Journal of Economic Geography Advance Access published September 8, 2014

Journal of Economic Geography (2014) pp. 1–23 doi:10.1093/jeg/lbu033

Local warming and violent conflict in North and South Sudan

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Abstract

Our article contributes to the emerging micro-level strand of the literature on the link between local variations in weather shocks and conflicts by focusing on a pixel-level analysis for North and South Sudan between 1997 and 2009. Temperature anomalies are found to strongly affect the risk of conflict, whereas the risk is expected to magnify in a range of 24–31% in the future under a median scenario. Our analysis also sheds light on the competition over natural resources, in particular water, as the main driver of such relationship in a region where pastoralism constitutes the dominant livelihood.

Key words: Weather shocks, violent conflict, Sudan, disaggregated spatial analysis, pastoralism
JEL classifications: D74, O13, Q54, R11
Date submitted: 1 April 2014 **Date accepted:** 29 July 2014

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 (Sachs and Warner, 1997; Homer-Dixon, 1999; Steinbruner et al., 2012). These claims lack consensual empirical support and would deserve a more careful investigation of the specific channels linking climatic phenomena and conflict events (Scheffran et al., 2012; Hsiang et al., 2013).

Quantitative assessments of the climate–conflict nexus have primarily focused on country–year approaches to shed light on the role of rainfall (Miguel et al., 2004) or temperature (Burke et al., 2009) variations in explaining conflict in Africa south of the Sahara (SSA). Burke et al. (2009) even found that temperature is the main climatic driver of conflict in a joint model. On a global basis, another analysis exploited the dominant inter-annual 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 (Hsiang et al., 2011). Nevertheless, the relationship between climate variations and conflicts has been found to be sensitive to the definition of the sample (years and countries) and of the main variables of interest (Buhaug, 2010; Burke et al., 2010; Ciccone, 2011; Miguel and Satyanath, 2011; Klomp and Bulte, 2013).

There is an emerging consensus confirming that the climate–conflict nexus needs to be better understood by moving beyond the conventional country–year focus and embracing shorter time intervals and subnational regions (Blattman and Miguel, 2009, 16; Klomp and Bulte, 2013). The sensitivity of country–year findings may result from the inability of country-level variables to capture the dynamics of local conflict events (Buhaug and Lujala, 2005; Buhaug and Rod, 2006). Case studies offer an alternative approach, but the lack of comparability and the selection of the most pressing cases make the results limited and, at best, complementary to quantitative analyses (Nordas and Gleditsch, 2007; Gleditsch, 2012).

The availability of disaggregated analyses paves the way to explore how local climatic variations may affect local violence within a deep understanding of the socioeconomic context. Using subnational units of analysis allows overcoming the shortcomings of the country–year approach while preserving the strength of the econometric approach recently advanced by scholars looking at the links between climatic variations and violence in SSA. A growing body of research is following this path. Harari and La Ferrara (2012) exploit the grid-cell-level (1° over 1°) annual variation to investigate the relationship between weather shocks and conflict in Africa. Negative weather shocks, occurring during the growing season of the main crops, significantly increase the incidence of conflict. Two other studies have focused on East Africa (Raleigh and Kniveton, 2012; O'Loughlin et al., 2012). Based on geo-referenced data, Raleigh and Kniveton (2012) find that the frequency of violent events in Uganda, Ethiopia and Kenya increases in periods of extreme rainfall variations. The second regional analysis evaluates the role not only of precipitation, but also of temperature changes using similar data and including nine entire countries (Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, Tanzania and Uganda). Wetter deviations from the precipitation norms decrease the risk of conflict, whereas warmer than normal temperature raises the risk (O'Loughlin et al., 2012). Finally, Maystadt and Ecker (2014) exploit monthly and regional variations within a single country, Somalia, and find a strong and positive relationship between more frequent and intense temperature-based droughts and the occurrence of violent conflicts.

A meta-analysis by Hsiang et al. (2013) of the most robust quantitative studies on the subject—including the ones mentioned above—recently revived the debate (Bohannon, 2013; Buhaug et al., in press). The meta-analysis concludes that warmer temperature and, to a lesser extent, extreme rainfall lead to an increase in intergroup conflict. A 1 standard deviation change in climate would translate into a median rise of 14% in the frequency of intergroup conflict. Given the controversial nature of these findings, our contribution is 2-fold.

First, we adopt a similar research design, but provide an out-of-sample confirmation of the strong relationship between warmer temperature and intergroup conflicts for a decade in which the strength of that relationship has been debated (Buhaug, 2010; Hsiang and Meng, in press) and for two countries (North and South Sudan, 'Sudan' hereinafter) not included in the research areas of past studies in east Africa (Raleigh and Kniveton, 2012; O'Loughlin et al., 2012; Maystadt and Eckers, 2014).[1] Therefore, our

1 That omission is striking as the former country (North and South Sudan) has been one of the most conflictive country in SSA (Supplementary Table S1). Understanding the role of weather variations in the Sudanese conflict is a goal in itself and it could also be a source of learning for other conflict-prone countries sharing similar characteristics.

article contributes to the spatially disaggregated strand of the literature by investigating the links between weather shocks and conflict in Sudan. We estimate at the pixel level the relationship between local warming and violent conflict between 1997 and 2009. Beyond the exclusive focus on Sudan and the finer grid-cell resolution (0.5°), our study differs from previous spatially disaggregated analysis by adopting a more restrictive methodological approach. Our main results are estimated using a fixed-effects framework at both pixel and quarterly levels, augmented by specific time trends, more likely to reduce estimation bias compared with an approach based on adding a limited number of potentially endogenous control variables (Angrist and Pischke, 2009). We also project the changes in violent conflict by 2030 under different climate models and scenarios. Temperature anomalies are found to strongly affect the risk of conflict, whereas the risk is expected to magnify in a range of 24–31% in the future under a median scenario.

