PRIO

Independent • International • Interdisciplinary

PRIO PAPER

Sensitivity Analysis of Climate Variability and Civil War

Halvard Buhaug, Håvard Hegre & Håvard Strand

Peace Research Institute Oslo (PRIO)

Peace Research Institute Oslo (PRIO)
PO Box 9229 Grønland, NO-0134 Oslo, Norway
Visiting Address: Hausmanns gate 7

Centre for the Study of Civil War (CSCW)
Peace Research Institute Oslo (PRIO)
PO Box 9229 Grønland, NO-0134 Oslo, Norway
Visiting Address: Hausmanns gate 7

Design: Studio 7 www.studiosju.no
ISBN: 978-82-7288-367-5

Image: iStock.

Sensitivity Analysis of Climate Variability and Civil War

Halvard Buhaug, Håvard Hegre & Håvard Strand

Centre for the Study of Civil War
Peace Research Institute Oslo, PRIO
P.O. Box 9229 Grønland
NO-0134 Oslo, NORWAY

Version: 17 November 2010

Halvard Buhaug is corresponding author: halvardb@prio.no. Research on this paper has been carried out with financial support from the Research Council of Norway. This study is part of a larger PRIO-based project on "Security Implications of Climate Change", see http://www.prio.no/cscw/sicc.

ISBN: 978-82-7288-367-5

Introduction

Burke et al. (2009) report that warming is robustly linked to civil war in Sub-Saharan Africa (SSA). Their analysis builds on an earlier article by some of the same authors that found negative rainfall deviation to increase civil war risk through its adverse impact on economic growth (Miguel, Satyanath & Sergenti, 2004). Although the most recent article departs from the original's instrumental variable approach and its non-result for rainfall undermines the earlier conclusion, both studies deserve credit for addressing an under-researched area and for innovative use of meteorological data in conflict research. Moreover, their conclusion seems to corroborate widespread notions about a powerful connection between environmental degradation and armed conflict.

A crucial question remains, however; is the reported link between temperature and civil war robust? A recent study by Buhaug (2010) addresses this question by conducting two complementary tests: adjusting the model specification and using alternative measures of climate variability and civil war. The claimed finding passed neither of these tests. This paper documents a wider set of sensitivity tests that provide further proof of the empirical disconnect between climate variability and civil war outbreak, incidence, and severity.[1]

Sensitivity of Baseline Model

Influence diagnostics

We start the sensitivity analysis by replicating Burke et al.'s Model 2, where current and last-year estimates of temperature and precipitation are regressed on major civil war incidence (baseline Model 1 in Table 1). The model is estimated through ordinary least squares (OLS) regression with country fixed effects and country-specific linear time trends. The positive and marginally significant effect for current-year temperature is reproduced. We also estimate a model without the climate variables, containing only the country dummies and linear trend terms (Model 2).

[1] Note that we only consider short-term effects of climate variability here, similar to Buhaug (2010), Burke et al. (2009), Miguel, Satyanath & Sergenti (2004), and others. A non-result in this analysis does not preclude the possibility that climate might be related to peace and security in other, more subtle ways.

Table 1. Baseline model and model without climate, 1981–2002

	(1) Baseline	(2) w/o climate
Temperature	0.043*	
	(0.022)	
Temperature $_{t-1}$	0.013	
	(0.023)	
Precipitation	-0.023	
	(0.052)	
Precipitation $_{t-1}$	0.025	
	(0.049)	
Intercept	-1.581*	1.168
	(0.854)	(.)
Country fixed effects	Yes	Yes
Country time trends	Yes	Yes
R^2	0.66	0.66
Civil war observations	98	98
Observations	889	889

Note: OLS regression estimates with country fixed effects and time trends; standard errors in parentheses. ** p<0.05, * p<0.1.

The dependent variable as operationalized by Burke et al. has 98 positive observations. Model 1, which is identical to Burke et al.'s Model 2, contains 84 variables, almost one covariate per conflict observation. This raises two interesting questions: How much extra information does each variable bring to the table, and, are there any observations that exercise undue influence on the outcome? The answer to the first question is not comforting. When the fixed effects and time trends are included, the temperature effect is already accounted for. In fact, in a regression model with temperature as the dependent variable the remaining variables (lagged temperature, country fixed effects, and linear time trends) explain 99.3% of the variation. A model with only lagged temperature on the right-hand side still explains 98.45% of the variation in temperature. And a model with fixed effects and trend terms only explains 99.23% of the variation. This is clear indication of prevalent multicollinearity structures in the data.

In a situation with few observations of interest, some observations are likely to exercise overly large influence on the regression line. Table 2 lists the six most influential cases in Model 1 based on the DFBETA statistic for temperature (current year). DFBETA measures the impact of each observation on the estimated effect of a covariate. A rule-of-thumb critical DFBETA value is $2/\sqrt{n}$. In our case, this amounts to 0.07; observations with higher values exert disproportionately large influence on the parameter coefficient. The far right column gives the coefficient for temperature if the given observation is dropped from Model 1 (recall that the original coefficient was 0.043). As we incrementally remove a few highly influential observations, the effect of temperature decreases dramatically. Since the fixed effects effectively control for average temperature in the period, it is not surprising that almost all of these observations are from years that were warmer than the country average.

