.016)						
Cold Shock > 1 s.d. Growing Period					0.021 (0.03)						
Heat Shock > 2 s.d. Growing Period						0.083** (0.037)					

Table A.10—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Cold Shock > 2 s.d.						-0.019					
Growing Period						(0.032)					
Heat Shock Pctile85							0.033*				
Growing Period							(0.018)				
Cold Shock Pctile15							-0.013				
Growing Period							(0.013)				
Heat Shock Pctile90								0.054**			
Growing Period								(0.022)			
Cold Shock Pctile10								0.008			
Growing Period								(0.018)			
Heat Shock Pctile95									0.074**		
Growing Period									(0.033)		
Cold Shock Pctile5									0.003		
Growing Period									(0.019)		
Moderate DD Anom										-0.044**	-0.047**
Growing Period										(0.022)	(0.021)
Extreme DD Anom										0.065*	0.104***
Growing Period										(0.036)	(0.03)
Moderate DD Anom Sq											0.009
Growing Period											(0.014)
Extreme DD Anom Sq											-0.024
Growing Period											(0.015)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436	12,532	12,532
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.027	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.028	0.066	0.066

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the state level. All regressions include state-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.
**p* < .1. ***p* < .05. ****p* < .01.

Table A.11—Effects of temperature shocks on violent conflict, model at the quarterly level without cell-fixed effects and with controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.023**	-0.004	0.021**	0.018**	0.02**	0.018**	0.019**	0.017**	0.017*		
	(0.01)	(0.016)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)		
Temp Anom Sq		0.014									
		(0.009)									
Temp Shock > 1 s.d. Growing Period			0.028*								
			(0.016)								
Temp Shock > 2 s.d. Growing Period				0.085**							
				(0.037)							
Heat Shock > 1 s.d. Growing Period					0.029						
					(0.017)						
Cold Shock > 1 s.d. Growing Period					0.022						
					(0.03)						
Heat Shock > 2 s.d. Growing Period						0.086**					
						(0.037)					
Cold Shock > 2 s.d. Growing Period						-0.005					
						(0.079)					
Heat Shock Pctile85 Growing Period							0.034*				
							(0.019)				
Cold Shock Pctile15 Growing Period							-0.016				
							(0.015)				
Heat Shock Pctile90 Growing Period								0.056**			
								(0.024)			
Cold Shock Pctile10 Growing Period								0.005			
								(0.018)			
Heat Shock Pctile95 Growing Period									0.076**		
									(0.033)		
Cold Shock Pctile5 Growing Period									0.0002		
									(0.033)		
Moderate DD Anom Growing Period										-0.045**	-0.048**
										(0.021)	(0.021)
Extreme DD Anom Growing Period										0.071*	0.113***
										(0.036)	(0.033)
Moderate DD Anom Sq Growing Period											0.01
											(0.015)
Extreme DD Anom Sq Growing Period											-0.026
											(0.015)

Table A.11—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Distance to Border (Ln)	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.031	0.031
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.028)	(0.028)
Urban Grid Cell	0.379***	0.378***	0.379***	0.379***	0.379***	0.379***	0.379***	0.379***	0.379***	0.393***	0.394***
	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.124)	(0.124)
Population (Ln)	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*	0.023	0.023
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.014)	(0.014)
Distance to Road (Ln)	-0.01	-0.014	-0.015	-0.015	-0.015	-0.015	-0.015	-0.015	-0.014	-0.017	-0.017
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.0103)	(0.01)	(0.01)	(0.059)	(0.06)
Observations	43,680	43,680	43,680	43,680	43,680	43,680	43,680	43,680	43,680	12,064	12,064
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.054	0.054	0.054	0.055	0.054	0.055	0.054	0.055	0.055	0.094	0.094

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the state level. All regressions include state-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

**p* < .1. ***p* < .05. ****p* < .01.

Table A.12—Effects of temperature shocks on violent conflict, model at the quarterly level without cell-fixed effects and with controls excluding cells that never experienced violent conflict

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.06**	-0.025	0.049*	0.043*	0.05**	0.042*	0.045*	0.04*	0.041		
	(0.027)	(0.042)	(0.025)	(0.024)	(0.024)	(0.025)	(0.024)	(0.023)	(0.025)		
Temp Anom Sq		0.041**									
		(0.019)									
Temp Shock > 1 s.d. Growing Period			0.089**								
			(0.037)								
Temp Shock > 2 s.d. Growing Period				0.197**							
				(0.071)							
Heat Shock > 1 s.d. Growing Period					0.087**						
					(0.04)						
Cold Shock > 1 s.d. Growing Period					0.111						
					(0.14)						
Heat Shock > 2 s.d. Growing Period						0.199**					
						(0.071)					
Cold Shock > 2 s.d. Growing Period						-0.02					
						(0.269)					

Table A.12—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Heat Shock Pctile85 Growing Period							0.095**				
							(0.044)				
Cold Shock Pctile15 Growing Period							-0.054				
							(0.06)				
Heat Shock Pctile90 Growing Period								0.154***			
								(0.053)			
Cold Shock Pctile10 Growing Period								0.028			
								(0.082)			
Heat Shock Pctile95 Growing Period									0.205***		
									(0.07)		
Cold Shock Pctile5 Growing Period									0.012		
									(0.102)		
Moderate DD Anom Growing Period										-0.056*	-0.062*
										(0.03)	(0.03)
Extreme DD Anom Growing Period										0.081*	0.135***
										(0.046)	(0.04)
Moderate DD Anom Sq Growing Period											0.011
											(0.021)
Extreme DD Anom Sq Growing Period											-0.038**
											(0.015)
Population (Ln)	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.028**	0.05**	0.0503**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.024)	(0.024)
Distance to Urban Center (Ln)	-0.102**	-0.1**	-0.101**	-0.101**	-0.101**	-0.101**	-0.101**	-0.102**	-0.101**	-0.206*	-0.207*
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.106)	(0.106)
Distance to Border (Ln)	0.013	0.014	0.013	0.013	0.014	0.013	0.013	0.014	0.013	0.038	0.038
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.04)	(0.04)
Observations	13,572	13,572	13,572	13,572	13,572	13,572	13,572	13,572	13,572	7,124	7,124
Grid-cells	261	261	261	261	261	261	261	261	261	137	137
R-squared	0.059	0.06	0.06	0.061	0.06	0.061	0.06	0.061	0.061	0.102	0.102

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the state level. All regressions include state-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

*$p < .1$. **$p < .05$. ***$p < .01$.

