THE
ECONOMIC
JOURNAL

The Economic Journal, **124** (*March*), 201–244. Doi: 10.1111/ecoj.12042 © 2013 The Author(s). The Economic Journal © 2013 Royal Economic Society. Published by John Wiley & Sons, 9600 Garsington Road, Oxford OX4 2DQ, UK and 350 Main Street, Malden, MA 02148, USA.

DROUGHT AND CIVIL WAR IN SUB-SAHARAN AFRICA*

Mathieu Couttenier and Raphael Soubeyran

We explore the relationship between drought and civil war. We show that the link between rainfall, temperature and civil war found in the literature may be driven by aggregate shocks (such as global climate) that were not accounted for. A standard differences-in-differences specification relying only on within country variation reveals a much weaker and insignificant link between weather variables and civil war. To increase statistical power, we propose a country-specific measure of drought that describes social exposure to water stress in a more efficient way than rainfall and temperature. We continue to find a weak positive link between drought and civil war.

According to the Intergovernmental Panel on Climate Change (2007), changes in the global climate will generate an increase in the number of abnormal climatic events across the world, such as droughts and floods. These climatic anomalies might have disastrous consequences for countries with a scarce fresh water supply and economies that depend on the local agriculture. Given that agricultural activities account for between 60% and 100% of the income of the poorest African households (Davis *et al.*, 2007) and that these households often have no access to safe water,[1] sub-Saharan Africa is one of the regions most adversely affected by climate change in the world. One of the possible consequences of climate change is an increase in conflicts. For instance, there is now a consensus that drought has been a contributory cause of the civil war in Darfur because it increased disputes over arable land and water, even if the conflict also had an ethnic component since it opposed Arabs and Black Africans (Faris, 2009).

The literature mainly focuses on the link between country-specific measures of climate (rainfall and temperature) and civil war (in sub-Saharan Africa).[2] The usual specification in the literature (Miguel *et al.*, 2004; Burke *et al.*, 2009) includes country fixed effects and country-specific time trends only; see also Buhaug (2010) and Burke *et al.* (2010*a, b*) for a debate on the inclusion of trends. A standard differences-in-differences specification relying only on within country variation reveals a much weaker and insignificant link between weather variables (rainfall and temperature) and civil war. The fact that these (within country) results do not replicate the results

* Corresponding author: Raphael Soubeyran, INRA, UMR1135 LAMETA, F-34000, Montpellier, France. Email: soubeyra@supagro.inra.fr.

The authors wish to particularly thank the Editor, Jörn-Steffen Pischke, for his invaluable comments and suggestions. The authors are also much indebted to the three anonymous referees for their very constructive and helpful comments and suggestions. We also benefited from invaluable comments by Nicolas Berman, Paola Conconi, Matthieu Crozet, James Fearon, David Laitin, Thierry Mayer, Edward Miguel, Nicolas Quérou, Elodie Rouvière, Julie Subervie, Mathias Thoenig, Thierry Verdier and participants in seminars at Stanford, Lausanne, DIAL and Montpellier. We thank Annie Hoffstetter for technical assistance. Mathieu Couttenier would like to thank Sciences Po. Paris and the Stanford Political Science Department for their welcome. He also acknowledges financial support from the European Research Council (ERC Starting Grant GRIEVANCES-313327). Raphael Soubeyran extends his thanks for financial support to the 'RISECO' ANR project, ANR-08-JCJC-0074-01.

[1] Many African people have no secure access to fresh water. Only 22% of Ethiopians, 29% of Somalis and 42% of Chadians have a secure access to fresh water.

[2] See Hsiang *et al.* (2011) for an analysis of the link between global climate change and an annual planet scale measure of conflict.

without time dummies underscores the worry that the aggregate relationship may be spurious. We then include country and year fixed effects to estimate the effect of our climate measure on the risk of civil war.[3]

We claim that drought cannot be represented as a simple (linear) function of rainfall and temperature measures. We use the most prominent meteorological index of drought – the Palmer Drought Severity Index (PDSI). This measure of drought is grounded on the theoretical model developed in hydrology by Palmer (1965). The PDSI is a function of the duration and the magnitude of abnormal moisture deficiency. It captures meteorological conditions on the ground. It also captures important effects that were missing in previous studies: non-linearities – the effect of contemporaneous rainfall and temperature depends on the climate history, interaction effects – for example, low rainfall is more important in hot years, and threshold effects due to the limited capacity of the soil – for example, rainfall water will run off when the soil layers are full.

We operationalise the idea that the impact of drought should be considered by exploiting a large data set of PDSI values. While most previous studies in the literature focused on the 1980s and the 1990s, our database covers a longer time period (1945–2005). We show that the relationship between drought and civil war in sub-Saharan Africa is statistically weak. We also show that usual rainfall and temperature linear models should not be preferred to the PDSI to explain civil war. We finally explore potential channels for the (weak) link between drought and civil war. We find that countries which are relatively more ethnically fractionalised and are hit by a drought are more prone to conflict than countries with less ethnic fractionalisation. In addition, countries with a relatively low level of democracy which are hit by a drought are more prone to civil war than countries with a relatively high level of democracy.

Our article is not the first one to argue that there may be climate measures which describe social exposure to water stress in a more efficient way than rainfall and temperature linear models. Ciccone (2011) and Miguel and Satyanath (2011) discuss the appropriate way to model climate. However, their discussion focuses on the use of lagged climate variables instead of climate variations but does not discuss the hydrological relevance of the climate index. Harari and La Ferrara (2012) exploit the within year and within country variation using fine-grained conflicts and drought data over the 1997–2011 period. They use the standardised precipitation–evapotranspiration index (SPEI).[4] Both the SPEI and the PDSI have merits: the SPEI has the practical advantage to be simple and available at a more dis-aggregated level than the PDSI. The PDSI has the advantage to be grounded on a theoretical model (Dai, 2011*a*).[5] Levy *et al.* (2005) use the Weighted Anomaly Standardised Precipitation Index

[3] Our estimates also take both spatial correlation and serial correlation into account (Conley, 1999, 2008). See Jensen and Gleditsch (2009) for a discussion regarding spatial correlation in Miguel *et al.*'s (2004) analysis.

[4] This index was first developed in Vicente-Serrano *et al.* (2010*a*).

[5] Vicente-Serrano *et al.* (2010*b*) argue that the SPEI has the advantage over the PDSI in being able to depict droughts on time scales shorter than 12 months. However, this criticism is not a problem because the monthly values used to compute the PDSI can be used to depict such droughts (Dai, 2011*a*). Dai (2011*a*) provides a criticism of the SPEI. He argues that it is the actual evapotranspiration and not the potential evapotranspiration that affects the water balance. The problem is that the SPEI uses the latter.

(WASP),[6] which is a measure of precipitation deviation from normal. The WASP index is based on precipitation only, while the PDSI is based on precipitation, temperature, soil horizon thickness and texture, vegetation and texture-based estimates of the available soil moisture. Using a quite different perspective, Hsiang *et al.* (2011) focus on global climate variations (El Niño Southern Oscillation) rather than on the idiosyncratic variations of rainfall and temperature and they analyse the link between global climate and a global measure of the risk of civil conflict.

The remainder of the article is structured as follows. Section 1 describes the PDSI data and the data on civil wars. Our estimation framework is introduced in Section 2. Our results regarding the effect of drought on the incidence of civil war are provided in Section 3. Section 4 concludes.

1. Data and Measurement

1.1. *Palmer Drought Severity Index*

1.1.1. *Data description*

Our measure of drought is the (theoretically grounded) PDSI developed in meteorology by Palmer (1965). It is the most prominent meteorological drought index. This drought severity index is a function of the duration and the magnitude of abnormal moisture deficiency. The PDSI captures meteorological conditions on the ground and combines contemporaneous and lagged values of temperature and rainfall data in a non-linear model (with thresholds). First, the index captures important interactions that were missing in previous studies. For instance, low rainfall is more important in hot months because evapotranspiration is significant and there is in turn less moisture recharge (or more loss if the layers are full). Indeed, high temperatures can prevent abundant rainfall from recharging soil moisture. Second, the index depends both on the limited capacity of moisture accumulation of the soil and on the local characteristics of the soil. As a consequence, abundant precipitation that reaches the accumulation capacity of the soil will run off (and will not be captured by the ground). Third, the PDSI takes the heterogeneity in local conditions and the differences in local climate history into account. In other words, the PDSI values for two different countries with the same current temperature and rainfall levels may differ because of their differences in local conditions (e.g. the capacity of the soil that depends on the location). PDSI values may also vary within a given country even if temperature and rainfall levels are the same (at two different dates), because the climate history is different from one location to another.

The PDSI measures how moisture levels deviate from a climatological normal. It is based on a supply and demand model of soil moisture and is calculated on precipitation and temperature data, as well as on the local available water content (AWC) of the soil. The available soil moisture at the beginning of the period is used as a measure of past weather conditions. The abnormal aspect of the weather is also important: deficiency occurs when the moisture demand exceeds the moisture supply at some point in time, and an abnormal moisture deficiency occurs when the excess of

[6] This index was first developed in Lyon and Barnston (2005).

demand is large (i.e. compared to the average). All the basic terms in the water balance equation can be determined, including the evapotranspiration, soil recharge, run-off and moisture loss from the surface layer.

The cumulative measure of the PDSI for month m in year t at location l is obtained with a linear combination of the value of the previous month and a monthly contribution:[7]

$$Palmer_{ltm} = pPalmer_{ltm-1} + qZ_{itm}, \tag{1}$$

where p and q are calibrating parameters and Z_{itm} is the contribution of month m with $m \in (2,\ldots,12)$. The monthly contribution is calculated according to the supply and demand model of soil moisture.[8] Since the PDSI is cumulative and takes interactions between rainfall and temperature into account, we do not need to include lagged values and/or interaction terms in our specifications.

We use the monthly PDSI grid cell data from Dai *et al.* (2004). This database covers the world time series from 1870 to 2005; it is geolocalised and available at a resolution of $2.5° \times 2.5°$ (about 250 km at the Equator). Figure B1 in Appendix B provides maps of the raw PDSI data averaged over five periods of time: maps (*a*) to (*e*) provides the grid cell data averaged over successive periods of time between 1945 and 2005; darkest shaded areas are the driest regions and lightest shaded areas are the wettest regions of sub-Saharan Africa.

According to Palmer's classification,[9] $PDSI = 0$ means a normal climate, $PDSI >$ $+0.04$ means an extremely dry climate and $PDSI < -0.04$ means an extremely wet climate. Palmer (1965, Table 11) also defined nine intermediate classes: severe drought (0.03 to 0.04); moderate drought (0.02 to 0.03); mild drought (0.01 to 0.02); incipient drought (0.005 to −0.01); near normal (0.005 to −0.005); incipient wet spell (−0.005 to −0.01); slightly wet (−0.01 to −0.02); moderately wet (−0.02 to −0.03); and very wet (−0.03 to −0.04).

We carry out a country-year analysis of the effect of drought on the risk of civil conflict; in a given country-year, drought is measured as an average of the monthly grid cell PDSI values. At the country level, the data contain observations for countries larger than one 2.5×2.5 grid cell degree.[10]

Formally, the PDSI for country i in year t is:

$$PDSI_{it} = \frac{1}{L_i} \sum_{l \text{ belongs to } i} \left(\frac{1}{12} \sum_{m=1,\ldots,12} Palmer_{ltm} \right), \tag{2}$$

where L_i is the number of cells in country i.

[7] The Palmer model is calibrated so that $p = 0.897$ and $q = 1/3$ (Dai *et al.*, 2004).
[8] See Appendix C for an exposition of the PDSI hydrological model.
[9] After rescaling. In practice, most of the time, PDSI values are between −10 and +10 (some values may be outside this interval, because the index is not bounded theoretically), with negative values referring to dry months and positive values to wet months. For the ease of exposition, we have chosen to revert the initial scale so that the greater the value of the index, the drier the climate. We also divide the values by 100 in order to avoid reporting 10^{-X} coefficients in the Tables.
[10] The list of countries included in our analysis is provided in Table 1. The countries for which we have no PDSI data are: Gambia, Rwanda, Burundi, Djibouti, Cape Verde, Sao Tomé and Príncipe, Comoros and Mauritius. The largest country is Burundi – 27,000 km^2 – and its area is roughly a square measuring 160 km on each side, which is smaller than one grid cell that measures 250 km on each side.

Table 1

Descriptive Statistics of PDSI

Country	Mean PDSI	SD PDSI	Maximum PDSI	Minimum PDSI	No. stations
Angola	0.0071984	0.0107785	0.0274556	−0.019194	216
Benin	0.0411368	0.03853	0.1165667	−0.036375	12
Botswana	0.0130075	0.0248074	0.0460139	−0.0636972	108
Burkina Faso	0.0345842	0.0264598	0.0965361	−0.0195167	36
Cameroon	0.0205576	0.0254717	0.102646	−0.019745	60
Central African Republic	0.0164558	0.0200309	0.0598714	−0.0265631	84
Chad	0.0147019	0.014445	0.0437842	−0.0192711	228
Congo	0.0029642	0.0181206	0.0462563	−0.0263271	48
Democratic Republic of Congo	−0.0017612	0.0086887	0.0165686	−0.0321497	360
Equatorial Guinea	0.0285614	0.0219395	0.0995095	−0.0004417	24
Eritrea	0.0019821	0.0168117	0.0204083	−0.0247667	24
Ethiopia	0.0054814	0.0146646	0.0299699	−0.0368096	156
Gabon	0.0104718	0.0267633	0.0933485	−0.0452917	36
Ghana	0.0253675	0.0333554	0.0830083	−0.0424792	24
Guinea Bissau	0.0277526	0.0261821	0.0700375	−0.0177313	48
Ivory Coast	0.0286724	0.0271378	0.0729271	−0.0381312	48
Kenya	0.0021568	0.0196988	0.0297635	−0.0581708	96
Lesotho	0.011265	0.021537	0.0538083	−0.0356417	12
Liberia	0.0189005	0.0248124	0.0721667	−0.0319333	12
Madagascar	0.0037987	0.014909	0.0405948	−0.0283302	96
Malawi	0.0184314	0.0290299	0.097125	−0.0272625	24
Mali	0.0191649	0.0143314	0.0484657	−0.0060814	204
Mauritania	0.0195388	0.0120298	0.0421617	−0.0099106	180
Mozambique	0.0175786	0.0205434	0.0653042	−0.016535	120
Namibia	0.013263	0.0106717	0.0294477	−0.0024326	132
Niger	0.0164668	0.0146296	0.0462526	−0.0098866	192
Nigeria	0.0232486	0.0228473	0.0727674	−0.0195644	132
Senegal	0.0344408	0.0242616	0.0745833	−0.0158917	36
Sierra Leone	0.0244459	0.0221126	0.074225	−0.019175	12
Somalia	0.0021149	0.0122863	0.0198657	−0.0420463	108
South Africa	0.008476	0.0167565	0.0388681	−0.0440833	216
Sudan	0.0204686	0.0185983	0.061752	−0.0173794	408
Swaziland	0.0169079	0.0298251	0.0864917	−0.0333917	12
Togo	0.0206309	0.0305059	0.0749333	−0.0614458	24
Tanzania	−0.0015626	0.0161149	0.0314391	−0.0454378	156
Uganda	0.0230863	0.0308077	0.0811417	−0.0543583	48
Zambia	0.0192661	0.0264835	0.0941342	−0.0274933	120
Zimbabwe	0.028104	0.0237525	0.0756861	−0.0209417	72
Total	0.0169	0.0247	0.1166	−0.0637	3,924

Notes. This Table reports the mean, the standard deviation, the maximum and the minimum for PDSI values. We also report the number of stations for the measure of the PDSI. The descriptive statistics are computed using the same sample as in our baseline estimates (Table 3, column (3)).

1.1.2. *Descriptive statistics*

The basic descriptive statistics of this measure are provided in Table 1. The number of meteorological stations varies from 12 in the smallest countries (Benin, Liberia, Lesotho, Sierra Leone and Swaziland) to more than 300 in the largest countries (Democratic Republic of the Congo and Sudan). The vast majority of sub-Saharan countries (76%) have experienced at least one extremely dry year (maximum PDSI value above 0.04) and 23% have experienced at least one extremely wet year (minimum value below −0.04). The average PDSI value is 0.0169 and its standard deviation is 0.0247. The density curve of the PDSI for the sub-Saharan region moves to the right over the decades (see Figure B2 in Appendix B), that is, the sub-Saharan climate has become drier. The density curve becomes flatter and more right-skewed, that is, the climate of more and more countries is approaching extreme dryness.

