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Apocalypse Now?
Climate Change and War in Africa

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Apocalypse now? Climate change and war in Africa

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Abstract

There is a large empirical literature trying to quantify the potentially adverse affects of climate change on the risk of violent armed conflict, which focuses almost exclusively on linking annual variation in climatic conditions to violence. A major shortcoming of this approach is that it conflates climate variability with climate change, while also implicitly assuming that adverse weather shocks will immediately trigger violent contests over scarce resources. In contrast, this study exploits changes in local climate over a longer time period; using differences in the average standardised deviation of temperature and precipitation levels between 1989-2002 and 2003-2017 across the African continent. Bayesian model averaging is used to test whether variables measuring changes in local climate contribute consistently in explaining conflict risk between 2003-17. Using disaggregated data to account for local dynamics, the reduced-form estimation shows that temperature is robustly linked to violent armed conflict: moving from low to high temperature levels corresponds to a 31% increase in conflict risk. Changes in precipitation have no discernible effect. The results are robust to changing the benchmark period for the climate variables, accounting for conflict prevalence, and considering different types of violent conflict. Examining the predictive power of the models, a leave-one-out cross-validation highlights that including information on changes in local climate improves the predictive performance of the model, as measured by the area under the precision-recall curve, by seven points, from 0.51 to 0.58; 33 points above the baseline.

JEL-classification: D74, N47, Q54
Keywords: Climate, civil war, Bayesian model averaging

1 Introduction

The 2018 global heat wave, with temperature records being bested across the world and an unprecedented rate of forest fires within the Arctic circle, was a stark reminder that global warming is not a hypothetical future event but that it effects can already be felt today Given the scale and pace of contemporaneous global warming there are concerns about the potentially negative effects it could have on human society if prevention of future temperature increases fails and in the absence of appropriate adaptation or mitigation mechanisms. High on the list of concerns is violent armed conflict, where global warming might reduce access to natural resources such as arable land and water, which increases tensions between competing groups which can escalate into violence in the absence of the right institutions or conflict resolution mechanisms. There is now a growing and productive research strand dedicated to so called climate-conflict which examines the possible link between climatic conditions and conflict risk. Over the past decade this literature has produced a number of interesting results, for instance that livestock raiding tends to be more violent during wet times (Witsenburg and Adano, 2009); that drought affects conflict through livestock prices (Maystadt and Ecker, 2014); that insurgency violence is more likely following a bad harvest as result of too much precipitation (Crost et al., 2018); but also that the main correlates of conflict are economic or socio-political in nature rather than climatological (Wischnath and Buhaug, 2014).[1]

Although most published research within this field share similarities with regard to datasets analysed and statistical methods used, there is a sort of schism in terms of interpretation of the results. Two recent papers argued that most results tend to be in agreement with the hypothesis that climate affects conflict, where deteriorating climatic conditions, such as higher temperatures and lower precipitation levels, are linked to increased conflict risk (Hsiang et al., 2013; Hsiang and Burke, 2014). Quantifying this effect, (Hsiang et al., 2013) found that a standard deviation increase in temperature is associated with a 14% increase in the chance of conflict. However, these conclusions contrast with other large literature reviews (Klomp and Bulte, 2013; Theisen et al., 2013) and the results are heavily contested (Buhaug et al., 2014).[2] This lack of consensus might not be that surprising given the sensitivity of research results within the conflict literature (Hegre and Sambanis, 2006). More importantly, one major issue that has remained largely unaddressed

[1] See also the case-study on Kenya by Linke et al. (2015).

[2] See also (Hsiang et al., 2014).

is the fact climate variability, particularly variation in climate across years, is often conflated with climate change (Buhaug, 2015). Annual variation in weather might not be such a good proxy for climate change (Selby, 2014). For illustration consider the following standard empirical framework which is typically used in quantitative research:

$$y_{it} = \alpha + \beta_1 x_{it} + \beta_2 x_{it-1} + \epsilon_{it} \tag{1}$$

Here outcome variable y_{it}, often a binary indicator for conflict incidence, is linked to contemporaneous and, sometimes lagged, changes or shocks in weather variables x, such as average temperature - α is the constant, ϵ is a random error term. Although this empirical model can help identify the effect of shocks in local weather on conflict risk, it provides scant information on the effect of climate change, which is a longer and more gradual process, event at its current unprecedented pace. The main shortcoming of the model given in equation 1 is the implicit assumption that changes in climate-related resources have an immediate effect on competition and trigger conflict, which seems untenable (Selby, 2014). Indeed, most research on the link between climate and conflict focuses on rural Africa, where the local population have a long history of applying adaptive measures to deal with the local climate, e.g. Berhe et al. (2017).

Therefore, in contrast with the existing literature, which almost exclusively exploits the relative high-frequency of the available data, this study follows the example of Burke and Emerick (2016) who study the effect of climate change on US agricultural output using a long differences approach. Specifically, in this case conflict incidence is linked to long-term (15 year) changes in temperature and precipitation; the functional form of the empirical model can therefore be given by:

$$y_i = \alpha + \beta \overline{x_i} + \epsilon_i \tag{2}$$

where conflict incidence y_i is linked to the change in local climatic conditions, measured by the difference in average anomalies for temperature and precipitation (x_i). Note that the outcome variable is a binary indicator, rather than a change in averages, as the latter makes little conceptual sense in the context of conflict in contrast with the subject in Burke and Emerick (2016) which was agricultural output. Similar to Harari and La Ferrara (2018) this study focuses on Africa and uses the grid-cell as unit-of-analysis. The difference with their pioneering work is that this study covers a longer period (1989-2017) and more importantly that it focused on long-term changes, using the years between 1989 and 2002 as a benchmark and the change in average climate between 2003 and 2017 to predict conflict incidence. The main contribution of this paper is therefore providing an analysis of the effect of long-term change on conflict risk, which helps overcome some of the previously discussed issue in the literature. As in (Burke and Emerick, 2016), focusing on long-term changes can help shed some light on whether households living in areas adversely affected by climate change posses adaptive capabilities to deal with changing conditions. One remaining shortcoming of the approach is that it still is a reduced-form estimation, directly linking climate to conflict, telling little about the specific mechanisms. This limitation is partially imposed to data availability as there is little information on for instance local commodity prices or trade for a long enough period that would allow us to test particular mechanisms as in Maystadt and Ecker (2014); Crost et al. (2018) or the theory of market collapse by Olsson (2016).

