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Communal violence in the Horn of Africa following the 1998 El Niño

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Abstract:

This study exploits a shift in Spring precipitation patterns in the Horn of Africa following the 1998 El Niño to examine the effect of climate change on conflict. Using data for Ethiopia and Kenya and focusing on communal conflict the regression analysis links districts that have experienced drier conditions since 1999 relative to 1981-1998 with higher conflict levels. However, the magnitude of the estimated effect is low and the direction of the effect is as likely to be positive as negative. Moreover the results are sensitive to model specification, not robust to using another outcome variable, and do not generalise well to out-of-sample data. The cross-validation illustrates that the model linking droughts with conflict has a relatively poor predictive performance. The results also show that districts with substantial shares of pastoralism experience higher levels of communal violence, something that is well documented in the qualitative literature, but don't face higher risks following decreases in precipitation levels.

Keywords: Horn of Africa, climate change, rainfall, communal violence

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Introduction

Due to its relevance there has been a large surge in research on the link between climate change and violent armed conflict in recent years (see Klomp and Bulte (2013) for an overview). An extensive meta-analysis by Hsiang et al. (2013), using data from 60 studies, found that a standard deviation increase in temperature or extreme rainfall corresponds to a 14% increase in intergroup conflict. However, these results have been heavily contested (Buhaug et al., 2014) and various recent studies have shown that although climatic conditions can be linked to conflict its salience often seems limited (O'Loughlin et al., 2012; Ayana et al., 2016; Uexkull et al., 2016). Indeed, in contrast with the work by Hsiang et al. (2013); Hsiang and Burke (2014), who find a strong convergence of results, there are a number of review papers, studying the same strain of literature, that fail to find a consensus concerning the climate-conflict nexus (Bernauer et al., 2012; Gleditsch, 2012; Scheffran et al., 2012; Klomp and Bulte, 2013).
With regard to this strain of quantitative research on climate-conflict, one important critique is that the use of inter-annual or intra-annual variation in weather is not a suitable proxy for global climate change (Selby, 2014). Although using data with relatively high frequency can help uncover dynamics related to for instance the seasonality of conflict (Witsenburg and Adano, 2009) or the strategic importance of weather (Carter and Veale, 2014), a major limitation of this approach is the implicit assumption that variation in weather will have an almost immediate impact on conflict risk. Whereas using more fine-grained spatial data can help account for subnational variation in climate, as is done by O'Loughlin et al. (2012, 2014); Maystadt and Ecker (2014); Maystadt et al. (2015), this doesn't necessarily apply to the temporal scale, except for the reasons mentioned previously. Of course certain delayed effects can be modeled adjusting the lag structure of the empirical framework, but the included lags often cover only a few additional years which is relatively short in climatic terms.

As such the empirical models currently used at best capture the link between weather variation and conflict, but arguably they provide little information on the effects of climate change. Although the speed of the current increase in average global temperature might be unprecendent, the change is still relatively gradual on a human time scale. Therefore, to enhance our understanding of the influence of climate change on conflict, it might be advisable to use data at a lower frequency to account for delayed effects, similar to what is done by Zhang et al. (2007); Tol and Wagner (2009). In contrast with much of the existing literature this study provides another approach, focusing on cross-sectional variation by exploiting a shift in precipitation patterns in the Horn of Africa following the 1998 El Niño. Since this cycle of the El Niño oscillation there has been a reduction in precipitation levels in the Spring raining season, which has increased the number and severity of droughts in this part of East Africa (Funk, 2012).[1] Unlike relying on inter- and intra-year variation in temperature or rainfall, this phenomenon truly provides an opportunity to examine the effect of climate change.[2]

To estimate the impact of climate change on conflict this study focuses on two countries in the Horn of Africa: Ethiopia and Kenya. Both these countries have been harried by various sorts of violence over the past decades, particularly communal conflict which has been on the increase in the past 15 years. Given the importance of the agricultural sector in each country in combination with the shift in precipitation patterns and the incidence of communal conflict, Ethiopia and Kenya therefore provide interesting case studies. I focus here on communal conflict as this type of violence has been identified as a possible outcome of conflict variability (Fjelde and von Uexkull, 2012). Communal conflicts often involve violent confrontations concerning access to natural resources such as water or pasture. As an example, Markakis (2003) analyses the case of the Afar, a pastoralist group in Eastern Ethiopia. This ethnic group often clashes with neighbouring groups, both sedentary farmers and mobile pastoralists, over water, pasture, and access routes. The more serious of these clashes are with the Ise Somali, a competing pastoralist group, with whom they have a conflict concerning exclusive claims on grazing land, amongst others and these clashes tend to be more frequent during droughts (Markakis, 2003). Analysing the frequency of farmer-herder conflicts in semi-arid regions in Africa, Hussein et al. (1999) note that the alleged increase in conflict is partially due to i) changing patterns of resource use and the associated increased competition, and ii) a breakdown of traditional mechanisms managing both resource use and conflict. Indeed, the link between climate and conflict is often framed in a neo-Malthusian model. Here stakeholders compete over a prize, such as pasture, and when this prize becomes more valuable for instance due to increased scarcity as a result of climate change, violence will become the dominant strategy to capture the prize. Now as Olsson (2016) argues the mechanisms linking climate and conflict within this discourse can be vague; instead he provides a general model linking climate change and conflict through market disintegration. Using the conflict in Darfur as an example, he argues that a decrease in resource availability will lead to a reduction in trade between different groups competing over the resource, such as farmers and herders in the Darfur case, which makes each group's welfare independent of each other which can lead to increases in conflict risk.

[1] The Spring raining season lasts from March till June.

[2] Hsiang et al. (2011) provides a study using the El Niño cycle to examine the link between climate and conflict.

