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Short term effects of drought on communal conflict in Nigeria

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Abstract:

Despite the surge in quantitative research examining the link between climate variability and conflict, a lot of uncertainty exists concerning whether there is a link. One shortcoming of the current literature is that it focuses mainly on statistical inference in order to establish causation with little attention for the predictive performance of the model. In contrast, this study extends the current literature by focusing on the predictive accuracy of a model linking droughts to communal conflict using data for Nigeria for the period 2006-2014. Using a number of different model specifications and estimation methods to test the robustness of the results, the analysis shows that although the regression results show a positive link between the occurrence of droughts and communal conflict, the predictive accuracy of the model is relatively low. In contrast, accounting for the temporal and spatial dynamics of conflict leads to better forecasts compared to the climate variable.

Keywords: Nigeria, droughts, communal conflict, cross-validation

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1 Introduction

In the past decade there has been a large surge in quantitative research on the potential link between climate and conflict. Yet despite this increased research effort, the literature seems no closer to reaching a consensus regarding the estimated effect of climate change on conflict, as this strain of research suffers from the same shortcomings as the larger conflict literature which is hampered by a lack of generalisation of results (Hegre and Sambanis, 2006; Blattman and Miguel, 2010). However, recently some scholars argued that the existing research does provide sufficient evidence for a link between global warming and violence (Hsiang et al., 2013; Hsiang and Burke, 2014). A claim that is heavily contested by others (Buhaug et al., 2014).[1] Much of the disagreement within the literature stems from the sensitivity of the results, for instance due to the sample selection such as countries and years that are included (Klomp and Bulte, 2013).

One other possible explanation for why results tend to generalise poorly to out-of-sample data is the fact that current research focuses almost exclusively on hypothesis testing, without examining the predictive accuracy of the model as for instance discussed by Ward et al. (2010). Within the climate-conflict literature there are some exceptions, where the results undergo further scrutiny than just examining p-values, such as recent work by O'Loughlin et al. (2012) on East Africa and Wischnath and Buhaug (2014) on South East Asia, as well as some other more general studies on political violence (Goldstone et al., 2010; Weidmann and Ward, 2010; Gleditsch and Ward, 2013). It is important to focus on predictive accuracy of a model given that existing theories on the climate-conflict nexus, such as linking the occurrence of drought to higher violence risk due to increases competition over resources or reduction in income, generated observable predictions. Therefore, the empirical analysis should not be limited to only discussing the estimated effects, to see how well the model explains the variation in the data, but actively examine the generated predictions to check whether the theories are actually any good. Of course this can be a challenging task, and models will often be wrong, but it is an important step to take in order to improve the degree to which obtained results can be generalised. In contrast with much of the existing literature, this study will therefore focus on the predictive performance of a model linking drought to the incidence of communal violence, using data for Nigeria between 2006-2014. Additionally, this study is, to the best of my knowledge, the first to offer a quantitative analysis of the effect of drought on the incidence of communal conflict in Nigeria.

[1] There are also scholars, specifically from the field of political economy and ecology, that raise some serious concerns regarding the validity of much of the quantitative literature (see Selby (2014) for a critique).

This study focuses on the link between conflict and drought as droughts are often linked to violence. Within the neo-Malthusian discourse, droughts are expected to increase competition over water and arable land, thereby causing frictions between different stakeholders which might lead to violence in the absence of other coping mechanisms. Similarly, since droughts have a negative impact on agricultural output, reducing farm income for instance, this might lower the opportunity costs for armed conflict Collier and Hoeffler (1998) in societies largely dependent on the agricultural sector. For instance, the civil war in Darfur, Sudan, has been linked to the occurrence of severe drought (Olsson, 2016) although Kevane and Gray (2008) found that rainfall patterns are not sufficient in explaining the outbreak of violence. In general the empirical evidence for a link between droughts and conflicts has been somewhat mixed: Couttenier and Soubeyran (2014) found a weak positive link for Sub-Sahara Africa and O'Loughlin et al. (2012) show that higher temperatures, but not lower rainfall levels, were associated with increased risks of violence using subnational data for East Africa, while Fjelde and von Uexkull (2012) found low rainfall to correspond to higher risks of communal conflict. All these studies exploited annual data, which might potentially obscure interesting within-year dynamics in both climate variability and conflict patterns, as illustrated by Witsenburg and Adano (2009). In contrast, Maystadt et al. (2014) exploit regional and monthly variation in weather and conflict for Somalia and find a strong link between droughts, measured by temperature anomalies, and the incidence of violent events. Similar results, linking drought to conflict, are obtained by Maystadt et al. (2015) for Sudan using quarterly data.

This study will follow Maystadt et al. (2015) and exploit quarterly data to analyse the relation between droughts and communal conflict, at the state level, in Nigeria between 2006-2014. In contrast with much of the existing literature, the empirical analysis will focus mainly on the predictive performance of the model, and as a result slightly less on the causal inference. Practically this entails that parsimonious models are preferred over more complex ones, including various exploratory variables to control for confounding factors. Including a whole battery of other exploratory variables and unit or time indicators leads to the risk of overfitting the model, which might explain a lot of the in-sample variation, but generalises poorly to out-of-sample data. Using a number of different model specifications, the analysis shows that although the regression results show a positive link between drought and conflict, the predictive accuracy of the model is relatively low. In general, including variables to account for the temporal and spatial dynamics of conflict are better predictors compared to the variable measuring droughts.

2 Background

Nigeria has a long history of violence dating back to the pre-colonial period. After gaining independence from the United Kingdom in 1960, tensions between different groups quickly intensified culminating into the civil war between 1967-1970 which saw secessionists in Biafra take up arms against the federal government. Indeed, a main area of contention in Nigeria is the distribution of political power across different ethnic groups, specifically between the North and South (Papaioannou and Dalrymple-Smith, 2015).[2] The federal government has faced severe difficulties concerning state and territorial legitimacy, with certain groups excluded from power at the national or regional level.[3] A major issue has been the dominance of the political landscape by civilian and military leaders from the North. Tensions have lead to various episodes of violence, most notably during the 1980's in Kaduna state as well as violence in Lagos and other parts of the South West after the nullification of the 1993 election by the military regime.

It wasn't until 1999 that military rule was formally ended and Nigeria returned to democracy. Although a welcome development, this also meant a decrease in repression which provided opportunities for different armed factions to mobilize. As a result, numerous armed groups exist in Nigeria, ranging from criminal gangs and small militias to larger politically motivated armed groups (Small Arms Survey, 2005). This development has lead to an intensification in violence, especially communal violence, across the country, but most notably in the Delta region and around the Jos plateau.[4] Since 2009 the North Eastern part of the country, which includes Borno and Yobe state, has been harried by Islamic militants from Boko Haram, claiming an estimated 13,000 lives.[5] It was only in 2015, after military involvement of other West African countries that the federal government has been able to contain the group.

Although one of the economic powerhouses on the African continent, due to its oil wealth, Nigeria is marred by various forms of political instability,

[2] The British colonial power preferred to govern the North, roughly the area above the Niger and Benue river, via indirect rule granting privileges to local tribal leaders and emirs preserving the traditional power structure, in contrast the South was gradually administered via direct rule, creating a secular system similar to that of the U.K. (Sampson, 2014). See also Bleaney and Dimico (2016).