There are currently two other studies that focus on the, relatively, long-term, rather than using climate variability as a proxy for climate change. Hsiang et al. (2011) use the El Niño Southern Oscillation to show that conflict risk doubles during El Niño years compared to the cooler La Niña years. One shortcoming of their approach is that the quasi-experiment they use, the shifting between El Niño and La Niña years, only works when you make the heroic assumption that households don't develop some sort of adaptation strategy. van Weezel (2017) exploits a shift in precipitation in the Horn of Africa that happened after 1998 resulting in lower precipitation levels during the long rainy season and finds that regions where this shift was more pronounced experience higher rates of communal conflict. Although using such a specific shock is interesting, it is unclear how the results generalise. In addition to these two papers there is also the work Zhang et al. (2007) and Tol and Wagner (2009), who focus largely on the pre-industrial era for Europe and China. For instance, Tol and Wagner (2009) find that in the past millennium conflict was more intense during cooler periods in Europe, but this effect has waned in the industrial era.

Focusing on differences in local climate between 1989-2002 and 2003-17, the regression analysis shows that changes in temperature are robustly linked to conflict incidence. Using Bayesian model averaging to account for model uncertainty, and cherry-picking results, the estimates shows that across a large number of possible model specifications the variable measuring the change in temperature has an inclusion probability of 96.9%, indicating that the variable contributes consistently to explaining the variation in conflict. In contrast, the precipitation variable has an inclusion probability if just 16.4%, reflecting the generally weaker link found between precipitation and conflict in the literature. The estimated effect of temperature on conflict is substantial as moving from low to high values corresponds to a 31% increase in the chance of conflict. The results are quantitatively similar when i) changing the benchmark period to include more years, ii) focusing on conflict prevalence, and iii) considering different types of conflict such as communal violence. Further scrutiny using leave-one-out cross validation shows that including variables to account for changes in local climate reduce the predictive error of the model by 7% when considering the root mean squared error and correspond to a 7 point increase in the area under the curve of the precision-recall curve.

2 Data

To estimate the explanatory and predictive power of climate in relation to civil conflict in Africa, georeferenced data is used, aggregated to a resolution of a 1 degree square grid covering the African continent.[3] This entails that there are 2,557 spatial units in total, 2,525 when we omit grid-cells with missing values for particular variables, such as population. The focus of this study is conflict incidence at the local level between 2003-17, exploiting the cross-sectional variation in conflict, climate, and a number of other possible conflict determinants such as population density, economic activity, and ethnic polarization.

2.1 Temperature and precipitation

The possible effect of climate on conflict risk is estimated using local level data on changes in average temperature and precipitation relative to a long-term baseline. Temperature data is taken from the relatively new Berkeley Earth surface temperature (BEST) dataset (Rohde et al., 2013), which combines temperature data from various measurements stations and produces averages using a spatial technique called Kriging to account for statistical outliers and create a homogeneous climatology presented on a 1 degree lattice. Importantly, the BEST data is not as vulnerable to conflict-related station loss compared to other commonly used datasets introducing a downward bias in estimates (Schultz and Mankin, 2017). The dataset contains information on the average

[3] One degree corresponds to about 110 Kilometers at the equator.

monthly temperature, where temperature is expressed as a standardized deviation, or anomaly, from the 1951-80 mean. Although the data covers the period from present back till 1750, for most grid-cells on the African continent the data goes back about a 100 years till 1900.

The monthly data is aggregated to calculate an annual average temperature, and these annual averages are subsequently used to measure the shift in average annual temperature between 1989-2002, the benchmark period, and 2003-17, i.e.

$$\Delta T = \overline{T_{2003-2017}} - \overline{T_{1989-2002}} \tag{3}$$

The lower bound of the sampled years is imposed by the constraints of data availability on conflict, whereas the upper bound is used as a demarcation to create two roughly equal periods (14 and 15 years) with a long enough baseline. 15 years is a relatively short time in climatic terms, but given the unprecedented pace of anthropogenic global warming there has been a substantial increase in average temperature across Africa with an average shift in the anomaly of 0.42 (s.e.=0.15) relative to the 1951-80 baseline.

Precipitation data is taken from Climate Hazards Group InfraRed Precipitation with Station data or CHIRPS dataset (Funk et al., 2015). The advantage of this dataset is that it combines estimates on infrared cold cloud duration, a precipitation proxy measured by satellites, with station data to provide a comprehensive dataset on monthly precipitation for the whole African continent. The data, which covers the years since 1981, is projected on a 0.05 degree grid (about 5 Kilometers at the equator), accounting for local variation in precipitation. A disadvantage of the data is the relatively short period, induced by the use of satellite measurements, which means that all the available data, spanning the years from 1981 till 2018, is used to calculate the baseline for each individual grid-cell. The data is aggregated to calculate an annual total for a 1 degree grid, and identical to the temperature data the change in the average anomaly between 1989-2002 and 2003-17 is calculated as a measure for a shift in local climate.