Table A.13—Partial effects for the number of violent events

	(1)	(2)	(3)	(4)	(5)	(6)
	Table A10. Model without grid cell fixed effects		**Table A11. Model without grid cell fixed effects & with controls**		**Table A12. As in Table A11 excluding grid cells that never experienced conflict**	
	β / s.d	part. eff.	β / s.d.	part. eff.	β / s.d.	part. eff.
Temp Anom	0.011	20.5	0.017	32.46	0.047	25.98
Temp Anom + Temp Anom Sq	0.025	47.28	0.023	42.98	0.074	40.81
Temp Shock > 1 s.d. Grow. Per.	0.01	18.75	0.01	19.3	0.035	19.28
Temp Shock > 2 s.d. Grow. Per.	0.01	18.68	0.01	19.29	0.034	18.58
Heat Shock > 1 s.d. Grow. Per.	0.015	28.23	0.016	29.27	0.042	23.25
Heat Shock > 2 s.d. Grow. Per.	0.015	28.53	0.016	29.56	0.043	23.44
Heat Shock Pctile85 Grow. Per.	0.011	21.07	0.012	21.77	0.035	19.35
Heat Shock Pctile90 Grow. Per.	0.016	29.45	0.017	30.77	0.049	27.05
Heat Shock Pctile95 Grow. Per.	0.017	30.97	0.017	31.64	0.051	27.78
Moderate DD Anom Grow. Per.	-0.026	-13.12	-0.026	-13.24	-0.035	-10.16
Extreme DD Anom Grow. Per.	0.017	8.67	0.019	9.52	0.025	7.16
Mod DD An GP + M DD An Sq GP	-0.028	-14.01	-0.028	-14.1	-0.039	-11.15
Ext DD An GP + E DD An Sq GP	0.028	13.89	0.03	15.09	-0.027+0.042	4.09

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Columns 1, 3, 5, 7, and 9 report only the coefficients that were statistically significant in the models' equations. Descriptions of the weather variables are given in Table A.1. s.d. = standard deviation; part. eff. = partial effects.

Table A.14—Effects of temperature shocks on violent conflict, model at the monthly level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.004*** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)		
Temp Anom Sq		0.0006 (0.0009)									
Temp Shock > 1 s.d. Growing Period			0.004 (0.005)								
Temp Shock > 2 s.d. Growing Period				0.017 (0.012)							
Heat Shock > 1 s.d. Growing Period					0.005 (0.005)						
Cold Shock > 1 s.d. Growing Period					-0.007 (0.008)						
Heat Shock > 2 s.d. Growing Period						0.018 (0.012)					
Cold Shock > 2 s.d. Growing Period						-0.02* (0.012)					

Table A.14—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Heat Shock Pctile85 Growing Period							0.007				
							(0.006)				
Cold Shock Pctile15 Growing Period							-0.009				
							(0.007)				
Heat Shock Pctile90 Growing Period								0.014*			
								(0.008)			
Cold Shock Pctile10 Growing Period								-0.009			
								(0.007)			
Heat Shock Pctile95 Growing Period									0.022**		
									(0.011)		
Cold Shock Pctile5 Growing Period									-0.016*		
									(0.009)		
Moderate DD Anom Growing Period										-0.011*	-0.011*
										(0.006)	(0.006)
Extreme DD Anom Growing Period										0.034**	0.021
										(0.016)	(0.013)
Moderate DD Anom Sq Growing Period											-0.007**
											(0.003)
Extreme DD Anom Sq Growing Period											0.007
											(0.008)
Observations	139,308	139,308	139,308	139,308	139,308	139,308	139,308	139,308	139,308	37,596	37,596
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.049	0.049

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.
*$p < .1$. **$p < .05$. ***$p < .01$.

Table A.15—Effects of temperature shocks on violent conflict, model at the monthly level with the time lags of the temperature variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
					Number of Violent Events (ACLED)						
Temp Anom	0.004***	0.003**	0.004**	0.003**	0.004**	0.003**	0.003**	0.003**	0.003**		
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)		
Temp Anom (t-1)	0.002	0.0	0.001	0.001	0.001	0.001	0.001	0.001	0.001		
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
Temp Anom (t-2)	0.002	-0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001		
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
Temp Anom Sq		0.0003									
		(0.001)									
Temp Anom Sq (t-1)		0.001									
		(0.001)									
Temp Anom Sq (t-2)		0.003**									
		(0.001)									
Temp Shock > 1 s.d. Growing Period			0.003								
			(0.005)								
Temp Shock > 1 s.d. Growing Period (t-1)			0.003								
			(0.003)								
Temp Shock > 1 s.d. Growing Period (t-2)			0.002								
			(0.004)								
Temp Shock > 2 s.d. Growing Period				0.015							
				(0.011)							
Temp Shock > 2 s.d. Growing Period (t-1)				0.015*							
				(0.008)							
Temp Shock > 2 s.d. Growing Period (t-2)				0.026**							
				(0.012)							
Heat Shock > 1 s.d. Growing Period					0.005						
					(0.005)						
Heat Shock > 1 s.d. Growing Period (t-1)					0.002						
					(0.004)						
Heat Shock > 1 s.d. Growing Period (t-2)					0.004						
					(0.004)						
Cold Shock > 1 s.d. Growing Period					-0.007						
					(0.008)						
Cold Shock > 1 s.d. Growing Period (t-1)					0.007						
					(0.011)						
Cold Shock > 1 s.d. Growing Period (t-2)					-0.012						
					(0.008)						
Heat Shock > 2 s.d. Growing Period						0.016					
						(0.011)					
Heat Shock > 2 s.d. Growing Period (t-1)						0.016*					
						(0.008)					

Table A.15—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
				Number of Violent Events (ACLED)							
Heat Shock > 2 s.d. Growing Period (t-2)						0.028**					
						(0.012)					
Cold Shock > 2 s.d. Growing Period						-0.021*					
						(0.012)					
Cold Shock > 2 s.d. Growing Period (t-1)						-0.009					
						(0.01)					
Cold Shock > 2 s.d. Growing Period (t-2)						-0.02					
						(0.013)					
Heat Shock Pctile85 Growing Period							0.007				
							(0.006)				
Heat Shock Pctile85 Growing Period (t-1)							0.004				
							(0.004)				
Heat Shock Pctile85 Growing Period (t-2)							0.003				
							(0.005)				
Cold Shock Pctile15 Growing Period							-0.01				
							(0.007)				
Cold Shock Pctile15 Growing Period (t-1)							-0.006				
							(0.006)				
Cold Shock Pctile15 Growing Period (t-2)							-0.008				
							(0.008)				
Heat Shock Pctile90 Growing Period								0.014*			
								(0.007)			
Heat Shock Pctile90 Growing Period (t-1)								0.003			
								(0.004)			
Heat Shock Pctile90 Growing Period (t-2)								0.011*			
								(0.005)			
Cold Shock Pctile10 Growing Period								-0.01			
								(0.007)			
Cold Shock Pctile10 Growing Period (t-1)								-0.014**			
								(0.006)			
Cold Shock Pctile10 Growing Period (t-2)								-0.013*			
								(0.007)			
Heat Shock Pctile95 Growing Period									0.02*		
									(0.01)		
Heat Shock Pctile95 Growing Period (t-1)									0.018**		
									(0.007)		
Heat Shock Pctile95 Growing Period (t-2)									0.017*		
									(0.009)		
Cold Shock Pctile5 Growing Period									-0.016*		
									(0.009)		