Table 2. Influential observations

Country	Year	DFBETA	Temp	Temp (t-1)	Coef.
Guinea-Bissau	1998	0.410	27.9	27.3	0.034
Sierra Leone	1998	0.305	27.2	26.3	0.027
Chad	1990	0.280	27.5	26.2	0.020
Congo, Republic of	1998	0.245	25.3	24.7	0.015
Sudan	1994	0.189	27.2	27.5	0.010
Chad	1987	0.162	27.3	26.9	0.006

Removing the individual observations that are the clearest examples of a statistical link between temperature and conflict may not be warranted; it could be that these cases are important examples of how warming are causally related to civil war incidence. A closer look at these observations does not seem to support such an assumption, however.

The conflict in Guinea-Bissau was a serious conflict with wide-ranging implications, although the number of fatalities was rather modest in comparison with other consequences of the conflict. In fact, this case is wrongly coded as civil war in Burke et al.'s replication data as updated information has lead to a downgrading of this conflict in recent versions of the UCDP/PRIO Armed Conflict Dataset.[2] One of the more immediate sources of this conflict was the demand from Senegal that rogue officers in Guinea-Bissau's army should cease supporting Senegalese rebels. When President Veira tried to enforce a ban, he was ousted by the so-called Military Junta for the Consolidation of Democracy, Peace and Justice, whereupon Senegal and Guinea intervened on Veira's side and the conflict escalated.

Sierra Leone, 1998, is another case of large-scale foreign intervention. A joint coup by former rebels and military officers in 1997 replaced the government of Kabbah, in an attempt to avoid the demobilization demanded by the Abidjan agreement. The coup was opposed by a regional intervention force (ECOMOG), led by Nigeria. In January 1998, more than 10,000 professional soldiers were present in Sierra Leone. In March 1998, the Kabbah government was reinstalled.

The two observations in Chad, 1987 and 1990, are part of the same conflict. What makes the fatalities for these two years stand out is, apparently, the involvement of Libya and France. A highly fractionalized and utterly poor country, Chad has seen more or less continuous conflict for the last 45 years. Some years have peaked, such as 1980, 1987, 1990, and 2006, with Libya and France backing various and changing factions either financially or military. Epitomizing the role of foreign powers in Chad, the current president, Deby, was installed with the help of Libya and Sudan and has managed to hold on to power with the support of France.

The civil war observation in Congo in 1998 was also very much part of an ongoing conflict. In fact 1997 was the peak year in this conflict in terms of fatalities. While the conflict between the Ninjas, Cobras, and Coyotes had been going on for years, the escalation during the summer of 1997 led to international involvement from Angola and Chad, the latter possibly under the financial influence of France and Elf-Aquitaine. Several Angolan rebel movements had been based in Congo,

[2] Guinea-Bissau perfectly illustrates the uncertainty in how civil wars are coded (cf. footnote 5). The 1998 coup in Guinea-Bissau with the resulting armed conflict drove several hundred thousands of people away from their homes, and early estimates indicated that more than 1,500 people were killed. More recent estimates are closer to 500. Accordingly, this conflict has been recoded minor civil war (less than 1,000 annual deaths) in recent versions of the UCDP/PRIO Armed Conflict Dataset. Had Burke et al. (2009) used the latest update of the conflict data, this case would not be coded as a civil war and the parameter estimate for temperature would have been reduced by more than 20%.

and Angola saw this as an opportunity to remove that particular problem. Sudan, 1994, is the odd case on this list as this is an observation without civil war incidence (although the conflict is Southern Sudan caused at least 500 casualties that year according to the PRIO Battle Deaths dataset; Lacina & Gleditsch, 2005).

A common feature among all of these influential cases is an omitted variable: foreign intervention. The external dimension of the conflicts, which fail to be captured by the trend variables or the fixed effects dummies, is likely to have a significant bearing on civil war severity. Another apparent commonality between these cases is the scarcity of references to climate anomalies and loss of agricultural income in news reports and narratives of the conflicts.[3] It is unclear to us why the causal effect of temperature on civil war would depend on third-party intervention, as Table 2 suggests.

Civil war operationalization

Disregarding for now the issues raised above, we next turn to the operationalization of the dependent variable (DV). As pointed out by Buhaug (2010), Burke et al. (2009) apply a rather unusual definition of civil war, counting only the country years in which the number of battle-related deaths (BRD) crosses the 1,000 fatalities threshold. In some cases, this implies that the first year of civil war occurs several years after the conflict started (e.g., Sierra Leone 1998 vs. 1991); in other cases, civil wars enter and exit the dataset with little change in the underlying conflicts (e.g., Rwanda, whose two recent spells of conflict (1990–94 and 1997–2002) are coded as civil war in 1991–92, 1998, and 2001 only.[4]

Although the causal mechanisms are never fleshed out in detail, Burke et al. hint at an individualistic political economy explanation for the positive effect of temperature: higher temperatures depress rural incomes and lower the opportunity cost of joining a rebellion. This should lead to a higher number of rebels and, consequently, fiercer battles with government forces. Apparently, there should be hardly any time lag to this causal process; battlefield intensity reportedly goes up in the same calendar year as warming is recorded. If this reasoning is descriptive of a general pattern – if warming has a positive and measurable impact on the severity of ongoing conflicts – it should show up in our data also when we apply slightly different casualty thresholds for major civil war. Even more appropriate, however, would be to demonstrate that the annual rate of BRD goes up with higher temperatures.[5]

---

[3] C.f., the Uppsala Conflict Data Program's (UCDP) online conflict database, http://www.pcr.uu.se/research/ucdp/database/.