There is an extensive body of work studying the link between climate and conflict in East Africa, including Ethiopia and Kenya. For Kenya, Theisen (2012) finds that years with below average precipitation levels are generally followed by years with lower violence levels, whereas Detges (2014) shows that pastoralist violence in Northern Kenya tends to occur near well sites and in locations with higher rainfall levels. Similarly the study by Raleigh and Kniveton (2012) links higher rates of communal conflict with anomalous wet periods. While Maystadt and Ecker (2014); Maystadt et al. (2015) find, for both Sudan and Somalia, that conflict events are associated with higher temperatures, and thus drier circumstances. Whereas these these studies all find a link in one direction or the other, the work by O'Loughlin et al. (2012); Ayana et al. (2016) illustrate that variables proxying climate change are only very moderate predictors of conflict events.
Although the existing literature is insightful, there is the possiblity that the provided results have been affected by the fact that since 2000 there has been a decline in the number of gauge stations in the region measuring precipitation levels (Funk et al., 2015). This development is particularly problematic given that most of the studies focus largely on the post-2000 period. In contrast with the existing literature, this study uses a different source for precipitation data exploiting the recently released CenTrends dataset. This dataset was constructed to overcome the issues of measurement error resulting from the declining number of observations as discussed in Funk et al. (2015).

This study makes at least two contributions to the existing literature. First, it analyses the link between climate and conflict exploiting a shift in precipitation patterns which is a better measure for climate changes compared to the commonly used proxies such as interannual variation in rainfall. Second, it uses a new precipitation dataset which deals with missing data issues that might have affected previous research on the climate-conflict nexus in the Horn of Africa.
Comparing the shift in Spring rainfall with the years between 1981-1998 as baseline period with the period 1999-2014, the results show that there is no strong association between a reduction in precipitation levels and conflict risk, measured by the number of communal conflict events or the fatality numbers. However, using an alternative variable to capture climate change, measuring the probability that a significant shift in precipitation occurred, does provide some empirical evidence for a link between climate change and higher violence levels. Testing the robustness of the results, a cross-validation exercise shows that a model including only information on conflict dynamics has about the same explanatory power as a similar model that additionally includes a measure for the shift in precipitation. The analysis illustrates that the results do not generalise well to out-of-sample data and that the climate variable has little predictive power echoing earlier results in the literature

(O'Loughlin et al., 2012; Wischnath and Buhaug, 2014; Ayana et al., 2016). The regression analysis does suggest a strong effect of pastoralism, where violence levels are higher in areas where pastoralism is the main livelihood strategy, although the interaction with precipitation shows no additional effect.

Data and measurement

This study uses districts as unit of analysis, which are the second level of administrative division for both Ethiopia and Kenya. A main reason for using districts is because they are the smallest sub-national unit for which the conflict data can still be accurately geocoded (Weidmann, 2015). As an alternative grid-cells could have been used, which have the advantage that they cover a fixed area (Buhaug and Rød, 2006), but using a more abstract unit also entails a reduction in the number of conflict events that can be located accurately. In general districts also make more intuitive sense since they capture social heterogeneity following sub-national boundaries (Ostby et al., 2009; Aas Rustad et al., 2011). Information on the district boundaries is taken from the GAUL dataset produced by the FAO[3]

Precipitation

Precipitation data is taken from CenTrends which is a dataset that provides high quality precipitation estimates for the Greater Horn of Africa, made available on a 1°x1°grid covering the period 1900-2014 (Funk et al., 2015). This dataset has been constructed giving special attention to the years 2000-2014 since there are few actual observations for this period, due to a reduction in the number of gauge stations, as well as an inhomogeneous monitoring network. To overcome these limitation data from various station archives were combined and gaps in coverage filled with data from nearby stations or additional data from national meteorological agencies. The remaining missing values were imputed using spatial kringing, taking into account the station-specific measurement errors, as described in more detail in Funk et al. (2015). As such, CenTrends provides the most comprehensive precipitation climatology for the Horn of Africa currently available, overcoming limitations that hamper other datasets which have seen a decline in observation numbers since the 1990s and specifically since 2000.

To account for climate change, this study exploits the shift in the patterns of the Spring raining season which lasts from March till June. Since the 1998 El Niño precipitation levels have been significantly lower in the Horn of Africa (Funk, 2012; Lyon and Dewitt, 2012; Lott et al., 2013) as

[3]Reference year is 1999.

illustrated by figure 1. The figure plots the region's 15-year moving average of the standardised precipitation anomaly for the Spring season. This standardised anomaly for precipitation (P) is calculated by subtracting the long-term mean from the observed level in year t and dividing it by the standard deviation of the time-series: $\frac{P_t - \overline{P}}{\sigma_P}$. Precipitation normally follows a cyclical pattern, as rainfall is mean reverting as illustrated by (Ciccone, 2011), were relatively abundant years are followed by drier periods . For instance, the figure shows the 1984-85 drought responsible for the infamous famine which followed after some relatively wet years. However, although the late 1980s and early 1990s were relatively wet again, there has been a significant decrease in precipitation levels since 1998. Since the 1998 El Niño the 15-year moving average of the standardised anomaly has been negative. Additionally, the magnitude of the anomaly has increased considerably accounting for the historical record. So not only does the region experience a prolonged period of relatively drought, the severity of the drought seems to have increased.