[3] To address power-sharing issues there has been a gradual proliferation in the number of states in Nigeria. At independence there were 3 states, currently there are 37 (including the capital city).

[4] As a result of armed conflict the emergency rule was temporarily re-established in Plateau state in 2004.

[5] Using data from the Uppsala Conflict Data Programme (UCDP) the best estimate for the number of fatalities as a result of Boko Haram violence is 12,693 with a lower estimate of 12,208 and high estimate of 16,283 (own calculations).

and the central government seems unable keeping its monopoly on violence and providing basic services. A report from the Small Arms Survey showed that key motivating factors behind the violence are the perceived injustice perpetrated by the government along with economic marginalisation (Small Arms Survey, 2005).[6] Despite its oil revenues, a large share of the population still relies on the agricultural sector for income. Recent figures show that this sector employs about 48% of the population (estimate from 2007) and added 20-37% to GDP annually between 2006-2015 (World Bank, 2016). Modernisation efforts notwithstanding, the agricultural sector is still fairly traditional with certain activities strongly associated with particular ethnic groups, such as Fulani herdsman.[7] Due to disputes related to herders traversing farmer's land, there have been numerous clashes between the two groups over the years. Farmer-herder violence has escalated due to the increased use of firearms by herders (Small Arms Survey, 2005).[8] A most notable example of this violence is the Egbe massacre in 2015, where a group of Fulani herdsmen entered an Egbe village and killed 80 people. According to Nigerian media sources this type of violence has claimed more than 600 lives in 2015 (Baca, 2015).

Given the link between violence and competition over water and arable land, there are concerns that communal violence could increase due to climate change. A recent study by Müller et al. (2014) identified Nigeria as a climate change hotspot, which entails that there is a relatively high likelihood of i) negative impacts across different vegetation zones in the country, ii) the possibility of extreme impacts, and iii) impacts that are large on average.[9]

[6] Round 6 of the Afrobarometer survey, held in 2015, showed that a majority of the Nigerian population thinks that the government performs poorly in managing the economy and does too little to improve living standards. The respondents also found that government was not very effective in addressing problems caused by armed extremists. In addition, only 27% of respondents felt that their ethnic group was never treated unfairly by the government.

[7] Despite the importance of the agricultural sector in providing employment and the production potential, the sector receives little public spending (Ahmad et al., 2011).

[8] Firearms were initially used by pastoralists to protect themselves, and their livestock, from organised gangs of cattle thieves. However, it has altered the power balance with the farmers.

[9] The country's average temperature has increased by about 1.1 °Cover the past 100 years while rainfall has decreased, especially since the 1970's, by 81 mm (Odjugo, 2010). According to the projections for 2100 made by the Intergovernmental Panel on Climate Change (IPCC), it is likely that these trends will continue (IPCC, 2014). The estimated impact is estimated to be more severe in the arid regions in Nigeria's North as relatively small reductions in rainfall levels correspond with large absolute reductions in water availability. Storing water might be an adaptation strategy in Nigeria, especially given the fact that currently almost all irrigation is rain fed. Also note that there is large spatial variation in local weather patterns: the Northern part of the country is characterised by a desert-like climate, while moving across the semi-arid savanna in the centre, the mangrove swamps in the South have a monsoon climate.

Although the estimated decline of total water availability is low, it is likely that certain parts of the country, specifically the semi-arid North could experience reductions in fresh water availability up to 25-30% due to higher temperature and decreases in rainfall, while in contrast, the Niger Delta region in the South is likely subject to more frequent flooding, also due to increased irregularity in rainfall (Müller et al., 2014). These developments will likely impact agriculture negatively by damaging crops and reducing arable land.

Given these circumstances, it is easy to envisage a scenario where changes in crop cultivation and herder migration patterns could increase competition over access to renewable resources, opening the door to violence when traditional conflict resolution mechanisms break down.[10] Sayne (2011) provides anecdotal evidence where weather-induced changes have damaged the symbiotic relation, and institutions that acted as a barrier to violence, leading to certain levels of distrust between different groups. Additionally, given the importance of the agricultural sector, the harmful effects of increased climate variability could reduce economic activity, and with other opportunities lacking, increase the pool of potential recruits to join insurgencies (Collier and Hoeffler, 1998). These are troublesome development for a state like Nigeria, where the government already faces problems in maintaining peace in different parts of the country. There is a lot of uncertainty concerning the effect of local weather variation on conflict risk, which the empirical part of this study will examine into closer detail.

3 Data and measurement

3.1 Communal conflict

Conflict data is taken from the Georeferenced Event Dataset (GED) provided by the Uppsala Conflict Data Programme. This is currently the most comprehensive and accurate georeferenced conflict event dataset available (Eck, 2012; Weidmann, 2013, 2015) and contains detailed information on the location, timing, and severity of conflict events, along with information on the warring parties involved. Although this dataset is state-of-the-art, there is a caveat with regard to the coding of conflict. One of the restrictions, to be included in the dataset, is that an armed conflict must have reached a fixed fatality threshold of 25 battle-related deaths in a given year. So violent incidents are only included when they can be matched with a conflict that has past this threshold. As such, certain types of violence, specifically non-fatal ones like protests or most riots, are not included in the dataset.

[10]The Nigerian government has tried to reduce farmer-herder conflicts b creating grazing reserves. This attempt has been largely unsuccessful since there is a lot of resistance to land redistribution.

As a result of this coding rule, the estimation results don't account for what are often very incidental types of violence, or violence at lower intensity levels.

This study focuses on the incidence of communal conflict, these are events coded in the dataset as "non-state conflict", which is defined as "the use of force between two organised armed groups, neither of which is the government". The term "organised" is used relatively loosely here and can include formally organised groups with an announced name, such as a gang, or informally organised groups without an announced name, such as an ethnic group. In the latter case there must be a pattern of violent incidents connected to the groups involved, such as farmer-herder conflicts or clashes between Christian and Muslims in the case of Nigeria. In coding the outcome variable some events are removed such as those by parties involved in armed conflict against the government (following Fjelde and von Uexkull (2012)), and events involving supporters of different political parties (following Ayana et al. (2016)).[11] The outcome variable therefore only captures true communal conflict events, assuming that these types of conflicts will be the most likely violent outcome of climate variability as suggested by some existing work (Fjelde and von Uexkull, 2012).

3.2 Droughts

Within the quantitative research on the link between climate and conflict, different measures have been used to proxy for climate change and estimate the impact of variation in weather on conflict. These proxies range from relatively straightforward variables measuring average temperature and precipitation levels to more sophisticated precipitation-evoporation indices. Similar to Couttenier and Soubeyran (2014) this study uses the Palmer Drought Severity Index (PDSI), which is one of the most prominent indices measuring meteorological drought. One of the main advantages of the PDSI over other measures is that it accounts for the interaction between temperature, rainfall, and soil conditions. The index is a function of the magnitude and duration of soil moisture deficiency based on a theoretical supply-and-demand model of soil moisture and offers a standardised measures on a -10 to 10 scale going from dry to moist conditions.[12] For a given location the index for month m is calculated as:

$$PDSI_m = a * PDSI_{m-1} + b * Z_m \tag{1}$$

Here a and b are calibration parameters and Z is the moisture anomaly index which is a measure for the surface moisture of the current month and can

[11] I also remove observation that cannot be geolocated accurately within the boundaries of the unit of analysis.