Second, not only the recent meta-analysis by Hsiang et al. (2013), but also previous global studies (Miguel et al., 2004; Burke et al., 2009; Hsiang et al., 2011) called for narrowing the number of competing hypotheses to explain the climate–conflict nexus. Sudan is an interesting case study in this respect because competition over natural resources and the role of climatic factors has often been heralded without much quantitative evidence. Our analysis explores how some characteristics magnify or reduce the strength of the relationship between climate and conflict. It suggests that the competition over natural resources, in particular water, is the main driver of such relationship in a region where pastoralism constitutes the dominant livelihood. Our analysis also shows that focusing on one particular country (former Sudan) allows us to come up with context-specific explanations that may be unduly overlooked in global studies. Our article paves the way for further integrating the pastoralist dimension in these studies. It also concludes on the need for more decisive and coordinated action to help pastoralist and agro-pastoralist communities to better cope with weather shocks.

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 or even before the 19th century (Johnson, 2011). 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 et al., 2005). After independence, the 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 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]. Alix-Garcia et al. (2013) provides a more specific description of the conflict events in Darfur and the consequences of displacement for land use in that region.

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 (Ali et al., 2005). 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 semi-mechanized 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 semi-mechanized agriculture increased from about 2 million feddans (i.e. about 0.84 million hectares) at the beginning of the 1970s to 14 million feddans (i.e. about 6 million hectares) by 2003.

In addition, pastoralist and agro-pastoralist 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% 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-km southward shift of the boundary between desert and semi-desert has occurred since the 1930s and the remaining semi-desert 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, 1999), especially for Sudan and pastoralist communities (Hendrickson et al., 1996; UNEP, 2007), 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

3.1. Methodology

We combine climatic and conflict data for each 0.5° 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:

$$Conflict_{i,t} = c + \alpha_i + \phi_t + \alpha_{c(i)} * t + \beta\, Weather_{i,t} + \eta X_{i,t} + \varepsilon_{i,t}$$

We estimate the relationship with a linear least squares specification because nonlinear models with fixed effects yield inconsistent slope estimates due to the incidental parameter problem. To be able to draw causal inferences, we introduce grid-cell fixed effects (α_i) and time fixed effects (ϕ_t) that reduce the importance of time-constant socioeconomic factors and of those factors that would affect equally over time the units of observations. The model is fully consistent with the criteria used for inclusion in the recent meta-analysis by Hsiang et al. (2013). Intuitively, we investigate how climate changes (compared with the pixel mean) affect the frequency of conflict events within each grid-cell (compared with the mean). In addition, we augment the specification by introducing a county-specific time trend [$\alpha_{c(i)}*t$] 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 related to climate. For instance, night-lights density is likely to capture changes in urbanization (Storeygard, 2014). On the one hand, weather shocks may strengthen urbanization (Barrios et al., 2006; Marchiori et al., 2012) and, on the other hand, urbanization has been found to be associated with insecurity in rural areas [e.g. in Darfur, Alix-Garcia et al. (2013)]. Thus, controlling for night-lights density may reduce the risk of omitted bias.[2] The time indicators are critical in controlling for spurious seasonal correlations in weather variations and conflicts and for time-varying factors common to all units of observations. Quarterly weather variables are also explicitly introduced in an alternative specification.

Embracing shorter time intervals and subnational units of observations may help to better capture the dynamics of the conflicts, but has the disadvantage to increase the risks of spatial and temporal dependency. That is particularly true when using weather data that are interpolated for missing weather stations (Aufhammer et al., 2013). Therefore, we adjust the standard errors for spatial dependency of an unknown form (Conley, 1999). We assume that such spatial dependency disappears beyond a cutoff point of 142 km, which is more than twice the distance between the centroids of any pair of neighboring pixels. Such distance is about four times the average distance between the lowest administrative levels in Sudan (i.e. county). Similar results are obtained when the cut-off point increases to the distance between four (284 km) or even eight

2 Another motivation to include a proxy for urbanization is the possible urban bias in reported conflict events (see Footnote 4). Nevertheless, we cannot exclude that night-lights density may also capture climate-induced changes in economic activities and therefore act as a 'bad control' (Angrist and Pischke, 2009) by introducing a potential downward bias. Given the use of our estimates for projection purposes, we adopt the most restrictive specification (including night-lights density), while showing the robustness of our results to the exclusion of night-lights density.

neighboring pixels (568 km) or when standard errors are clustered at the county level. Time dependency is allowed for up to four quarters. In the robustness analysis, we also explicitly control for serial and spatial correlation by implementing a simple dynamic model (using the Arellano–Bover/Blundell–Bond estimator) and a dynamic model with the spatial lags of the independent variables included. These spatial lags are obtained by multiplying the vector of observations by a normalized spatial matrix of order 1 (or order 2). The estimates of the latter model represent a credible lower bound for the effects of weather shocks on conflict.

The main dependent variable, $Conflict_{i,t}$, is given by the quarterly sum of violent conflict events by grid-cell (i). Riots are excluded unless directly tested in an alternative model. Our main variable of interest, $Weather_{i,t}$, seeks to capture weather deviations at the grid-cell (i) and quarter (t) levels. 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. The quarterly basis for the normal conditions is used to correct for seasonality effects. The variable is denoted 'Temp Anom'. A linear functional form is preferred. Alternatively, we also use as robustness check a series of variables more likely to capture extreme events. Finally, the results on potential mechanisms are obtained by introducing interaction terms between temperature anomalies and time-constant characteristics.

To take into account the uncertainly inherent in projections of future temperature changes (Burke et al., in press), we incorporate our estimated responses of conflict to climate with climate projections by 2030 for the corresponding Sub-Saharan sub-region (Sahel) from 20 climate models and three scenarios resulting from the World Climate Research Project Program's Coupled Model Inter-comparison Project phase 3.[3] To quantify regression 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 of both climate and regression uncertainty. 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.