[4] Burke et al. also include an indicator of civil war onset. In their interpretation, Rwanda experienced a new civil war outbreak in 1991, 1998, and 2001. In all three instances, the ACD dataset (the source of their conflict variables) codes Rwanda in conflict in the previous year.

[5] One should also remember that the dependent variable is not measured without error. The data used in this paper, as well as in Burke et al. (2009) and most other recent civil war studies, are based on (various versions of) the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002; Harbom & Wallensteen, 2010). Behind this dataset is a contentious decision to err on the conservative side. If a conflict is listed as a war (at least 1,000 annual BRD), then the coders behind that decision is quite certain that the observation in question indeed qualifies as a 'war'. The fact that a conflict is not listed as a war does not necessarily imply that it wasn't. Hence, it is widely considered a good idea to verify the robustness of any analysis by using different levels of severity thresholds.

Table 3 includes five models with alternative DVs. The first model (3) is a replication of Model 1 above, the only modification is that the dependent variable (civil war with at least 1,000 BRD in year) is generated from the PRIO Battle Deaths Dataset v. 3.0 (Lacina & Gleditsch, 2005) rather than directly from the UCDP/PRIO Armed Conflict Dataset (Gleditsch et al., 2002). Due to slight differences in coding criteria (see Wischnath & Gleditsch 2010 for more on this) and aggregation method, the Battle Deaths data indicate a higher number of observations with the specified severity level than the ACD data (125 vs. 98); yet, the finding from Model 1 is reproduced where the coefficient for temperature (current year) is almost identical to the original result. Models 4–5 use alternative binary DVs where the minimum severity threshold for civil war is halved (500 BRD) and doubled (2,000 BRD), respectively. Finally, Models 6–7 use count and logged BRD counts as continuous DV. In all other respects, these models are identical to Model 1, including country fixed effects and linear time trends.

Table 3. Alternative civil war definitions and battle deaths data, 1981–2002

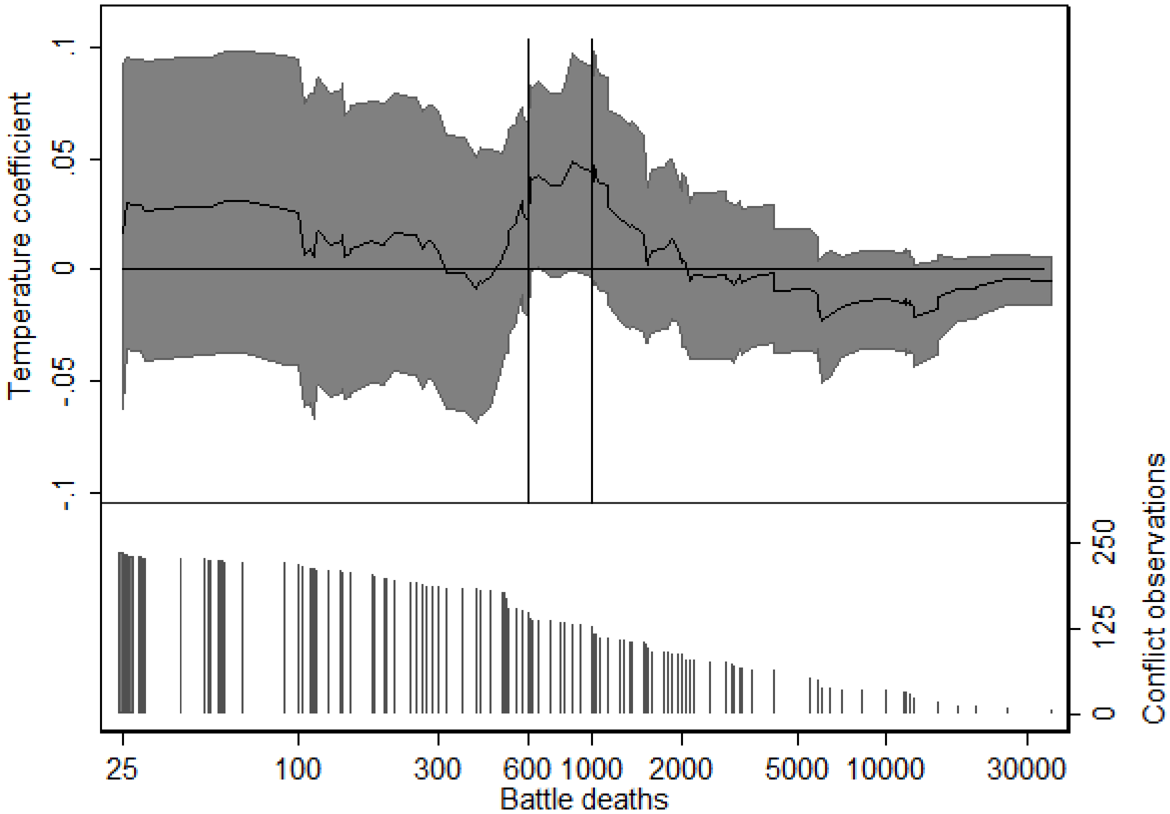
	(3) War years 1,000+	(4) War years 500+	(5) War years 2,000+	(6) BRD count	(7) BRD log
Temperature	0.044*	0.008	0.003	-248.4	0.113
	(0.024)	(0.024)	(0.017)	(261.4)	(0.222)
Temperature $_{t-1}$	0.010	-0.001	-0.008	-19.5	-0.120
	(0.031)	(0.035)	(0.023)	(268.7)	(0.218)
Precipitation	-0.010	0.048	-0.042	-380.5	0.692
	(0.070)	(0.072)	(0.057)	(690.6)	(0.503)
Precipitation $_{t-1}$	0.054	0.057	-0.052	-96.8	0.191
	(0.051)	(0.075)	(0.054)	(711.6)	(0.506)
Intercept	-1.619	-0.511	0.233	7,350.4	-3.066
	(1.214)	(1.445)	(0.777)	(13,695.7)	(10.118)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Country time trends	Yes	Yes	Yes	Yes	Yes
R^2	0.67	0.69	0.62	0.54	0.72
Civil war observations	125	173	85	226	226
Observations	889	889	889	889	889