[12] For a concise discussion on the model on which the index is based see Couttenier and Soubeyran (2014).

track agricultural droughts (Dai et al., 2004). The index is based on the historical climate record and is in theory comparable across regions and time. However, the index has received some criticism concerning the modeling assumptions (Alley, 1984; Dai et al., 2004), such as the evapotranspiration rate or the fact that all precipitation is treated as immediately available rainfall (i.e. discounting snow cover). Snow cover won't be much of an issue in Nigeria but using the original calibration of the parameters as used by Palmer does bias the index for Nigeria as the original calibration was based on data from the central United States. Therefore, the self-calibrated version of the index is used as provided by Dai (2011), which is available on a 2.5°x2.5°grid.[13] This data is aggregated to create a quarterly average for each Nigerian state.

4 Estimation framework

The state is used as unit of analysis as it captures social heterogeneity following sub-national boundaries (Ostby et al., 2009; Aas Rustad et al., 2011) and additionally also accounts for possible displacement effects (Maystadt et al., 2014). To estimate the link between droughts and conflict and generate predicted values a multilevel model is fitted to the data. One of the main advantages of a multilevel model is the ease with which the model can account for the hierarchical structure of the data (Gelman, 2006), with the time periods nested within the states, and model the differences between the states (Bell and Jones, 2015).[14]

In the main model specification the outcome variable, which measures the incidence of communal conflict ($C_{jt} = 1$ if there was a conflict in state j at time t, 0 otherwise), is linked to the drought index (PDSI) and the spatial and temporal lag of the outcome variable (Eq.2). Since conflicts tend to be persistent over time the lagged outcome variable is included in the model. The lagged outcome also effectively captures common trends and accounts for temporal dynamics, ignoring these dynamics would introduce a bias in the results (Plümper and Neumayer, 2010). Similarly, conflicts can exhibit certain spatial patterns such as spillover effects (Buhaug and Gleditsch, 2008), therefore the spatial lag of the outcome variable is included to account for possible spatial interdependence. The direction and magnitude of this effect is estimated by $\rho \sum_k W_{jkt} Conflict_{kt}$. Here W is the autoregressive term and

[13] A shortcoming of the data is that the input data for temperature and rainfall comes exclusively from gauge stations, meaning that there is some risk of measurement error.

[14] Since I am using cross-sectional time-series data we can see the state-quarter as nested within states, resulting in two levels of hierarchy: the state level and the time component. The multilevel model accounts for this hierarchy by allowing residual components at each level.

ρ the spatial autoregressive parameter.[15]

Very often unit-indicators, or fixed effects, are included in the regression model to account for time-invariant factors (see discussion in Hsiang et al. (2013)). These fixed effects control to some extent for omitted variables bias and can help reduce causal inference and also reduce the bias in the estimation compared to an approach where potentially endogenous variables are included (Angrist and Pischke, 2008; Maystadt et al., 2015). However, a main disadvantage is that including these indicators will eliminate all the between-unit variation. In contrast, in a multilevel model this between-variation can be modeled as illustrated by Bell and Jones (2015) and applied by O'Loughlin et al. (2014). Here a partial pooling procedure is used, similar to that of Danneman and Ritter (2014), where intercept α_j is an outcome in the model and α_0 represents the average intercept across states(Shor et al., 2007). ϕ is the unique effect of state j on α based on state-level averages of the exploratory variables $(\overline{X_j})$ as described in Bell and Jones (2015).

$$C_{jt} = \alpha_j + \beta PDSI_{jt} + \gamma C_{jt-1} + \rho \sum_k W_{jkt} C_{kt} \tag{2}$$

$$\alpha_j = \alpha_0 + \phi \overline{X_j} \tag{3}$$

Given the binary outcome variable, it makes little sense to fit a continuous linear regression model to the data. Therefore, a logit model is used which is estimated using Bayesian regression methods.[16] Given the inclusion of the spatial lag, an advantage of Bayesian regression is that it will produce consistent estimated in the presence of spatial interdependence (LeSage, 2000). Another major advantage of this approach is that the estimates have an intuitive probabilistic interpretation. In contrast with standard uncertainty intervals produced by Frequentist methods, which only provide a range of outcomes, Bayesian uncertainty intervals provide a probability distribution of the parameter given better insights into the uncertainty of the estimates.

[15]See work by by Beck et al. (2006); Franzese and Hays (2007); Plümper and Neumayer (2010) for an extensive overview of model specification in the presence of interdependence and LeSage and Pace (2014); Neumayer and Plümper (2016) for more details on constructing the spatial lag.

[16]Sometimes scholars prefer a linear model as the estimates are easier to interpret. However, with the linear approach the fitted values are not bounded to the 0-1 interval which makes the predicted probabilities actually hard to interpret. Additionally it makes sense to use a (conditional) maximum likelihood estimator here due to the inclusion of the spatial lag. Using OLS, estimates would suffer from simultaneity bias when including the spatial lag as errors are no longer independent. Omitting this lag on the other hand would lead to omitted variable bias.

To calculate the posterior distribution of the parameters, from which the coefficients and uncertainty intervals are calculated, I use a Gibbs sampler − JAGS by Plummer (2014) −, which is a Markov Chain Monte Carlo (MCMC) algorithm. I run three parallel MCMC chains, each with 40,000 iterations, the first 10,000 iterations of each chain are discarded as burn-in to guarantee that the estimates are taken from the posterior distribution (Brooks and Gelman, 1998; Brooks et al., 2011). The coefficients and their uncertainty intervals are constructed as averages across the remaining iterations.[17] The parameters in the model, such as γ and ρ, are modelled using vague or non-informative priors with distribution $N(0, 10)$ (Gelman et al., 1995). The prior distribution should not add to the analysis and influence the posterior. As a result of using non-informative priors the estimated coefficients will be similar to maximum likelihood estimation. Details on the out-of-sample testing of the model will be given in the relevant sections.

5 Results

5.1 Exploratory data analysis

If there is a link between climate, proxied by variation in the drought index, and communal conflict, than we would expect to observe certain patterns emerge in the data illustrating this link. To probe the climate-conflict nexus I therefore start with an exploratory data analysis, examining whether the data indeed provides some initial insights. Figure 1 plots the quarterly data for the period 1989-2014 showing the proportion of states experiencing communal conflict (upper panel) and the average PDSI level across the 37 states. Although this study focuses on the years between 2006-2014, it is good practice to plot longer time-series, when the data is available, to analyse trends. The figure illustrates the sharp increase in communal violence across states in the past decade, with a large surge since 2009. This surge coincides with the intensification of the Boko Haram insurgency in the North East of the country. The Boko Haram insurgency is largely a violent armed conflict between the state and the insurgents, with some associated events of violence against civilians. However, the conflict with Boko Haram should be unrelated to incidents of communal conflict in other parts of the country. Nonetheless, one could wonder whether the general increase in violence since 2009 is part of a larger development that triggers these events related to Nigeria's specific context. For instance the increase in communal conflict could be linked to climate change, however there are other factors at play at well such as the proliferation of small arms (Hazen and Horner, 2007), a general acceptance of the use of violence (Linke et al., 2015), or the loss of the monopoly of violence by the state. Considering the link with climate change,