Table A.15—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Cold Shock Pctile5 Growing Period (t-1)									-0.002		
									(0.007)		
Cold Shock Pctile5 Growing Period (t-2)									-0.011		
									(0.01)		
Moderate DD Anom Growing Period										-0.01*	-0.01
										(0.006)	(0.006)
Moderate DD Anom Growing Period (t-1)										-0.004	-0.003
										(0.004)	(0.004)
Moderate DD Anom Growing Period (t-2)										-0.007	-0.009
										(0.007)	(0.007)
Extreme DD Anom Growing Period										0.035**	0.023*
										(0.016)	(0.013)
Extreme DD Anom Growing Period (t-1)										-0.008	-0.007
										(0.011)	(0.012)
Extreme DD Anom Growing Period (t-2)										0.001	0.016
										(0.014)	(0.017)
Moderate DD Anom Sq Growing Period											-0.007**
											(0.003)
Moderate DD Anom Sq Growing Period (t-1)											0.001
											(0.003)
Moderate DD Anom Sq Growing Period (t-2)											0.001
											(0.003)
Extreme DD Anom Sq Growing Period											0.007
											(0.008)
Extreme DD Anom Sq Growing Period (t-1)											-0.001
											(0.004)
Extreme DD Anom Sq Growing Period (t-2)											-0.009**
											(0.004)
Observations	139,308	139,308	139,308	139,308	139,308	139,308	139,308	139,308	139,308	37,596	37,596
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.049	0.049

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

**p* < .1. ***p* < .05. ****p* < .01.

Table A.16—Effects of temperature shocks on violent conflict, model at the yearly level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Temp Anom	0.118**	-0.373***	0.106*	0.091*	0.099*	0.088*	0.089	0.0752	0.0881		
	(0.058)	(0.139)	(0.057)	(0.053)	(0.054)	(0.053)	(0.054)	(0.0531)	(0.0531)		
Temp Anom Sq		0.251***									
		(0.087)									
Temp Shock > 1 s.d. Growing Period			0.081**								
			(0.031)								
Temp Shock > 2 s.d. Growing Period				0.361**							
				(0.18)							
Heat Shock > 1 s.d. Growing Period					0.096***						
					(0.033)						
Cold Shock > 1 s.d. Growing Period					0.002						
					(0.08)						
Heat Shock > 2 s.d. Growing Period						0.385**					
						(0.19)					
Cold Shock > 2 s.d. Growing Period						-0.063					
						(0.082)					
Heat Shock Pctile85 Growing Period							0.116***				
							(0.04)				
Cold Shock Pctile15 Growing Period							-0.1				
							(0.073)				
Heat Shock Pctile90 Growing Period								0.219***			
								(0.071)			
Cold Shock Pctile10 Growing Period								-0.018			
								(0.074)			
Heat Shock Pctile95 Growing Period									0.286**		
									(0.11)		
Cold Shock Pctile5 Growing Period									0.057		
									(0.123)		
Moderate DD Anom Growing Period										-0.55**	-0.559**
										(0.23)	(0.225)
Extreme DD Anom Growing Period										0.12	0.225
										(0.292)	(0.289)
Moderate DD Anom Sq Growing Period											0.024
											(0.312)
Extreme DD Anom Sq Growing Period											-0.267
											(0.286)
Observations	11,609	11,609	11,609	11,609	11,609	11,609	11,609	11,609	11,609	3,133	3,133
Grid-cells	893	893	893	893	893	893	893	893	893	241	241
R-squared	0.061	0.064	0.061	0.062	0.061	0.062	0.062	0.062	0.062	0.188	0.189

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects and night-lights. Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

**p* < .1. ***p* < .05. ****p* < .01.

Table A.17—Partial effects for the number of violent events

	(1)	(2)	(3)	(4)	(5)	(6)
	Table A14. Model at the monthly level		**Table A15. Model at the monthly level with the time lags**		**Table A16. Model at the yearly level**	
	β / s.d	part. eff.	β / s.d.	part. eff.	β / s.d.	part. eff.
Temp Anom	0.004	22.04	0.003	19.18	0.063	29.31
Temp Anom + Temp Anom Sq	0.003	17.7	0.003+0.005	42.36	-0.199+0.297	45.21
Temp Shock > 1 s.d. Grow. Per.					0.03	13.8
Temp Shock > 2 s.d. Grow. Per.			0.002+0.004	32.41	0.056	26.0
Heat Shock > 1 s.d. Grow. Per.					0.034	15.81
Heat Shock > 2 s.d. Grow. Per.			0.002+0.004	33.66	0.059	27.3
Heat Shock Pctile85 Grow. Per.					0.038	17.77
Heat Shock Pctile90 Grow. Per.	0.003	17.54	0.003+0.002	29.23	0.062	28.83
Heat Shock Pctile95 Grow. Per.	0.004	20.14	0.003+0.003+0.003	50.34	0.061	28.51
Moderate DD Anom Grow. Per.	-0.005	-8.02	-0.004	-6.75	-0.187	-23.44
Extreme DD Anom Grow. Per.	0.007	10.73	0.008	11.3		
Mod DD An GP + M DD An Sq GP	-0.005-0.005	-15.19	-0.006	-8.5	-0.19	-23.82
Ext DD An GP + E DD An Sq GP			0.005-0.005	-0.11		

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Columns 1, 3, 5, 7, and 9 report only the coefficients that were statistically significant in the models' equations. Note that columns 3 and 4 refer to the additional effect of the variables listed plus their two time lags. Descriptions of the weather variables are given in Table A.1. s.d. = standard deviation; part. eff. = partial effects.