** p<0.05, * p<0.1

The reported risk-inducing effect of temperature disappears completely once we impose minor adjustments to the original model. The reduction in the size of the regression coefficient for current-year temperature when we shift the severity threshold downwards (Model 4) or upwards (Model 5) is little short of astonishing. The models that replace the binary indicator of major civil war with a continuous measure of BRD leave a similar impression. All four climate parameters are negatively related to the absolute number of annual fatalities, other factors accounted for (Model 8). Model 9 uses a log-transformed casualty measure to counter the skewness of the distribution and reduce possible outlier bias. The coefficient for temperature is now positive again, as expected, but not distinguishable from zero with an acceptable margin of error.

To further illustrate the sensitivity of the temperature effect to DV operationalization, Figure 1 visualizes the size of the estimated effect of current-year temperature on civil war incidence for various BRD thresholds. Evidently, temperature attains a (near) significant coefficient only in a narrow part of the range of possible cut-off points.

Figure 1. Size of temperature coefficient by civil war severity threshold, 1981–2002



Note: The black line in the upper part of the figure depicts the size of the estimated effect of temperature (current year) on civil war incidence for various severity thresholds (horizontal axis). The grey area visualizes 95% confidence interval around the estimate. The lower part of the figure illustrates the frequency of civil war observations for various severity thresholds. Estimates based on Model 1.

For each stepwise increase in cut-off value for civil war, an observation that was considered civil war is recoded non-war. So when we move the threshold above 1,000 BRD, an increasing number of severe armed conflicts are coded into the control group along with minor conflicts and countries at peace. Introducing an increasingly heterogeneous control group undoubtedly weakens the results, but the decline seen in Figure 1 is too large to be explained by control group pollution. The fact that the coefficient becomes negative when the threshold moves beyond 2,500 BRD indicates that temperature is not associated with very large conflicts.

Sample period

Next, we assess the sensitivity of the climate parameters to changes in the sample period. All models considered so far have been estimated for the years 1981–2002, the sample period chosen by Burke et al. (2009). The increase in civil wars throughout most of this period corresponds well with the contemporaneous warming of the continent. As we know that temperatures have been consistently high throughout the first decade of the 2000s, we would expect a correspondingly high rate of civil wars in Sub-Saharan Africa. However, since Burke et al.'s climate measures are unavailable for years outside their sample period, we created new country-year estimates for the full post-colonial period in Africa based on high-resolution gridded time-series climate statistics from the University of Delaware.[6] We also updated the civil war incidence variable based on v4-2009 of the UCDP/PRIO Armed Conflicts Dataset. Table 4 shows the results from a set of regression models that are identical to the model specification for Model 1 except for changes in the temporal coverage.

Table 4. Alternative sample periods

	(8)	(9)	(10)	(11)
	1981–2002	2003–08	1981–2008	1960–2008
Temperature	0.049**	-0.006	0.029	0.013
	(0.023)	(0.015)	(0.020)	(0.017)
Temperature $_{t-1}$	-0.002	-0.020	-0.009	-0.019
	(0.027)	(0.037)	(0.025)	(0.017)
Precipitation	0.035	0.110	0.042	-0.016
	(0.038)	(0.105)	(0.035)	(0.030)
Precipitation $_{t-1}$	0.054	0.043	0.034	0.004
	(0.036)	(0.045)	(0.028)	(0.023)
Intercept	-1.331	0.696	-0.412	0.165
	(1.186)	(0.700)	(0.751)	(0.787)
Country fixed effects	Yes	Yes	Yes	Yes
Country time trends	Yes	Yes	Yes	Yes
R^2	0.65	0.59	0.56	0.39
Civil war observations	100	8	108	146
Observations	947	264	1,211	1,974