The variation in the PDSI between and within countries is such that 54% of the PDSI is explained by the specific year, whereas 44% is explained by the specific country and 67% is explained by both.[11] We find that the contemporaneous country–year average of the PDSI is significantly correlated with its lagged value within countries, which is consistent with the recursive formula. Indeed, as mentioned before, the contemporaneous monthly value is the sum of the value in the previous month and a monthly contribution. However, the PDSI is not significantly correlated with its value at $t-2$.[12]

The inputs of the Palmer index are temperature, precipitation and available soil water capacity. Time series highlight that the PDSI and rainfall generally vary in opposite directions (see Figure B3 in Appendix B) and that the PDSI and temperature generally vary in the same direction (see Figure B4 in Appendix B). Temperature and rainfall together explain 60% of the PDSI variation[13] and 70%–90% of the within-country PDSI variation.[14] This is consistent with the theoretical formula of the PDSI, which is based on precipitation, temperature and available soil water content. Notice that consistently with the Palmer model, we find that rainfall decreases the PDSI, but less so during hot years.[15]

1.2. *Data on Civil Wars*

We use the UCDP/PRIO Armed Conflict Dataset (v4-2011), over the 1945–2005 period,[16] where some errors have been corrected and the data have been extended compared to previous versions. We use the civil war incidence dummy variable, which is equal to 1 for years with a number of battle deaths greater than 1,000 and 0 otherwise (we further discuss our results for alternative coding such as the onset or intensity of civil war).

The history of sub-Saharan Africa reveals that there were important political changes throughout the twentieth century. Many African countries were colonised before World War II and decolonised after World War II and the process of decolonisation and the emergence of new states embody a theoretical and empirical challenge. This

[11] These values are the R^2 of least square estimates of panel models including country fixed effects and/or year fixed effects. The estimates are not reported here.
[12] See Table B2 in Appendix B.
[13] Estimates not reported here.
[14] See Appendices A and B for more descriptive statistics results.
[15] See Table B5 in Appendix B. We find that rainfall decreases the PDSI and the interaction term between rainfall and temperature has a positive effect on the PDSI.
[16] Available at http://www.pcr.uu.se/research/ucdp/datasets/ucdp_prio_armed_conflict _dataset/.

raises questions about the inclusion or exclusion of anti-colonial civil wars in the analysis. We follow Fearon and Laitin (2003) who argue that there are ways to include anti-colonial civil wars but that the most conservative strategy is to focus on civil wars in independent African states and to exclude the colonial period (see Appendix A for a discussion). Hence, the time frame we consider is the period from a country's independence to the most recent year in our data, 2005. For example, the time frame for Ghana starts in 1957 for Mozambique and Angola in 1975 and for the former French colonies in 1960.

2. Estimation Framework

To estimate the effect of climate on the incidence of civil war, our baseline equation is the following:

$$War_{it} = \beta\, Climate_{it} + \eta_i + \chi_t + \varepsilon_{it}, \tag{3}$$

where War_{it} is the index of civil war in country i at time t and ε_{it} is the error term. The $Climate_{it}$ variable denotes a country-specific measure of climate, which can be rainfall, temperature or the PDSI. Parameter β captures the effect of the country-specific climate measure on the risk of civil war. We include country fixed effects (η_i) to control for time-invariant country-specific characteristics. We control for time-specific shocks that are common to all countries by including year dummies (χ_t). They absorb yearly worldwide changes such as economic shocks, global climate shocks or natural resource price shocks. We do not add other control variables to the model in order to avoid the 'bad control' problem (Angrist and Pischke, 2009).[17]

As our index of civil war is a binary variable, we could have used a logit model. However, we have preferred to consider the linear probability model throughout the article and to report the estimated effects using least squares. On the one hand, the logit methodology is undoubtedly preferable to the linear probability model if we want predictions with more than marginal changes in the variables. On the other hand, as argued by Wooldridge (2002), the linear probability model (in binary response models) should be seen as a convenient approximation to the underlying response probability. The linear probability model does not always predict values within the unit interval, but it is usual and it seems to be a convenient approximation in our case. One of the advantages of the linear model is that it enables us to use econometric tools to take serial correlation and spatial correlation into account in the climate data.

An important issue here is inference. As mentioned before, since we use climate data, serial correlation within countries and spatial correlation between countries have to be corrected when we estimate the standard errors. We follow Hsiang (2010) and deal with the two problems simultaneously in all our regressions. This method uses a non-parametric estimation of the variance–covariance matrix for the error term with

[17] See subsection 2.2.3. Many variables that we may want to add are outcome variables of climate variations themselves. For instance, we know that climate affects the GDP per capita (Dell *et al.*, 2012). The estimated coefficient of the climate measure will capture the effect of climate on the risk of civil war for a given level of GDP per capita. The problem is that this is not a causal argument.

weights that are uniform up to a cut-off distance of 1,000 km (Conley, 1999). Linear weights that fall to zero after a lag length of five years are used to take serial correlation into account (Conley, 2008).[18]

3. Empirical Results

3.1. *Preliminaries: Differences-in-differences Estimates of the Effect of Rainfall and Temperature*

The robustness of the link between weather variables and civil war has been challenged with arguments related to the sensitivity of the result with respect to the way climate is modelled, to changes in the data and in the coding choices, or to the way spatial correlation is controlled for.[19]

In this Section, we highlight an additional issue. Time series plots of civil war, temperature and precipitation variables are provided in Figures 1 and 2. These time series highlight that the evolution of the proportion of countries in civil war is negatively related to the evolution of rainfall (the correlation is −0.51, significant at

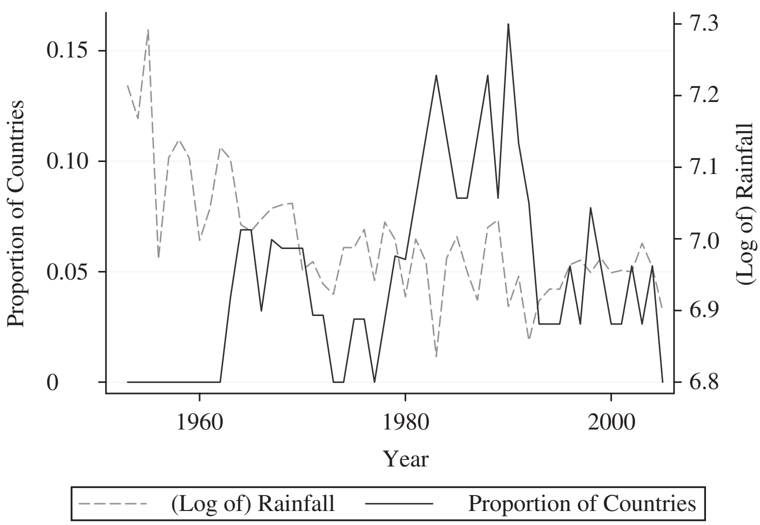

Fig. 1. *Proportion of Countries in Civil War and Rainfall: 1952–2005*
Notes. This Figure displays time series of the proportion of countries in civil war and (log of) rainfall (1952–2005). Correlation is −0.51 (significant at the 99% level). The proportion of countries in civil war at time *t* is the number of countries with dummy Civil War (a dummy which is equal to 1 for a number of battle deaths greater than 1,000) being 1 at time *t* divided by the number of countries.
Sources. The source of civil war data is UCDP/PRIO Armed Conflict v4-2011 (1952–2005). The sources of rainfall data are Ciccone (2011) and Tyndall Centre for Climate Change Research.

[18] We checked for the sensitivity of our baseline estimates to the distance cut-off of 1,000 km and to the lag length cut-off. We considered different cut-offs, from 4 to 10 years, for the temporal dimension and 1,000 km/3,000 km/5,000 km for the spatial cut-off. Table B6 in Appendix B reports the standard errors for the various possible combinations of the cutoff values (we do not report the coefficient, which is 0.275). We also used a two-way clustering method to compute the standard errors (Cameron *et al.*, 2011).

[19] See Ciccone (2011) or Miguel and Satyanath (2011) for a broad picture of the current debate.

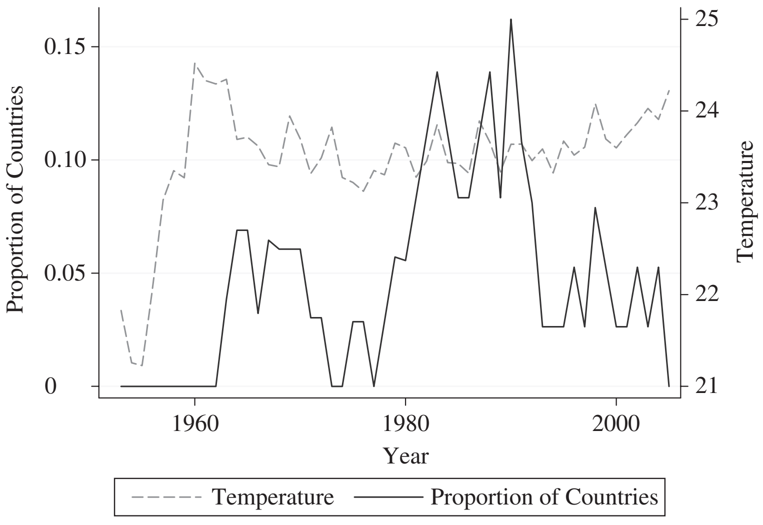

Fig. 2. *Proportion of Countries in Civil War and Temperature: 1952–2005*
Notes. This Figure displays time series of the proportion of countries in civil war and temperature (1952–2005). Correlation is 0.33 (significant at the 95% level of confidence). The proportion of countries in civil war at time *t* is the number of countries with dummy Civil War (a dummy which is equal to 1 for a number of battle deaths greater than 1,000) being 1 at time *t* divided by the number of countries.
Sources. The source of civil war data is UCDP/PRIO Armed Conflict v4-2011 (1952–2005). The source of temperature data is Hsiang *et al.* (2011).

the 99% level) and is positively related to the evolution of temperature (the correlation is 0.33, significant at the 95% level). There is evidence that yearly worldwide changes may explain the coincident movement of these variables. Indeed, the annual (worldwide) risk of conflict is positively correlated with the El Niño Southern Oscillation (ENSO) (Hsiang *et al.*, 2011) and the temporal patterns of PDSI are positively correlated with ENSO (Dai *et al.*, 2004). However, the usual specification in the literature (Miguel *et al.*, 2004; Burke *et al.*, 2009) includes country fixed effects and country-specific time trends only. These dummies do not capture the effect of yearly worldwide changes, while year fixed effects will. The omission of year fixed effects may generate a spurious regression phenomenon (Granger and Newbold, 1974). In other words, one may conclude that there is a link between weather variables and civil war that is in fact only driven by coincident aggregate time series variation. We then need to include both country and year fixed effects in order to estimate a causal link between climate and civil war. Estimates of (3) using (log) rainfall and temperature as climate variables (with two lags each) are provided in Table 2.[20] Estimates when $Climate_{it}$ is (log of) rainfall are provided in columns (1)–(3). We find that rainfall has no significant effect on civil war. When only country fixed effects are included (column (1)), the effect of

[20] The sample is longer (1952–2005) than the samples used previously in the literature. Table B1 in Appendix B provides estimates for the samples used in the literature.

Table 2

The Effect of Rainfall and Temperature on Civil War

Dependent variable	Civil war					
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Log Rainfall t	−0.0110	−0.00609	0.0236			
	(0.0256)	(0.0269)	(0.0243)			
Log Rainfall $t-1$	0.00918	0.0154	0.0116			
	(0.0276)	(0.0274)	(0.0290)			
Log Rainfall $t-2$	0.0311	0.0369	0.0409			
	(0.0292)	(0.0290)	(0.0296)			
Temperature t				0.0287*	0.00378	0.00825
				(0.0170)	(0.0172)	(0.0208)
Temperature $t-1$				0.0125	−0.00701	0.000589
				(0.0173)	(0.0191)	(0.0204)
Temperature $t-2$				−0.0147	−0.0384**	−0.0161
				(0.0148)	(0.0159)	(0.0201)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trends	–	Yes	–	–	Yes	–
Year fixed effects	–	–	Yes	–	–	Yes
Observations	1,463	1,463	1,463	1,463	1,463	1,463
R^2	0.325	0.325	0.372	0.327	0.327	0.371
F-test	0.53	1.62	0.85	1.62	0.25	2.04
	(0.690)	(0.1823)	(0.4689)	(0.1833)	(0.8611)	(0.1063)

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. The dependent variable is Civil War. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. Rainfall is the amount of precipitation. Columns (1) and (4) include only country fixed effects. Columns (2) and (5) include country and country-specific time trends. Columns (3) and (6) include country fixed effects and year fixed effects. In columns (1)–(3), we report F-tests of the joint significance of the three measures of rainfall. In columns (4)–(6), we report F-tests of the joint significance of the three measures of temperature. p-values are in parenthesis.
Sources. UCDP/PRIO Armed Conflict Dataset v4-2011 (1952–2005). We use precipitation data from Ciccone (2011) and Tyndall Centre for Climate Change Research. We use temperature data from Hsiang *et al.* (2011) over the 1952–2005 period.

rainfall on civil war is negative (as expected). The inclusion of country-specific time trends (Miguel *et al.*, 2004; Burke *et al.*, 2009) leads to an increase in the effect of rainfall on civil war (column (2)). The estimates of a standard differences-in-differences specification are provided in column (3). The effect of rainfall on civil war remains insignificant and turns out to be positive. The increase in the magnitude of the effect is due to year fixed effects that control for the temporal negative relationship between the aggregate measures of rainfall and civil war (as illustrated in Figure 1). Columns (4)–(6) provide our estimates when $Climate_{it}$ is temperature. The effect of temperature on civil war is positive and significant at the 10% level when we include country fixed effects only (column (4)). When we add country-specific time trends, the effect of temperature is still positive but insignificant (column (5)). When year fixed effects are included (column (6)), the effect of temperature is reduced by more than 2/3 (compared to column (1)) and is not significant. The decrease in the magnitude of the effect is due to year fixed effects that control for the temporal positive relationship between the aggregate measures of temperature and civil war (as illustrated in Figure 2).

3.2. *The Effect of Drought on Civil War*

An argument in favour of the PDSI and against rainfall and temperature is that it conserves degrees of freedom compared to a more general and possibly complicated specification with rainfall, temperature and interaction terms (see Table B5 in Appendix B for results with interaction terms). In the next Section, we also show that the PDSI performs well in explaining civil war compared to simple rainfall and temperature measures. Before going further, let us provide our estimates of the effect of the PDSI on civil war. Table 3 displays our main results. We first run a model with only country fixed effects (column (1)). Country fixed effects control for time invariant cross-country differences such as terrain roughness, ethnic and religious fractionalisation and the origin of the coloniser (for instance). The within-country drought variation has a positive effect on the within-country variation of the probability of civil war over time (column (1)).

Column (2) provides our estimates of the effect of the PDSI on civil war when we use the usual specification in the literature (Miguel *et al.*, 2004; Burke *et al.*, 2009) and include country fixed effects and country-specific time trends. We find that the coefficient of the PDSI is 0.677 and the effect is significant at the 99% level of confidence. However, we have argued in subsection 4.1 that this link may be spurious.

In column (3), we run a standard differences-in-differences model including country fixed effects and year fixed effects. Year fixed effects control for yearly worldwide changes in economic conditions, in technological progress, in natural resource prices, or in global political conditions (such as the Cold War). Moreover, they absorb the temporal coincident fluctuations of the aggregate measures of PDSI and civil war. Our estimates highlight that the effect of the PDSI becomes marginally insignificant (p-value = 0.12) and that the effect of the PDSI on civil war decreases by 2/3 when year fixed effects are included (the coefficient decreases from 0.700 to 0.275). Figure 3 illustrates this result. It provides aggregate time series of both the proportion of

Table 3
The Effect of Drought on Civil War

Dependent variable	Civil war		
Specifications	(1)	(2)	(3)
PDSI	0.700***	0.677***	0.275
	(0.141)	(0.191)	(0.180)
Country fixed effects	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effects	–	–	Yes
Observations	1,643	1,643	1,643
R^2	0.305	0.350	0.349

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. The dependent variable is Civil War. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. PDSI is the Palmer Drought Severity Index. Column (1) includes country fixed effects. Column (2) includes country fixed effects and country-specific time trends. Column (3) includes country fixed effects and year fixed effects. We use PDSI data from Dai *et al.* (2004).
Sources. UCDP/PRIO Armed Conflict Dataset v4-2011 (1945–2005).

sub-Saharan African countries in civil war and of the average annual PDSI values over the post-colonial period. These two aggregate variables are positively correlated (the correlation is 0.44, significant at the 99% level of confidence). Indeed, both the PDSI and the proportion of sub-Saharan African countries in civil war increased in the early 1980s and their movements coincided quite well after the end of the Cold War (after 1990). Time dummies absorb the effects of these coincident movements and reduce the effect of the PDSI on civil war by 2/3. This means that the effect of the PDSI on civil war highlighted in column (1) is mainly driven by the coincident movements of the aggregate time series. Even though it is not significant, the effect of the PDSI on civil war is positive (as expected) and the t-statistic is 1.5. This is an improvement compared to rainfall and temperature. Specifically, the effect of rainfall (and its lags) is also not significant, but unexpectedly positive (see column (3) in Table 2) and the F-statistic is 0.85. The effect of temperature (and its lags) is also marginally not significant, but it has an ambiguous sign (temperature at $t-2$ is unexpectedly negative) and the F-statistic is 2.04 (see column (6) in Table 2). The PDSI has a positive effect on civil war but the data are not rich enough to really allow us to draw firm conclusions regarding its significance.