Table A.18—Effects of temperature shocks on violent conflict, dynamic model at the quarterly level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Violent Events (t-1)	0.213**	0.212***	0.213***	0.212***	0.213***	0.212***	0.213***	0.212***	0.212***	0.21***	0.21***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.044)	(0.044)
Temp Anom	0.023*	0.007	0.02*	0.019*	0.02*	0.019*	0.019*	0.018*	0.018*		
	(0.012)	(0.01)	(0.011)	(0.01)	(0.011)	(0.01)	(0.011)	(0.011)	(0.011)		
Temp Anom Sq		0.008									
		(0.007)									
Temp Shock > 1 s.d. Growing Period			0.034**								
			(0.013)								
Temp Shock > 2 s.d. Growing Period				0.076*							
				(0.04)							
Heat Shock > 1 s.d. Growing Period					0.036**						
					(0.014)						
Cold Shock > 1 s.d. Growing Period					0.014						
					(0.032)						
Heat Shock > 2 s.d. Growing Period						0.076*					
						(0.04)					
Cold Shock > 2 s.d. Growing Period						0.034					
						(0.045)					
Heat Shock Pctile85 Growing Period							0.038**				
							(0.016)				
Cold Shock Pctile15 Growing Period							-0.03				
							(0.023)				
Heat Shock Pctile90 Growing Period								0.055***			
								(0.021)			
Cold Shock Pctile10 Growing Period								-0.003			
								(0.024)			
Heat Shock Pctile95 Growing Period									0.072**		
									(0.031)		
Cold Shock Pctile5 Growing Period									-0.018		
									(0.041)		
Moderate DD Anom Growing Period										-0.023	-0.027
										(0.022)	(0.022)
Extreme DD Anom Growing Period										0.058	0.114*
										(0.044)	(0.059)
Moderate DD Anom Sq Growing Period											0.006
											(0.014)
Extreme DD Anom Sq Growing Period											-0.034*
											(0.02)
P-values of the Arellano-Bond Test for											
j =1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
j =2	0.9	0.9	0.896	0.898	0.896	0.897	0.898	0.903	0.901	0.613	0.607
Observations	45,543	45,543	45,543	45,543	45,543	45,543	45,543	45,543	45,543	12,291	12,291
Grid-cells	893	893	893	893	893	893	893	893	893	241	241

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors are in parentheses. All regressions include time-fixed and time-trend effects, night-lights, and the growing period variable defined at the state level (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset. *$p < .1$. **$p < .05$. ***$p < .01$.

Table A.19—Effects of temperature shocks on violent conflict, dynamic model at the quarterly level with the spatial lags of the temperature variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Violent Events (t-1)	0.212***	0.21***	0.211***	0.208***	0.21***	0.207***	0.210***	0.209***	0.208***	0.209***	0.209***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)	(0.037)	(0.037)	(0.037)	(0.043)	(0.043)
Temp Anom	0.021*	0.019	0.017	0.015	0.018*	0.015	0.018	0.016	0.015		
	(0.011)	(0.011)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.011)	(0.01)		
Temp Anom x W	0.052	-0.118**	0.053	0.031	0.047	0.031	0.041	0.032	0.035		
	(0.039)	(0.048)	(0.041)	(0.039)	(0.039)	(0.039)	(0.039)	(0.04)	(0.04)		
Temp Anom Sq		0.001									
		(0.006)									
Temp Anom Sq x W		0.096***									
		(0.026)									
Temp Shock > 1 s.d. Growing Period			0.029**								
			(0.013)								
Temp Shock > 1 s.d. Growing Period x W			0.158**								
			(0.064)								
Temp Shock > 2 s.d. Growing Period				0.063*							
				(0.035)							
Temp Shock > 2 s.d. Growing Period x W				0.575***							
				(0.216)							
Heat Shock > 1 s.d. Growing Period					0.025*						
					(0.013)						
Heat Shock > 1 s.d. Growing Period x W					0.149**						
					(0.063)						
Cold Shock > 1 s.d. Growing Period					0.044						
					(0.034)						
Cold Shock > 1 s.d. Growing Period x W					-0.386*						
					(0.231)						
Heat Shock > 2 s.d. Growing Period						0.064*					
						(0.036)					
Heat Shock > 2 s.d. Growing Period x W						0.594***					
						(0.215)					
Cold Shock > 2 s.d. Growing Period						0.018					
						(0.042)					
Cold Shock > 2 s.d. Growing Period x W						-5.733*					
						(3.031)					
Heat Shock Pctile85 Growing Period							0.027*				
							(0.015)				
Heat Shock Pctile85 Growing Period x W							0.171**				
							(0.067)				
Cold Shock Pctile15 Growing Period							-0.001				
							(0.021)				
Cold Shock Pctile15 Growing Period x W							-0.432*				
							(0.258)				

Table A.19—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Number of Violent Events (ACLED)										
Heat Shock Pctile90 Growing Period								0.043**			
								(0.02)			
Heat Shock Pctile90 Growing Period x W								0.302***			
								(0.092)			
Cold Shock Pctile10 Growing Period								0.02			
								(0.025)			
Cold Shock Pctile10 Growing Period x W								-0.438			
								(0.391)			
Heat Shock Pctile95 Growing Period									0.059**		
									(0.028)		
Heat Shock Pctile95 Growing Period x W									0.418***		
									(0.151)		
Cold Shock Pctile5 Growing Period									-0.007		
									(0.041)		
Cold Shock Pctile5 Growing Period x W									-0.741		
									(1.000)		
Moderate DD Anom Growing Period										-0.017	-0.021
										(0.021)	(0.022)
Moderate DD Anom Growing Period x W										-0.656	-0.627
										(0.434)	(0.449)
Extreme DD Anom Growing Period										0.058	0.107*
										(0.044)	(0.058)
Extreme DD Anom Growing Period x W										0.023	-0.575
										(1.14)	(1.204)
Moderate DD Anom Sq Growing Period											0.005
											(0.014)
Moderate DD Anom Sq Growing Period x W											0.235
											(0.326)
Extreme DD Anom Sq Growing Period											-0.03
											(0.021)
Extreme DD Anom Sq Growing Period x W											0.308
											(0.945)
P-values of the Arellano-Bond Test for zero autocorrelation in first-differenced errors of order j											
j =1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
j =2	0.902	0.915	0.907	0.922	0.909	0.923	0.912	0.918	0.92	0.611	0.606
Observations	45,543	45,543	45,543	45,543	45,543	45,543	45,543	45,543	45,543	12,291	12,291
Grid-cells	893	893	893	893	893	893	893	893	893	241	241

Source: Authors' estimation based on ACLED, UEA CRU-TS, and NASA POWER.

Notes: Robust standard errors are in parentheses. All regressions include time-fixed and time-trend effects, night-lights and corresponding spatial lag, the growing period variable defined at the state level, and the corresponding spatial lag (except for regressions in columns 1 and 2). Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