** p<0.05, * p<0.1

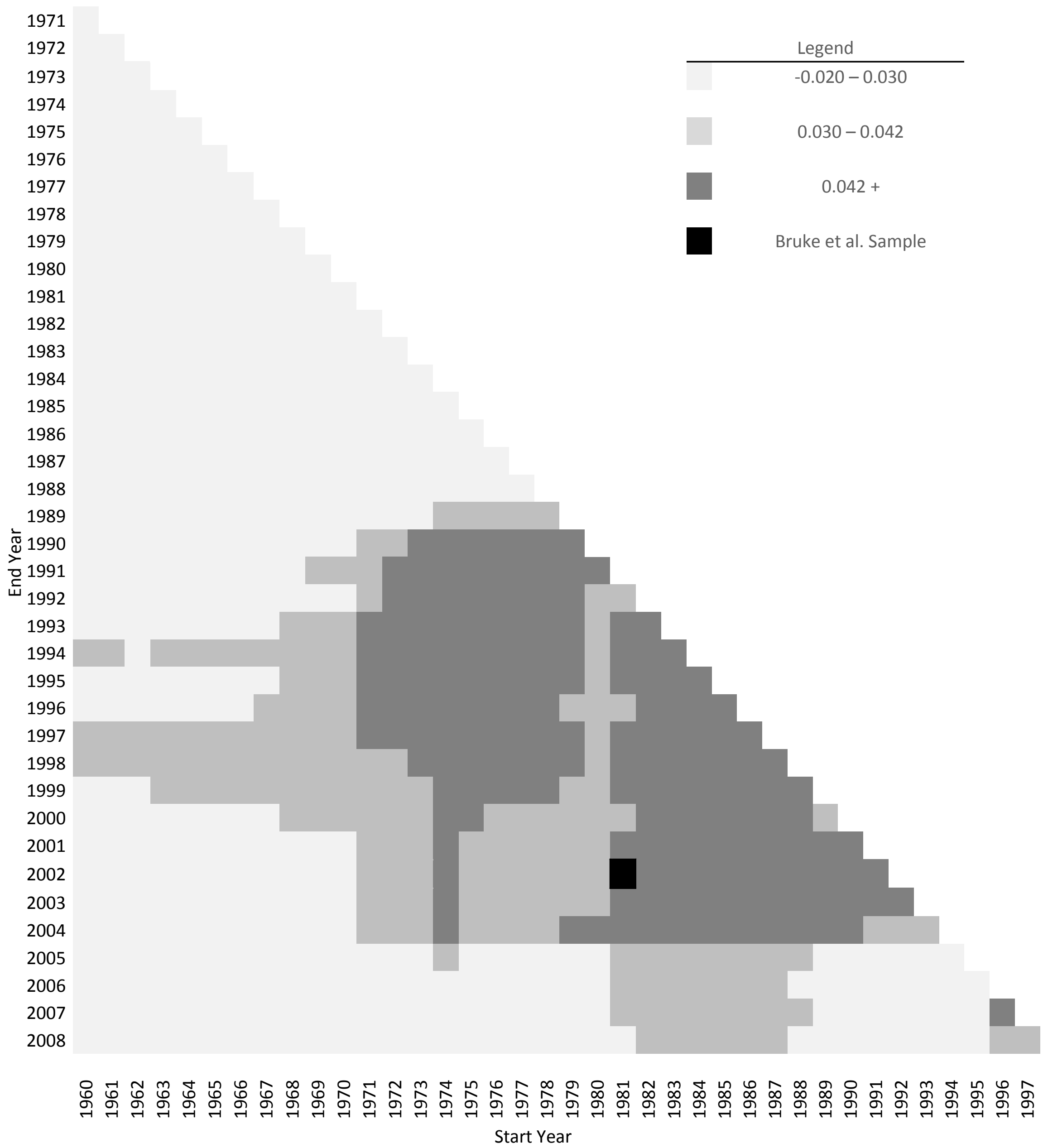
Again, we find that the claimed positive and significant effect of temperature on civil war prevalence is highly tenuous. For the original sample period (Model 8), the UDel temperature measure indicates a marginally stronger effect on civil war, compared to Model 1. When we expand the temporal domain to include more recent years (Model 10), however, the size of the regression coefficient drops by 40% and it is no longer statistically significant. In fact, the isolated effect of temperature for the most recent years (Model 9) appears to be weakly negative. Finally, neither of the four climate parameters has a significant bearing on the likelihood of major civil war when the entire post-colonial Sub-Saharan African sample is analyzed (Model 11).

A further assessment of the sensitivity of the temperature effect to changes in the temporal domain is illustrated in Figure 2. Here we re-estimate Model 1 for all possible time intervals (minimum 10 consecutive years) between 1960 and 2008. Darker cells in the matrix indicate larger estimated effects. There are two evident clusters of sample years where Model 1 would return a positive coefficient for current-year temperature at least as large as the effect reported in Model 1, roughly from the early 1970s to the early 2000s. This period corresponds quite well with the years

[6] See http://climate.geog.udel.edu/~climate/. The UDel climate measures are for all practical purposes identical (r=0.98) to the climate variables used above.

when civil war and temperature both trended upwards (see Fig.1 in Buhaug, 2010). Note also that the figure generally indicates that the size of the coefficient is negatively related to the length of the sample period. Finally, we note that regardless of start year, the coefficient is smaller than the original result if the period extends beyond 2004.

Figure 2. Size of temperature coefficient for various time periods since 1960



Note: the figure illustrates how the size of the temperature coefficient varies with temporal domain. Dark gray cells represent periods where the baseline model would return an estimated effect at least as large as Model 1. Medium gray cells represent somewhat weaker results whereas light gray cells indicate a small regression coefficient.