In the remainder of the article, we focus on the differences-in-differences specification (i.e. the specification that includes country and year fixed effects). Our estimate of the effect of drought on civil war highlights that a one-standard-deviation increase in the PDSI increases the annual risk of conflict by an additional 0.7% (the standard deviation of the PDSI is 0.025, see Table 1). Note that according to

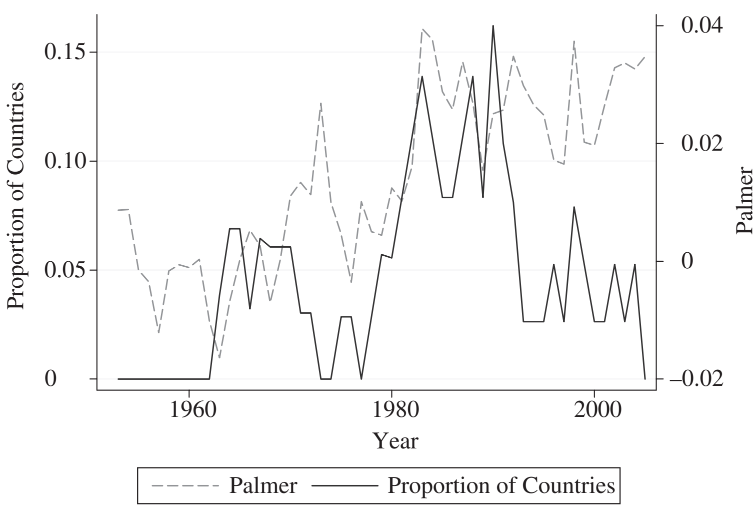

Fig. 3. *Proportion of Countries in Civil War and PDSI: 1952–2005*
Notes. This Figure displays time series of the proportion of countries in civil war and the Palmer Drought Severity Index (1952–2005). Correlation is 0.44 (significant at the 99% level of confidence). The proportion of countries in civil war at time t is the number of countries with dummy Civil War (a dummy which is equal to 1 for a number of battle deaths greater than 1,000) being 1 at time t divided by the number of countries. PDSI is the Palmer Drought Severity Index.
Sources. The source of civil war data is UCDP/PRIO Armed Conflict v4-2011 (1952–2005). The PDSI data is from Dai *et al.* (2004).

Palmer's classification, a one standard deviation increase in drought may correspond to a change from a near normal climate (PDSI between −0.005 and + 0.005) to a moderate drought (0.02–0.03). A change of greater magnitude such as a change from normal (PDSI = 0) to extremely dry (PDSI = 0.04) would increase the annual risk of civil war by 1.1%. Assuming that without PDSI variations (PDSI = 0, normal climate) the probability of civil war evolves in a linear way (i.e. the probability of civil war is explained by country fixed effects and year fixed effects), we find that the PDSI may have affected 9% of all civil wars (in our sample).[21] The model explains 34.9% of the variance of the risk of civil war. If we relax the assumption on the linearity of the effect of the PDSI, we find that the effect of the PDSI on the risk of civil war is greater for the highest PDSI values, that is, for PDSI values which are classified as mild drought or drier according to Palmer's classification (above the seventh decile of the PDSI distribution, i.e. for a PDSI > 0.02). The magnitude of the effect is such that PDSI values above the first decile are associated with a 1.5% to 5% increase in the risk of civil war (see Appendix A).

We also run many robustness checks using column (3) of Table 3 as a baseline. In Appendices A and B, we show how the result is affected when we remove the most influential observations, when we use alternative sample periods and when we modify the battle-death threshold.

3.3. *Comparison of the Effect of Drought, Rainfall and Temperature*

In order to compare the effect of the PDSI with that of rainfall and temperature, we consider the longest available sample (1952–2005) for which we can include the PDSI, rainfall (with two lags) and temperature (with two lags). Table 4 provides our results. Column (1) reports our estimates of the effect of the PDSI on civil war using (3).[22] The effect of the PDSI is still not significant. Columns (2) and (3) report our estimates of the effect of (log) rainfall and temperature (with two lags), respectively. The effect of (log) rainfall is still surprisingly positive and the effect of temperature is still positive. Their effects are insignificant and the contemporaneous and lagged measures are jointly insignificant (according to F-tests, see columns (2) and (3)).[23]

We find that rainfall and/or temperature should not be used instead of the PDSI (see J-tests in columns (2) and (3)). Moreover, we cannot reject that the PDSI should be used instead of temperature (see J-test in column (3)). Adding rainfall or temperature to the PDSI does not improve the performance of the model significantly (see LR-tests provided in columns (5) and (6)).[24] Finally, we find that the performance of the model has not significantly improved when rainfall and

[21] We project the observed sequence of PDSI realisations onto our linear model ($\mathrm{d}War_{ij}/\mathrm{d}PDSI = 0.275$). We compute the value $(\hat{\beta}\sum_t \sum_i PDSI_{it})$ that we divide by the total number of civil war years in the sample (which is 88). We find that eight civil war years were associated with the PDSI.

[22] The results in column (1) differ from those provided in Table 3 (column (3)) because we have to use a smaller sample.

[23] The results are not affected if we only include the current measure of rainfall (or temperature) or if we only include one lag.

[24] The rainfall and temperature measures are jointly insignificant (see F-tests in columns (2)–(7)).

Table 4

Comparison of the Effects of Drought, Rainfall and Temperature on Civil War

Dependent variable	Civil war						
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	M1	M2	M2	M2	M3	M3	M3
PDSI	0.171				0.499*	0.172	0.509*
	(0.195)				(0.264)	(0.194)	(0.264)
Log Rainfall t		0.0236		0.0251	0.0479*		0.0493*
		(0.0243)		(0.0244)	(0.0284)		(0.0281)
Log Rainfall $t-1$		0.0116		0.0117	0.0284		0.0290
		(0.0290)		(0.0294)	(0.0315)		(0.0321)
Log Rainfall $t-2$		0.0409		0.0380	0.0413		0.0388
		(0.0296)		(0.0291)	(0.0296)		(0.0292)
Temperature t			0.00825	0.00766		0.00705	0.00477
			(0.0208)	(0.0209)		(0.0209)	(0.0211)
Temperature $t-1$			0.000589	−0.000575		−3.46e −06	−0.00165
			(0.0204)	(0.0205)		(0.0203)	(0.0204)
Temperature $t-2$			−0.0161	−0.0139		−0.0160	−0.0140
			(0.0201)	(0.0198)		(0.0202)	(0.0198)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,463	1,463	1,463	1,463	1,463	1,463	1,463
R^2	0.371	0.372	0.371	0.372	0.373	0.371	0.373
J-test (t-statistic)†							
H0:M2/H1:M1	–	2.29	1.74	1.98	–	–	–
		[0.022]	[0.082]	[0.048]			
H0:M1/H1:M2	–	2.26	0.83	2.45	–	–	–
		[0.024]	[0.41]	[0.014]			
LR-test (LR chi2)	–	–	–	–	4.17	0.62	4.70
(M1/M3)					[0.2437]	[0.8917]	[0.5832]
F-test‡	–	1.62	0.25	1.56	1.30	0.27	1.29
		[0.1823]	[0.8611]	[0.1981]	[0.2721]	[0.8501]	[0.2570]

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. p-values are in brackets. The dependent variable is Civil War. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. PDSI is the Palmer Drought Severity Index. All specifications include country fixed effects and year fixed effects. † J-test reports the result of a Davidson–MacKinnon non-nested test of model M1 against model M2 (PDSI against rainfall in column (2), PDSI against temperature in column (3) and PDSI against both rainfall and temperature in column (4)). Model M1 refers to column (2), (3) and (4), successively. ‡ F-test reports a test for the joint significance of the current measure of rainfall and its two lags (column (2)); the joint significance of the current measure of temperature and its two lags (column (3)); the joint significance of the current measure of rainfall and temperature and their two lags (column (4)); the joint significance of the current measure of rainfall and its two lags (column (5)); the joint significance of the current measure of temperature and its two lags (column (6)); the joint significance of the current measure of rainfall and temperature and their two lags (column (7)).
Sources. UCDP/PRIO Armed Conflict Dataset v4-2011 (1952–2005). We use precipitation data from Ciccone (2011) and Tyndall Centre for Climate Change Research. We use temperature data from Hsiang *et al.* (2011).

temperature measures are added to the PDSI (see the LR-test in column (7), the p-value is 0.58). These results are consistent with the fact that the PDSI captures important interactions (see Table B5 in Appendix B) and threshold effects and it contains information (soil texture) that simple rainfall and temperature measures do not take into account. The results also suggest that the Palmer drought severity index describes social exposure to water stress in a more efficient way than rainfall or temperature measures.

3.4. *Other Outcome Variables and Interaction Between PDSI and Country Characteristics*

To provide insights on the effect of drought, we check whether the PDSI affects other economic and political outcomes. Blattman and Miguel (2010) argue that drought may increase the risk of civil war because it decreases the opportunity cost of fighting among rural populations; however, crop failure may also reduce government revenues and/or state capacity. We first provide estimates of the effect of the PDSI on various measures of economic productivity and production.[25] Table 5 displays our findings regarding the effect of the PDSI on agricultural and total economic production and on different measures of government finances. We find that the PDSI has a positive effect on local food prices and a negative effect on productivity (cereal yields). These results are consistent with previous studies that documented the significant impact of climate variations on crop yields (Schlenker and Lobell, 2010; Hsiang *et al.*, 2011). We find that the PDSI has a negative but insignificant effect on production (agricultural income, GDP per capita and economic growth). These results contrast with recent but growing evidence that climate affects economic performance (Schlenker and Roberts, 2006; Barrios *et al.*, 2010; Hsiang, 2010; Jones and Olken, 2010; Zivin and Neidell, 2010; Dell *et al.*, 2012). This suggests that an opportunity cost mechanism may explain the effect of drought on civil war, through the effect of drought on yields. In columns (5) and (6), we use two measures of government expenditures. We find that the PDSI has a positive and significant effect

Table 5

The Effect of Drought on Different Outputs

Dependent variable	ln cereal yield	ln agricultural income/cap	ln GDP/cap	GDP growth	Government consumption expenditure (% of GDP)	Government consumption share	ln local food prices
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PDSI	−67.87**	−0.398	−0.0160	−4.005	21.05***	5.029	4.651***
	(30.86)	(0.278)	(0.109)	(10.92)	(6.315)	(3.857)	(0.509)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,483	1,213	1,543	1,413	1,375	1,581	32,569
R^2	0.999	0.998	1.000	0.317	0.922	0.949	0.874

Notes. Conley standard errors clustered at country level in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. PDSI is the Palmer Drought Severity Index. All specifications include country fixed effects and year fixed effects. Column (7) also includes product fixed effects. We estimate (5) provided in Appendix A. See Appendix D for further details on the dependent variables. *Sources.* The source of ln Cereal Yield and ln Agricultural Income/cap data is Hsiang (2010). ln GDP/cap and GDP Growth come from Penn World Table 7.0. The source of Government Consumption and Government Consumption Share data is World Development Indicator. The source of ln local food prices data is FAO (161 different food prices).

[25] See Appendix A for a more detailed exposition of the results and Appendix D for a description of dependent variables.

on government consumption expenditures (% of GDP) but no significant effect on government consumption share (% of GDP per capita). All together, these results suggest that drought may have an effect on both the opportunity cost of fighting among rural populations and the state capacity.

Democratic change is an important political outcome related to civil wars. Brückner and Ciccone (2011) have shown that country-specific variations in rainfall are followed by significant improvements in the democratic institutions of sub-Saharan African countries. Table 6 relates the PDSI with various indices of democratic change. We find that the PDSI has a positive effect on the variation in the polity score but no effect on other measures of democratisation (indices).[26]

We also consider the effect of interactions between drought and country characteristics on the risk of civil war. Table 7 displays our estimates on the effect of the interactions between the PDSI and various country characteristics. Let us summarise our most interesting results.[27] The development interaction result indicates that relatively poor countries hit by drought are as prone to civil war as relatively rich countries (we use the log GDP per capita in 1965 in order to avoid reverse causality problems, see column (1)). This result differs from the (worldwide) cross-country evidence suggesting that poor countries are more prone to conflict (Fearon and Laitin, 2003), but this may be due to our focus on sub-Saharan Africa and to the fact that this area of the world was relatively homogeneous in terms of economic conditions in 1965.

Interestingly, we find (in column (2)) that countries which are relatively more ethnically fractionalised and are hit by a drought are more prone to conflict than countries with less ethnic fractionalisation (the total estimated effect is negative for five countries in the sample – Botswana, Equatorial Guinea, Lesotho, Swaziland and Zimbabwe). The role of ethnic groups in conflicts is a contentious issue and the debate is still very active.[28] This result contrasts with cross-country studies that find that ethnic diversity is not significantly correlated to conflict across countries (Easterly and Levine, 1997; Collier and Hoeffler, 1998, 2004; Fearon and Laitin, 2003). However, our result is consistent with recent studies by Esteban *et al.* (2012*a, b*) who provide (theoretically grounded) cross-country evidence that civil conflict is correlated with ethnic polarisation and fractionalisation.[29]

We also find that countries with a relatively higher percentage of mountainous terrain suffering from drought are more prone to conflict than countries with a lower percentage of mountainous terrain (see column (3)). This result is consistent with

[26] Again, see Appendix A for a more detailed exposition of the results.

[27] Additional comments are provided in Appendix A.

[28] Fearon (2006) reports that 709 minority ethnic groups are identified around the world and that at least 100 had members who engaged in an ethnically-based rebellion against the state between 1945 and 1998. Blattman and Miguel (2010) provide a summary of the debate between ‘primordialists’ (Horowitz, 1985) and ‘modernists’ (Gellner, 1983; Bates, 1986), who argue that ethnic conflict arises when groups excluded from social and political power begin to experience economic modernisation.

[29] Esteban *et al.* (2012*a, b*) also argue that ethnic conflicts are likely to be instrumental, rather than driven by primordial hatreds.

Table 6

The Effect of Drought on Democratic Change

Dependent variable	ΔPolity	ΔExecutive recruitment	ΔPolitical competition	ΔExecutive constraint	Coup	Coup in democracy	Democratic transition	Autocratic transition	Democratisation step
Specifications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PDSI	6.985**	−11.69	−11.22	−10.57	0.675	−0.0111	0.0491	−0.878	0.232
	(3.210)	(22.49)	(22.47)	(22.78)	(0.452)	(0.224)	(0.297)	(0.639)	(0.240)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,550	1,552	1,552	1,552	1,643	1,643	1,102	467	1,474
R^2	0.108	0.056	0.056	0.056	0.239	0.115	0.142	0.717	0.695

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects and year fixed effects (see Appendix B for a detailed description). PDSI is the Palmer drought severity index. Dependent variables are constructed thanks to Polity IV data. ΔPolity captures the variation of the polity score from t to $t + 1$. ΔExecutive Recruitment denotes the variation of the executive recruitment from t to $t + 1$. ΔPolitical Competition denotes the variation of the political competition from t to $t + 1$. ΔExecutive Constraint denotes the variation of the executive constraint from t to $t + 1$. Coup is a dummy equal to 1 if there was a coup in a country at time t. Coup in Democracy is a dummy equal to 1 if there was a coup in a democratic country at time t. Democratic Transition is a dummy coded 1 if a country was non-democratic at time t but democratic at time $t + 1$. Autocratic Transition is a dummy coded 1 if a country was democratic at time t and non-democratic at time $t + 1$. Democratisation Step is a dummy coded 1 if the country was upgraded to either a partial or full democracy between t and $t + 1$.