3.2. Data

3.2.1. Conflict data

Data on conflict events come from the Armed Conflict Location and Event Dataset (ACLED; Raleigh et al., 2010). 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, 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. However, such reporting bias is not likely to be systematically correlated with our

3 We use the climate projections by 2030 for Sahel that come from the B1, A1B and A2 scenarios 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.

weather indicators and should not constitute a major problem for our identification strategy.[4] 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’ (Raleigh et al., 2012). The number of 2497 violent events represents the overwhelming majority of events (97%) reported in the ACLED dataset for North and South Sudan. Although our results do not depend on that restriction, we exclude nonviolent events (establishment of rebel headquarters, nonviolent rebel presence, changes of territorial control without violence, protests and riots) as they are not directly related to resource-based conflicts. In an alternative specification, we also use riots as an outcome variable to investigate the grievances channel in the climate–violence relationship. Figure 1 illustrates the location of violent events in Sudan.

3.2.2. Climate data

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° grid resolution (equivalent a 50-km grid resolution at the equator). However, the accuracy of these data has been questioned (Mitchell and Jones, 2005, 702), as 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 (Lobell, 2013). In spite of the critics, most studies on the climate–conflict nexus use this dataset because it has the advantage of providing precipitation and temperature data since 1901 and consequently, it 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, anomalies have been computed based on a long-term reference period starting in 1949. Figure 2 shows the quarterly variation over time.

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.[5] Beyond offering

4 Based on one randomly selected year for Algeria and Burundi, Eck (2012) points to the problems of miscoded locations and urban bias due to misuse of geo-precision codes. The fact that no spatial spillover is found in Table 1 is reinsuring with respect to the former problem. For the latter, our results are robust to excluding urban areas suggesting that the potential urban bias in the ACLED dataset is unlikely to drive our results. Urban centers are identified using the Global Rural-Urban Mapping Project (2000) data from the Center for International Earth Science Information Network (CIESIN, see http://sedac.ciesin.columbia.edu/data/collection/grump-v1).

5 These data were obtained from the NASA Langley Research Center POWER Project funded through the NASA Earth Science Directorate Applied Science Program, available at http://power.larc.nasa.gov/index.php.

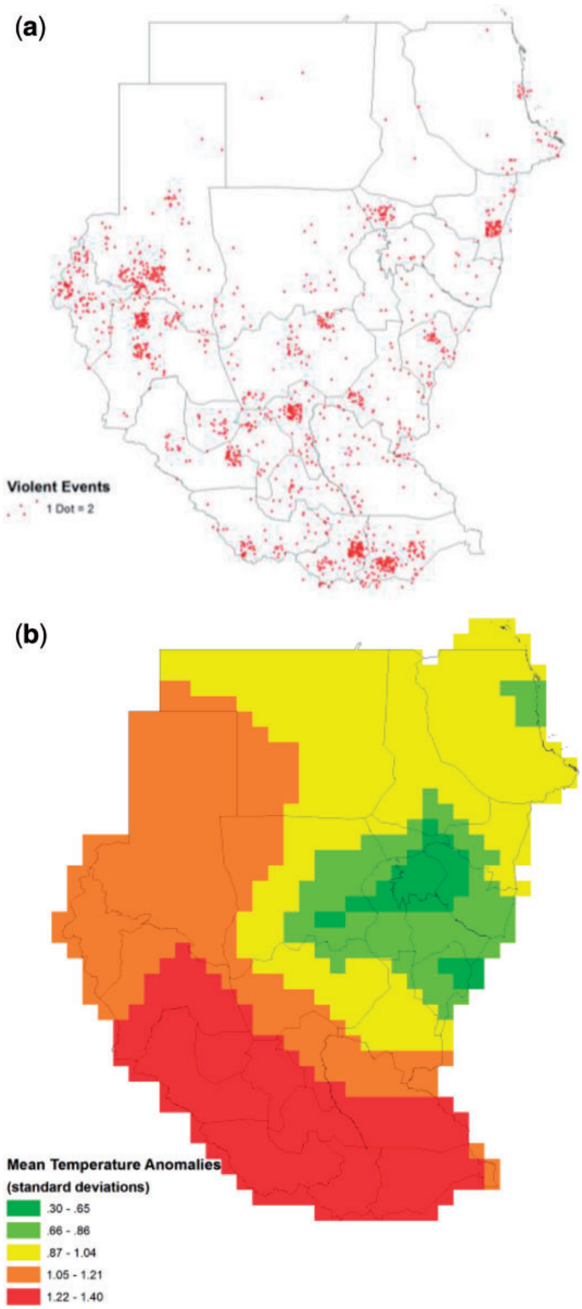

Figure 1. Location of violent events.

a robustness check on the quality of the East Anglia data, this dataset also offers us the possibility to compute the degree–days variables based on daily data. Moreover, it is 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 (MAUP) and, in particular, by the scale

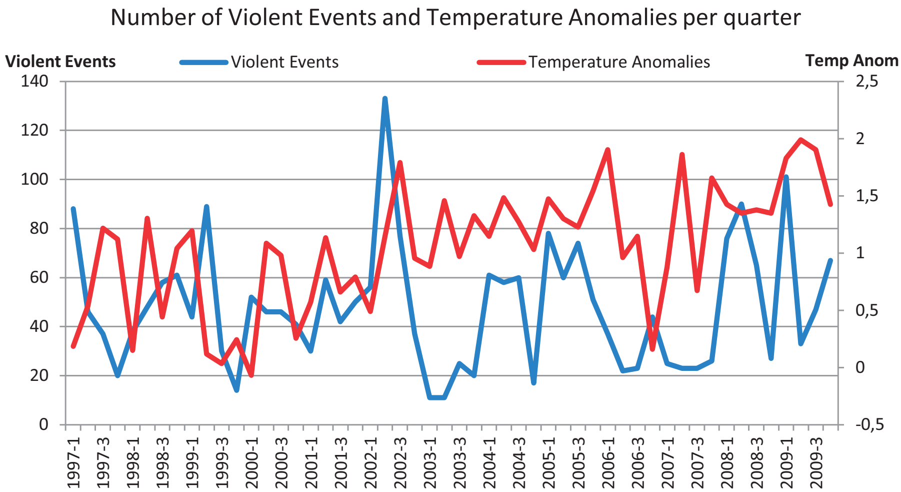

Figure 2. Mean quarterly temperature anomalies and violent conflicts.