Marginal impact and predictions

Marginal impact

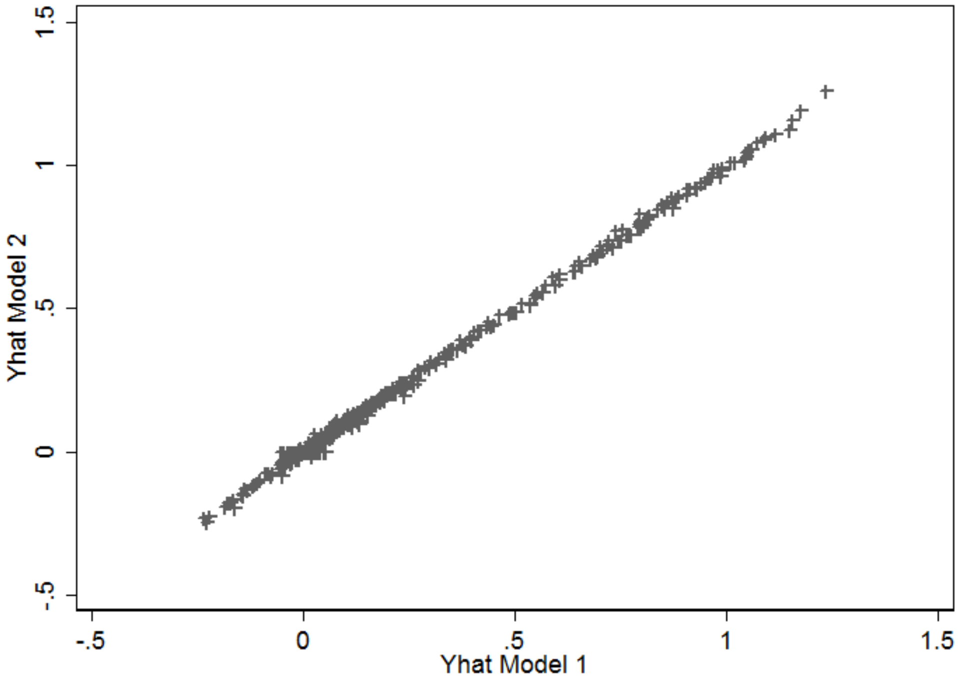
There are both methodological and substantive causes for concern about the claimed robustness of the climate-civil war connection. But even if we accept the model specification and measurement of civil war proposed by Burke et al. (2009), the marginal impact of temperature on civil war risk is – as we demonstrate in this section – trivial. The coefficient for temperature (current year) in Model 1 indicates that a 1°C increase in temperature corresponds to a 4.3% increase in civil war risk, all else held constant.[7] Since the mean conflict propensity in the SSA 1981–2002 sample is 11%, an absolute increase of 4.3 points appears quite large. Indeed, Burke et al. predict a 54% increase in the incidence of civil war by 2030 on current temperature trends and conclude that the adverse impact of warming "appears likely to outweigh any potentially offsetting effects of strong economic growth and continued democratization" (2009: 20673). But how important is climate variability compared to all other sorts of factors – political, economic, cultural, demographic, etc. – that influence civil war risk?

There are various ways to interpret the real effect of a variable beyond interpreting regression coefficients and refer to aggregate probabilities. One method is to assess a given variable's contribution to the overall fit of the model, normally through a likelihood ratio or chi-square test. A natural extension would be to compare and plot predicted values for a model against predictions for a similar model without the variable of interest. A more demanding test is out-of-sample prediction, regressing the model on one part of the data and see how well it predicts positive outcomes in the remaining sample. In the following, we evaluate the performance of the climate parameters in all of these tests.

A first indication of the feeble substantive impact of temperature and precipitation is given by comparing Model 1's explained variance (R^2) with the same statistic for a model with only country fixed effects and country time trends (Model 2). The difference is 0.002 points (R^2=0.657 vs. 0.655). In other words, virtually all explained variance in Model 1 is caused by unknown country features and trends hidden beneath the specified fixed effects and time trend terms. As a follow-up inspection, we compare the predicted scores ($\hat{y}$) for Model 1 with corresponding predictions from the reduced model. As illustrated in Figure 3, the estimates are for all practical purposes identical; climate characteristics have a minuscule impact on individual country years' estimated likelihood of civil war incidence (the predictions for these two models correlate at r=0.999).

[7] Note that the risk scores are not expressed as probabilities, given that the estimates are derived from a linear regression model that generates predicted values below 0 as well as above 1.

Figure 3. Scatter plot of predicted values with and without climate parameters



Note: The figure plots predicted values of civil war for the baseline model (horizontal axis) and a similar model without climate parameters (vertical axis).

To get a better grip of the impact of climate variability on civil war incidence for specific countries, Table 5 lists the ten observations with the highest predicted scores in Model 1 (the plots at the top right of Figure 3) and corresponding scores from the reduced model. The far right column gives the relative contribution of the climate parameters. In most cases, the relative impact of climate on predicted civil war incidence is less than 1% positive or negative. Note also that all these observations are from the initial years in the sample period with the highest estimates found in 1981. This is no coincidence; all these countries experienced severe civil war in this period and have strong negative time trends. Due to the powerful trends, three of the four countries in the table actually have negative predictions in the final years of the sample period.