Table 7

Interactions Between Drought and Country Characteristics

Dependent variable	Civil war			
Specifications	(1)	(2)	(3)	(4)
PDSI	0.736	−0.889**	−0.502***	0.110
	(2.089)	(0.368)	(0.179)	(0.171)
PDSI × ln GDP/cap (initial)	−0.055			
	(0.411)			
PDSI × ethnic fractionalisation		1.679***		
		(0.556)		
PDSI × % mountainous terrain			0.633***	
			(0.116)	
PDSI × population density $t-1$				4.92e−05
				(0.000668)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,148	1,643	1,592	1,560
R^2	0.408	0.350	0.356	0.364
	(5)	(6)	(7)	(8)
PDSI	0.440**	0.409**	0.407**	0.401**
	(0.193)	(0.168)	(0.168)	(0.168)
Polity $t-1$	0.00435			
	(0.00116)			
PDSI × polity $t-1$	0.0447			
	(0.0311)			
PDSI × executive recruitment $t-1$		0.0178		
		(0.0136)		
Executive recruitment $t-1$		−0.00137***		
		(0.000461)		
PDSI × political competition $t-1$			0.0180	
			(0.0136)	
Political competition $t-1$			−0.00135***	
			(0.000464)	
PDSI × executive constraint $t-1$				0.0192
				(0.0135)
Executive constraint $t-1$				−0.00138***
				(0.000457)
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	1,555	1,552	1,552	1,552
R^2	0.359	0.367	0.367	0.367

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects and year fixed effects. PDSI is the Palmer drought severity index. The dependent variable is Civil War. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. See Appendix D for more details on the independent variables.
Sources. UCDP/PRIO Armed Conflict Dataset v4-2011 (1945–2005). See Appendix D for other data sources.

previous studies that found that mountainous terrain is a correlate of civil war (Collier and Hoeffler, 1998, 2004; Fearon and Laitin, 2003). The democracy interaction results indicate that countries with a relatively low level of democracy which are hit by a drought are more prone to civil war than countries with a relatively high level of democracy (columns (6)–(8)).

4. Conclusion

In this article, we have explored the link between drought and civil war. We have shown that the link between rainfall, temperature and civil war found in the literature may be driven by aggregate shocks that were not accounted for. We have used a meteorological measurement of drought, the Palmer drought severity index, which describes social exposure to water stress in a more efficient way than rainfall and temperature. This index combines rainfall and temperature (and soil texture) and accounts for important aspects that were missing from previous studies (non-linearities, rainfall–temperature interactions and threshold effects). However, we have shown that evidence for a positive link between drought and civil war is weak. We think that richer data are needed to obtain firm conclusions regarding the climate–conflict relationship.

Appendix A. Complementary Results

One of the criticisms of Miguel *et al.*'s (2004) seminal work is that the link between rainfall and civil war fails to pass several sensitivity tests (Buhaug, 2010). In this Appendix, we make sensitivity tests, using our differences-in-differences specification (Table 3, column (3)). We also provide a detailed description of our results regarding potential channels for the (weak) link between drought and civil war.

A.1. *Different Time Frame*

We test the sensitivity of our results to a change in the time frame of the sample considered. The processes of democratisation and the development of sub-Saharan Africa might have induced changes in the relationship between drought and civil war during the post-World War II period. Thus, the effect of drought on civil war may be sensitive to the time frame in our sample. We re-estimate the effect of the PDSI on civil war for each time interval of a minimum of 20 consecutive years (i.e. 861 estimates) between 1965 and 2005 using our standard differences-in-differences specification. In all cases, the value of the estimated PDSI coefficient is positive. Figure B6 provides the significance of the estimated PDSI coefficient (whether insignificant, significant at the 5% or at the 10% levels). The PDSI coefficient is significant at 5% for most of the periods considered between 1970 and 1999 but it is non-significant for many other time scales. Overall, these results show that the degree of significance of the effect of drought on civil war is sensitive to a change in the time frame; see Buhaug *et al.* (2010) for a discussion on the sensitivity of the effect of rainfall and temperature to variations in the sample period).

A.2. *Illustration: Sudan and Uganda*

We have picked two cases where drought periods coincide with civil war periods. Figure B5 plots the PDSI level and reports periods of civil war for Sudan and Uganda. The time series of PDSI values for Sudan reached a peak in the early 1980s and the civil war began in 1983; there are two large peaks in the time series of PDSI values for Uganda, one during the 1980s and one around 2003–5. These periods correspond precisely to two periods of civil war in Uganda. These two cases illustrate a positive correlation between drought and the incidence of civil war.

A.3. *Outliers*

Buhaug *et al.* (2010) argue that the estimates in Burke *et al.* (2009) regarding temperature data are sensitive to the exclusion of outliers from the main specification. We provide the same analysis here. Figure B7 provides a plot of our observations and the two and the three standard error limits (the two-sigma and the three-sigma outliers are the observations outside the '2SD' and '3SD' limits, respectively). Table B7 provides our results using our baseline specification with different samples (Table 3, column (3)). Column (1) reports our estimates over the whole sample (identical to column (3) in Table 3), column (2) provides our estimates over a sample without the three-sigma outliers and column (3) provides our estimates over a sample without the two-sigma outliers. The effect of the PDSI is reduced compared to our baseline estimates, but turns out to be significant (at the 99% and 90% level of confidence, respectively).

A.4. *Non-linear Effect of PDSI on Civil War*

So far, we have made implicit the assumption that the response of the risk of civil war to the PDSI is linear. We relax this assumption and first include the square of the PDSI in the right-hand side of (3). We find that the effect of this additional variable is insignificant (estimates are not shown here). Second, we use a non-parametric estimate of the effect of the PDSI (Deschênes and Greenstone, 2011): we compute the 10 deciles of the PDSI and run our preferred specification, including a variable for each of the second to the tenth decile of the PDSI (nine bins, with the first decile being our reference). Figure B8 plots the estimated response function linking civil war and the nine PDSI bin variables. The Figure also plots the coefficients plus and minus two standard errors. Our response function increases slightly for the last bins, meaning that the effect of the PDSI on the risk of civil war is greater for the highest PDSI values, that is, for PDSI values which are classified as mild drought or drier according to Palmer's classification (above the seventh decile of the PDSI distribution, i.e. for a $PDSI > 0.02$). Overall, the magnitude of the effect is such that PDSI values above the first decile are associated with a 1.5%–5.5% additional risk of civil war. A one standard deviation increase in the PDSI (from a normal climate) translates into a 4% increase in the risk of civil war, which is more than five times greater than in our baseline estimates (0.7%).

A.5. *Drought and the Number of Battle-related Deaths*

We propose two strategies to investigate the effect of PDSI on the intensity of civil wars. First, we test whether the effect of the PDSI is sensitive to a change in the battle-related death threshold. We re-code our dependent variable War_{it} for each threshold between 25 and 200,000 battle-related deaths per year and re-estimate our preferred specification. Figure B9 reports the value of the estimated coefficient of the PDSI (and the 95% interval of confidence). The PDSI has a positive effect on civil war and it is significant at the 95% level of confidence in most cases as long as the battle–death threshold is at least 1,000. The coefficient of the PDSI is positive in most cases for thresholds between 25 and 999 (number of battle deaths each year) but not significant. The 1,000 battle-related death threshold corresponds perfectly to the usual limit considered in the literature to distinguish between civil war and civil conflict. However, we cannot assert whether this threshold we find is due to a real phenomenon or to a variation in the precision of the data. It remains that the effect of the PDSI on the intensity of civil war is positive and significant at the 95% level of confidence, no matter the battle-death threshold we consider.[30] The effect of drought on civil war (i.e. for

[30] The effect becomes non-significant for thresholds higher than 50,000 deaths per year but in that case only two observations are still considered as civil war years.

thresholds that are greater than 1,000 battle-related deaths) is such that a one standard error increase in the PDSI is associated with a 0.5%–1.2% increase in the risk of civil war (our baseline estimates predict a 0.7% increase).

Second, we maintain the same set of explanatory variables but we replace the left-hand-side dependent variable with different measures of the intensity of civil war (Table B8). We use two different approximations for the number of battle deaths: a lower bound and a higher bound estimates (according to the Peace Research Institute Oslo (PRIO) data set). As an alternative we also use the square root of the number of battle deaths or the number of battle deaths. Columns (1) and (4) contain our results when the left-hand-side dependent variable is the square root of the number of battle deaths. In both cases, the PDSI increases the intensity of civil war and the effect is significant at the 99% level of confidence. Columns (2) and (5) report our results when the left-hand-side dependent variable is the number of battle deaths. Column (2) presents our results for the lower bound measure. Our results indicate that a one standard deviation increase of the PDSI leads to 111 additional battle deaths and the effect is significant at the 99% level of confidence. Column (5) reports our estimates for the higher bound measure. Our results indicate that a one standard deviation increase of the PDSI leads to 457 additional battle deaths and the effect is significant at the 95% level of confidence. Columns (3) and (6) provide our estimates when the left-hand-side variable is the number of battle deaths but we use a Poisson regression instead of least squares in order to account for the discrete nature of the dependent variable and the presence of a large number of 0. Again, the PDSI has a positive effect on the number of battle-related deaths. The effect is significant at the 99% level of confidence.

A.6. *Onset of Civil War*

A usual alternative measure of civil war is the onset (or outbreak) of civil war index. It is set at 1 for the first year of civil war set to missing for the subsequent civil war years and at 0 for peace years.[31] Table B9 in Appendix B provides our results. The PDSI has a positive and significant effect on the probability of the outbreak of civil war if we only include country fixed effects (column (1)). However, columns (2) and (3) show that the PDSI has a non-statistically significant effect on the onset of civil war when country-specific time trend or year fixed effects are included, respectively, suggesting that the PDSI is not a strong predictor of the onset of civil war index.

A.7. *Other Outcome Variables*

To give some insights into potential channels through which drought might affect the risk of civil war (e.g. economic development, agricultural production, fractionalisation indices, political indices, food prices etc.), we estimate the following equation:

$$y_{it} = \gamma PDSI_{it} + \eta_i + \chi_t + \zeta_{it}, \tag{A.1}$$

where, y_{it} is the country-specific measure of the potential channel, $PDSI_{it}$ our measure of drought, ζ_{it} is the error term, η_i the country fixed effect and χ_t the year fixed effect.

Table 5 reports our results regarding the effect of drought on agricultural productivity and production. We use the specification of (A.1) where (log of) cereal yields (tons/ha) is the left-hand-side variable (column (1)). The PDSI has a negative and significant impact on cereal yields, as expected and the effect is significant at the 99% level of confidence. However, the

[31] We take multiple contemporaneous conflicts in the same country into account. In our sample, there is only one country with two contemporaneous civil wars: PRIO data report that Ethiopia has experienced several contemporaneous civil wars. The onset index is then set to 1 for Ethiopia in 1976, 1980 and 1981.

PDSI has an insignificant effect on the agricultural income per capita (column (2)), on the national income per capita (column (3)) and on the national income growth (column (4)). We present estimates of the effect of the PDSI on two measures of government finances (columns (5) and (6) in Table 5). Column (5) presents the effect of the PDSI on government consumption expenditure (% of GDP). We find that the PDSI has a positive effect on government consumption expenditure and the effect is significant at the 99% level. A one standard deviation increase of the PDSI increases government consumption expenditure (% of GDP) by 0.53%. Column (6) shows that the PDSI has an insignificant effect on government consumption (% of GDP per capita). We also estimate the effect of the PDSI on local food price. Since food price indices are available for various food products (161), we use a country-product-year analysis and we estimate the following equation:

$$y_{ikt} = \gamma PDSI_{it} + \eta_i + \chi_t + v_k + \zeta_{ikt}, \tag{A.2}$$

where y_{ikt} is the (log of) local food price of product k and v_k is a product-specific dummy (eg, cattle meat, ginger, maize etc.). Column (7) shows our estimates. We find that the PDSI has a positive effect on local food prices. A one standard deviation increase in the PDSI translates into a 12% increase in local food prices.

Table 6 links the PDSI to various indices of democratic change. We use (3), where the left-hand-side outcome variable is a democratic change index. From column (1) to column (9), we successively use nine different indices of democratic change (see Appendix D for a description of the indices). Column (1) shows that a one standard deviation increase in the PDSI raises the variation in the polity score by 0.17 (the average variation being 0.07) and the effect is significant at the 95% level of confidence. However, we find that the PDSI has an insignificant effect on the variation in executive recruitment (column (2)), on the variation in political competition (column (3)), on the variation in executive constraint (column (4)), the risk of a *coup d'état* (column (5)), on the occurrence of a *coup d'état* in a democracy (column (6)), on democratic transition (column (7)), and on autocratic transition (column (8)).

A.8. *Interaction Between PDSI and Country Characteristics*

We include interaction terms between drought and country-specific characteristics (time-invariant or time-varying) in the right-hand-side set of explanatory variables of (3). Denoting C_{it} the country characteristic, we estimate:

$$War_{it} = \delta PDSI_{it} + \lambda PDSI_{it} \times C_{it} + \rho C_{it} + \eta_i + \chi_t + \xi_{it}, \tag{A.3}$$

where ξ_{it} is the error term. δ captures the mean effect of drought and λ captures the differentiated effect of drought on the risk of civil war according to the country characteristic. Table 7 contains our estimates of (A.3) on the effect of the interactions between the PDSI and various country characteristics. The development interaction result (we use the log GDP per capita in 1965 in order to avoid reverse causality problems, column (1)) indicates that relatively poor countries hit by drought are as prone to civil war as relatively rich countries.

In column (2), we interact our measure of the PDSI with a measure of ethnic fractionalisation. Interestingly, we find that the effect of the interaction term is significant (at the 99% level of confidence) and positive: countries which are relatively more ethnically fractionalised and are hit by a drought are more prone to conflict than countries with less ethnic fractionalisation. We also test for the effect of interaction terms between drought and linguistic or religious fractionalisation but we find no significant results (we have not reported these estimates). In column (3), we test for the effect of an interaction term between drought and the percentage of mountainous terrain in a given country. The interaction term is positive and significant at the 99% level of confidence. We find that countries with a relatively higher percentage of mountainous terrain suffering from drought are more prone to conflict than countries with a lower percentage of mountainous terrain.

We also interact the PDSI with the population density at time $t-1$ and find a positive effect, as expected, but it is not significant (column (4)). In columns 5–8, we interact the PDSI with indices of the level of democracy. In column (5), we include an interaction term between the PDSI and the aggregated level of democracy (polity score) and find that the effect of the interaction term is (surprisingly) positive but not significant. In columns (6)–(8), we include an interaction term of the PDSI and three different indices of democracy: the executive recruitment level, the level of political competition and the level of executive constraint, respectively. The effect of the interaction term is always negative and significant at 99%. These democracy interaction results suggest that countries with a relatively low level of democracy which are hit by a drought are more prone to civil war than countries with a relatively high level of democracy.

Another empirical strategy to investigate the potential underlying mechanisms linking drought to civil war is to estimate the effect of drought on civil war on sub-samples split by country characteristics. We focus on the agricultural share of GDP, GDP per capita, and ethnic and linguistic fractionalisation. For each of these variables, we plot the estimated coefficient (black curve) and the 95% of confidence interval (see Figures B10–B13). The x-axis is the cut-off of the variable of interest used to define the sub-sample (cutoff of the agricultural share of GDP, GDP per capita or ethnic fractionalisation). The model is re-estimated for each sub-sample from which the country with the lowest value is excluded and countries are also excluded with respect to increasing values for this variable. Our results show that countries with a relatively large agricultural sector which are hit by a drought are more prone to civil war (Figure B10 in Appendix B).[32] Figure B11 presents the results when we split the sample based on GDP per capita in 1965. It indicates that the poorest countries are relatively more prone to civil war than relatively more developed countries. Figures B12–B13 suggest that relatively ethnically and linguistically diverse countries hit by a drought are more prone to civil war than relatively ethnically and linguistically uniform countries, respectively.

A.9. *Alternative Measure of Drought*

In Table B10, we consider three alternative measures of drought. We compute the yearly average for each grid cell, and we take the maximal value of these averages for a given country. Columns (1)–(3) report our estimates of the specifications provided in Table 3 where we replace the PDSI by the maximal value. Our results are not affected. Specifically, the effect of drought on civil war is significant if we include country fixed effects only, if we use the specification used in the literature (country fixed effects + country-specific time trends), but it is no more significant when we use a standard differences-in-differences specification. We compute the intra-annual PDSI variation for each country (moments of order 1, 2 and 3). In columns (4)–(6), we report our estimates of the same specifications as in Table 3, but we add the moment of order 2 of the temporal variation of the PDSI (we also include the PDSI). In columns (7)–(9), we replace the moment of order 2 by the moment of order 3 of the temporal variation. The effect of these two measures is never significant. We computed the spatial PDSI variations within each country by computing various moments of the PDSI using the grid cell year averages (within year variation is eliminated). In columns (10)–(12), we include the moment of order 2; in columns (13)–(15), we include the moment of order 3 (all the specifications include the PDSI). We find that the effect of the higher moments of PDSI are never significant.