Figure 1 shows the measures for change in local climate for temperature (panel a) and precipitation (panel b). As the data illustrates, temperature has increased between 1989-2002 and 2003-2017 across the continent, with a minimum increase of 0.08 and a maximum of 0.76. A number of regions have experienced more substantial temperature increases such as Egypt, the Horn of Africa, and a large stretch of land covering the South of Algeria, most parts of Niger, and the north of Nigeria. In contrast, changes in average temperature has been relatively modest in most parts of Africa south of the Equator.

Changes in precipitation have been more varied, which is likely the result of variation in local geography, which influences precipitation patterns, as well as interdecadal variation in precipitation. Interestingly the data shows that the Sahel region, a supposed hotbed of communal violence, has seen minor increases in precipitation, whereas precipitation has considerably decreased in the the Cape region in South Africa, and in the north of the continent in Libya and Egypt. Except for Egypt, there does not seem to be a very strong overlap or pattern in terms of regions that have seen an increase in temperature and a decrease in precipitation.

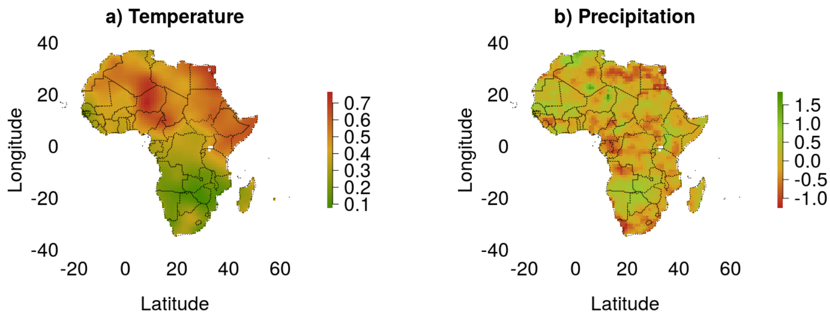

Figure 1: Change in average temperature (a) and precipitation (b) anomaly per grid-cell between 1989-2002 and 2003-17. Note that there is no precipitation estimate for the island of Mauritius.

2.2 Civil conflict

Conflict data is taken from the Georeferenced Event Dataset (GED) provided by the Uppsala Conflict Data Programme (Sundberg and Melander, 2013). The GED contains detailed information on the location and timing of conflict events, as well as the type of conflict, and includes a variable indicating the geographic precision of the geolocated conflict events. The most recent dataset available (version 18.1) covers the years 1989-2017 and has a global coverage. Currently this is the most comprehensive publicly available conflict event dataset, superior to other similar datasets in terms of the geocoding precision (Eck, 2012) and accuracy of included events (Weidmann, 2013, 2015). The quality of the data notwithstanding, there are some important caveats concerning the inclusion criteria and the sources used. First, a conflict events is only included if the conflict the particular events is associated with has reached a fixed fatality threshold of at least 25 battle-related deaths (Croicu and Sundberg, 2015). This entails that conflicts at the lower end of the violence spectrum, such as riots or protests are not included. As a result, from the analysis we can only draw conclusions with regard to fatal conflicts, as opposed to other types of conflict. Second, the majority of observations are coded on the basis of media reports, which might introduce a reporting bias into the data. Recent research has shown though that the effect of such a bias for this particular dataset is likely to be small (Croicu and Kreutz, 2016). Third, and final, there is the issue of Known Geographically Imprecision (Croicu and Hegre, 2018), which concerns the information available on the precision of the geocoding. For this study, conflict events that cannot be accurately located within a 25 Kilometer radius are dropped from the data, which means a loss of information. As a result, some grid-cells will appear more peaceful than they actually are, problem is that we cannot accurately match the conflict event with the grid-cell. Alternatively we could leave in all the observations, but in that case conflict is linked to certain grid-cell characteristics that are incorrect, arguably introducing a more severe bias in the estimates.

Using the GED to match conflict events with grid-cells, the data is used to construct three main variables: the outcome variable, conflict incidence between 2003-17[4]; the temporal lag, a binary indicator for conflict incidence between 1989-2002; and the spatial lag of lagged conflict incidence. The spatial lag counts the number of neighbouring cells that reported at least one conflict event between 1989-2002. Given the temporal and spatial correlation of conflict, it is imported to account for these dynamics in the model.

Figure 2 plots the conflict data, aggregating the number of conflict years between 2003-17 per grid-cell. As the figure illustrates, in general conflict tends to be localized, clustering in particular places. A large number of these clusters seem to be located in and around the Sahel region. The data also shows the high prevalence of conflict in the eastern part of the DRC, a region that has been restless since the end of the Second Congo War in 2003. The

[4]In addition a model is estimated using conflict prevalence, which counts the number of years relative to the whole period for which there was reported conflict.

lower southern part of the continent seems relatively peaceful with only a number of isolated incidents in Mozambique and Zimbabwe.

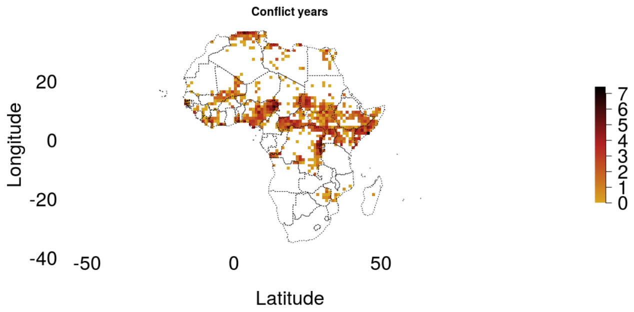

Figure 2: Number of conflict years per grid-cell between 2003-17

2.3 Other possible determinants

Besides climatic conditions, this study considers a number of additional variables to account for factors commonly associated with civil conflict. As larger populations increase the pool of potential insurgents, as well as putting more pressure on available local resources, population density is included in the model.[5] Discussion on the determinants of conflict is often framed in terms of greed and grievance (Collier and Hoeffler, 2002), to distinguish between economic and identity based motives for rebellion or violence. Concerning economic motives, to account for lower opportunity costs for conflict, I follow Henderson et al. (2012) and use the change in night light emissions, measured by satellites as a proxy for economic activity. In this case change is measured subtracting the grid-cell average between 1992-93 from the average for 2001-02. The last years before measurement of the outcome variable are used to prevent endogeneity issues as a result of reverse causality.[6] Concerning identity-based motivations for conflict an ethnic polarization index is included in the model (Garcia-Montalvo and Reynal-Querol, 2005) using data from

[5]Data provided by Gridded Population of the World (version 4), using the 2000 estimate (Center for International Earth Science Information Network, 2016).

