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Water Scarcity, Climate Adaptation, and Armed Conflict

Abstract: The dynamic relationships between climate change and conflict have been discussed at length, but there have been few studies that integrate spatial-temporal dimensions of climate adaptation into armed conflict. By using geospatial grids for climate change and armed conflict, and country level climate vulnerability measures of sensitivity and adaptive capacity, we empirically examine the effects of climatic and non-climatic conditions on the probability of armed conflict in Africa. Results suggest that there are close links between climate drivers and armed conflict. Importantly, greater levels of adaptive capacity lead to a lower likelihood of armed conflict. From a policy perspective our results suggest that enhancing adaptive capacity under conditions of climate pressure will reduce the probability of people taking up arms in response to water scarcity.

Keywords: Adaptive capacity; Africa; Climate change; Sensitivity; Water scarcity

1. Introduction

Recent evidence links water scarcity driven by climate change to the civil war in Syria (Kelley et al., 2015); the war and genocide in Darfur, Sudan (United Nations Environment Programme, UNEP, 2007), and climate driven extreme weather disasters have been linked to armed conflict (Schleussner et al., 2016). Evidence is at best mixed as to whether climate change is causing armed conflict, or more precisely, what types of climate driven pressures on the physical environment are generating more (or less) social conflict.

Moreover, controversy surrounds the research describing a relationship between weather events, climate change and armed conflict. Buhaug et al. (2014), Burke et al. (2009), Hsiang et al. (2013), Hsiang and Meng (2014), O'Loughlin et al. (2014; 2012), Salehyan and Hendrix (2014), and Schleussner et al. (2016) reflect the broader exchange explored in a recent special issue of the *Journal of Peace Research* (2012). In general scholarship finds an ambiguous relationship between recent climatic pressures and armed conflict, or at worst a relationship that many would consider counter-intuitive. Burke et al. (2009) and Hsiang et al. (2013) demonstrate that temperature increases are strongly linked to the onset of armed conflict. Scarcity tied to water resources forms the core theoretical explanation in nearly all arguments, but not all research finds that water deficits increase conflict. Salehyan and Hendrix (2014) demonstrate that increases in rainfall are associated with increased armed conflict. Intuition, conventional wisdom and contemporary policy do not always comport with empirical evidence (e.g., The US Department of Defense, US DoD, 2011). The empirical relationships or the conditions under which they hold can have profound political consequences.

Much of the recent debate turns on the specification of the research design, statistical estimation, and spatial scaling (O'Loughlin et al., 2014; Schleussner et al., 2016). The

relationship between climate and conflict is 'in the data' and the ability to uncover it must be a function of more than fixed or random errors and other forms of statistical controls (Hsiang and Meng, 2014). We bring some clarity by addressing issues of model specification and adaptive capacity and climate sensitivity in the climate-conflict nexus.

We make three core arguments that we support with empirical evidence: 1) temporal scale, 2) spatial scaling, and 3) climate adaptation. Climate science forecasts work from a spatial and temporal scaling that makes picking up social consequences difficult at national or annual levels of aggregation. Climate drivers of armed conflict are difficult to think of in terms instantaneous affects (Pierson, 2004), so temporal scaling is important. Furthermore, adaptation to climatic-driven pressures will influence observations of armed conflict. Contemporary changes in potential climate drivers of armed conflict are relatively small and the dramatic forecasts of climate scientists are temporally distant. The human species is a model of adaptation to environmental pressures (Potts, 2012) – sometimes climate driven – and when changes are small, adaptation is easy. Scholarship, therefore, has been looking for the effects of relatively small changes on relatively rare events during periods when human social adaptation is relatively easy. Ambiguity in understanding the social consequences may be one result.

If communities are perfectly able to adapt to contemporary climate conditions there will be few climate driven stressors on the social environment. In combination, questions of temporal and spatial scaling along with adaptive capacity must be part of a research design that accounts for the climatic impact on armed conflict. We advance scholarship by narrowing these three dimensions. Specifically, we use geospatial grids to capture climate pressures and armed conflict, and we incorporate climate vulnerability measures of sensitivity and adaptive capacity

in our models. The centrality of adaptive strategies makes the link between climate and conflict a human political as well as a biophysical issue.