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).

3.2.3. Other data

3.2.3.1. Data on night-lights density. Geo-referenced yearly information on night-lights density comes from the database introduced by Henderson et al. (2012).

3.2.3.2. Data on crop-type and on share of irrigated land. Crop-type data are drawn from the Spatial Production Allocation Model (2000, version 3, release 6) of the International Food Policy Research Institute (IFPRI). The IFPRI Spatial Production Allocation Model (You et al., 2009) generates highly disaggregated, crop-specific production data by a triangulation of 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 sq. km) 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). We focus on the two crops that are more important in the economy of Sudan.

3.2.3.3. Data on livestock density. Data on livestock density (head/square kilometers, 2005) are drawn from the Gridded Livestock of the World (Robinson et al., 2011).

3.2.3.4. Data on ethnic groups. Information on the location of ethnic groups is based on the University of Zurich's Geo-referencing of Ethnic Groups dataset[6] that relies on maps from the classical Soviet Atlas Narodov Mira. 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), agro-pastoral or mostly based on agriculture. Pastoral groups include nomad (Baggara/Shoa Arabs) and seminomad (Karamojo, Teso, Zagawa and Tubu) groups. Agro-pastoral 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.

3.2.3.5. Data on oil fields and oil prices. Data on the location of oil fields come from the PETRODATA (Lujala et al., 2007). As control, we also interact this location-specific information on the presence of oil fields with the oil prices drawn from the UNCTADstat Commodities Database of the United Nations Conference on Trade and Development.[7]

3.2.3.6. Data on alluvial soil. Information on alluvial soil is based on the Digital Soil Map of the World (Sanchez et al., 2009). We extracted the Sudan soil map and overlaid it with our 5-min grid. If the pixel is occupied by over 50% of alluvial soil, we identify this pixel as an alluvial soil pixel. This indicator proxies for land fertility, as alluvial soils are usually found near wadis and offer good pasture for livestock and land for cultivation.

3.2.3.7. Data on distance to rivers. Information about the distance to a major river or a lake comes from the Yale Geographically Based Economic Database version 4 (Nordhaus et al., 2006).[8] Specifically, a grid-cell is classified as 'Near to Major River' if its distance to a major river is lower than the 25th percentile.

3.3. Results

A change in temperature anomalies of 1 standard deviation is found to increase the frequency of violent conflict by 32% (Model 1 in Table 1). The corresponding result is also displayed in a nonparametric form in Supplementary Figures S1 and S2. Given the density of observations, the assumption of linearity constitutes a good approximation of a potentially more complex response function. Such assumption is also validated by finding little evidence for non-linearity using parametric indicators of extreme events, such as a quadratic term for temperature anomalies, temperature anomalies above certain thresholds or a distinction between moderate and extreme events using degree–days thresholds (Supplementary Table S2). Projecting the observed sequence of temperature anomaly realizations into our linear model, similar to Hsiang et al. (2011), we find that temperature variations may have affected about one quarter (26%) of violent events in Sudan. On the contrary, no significant impact is found for rainfall

6 Available at http://www.icr.ethz.ch/data/other/greg.
7 Available at http://unctadstat.unctad.org/ReportFolders/reportFolders.aspx?sCS_referer=&sCS_ChosenLang=en.
8 Available at http://gecon.yale.edu/data-and-documentation-g-econ-project.

Table 1. Results for the number of violent events

	(1) Baseline model	(2) Model with quarterly anomalies	(3) Model without time trends and night lights	(4) Dynamic model	(5) Dynamic model with spatial lags
	Violent events				
Violent Events (t−1)				0.213***	0.212***
				(0.037)	(0.037)
Temp Anom	0.022***		0.028***	0.024**	0.021**
	(0.007)		(0.008)	(0.012)	(0.011)
Temp Anom Q1		0.016			
		(0.011)			
Temp Anom Q2		0.04			
		(0.025)			
Temp Anom Q3		0.028**			
		(0.013)			
Temp Anom Q4		0.004			
		(0.008)			
Temp Anom × W					0.052
					(0.038)
Prec Anom	0.005	0.005	0.006	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Prec Anom × W					0.005
					0.042
Observations	46,436	46,436	46,436	45,543	45,543
Joint test of significance	3.86***	2.19**	6.78***	42.23***	53.92***
Part. Eff. Temp Anom	31.89	34.03 (Q3)	40.14	41.28	37.09

***$p<0.01$, **$p<0.05$; statistical significance of parameters based on t-test.
Notes: Joint tests of significance based on F-tests. All models include grid-cell fixed effects and time indicators, with robust standard errors corrected for time and spatial dependency (Conley, 1999). All models include time trends and night lights, with the exception of Model 3. Model 1 provides the baseline results. Model 2 replicates Model 1, but investigates quarter-specific temperature effects. Model 3 replicates Model 1 excluding night-lights density and time trends. Model 4 adapts Model 1 with a dynamic model, while Model 5 augments the dynamic model with spatially lagged independent variables. The partial effects of Models 4 and 5 include both direct and indirect effects. For Model 4 direct and indirect effects are 34.03 and 7.25, respectively, and for Model 5 the effects are 30.6 and 6.49, respectively.
Temp Anom, temperature anomalies; Prec Anom, precipitation anomalies; Part. Eff., partial effects (the estimated effect of 1σ increase in temperature anomalies, expressed as a percentage change in violent conflict relative to its mean).

anomalies using parametric (Model 1 in Table 1) or nonparametric (Supplementary Figure S2) methods.