[32] Note that the slight decrease for an agricultural share above 50% is notably due to the small size of the sample.

Appendix B. Tables and Figures

Table B1

Literature and Year Fixed Effects

Dependent variable	Civil war					
	Miguel *et al.*'s (2004) data		Ciccone's (2011) data		Hsiang *et al.*'s (2011) data	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Rainfall t	−0.0529	−0.0176	0.0400	0.0745	−0.00837	0.0103
	(0.0651)	(0.0613)	(0.0705)	(0.0621)	(0.0213)	(0.0190)
Log Rainfall $t-1$	−0.102	−0.184**	0.0594	−0.0241	−0.00185	−0.0140
	(0.0738)	(0.0819)	(0.0505)	(0.0494)	(0.0158)	(0.0145)
Log Rainfall $t-2$	0.128*	0.102	0.0764	0.0621	−0.00554	−0.0236
	(0.0717)	(0.0653)	(0.0461)	(0.0458)	(0.0154)	(0.0177)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trends	Yes	–	Yes	–	Yes	–
Year fixed effects	–	Yes	–	Yes	–	Yes
Observations	743	743	1,179	1,179	899	899
R^2	0.731	0.677	0.597	0.588	0.562	0.523

Dependent variable	Civil war					
	Ciccone's (2011) data		Ciccone's (2011) data		Hsiang *et al.*'s (2011) data	
	(7)	(8)	(9)	(10)	(11)	(12)
Rainfall growth t	−0.0715*	−0.0320				
	(0.0404)	(0.0453)				
Rainfall growth $t-1$	−0.0341	−0.00751				
	(0.0322)	(0.0246)				
Temperature t			1.612**	0.0356	0.00421	−0.00284
			(0.693)	(0.897)	(0.0158)	(0.0215)
Temperature $t-1$			0.880	1.025	−0.0125	−0.00175
			(1.005)	(1.175)	(0.0142)	(0.0215)
Temperature $t-2$			0.282	0.417	−0.0310*	−0.0106
			(0.611)	(0.627)	(0.0165)	(0.0130)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time trends	Yes	–	Yes	–	Yes	–
Year fixed effects	–	Yes	–	Yes	–	Yes
Observations	725	725	580	580	1,508	1,508
R^2	0.556	0.517	0.603	0.576	0.498	0.510

Notes. Robust standard errors clustered at country level in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. PDSI is the Palmer drought severity index. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. Column (3) replicates Ciccone's (2011) results using rainfall and civil war data from Ciccone (2011) over the 1979–2009 period (Table 2, column (8)). The dependent variable is Civil War. In columns (7)–(10), we use data from Ciccone (2011) over the 1981–2005 period. In columns 11 and 12, we use temperature data from Hsiang *et al.* (2011) over the 1952–2005 period.
Sources. The source of civil war data differs according to the specifications. Column (1) replicates Miguel *et al.*'s (2004) results using rainfall and civil war data from Ciccone (2011) over the 1979–99 period (Table 2, column (4)). Source is UCDP/PRIO Armed Conflict v4-2011 over the 1945–2005 period (columns (5)–(12)). In columns (5) and (6), we use rainfall data from Hsiang *et al.* (2011) over the 1981–2005 period.

Table B2

PDSI Lags

Dependent variable	Palmer drought severity index (PDSI t)	
Specifications	(1)	(2)
PDSI $t-1$	0.660***	0.629***
	(0.0313)	(0.0445)
PDSI $t-2$		0.0391
		(0.0382)
Observations	1,605	1,567
R^2	0.693	0.698

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects. The dependent variable is the contemporaneous Palmer drought severity index. Specification (2) runs over the 1947–2005 period. PDSI $t-k$ is the lag of k year(s) of PDSI.

Table B3

The Effect of Rainfall/Temperature on PDSI

Dependent variable	Palmer drought severity index (PDSI)					
	Hsiang *et al.*'s (2011) data			Ciccone's (2011) data		
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Log Rainfall t	−0.0142***	−0.0114***	−0.0122***	−0.0591***	−0.0541***	−0.0555***
	(0.00217)	(0.00249)	(0.00247)	(0.00442)	(0.00387)	(0.00390)
Log Rainfall $t-1$		−0.00502*	−0.00597*		−0.0435***	−0.0427***
		(0.00272)	(0.00314)		(0.00467)	(0.00470)
Log Rainfall $t-2$			0.00480*			−0.00597
			(0.00269)			(0.00368)
Observations	973	936	899	891	855	819
R^2	0.736	0.752	0.766	0.799	0.840	0.847
	(7)	(8)	(9)	(10)	(11)	(12)
Temperature t	0.0239***	0.0185***	0.0171***	0.524***	0.512***	0.483***
	(0.00191)	(0.00241)	(0.00257)	(0.0537)	(0.0582)	(0.0614)
Temperature $t-1$		0.0110***	0.00934***		0.0403	0.0543
		(0.00249)	(0.00268)		(0.0613)	(0.0681)
Temperature $t-2$			0.00504**			−0.121*
			(0.00242)			(0.0637)
Observations	1,582	1,545	1,508	782	746	710
R^2	0.539	0.565	0.578	0.776	0.784	0.790

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects. The dependent variable is the Palmer drought severity index.
Sources. The source of rainfall and temperature data is Hsiang *et al.* (2011) for columns (1)–(3) and (7)–(9) and Ciccone (2011) for columns (4)–(6) and (10)–(12).

Table B4

The Effect of Rainfall and Temperature on PDSI

Dependent variable	Palmer drought severity index (PDSI)	
	Hsiang *et al.*'s (2011) data	Ciccone's (2011) data
Specifications	(1)	(2)
Log Rainfall t	−0.00975***	−0.0484***
	(0.00241)	(0.00407)
Log Rainfall $t-1$	−0.00551*	−0.0443***
	(0.00323)	(0.00544)
Log Rainfall $t-2$	0.00381	−0.00964***
	(0.00279)	(0.00384)
Temperature t	0.0118***	0.342***
	(0.00319)	(0.0471)
Temperature $t-1$	0.00118	−0.0287
	(0.00323)	(0.0565)
Temperature $t-2$	−0.00143	−0.00823
	(0.00282)	(0.0448)
Observations	899	710
R^2	0.775	0.861

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects. The dependent variable is the Palmer Drought Severity Index.
Sources. The source of rainfall and temperature data is Hsiang *et al.* (2011) for column (1) and Ciccone (2011) for column (2).

Table B5

The Cross Effect of Rainfall and Temperature on PDSI

Dependent variable	Palmer drought severity index (PDSI)					
Rainfall data	Hsiang *et al.*'s (2011) data			Ciccone's (2011) data		
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Temperature t	−0.000282	−0.00113	−0.00137	−0.0571	−0.123	−0.109
	(0.00299)	(0.00306)	(0.00315)	(0.137)	(0.123)	(0.142)
Log Rainfall t	−0.133***	−0.129***	−0.128***	−0.228***	−0.245***	−0.237***
	(0.0167)	(0.0171)	(0.0178)	(0.0599)	(0.0530)	(0.0608)
Temperature t × rainfall t	0.00507***	0.00499***	0.00493***	0.0544***	0.0622***	0.0595***
	(0.000700)	(0.000734)	(0.000759)	(0.0184)	(0.0165)	(0.0188)
Temperature $t-1$		−0.00581	−0.00622		−0.0965	−0.105
		(0.00369)	(0.00381)		(0.145)	(0.139)
Log Rainfall $t-1$		−0.0662***	−0.0648***		−0.0626	−0.0592
		(0.0189)	(0.0198)		(0.0680)	(0.0660)
Temperature $t-1$ × rainfall $t-1$		0.00249***	0.00242***		0.00535	0.00495
		(0.000801)	(0.000854)		(0.0212)	(0.0206)
Temperature $t-2$			−0.00170			0.217*
			(0.00325)			(0.123)
Log rainfall $t-2$			−0.00832			0.104*
			(0.0182)			(0.0538)
Temperature $t-2$ × rainfall $t-2$			0.000426			−0.0355**
			(0.000793)			(0.0167)

Table B5

(*Continued*)

Dependent variable	Palmer drought severity index (PDSI)					
Rainfall data	Hsiang *et al.*'s (2011) data			Ciccone's (2011) data		
Specifications	(1)	(2)	(3)	(4)	(5)	(6)
Observations	973	936	899	638	609	580
R^2	0.769	0.790	0.801	0.819	0.857	0.866

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects. The dependent variable is the Palmer drought severity index.
Sources. The source of rainfall data is Hsiang *et al.* (2011) for specifications (1)–(3) and Ciccone (2011) for specifications (4)–(6).

Table B6

Standard Errors Using Various Spatial and Temporal Cut-offs

Year: 4–Distance: 1,000	(0.197)	Year: 8–Distance: 1,000	(0.198)
Year: 4–Distance: 3,000	(0.198)	Year: 8–Distance: 3,000	(0.199)
Year: 4–Distance: 5,000	(0.175)	Year: 8–Distance: 5,000	(0.177)
Year: 6–Distance: 1,000	(0.173)	Year: 10–Distance: 1,000	(0.189)
Year: 6–Distance: 3,000	(0.175)	Year: 10–Distance: 3,000	(0.190)
Year: 6–Distance: 5,000	(0.149)*	Year: 10–Distance: 5,000	(0.167)*
		Two-way clustering	(0.013)***

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. We provide standard errors in parentheses for the estimates of our baseline (see Table 3, column (3)) with different spatial and temporal cut-offs. Country fixed effects and year fixed effects are included. Coefficient is 0.275.

Table B7

Robustness to the Exclusion of Outliers

Dependent variable	Civil war		
Sample	All	3SD	2SD
	(1)	(2)	(3)
PDSI	0.275	0.195***	0.0695*
	(0.180)	(0.0380)	(0.0371)
Country fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	1,643	1,574	1,549
R^2	0.382	0.798	0.972

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. All specifications include country fixed effects and year fixed effects. In specification (2), we exclude three standard deviation outliers (labelled 3SD). In specification (3), we exclude two standard deviation outliers (labelled 2SD). The dependent variable is Civil War. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. PDSI is the Palmer Drought Severity Index.
Source. Source is UCDP/PRIO Armed Conflict Dataset v4-2011 (1945–2005). We use PDSI data from Dai *et al.* (2004).

Table B8

The Effect of Drought on the Number of Battle Deaths

Dependent variable	No. of deaths (low estimate)		
Methodology	Square root – OLS	Linear – OLS	Poisson
Specifications	(1)	(2)	(3)
PDSI	38.44***	4,449***	15.90***
	(12.79)	(1,487)	(0.0967)
Observations	1,643	1,643	1,351
R^2	0.347	0.186	
Dependent variable	No. of deaths (low estimate)		
Methodology	Square root – OLS	Linear – OLS	Poisson
Specifications	(4)	(5)	(6)
PDSI	72.94***	18,292**	10.47***
	(25.99)	(8,078)	(0.0439)
Observations	1,643	1,643	1,351
R^2	0.398	0.151	

Notes. Conley standard errors in parentheses (except for columns (3), (6) and (9)) with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. The dependent variable, *No. of deaths*, is an estimate of the number of battle-related deaths. The UCDP/PRIO provides two estimates: a low and a high estimate for battle-related deaths in the conflict. The dependent variable in columns (1) and (3) is the square root of the number of battle-related deaths. We report least square estimates in columns (1), (2), (4) and (5). In columns (3) and (6), we use a Poisson model. PDSI is the Palmer Drought Severity Index. Country fixed effects and year fixed effects are included in all specifications.
Source. UCDP/PRIO Armed Conflict Dataset. We use PDSI data from Dai *et al.* (2004).

Table B9

The Effect of Drought on the Onset of Civil War

Dependent variable	Onset of civil war		
Specifications	(1)	(2)	(3)
PDSI	0.296**	0.187	0.182
	(0.126)	(0.144)	(0.144)
Country fixed effects	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effects	–		Yes
Observations	1,583	1,583	1,583
R^2	0.080	0.114	0.115

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. The dependent variable is Civil War. Onset of Civil War is coded 1 for the first year of civil war (more than 1,000 battle deaths), set to missing for the subsequent civil war years, and at 0 for peace years. PDSI is the Palmer Drought Severity Index. Column (1) includes country fixed effects. Column (2) includes country fixed effects and country-specific time trends. Column (3) includes country fixed effects and year fixed effects.
Sources. Source is UCDP/PRIO Armed Conflict Dataset v4-2011 (1945–2005).

Table B10

Alternative Measure of Drought

Dependent variable	Civil war		
Specifications	(1)	(2)	(3)
Max PDSI	0.580***	0.460***	0.112
	(0.129)	(0.173)	(0.195)
Country fixed effect	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effect	–	–	Yes
Observations	1,643	1,643	1,643
R^2	0.305	0.349	0.349
	(4)	(5)	(6)
Temporal variation order 2	0.000208	0.000222	1.85e-05
	(0.000150)	(0.000159)	(0.000173)
Country fixed effect	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effect	–	–	Yes
Observations	1,643	1,643	1,643
R^2	0.306	0.350	0.349
	(7)	(8)	(9)
Temporal variation order 3	−6.11e −05	−0.000102	−8.13e −05
	(5.74e−05)	(7.13e−05)	(6.46e−05)
Country fixed effect	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effect	–	–	Yes
Observations	1,643	1,643	1,643
R^2	0.306	0.351	0.350
	(10)	(11)	(12)
Spatial variation order 2	1.91e−05	3.16e−06	2.15e−06
	(1.50e−05)	(1.66e−05)	(1.63e−05)
Country fixed effect	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effect	–	–	Yes
Observations	1,643	1,643	1,643
R^2	0.306	0.350	0.349
	(13)	(14)	(15)
Spatial variation order 3	3.68e−06	7.61e−06	3.09e−06
	(5.70e−06)	(5.31e−06)	(5.61e−06)
Country fixed effect	Yes	Yes	Yes
Country-specific time trends	–	Yes	–
Year fixed effect	–	–	Yes
Observations	1,643	1,643	1,643
R^2	0.306	0.352	0.350

Notes. Conley standard errors in parentheses with ***, ** and * respectively denoting significance at the 1%, 5% and 10% levels. The dependent variable is Civil War. Civil War is a dummy which is equal to 1 for a number of battle deaths greater than 1,000. It includes only internal civil wars. Columns (4)–(15) include PDSI but not reported in the Table. Max PDSI is the maximum value of PDSI by country each year. Temporal Variation 2 or 3 is the intra-annual PDSI variation for each country with moments of order 2 or 3. Spatial Variation 2 or 3 denotes spatial PDSI variations within each country by computing various moments (2 or 3) of the PDSI using the grid cell year averages (within-year variation is eliminated).
Sources. Source is UCDP/PRIO Armed Conflict Dataset v4-2011 (1945–2005). We use PDSI data from Dai *et al.* (2004).