[6]1992-93 are the first available years.

GeoEPR (Wucherpfennig et al., 2011). Normally the ethnic polarization index would be calculated on the basis of population figures, associated with different ethnic groups, but that kind of data is not readily available at the level of the unit-of-analysis. Therefore, the area in a grid-cell covered by a particular group is used. One caveat using this approach is that there can be some overlap between different groups, meaning that the index exceeds the unity interval. To correct for this, the values are normalized to restrict it to values between zero and one.

Figure 3 provides an overview of the distribution of the data of various variables in relation to conflict incidence: the black vertical line indicates the value of an individual grid-cell with conflict incidence between 2003-2017, the red lines indicate the averages for the whole sample. The figure illustrates that for many variables there does not seem to be a particular strong patterns in relation to conflict.

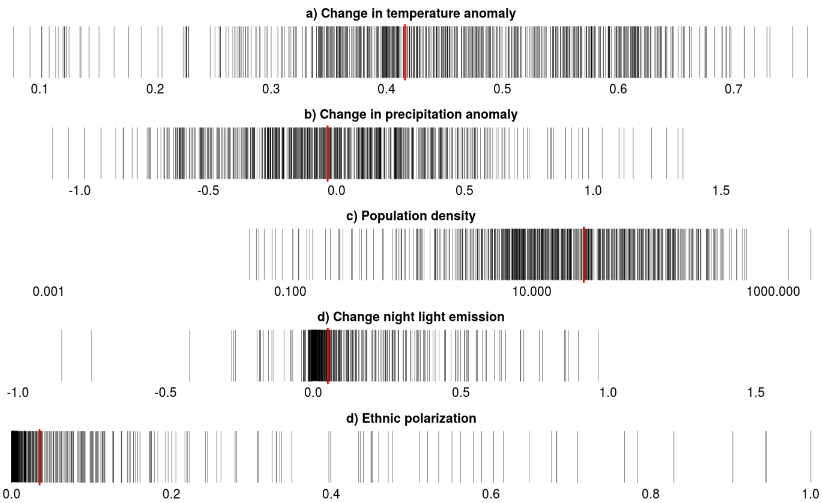

Figure 3: Overview of distribution of conflict determinants in relation to conflict incidence. Each black line indicates the value for a grid-cell with conflict between 2003-2017. The red line indicates the mean over the whole distribution.

2.4 Data patterns

An exploratory analysis of the data reveals two important patterns, which are i) that changes in temperature are not necessarily correlated with changes in precipitation and ii) that there is a weak correlation between temperature and precipitation increases on the one hand and conflict incidence on the other. For instance, the average change in the temperature anomaly is 0.46 (s.e.= 0.13) for grid-cells with reported conflict between 2003-17 compared to 0.40 (s.e.=0.16) for the other grid-cells. The data shows a correlation of 0.17 between temperature and conflict incidence, which is considerably higher compared to the correlation between precipitation change and conflict at 0.03. Somewhat surprising is the fact that this correlation between precipitation and conflict is positive, meaning that increases in precipitation are associated with higher conflict risk, on average, although the magnitude is rather small.

Figure 4 plots the relation between temperature, precipitation, and conflict, where the dotted lines indicate the sample averages for precipitation and temperature; dividing the plot into four quadrants. The tick marks on the x and y axis indicate the measured values for the grid-cells with reported conflict (also indicated by the rod dots in the plot) and a visual inspection shows that there does not seem to be a very strong pattern. Although there is some clustering for temperature around the 0.4 and to a lesser extent the 0.6 mark, the precipitation distribution for conflict grid-cells seems to be normally distributed around the mean. Indeed, the data shows that out of 639 cells with conflict incidence, 167 grid-cells have changes in temperature that are above the sample average and precipitation changes below the sample average. This represents just 26% of the total similar to the percentage of observations with conflict that have below average changes in both temperature and precipitation. Again, there does not seem to be a strong empirical pattern that links adverse changes in conflict - higher temperature and less precipitation - with higher conflict risk.

Closer examination of the link between temperature and conflict shows that there is a 14% chance of conflict onset in a grid-cell following a temperature increase of at least half a standard deviation, compared to 11% for grid-cells with temperature changes below this threshold.[7] As a preliminary test I further examine the conditional probability of conflict on temperature, accounting for the temporal persistence in conflict by limiting the sample to grid-cells that did not have reported cases of conflict incidence between 1989-2002. This approach does reduce the sample size from 2,557 to 1,882

[7]This probability is conditional on the grid-cell not having any reported conflict between 1989-2002. The autocorrelation in the conflict data is pretty strong as the probability of conflict in a grid-cell conditional on having conflict in the respective grid-cells between 1989-2002 is 0.49. Similarly, for those grid-cells that did not experience any violent conflict, or where there was none reported at least, the probability of conflict is just 0.16 between 2003-2017. This entails that there is a 51% chance of conflict offset so to speak between the two periods and a 16% chance of conflict onset.