[17] 18,000 in this case as the thinning rate is set to 5.

the data does not exhibit a very strong pattern where low levels of the PDSI correspond to a higher rate of communal conflict. The data does show that in the past 5 years the climate, as proxied by the PDSI, has become more variable, specifically compared to the period between 1995-2007. Although

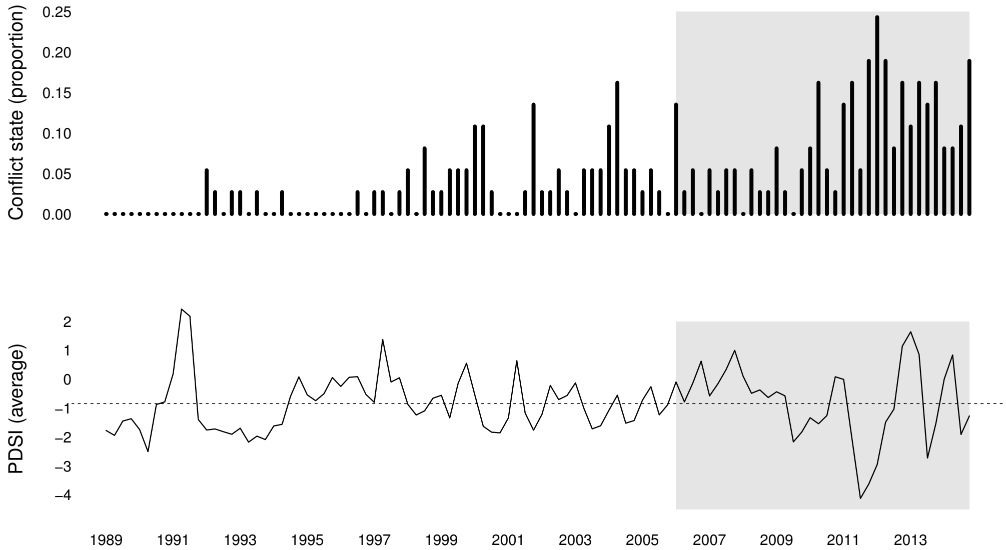

Figure 1: Proportion of Nigerian states experiencing communal violence (*top*) and average PDSI level for Nigeria (*bottom*) over time. Data: UCDP-GED, Dai et al. (2004).

informative, a disadvantage of aggregating the time-series data at the country level is that it obscures local dynamics. To examine these dynamics I focus on the timing of conflict relative to the level of the drought index. Figure 2 plot the average PDSI value ranging from 10 months before to 10 months after conflict incidence, for both communal conflict and all types of conflict. In general conflict tends to occur in months with below average index values, as is shown by the figure. There is a large range in PDSI values associated with conflict though, as for the months with communal conflict the PDSI ranges from -5.0 to 3.9, with 63% of the observations being negative. The figure also illustrates that communal conflict occurs often after a few months of gradual decline in the PDSI level, but that it doesn't coincide with the driest points, on average 9 months before and 3 months after the conflict.

5.2 Regression analysis

A number of different model specifications are used to estimate the effect of climatic conditions, measured by the PDSI, on conflict incidence. I start with a simple pooled model and proceed by adding complexities accounting

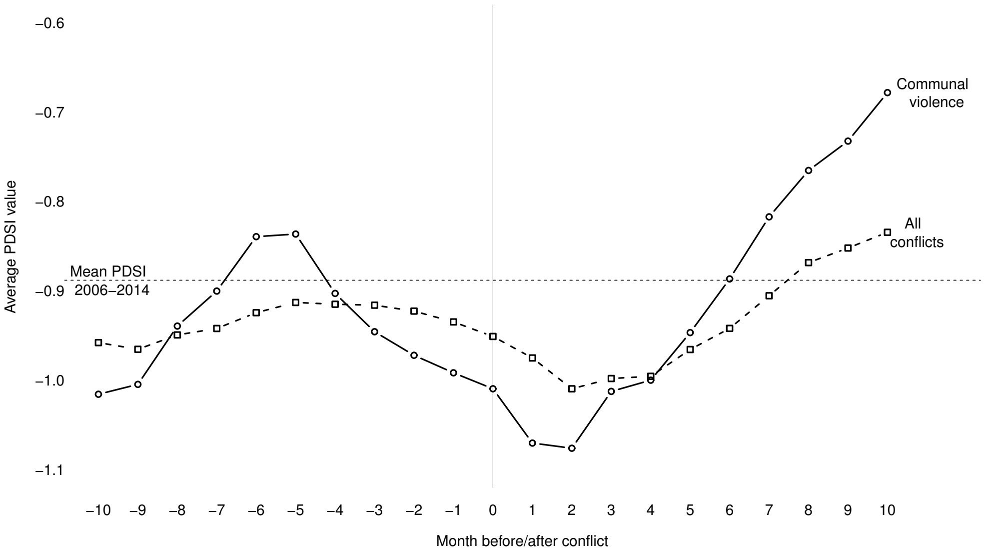

Figure 2: Variation in drought levels for all types of conflict and communal violence in the months before and after conflict incidence. Data: UCDP-GED, Dai et al. (2004).

Table 1: Predicting communal conflict in State j, 2006-2011

Specification	Pooled (1)	Multilevel (2)	Dynamic (3)	Additional controls (4)
PDSI_{jt}	−0.6 (0.3)	−0.7 (0.3)	−0.5 (0.4)	−0.5 (0.3)
PDSI_{j}		1 (2)	1 (1)	1 (2)
$\text{Conflict}_{jt}\ t-1$			0.4 (0.2)	0.4 (0.2)
$\text{Conflict}_{j}\ t-1$			5 (1)	5 (1)
Conflict $\text{neighbourhood}_{jt}$			0.7 (0.4)	0.7 (0.3)
Conflict neighbourhood_{j}			−0.9 (0.9)	−0.8 (0.9)
Population_{j}				0.3 (0.5)
Ethnic polarisation_{j}				−0.3 (0.7)
Lived Poverty Index_{j}				−0.4 (0.7)
Intercept	−2.7 (0.2)	−3.7 (0.5)	−3.4 (0.3)	−3.5 (0.3)
DIC	463.0	365.7	348.1	365.5
AUC	0.5692	0.8823	0.8695	0.8709
Brier	0.0600	0.0505	0.0500	0.0497

Notes. N=888. Table presents average estimate with their standard deviation between parentheses. The intercept is the average intercept for columns 2−4. Estimates are taken as the mean from 4 parallel chains with 40,000 iterations each where the first 10,000 are discarded as burn-in, thinning rate was set to 10. Priors are $N(0, 10)$.