2. Water scarcity, climate adaptation, and armed conflict

The recent debates on the relationship between climate change and armed conflict focus on a common theoretical perspective but come to differing conclusions. Most recently Schleussner et al. (2016) linked climate generated disasters to armed conflict through the vehicle of ethnic tensions. They report that 23% of ethnic conflicts coincide with climate disasters. Burke et al. (2009; 2015) frame arguments in terms of scarcity that results from increasing temperature and precipitation anomalies. When the temperature rises agricultural and other water security issues generate social tension that can lead to armed conflict. They rely on a meta-analysis of others' results to reach their conclusions. The US DoD (2011) addresses a similar concern regarding water scarcity issues and unrest on the African continent. For example, results from the US DoD report suggest that 600, 000 square kilometers of currently arable land will become non-productive by 2060 due to drought related climate pressures. Presumably taking this much productive capacity out of the African agricultural sector will increase discord over resource availability.

If drought leads to scarcity, the mechanism in part runs through the ability of agricultural land and industrial capacity to remain productive. Lesk et al. (2016) demonstrate that sustained drought and extreme heat reduce crop yields by up to 10%. A one-year short fall in precipitation may lead to near-term productivity declines, but drought captures more than precipitation deficits. Droughts are a function of rainfall but also tied to temperature through evapotranspiration rates, snowmelt, and river discharge rates, and can reflect in declining soil moisture content (Dai et al., 2004). Moreover, soil productivity can recover from short-term

deficits, and if the community is capable of adapting, its effects can be minimized by recourse to irrigation, among other adaptive strategies.

Long-term drought can leave the soil in an unrecoverable condition where the soil will filter but not retain moisture. Under these conditions agricultural productivity cannot easily be offset by irrigation, and crop yields will decline (Lesk et al., 2016). When an agrarian society can no longer remain agriculturally viable, migration can be one result. If conventional wisdom and soil science is correct, evidence should reveal a direct relationship between predictors of drought and the social consequences that result from it (Dai et al., 2004; US DoD, 2011). At the community level a dramatic decline in resources requires either the ability to adapt or suggests the possibility of conflict (Yang and Choi, 2007). Consistent with this, Hsiang et al. (2013) find that warmer temperatures and lower rainfall predict an increase in communal violence. However, Salehyan and Hendrix (2014) demonstrate that water scarcity has at best a tenuous relationship to armed conflict, and they, in fact, see water abundance as a potentially larger problem. This theme of excess precipitation leading to armed conflict is evident in Bergholt and Lujala (2012), O'Loughlin et al. (2012), Raleigh and Kniveton (2012), and Theisen et al. (2011/12). Yet the abundance-leads-to-conflict argument is contested by Fjelde and von Uexkull (2012).

Evidence suggests, therefore, that excessive precipitation *or* drought can cause the types of scarcity that might generate social unrest, but the difference between drought and extreme precipitation can be one of temporal scaling. Both could generate conditions of scarcity, but drought would take longer to root and impose longer-term consequences. Excess precipitation could cause short-term flooding and associated dislocations, but its effects are remediated relatively quickly. Seasonality of weather-related scarcity might also drive the climate-conflict nexus (Landis, 2014).

The debate about the direction and strength of the postulated relationships between climate driven pressures and armed conflict leads scholars to turn to model specification in order to explain discordant results rather than theory to account for missing variables that reflect other explanations. Country and time fixed effects, instrumenting variables, and functional form all can influence the direction of the estimated relationships (O'Loughlin et al., 2014). We argue instead that temporal and spatial aggregation are critical to the processes by which climate pressures might cause conflict, and are critical to estimating those relationships (Fjelde and von Uexkull, 2012; Landis, 2014; O'Loughlin et al., 2012). Moreover, human social and physical adaptation can intervene between climate-driven pressures and armed conflict.