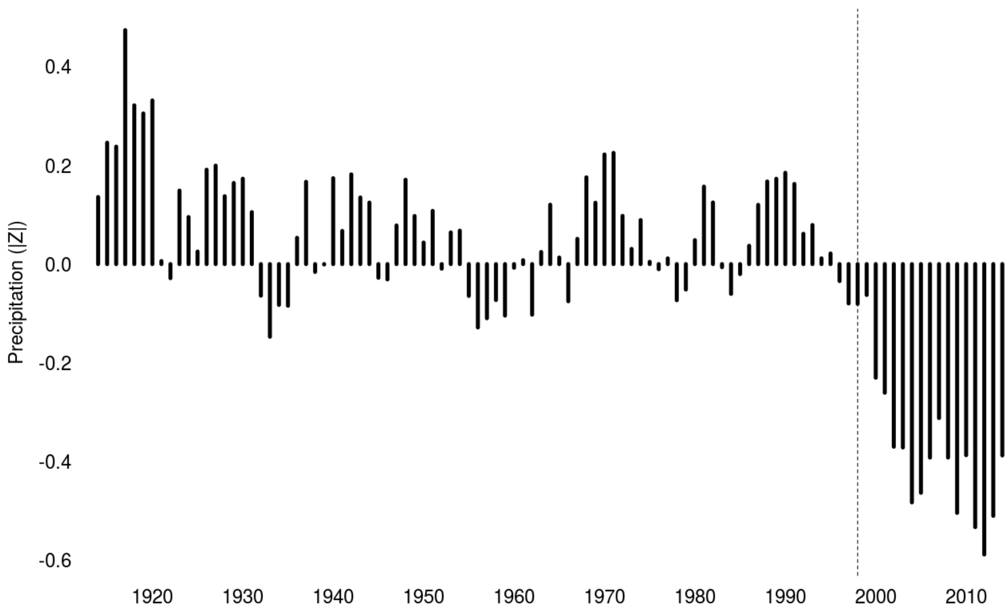

Figure 1: Precipitation patterns 1915-2014

Figure 1 shows the development of precipitation patterns aggregated at the greater regional level which ignores existing local variation. To account for this variation the data is aggregated at the district level, the unit of analysis, the results for which are shown in figure 2 for two periods: 1981-1998 and 1999-2014. Following Pricope et al. (2013) the years between 1981 and 1998 are used as a benchmark period. The mean standardised anomaly for this period is compared to the following years up to 2014. The data for the benchmark period illustrates that the region was already relatively arid, but the level of aridity seems to have increased in the past 15 years. The figure shows that most districts have experienced decreases in Spring precipitation levels, while only a handful of districts actually saw a slight increase.[4] In general the reduction in precipitation levels has been particularly severe in the Ethiopian highlands in the West of Ethiopia and also in the Western part of Kenya. These are both important agricultural regions relying on farming (Ethiopia) and a mix of farming and herding (Kenya).

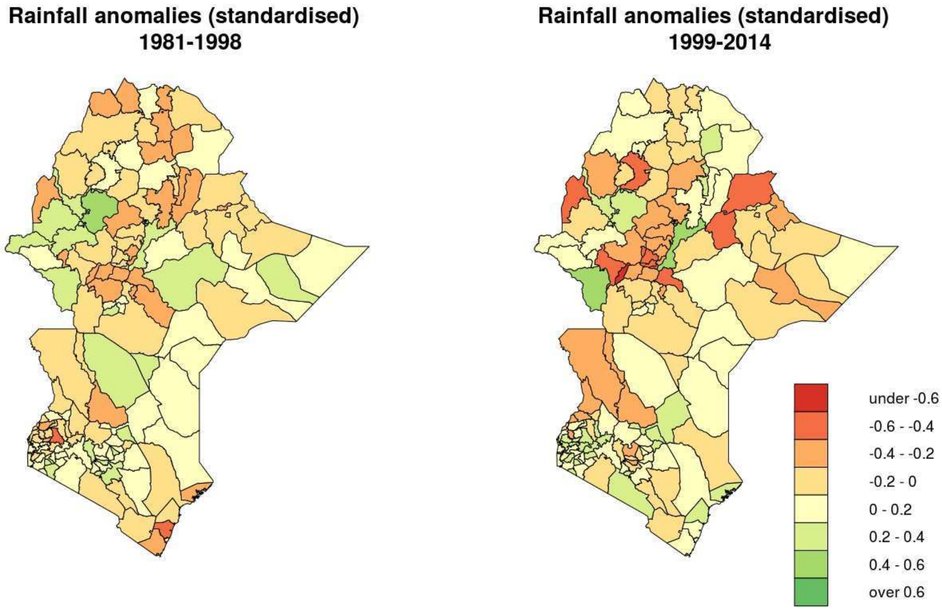

Figure 2: Precipitation patterns per district.

Conflict data

Information on conflict is taken from the Georeferenced Event Dataset (GED) which is provided by the Uppsala Conflict Data Programme (Sundberg and Melander, 2013). The GED contains detailed information on the location, timing, and severity of conflict events, along with information on the warring parties involved and an estimate of the number of fatalities. Currently this is the most comprehensive conflict event data set available (Eck, 2012; Weidmann, 2013, 2015)
However, although the dataset represents the state-of-the-art in the field,

[4]Note that there already had been a longer decrease in the raining season lasting from June to September since the 1970s, which has been very gradual and not as swift as the Spring season shift.

there is a caveat concerning the data, the result of certain coding rules related to the definition of conflict. In the dataset, conflict events are only included if the associated conflict has reached a fixed fatality threshold of 25 battle-related deaths in a given year (Croicu and Sundberg, 2015). This means that certain types of violence, that don't pass this threshold, are not included. Particularly the dataset omits events with relatively low intensities such as riots, and events without fatal consequences such as most strikes and protests. Concerning the estimation this entails that the results won't account for very incidental types of violence at very low intensity levels. Additionally, given that a large share of the data is compiled from media sources there is a risk of reporting bias. However recent work has shown that the bias, induced to for instance the availability of communication technology, on event reporting is very small (Croicu and Kreutz, 2016).