for the structure of the data and important other dynamics as reported in table 1. For ease of interpretation all the input variables are standardised by centering them around the mean and dividing by twice the standard deviation. As such, the coefficients can be interpreted as the estimated effect of moving from low to high values (Gelman, 2008). I start with a very simple pooled model which links the binary outcome variable, measuring communal conflict incidence, to the PDSI (col.1). The coefficients indicates a negative association between the PDSI and conflict; a unit increase in the PDSI, i.e. wetter conditions, correspond to a 14% decrease in conflict risk. The direction of the estimated effect is negative with a probability of 0.97. The estimated coefficient shows a substantial effect, but note that this effect follows after a substantial increase in the drought index going from moderately dry conditions to moderately wet conditions. I proceed by modeling the between-variation using a partially pooled multilevel model as described in Bell and Jones (2015). The results (col.2) again show a negative relation between the PDSI and conflict where conflict risk decreases by 16% following an increase in the PDSI ($P(\beta_{-ve}) = 0.97$). Surprisingly, the coefficient for the between-effect indicates that states that have relatively moist conditions are also associated with a higher risk of communal conflict at about 24%, although this estimate does come with a certain degree of uncertainty ($P(\beta_{+ve}) = 0.66$) where the effect is positive about as likely as not.[18] Important to note is also the fact that modeling the hierarchy in the data leads to a better fit of the model given the reduction in the Deviance Information Criterion. More interestingly for this analysis is of course the predictive performance of the model. To gauge the accuracy of the predicted probabilities I use the Area Under the Curve (AUC) of the Receiver Operator Characteristics (ROC) curve and the Brier Score. The AUC is measured on a $0-1$ scale where higher values indicate a better performance and a value of 0.5 would be as good as random guessing. Examining the results we see that the simple pooled model performs rather poorly in this respect, while the multilevel model reports a very respectable AUC value of 0.88. Additionally I also use the Brier score which is calculated as $Brier\ score = \frac{1}{N}\sum_{i=1}^{N}(forecast_i - observed_i)^2$, basically the squared prediction error. In this case lower values indicate a better performance, and the results show that the two models do not have much daylight between them although the multilevel model still outperforms the pooled model.[19]

The models in column 1 and 2 provide some initial empirical evidence for a link between droughts and communal conflict, but of course due to their relatively simplicity they ignore a lot of important dynamics. For instance

[18] See Mastrandrea et al. (2010) for classifying uncertainty.

[19] These results hold when specifying a vary-slope model to acocunt for state-specific affects as discussed in the appendix.

they fail to account for the persistence and interdependence of conflict over time and space. I therefore re-estimate the multilevel model including the temporal lag of the outcome variable, to account for serial correlation, and the spatial lag, to account for spillover effects (col.3). The estimated effect of climatic conditions on conflict is robust to this alternative model specification, registering only a slight reduction in the magnitude of the average effect. Concerning the conflict dynamics the results show that the coefficients for the temporal and spatial lag have the hypothesised sign, associating past conflict and conflict in neighbouring states with higher current levels of conflict risk. Rather counter-intuitively we see that states in a neighbourhood with other states that have higher levels of communal conflict are themselves actually less likely to experience conflict. Here there is a likely chance that the estimated is negative at 86%. This might suggest that on the long term the risk of contagion of communal violence across state boundaries is actually fairly limited.

Finally, I specify a model including a number of additional variables accounting for factors commonly associated with conflict such as population, ethnic diversity, and well-fare (col.4). Within the conflict literature population levels have been robustly linked to conflict risk (Hegre and Sambanis, 2006). Larger populations tend to be more difficult to control and also provide larger pools from which potential insurgents can be recruited. For each state the population total is calculated using the 2005 estimates from the most recent version of Gridded Population of the World. A number of recent studies have highlighted the salience of ethnicity with regard to conflict Buhaug and Gleditsch (2008); Weidmann (2009); Costalli and Moro (2012); Beardsley et al. (2015). Therefore, a measure for ethnic diversity is included in the model based on the polarisation index from Garcia-Montalvo and Reynal-Querol (2005) which is constructed using data from the Georeferencing of Ethnic Groups (GREG) by Weidmann et al. (2010). To account for well-fare or local economic conditions, I follow Wig and Tollefsen (2016) and include a Lived Poverty Index (LPI) which measures the subjective perceptions of poverty. The LPI is constructed using survey data from Afrobarometer (round 3 from 2005) which measures how often the respondents went without basic necessities such as food, water, and income. Given the fact that there is only limited data availability for these control variables, and that they are often slow moving, they are all modeled on the intercept capturing variation between states.

In terms of the model's fit with the data, the results indicate that including additional variables does not necessarily improve the performance of the model given the DIC value of 365.5, which is very close to the DIC of the parsimonuous model reported in column 2.[20] The results for this type of kitchen sink model are also visually summarised in figure 3. Including additional explanatory variables does not alter the results much; higher PDSI values are associated with reduced conflict risk ($P(\beta_{-ve}) = 0.93$). The figure illustrates that the between-variation in past conflict is the strongest explanatory variable in the model. The estimated effect of the lived poverty index and the ethnic polarisation measure are a bit surprising as in both cases higher levels are associated with a reduction in conflict risk. Although in the case of ethnic polarisation the estimated effect is as about as likely to be negative as positive ($P(\beta_{-ve}) = 0.67$). For the lived poverty index ($P(\beta_{-ve}) = 0.71$) a two standard deviation increase corresponds to a 9% reduction in conflict risk. Although the survey data used to create this measure has been used in other studies (Linke et al., 2015; Wig and Tollefsen, 2016), there is the possibility of bias in the data that might also affect the estimates (Kuriakose and Robbins, 2016). The estimate for population levels does have the expected sign, here moving from low to high population levels corresponds to a 7% increase in conflict risk ($P(\beta_{+ve}) = 0.71$).

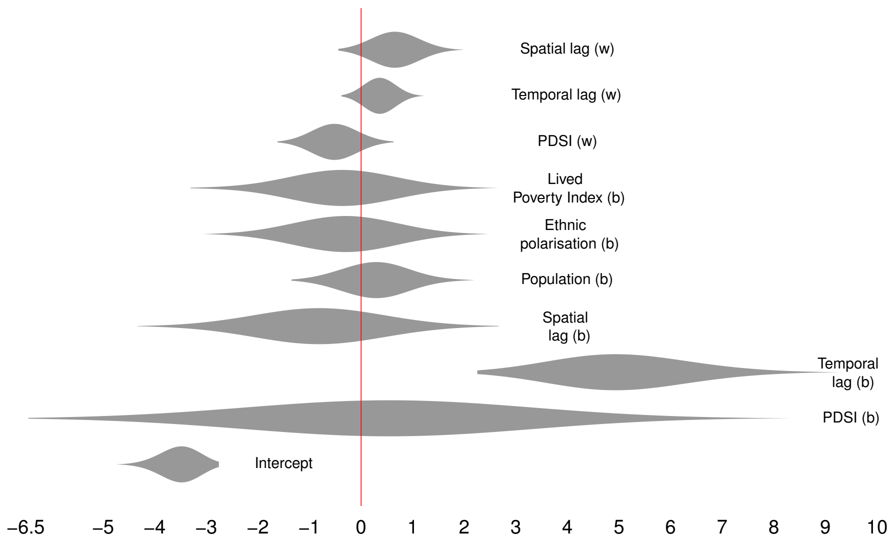

Figure 3: Distribution of estimated coefficients for model as specified in column 4 table 1.

[20]In general it can be advisable to focus on simpler model in the data analysis as discussed in Achen (2002) who recommends not to include more than 3 variables. Bohmelt and Bove (2014) show that simpler models tend to generate better predictions in their study on forecasting military expenditures.