Table 5. Observations with the highest within-sample predicted values, 1981–2002

Country	Year	Ŷ Model 1	Ŷ Model 1 w/o climate	Δŷ (%)
Mozambique	1981	1.23	1.26	-1.78
Mozambique	1982	1.18	1.19	-1.10
Uganda	1981	1.15	1.15	<0.01
Mozambique	1983	1.15	1.12	2.28
Ethiopia	1981	1.12	1.11	0.75
Angola	1981	1.09	1.10	-0.73
Uganda	1982	1.09	1.09	-0.06
Angola	1982	1.07	1.08	-0.46
Angola	1983	1.06	1.05	0.38
Mozambique	1984	1.05	1.05	-0.28

Predictions

Next, we consider the impact of temperature and precipitation on the model's ability to predict out of sample. We start by re-estimating the baseline Model 1 and a reduced model for a slightly shorter time period, 1981–98 (Models 12 and 13, respectively), and use estimates from these models and known climatic conditions in subsequent years to predict civil wars that occurred between 1999 and 2002. Table 6 shows that the reported positive and statistically significant coefficient for current-year temperature is reproduced. In fact, the effect is about 30% larger in the reduced time period. This comes as no surprise, though; we know that the opposing trends in temperature and conflict are particularly strong in the final years of the original sample period (Buhaug, 2010). More surprising, perhaps, is the positive and now significant estimate for precipitation last year. It thus appears that in this particular period, excess rainfall rather than drought increased the short-term risk of civil war incidence. This result is at odds with dominant environmental security theories (see Homer-Dixon, 1999 and Kahl, 2006 for examples) and it also counters the main conclusion of Miguel, Satyanath & Sergenti (2004). While there may be many plausible explanations for this result (e.g., Ciccone, 2010; see also Witsenburg & Adano, 2009), we prefer not to speculate at this point as the finding evidently is as sensitive to sample inclusion criteria, operationalization of key dependent and independent variables, and model specification as the temperature effect. In any case, the significant and quite large parameter estimates for temperature (current year) and rainfall (previous year) suggest that Model 12 ought to outperform Model 13 by some margin when it comes to predicting future civil wars.

Table 6. Baseline model and model without climate variables, 1981–98

	(12) Baseline	(13) w/o climate
Temperature	0.057**	
	(0.026)	
Temperature $_{t-1}$	0.021	
	(0.026)	
Precipitation	-0.009	
	(0.075)	
Precipitation $_{t-1}$	0.112**	
	(0.047)	
Intercept	-1.464**	<0.001
	(0.628)	(<0.001)
Country fixed effects	Yes	Yes
Country time trends	Yes	Yes
R^2	0.68	0.67
Civil war observations	86	86
Observations	728	728

** p<0.05, * p<0.1

Based on the parameter estimates in Models 12 and 13 and updated temperature and precipitation statistics, we calculate country-specific predicted values for the subsequent four years. The continuous predictions were converted into a binary war/no war categorization by using $\hat{y}$=0.5 as the classification criterion. Accordingly, observations with predicted values above 0.5 (analogous to a >50% estimated probability in a maximum likelihood model) are treated as civil war and lower values predict non-war. Table 7 shows the classification table for the 1999–2002 period. The two columns to the left show the classification based on Model 12. According to this model, eight of the 161 country-years should experience civil wars during the four-year period ($\hat{y}$>0.5). Five of these predictions are accurate. Since another seven wars are not picked up, the model with the climate variables correctly predicts five of twelve war country years. This yields a sensitivity of 5/12=0.417. The remaining 153 country-years have $\hat{y}$<0.5 which corresponds to no war. 146 of these were accurate while three non-war observations are missed (false positives). The specificity of the classification, then, is 146/149=0.980.

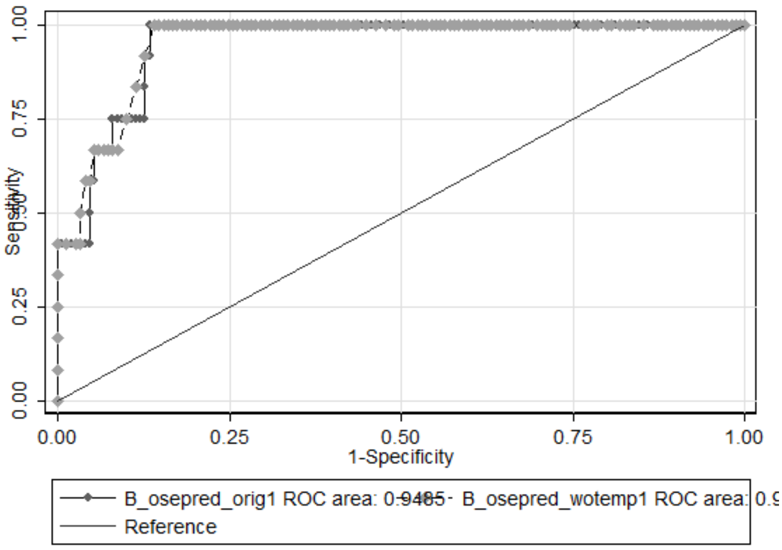
The two columns to the right show that the sensitivity of the model without the climate variables (Model 13) is identical to the baseline model – five of twelve wars are correctly predicted – but the specificity is slightly higher (147/149=0.987). In other words, the climate variables lead the model to produce more false positives but not more true positives. This is further testimony of the miniscule contribution of climate even in the specification preferred by Burke et al. (2009).