**p* < .1. ***p* < .05. ****p* < .01.

Table A.20.a—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Main Crop is Maize"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Violent Events (ACLED)						
Temp Anom	0.033***	0.03***	0.033***	0.029***	0.031***	0.028**	0.029**
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)
Temp Shock > 1 s.d. Grow. Per.	0.035**						
	(0.015)						
Temp Shock > 2 s.d. Grow. Per.		0.106***					
		(0.033)					
Heat Shock > 1 s.d. Grow. Per.			0.036**				
			(0.017)				
Cold Shock > 1 s.d. Grow. Per.			0.017				
			(0.044)				
Heat Shock > 2 s.d. Grow. Per.				0.107***			
				(0.034)			
Cold Shock > 2 s.d. Grow. Per.				0.016			
				(0.052)			
Heat Shock Pctile85 Grow. Per.					0.042**		
					(0.02)		
Cold Shock Pctile15 Grow. Per.					-0.031		
					(0.026)		
Heat Shock Pctile90 Grow. Per.						0.075***	
						(0.026)	
Cold Shock Pctile10 Grow. Per.						-0.009	
						(0.047)	
Heat Shock Pctile95 Grow. Per.							0.1***
							(0.038)
Cold Shock Pctile5 Grow. Per.							-0.035
							(0.07)
Temp Shock > 1 s.d. Grow. Per. X Main Crop is Maize	0.05						
	(0.061)						
Temp Shock > 2 s.d. Grow. Per. X Main Crop is Maize		-0.021					
		(0.078)					
Heat Shock > 1 s.d. Grow. Per. X Main Crop is Maize			0.027				
			(0.063)				
Cold Shock > 1 s.d. Grow. Per. X Main Crop is Maize			0.471***				
			(0.158)				
Heat Shock > 2 s.d. Grow. Per. X Main Crop is Maize				-0.021			
				(0.078)			
Heat Shock Pctile85 Grow. Per. X Main Crop is Maize					-0.019		
					(0.06)		
Cold Shock Pctile15 Grow. Per. X Main Crop is Maize					-0.056		
					(0.047)		
Heat Shock Pctile90 Grow. Per. X Main Crop is Maize						-0.108***	
						(0.035)	
Cold Shock Pctile10 Grow. Per. X Main Crop is Maize						-0.064	
						(0.066)	
Heat Shock Pctile95 Grow. Per. X Main Crop is Maize							-0.073
							(0.071)
Observations	30,212	30,212	30,212	30,212	30,212	30,212	30,212
Grid-cells	581	581	581	581	581	581	581
R-squared	0.006	0.007	0.006	0.007	0.006	0.007	0.007

Table A.20.b—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Main Crop is Sorghum"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Violent Events (ACLED)						
Temp Anom	0.033***	0.029***	0.0328***	0.029***	0.031***	0.028**	0.029**
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)
Temp Shock > 1 s.d. Grow. Per.	0.043*						
	(0.025)						
Temp Shock > 2 s.d. Grow. Per.		0.13					
		(0.079)					
Heat Shock > 1 s.d. Grow. Per.			0.047				
			(0.028)				
Cold Shock > 1 s.d. Grow. Per.			-0.033				
			(0.043)				
Heat Shock > 2 s.d. Grow. Per.				0.13			
				(0.079)			
Cold Shock > 2 s.d. Grow. Per.				0.008			
				(0.038)			
Heat Shock Pctile85 Grow. Per.					0.051		
					(0.032)		
Cold Shock Pctile15 Grow. Per.					-0.055*		
					(0.028)		
Heat Shock Pctile90 Grow. Per.						0.082*	
						(0.045)	
Cold Shock Pctile10 Grow. Per.						-0.066*	
						(0.038)	
Heat Shock Pctile95 Grow. Per.							0.129*
							(0.072)
Cold Shock Pctile5 Grow. Per.							-0.012
							(0.022)
Temp Shock > 1 s.d. Grow. Per. X Main Crop is Sorghum	-0.013						
	(0.031)						
Temp Shock > 2 s.d. Grow. Per. X Main Crop is Sorghum		-0.043					
		(0.096)					
Heat Shock > 1 s.d. Grow. Per. X Main Crop is Sorghum			-0.018				
			(0.033)				
Cold Shock > 1 s.d. Grow. Per. X Main Crop is Sorghum			0.1				
			(0.078)				
Heat Shock > 2 s.d. Grow. Per. X Main Crop is Sorghum				-0.042			
				(0.096)			
Cold Shock > 2 s.d. Grow. Per. X Main Crop is Sorghum				0.008			
				(0.057)			
Heat Shock Pctile85 Grow. Per. X Main Crop is Sorghum					-0.017		
					(0.036)		
Cold Shock Pctile15 Grow. Per. X Main Crop is Sorghum					0.037		
					(0.044)		
Heat Shock Pctile90 Grow. Per. X Main Crop is Sorghum						-0.015	
						(0.054)	
Cold Shock Pctile10 Grow. Per. X Main Crop is Sorghum						0.091	
						(0.076)	
Heat Shock Pctile95 Grow. Per. X Main Crop is Sorghum							-0.057
							(0.078)
Cold Shock Pctile5 Grow. Per. X Main Crop is Sorghum							-0.033
							(0.098)
Observations	30,212	30,212	30,212	30,212	30,212	30,212	30,212
Grid-cells	581	581	581	581	581	581	581
R-squared	0.006	0.007	0.006	0.007	0.006	0.007	0.007

Table A.20.c—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Main Crop is Millet"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Violent Events (ACLED)						
Temp Anom	0.033***	0.03***	0.033***	0.029***	0.031***	0.028**	0.029**
	(0.012)	(0.011)	(0.012)	(0.0110)	(0.012)	(0.011)	(0.011)
Temp Shock > 1 s.d. Grow. Per.	0.038**						
	(0.016)						
Temp Shock > 2 s.d. Grow. Per.		0.112***					
		(0.035)					
Heat Shock > 1 s.d. Grow. Per.			0.039**				
			(0.017)				
Cold Shock > 1 s.d. Grow. Per.			0.028				
			(0.045)				
Heat Shock > 2 s.d. Grow. Per.				0.113***			
				(0.035)			
Cold Shock > 2 s.d. Grow. Per.				0.016			
				(0.052)			
Heat Shock Pctile85 Grow. Per.					0.045**		
					(0.021)		
Cold Shock Pctile15 Grow. Per.					-0.032		
					(0.026)		
Heat Shock Pctile90 Grow. Per.						0.078***	
						(0.027)	
Cold Shock Pctile10 Grow. Per.						-0.009	
						(0.048)	
Heat Shock Pctile95 Grow. Per.							0.105***
							(0.039)
Cold Shock Pctile5 Grow. Per.							-0.034
							(0.071)
Temp Shock > 1 s.d. Grow. Per. X Main Crop is Millet	-0.059***						
	(0.022)						
Temp Shock > 2 s.d. Grow. Per. X Main Crop is Millet		-0.095**					
		(0.046)					
Heat Shock > 1 s.d. Grow. Per. X Main Crop is Millet			-0.059**				
			(0.023)				
Cold Shock > 1 s.d. Grow. Per. X Main Crop is Millet			-0.069				
			(0.055)				
Heat Shock > 2 s.d. Grow. Per. X Main Crop is Millet				-0.096**			
				(0.046)			
Heat Shock Pctile85 Grow. Per. X Main Crop is Millet					-0.075***		
					(0.027)		
Cold Shock Pctile15 Grow. Per. X Main Crop is Millet					-0.002		
					(0.033)		
Heat Shock Pctile90 Grow. Per. X Main Crop is Millet						-0.09***	
						(0.031)	
Cold Shock Pctile10 Grow. Per. X Main Crop is Millet						-0.025	
						(0.053)	
Heat Shock Pctile95 Grow. Per. X Main Crop is Millet							-0.104**
							(0.041)
Cold Shock Pctile5 Grow. Per. X Main Crop is Millet							-0.041
							(0.07)
Observations	30,212	30,212	30,212	30,212	30,212	30,212	30,212
Grid-cells	581	581	581	581	581	581	581
R-squared	0.006	0.007	0.006	0.007	0.006	0.007	0.007