To delve a bit deeper into the the explanatory power of some of the state characteristics, the interaction effects between drought and, amongst others, population levels and ethnic polarisation are examined. In addition to the variables accounting for state-specific factors in column 4 of table 1, I also estimate a model with interaction effects accounting for the area under cultivation and the livestock density. These two variables are used as a proxy for the importance of the agricultural sector. The cultivated area is measures in square kilometers and includes all types of crops, the data is taken from MapSPAM. Livestock density is measured as the combined total of the number of cattle, goats, and sheep per square kilometer as reported by Robinson et al. (2014). Both these datasets were revised relatively recently and have 2005 as reference year, hence the sample starts in 2006 to avoid any bias arising from endogeneity issues.

For each of the variables a model is specified similarly to the one reported in column 3 of table 1 including the interaction term and the additional explanatory variable. The distribution of the estimates of the interaction effects are visually summarised in figure 4. Again we observe that states with higher population levels experience higher conflict risks, but this risk is amplified by more moist conditions. The same applies for the lived poverty index. This might suggest that in terms of relatively good circumstance prize-capturing circumstances might prevail over an opportunity cost mechanism. In contrast, ethnic polarisation hardly seems to matter which is rather surprising given the fact that the outcome variable is the incidence of communal conflict. It could be that the operationalisation of ethnic polarisation here is not adequate to capture tensions between groups or that the level of diversity simply doesn't matter that much and other factors are more important. Concerning the agricultural factors the results show that higher livestock densities interacted with the PDSI correspond to higher conflict risks. Possibly this is due to more rampant livestock raiding in relatively good times, although the data doesn't allow for very strong conclusions in this respect. The estimated effect for the interaction with cultivated area is negative but close to zero.

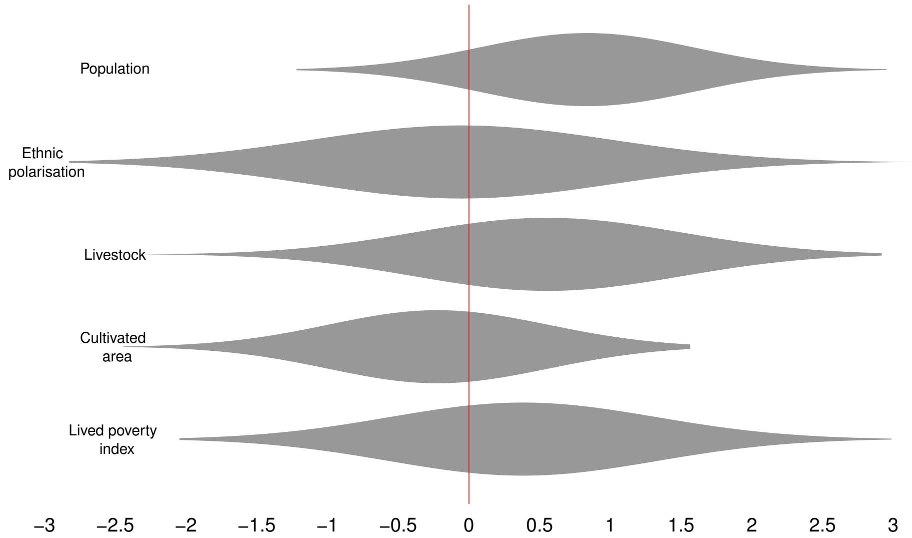

Figure 4: Distribution of estimated coefficients on interaction effects.

5.3 Cross-validation

The regression results provide some empirical evidence for a link between droughts and an increased risk of communal conflict. The analysis has shown that these results are robust to a number of different model specifications, accounting for the structure of the data, conflict dynamics, and other potential determinants of conflict. To further scrutinise the results we now turn our attention to examining how well the model generalises to out-of-sample data, by cross-validating the model and measuring the accuracy of the generated predictions following the recommendations made by Ward et al. (2010); Ward (2016); Schrodt (2013). As Bohmelt and Bove (2014) discuss, examining the performance of the model on out-of-sample data is important as the estimates could be the result of certain peculiarities in the data. Although the model could provide a good description of the available data, it might fail to identify the underlying mechanisms or structure that define the relation between droughts and communal conflict. For the cross-validation I take two approaches. First, using the estimates based on the data for 2006-2011 I let the model predict the outcome for the period 2012-2014. Second, I re-estimate the model using the data for 2006-2011 but leave out one state at a time, and let the model predict the outcome for this state.

I start with the analysis on the cross-validation using the out-of-sample data for 2012-2014. To examine the performance of the model at the aggregate level I use the ROC curve which plots the specificity of the model, or

true negative rate, on the x-axis versus the sensitivity, or true positive rate, on the y-axis.[21] Figure 5 shows the ROC curves for four different model specifications using both in- and out-of-sample data. The model specification here are i) a baseline model, ii) a pooled model (col.1 table 1), ii) a multilevel model (col.2 table 1), and iv) a dynamic multilevel model (col.3 table 1). The baseline model is a simple pooled model which includes only the spatial and temporal lag of the outcome variable, and omits the variable capturing droughts.
Starting with the in-sample data, the baseline model performs reasonably well given the location of its line relative to the 45°line which represents randomly guessing the outcome (and an AUC of 0.5). The AUC is acceptable at 0.64 but not really great. Nonetheless, the model performs better compared to the pooled model which regresses the outcome on the PDSI variable which has an AUC of only 0.57. Only including the proxy for climate we do see that large gains can be made in predictive power when we explicitly model the between-variation as the multilevel model reports an AUC of 0.88. This model even performs slightly better than the dynamic multilevel model which has an AUC of 0.87. I must note though that fitting a model with only the intercept also scores very high with an AUC of 0.88 for the in-sample data and 0.85 for the out-of-sample data. Indeed, considering the out-of-sample data only the dynamic multilevel model performs better with an AUC of 0.92. The results show that for both models which only include the drought variable the predictive performance deteriorates. In contrast, the baseline model performs rather well with an AUC of 0.84. The Brier scores tell a similar story with the dynamic multilevel (0.08) and the baseline (0.09) model ranking above the multilevel (0.11) and pooled (0.13) model.

To examine how well the model matches the predicted values with the observed outcome I use a separationplot as shown in figure 6. A separation plot orders the fitted/predicted values from low to high and the dark stripes indicate the observed cases of conflict (Greenhill et al., 2011). If a model is accurate in its predictions, than we should be able to observe a good degree of separation in the figure between the light shades, indicating the observations without conflict, and the darker shades, indicating conflict. I use the same four model specifications as for the ROC plots. Again we see that the pooled models perform rather poorly for the in-sample data (a,c), where the models do not seem to be able to match the observed conflicts with higher fitted values. The results show that the pooled model with the drought variable fits low values in general based on the plot for the out-of-sample data (d). In contrast, the baseline exhibits some sort of clustering at the higher end, matching conflict with larger fitted values. As was shown for the ROC curve, the baseline model performs surprisingly well for the out-of-sample data (b).

[21] See Fawcett (2006) for a more thorough explanation on ROC analysis.