The conflict data is processed to include only observations that can be accurately located at the district level following the recommendations made by Weidmann (2015). Furthermore, non-unique events are excluded as well as conflict events that are theoretically irrelevant to this study. To be more precise this means that particular military actions on Ethiopian or Kenyan territory conducted by the army of neighbouring countries are excluded. This includes for instance events related to the Ugandan army pursuing elements of the Lord's Resistance Army that have crossed the border. Therefore, the analysis focuses exclusively on the incidence of communal conflict, which is defined here as violence between different ethnic groups or between farmers and herders. Given results in the literature, communal conflict could be a likely outcome of climate change as people living in a vulnerable environment, where secure livelihoods have a large dependency on natural factors such as precipitation, face adverse shocks that reduce their coping capabilities.

To illustrate, figure 3 provides an overview of the data, plotting the location of communal violence for two periods: 1989-1998 and 1999-2014.[5] The map indicates besides the district boundaries (dashed lines) also what are called livelihood zones. Data on livelihood zones is taken the Famine Early Warning System Network (FEWS Net) who define a livelihood zone as "an area where people generally rely on the same options to obtain food and income and engage in trading". Included here are three different types of livelihood zone: i) pastoral, ii) agropastoral, and iii) farming. The reason for including these zones in the analysis is that households within these zones likely react similarly to changes in the local climate due to the similarities in livelihood strategies.

[5]Note that for the climate data the period 1981-1998 is used as a baseline, but unfortunately the conflict data is only available from 1989 onward.

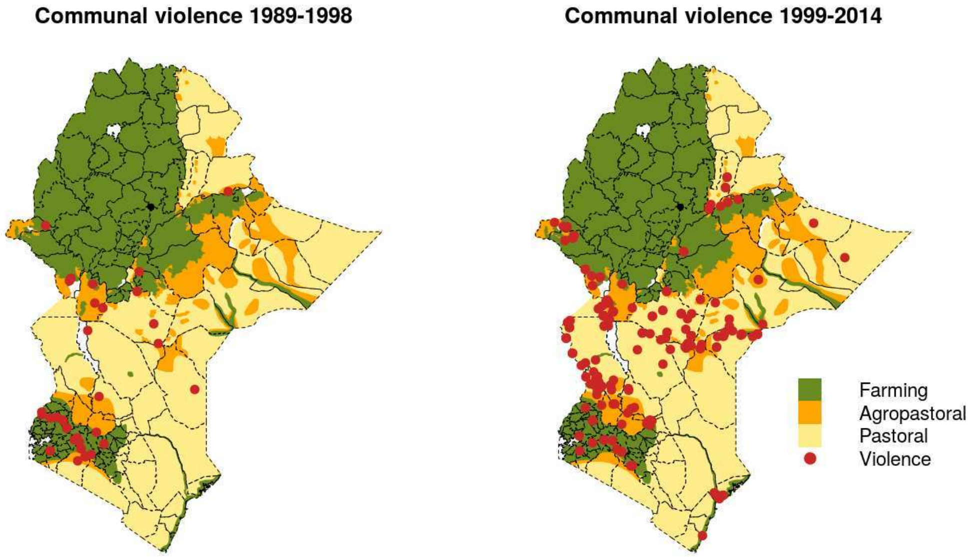

Figure 3: Communal violence 1989-1998 and 1999-2014.

For the period 1989-1998 the data shows that the incidence of communal violence was concentrated mainly in the South West of Kenya and some isolated pockets in the South of Ethiopia. Since 1999 this pattern has changed as there seems to have been a spread of violence to a much larger area; covering a large part of Western Kenya, parts of central Ethiopia, and the pastoral border region between the two countries. A lot of these violent events occur along the border lines of the different livelihood zones, which might indicate the presence of some level of animosity between people relying on different type of agricultural activities for their subsistence. Markakis (2003) discussed how the Afar in Ethiopia clashed with other groups at the fringes of their ethnic homeland, something that is also exhibited here. The data itself shows that most communal conflicts involve members from different ethnic groups. For instance, in 2003 in a confrontation between members of the Afar and Ise in the Afar region in Ethiopia, an estimated 40 people were killed. The Ise and Afar are neighbours and often involved in conflicts concerning access to pasture and water points as discussed before. Similarly, in 2006 a battle in Northern Kenya between Ethiopian and Kenyan nomads left 38 people dead.

Estimation framework

The data aggregated at the district level, I exploit the cross-sectional variation in changes in precipitation levels and estimate the effect on the level of communal violence. Specifically, the statistical model has the following functional form:

$$V_j = \alpha + \beta \Delta R_j + \gamma V_{1989-1998} + \rho \sum_k W_{jk} V_k \tag{1}$$

In the main model specification outcome variable V_j is a count of the number of communal conflict events in a district between 1999-2014. Besides examining the effect of climate change on the quantity of conflict I also carry out a robustness check using the number of fatalities to account for the intensity of conflict. The explanatory variable of interest is ΔR_j which measures the change in the average anomaly, subtracting the value for the baseline period 1981-1998 from the value for the period 1999-2014. Since conflicts tend to be persistent over time and display spatial interdependence as well (Buhaug and Gleditsch, 2008), it is important to account for conflict dynamics to isolate the effect of climate change. Therefore, the temporal lag of the outcome variable is included in the model, measuring the number of events or fatalities between 1989-1998, to capture conflict persistence over time. Additionally, the spatial lag is included to deal with spillover effects. The spatial lag is constructed as the sum of the outcome variable in neighbouring districts, irrespective of national borders since these tend to be porous.[6]