Table A.20.d—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Main Crop is Groundnut"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Violent Events (ACLED)						
Temp Anom	0.034***	0.03***	0.033***	0.029***	0.031***	0.028**	0.029**
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)
Temp Shock > 1 s.d. Grow. Per.	0.025*						
	(0.014)						
Temp Shock > 2 s.d. Grow. Per.		0.095**					
		(0.037)					
Heat Shock > 1 s.d. Grow. Per.			0.024*				
			(0.014)				
Cold Shock > 1 s.d. Grow. Per.			0.052				
			(0.049)				
Heat Shock > 2 s.d. Grow. Per.				0.096**			
				(0.037)			
Cold Shock > 2 s.d. Grow. Per.				0.017			
				(0.056)			
Heat Shock Pctile85 Grow. Per.					0.029*		
					(0.018)		
Cold Shock Pctile15 Grow. Per.					-0.024		
					(0.028)		
Heat Shock Pctile90 Grow. Per.						0.062**	
						(0.025)	
Cold Shock Pctile10 Grow. Per.						0.017	
						(0.055)	
Heat Shock Pctile95 Grow. Per.							0.077**
							(0.035)
Cold Shock Pctile5 Grow. Per.							-0.04
							(0.093)
Temp Shock > 1 s.d. Grow. Per. X Main Crop is Groundnut	0.082						
	(0.063)						
Temp Shock > 2 s.d. Grow. Per. X Main Crop is Groundnut		0.099					
		(0.152)					
Heat Shock > 1 s.d. Grow. Per. X Main Crop is Groundnut			0.096				
			(0.069)				
Cold Shock > 1 s.d. Grow. Per. X Main Crop is Groundnut			-0.137*				
			(0.074)				
Heat Shock > 2 s.d. Grow. Per. X Main Crop is Groundnut				0.1			
				(0.153)			
Cold Shock > 2 s.d. Grow. Per. X Main Crop is Groundnut				-0.009			
				(0.058)			
Heat Shock Pctile85 Grow. Per. X Main Crop is Groundnut					0.092		
					(0.076)		
Cold Shock Pctile15 Grow. Per. X Main Crop is Groundnut					-0.044		
					(0.05)		
Heat Shock Pctile90 Grow. Per. X Main Crop is Groundnut						0.102	
						(0.106)	
Cold Shock Pctile10 Grow. Per. X Main Crop is Groundnut						-0.103	
						(0.07)	
Heat Shock Pctile95 Grow. Per. X Main Crop is Groundnut							0.17
							(0.148)
Cold Shock Pctile5 Grow. Per. X Main Crop is Groundnut							0.035
							(0.092)
Observations	30,212	30,212	30,212	30,212	30,212	30,212	30,212
Grid-cells	581	581	581	581	581	581	581
R-squared	0.006	0.007	0.007	0.007	0.007	0.007	0.008

Table A.20.e—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Main Crop is Cassava"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Violent Events (ACLED)						
Temp Anom	0.033***	0.029***	0.033***	0.029***	0.031***	0.028**	0.029**
	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Temp Shock > 1 s.d. Grow. Per.	0.033**						
	(0.016)						
Temp Shock > 2 s.d. Grow. Per.		0.081***					
		(0.024)					
Heat Shock > 1 s.d. Grow. Per.			0.033*				
			(0.017)				
Cold Shock > 1 s.d. Grow. Per.			0.024				
			(0.045)				
Heat Shock > 2 s.d. Grow. Per.				0.082***			
				(0.025)			
Cold Shock > 2 s.d. Grow. Per.				0.013			
				(0.05)			
Heat Shock Pctile85 Grow. Per.					0.036*		
					(0.02)		
Cold Shock Pctile15 Grow. Per.					-0.034		
					(0.026)		
Heat Shock Pctile90 Grow. Per.						0.063**	
						(0.025)	
Cold Shock Pctile10 Grow. Per.						-0.012	
						(0.046)	
Heat Shock Pctile95 Grow. Per.							0.079**
							(0.032)
Cold Shock Pctile5 Grow. Per.							-0.038
							(0.069)
Temp Shock > 1 s.d. Grow. Per. X Main Crop is Cassava	0.049						
	(0.097)						
Temp Shock > 2 s.d. Grow. Per. X Main Crop is Cassava		0.249					
		(0.39)					
Heat Shock > 1 s.d. Grow. Per. X Main Crop is Cassava			0.048				
			(0.098)				
Cold Shock > 1 s.d. Grow. Per. X Main Crop is Cassava			0.051				
			(0.063)				
Heat Shock > 2 s.d. Grow. Per. X Main Crop is Cassava				0.249			
				(0.39)			
Heat Shock Pctile85 Grow. Per. X Main Crop is Cassava					0.074		
					(0.12)		
Cold Shock Pctile15 Grow. Per. X Main Crop is Cassava					0.141**		
					(0.056)		
Heat Shock Pctile90 Grow. Per. X Main Crop is Cassava						0.147	
						(0.228)	
Heat Shock Pctile95 Grow. Per. X Main Crop is Cassava							0.281
							(0.415)

Table A.20.e—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Main Crop is Cassava"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Violent Events (ACLED)						
Observations	30,212	30,212	30,212	30,212	30,212	30,212	30,212
Grid-cells	581	581	581	581	581	581	581
R-squared	0.006	0.007	0.006	0.007	0.006	0.007	0.008

Source: Authors' estimation based on ACLED and UEA CRU-TS. The sources for the interaction terms are detailed in Section 3.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level. Descriptions of weather variables given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.