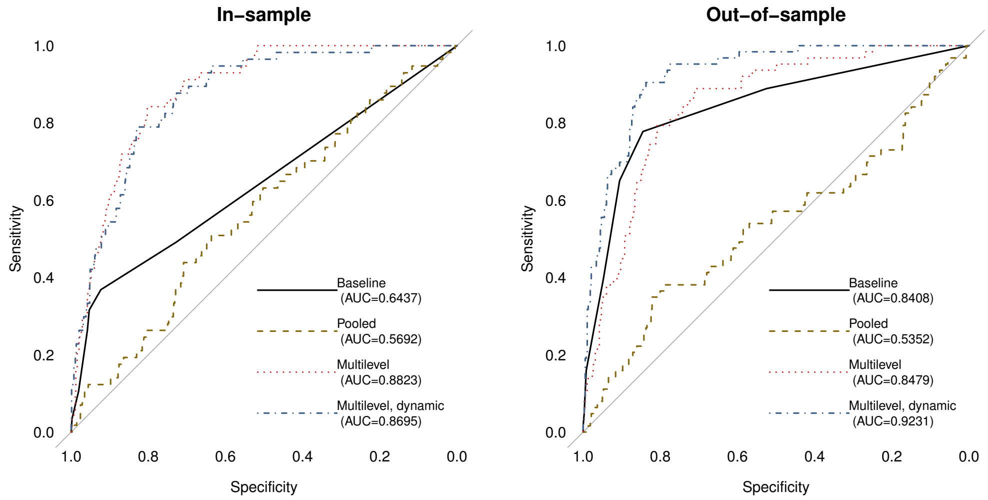

Figure 5: Receiver Operator Characteristic curves for in- and out-of-sample data.

This result echos those by Ward and Gleditsch (2002) who illustrated that a relatively simple model can perform well on out-of-sample data.

Similarly, the multilevel models, with (e) or without (g) the conflict dynamics, perform much better on the in-sample data compared to the pooled model, leading to a clearer separation.
Based on the ROC plots and the seperationplots it seems that the predictive performance of a model improves when i) modeling the between and within variation of the data, and ii) by including the variables on conflict dynamics.

The second part of the cross-validation focuses on the predictive performance of the model for each state by re-estimating the model with data for 2006-2011 but leaving out one state at a time and predicting the outcome for the left out state. The Brier score is used as a measure for predictive error and is plotted against the estimated effect of the drought variable based on the $k-1$ states in the sample Figure 7 shows the results where the black square gives the estimated effect and Brier score for the main model as reported in column3 table 1 as a reference. There is some variation in the estimated effect when one leaves out a particular state but all the estimated coefficients fall within one standard deviation of the estimated effect of the main model using all of the data. The figure shows that there are some states for which the predicted error is significantly large compared to the others. These include Benue, Lagos, and Plateau. This

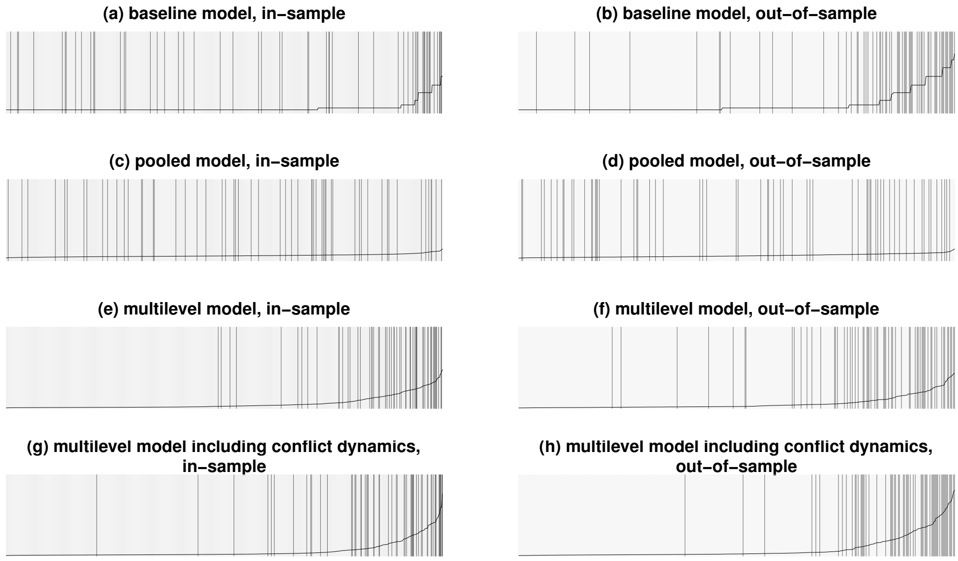

Figure 6: Separationplots for in- and out-of-sample data.

raises some concerns about the accuracy of the model, and the link between droughts and communal conflict, as these and the other labelled states all experience relatively high incidence of communal conflict. Indeed, these state represent 72% of the total number of communal conflicts between 2006−2011.

As a final test for the predictive performance of the drought variable specifically the model as reported in column 3 table 1 is compared with an identical model that omits the PDSI. For both model I analyse the ROC curve (panel a figure 8) and the Brier score for each individual state when predicting its outcome (panel b figure 8). The figure illustrates that concerning the ROC curve the two different models are very close. The model omitting the PDSI variable actually performs slightly better with an AUC of 0.8778 compared to 0.8759 when including the variable capturing drought. Looking at the predictive performance for the individual states the figure illustrates that there is not much difference and that including the drought variable does not necessarily leads to improvements in forecasting the conflict risk per state.

6 Conclusions

Despite a surge in research on the link between climate and conflict, the main result so far seems to be a polarised field, with little perspective on a consensus concerning how weather variation influences conflict. Shortcoming

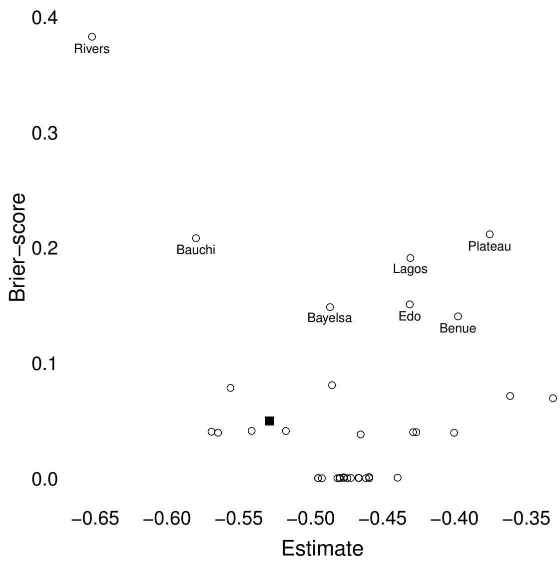

Figure 7: Brier scores and estimated effects per individual state.