Using the count of the number of conflict events as outcome variable, the data shows that the distribution is overdispersed with 21.9% of observations being non-zero.[7] To deal with this overdispersion a negative binomial model is used (Hausman et al., 1984; Lloyd-Smith, 2007). Working with count data one would normally prefer to use a Poisson model, but given that the variance exceeds the mean such a model would fit the data poorly.
The model is estimated using Bayesian regression which has the advantage that it produces consistent estimates in the presence of spatial dependence as well as the fact that the estimated parameters have an intuitive probabilistic interpretation. In contrast with standard uncertainty intervals produced by Frequentist methods, which only provide a range of outcome, Bayesian uncertainty intervals provide a probability distribution of the parameter which gives a better insight into the uncertainty of the estimates. The posterior distribution of the parameters, from which the coefficients and uncertainty intervals are calculated, are constructed using JAGS Plummer (2014), which is a Markov Chain Monte Carlo (MCMC) algorithm. All parameters in the model are modelled using non-informative priors with distribution $N(0, 10)$. This means that the estimates will be similar to those obtained by maximum

[6] Additionally, I don't row-standardise the adjacency matrix as this would imply that the effect of neighbouring conflict is larger for districts with few neighbours which is not theoretically justifiable. Note though that the specification of the adjacency matrix should have little effect on the estimated spatial effect (LeSage and Pace, 2014).

[7] $\mu = 1.5, \sigma = 34.2$

likelihood estimation (Gelman et al., 1995). To scrutinise the regression results I will use out-of-sample cross-validation, the details for which will be discussed in the relevant sections.

Regression results

Table 1 presents the estimation results for a number of different model specifications. Based on the recommendations made by Gelman (2008) all input variables have been standardised by subtracting the mean and dividing by twice the standard deviation. Placing the variables on a common scale facilitates easier comparison of the estimated effects, specifically when using interaction effects. In this case the coefficients can be interpreted as the effect of moving from low to high values, where the intercept is the expected outcome when all variables are at their mean.

Table 1: Predicting communal conflict in district j, 1999-2014

	Number of events						Battle-related fatalities	
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta Rain$		-0.1	-0.5		-0.2	-0.4	0	
		(-1.5; 1.4)	(-1.6; 0.7)		(-1.8; 1.4)	(-1.8; 1.0)	(-2; 3)	
BEST				0.5				0
				(-0.7; 1.6)				(-2; 2)
$\text{Violence}_{1989-1998}$	0.9	1.0	1.3	1.3	1.0	1.3	2	3
	(0.1; 2.4)	(0.1; 2.3)	(0.5; 2.6)	(0.4; 2.5)	(.1; 2.3)	(0.5; 2.6)	(0; 8)	(0; 9)
$\text{Violence}_{neighbours}$	2.2	2.2	1.4	1.4	2.1	1.4	2	2
	(1.1; 3.8)	(1.0; 3.9)	(0.5; 2.7)	(0.5; 2.7)	(0.8; 3.8)	(0.4; 2.7)	(0; 6)	(0; 5)
Population density			-1	-1	-2		-2	-3
			(-4; 2)	(-4; 2)	(-7; 2)		(-8; 4)	(-8; 3)
Pastoral area			2.0	1.9		2.1	2.2	2.2
			(0.9; 3.0)	(0.9; 3.0)		(1.0; 3.1)	(0; 4)	(0.4; 4.2)
$\Delta Rain$*population density					-2			
					(-11;6)			
$\Delta Rain$*pastoral area						0		
						(-3;3)		
Intercept	-0.2	-0.2	-1.2	-1.1	-0.3	-1.2	1.5	1.5
	(-0.7; 0.3)	(-0.7; 0.3)	(-1.8; -0.6)	(-1.7;-0.5)	(-0.9; 0.3)	(-1.7; -0.6)	(0.6; 2.6)	(0.6; 2.5)
Deviance	332.9	334.2	320.6	320.7	335.7	320.4	520.4	520.3

As a benchmark I start with fitting a baseline model which only accounts for conflict dynamics (col.1). The estimates show that the level of communal violence tends to be higher in districts which had comparatively high communal violence levels in the period 1989-1998, illustrating the persistence of conflict over time. Moving from low to high violence levels increases the log count of the outcome variable by 0.9, corresponding to 2.5 events (the average is 1.5 events). Similarly, districts with violent neighbours also tend to experience higher violence levels. Again the effect is substantial with an increase of 2.2 in the log count of the outcome variable or 9 events (the average is 10.2 events). These results indicate that there seems to be a large spillover effect, where the observed violence in one district is influenced by the violence level in neighbouring districts. I proceed by including the variable that measures the shift in average precipitation levels between the two periods (col.2). Given some of the existing results in the literature, that link drought with communal conflict (Fjelde and von Uexkull, 2012), we would expect that negative changes will be associated with an increase in the number of conflict events. The mean estimated effect indeed shows that a positive growth rate is associated with a reduction in violence. However, the magnitude of the effect is small, especially compared to the variables accounting for conflict dynamics, and the uncertainty interval is centered around 0. Looking at the estimated parameter distribution, the probability of a negative effect is just 0.54 where the 50% uncertainty interval ranges from -0.5 to 0.4. Using this measure in the model specification the effect of the shift in rainfall is as likely to be negative as it is to be positive.

Some additional models are specified to account for other factors that could be linked to the incidence of communal conflict and that could also have an effect on conflict risk interacting with the change in precipitation patterns. Specifically I focus here on the effect of two factors: i) population density and ii) the salience of pastoralism as a livelihood strategy. Larger populations have often been linked to conflict risk (Hegre and Sambanis, 2006) as it increases the pool of possible recruits for an insurgency when the population are dissatisfied with the status quo.[8] Moreover, in a neo-Malthusian context, larger populations will put additional pressure on available resources which might culminate into violence. To account for these dynamics a measure for population density is therefore included in the model (col. 3).[9] The results show that the estimated effect of population density is negative,

[8]See also Urdal (2011) for an overview of the literature linking population dynamics and conflict.