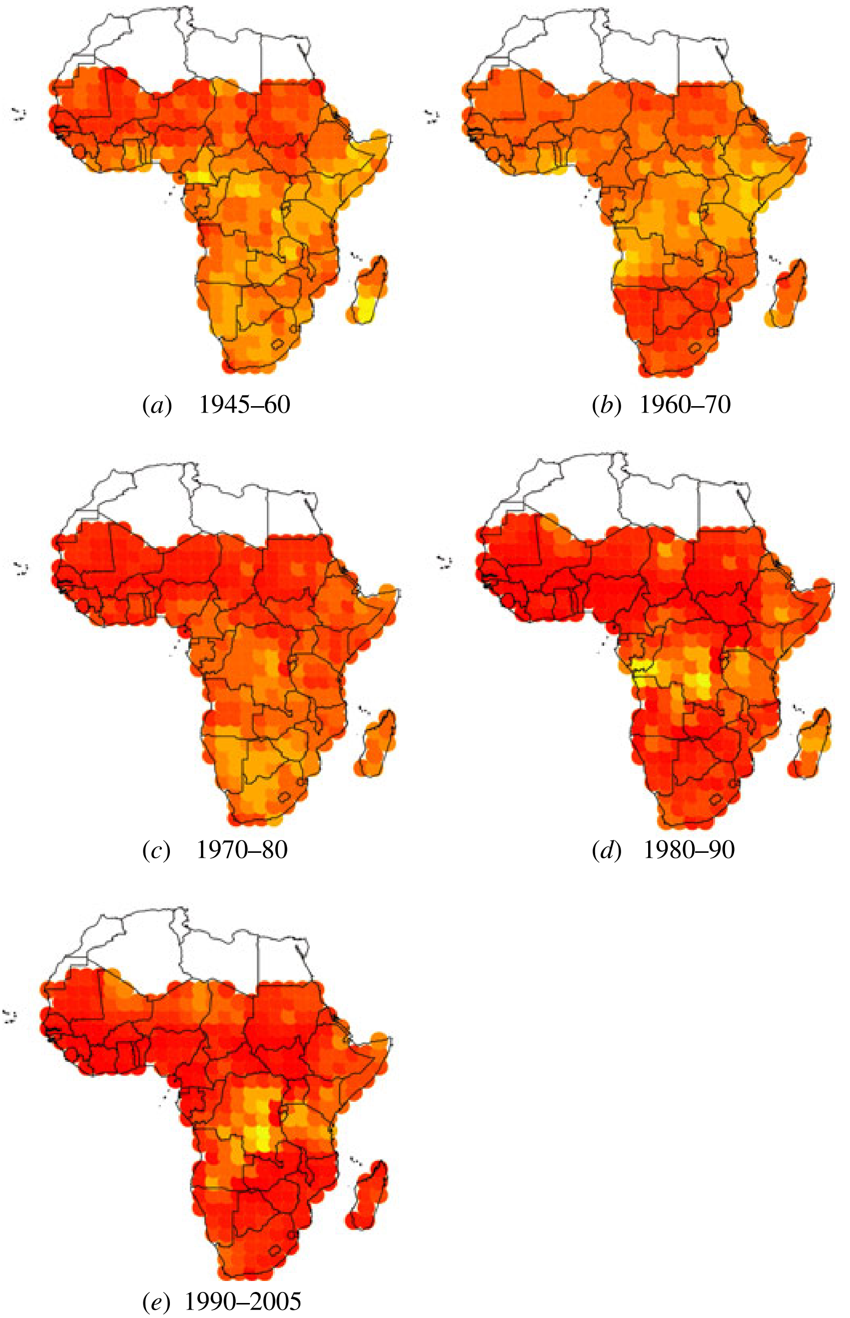

Fig. B1. *Maps of PDSI*

Notes. This Figure displays the evolution of the PDSI over time. Dark grey indicates a drier climate (a higher PDSI level). We use PDSI data from Dai *et al.* (2004).

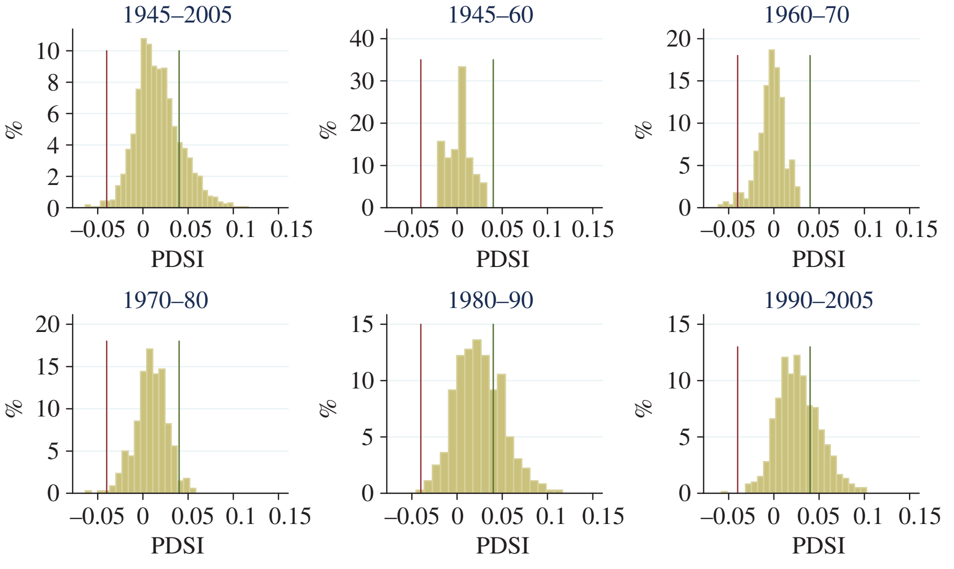

Fig. B2. *PDSI Density*

Notes. This Figure shows the distribution of the PDSI for the sub-Saharan region for the 1946–2005 period and its evolution over the decades. A value of 0 refers to a 'normal' climate, a value of +0.04 to an 'extremely dry' climate, and a value of −0.04 to an 'extremely wet' climate.

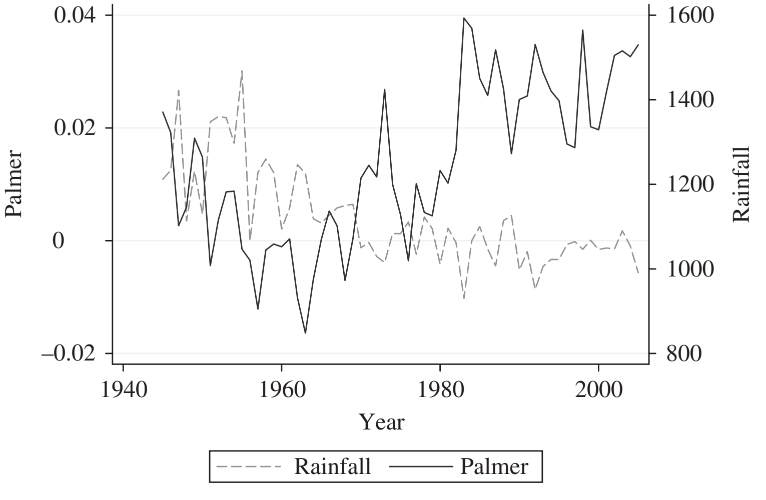

Fig. B3. *PDSI and Rainfall*

Notes. This Figure plots the evolution of the PDSI and rainfall for sub-Saharan African countries (yearly averages over countries). See Appendix D for more details on the data.

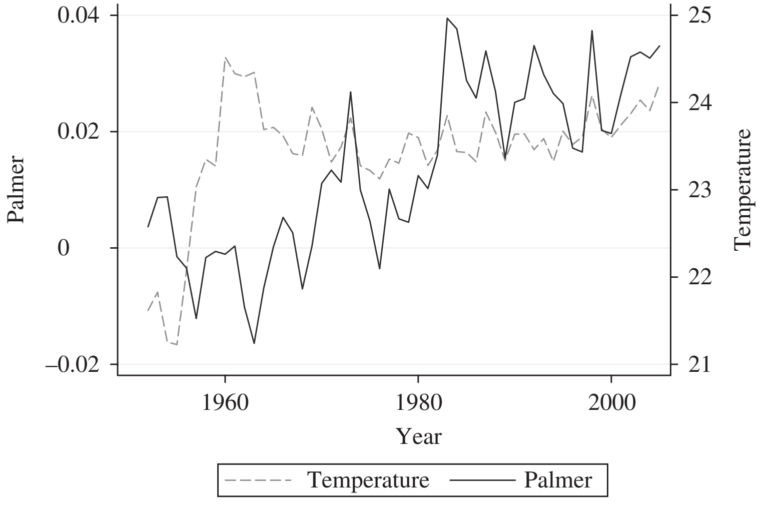

Fig. B4. *PDSI and Temperature*

Notes. This Figure plots the evolution of the PDSI and temperature for sub-Saharan African countries (yearly averages over countries). See Appendix D for more details on the data.

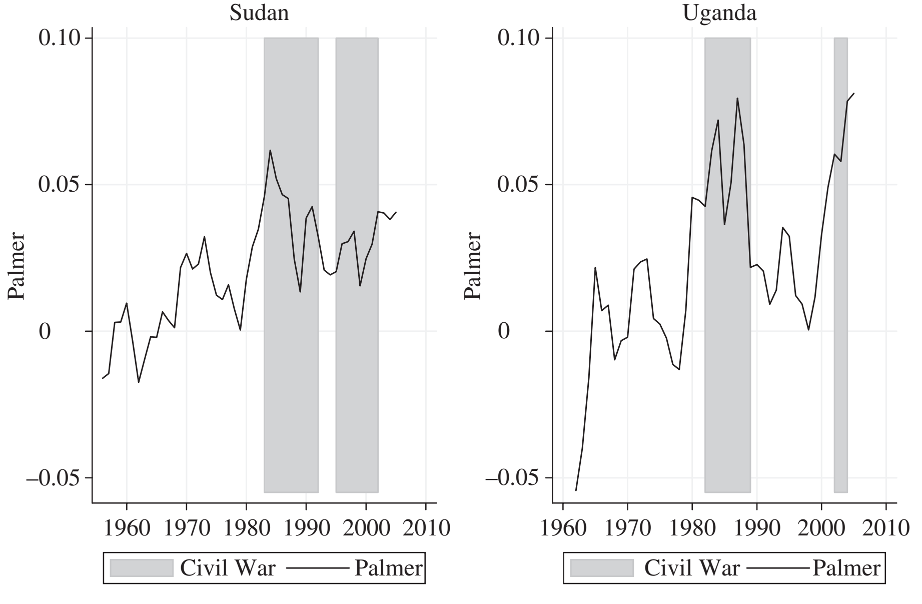

Fig. B5. *Time Series of PDSI and Civil Wars for Sudan and Uganda*

Notes. The grey areas correspond to the years of civil war from the UCDP/PRIO Armed Conflict Dataset v4-2011 over the 1945–2005 period. Only internal civil wars are included. The *y*-axis reports the PDSI values. The black line describes the evolution of the PDSI.

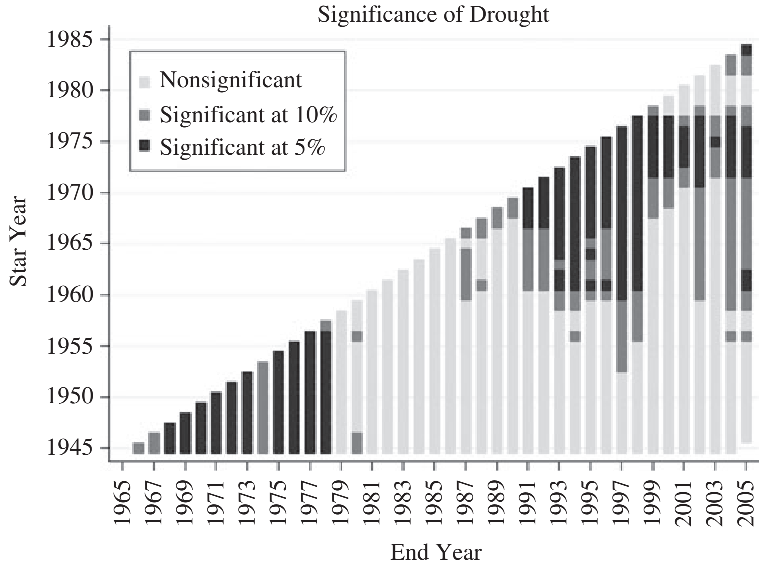

Fig. B6. *Drought Effect with Different Time Frame*

Notes. The Figure provides (re-)estimates of our baseline specification (Table 3, column (3)) for all possible time intervals of a minimum of 20 consecutive years (i.e. 861 estimates). Each square illustrates the degree of significance of the coefficient of the PDSI ($\hat{\beta}$) for every possible start and end year in the time scale. The Figure describes the degree of significance of the estimated coefficient of the PDSI (whether non-significant, significant at 10% or significant at the 5% level of confidence).

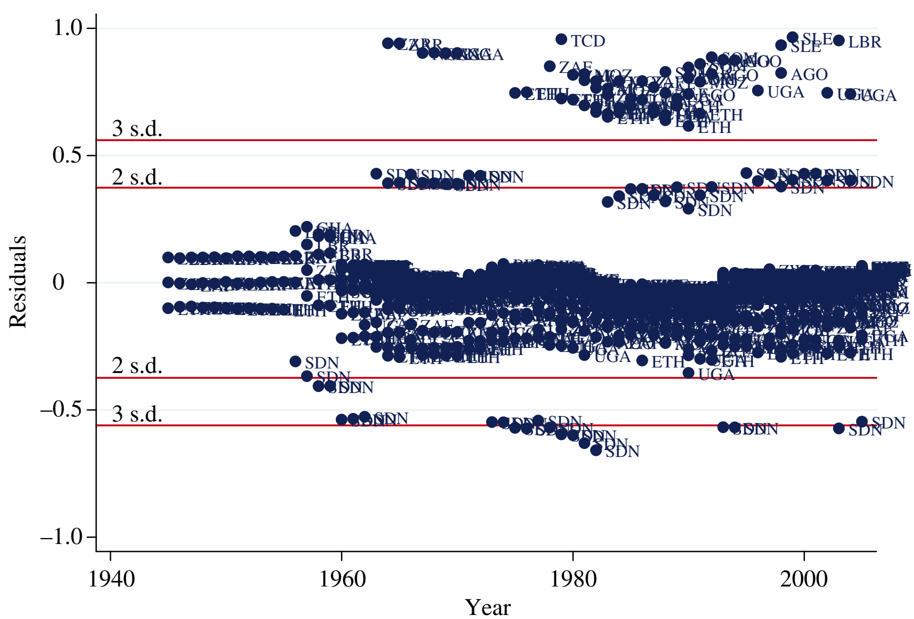

Fig. B7. *Outliers*

Notes. This Figure reports two-sigma outliers or three-sigma outliers computed thanks to Table 3, column (3).

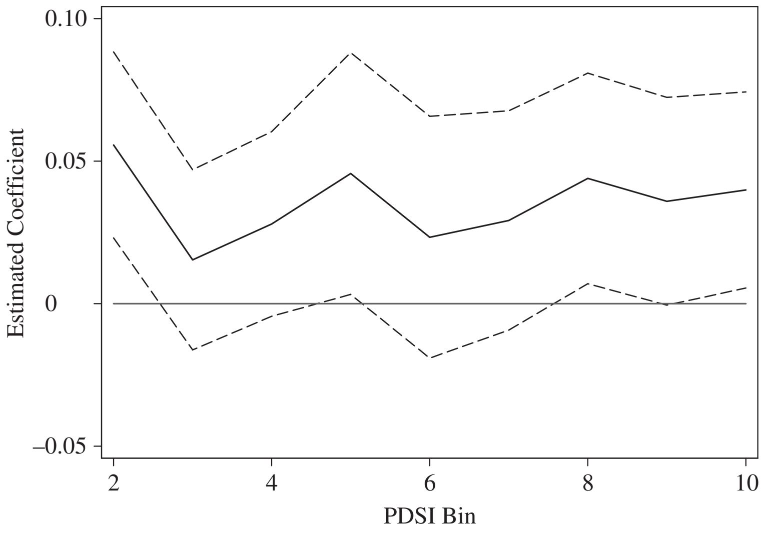

Fig. B8. *Non-linear Effect of PDSI*

Notes. We follow the same methodology as Deschênes and Greenstone (2011) and compute ten deciles of the PDSI (bin 1 is the reference). We estimate (3) with country fixed effects and year fixed effects. We plot the coefficient of each bin (black line) and two standards errors (dashed lines). Bins 4, 5, 8, 9 and 10 are significant at (at least) 10%.

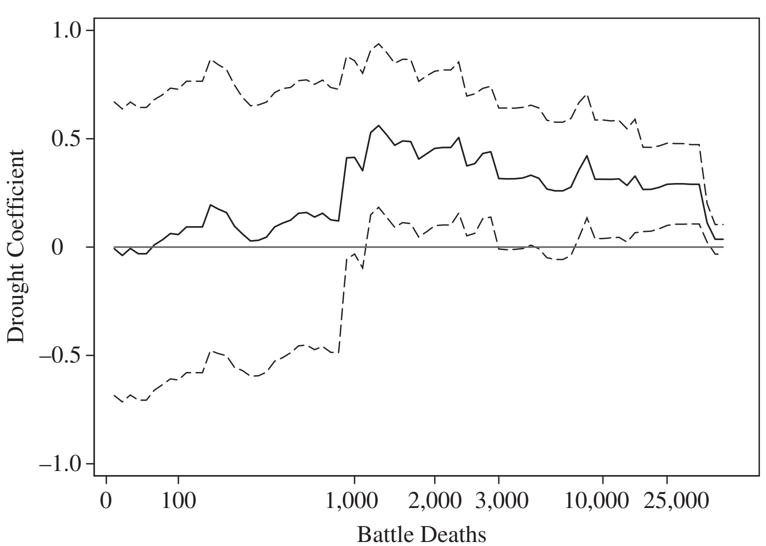

Fig. B9. *Drought Effect and Intensity*

Notes. We re-code our dependent variable War_{it} for each threshold between 25 and 200,000 battle-related deaths per year and re-estimate our baseline specification (Table 3, column (3)). The Figure reports the value of the estimated coefficient of the PDSI at the 5% confidence interval (dashed lines).