The results seem to be driven by temperature variations during the third quarter of the year, when it matters the most for Sudanese agriculture (Model 2 of Table 1). When estimated without night-lights density and/or without time trends, the effects remain essentially unchanged (Model 3 of Table 1). The results are also robust to the exclusion of rainfall-related variables and to explicitly modeling time and spatial dependency (Models 4 and 5 of Table 1). The last finding indicates no evidence of spatial spillovers in our study.

3.4. Robustness

We investigate the robustness of our results (1) with other measures for temperature shocks; (2) to other proxies, functional forms and data sources for precipitation shocks and (3) to other modeling choices and levels of aggregation.[9]

First, we test the validity of our linearity assumption using different proxies to capture temperature extreme events (Supplementary Tables S2 and S3). In particular, we introduce the quadratic term of the weather anomalies. In addition, we try to capture extreme events that could lead to yield losses by defining an indicator for positive and negative deviations above 1 (or 2) standard deviation(s) and by introducing a dummy equal to 1 for deviations <15% (or 10 or 5) and above 85% (or 90 or 95) of the grid-cell-specific distribution. We also exploit daily climate data to compute degree–days transformations (Schlenker et al., 2006). Based on agronomist literature specifically for SSA (Schlenker and Lobell, 2010), we define a lower threshold at 10°C and a higher threshold at 30°C. The first variable provides the sum of degree–days above the lower threshold of 10°C and below the upper threshold of 30°C. The second variable sums the number of degree–days above the upper threshold of 30°C. The two variables are considered together to capture the nonlinearity of temperature shocks (Schlenker and Roberts, 2009) and are expressed in degree–days per quarter and then transformed into anomalies. These variables are interacted with our state-level indicator of the growing season (De-Pauw and Wu, 2012) and a quadratic term is introduced to capture nonlinear effects (Schlenker et al., 2006). Last, 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.[10] Compared with 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. None of these modifications led us to revise our assumption of linearity as a good approximation of the complex response function of violent conflict to temperature shocks.

Second, we test whether the fact that variations in precipitation have little effect on violence is related to the lack of accuracy of the adopted proxies for precipitation shocks. Precipitation shocks may be better captured by variations in SPEI (Lobell, 2013). Our results suggest that it is not the case for Sudan, without altering the impact of temperature shocks (Supplementary Table S4). We also exclude the possibility that the lack of impact of precipitation shocks may be driven by the absence of a time-lagging effect, because including the time lags does not alter the coefficients of the temperature indicators and changes only slightly the partial effects (Supplementary Table S4). Interestingly, these results tend to reject the hypothesis of time displacement of violence found in the related literature on crime (Jacob et al., 2007). Higher temperature does not seem to simply displace violence to the following quarters.[11]

9 The regression results of all alternative specifications are shown in the Supplementary Appendix.

10 The SPEI comes from SPEIbase, version 2.0, a global dataset with a spatial resolution of 0.5° latitude/longitude and temporal coverage between 1901 and 2009 (Vicente-Serrano et al., 2010). Available at: http://sac.csic.es/spei/spei_index.html.

11 Our results (Table 1, Model 5) have also been shown to be immune to another source of displacement: the geographical displacement of violence, as shown in related literature (Johnson et al., 2012; Maystadt et al., 2014).

Overall, these results clearly point to the role of temperature shocks in explaining variations in violence in Sudan. Still, the explanatory dominance of temperature shocks in contrast to rainfall shocks might be due to larger errors in measuring precipitation. 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 (Supplementary Table S4). This is a first indication that such measurement errors do not drive 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 (Supplementary Table S4). Finally, despite the advantage of its inclusion to reduce the risk of omitted bias, night-lights density may act as a bad control. However, Supplementary Table S5 indicates that our results are almost identical when that control variable is excluded.

Third, we acknowledge that the use of fixed effects at a disaggregated level results in an identification relying on slight margins and potentially amplifying measurement errors (Fisher et al., 2012). Thus, we show that our results are confirmed even when we use random-effects estimation with fixed effects at the state level (Supplementary Table S6). Although introducing potential selection bias and changing the external validity of the results, we implement a model with state fixed effects excluding the cells that never experienced violent conflict. Even in this case, our results remain unaltered (Supplementary Table S6). We also show that our results are robust to the exclusion of urban pixels, suggesting that our results are not driven by an urban bias in reported conflict events (Supplementary Table S6). Furthermore, we confirm the validity of our findings using alternative time aggregations. At the monthly level, our findings are equally confirmed (Supplementary Table S6), whereas at the yearly level our results maintain the same sign, but with a lower significance level at only 80% (Supplementary Table S6). This lack of efficiency is likely due to the reduction of variations in weather deviations and to the reduction of analytical sample size.

4. Discussion

The increase in conflict of about 32% stands in the upper part of the distribution in the meta-analysis by Hsiang et al. (2013). However, the magnitude of this response to temperature shocks is still in the range found in comparable studies (Figure 3)—i.e. a replication of a regional study on surrounding countries (O'Loughlin et al., 2012; replicated by Hsiang et al., 2013), a study on Somalia (Maystadt and Ecker, 2014) and another replication on Kenya (Theisen 2012, replicated by Hsiang et al., 2013). Plotting the predicted violent conflicts resulting from our main model (Model 1 in Table 1) reveals four major warfare episodes (Johnson, 2011) where observed conflicts seem to be largely explained by our model (Figure 4). This finding is a further indication of the importance of temperature shocks as a catalyst for violence. Despite the lack of information on conflict intensity, it also suggests we are not only capturing low-intensity conflict events but also major episodes of the Sudanese conflicts. The response of violent conflicts to temperature shocks is also expected to magnify in the future. Including both climate and regression uncertainties (Burke et al., in press), our model predicts more frequent violence as a result of projected temperature anomalies, with a