[9]Data on population density is taken from the Global Rural-Urban Mapping Project, which provides gridded population estimates at five year intervals from 1990 to 2000. Give the research design, I rely on the 2000 estimate. The data, original in grid format, is aggregated to the district level and divided by its area to arrive at a population density measure in people per square kilometres.

linking more densely populated areas to lower levels of communal conflict, echoing the results in Theisen (2012). The direction of the effect can be partially explained by fact that more densely populated districts possibly have higher levels of economic specialisation. This entails that these districts are less dependent on agriculture for their welfare, which is the economic sector probably to be worst affected by downturns in precipitation levels. Interestingly, interacting population density with the precipitation variable (col.5) results in a large estimated negative effect for more densely populated districts. Note however that the estimate comes with a very wide uncertainty interval; the probability of a negative effect is 0.64 compared to 0.82 for the main effect of population density.

Besides population I also examine the link between livelihood strategies and communal conflict, specifically the relation between pastoralism and communal conflict.[10] To estimate the effect a binary variable is included in the model indicating districts where at least 25% of the district's area falls within a pastoralist livelihood zones as defined by the FEWSNet data. Based on the thesis of Nisbett and Cohen (1996) as discussed in Pinker (2012), we could expect that districts with substantial levels of pastoralism (I will refer to these districts as pastoralist districts henceforth) have higher violence levels due to certain cultural characteristics associated with pastoralism. Informative in this respect is the case study on the Turkana district in Kenya as discussed in Zefferman and Mathew (2015) as well as the analysis on the violence between Afar and Ise in Ethiopia by Markakis (2003). Additionally, pastoralist areas tend to be neglected by central governments leading to higher poverty levels, higher rates of malnutrition and lower standards of life in general (Stockton, 2012). These factors might make these particular areas more susceptible to violence (Pinstrup-Andersen and Shimokawa, 2008). Looking at the estimated effect, there certainly seems to be some credibility to the idea that pastoralist districts indeed have higher levels of communal violence. On average, in a pastoralist district the log count of violence is higher by 2.0, corresponding to 7 events. The distribution of the estimated parameter shows that the additional number of conflict events can range from about 2 to 20.[11] Interestingly, interacting the dummy variable with the variable measuring the change in precipitation shows that the effect of rainfall on communal violence is not different for pastoralist districts (col.6). Both the estimates on the main variable capturing the salience of pastoralism and the interaction effect are robust to changes in the coding of the indicator variable to account for districts where pastoralism covers at least 50% or 80% of the district's area.

[10] See also the work by on pastoralism and conflictGray et al. (2003); Meier et al. (2007); Schilling et al. (2012); Ayana et al. (2016)

[11] The majority lays between 4.7 and 10 events.

So far the analysis has relied on model specifications that used the actual change in the average precipitation anomaly between the two periods to estimate the effect of climate change on conflict. As an additional check I re-estimate the model switching the variable capturing the change in rainfall with a variable that measures the probability that this shift in precipitation patterns is indeed statistically significant. This is done using the Bayesian equivalent of the *t*-test called the Bayesian Estimation Supersede the t Test (BEST) developed by Kruschke (2012). This Bayesian equivalent is used as it can be interpreted probibalistically providing a continuous measure on the 0-1 interval.[12] To further clarify, the BEST is used to test whether the rainfall anomalies for the years 1999-2014 were lower compared to the 1981-1998 baseline.[13] This test produces an estimated probability which is then included in the model specification as shown in column 4 of table 1. Given existing results we could expect that districts with higher probabilities of a significant negative change will experience higher levels of communal conflict. The results do provide some empirical evidence for this case; moving from low to high probabilities of precipitation shift corresponds to a 0.5 increase in the log count of the outcome variable. The direction of this effect is likely to be positive with a probability of 0.8. Concerning the magnitude, the estimated effect is similar to that of the other rainfall measure.

Besides the quantity of conflict I also examine the impact of climate change on the intensity of conflict as a robustness check. Conflict intensity is measured by the number of fatalities, with information on fatality numbers taken from the GED, the for which are shown in columns 7 and 8. Changing the outcome variable to fatality levels leads to very minor changes in most of the explanatory variables. In all cases the direction of the effect is robust to changing the outcome variable, and only for the variables capturing conflict dynamics we observe some increases in the magnitude of the estimated effect. However, the effect of the change in precipitation patterns ceases to be meaningful with an estimate of 0, accounting for the standard error, and wide uncertainty intervals.

The regression results provide some mixed evidence for an effect of climate change on conflict as the analysis shows that the estimated effect tends to be very sensitive to model specification. For further scrutiny I examine whether the regression results can be generalised to out-of-sample data. In the cross-validation I focus on the model specification from column 4 in

[12] In contrast, an orthodox Frequentist *t*-test would just provide a test statistics with a *p*-value.