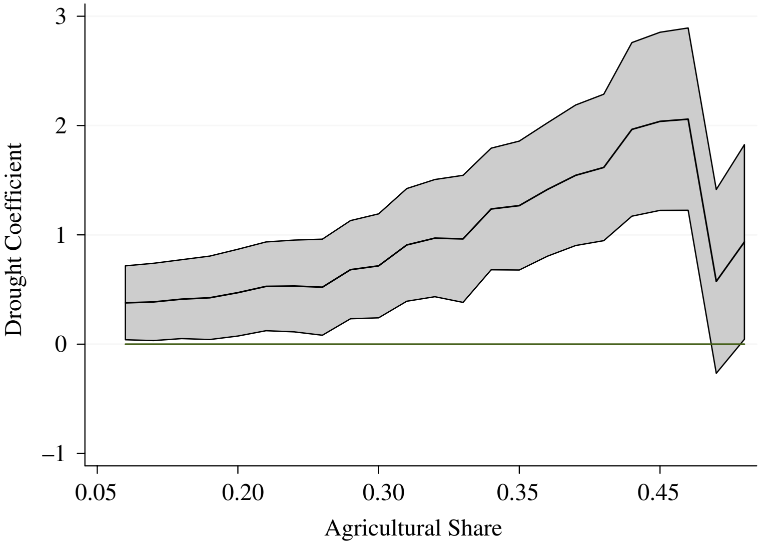

Fig. B10. *Split with Agricultural Share*

Notes. This Figure reports coefficient estimates of (3) that include country fixed effects and year fixed effects. The equation is re-estimated for each sub-sample where the country with the lowest value of agricultural share in 1965 is excluded and where countries are excluded with respect to increasing values of agricultural share in 1965. We report the values of the effect of the PDSI on civil war (black line) and we report the 95% confidence interval (grey area).

Fig. B11. *Split with GDP Per Capita*

Notes. This Figure reports coefficient estimates of (3) that include country fixed effects and year fixed effects. The equation is re-estimated for each sub-sample where the country with the lowest value of GDP per capita in 1965 is excluded and where countries are excluded with respect to increasing values of GDP per capita in 1965. We report the values of the effect of the PDSI on civil war (black line) and we report the 95% confidence interval (grey area).

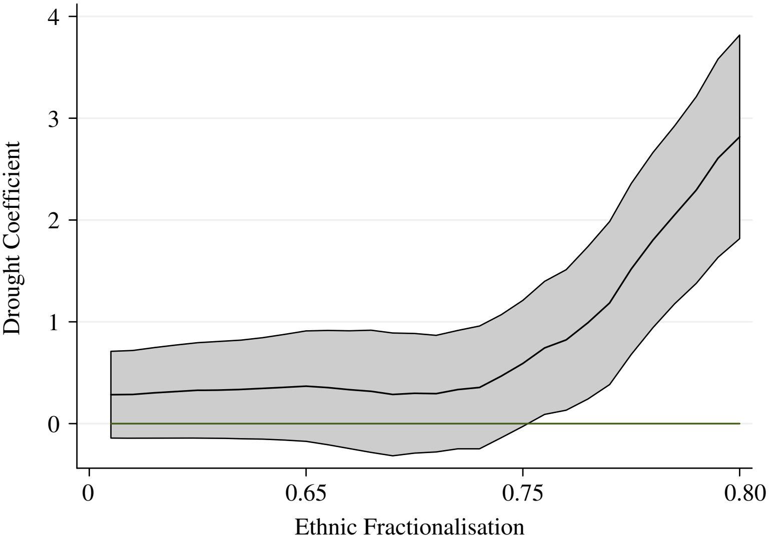

Fig. B12. *Split with Ethnic Fractionalisation*

Notes. This Figure reports coefficient estimates of (3) that include country fixed effects and year fixed effects. The equation is re-estimated for each sub-sample where the country with the lowest value of ethnic fractionalisation is excluded and where countries are excluded with respect to increasing values of ethnic fractionalisation. We report the values of the effect of the PDSI on civil war (black line) and we report the 95% confidence interval (grey area).

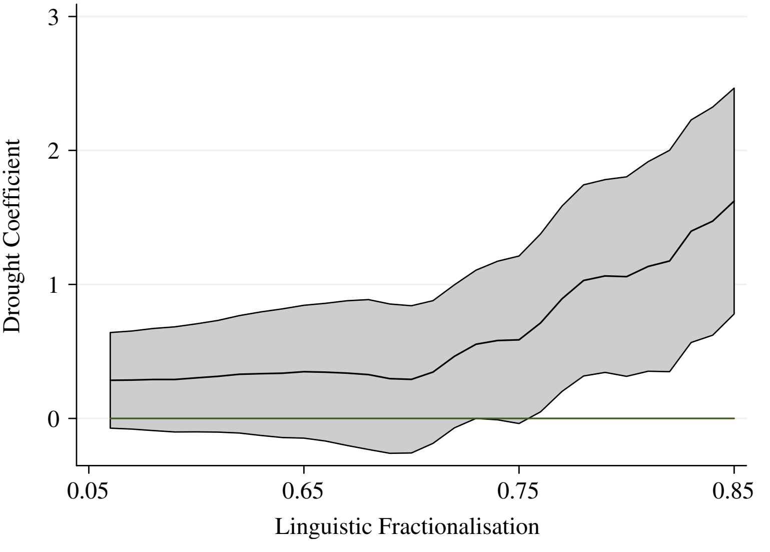

Fig. B13. *Split with Linguistic Fractionalisation*

Notes. This Figure reports coefficient estimates of (3) that include country fixed effects and year fixed effects. The equation is re-estimated for each sub-sample where the country with the lowest value of linguistic fractionalisation is excluded and where countries are excluded with respect to increasing values of linguistic fractionalisation. We report the values of the effect of the PDSI on civil war (black line) and we report the 95% confidence interval (grey area).

Appendix C. Summary of the Palmer Model

In this Appendix, we briefly present the way the PDSI is formulated (Palmer, 1965; Alley, 1984; Karl, 1986; Wells *et al.*, 2004, Dai, 2011*a*). Palmer considered monthly values of precipitation (P) and four other surface water fluxes: evapotranspiration (E) which is the return flow of water to the atmosphere, recharge to soils (R), runoff (RO) and water loss of the soil layers (L). He also considered the potential values of these four fluxes, namely PE, PR, PRO and PL, respectively (they depend on the available water capacity (AWC) of the soil, Thornthwaite, 1948). Palmer introduced the 'climatically appropriate for existing conditions' (CAFEC) potential values.

Evapotranspiration (E) in location i, year t and month m is computed as a function of monthly average temperatures with the Thornthwaite (1948) method:

$$E_{itm} = c_{it} \times T_{itm}^{a_{it}},$$

$$a_{it}, = 6.75 \times 10^{-7} I_{it}^3 - 7.71 \times 10^{-5} I_{it}^2 + 17.92 \times 10^{-3} I_{it} + 0.49239,$$

$$c_{it} = 1/I_{it},$$

$$I_{it} = \sum_{m=1,\ldots,12} \left(\frac{T_{itm}}{5}\right)^{1.514},$$

and the potential evapotranspiration in location i, year t and month m is:

$$PE_{itm} = 1.6 \left(\frac{10T_{itm}}{I_{it}}\right)^{a_{it}}.$$

Palmer considers a model with two layers, a surface layer s and an underlying layer u.

The moisture loss from the surface layer is:

$$LS_{itm} = \begin{cases} \min\left(S'_{itm}, PE_{itm} - P_{itm}\right) & \text{if } PE_{itm} > P_{itm} \\ 0 & \text{otherwise} \end{cases},$$

where S'_{itm} is the available moisture stored in the surface layer at the start of the month. There is no loss when potential evapotranspiration is lower than precipitation. When the difference between potential evapotranspiration and precipitation is greater than the stock, the entire moisture stock is lost. When the difference is smaller than the stock, the loss is equal to this difference.

The loss from the underlying layer is:

$$LU_{itm} = \begin{cases} \min\left\{U'_{imt}, [(PE_{itm} - P_{itm}) - LS_{itm}]\dfrac{U'_{imt}}{AWC_i}\right\} & \text{if } LS_{itm} = S_{itm}, \\ 0 \quad \text{otherwise,} & \end{cases}$$

where U'_{itm} is the available moisture stored in the underlying layer at the start of the month. There is some loss of moisture in the underlying layer only if the surface layer is empty, that is, if $LS_{itm} = S_{itm}$. In that case, the loss is either the entire stock, or the difference between potential evapotranspiration and precipitation (net of the moisture stock of the surface layer) times the stock of the underlying layer over the available water capacity of the soil (that depends on the depth of the 'effective root zone' and on the local characteristics. AWC_i is computed using Webb *et al.*'s (1993) computations for the global distributions of soil profile thickness, potential storage of water in the soil profile, potential storage of water in the root zone and potential storage of water derived from the soil texture. The moisture recharge, R_{itm}, is defined in a symmetric (complementary) way to the moisture loss.

The runoff, RO_{itm} is the excess of precipitation relatively to the available capacity of the soil,

$$RO_{itm} = \min(P_{itm} - AWC_i, 0).$$

The potential recharge is defined as:

$$PR_{itm} = AWC_i - S'_{itm} - U'_{imt},$$

that is the available water capacity minus the moisture stocks of the two layers.

The potential loss is the maximum possible loss, that is, the moisture loss when the precipitation level is set to 0:

$$PL_{itm} = PLS_{itm} + PLU_{itm},$$

where

$$PLS_{itm} = \min(S_{itm}, PE_{itm}),$$

and,

$$PLU_{itm} = \min\left[U_{imt}, (PE_{itm} - PLS_{itm})\frac{U'_{imt}}{AWC_i}\right].$$

The potential runoff is the difference between the potential precipitation and the potential recharge. Palmer assumed that the potential precipitation is equal to the AWC and then:

$$PRO_{itm} = S'_{itm} + U'_{imt}.$$

Given a specific month m, he defined the water-balance coefficients and they are computed as follows:

$$\alpha_{im} = \frac{\bar{E}_{im}}{\overline{PE}_{im}}, \quad \beta_{im} = \frac{\bar{R}_{im}}{\overline{PR}_{im}}, \quad \gamma_{im} = \frac{\overline{RO}_{im}}{\overline{PRO}_{im}}, \quad \delta_{im} = \frac{\bar{L}_{im}}{\overline{PL}_{im}},$$

where the upper-bar indicates that values where averaged over the calibration period (1950–79). These ratios measure the ratio of the long-term mean values of a water flux and its potential value.

The CAFEC value is the potential value of a water flux times its calibrated ratio (e.g. $\alpha_{im} \times PE_{itm}$ is the CAFEC value of evapotranspiration). The CAFEC precipitation ($\hat{P}$) is the amount of precipitation needed to maintain a normal soil moisture level for a single month and it is computed as follows (location i, year t, month m):

$$\hat{P}_{itm} = \alpha_{im}PE_{itm} + \beta_{im}PR_{itm} + \gamma_{im}PRO_{itm} - \delta_{im}PL_{itm}.$$

The excess of precipitation or the moisture departure, d, is the difference between the actual precipitation in a specific month and the CAFEC precipitation:

$$d_{itm} = P_{itm} - \hat{P}_{itm}.$$

In order to make the moisture departure comparable in time and space, it is weighted using a factor K, which is a general approximation for the climate characteristics of a location.

$$K'_{im} = 1.5\log\left(\frac{L_{im} + 2.8}{\bar{d}_{im}}\right) + 0.5$$

where $\bar{d}_{im}$ and $\bar{P}_{im}$ are values averaged over the years; they are the average moisture precipitation and the average precipitation for a location in a specific month. L_{im} is a measure of the ratio of 'moisture demand' to 'moisture supply' in location i for month i:

$$L_{im} = \frac{\overline{PE}_{im} + \bar{R}_{im} + \overline{RO}_{im}}{\bar{P}_{im} + \bar{L}_{im}},$$

$$K_{im} = \frac{17.67}{\sum\limits_{j=1,\ldots,12} \bar{d}_{jm} K'_{jm}} K'_{im},$$

where 17.67 is an empirical constant derived from data from the US. Furthermore, Palmer defined the moisture anomaly index Z:

$$Z_{itm} = K_{im} d_{itm}.$$

This value is used in the recursive formula of the PDSI.

Appendix D. Data Description

D.1. *PDSI Data*

The source for the PDSI data is Dai *et al.* (2004) extended to 2005. The inputs to PDSI data are precipitation and temperature time series over all months and climatological maps of the AWC of the soil at a given grid cell (2.5° × 2.5°). As in Burke *et al.* (2009), the climate data are weather station data. The source of surface air temperature data is the Climate Research Unit (Jones and Moberg, 2003) and the source of precipitation data is the National Centers for Environmental Prediction (Chen *et al.*, 2002). The AWC of the soil is computed using Webb *et al.* (1993) computations for the global distributions of soil profile thickness, potential storage of water in the soil profile, potential storage of water in the root zone and potential storage of water derived from soil texture; see Webb *et al.* (1993) for a complete description.[33]

D.1.1. *Accuracy of the data*

We provide some information regarding the accuracy of precipitation and temperature data inputs for the PDSI. Brohan *et al.* (2006) report three categories of usual potential errors: station error (the uncertainty of individual station anomalies), sampling error (the uncertainty in a grid box mean caused by estimating the mean from a small number of point values) and the bias error (the uncertainty in large-scale temperatures caused by systematic changes in measurement methods). The Climate Research Unit (CRU) surface air temperature data set has been created by gridding data (0.5° × 0.5° grid cells) from 5,159 stations. The estimates of accuracy reported by the CRU[34] indicate that the annual values have been approximately accurate to ±0.05°C (two standard deviations) since 1951. They also report that the accuracy is four times less accurate for the 1850s and improves gradually up to 1950. Our analysis covers the period after independence for each country, thus covering the period with the highest accuracy. The National Centres for Environmental Prediction (NCEP) precipitation from Chen *et al.* (2002) is based on a previous version by Dai *et al.* (1997) who report a 10% sampling error estimate in well-covered regions (in terms of the number of stations) including the Sahel

[33] They computed these values by using: (*i*) the data set of soil horizon thicknesses and textures, the Food and Agriculture Organization of the United Nations/United Nations Educational, Scientific and Cultural Organization (FAO/UNESCO) Soil Map of the World (includes the top and bottom depths and the percent abundance of sand, silt and clay of individual soil horizons in each of the 106 soil types cataloged or nine continental divisions); (*ii*) the World Soil Data File (Zobler, 1986) and (*iii*) the Matthews (1983) global vegetation data set and texture-based estimates of available soil moisture. Data on soil characteristics are available at: http://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=548.

[34] Available at: http://www.cru.uea.ac.uk/cru/data/temperature/, accessed in June 2012.

and southern Africa, whereas the sampling error is as high as 45% in poorly covered areas. They argue that the data need correction for station error and bias error in high-latitude stations. Thus, potential errors in gauge records are relatively limited in our context.

D.1.2. *Descriptive statistics*

The inputs of the Palmer index are temperature, precipitation and the available water capacity of the soil. This contrasts with previous studies that looked at the impact of precipitation and/or temperature on the risk of conflict (Miguel *et al.* 2004; Burke *et al.*, 2009). Time series show that PDSI and rainfall generally vary in opposite directions (see Figure B3) and that PDSI and temperature generally vary in the same direction (see Figure B4). Rainfall (with lags) explains 50% of the PDSI variation[35] and 70%–85% of the within-country PDSI variation.[36] Temperature (with lags) explain 60% of the PDSI variation[37] and 50%–80% of the within-country PDSI variation.[38] Temperature and rainfall together explain 60% of the PDSI variation[39] and 70%–90% of the within-country PDSI variation.[40] This is consistent with the theoretical formula of the PDSI, which is based on precipitation, temperature and the available water content of the soil. Notice that consistent with the Palmer model, we find that rainfall decreases the PDSI but less so during hot years (see Table B5).[41]

D.2. *Civil War Data*

We use the latest UCDP/PRIO Armed Conflict Dataset (v4-2011), over the 1946–2005 period,[42] The UCDP/PRIO database includes two categories of civil conflict: internal and internationalised armed conflict. An *internationalised* civil armed conflict occurs between the government of a state and one or more internal opposition group(s) with intervention from other states. An *internal* civil armed conflict occurs between the government of a state and one or more internal opposition group(s) without intervention from other states. We follow Jensen and Gleditsch (2009) who point out that internationalised civil armed conflicts should not be included in the analysis[43] and focus on internal conflicts.