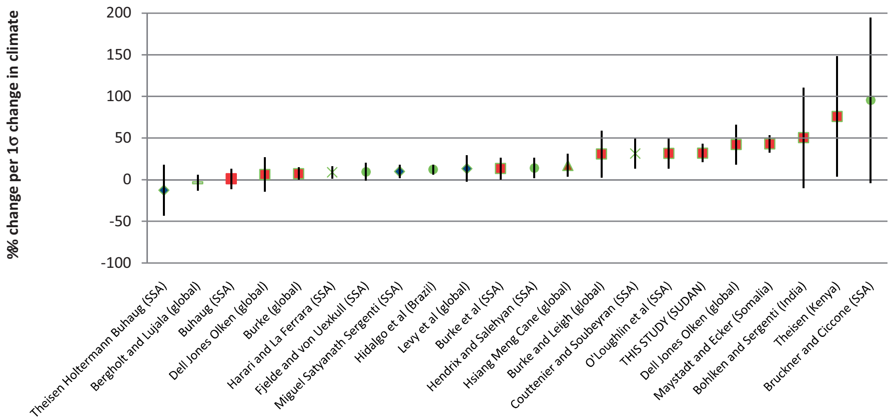

Figure 3. Comparison of the response of intergroup conflict to temperature variations in Sudan with other case studies (Hsiang et al., 2013). With the exception of our study, the chart uses replication data (Hsiang et al., 2013). Each marker represents the estimated effect of 1σ increase in the climatic variable, expressed as a percentage change in the outcome variable relative to its mean. Whiskers represent the 95% confidence interval on this point estimate. Colors indicate the forcing climate variable. A coefficient is positive if conflict increases with higher temperature (square), greater rainfall loss (diamond), greater rainfall deviation from normal (circle), more floods and storms (bar), more El-Niño-like conditions (triangle) or more drought (asterisk) as captured by different drought indices. More details on the individual studies are given in the original manuscript and its supplementary materials (Hsiang et al., 2013).

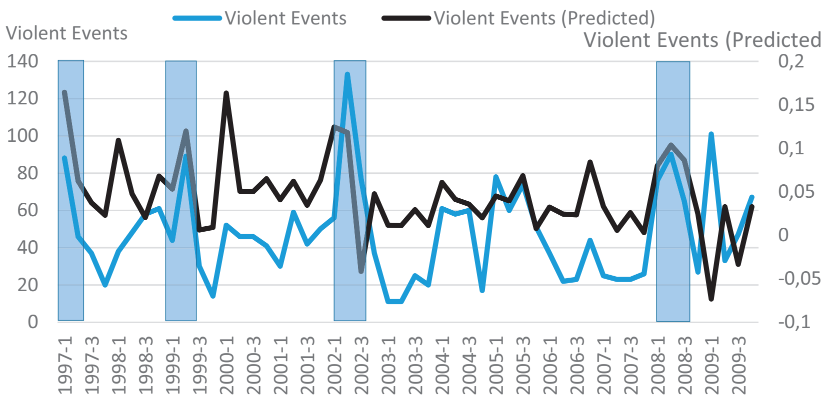

Figure 4. Predicted (black) and observed (grey) violent conflicts. According to detailed description of the conflicts in North and South Sudan (Johnson, 2011), four major warfare episodes where observed conflicts seem to be largely explained by our model are highlighted in the shading areas. The shading area in early 1997 corresponds to operations conducted by the Ethiopian army in collaboration with SPLA and the operation launched in Central Equatoria; in early 1999, 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, 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, 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).

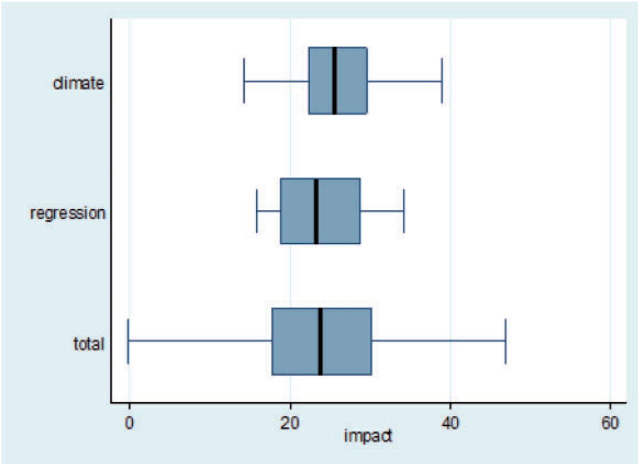

Figure 5. Projected percentage point change in the frequency of violent conflict events by 2030 due to projected changes in temperature anomalies for Sudan. Boxplot (1) represents projections including uncertainty only in violent conflict response to temperature. Boxplot (2) represents projections including uncertainty only in temperature projections. Boxplot (3) represents projections including uncertainty in both climate model projections and in violent conflict response to temperature. All boxplots show the range of projected changes based on the 20 climate models and three scenarios for temperature changes between 2030 and 1980–1999. The dark vertical line represents the median prediction, the box shows the 5th and 95th percentiles of projections and the other vertical lines indicate the extreme projections. Taking the ratio of the difference between the 95th and 5th percentiles for the climate-uncertainty-only projections and the regression-uncertainty-only projections, climate uncertainty is about 1.46 times larger than regression uncertainty.

24.96% median projected increase by 2030 (Figure 5). Such additional increase would vary in a range between 24% and 31% for lower-bound (from the most structured Model 5 of Table 1) and upper-bound estimates (from the most reduced-form Model 3 of Table 1). Similar to Burke et al. (in press), climate uncertainty is larger than regression uncertainty in predicting changes in violence by 2030.

Our disaggregated analysis paves the way to explore how local climatic variations affect local violence within a deeper understanding of the socio-economic context. It also explores how some characteristics magnify or reduce the strength of such relationship and sheds light on the possible mechanisms. The evidence here is only suggestive as we cannot give causal interpretation to these interactions terms, plausibly endogenous to conflict. First, the most obvious channel to be hypothesized is the detrimental impact of weather shocks on agricultural income (Schlenker and Lobell, 2010) and the resulting change in the opportunity cost to participate in violence (Miguel et al., 2004). The detrimental impact of temperature shocks on crops does not seem to be a key driver of our results. We observe that variations in temperature are particularly conflictive during the growing period (Model 2 of Table 1), but there is no evidence that the detrimental impact on crops is the main channel. On the contrary, in Sudan, the presence of temperature-sensitive crops (Schlenker and Lobell, 2010; sorghum and millet, Models 1 and 2 of Table 2) is not a significant exacerbating factor.