[13] The results of this exercise are visually summarised in figure A1

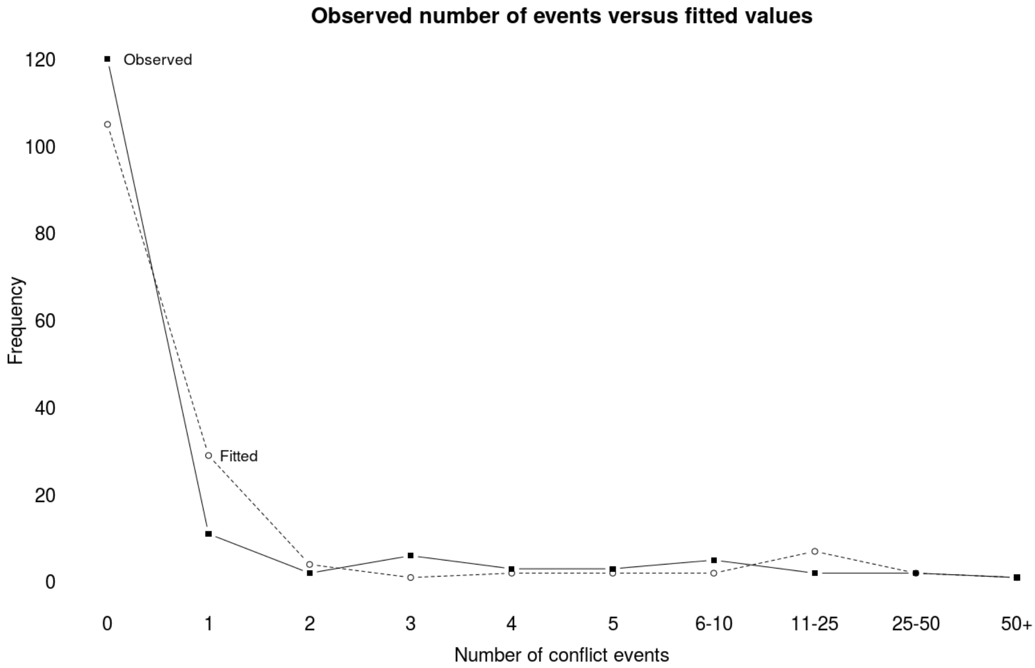

Figure 4: Marginal calibration diagram

table 1, which includes the BEST measure to capture the effect of climate change on conflict, as this model exhibited the strongest relation between climate change and communal conflict. The model is re-estimated leaving out one district at a time and used to predict the outcome for the left-out district.

For the analysis I start with examining the accuracy of the model at the aggregate level, comparing the frequency of the predicted number of events with the observed levels. This is a useful step as it provides information on whether the negative binomial model indeed accounts for the overdispersion in the data. Following the recommendations made by Bagozzi (2015) a marginal calibration diagram is used, plotting the observed number of events along with the predicted values as shown in figure 4. The results illustrate that the model does quite a respectable job in modeling the number of zeroes, albeit slightly underestimating the observed number. In contrast, the number of districts with just one event is slightly over predicted. Concerning other frequencies the figure shows that the predicted values tend to be reasonably close to the observed levels of violence, the notable outlier being the district with 56 conflict events.

Moving beyond the aggregate level, examining point predictions I plot the predicted values against the observed change in precipitation and the BEST

results (panel a and b respectively in figure 5). In both cases there does not seem to be a very strong relation between either i) rainfall and communal violence and ii) observed violence and higher predicted values. Focusing on the observed change in precipitation the results show that larger negative change are not necessarily matched with higher fitted values by the model. Additionally, districts that experienced communal conflict did also not necessarily experience larger decreases in rainfall. In general it does seem that districts with communal violence are matched with higher predicted values, but still we see that there are a large number (13) of false negatives.
Plotting the predicted values against the BEST score a similar pattern emerges, although the model does perform slightly better; above the threshold of 10 events there is only one false positive. The figure also illustrates that a fair share of districts with communal conflict did not experience significant decreases in precipitation patterns based on the BEST result. These results provide some support for the findings of Theisen (2012) and Detges (2014) who found that violence tends to occur in relatively wet places.[14]

Besides a visual inspection I also calculate the absolute predictive er-

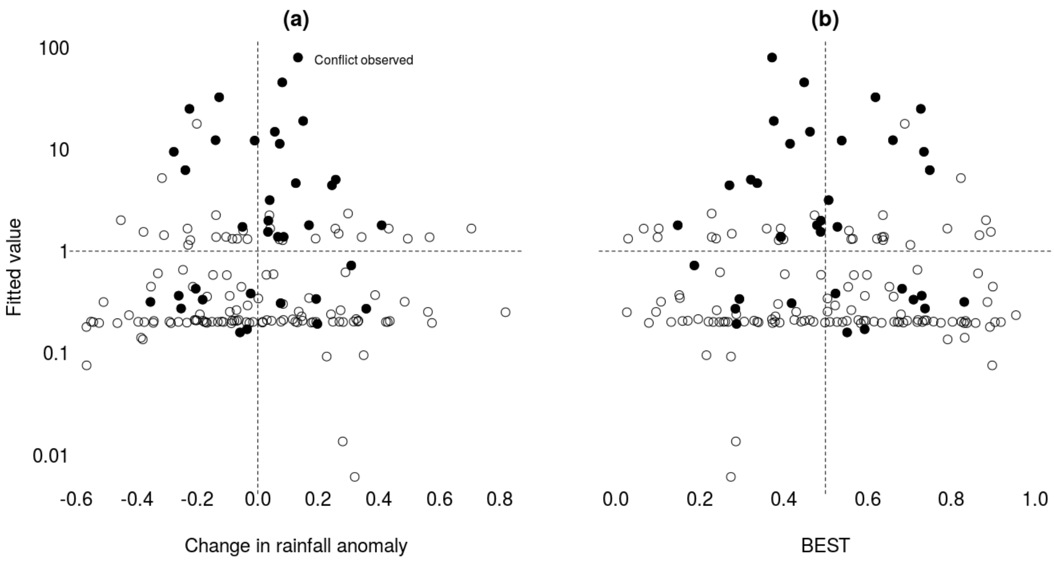

Figure 5: Fitted values versus the change in precipitation (a) and the BEST measure (b)

ror for each district and plot this against the observed number of conflict

[14]It could be that there is some displacement effect as shown for instance in the study by Detges (2014), but estimating a model including the spatial lag of change in precipitation did not show a strong correlation.

events, as shown in panel a of figure 6. The predictive accuracy of the model is reasonable for the large number of districts that did not have any recorded case of communal conflict between 1999-2014. However, moving to districts that did experience conflict, the model seems to have difficulties in matching higher levels of communal conflict with higher fitted values. The model does not adequately predict the quantity of conflict a district experiences, despite modeling the conflict dynamics and other factors that might influence conflict. This is further illustrated by panel b of figure 6 which compares the predictive error of the full model, i.e. the model in column 4 of table 1, with a model that omits the BEST variable accounting for the change in precipitation. The results show that including a variable accounting for the shift in precipitation patterns does not lead to any significant improvement in predicting the outcome as most districts are clustered around the 45 degree line.