Table 7. Classification table for out-of-sample prediction, 1999–2002

	Model 12		Model 13	
	Observed war	Observed non-war	Observed war	Observed non- war
Predicted war	5	3	5	2
Predicted non-war	7	146	7	147
Total	12	149	12	149

Classification tables are often useful for illustrating and comparing the predictive ability of models, but they could be sensitive to small changes in the choice of cut-off point, much in the same manner as the severity threshold for the civil war variable (Table 3). A Receiver Operating Characteristic, or ROC curve, allows assessing the predictive contribution of the climate parameters across the full range of possible cut-off points [0, 1] (see Hosmer & Lemeshow, 2000). ROC curves are generated by plotting sensitivity against 1–specificity, comparing the rate of true positives with the rate of false positives. The better a model predicts, the more steeply the curve rises and the larger the area under the curve (AUC, expressed as share of the total area of the plot). Figure 4 plots ROC curves for the same pair of models as presented above; the baseline climate variability model and a model with fixed effects and time trends only, regressed on the SSA sample for 1981–98 and then used for predicting civil war, 1999–2002. Again, we find that Model 12, which includes measures of temperature and precipitation, produce almost identical predictions to the simpler Model 13; the difference in AUC scores is statistically insignificant.[8]

Figure 4. ROC graphs for model predictions with and without climate variables, 1999–2002



[8] In fact, in tests not shown we find that Burke et al.'s Model 3, which includes a limited selection of time-varying controls and uses a common time trend instead of the country trends, performs significantly worse in terms of AUC scores than a similar model without the climate variables (p=0.015).

Conclusion

In conclusion, the sensitivity assessments documented here reveal little support for the alleged positive association between warming and higher frequency of major civil wars in Africa. Instead, this paper adds further substance to the critique raised by Buhaug (2010). In almost all specifications, for almost all possible civil war definitions, and for almost all years in post-colonial Africa, climate variability is statistically unrelated to civil war occurrence. This does not preclude the possibility that adverse climates may have other, more subtle and long-term effects on political stability, economic prosperity, and peace. We also should not take results reported here as evidence that climate anomalies cannot trigger other forms of societal upheavals, such as urban riots (e.g., in response to accelerating food prices) and rural intercommunal fighting (e.g., farmer-herder clashes over access to freshwater or fertile land). More research is needed to get a better understanding of the full range of possible social dimensions of climate change.

References

Buhaug, Halvard, 2010. 'Warming Not to Blame for African Civil Wars', *Proceedings of the National Academy of Sciences of the USA* 107(38): 16477–16482.

Burke, Marshall B.; Edward Miguel, Shanker Satyanath, John A. Dykema & David B. Lobell, 2009. 'Warming Increases the Risk of Civil War in Africa', *Proceedings of the National Academy of Sciences of the USA* 106(49): 20670–20674.

Ciccone, Antonio, 2010. 'Transitory Economic Shocks and Civil Conflict', unpublished ms.

Gleditsch, Nils Petter; Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand, 2002. 'Armed Conflict 1946–2001: A New Dataset', *Journal of Peace Research* 39(5): 615–637.

Harbom, Lotta & Peter Wallensteen, 2010. 'Armed Conflicts, 1946–2009', *Journal of Peace Research* 47(4): 501–509.

Homer-Dixon, Thomas, 1999. *Environment, Scarcity, and Violence*. Princeton, NJ: Princeton University Press.

Hosmer, David W. & Stanley Lemeshow, 2000. *Applied Logistic Regression*. New York: Wiley-Blackwell.

Kahl, Colin, 2006. *States, Scarcity, and Civil Strife in the Developing World*. Princeton, NJ: Princeton University Press.

Miguel, Edward; Shanker Satyanath & Ernest Sergenti, 2004. 'Economic Shocks and Civil Conflict: An Instrumental Variable Approach', *Journal of Political Economy* 112(4): 725–753.

Lacina, Bethany & Nils Petter Gleditsch, 2005. 'Monitoring Trends in Global Combat: A New Dataset of Battle Deaths', *European Journal of Population* 21(2–3): 145–166.

Ward, Michael D.; Brian Greenhill & Kristin Bakke, 2010. 'The Perils of Policy by P-value: Predicting Civil Conflicts', *Journal of Peace Research* 46(4): 363–375.

Wischnath, Gerdis & Nils Petter Gleditsch, 2010. 'Battle Deaths – Comparing the UCDP and PRIO Data', unpublished manuscript.

Witsenburg, Karen M. & Wario R. Adano, 2009. 'Of Rain and Raids: Violent Livestock Raiding in Northern Kenya', *Civil Wars* 11(4): 514–538.

Sensitivity Analysis of Climate Variability and Civil War

Burke et al. (2009) report that warming is robustly linked to civil war in Sub-Saharan Africa (SSA). Their analysis builds on an earlier article by some of the same authors that found negative rainfall deviation to increase civil war risk through its adverse impact on economic growth (Miguel, Satyanath & Sergenti, 2004). Although the most recent article departs from the original's instrumental variable approach and its non-result for rainfall undermines the earlier conclusion, both studies deserve credit for addressing an under-researched area and for innovative use of meteorological data in conflict research. Moreover, their conclusion seems to corroborate widespread notions about a powerful connection between environmental degradation and armed conflict.

A crucial question remains, however; is the reported link between temperature and civil war robust? A recent study by Buhaug (2010) addresses this question by conducting two complementary tests: adjusting the model specification and using alternative measures of climate variability and civil war. The claimed finding passed neither of these tests. This paper documents a wider set of sensitivity tests that provide further proof of the empirical disconnect between climate variability and civil war outbreak, incidence, and severity.

Halvard Buhaug, Håvard Hegre & Håvard Strand

Peace Research Institute Oslo (PRIO)

PRIO