Second, conflict in Sudan has often been described as a struggle over natural resources. The impact of weather shocks on natural resources has also been associated

Table 2. Channels through heterogeneous impacts

	(1) Opportunity cost	(2)	(3) Looting	(4) Competition over natural resources	(5)	(6) Grievances
	Main crop is sorghum	Main crop is millet	Oil fields	Livestock density (TLU)	Pastoral and agro-pastoral groups	
	Violent events					Riots
Temp Anom	0.03***	0.029***	0.021**	0.022***	0.02***	−0.0003
	(0.011)	(0.011)	(0.009)	(0.008)	(0.007)	(0.0004)
Inter Term	−0.007	−0.003	−0.023**	0.007***	0.022***	
	(0.006)	(0.002)	(0.011)	(0.003)	(0.008)	
Prec Anom	0.01	0.01	0.004	0.005	0.004	−0.001**
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.0003)
Observations	30,212	30,212	39,292	46,436	44,668	46,436
Joint test of significance	2.43**	2.43**	3.2***	4.8***	3.17**	1.43
Part. Eff. Temp Anom	42.28	41.85	30.46	31.89	28.61	−10.9
Part. Eff. Inter Term	−10.48	−4.31	−32.93	9.09	32.43	−10.48

***$p < 0.01$, **$p < 0.05$; statistical significance of parameters based on t-test.
Notes: Joint tests of significance based on F-tests. All models include grid-cell fixed effects, time indicators, time trends and night lights, with robust standard errors corrected for time and spatial dependency (Conley, 1999). The partial effects of the interaction terms ‘Main crop is sorghum’, ‘Main crop is millet’ and ‘Pastoral and agro-pastoral groups’ are calculated for the indicator equal to 1. The values of the interaction terms ‘Oil fields’ and ‘Livestock density’ are calculated for the median value. When all the interaction terms are included in the same regression, they all maintain their level of significance.
Temp Anom, temperature anomalies; Inter Term, interaction term; Prec Anom, precipitation anomalies; Part. Eff., partial effects (the estimated effect of 1σ increase in temperature anomalies, expressed as a percentage change in violent conflict relative to its mean)

with changing incentives and financial means for the warring parties to fight (Le Billon, 2001; Ross, 2004). A distinction is usually made between point and diffuse resources. The former definition is described as resources extracted from a narrow geographic or economic zone, such as oil and minerals, whereas the latter includes resources (i.e. agricultural products) spread throughout the economy (Wick and Bulte, 2006). Point resources are more susceptible to capture and violence. There is no obvious direct impact of weather shocks on the exploitation of point resources. At best, the presence of point resources may provide an alternative source of income or additional state capacity to reduce the risk of violence. We indeed find a mitigating factor in oil-dependent areas (Model 3 of Table 2). On the contrary, competition over diffuse resources is more likely to be affected by the increased scarcity induced by weather shocks.

In particular, competition between herders and farmers has been hypothesized as a major mechanism behind violence in Sudan (Hendrickson et al., 1996; Keen and Lee, 2007). Such mechanism is likely to be more prominent in areas with higher presence of pastoralist and agro-pastoralist communities. For long, herders have adopted coping strategies to deal with frequent weather shocks, but there is a general consensus that such coping strategies are breaking down due to a mix of factors, such as the limited mobility due to population growth, the lack of livelihood diversification, the fragmentation of grazing lands and fiercer water scarcity. In these circumstances, weather shocks exacerbate fodder and water shortages, leading not only to higher mortality but also to less-marketable animals.[12] Such increased vulnerability has often led pastoralist people to settle in environments unsuitable for such a livelihood, pushing them into a severe poverty trap when a major shock strikes (Lybbert et al., 2004; Thornton et al., 2009). The poverty trap is then associated with opportunist behaviors, such as cattle raiding or participation into armed groups (Gray et al. 2003; UNEP, 2007; Maystadt and Ecker, 2014). In accordance with the importance of livestock for livelihoods in Sudan, livestock densities (in tropical units) or the presence of pastoral and agro-pastoral ethnic groups constitute significant exacerbating factors (Models 4 and 5 of Table 2). The fact that the impact is stronger during the growing periods (Model 2 of Table 1) does not contradict the vulnerability of livestock-dependent areas as the seasonal calving usually coincides with the rainy seasons (Barrett et al., 2003).

An alternative mechanism is the increased competition resulting from climate-induced migration and rapid urbanization (Hsiang et al., 2013). This channel may be particularly relevant in our study, given the high mobility of pastoralist people in Sudan and the fine level of analysis we adopt. Such hypothesis is however not supported by the lack of spatial spillovers (Model 5 in Table 1).

A last set of possible channels relates to grievances. Weather shocks may affect grievances through food prices and resulting food riots due to a government's perceived inability to keep food affordable (Hsiang et al., 2013). In our study, no evidence could be found for the grievance channel more likely to result into riots (Model 6 in Table 2). Finally, other possible mechanisms (Hsiang et al., 2013), such as the logistics of human conflicts (i.e. road quality) or psychological channels, cannot be tested due to data limits.

The above results suggest that the relationship between temperature anomalies and intergroup violence is particularly strong in pastoralist and agro-pastoralist areas in North and South Sudan. Understanding why these areas are more prone to climate-induced violence has implications that go far beyond the Sudanese borders. The high vulnerability of these areas could potentially explain the presence of several countries from the Greater Horn of Africa (e.g. Kenya, Somalia and Sudan) at the upper part of the results in the literature (Figure 3).[13] Recent evidence suggests that coping strategies traditionally adopted in arid and semiarid regions are progressively breaking down due to different mutually reinforcing factors. To further explore these sources of vulnerabilities, we introduce additional interactions likely to capture appropriate resources over which farmers and herders compete in Sudan, that is, the density of

12 Lean animals reach lower prices than well-fatten ones, and only the well-fatten animals can be sold for export, whereas the local demand for livestock and meat might even collapse during times of widespread food shortage. Herding the animals to the market over long distances during drought also reduces weights further. possibly below the minimum acceptable price (and may even kill some), while transportation of herds by truck is often unaffordable (Maystadt and Ecker, 2014).