The question about the inclusion or exclusion of anti-colonial civil wars in the analysis is recurrent in the literature. The first way to code the data is to consider Ivory Coast as a single 'state' for the whole 1946–2005 period (in fact it was part of the French empire from 1895 to independence in 1960). 'States' that did not exist (such as 'Ivory Coast' from 1946 to 1960) are considered and the colonial empires are ignored. The second strategy is to consider colonial empires. For instance, Ivory Coast and Cameroon are categorised as belonging to the French empire before they gained independence (in 1960). Considering colonial empires requires the construction of explanatory variables for whole empires. Fearon and Laitin (2003) conclude that, although possible, it would be very problematic to code variables such as GDP, ethnic fractionalisation and democracy score. Also, in our context it makes little sense to assign a

[35] Estimates not reported here.
[36] We run several regressions of the PDSI on rainfall and temperature with some lags (and we use two data sources: the first one is the same as Hsiang *et al.*, 2011 and the second one is the same as Ciccone, 2011). See columns (1)–(6) in Table B3.
[37] Estimates not reported here.
[38] See columns (7)–(12) in Table B3.
[39] Estimates not reported here.
[40] See Table B4.
[41] We find that rainfall decreases the PDSI and the interaction term between rainfall and temperature has a positive effect.
[42] Available at: http://www.pcr.uu.se/research/ucdp/datasets/ucdp_prio_armed_conflict _dataset/.
[43] They show that the estimated effect of economic growth on civil war is reduced compared to Miguel *et al.*'s (2004) findings. They argue that according to Fearon and Laitin (2003), negative economic shocks should decrease the capacity of governments to send troops to civil wars in other states.

climate value to a whole colonial empire. For instance, it would be meaningless to assign the PDSI value of the French metropole (coloniser) to French colonies (such as Ivory Coast and Cameroon), or to assign the value of the PDSI averaged over the whole French empire to French colonies.

D.3. *Political Variables*

Our measure of democratic institutions is the revised combined Polity core (Polity2) of the Polity IV database (Marshall and Jaggers, 2005). We follow Brückner and Ciccone (2011) for the definition of the variables. ΔPolity captures the variation of the polity score from t to $t + 1$. A positive score means an improvement in democracy. ΔExecutive Recruitment is the variation of the executive recruitment from t to $t + 1$. A positive score means an improvement. ΔPolitical Competition is the variation of the political competition from t to $t + 1$. A positive score means an improvement. Δ Executive Constraint is the variation of the executive constraint from t to $t + 1$. A positive score means an improvement. Coup is a dummy equal to 1 if there was a coup in a country at time t. Coup in Democracy is a dummy equal to 1 if there was a coup in a democratic country at time t. Democratic Transition is a dummy coded 1 if a country was non-democratic at time t, but democratic at time $t + 1$. Autocratic Transition is a dummy coded 1 if a country was democratic at time t and non-democratic at time $t + 1$. Democratisation Step is a dummy coded 1 if the country was upgraded to either a partial or full democracy between t and $t + 1$.

D.4. *Other Climate Variables*

In the body of the article, we refer to alternative climate variables regarding temperature and rainfall as being the same as in Hsiang *et al.* (2011) or Ciccone (2011). The source of Hsiang *et al.*'s (2011) rainfall data is the Climate Prediction Center (CPC) (Xie and Arkin, 1996) and the source of their temperature data is the NOAA NCEP-NCAR Climate Data Assimilation System I (Kalnay *et al.*, 1996). Their data are available at: http://www.solomonhsiang.com/computing/data.

For rainfall, we also use Ciccone's (2011) data. The source is the Combined Precipitation Dataset of NASA's Global Precipitation Climatology Project (GPCP) version 2.1 (Huffman and Bolvin, 2009) and their temperature data come from Buhaug *et al.* (2010) who use data from the University of Delaware. These rainfall and temperature data are available at: http://www.aeaweb.org/aej/app/data/2010-0064_data.zip.

Rainfall data are completed thanks to data from Tyndall Centre for Climate Change Research when data from 1945 are needed.

D.5. *Other Outcome Variables and Country Characteristics*

Our Cereal Yield variable is obtained from the Food and Agricultural Organization (FAO) and the source of Agricultural Income/cap data is the United Nations Accounts database (same data as in Hsiang *et al.*, 2011). The GDP/cap, GDP Growth and Government Consumption Share variables are obtained from Penn World Table 7.0. The source of Government Consumption Expenditure data is the World Bank (World Development Indicator). The source of demographic data is the World Bank (World Development Indicator). Ethnic Fractionalisation, Linguistic Fractionalisation and % Mountainous Terrain are obtained from Fearon and Laitin (2003).

University of Lausanne
INRA-LAMETA

Submitted: 09 January 2012
Accepted: 01 March 2013

References

Alley, W. (1984). 'The Palmer Drought Severity Index: limitations and assumptions', *Journal of Applied Meteorology and Climatology*, vol. 23(7), pp. 1100–9.

Angrist, J.D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton, NJ: Princeton University Press.

Barrios, S., Bertinelli, L. and Strobl, E. (2010). 'Trends in rainfall and economic growth in Africa: a neglected cause of the African growth tragedy', *Review of Economics and Statistics*, vol. 92(2), pp. 350–66.

Bates, R.H. (1986). 'Modernization, ethnic competition, and the rationality of politics in contemporary Africa', in (M.E. Doro and N.M. Schultz, eds.), *Governing Black Africa*, pp. 152–71, New York and London: Africana Publishing Company.

Blattman, C. and Miguel, E. (2010). 'Civil war', *Journal of Economic Literature*, vol. 48(1), pp. 3–57.

Brohan, P., Kennedy, J.J., Harris, I., Tett, S.F.B. and Jones, P.D. (2006). 'Uncertainty estimates in regional and global observed temperature changes: a new data set from 1850', *Journal of Geophysical Research*, vol. 111 (D12), pp. 2156–202.

Buhaug, H. (2010). 'Climate not to blame for African civil wars', *Proceedings of the National Academy of Sciences*, vol. 107(38), pp. 16477–82.

Buhaug, H., Hegre, H. and Strand, H. (2010). 'Sensitivity analysis of climate variability and civil war', PRIO Paper, Centre for the Study of Civil War, Peace Research Institute Oslo, PRIO.

Burke, M.B., Miguel, E., Satyanath, S., Dykema, J.A. and Lobell, D.B. (2009). 'Warming increases the risk of civil war in Africa', *Proceedings of the National Academy of Sciences*, vol. 106(37), pp. 20670–4.

Burke, M., Dykema, J., Lobell, D., Miguel, E. and Satyanath, S. (2010*a*). 'Climate and civil war: is the relationship robust?', NBER Working Paper 16440.

Burke, M., Dykema, J., Lobell, D., Miguel, E. and Satyanath, S.(2010*b*). 'Climate robustly linked to African civil war', *Proceedings of the National Academy of Sciences*, vol. 107(51), pp. E185.

Brückner, M. and Ciccone, A. (2011). 'Rain and the democratic window of opportunity', *Econometrica*, vol. 79 (3), pp. 923–47.

Cameron, C., Gelbach, J. and Miller, D. (2011). 'Robust inference with multi-way clustering', *Journal of Business and Economic Statistics*, vol. 29(2), pp. 238–49.

Chen, M., Xie, P., Janowiak, J.E. and Arkin, P.A. (2002). 'Global land precipitation: a 50-yr monthly analysis based on gauge observations', *Journal of Hydrometeorology*, vol. 3(3), pp. 249–66.

Collier, P. and Hoeffler, A. (1998). 'On economic causes of civil war', *Oxford Economic Papers*, vol. 50(4), pp. 563–73.

Collier, P. and Hoeffler, A. (2004). 'Greed and grievance in civil war', *Oxford Economic Papers*, vol. 56(4), pp. 563–95.

Conley, T. (1999). 'GMM estimation with cross sectional dependence', *Journal of Econometrics*, vol. 92, pp. 1–45.

Conley, T. (2008). 'Spatial econometrics', in (S.N. Durlauf and L.E. Blume, eds.), *New Palgrave Dictionary of Economics*, pp. 741–7, New York: Palgrave Macmillan.

Ciccone, A. (2011). 'Economic shocks and civil conflict: a comment', *American Economic Journal: Applied Economics*, vol. 3(4), pp. 215–27.

Dai, A., Fung, I.Y. and Del Genio, A.D. (1997). 'Surface observed global land precipitation variations during 1900–1988', *Journal of Climate*, vol. 10(11), pp. 2943–62.

Dai, A., Trenberth, K.E. and Qian, T. (2004). 'A global data set of Palmer Drought Severity Index for 1870–2002: relationship with soil moisture and effects of surface warming', *Journal of Hydrometeorology*, vol. 5(6), pp. 1117–30.

Dai, A. (2011*a*). 'Characteristics and trends in various forms of the Palmer Drought Severity Index during 1900–2008', *Journal of Geophysical Research*, vol. 116(D12), pp. 2156–202.

Dai, A. (2011*b*). 'Drought under global warming: a review', *Wiley Interdisciplinary Reviews: Climate Change*, vol. 2 (1), pp. 45–65.

Davis, B., Winters, P., Carletto, G., Covarrubias, K., Quinones, E., Zezza, A., Stamoulis, K., Bonomi, G. and DiGiuseppe, S. (2007). 'Rural income generating activities; a cross country comparison', Working Paper 07-16, Agricultural and Development Economics Division of the Food and Agriculture Organization of the United Nations (FAO - ESA).

Dell, M., Jones, B. and Olken, B. (2012). 'Temperature shocks and economic growth: evidence from the last half century', *American Economic Journal: Macroeconomics*, vol. 4(3), pp. 66–95.

Deschênes, O. and Greenstone, M. (2011). 'Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US', *American Economic Journal: Applied Economics*, vol. 3(4), pp. 152–85.

Easterly, W. and Levine, R. (1997). 'Africa's growth tragedy: policies and ethnic divisions', *Quarterly Journal of Economics*, vol. 112(4), pp. 1203–50.

Esteban, J., Mayoral, L. and Ray, D. (2012*a*). 'Ethnicity and conflict: an empirical investigation', *American Economic Review*, vol. 102(4), pp. 1310–42.

Esteban, J., Mayoral, L. and Ray, D. (2012*b*). 'Ethnicity and conflict: theory and facts', *Science*, vol. 336, pp. 858–65.

Faris, S. (2009). *Forecast: The Surprising–and Immediate–Consequences of Climate Change*, New York: Holt Paperbacks, Henry Holt and Company.

Fearon, J. D. (2006). 'Ethnic mobilization and ethnic violence', in(B.R. Weingast and D.A. Wittman, eds.), *The Oxford Handbook of Political Economy*, pp. 852–68, Oxford and New York: Oxford University Press.

Fearon, J.D. and Laitin, D.D. (2003). 'Ethnicity, insurgency, and civil war', *American Political Science Review*, vol. 97(1), pp. 75–90.

Gellner, E. (1983). *Nations and Nationalism*, Ithaca and London: Cornell University Press.

Granger, C.W.J. and Newbold, P. (1974). 'Spurious regressions in econometrics', *Journal of Econometrics*, vol. 2 (2), pp. 111–20.

Harari, M. and La Ferrara, E. (2012). 'Conflict, climate and cells: a disaggregated analysis', Working Paper no. 461, IGIER.

Horowitz, D.L. (1985). *Ethnic Groups in Conflict*, Berkeley, CA and London: University of California Press.

Hsiang, S.M. (2010). 'Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America', *Proceedings of the National Academy of Sciences*, vol. 107(35), pp. 15367–72.

Hsiang, S.M., Meng, K.C. and Cane, M.A. (2011). 'Civil conflicts are associated with the global climate', *Nature*, vol. 476(7361), pp. 438–41.

Huffman, G.J. and Bolvin, D. (2009). 'GPCP version 2.1, combined precipitation data set documentation', Laboratory for Atmospheres, NASA Goddard Space Flight Center and Science Systems and Applications, http://precip.gsfc.nasa.gov/pub/gpcp-v2.1_comb_new.html (last accessed: December 2012).

Jensen, P.S. and Gleditsch, K.S. (2009). 'Rain, growth, and civil war: the importance of location', *Defence and Peace Economics*, vol. 20(5), pp. 359–72.

Jones, B. and Olken, B. (2010). 'Climate shocks and exports', *American Economic Review Papers and Proceedings*, vol. 100(2), pp. 454–9.

Jones, P.D. and Moberg, A. (2003). 'Hemispheric and large-scale surface air temperature variations: an extensive revision and an update to 2001', *Journal of Climate*, vol. 16(2), pp. 206–23.

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Leetmaa, A.., Reynolds, R., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K.C., Ropelewski, C., Wang, J., Jenne, R. and Joseph, D.(1996). 'The NCEP/NCAR 40-year reanalysis project', *Bulletin of the American Meteorological Society*, vol. 77(3), pp. 437–71.

Karl, T.R. (1986). 'The sensitivity of the Palmer Drought Severity Index and Palmer's Z-index to their calibration coefficients including potential evapotranspiration', *Journal of Climate and Applied Meteorology*, vol. 25(1), pp. 77–86.

Levy, M.A., Thorkelson, C., Vörösmarty, C., Douglas, E. and Humphreys, M. (2005). 'Freshwater availability anomalies and outbreak of internal war: results from a global spatial time series analysis', Paper presented at the annual meeting of the International Studies Association, San Diego, CA.

Lyon, B. and Barnston, A.G. (2005). 'ENSO and the spatial extent of interannual precipitation extremes in tropical land areas', *Journal of Climate*, vol. 18(23), pp. 5095–109.

Marshall, M. and Jaggers, K. (2005). *Polity IV Project: Dataset Users' Manual*. Fairfax, VA: Center for Global Policy, George Mason University (www.cidcm.umd.edu/polity).

Matthews, E. (1983). 'Global vegetation and land use: new high-resolution data bases for climate studies', *Journal of Climate and Applied Meteorology*, vol. 22(3), pp. 474–87.

Miguel, E. and Satyanath, S. (2011). 'Re-examining economic shocks and civil conflict', *American Economic Journal: Applied Economics*, vol. 3(4), pp. 228–32.

Miguel, E., Satyanath, S. and Sergenti, E. (2004). 'Economic shocks and civil conflict: an instrumental variables approach', *Journal of Political Economy*, vol. 112(4), pp. 725–53.

Palmer, W. (1965). 'Meteorological drought', Research Paper 45, US Department of Commerce.

Schlenker, W. and Roberts, M.J. (2006). 'Nonlinear effects of weather on corn yields', *Review of Agricultural Economics*, vol. 28(3), pp. 391–8.

Schlenker, W. and Lobell, D.B. (2010). 'Robust negative impacts of climate change on African agriculture', *Environmental Research Letters*, vol. 5(1), pp. 4313–5.

Thornthwaite, C.W. (1948). 'An approach toward a rational classification of climate', *Geographical Review*, vol. 38(1), pp. 55–94.

Vicente-Serrano, S.M., Begueria, S. and Lopez-Moreno, J.I. (2010*a*). 'A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index', *Journal of Climate*, vol. 23(7), pp. 1696–718.

Vicente-Serrano, S.M., Begueria, S., Lopez-Moreno, J.I., Angulo, M. and El Kenawy, A. (2010*b*). 'A new global 0.5 degrees gridded dataset (1901–2006) of a multiscalar drought index: comparison with current drought index datasets based on the Palmer Drought Severity Index', *Journal of Hydrometeorology*, vol. 11 (4), pp. 1033–43.

Webb, R.S., Rosenzweig, C.E. and Levine, E.R. (1993). 'Specifying land surface characteristics in general circulation models: soil profile data set and derived water-holding capacities', *Global Biogeochemical Cycles*, vol. 7(1), pp. 97–108.

Wells, N., Goddard, S. and Hayes, M.J. (2004). 'A self-calibrating Palmer Drought Severity Index', *Journal of Climate*, vol. 17(12), pp. 2335–51.

Wooldridge, J. (2002). *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press.

Xie, P. and Arkin, P.A. (1996). 'Analyses of global monthly precipitation using gauge observations, satellite estimates, and numerical model predictions', *Journal of Climate*, vol. 9(4), pp. 840–58.

Zivin, J.G. and Neidell, M.J. (2010). 'Temperature and the allocation of time: implications for climate change', NBER Working Paper 15717.

Zobler, L. (1986). 'A world soil file for global climate modelling', NASA Technical Memorandum 87802. NASA Goddard Institute for Space Studies, New York.