**p* < .1. ***p* < .05. ****p* < .01.

Table A.21.a—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Goat Density"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Temp Anom	0.027***	0.026***	0.023***	0.025***	0.023***	0.024***	0.022***	0.022***
	(0.01)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temp Shock > 1 s.d. Grow. Per.		0.007						
		(0.011)						
Temp Shock > 2 s.d. Grow. Per.			0.044					
			(0.028)					
Heat Shock > 1 s.d. Grow. Per.				0.009				
				(0.012)				
Cold Shock > 1 s.d. Grow. Per.				-0.006				
				(0.025)				
Heat Shock > 2 s.d. Grow. Per.					0.045			
					(0.028)			
Cold Shock > 2 s.d. Grow. Per.					-0.012			
					(0.037)			
Heat Shock Pctile85 Grow. Per.						0.011		
						(0.014)		
Cold Shock Pctile15 Grow. Per.						-0.008		
						(0.02)		
Heat Shock Pctile90 Grow. Per.							0.036*	
							(0.019)	
Cold Shock Pctile10 Grow. Per.							0.012	
							(0.029)	
Heat Shock Pctile95 Grow. Per.								0.036
								(0.025)
Cold Shock Pctile5 Grow. Per.								-0.039
								(0.045)
Temp Anom X Goat Density	0.0001							
	(0.0003)							
Temp Shock > 1 s.d. Grow. Per. X Goat Density		0.001*						
		(0.001)						
Temp Shock > 2 s.d. Grow. Per. X Goat Density			0.002*					
			(0.001)					
Heat Shock > 1 s.d. Grow. Per. X Goat Density				0.001				
				(0.001)				
Cold Shock > 1 s.d. Grow. Per. X Goat Density				0.001				
				(0.002)				
Heat Shock > 2 s.d. Grow. Per. X Goat Density					0.002*			
					(0.001)			
Cold Shock > 2 s.d. Grow. Per. X Goat Density					0.001*			
					(0.0003)			
Heat Shock Pctile85 Grow. Per. X Goat Density						0.001		
						(0.001)		
Cold Shock Pctile15 Grow. Per. X Goat Density						-0.001*		
						(0.001)		
Heat Shock Pctile90 Grow. Per. X Goat Density							0.001	
							(0.001)	
Cold Shock Pctile10 Grow. Per. X Goat Density							-0.001*	
							(0.001)	
Heat Shock Pctile95 Grow. Per. X Goat Density								0.002*
								(0.001)
Cold Shock Pctile5 Grow. Per. X Goat Density								0.0004
								(0.001)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436
Grid-cells	893	893	893	893	893	893	893	893
R-squared	0.004	0.005	0.005	0.005	0.005	0.005	0.005	0.006

Table A.21.b—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Pastoral and Agropastoral Groups"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Temp Anom	0.019***	0.026***	0.023***	0.025***	0.023***	0.024***	0.022***	0.023***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temp Shock > 1 s.d. Grow. Per.		0.015						
		(0.012)						
Temp Shock > 2 s.d. Grow. Per.			0.045*					
			(0.023)					
Heat Shock > 1 s.d. Grow. Per.				0.015				
				(0.013)				
Cold Shock > 1 s.d. Grow. Per.				0.023				
				(0.027)				
Heat Shock > 2 s.d. Grow. Per.					0.045*			
					(0.023)			
Cold Shock > 2 s.d. Grow. Per.					-0.003			
					(0.035)			
Heat Shock Pctile85 Grow. Per.						0.016		
						(0.014)		
Cold Shock Pctile15 Grow. Per.						-0.018		
						(0.017)		
Heat Shock Pctile90 Grow. Per.							0.034*	
							(0.018)	
Cold Shock Pctile10 Grow. Per.							0.006	
							(0.024)	
Heat Shock Pctile95 Grow. Per.								0.037*
								(0.02)
Cold Shock Pctile5 Grow. Per.								-0.002
								(0.024)
Temp Anom X Pastoral & AgroPastoral Groups	0.062**							
	(0.03)							
Temp Shock > 1 s.d. Grow. Per. X Pastoral & AgroPastoral Groups		0.065*						
		(0.039)						
Temp Shock > 2 s.d. Grow. Per. X Pastoral & AgroPastoral Groups			0.157					
			(0.097)					
Heat Shock > 1 s.d. Grow. Per. X Pastoral & AgroPastoral Groups				0.072*				
				(0.041)				
Cold Shock > 1 s.d. Grow. Per. X Pastoral & AgroPastoral Groups				-0.189**				
				(0.091)				
Heat Shock > 2 s.d. Grow. Per. X Pastoral & AgroPastoral Groups					0.157			
					(0.097)			
Heat Shock Pctile85 Grow. Per. X Pastoral & AgroPastoral Groups						0.083*		
						(0.045)		
Cold Shock Pctile15 Grow. Per. X Pastoral & AgroPastoral Groups						-0.143		
						(0.1)		
Heat Shock Pctile90 Grow. Per. X Pastoral & AgroPastoral Groups							0.125*	
							(0.073)	
Cold Shock Pctile10 Grow. Per. X Pastoral & AgroPastoral Groups							-0.277**	
							(0.131)	

Table A.21.b—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Heat Shock Pctile95 Grow.								0.204*
Per. X Pastoral & AgroPastoral Groups								(0.116)
Cold Shock Pctile5 Grow.								-0.97***
Per. X Pastoral & AgroPastoral Groups								(0.031)
Observations	44,668	44,668	44,668	44,668	44,668	44,668	44,668	44,668
Grid-cells	859	859	859	859	859	859	859	859
R-squared	0.005	0.005	0.006	0.005	0.006	0.005	0.006	0.007

Table A.21.c—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Near to Major River"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Temp Anom	0.141***	0.092***	0.081**	0.088**	0.081**	0.084**	0.071**	0.075**
	(0.044)	(0.034)	(0.032)	(0.034)	(0.032)	(0.033)	(0.032)	(0.033)
Temp Shock > 1 s.d. Grow. Per.		0.047***						
		(0.018)						
Temp Shock > 2 s.d. Grow. Per.			0.126**					
			(0.054)					
Heat Shock > 1 s.d. Grow. Per.				0.052***				
				(0.02)				
Cold Shock > 1 s.d. Grow. Per.				-0.01				
				(0.025)				
Heat Shock > 2 s.d. Grow. Per.					0.126**			
					(0.054)			
Cold Shock > 2 s.d. Grow. Per.					0.161***			
					(0.055)			
Heat Shock Pctile85 Grow. Per.						0.06**		
						(0.023)		
Cold Shock Pctile15 Grow. Per.						-0.028		
						(0.026)		
Heat Shock Pctile90 Grow. Per.							0.101***	
							(0.035)	
Cold Shock Pctile10 Grow. Per.							-0.013	
							(0.05)	
Heat Shock Pctile95 Grow. Per.								0.121**
								(0.051)
Cold Shock Pctile5 Grow. Per.								-0.031
								(0.062)
Temp Anom X Near to Major River	-0.129**							
	(0.05)							
Temp Shock > 1 s.d. Grow. Per. X Near to Major River		-0.065***						
		(0.019)						
Temp Shock > 2 s.d. Grow. Per. X Near to Major River			-0.107*					
			(0.063)					
Heat Shock > 1 s.d. Grow. Per. X Near to Major River				-0.071***				
				(0.02)				
Cold Shock > 1 s.d. Grow. Per. X Near to Major River				0.019				
				(0.034)				
Heat Shock > 2 s.d. Grow. Per. X Near to Major River					-0.105*			
					(0.063)			
Cold Shock > 2 s.d. Grow. Per. X Near to Major River					-0.238***			
					(0.074)			
Heat Shock Pctile85 Grow. Per. X Near to Major River						-0.079***		
						(0.023)		
Cold Shock Pctile15 Grow. Per. X Near to Major River						0.014		
						(0.021)		
Heat Shock Pctile90 Grow. Per. X Near to Major River							-0.101***	
							(0.033)	
Cold Shock Pctile10 Grow. Per. X Near to Major River							0.006	
							(0.046)	