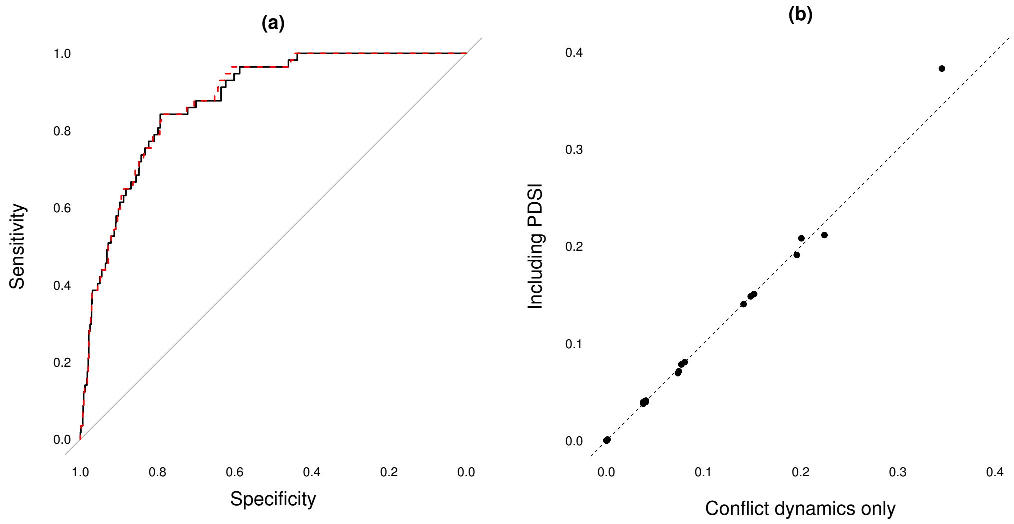

Figure 8: ROC plot (panel a) and Brier scores (panel b) for model with and without the PDSI variable.

of the current literature include a too heavy focus on cross-case generalisation and a lack of attention for predictive modeling. As a result we see that many findings are sensitive to sample selection and generalise poorly to out-of-sample data. Rather than limiting the analysis to hypothesis testing I argue that in order to provide more conclusive evidence we should focus on cross-validation methods, to rigorously test existing theories. This issue that has been raised before, and often more eloquently, but hasn't been picked up yet. Focusing on Nigeria, this study provides an example of how we can use cross-validation and examination of predictions to scrutinise results. The advantage of zeroing in on a single country is that it helps account for context-specific factors that shape causal pathways.

Using quarterly data at the state level, the regression analysis shows a negative association between the drought index and conflict risk between 2006−2011. Similar to some previous results I find that wetter periods lead to reductions in the likelihood of violence. A simple pooled model shows that an increase in the drought index reduces conflict by about 14%. Modeling both within- and between-variation in a multilevel model I find that while wetter states are 24% more likely to experience violence, the risk is higher in drier years where a one unit decrease in the drought index corresponds to a 16% increase in conflict risk. These results hold when including variables to account for the spatial and temporal dynamics of conflict. There is only a slight reduction in the estimate effect when controlling for factors such as population, ethnic polarisation, local economic conditions.

Although the regression results provide some empirical proof for a link between weather variation and communal conflict, I find that the evidence is not so strong when considering the predictive performance of the model. Similar to earlier results in the literature I find that the spatial and temporal lag of conflict are good predictors for current conflict risks. The predictive performance of a model also improves when specifically accounting for the hierarchical nature of the data, such as in a multilevel model. In contrast, including a variable capturing drought to proxy for climate variability adds very little to the predictive accuracy of the model.

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Appendix

Varying slope model

The analysis on the link between droughts and conflict relies on the result of models estimated assuming a homogeneous effect across all 37 states. However, although in general droughts are expected to exacerbate conflict risk, some studies have shown that more moist conditions are associated with conflict. These possible diverging effects per state are potentially averaged out with the current approach (Selby, 2014). Therefore, the model is re-estimated allowing the coefficients to vary per state, the results for which are shown in figure A1 which depicts the average estimated effect per state along with its 50 and 95% uncertainty interval. The figure illustrates that the results found for the pooled and partially pooled model hold when allowing the coefficients to vary. For the majority of states the average estimated effect is negative, although the uncertainty intervals include zero even in the 50% interval for most states. There are some exceptions where the empirical evidence for a negative link between the drought index and communal conflicts is slightly stronger in states such as Benue, Plateau, Nassarawa, and Kaduna. These states are all situated around the Jos plateau in central Nigeria which is an important agricultural area both for sedentary farmers and nomadic herders. Surprisingly the results also show that the effect is likely negative in Lagos state which is largely an urban area.

The varying-slope model model is also exploited to get state-specific estimates of conflict risk. For all states the fitted values are summed as a measure for the expected number of communal conflicts between 2012-2014 (figure A2, the squares indicate the observed number of conflicts). The figure illustrates that at the lower end we observe states with low estimated risks which indeed experienced very little to no communal conflict. Only a small number of states can be considered false negatives here, where the 95% uncertainty interval does not include the observed number of conflicts, such as Cross River, Adamawa, and Kogi. The differences here are small though. In contrast, at the higher end of the figure we see that the model tends to underestimate the number of conflicts for states that indeed experienced communal conflict. The states are all plotted based on a ranking according to their uncertainty intervals, and most of them seem to be a bit off. This might suggest that the conflict dynamics and drought variable have difficulties in generalising to out-of-sample data in the sense that they don't capture the underlying dynamics. Nonetheless, we see that certain states are associated with a higher risk of conflict which were discussed in other sections of this study such as Plateau, Benue, Taraba, Nassarawa, and Kaduna. These are all states up or around the Jos plateau, the area commonly linked to farmer-herder conflicts. So indeed the risk of communal conflict is higher in these states, but the model has some difficulties in gauging the exact risk for these particular states.

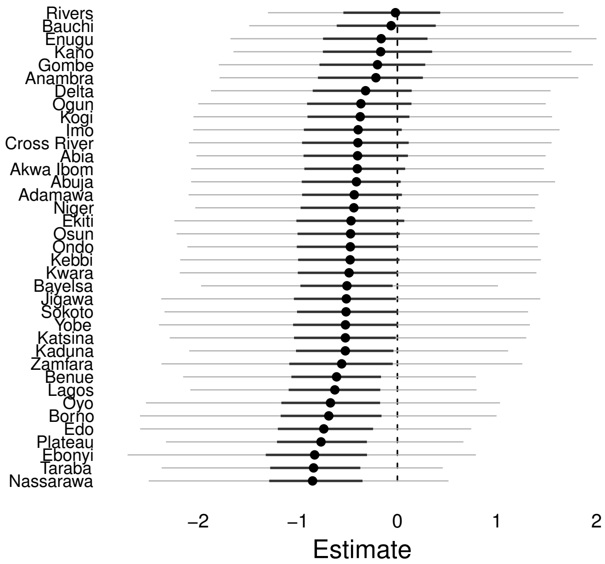

Figure A1: Estimated effect along with 50 and 95% uncertainty interval for each individual state.

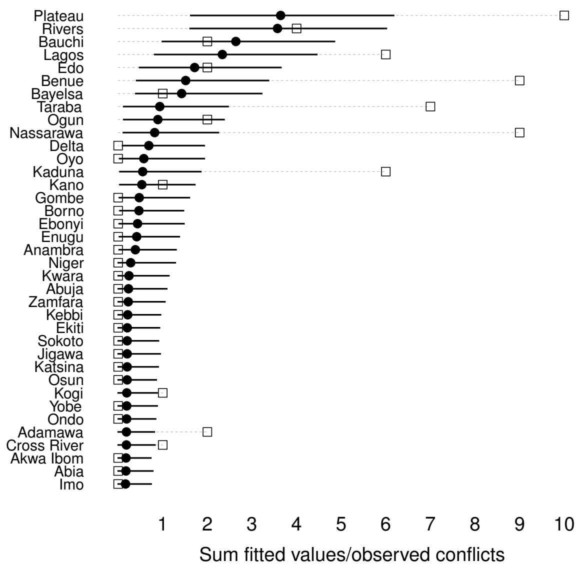

Figure A2: Cumulative estimates risk for each individual state along with observed number of quarters with conflict.