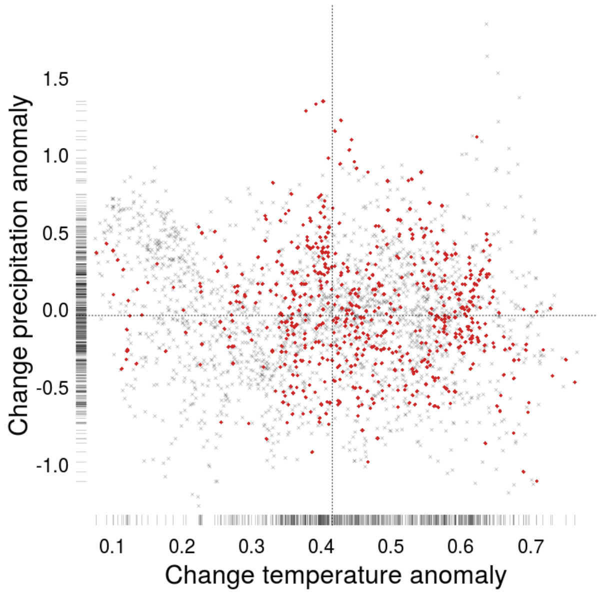

Figure 4: Plot of changes in precipitation versus changes in temperature, comparing the 1989-2002 benchmark period to 2003-2017. The red diamonds indicate grid-cells with conflict, grey crosses are grid-cells without conflict. Tick marks on the x and y axes show the distribution for the grid-cells with conflict.

cells, but still retains 73.6% of the original data. The conditional probability is calculated using different thresholds on the 0.1 to 0.7 interval, using 100 equally sized increments. In other words, I calculate the probability of conflict conditional on a temperature change of at least size i, where i is located on the 0.1-0.7 interval. For instance, as discussed, for $i = 0.5$ this probability corresponds to 0.23. The results of this exercise are summarized in figure5 which shows that there is a there is a gradual increase in conflict probability as temperature increases: this probability peaks at 0.23 corresponding to a temperature increase of about 0.61, after which it decreases again to reach a minimum of 0.10 at a temperature increase of 0.68.

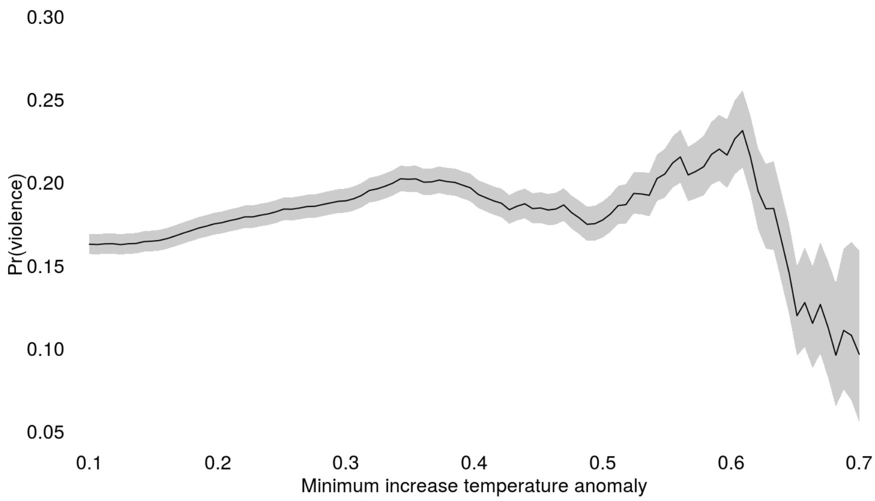

Figure 5: Conditional probability of conflict at different thresholds of the change in the average temperature anomaly for cells without conflict between 1989-2002. Grey-shaded area represents 50% uncertainty interval.

3 Empirical framework

The explanatory power of the variables in the model is estimated using Bayesian Model Averaging (BMA) (Raftery et al., 1997).[8] Within the Bayesian framework, the identification problem of conflict determinants is framed in terms of uncertainty with regard to the 'true' set of variables, or model uncertainty. If we have K different variables there are 2^K different models for the researcher to consider if we assume that no preference is given to a

[8]Using the 'BMA' package in R (Raftery et al., 2018).

particular specification beforehand. To account for model uncertainty the posterior probability is calculated for all possible model permutations, given the theoretically relevant variables included in the data, and from these posterior probabilities a weighted average is constructed over the most likely models.

We can collect the K possible explanatory variables in matrix X and the 2^K possible models make up model space $\mathcal{M} = \{M_1, ..., M_K\}$. The functional form of the model can be written as

$$y_i = \alpha + \beta_k X_{ki} + \epsilon_{ki} \tag{4}$$

where y_i is conflict incidence in cell i; α is a constant term; β_k the effect of the explanatory variable on conflict incidence in model k; and ϵ_{ki} the Gaussian error term. Within this framework the quantities of interest are the model-weighted posterior distributions of the coefficients

$$Pr(\beta|y, X) = \sum_{k=1}^{2^K} Pr(\beta|M_k, y, X) Pr(M_k|y, X) \tag{5}$$

This equation provides a way of summarizing model uncertainty after having observed the data. The latter term in this equation is the model weight - for model M_k - which is based on the model's posterior probability, or

$$Pr(M_k|y, X) = \frac{Pr(y|M_k, X)Pr(M_k)}{Pr(y|X)} \tag{6}$$

where $Pr(M_k)$ is the model's prior probability and $Pr(y|M_k, X)$ the marginal likelihood. Similar to Zhukov (2016) a uniform distribution is used for the model's prior as there if no justification to prefer on model specification over the other beforehand given the sensitivity of research results in the empirical study of conflict (Hegre and Sambanis, 2006). A major advantage of the BMA approach is that by estimating all 2^K possible models it provides a general assessment of a variable's performance across the whole model space. This means that we can assess whether a particular variable contributes consistently to the models' explanatory power by summing the posterior probabilities of all the models that include the variable of interest (Montgomery and Nyhan, 2010).