Table A.21.c—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Heat Shock Pctile95 Grow. Per. X Near to Major River								-0.083
								(0.053)
Cold Shock Pctile5 Grow. Per. X Near to Major River								-0.002
								(0.059)
Observations	12,480	12,480	12,480	12,480	12,480	12,480	12,480	12,480
Grid-cells	240	240	240	240	240	240	240	240
R-squared	0.015	0.016	0.018	0.016	0.018	0.016	0.019	0.019

Table A.21.d—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Share of Irrigated Land"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Temp Anom	0.029***	0.026***	0.024***	0.026***	0.023***	0.025***	0.022***	0.023***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temp Shock > 1 s.d.		0.027**						
Grow. Per.		(0.013)						
Temp Shock > 2 s.d.			0.086***					
Grow. Per.			(0.031)					
Heat Shock > 1 s.d.				0.029**				
Grow. Per.				(0.014)				
Cold Shock > 1 s.d.				0.01				
Grow. Per.				(0.027)				
Heat Shock > 2 s.d.					0.087***			
Grow. Per.					(0.031)			
Cold Shock > 2 s.d.					0.001			
Grow. Per.					(0.037)			
Heat Shock Pctile85						0.033**		
Grow. Per.						(0.017)		
Cold Shock Pctile15						-0.025		
Grow. Per.						(0.017)		
Heat Shock Pctile90							0.061***	
Grow. Per.							(0.022)	
Cold Shock Pctile10							-0.012	
Grow. Per.							(0.027)	
Heat Shock Pctile95								0.081**
Grow. Per.								(0.033)
Cold Shock Pctile5								-0.032
Grow. Per.								(0.049)
Temp Anom X	-0.001**							
Share of Irrigated Land	(0.0003)							
Temp Shock > 1 s.d. Grow. Per. X Share of Irrigated Land		-0.002*** (0.001)						
Temp Shock > 2 s.d. Grow. Per. X Share of Irrigated Land			-0.003** (0.001)					
Heat Shock > 1 s.d. Grow. Per. X Share of Irrigated Land				-0.002*** (0.001)				
Cold Shock > 1 s.d. Grow. Per. X Share of Irrigated Land				-0.0002 (0.001)				
Heat Shock > 2 s.d. Grow. Per. X Share of Irrigated Land					-0.003** (0.001)			
Cold Shock > 2 s.d. Grow. Per. X Share of Irrigated Land					0.001 (0.004)			
Heat Shock Pctile85 Grow. Per. X Share of Irrigated Land						-0.002*** (0.001)		
Cold Shock Pctile15 Grow. Per. X Share of Irrigated Land						0.001 (0.001)		
Heat Shock Pctile90 Grow. Per. X Share of Irrigated Land							-0.003*** (0.001)	

Table A.21.d—Continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Cold Shock Pctile10							0.001	
Grow. Per. X Share of Irrigated Land							(0.001)	
Heat Shock Pctile95								-0.003***
Grow. Per. X Share of Irrigated Land								(0.001)
Cold Shock Pctile5								0.001
Grow. Per. X Share of Irrigated Land								(0.001)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436
Grid-cells	893	893	893	893	893	893	893	893
R-squared	0.004	0.004	0.005	0.005	0.005	0.005	0.005	0.005

Table A.21.e—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Market Accessibility"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Temp Anom	0.029***	0.026***	0.024***	0.026***	0.023***	0.025***	0.022***	0.023***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Temp Shock > 1 s.d. Grow. Per.		0.027**						
		(0.013)						
Temp Shock > 2 s.d. Grow. Per.			0.086***					
			(0.03)					
Heat Shock > 1 s.d. Grow. Per.				0.029**				
				(0.014)				
Cold Shock > 1 s.d. Grow. Per.				0.011				
				(0.026)				
Heat Shock > 2 s.d. Grow. Per.					0.087***			
					(0.031)			
Cold Shock > 2 s.d. Grow. Per.					0.029			
					(0.022)			
Heat Shock Pctile85 Grow. Per.						0.033**		
						(0.017)		
Cold Shock Pctile15 Grow. Per.						-0.024		
						(0.017)		
Heat Shock Pctile90 Grow. Per.							0.06***	
							(0.022)	
Cold Shock Pctile10 Grow. Per.							-0.01	
							(0.027)	
Heat Shock Pctile95 Grow. Per.								0.081**
								(0.033)
Cold Shock Pctile5 Grow. Per.								-0.026
								(0.048)
Temp Anom X Market Accessibility	-0.057							
	(0.043)							
Temp Shock > 1 s.d. Grow. Per. X Market Accessibility		-0.059***						
		(0.022)						
Temp Shock > 2 s.d. Grow. Per. X Market Accessibility			-0.156***					
			(0.039)					
Heat Shock > 1 s.d. Grow. Per. X Market Accessibility				-0.055***				
				(0.017)				
Cold Shock > 1 s.d. Grow. Per. X Market Accessibility				-0.084				
				(0.09)				
Heat Shock > 2 s.d. Grow. Per. X Market Accessibility					-0.133***			
					(0.035)			
Cold Shock > 2 s.d. Grow. Per. X Market Accessibility					-0.393***			
					(0.018)			
Heat Shock Pctile85 Grow. Per. X Market Accessibility						-0.057***		
						(0.019)		
Cold Shock Pctile15 Grow. Per. X Market Accessibility						-0.0004		
						(0.054)		
Heat Shock Pctile90 Grow. Per. X Market Accessibility							-0.067***	
							(0.021)	

Table A.21.e—Effects of temperature shocks on violent conflict: Heterogeneity of the effects for "Market Accessibility"

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Violent Events (ACLED)							
Cold Shock Pctile10 Grow. Per. X Market Accessibility							-0.046	
							(0.094)	
Heat Shock Pctile95 Grow. Per. X Market Accessibility								-0.099***
								(0.028)
Cold Shock Pctile5 Grow. Per. X Market Accessibility								-0.129
								(0.157)
Observations	46,436	46,436	46,436	46,436	46,436	46,436	46,436	46,436
Grid-cells	893	893	893	893	893	893	893	893
R-squared	0.004	0.004	0.005	0.004	0.005	0.005	0.005	0.005

Source: Authors' estimation based on ACLED and UEA CRU-TS. The sources for the interaction terms are detailed in Section 3.

Notes: Robust standard errors, in parentheses, are clustered at the county level. All regressions include cell-fixed, time-fixed, and time-trend effects; night-lights; and the growing period variable defined at the state level. Descriptions of the weather variables are given in Table A.1. ACLED = Armed Conflict Location and Event Dataset.
$*p < .1$. $**p < .05$. $***p < .01$.

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