13 Among the most conflictive countries in SSA, it is worth to note that a majority has a large livestock population (Supplementary Table S1). Although the literature has given a large explanatory power to the presence of mineral resources (Ross, 2004), in particular in countries like Angola (Le Billon, 2001), the Democratic Republic of Congo (Reno, 2008; Maystadt et al., 2014), Liberia (Reno, 2008) or Sierra Leone (Reno, 2008; Bellows and Miguel, 2009), the pastoralist dimension has largely been overlooked in global or regional studies. Incorporating that dimension into an Africa-wide study like the one of Harari and La Ferrara (2012) is certainly a promising path for further research.

Table 3. Water scarcity as a source of resource competition in Arid and Semi-Arid Lowland Areas

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Non-pastoralist areas				Pastoralist areas			
	Violent events				Violent events			
Temp Anom	0.012** (0.005)	0.012** (0.005)	0.012** (0.005)	0.084*** (0.021)	0.072** (0.036)	0.071** (0.036)	0.06** (0.028)	0.177 (0.129)
Temp Anom × Alluvial Soil		−0.019* (0.01)				−0.023* (0.013)		
Temp Anom × Irrigated Area			−0.001 (0.001)				−0.333 (0.334)	
Temp Anom × Near Major River				−0.031** (0.012)				−0.222*** (0.085)
Prec Anom	−0.002 (0.003)	−0.002 (0.003)	−0.002 (0.003)	0.007 (0.014)	0.05* (0.029)	0.05* (0.029)	0.048* (0.028)	0.02 (0.06)
Observations	39,052	39,052	39,052	11,284	5,616	5,616	5,616	1,196
Joint test of significance	3.86***	3.93***	3.09**	6.35***	1.96	1.95*	1.87	2.56**
Part. Eff. Temp. Anom.	21.74	21.56	21.91	39.17	38.52	38.04	32.36	25.31
Part. Eff. Inter Term		−30.25	−2.15	−14.45		−12.59	0	−34.87

***$p<0.01$, **$p<0.05$; statistical significance of parameters based on t-test.
Notes: Joint tests of significance based on F-tests. All models include grid-cell fixed effects, time indicators, time trends and night lights, with robust standard errors corrected for time and spatial dependency (Conley, 1999). Temp Anom, temperature anomalies; Prec Anom, precipitation anomalies; Inter Term, interaction term; Part. Eff., partial effects (the estimated effect of 1σ increase in temperature anomalies, expressed as a percentage change in violent conflict relative to its mean)

vegetation, access to alluvial soils and distance to water surface (Olsson and Siba, 2013). We then assess how much these factors affect the response functions in pastoralist versus non-pastoralist areas.

Mitigating roles are found for water availability, either through the proximity to a major river or the presence of alluvial soil (Table 3). 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 conflicts about property rights and competition between pastoralists and farmers. The presence of irrigation systems seems not to matter. This may reflect either the (endogenous) location of irrigation systems in less resilient areas or the relatively limited potential of new investments in pastoralist areas (Headey et al., 2014).[14] Overall, our results on the security consequences of the

14 Given our definition of pastoralist areas, the fact there is still a significant (even if lower) impact in non-pastoralist regions is difficult to interpret. It may be the case that weather shocks affect violence through their impact on other temperature-sensitive crops other than the ones presented in Table 2, but also that there is sensitive livestock in non-pastoralist areas as well—because the distinction is based on the main livelihood of the ethnic groups (Section 3.2).

vulnerability of these areas make action even more pressing. The existing literature suggests not only to improve the resilience of the livestock sector through veterinary services, access to credit, provision of emergency feed and better access to water, but also to support income diversification, in particular through education investments (Headey et al., 2014).

5. Conclusions

There has been a long-standing dispute and a growing interest over the possible links between climate and conflict. Many studies are increasingly converging in identifying temperature shocks as a major driver of violence, but quantifying the climatic impact and underlying mechanisms still remains a challenge. We exploit highly disaggregated data to confirm the strong relationship between temperature and conflicts in Sudan. A change in temperature anomalies of 1 standard deviation is found to increase the frequency of violent conflict by about 32%. Between 1997 and 2009, temperature variations may have affected about one quarter (26%) of violent events in Sudan. Vulnerability to both climate and violence depends on various physical and socioeconomic factors that usually make marginalized areas more likely to be affected by substantial negative impacts. In Sudan, our analysis points to the vulnerability of pastoralist areas to climate. The strong competition over natural resources, in particular water in Sudan, seems to exacerbate the risk of inter-personal violence in these areas.

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.

Supplementary material

Supplementary data for this artcle are available at *Journal of Economic Geography* online.

Acknowledgements

J.-F.M. is grateful to the center for Institutions and Economic Performance (LICOS), KU Leuven and the International Food Policy Research Institute (IFPRI) for their support during his post-doctoral position, during which that research was initiated. We would like to thank Solomon Hsiang, Edward Miguel and participants at various conferences. We are grateful to Marshall Burke and to David Lister for sharing their data. Jose Funes provided valuable research assistance.

Funding

IFAD under the project Decreasing Vulnerability to Conflict in the Middle East and North Africa through Rural Development and from the CGIAR Research Program on Policies, Institutions, and Markets (PIM); the European Union Seventh Framework Programme (FP7/ 2007-2013) [under grant agreement no. 263905 (TAMNEAC)]; the KU Leuven research fund (Methusalem) and National Basic Research Program of China (973 Program no.2010CB951502).

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