Concerning statistical inference, we can obtain an estimate of the direction and magnitude of an effect by looking at the expected value of a coefficient which is obtained by averaging across the model space. Mathematically the expected values for coefficient β is given by

$$E(\beta|y, X) = \sum_{i=1}^{2^K} Pr(\mathcal{M}_k|y, X)\; E(\beta_k|\mathcal{M}_k, y, X) \tag{7}$$

As discussed in Zhukov (2016) there are a number of benefits associated with BMA, which include i) giving an overall performance assessment across different model specifications; ii) providing information on whether a variable consistently contributes to the models' performance; and iii) being a transparent model selection tool preventing cherry-picking based on statistical significance. In addition, it provides better predictions due to averaging across all the possible models (Raftery et al., 1997).

4 Model estimation

Logit estimation using conflict incidence as outcome variable shows that there is a strong link between temperature change and conflict risk, but weaker between precipitation change and conflict risk (illustrated in figure 6. For 512 possible models the inclusion probability of temperature is 96.9% and only 16.4% for precipitation (panel a). Overall, these results might not come as too big a surprise given the earlier discussion on empirical patterns in the data as well as results in the existing literature. Although shifts in climatic conditions at grid-cell level seem to be important in terms of explaining conflict risk, there do not seem to be strong spillover effects where the conflict risk in cell i is influenced by changes in climate in the k neighbouring cells, as the inclusion probabilities of the spatial lag of temperature and precipitation are 6.4% and 9.1% respectively. The three strongest predictors of conflict are population density and the temporal and spatial lag of conflict, each having a 100% inclusion probability. The almost classical greed-or-grievance motivations for conflict do not feature strongly across the models given the expected values of the coefficient for night light emission, a proxy for income, and the ethnic polarization index, accounting for identity-based motivations.

In terms of the estimated magnitude, for the best model - with a posterior probability of 0.57 - at the upper bound a two standard deviation increase in temperature is associated with a 31% increase in conflict risk; this is similar to the reported effect by the meta-analysis of Hsiang et al. (2013) (28%). The average estimated effect for precipitation is considerably lower, with a 1% increase in conflict risk following a two standard deviation increase. The results are somewhat sensitive to using a longer benchmark period - 1981 to 2002 instead of 1989 to 2002 - as the inclusion probability 37.2% for precipitation and 64.2% for the spatial lag of precipitation using the longer benchmark.[9] The results for temperature remain largely unaltered. In all, the contribution of including precipitation variables in the model seems to be minimal as there is almost no difference in the root mean squared error (-0.004) when excluding information on changes in precipitation.

At the extensive margin variables accounting for shifts in climatic conditions seem to be important factors explaining conflict risk, at least when considering temperature. To scrutinize these results, the models are re-estimated focusing on the intensive margin using the share of years between 2003-17 that a grid-cell reported conflict. Given that this particular outcome variable is bounded between 0 and 1, the data is fitted using a quasibinomial model as ordinary least squares (OLS) regression would likely give biased estimates as the fitted values are not constraint to the unity interval. Switching the outcome variable to account for the prevalence of conflict between 2003-2017 does not lead to qualitatively different results. The major change is that the inclusion probability of the precipitation variable increases by about 64 percentage points to 80.7 percent. The estimated magnitude of the effect is relatively small with a coefficient of 0.3.

At this point it is good to reflect on the interpretation of the effect of one of the other explanatory variables: population density. Given the use of conflict data that is largely based on media reports, a correct interpretation of the estimated effect of population on conflict is difficult as it is hard to differentiate between different processes. On the one hand the results could suggest that cells with higher population densities are subject to more competition over local resources, but on the other hand we have to be aware of the possibility of possible reporting bias, where events in rural areas might go unnoticed because they are not that news-worthy. In addition there is the fact that cities, increase population density, are important strategic targets and might therefore attract conflict. This is an issue that has received relatively little attention in the literature.

[9] Correlations are pretty high: 0.94 for temperature and 0.92 for precipitation.

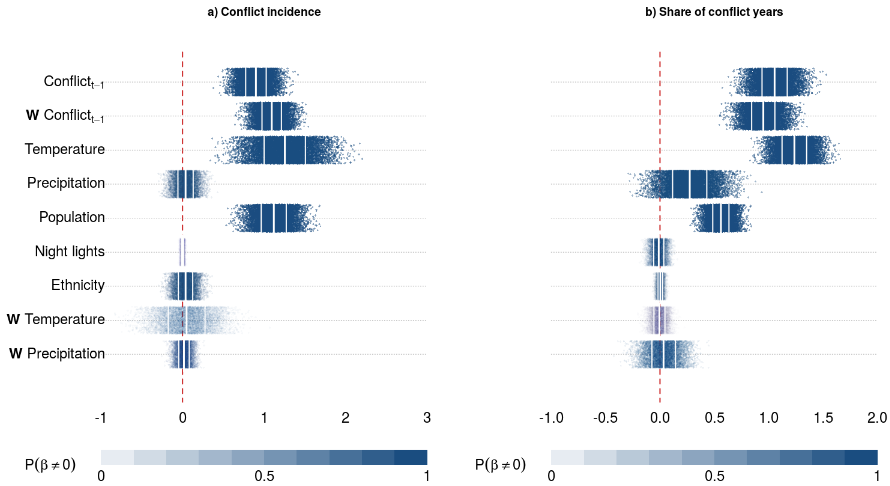

Figure 6: Local conflict determinants for conflict incidence (a) and the share of conflict years between 2003-2017 (b). Each blue point in the plot represent a draw from the posterior distribution for the respective variable coefficient; with vertical lines indicate the mean and 66% uncertainty interval. The posterior inclusion probability of a variable is reflected by the opacity of the points with full transparency indicating $P(\beta \neq 0|y, X) = 0$ and full opacity indicating $P(\beta \neq 0|y, X) = 1$.