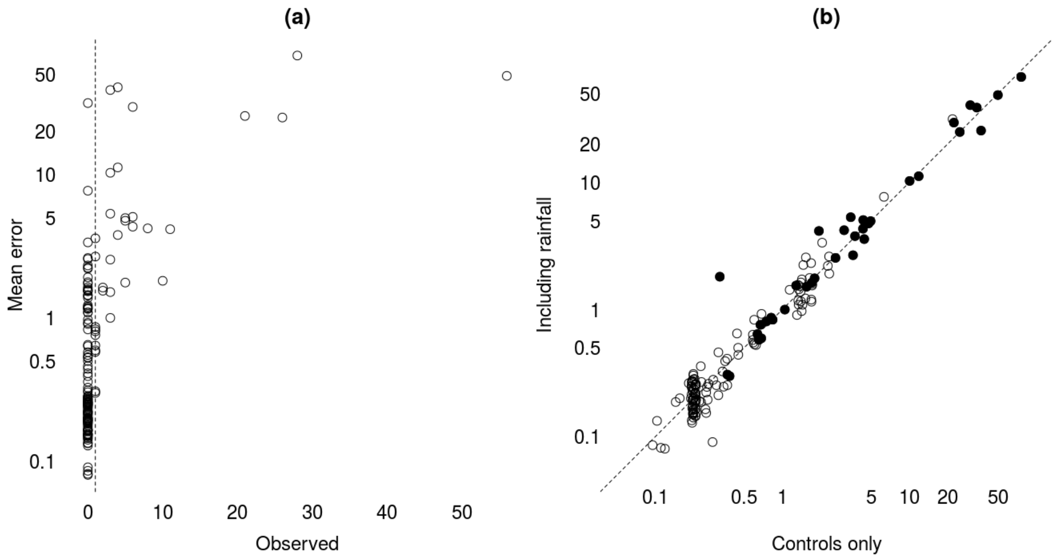

Figure 6: Forecast error per district compared to observed levels of communal violence (a) and comparing a model with a variable accounting for the shift in precipitation versus a model without this variable (b).

Conclusions

In recent years there has been a large surge in quantitative research on the link between climate and conflict. Within this field, most studies have relied on the use of relatively high frequency time series cross section data to examine the impact of variables proxying climate change on conflict risk. Although in some case this approach can provide useful insights into how weather influences conflict dynamics, there are a number of serious shortcomings to this approach. First, in most cases it is assumed that there is almost an immediate effect of a shock in weather at time t, for instance a sharp decrease in precipitation, on the observed level of violence in the same time period, thereby ignoring delayed effects. Second, due to the high frequency of the data, typically annual, it is rather hard to actually isolate the effect of climate change as this type of data only accounts for weather variation, and not so much change over longer time periods. As a result of this, there is for instance little attention for the cyclical nature of climate in regions which experience violence or regions vulnerable to climate change.

Therefore, in contrast with the existing literature this study exploited a significant shift in Spring precipitation patterns following the 1998 El Niño, which is a better measure for climate change, to estimate the impact of climate change on communal violence using a cross section of districts in Ethiopia and Kenya as unit of analysis. Although the regression analysis showed that the average estimated effect is indeed negative, i.e. linking districts that have experienced drier conditions, between 1999-2014 relative to 1981-1998, with higher conflict levels, the magnitude of the effect is low and the direction of the effect is as likely to be positive as negative. Examining the probability that a shift occurred in a district does provide some empirical support for a link between climate change and communal conflict, but the results are sensitive to model specification, not robust to using another outcome variable, and do not generalise well to out-of-sample data. Indeed, the cross-validation illustrated that the model linking droughts with conflict has a relatively poor predictive performance, although it must be stated that this also applies to some extent to a model without climate variables. Echoing earlier studies in the literature, the results show that conflict dynamics, such as the temporal and spatial lag, are important predictors for current conflict levels. Additionally, the regression results also showed that districts with substantial shares of pastoralism experience higher levels of communal violence, something that is well documented in the qualitative literature. However, the results do not seem to suggest that these districts face higher risks following decreases in precipitation levels.

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Appendix

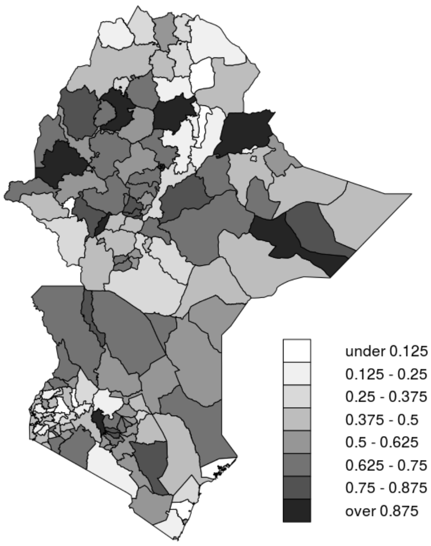

Figure A1: BEST (Bayesian Estimation Supersede the t Test) result per district. The numbers give the probability that the average precipitation anomaly for the Spring seasons is lower for 1999-2014 compared to the 1981-1998 baseline, i.e. giving the probability that the local climate has become drier.