The analysis so far has been agnostic about the type of conflict, whereas it could be the case that climate has a stronger link to particular types of violence as past research has shown for instance that there is a stronger link between climate variability and communal conflict compared to other types of conflict (Fjelde and von Uexkull, 2012). Therefore, the models are re-estimated changing the outcome variable to account for particular conflict types, distinguishing between state-based or civil conflict, non-state or communal conflict, and violence against civilians.[10] The results, shown in figure 7, are again qualitatively the same compared to the main model estimation, but there is an increase in uncertainty associated with the estimated parameters. For instance, with civil conflict as outcome variable (panel a) the probability inclusion for population density drops to 33.6%, while the inclusion probability of ethnic polarization increases to 90.5% when using violence against civilians as outcome variable (panel c)

Concerning the variable accounting for climatic conditions, the results are also fairly consistent although there is some heterogeneity across the different outcome variables in terms of the uncertainty associated with the direction of the estimated effect, as well as the magnitude. The largest changes occur in the model linking climate to non-state conflict, which includes communal conflict between different ethnic groups as well as violence between supporters from different political parties (panel b). In the best model for this particular type of conflict - with a posterior probability of 0.64 - the temperature variable is not included as the inclusion probability is 23.1%. In contrast, the spatial lag of temperature is included and has a magnitude similar to the temperature variable in the main model with an expected value of 1.3 (s.e.=0.7). This seems to suggest that in the context of communal conflict changes in the local climate are more important compared to changes in the grid-cell itself. Similarly, for the model focusing on civil conflict, increases in precipitation in the neighbouring cells are linked to increased conflict risk in the grid-cell.

[10] There are 423 grid-cells with civil conflict, 405 with violence against civilians, and 253 with communal conflict.

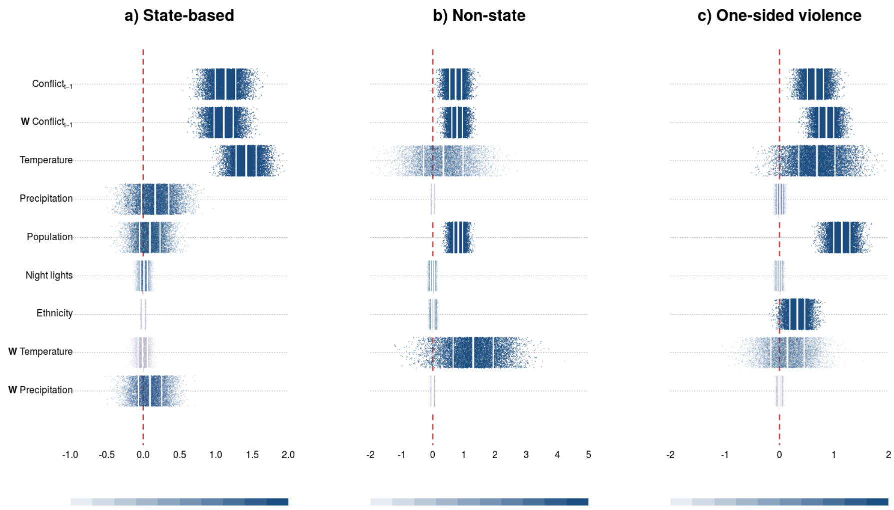

Figure 7: Local conflict determinants for different types of conflict: state-based (a), non-state (b), and violence against civilians (c). Each blue point in the plot represent a draw from the posterior distribution for the respective variable coefficient; with vertical lines indicate the mean and 66% uncertainty interval. The posterior inclusion probability of a variable is reflected by the opacity of the points with full transparency indicating $P(\beta \neq 0|y, X) = 0$ and full opacity indicating $P(\beta \neq 0|y, X) = 1$.

4.1 Cross-validation

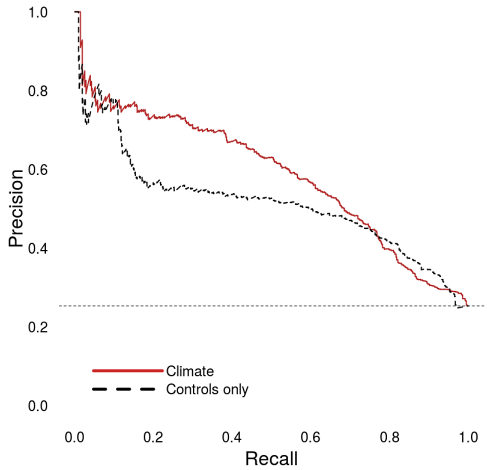

Figure 8: Precision-recall curve in-sample prediction of conflict between 2003-2017 per grid-cell for the main model of the Bayesian Model Averaging result (solid red line) and a benchmark model omitting the climate variables (dashed line); the dotted line indicates the baseline.

As a final robustness test the out-of-sample predictive power is examined to gauge if the variables accounting for the shift in local climate capture an underlying relationship with conflict or, in contrast, the model just fits the sample's idiosyncrasies. For this test a benchmark is considered that includes only information on population density and conflict patterns, i.e. the variables shown to have a 100% inclusion probability in the regression analysis, and compare this with a model space that includes variables accounting for the shift in climate.[11] The predictive performance is then compared to see whether including information on temperature and precipitation improves the predictive accuracy compared to a more parsimonious model. The predictions are generated by leaving out one grid cell at a time and using information from the remaining cells is to estimate the parameters and predict the outcome of the left out cell: this process is repeated for all 2,525 grid-cells in the sample.

To measure the predictive accuracy the precision-recall curve is used which plots the relation between the true positive rate (recall) and the precision of the model, or the number of true positives relative to the predicted number of positives as is shown in figure 8 (Davis and Goadrich, 2006; Saito

[11] The results do not change when the other variables such as ethnic polarisation and economic activity are considered as well.

and Rehmsmeier, 2015).[12] The precision-recall curve is preferred over the more commonly used Receiver-Operator Characteristics (ROC) curve as it is relatively easy for the ROC to correctly predict the large number of true negatives, at different thresholds, when the outcome is a rare event, such as conflict incidence, which will inflate the true negative rate.[13] Figure 8 plots the precision-recall curve for the two model spaces along with a baseline set at 0.25, which represent the proportion of grid-cells with reported conflict events in the data: a junk classifier randomly assigning probabilities would attain this curve. The results show that omitting information on temperature and precipitation produces poorer predictive results as the curve for the benchmark is closer to the baseline.

An examination of summary statistics confirm this conclusion: F-score, or harmonic mean of precision and recall (van Rijsbergen, 1979), is 046 for the benchmark compared to 0.48 including the variables accounting for changes in climate. In all a small difference. The divergence becomes slightly more pronounced considering the area under the curve (AUC) which is 0.51 for the benchmark compared to 0.58 when including information on climatic conditions. In both cases this is well above the baseline of random guessing (0.25) which shows, focusing on the benchmark, that reasonably accurate predictions can already be made on the basis of just a few structural factors such as past dynamics of conflict and population density. Adding information on climate, particularly temperature, improves the performance of the model by about 7 points. The results also highlight that a relatively simple benchmark, including only past information on population density and conflict patterns, scores relatively well (26 points above the baseline).

Panel a in figure 9, which shows the prediction error for the model space including the temperature and precipitation variables, illustrates that getting accurate point predictions remains a challenging task, which does not come as a very big surprise (Cederman and Weidmann, 2017). The model tends to overpredict conflict based on historical patterns, as seen in Angola and South Africa, while it has difficulties in correctly classifying new events, such as in the Central African Republic, Libya, Nigeria, and Zimbabwe. We can contrast these predictions with those of the benchmark to identify potential hot-spots of climate-conflict as is done in panel b. Here the blue shade indicates grid-cells

[12] Recall is also known as sensitivity and is simply the number of correct predictions relative to the total number of conflict cases in the sample. Precision is similar but it takes the number of correct predictions relative to the number of correct predictions and false positives, thereby penalising the latter.

[13] Rather than using precision, the ROC relies on specificity or the true negative rate, which is basically the recall for non-conflict cases.

where the benchmark predicts higher conflict probabilities; these are mainly located in southern Africa and driven by past conflicts such as the violent struggle against Apartheid in South Africa, and the civil wars in Angola and Mozambique. In contrast, the red shades indicate grid-cells with higher predicted probabilities when accounting for local changes in climate and these are concentrated in three areas: Egypt, the Horn of Africa, and the larger area around Lake Chad. The pattern in panel b reflects the temperature increase as shown in panel a of figure 1. Focusing on the difference in predicted values might be more fruitful to identify risk areas as is illustrated by the case of northern Nigeria.

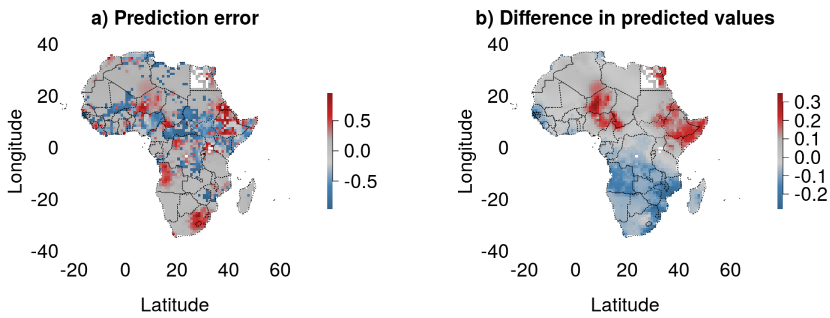

Figure 9: Prediction error (a) and difference in predicted value relative to benchmark model (b) per grid-cell for conflict incidence between 2003-2017 . For panel a red values indicate false positives while blue values indicate false negatives. For panel b red values indicate higher predicted values relative to the benchmark and blue vice versa.

5 Conclusions

Given the lively debate on the correct interpretation of the results in the climate-conflict literature, the jury seems to be still out concerning the issue whether local climate is a strong predictor for conflict risk or if its contribution is relatively marginal instead. An important limitation of the existing literature, which this study has tried to address, is the reliance on climate variability to proxy for climate change. As some have argued, it is unlikely that the possible mechanisms linking climate to conflict can be examined using high-frequency data, i.e. by relying on just annual variation in temperature and precipitation. Therefore, this study focused on changes in the long term, examining how the change in the average anomaly in temperature or precipitation between 1989-2002 and 2003-17 affected conflict risk between 2003-17 across the African continent. The empirical analysis does lend some support to the hypothesis that climate is linked to violent armed conflict. The regression results showed that changes in temperature contributed consistently to explaining variation in the conflict across a large number of different model specifications. This result was robust to changing the outcome variable, using longer benchmark periods, and accounting for spatial patterns in climate change. Accounting for climate in the empirical model also improved the predictive performance of the model. One remaining caveat of this study is that it ultimately is another reduced-form estimation, in contrast with some interesting recent contributions to the literature such as Maystadt and Ecker (2014) and Crost et al. (2018). Although using the long-differences approach gives some insight into local adaptive capabilities, the used research design provides no information on the particular mechanisms linking climate and conflict. The limitation of this study is partially due to data constraints as there is relatively little information on for instance local commodity prices, both in terms of spatial and temporal coverage. While there is no information at all on local trade allowing to empirically test promising theories linking climate change to conflict through market collapse as in Olsson (2016). These remain challenges to be dealt with by further future research.

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