2.1 Spatial and temporal aggregation and adaptation

Expectations about the impact of climate pressures on social consequences are generally developed from climate model projections as far out as 2100. The actual changes in the observed climate over the past 100 years, however, are relatively small (<.9°C). Social scientists, on the other hand, fit historical data to theoretically specified models; levels of precision differ. This tension between expectations driven by climate science and the relative rarity of dramatic social armed conflict requires that model development be attuned to these differences. Moreover, the relatively small temperature changes during the industrial period allow for human social adaptation to offset observed or expected geophysical changes.

Water is a resource for which we have a reasonably strong empirical foundation to link as a driver of armed conflict (e.g., Ross, 2004; Tir and Stinnet, 2012; Vasquez, 1993). If water scarcity decreases crop yields (Lesk et al., 2016; Yang and Choi, 2007) and food security is one element that can put populations at risk, recurring drought conditions that are partly a function of temperature and precipitation deficits will increase the risk of conflict (Brown and Funk, 2008;

Lobell et al., 2008). Most African agriculture relies on rainfall-based irrigation and estimates put the amount of groundwater irrigation in Africa at just 6% (You et al., 2010). Sustained drought conditions could generate either adaptation to the drier conditions or a reduction in crop yields; one might generate cooperation, the other conflict.

The response to regional drought conditions could involve infrastructure development, such as the extraction of ground water for irrigation, thereby adapting in ways that mitigate the resort to conflict over scarce water. Adaptive strategies act as an intervening process between climatic pressures and armed conflict (Ford and King, 2015) and adaptive capabilities can be a function of state level characteristics and preparation (Chen et al., 2016). The smaller the direct pressure from climate-induced scarcity, the easier are the efforts to adapt. Adaptation efforts could also facilitate cooperation across geo-political boundaries and reduce the resort to conflict.

Climate modeling forecast dramatic regional variation in temperature and precipitation anomalies as a result of changing pressures on weather systems (Hamlet, 2011; Hansen et al., 1981; 2012; Intergovernmental Panel on Climate Change, IPCC, 2014; US DoD, 2011). Within geographically expansive countries the variation is expected to be large (Hamlet, 2011), such that in large African countries topography and distance provide room for significant regional variation in temperature and precipitation. For example, on the African continent a 2.5° square grid generates 42 separate grids incorporating all or part of the Democratic Republic of Congo, with each grid comprising a land area of approximately 270 by 270 kilometers. On the African continent there are 495 individual grids at a resolution of 2.5° square. Variation in temperature and precipitation is not uniform across the 42 grids in the Congo, even though smaller countries, such as Togo with four grids, might have more uniform anomalies. In short, there is no theoretical reason to see the most dramatic social consequences resulting from national level

variation rather than local temperature and precipitation anomalies, particularly when much of the armed conflict is local. Contemporary scholarship tends to use the annual national average of temperature and precipitation anomalies to predict armed conflict which can mask local level effects (e.g., Couttenier and Soubeyran, 2013; Salehyan and Hendrix, 2014; exceptions include Fjelde and von Uexkull, 2012; O'Loughlin et al., 2012; von Uexkull, 2014).

2.2 Climate science, regional variation and armed conflict

Projected regional variations influence how to test for climatic effects on conflict and suggests that attention to spatial and temporal scale is important; the implications are broad ranging. To put the projected African arable land deficit into context of scarcity (US DoD, 2011), if these 600,000 square kilometers were planted with corn, the yield would be roughly 150 million bushels/year based on a US average production rate. Removing 600, 000 square kilometers from production leaves a significant annual deficit in crop yields to be distributed to at best a constant number of people. There is no expectation in the climate modeling that the land that loses its productive capacity will be contiguous, or confined within geopolitical borders so attention to spatial distributions is important. In short, where the deficit occurs will be as important as that it occurs.

Declining supplies of food can be one mechanism to generate price shocks, such as those linked to riots (Smith, 2014). Land productivity, industrial capacity and social resiliency can all result from the scarcity of water resources, either in the form of rainfall or irrigation. As water becomes increasingly scarce in one sector its demand on other sectors will increase tension. Competition between the agricultural and industrial or urban and rural sectors provides a causal mechanism and competing groups.

Agriculture, industry, and infrastructure can be affected by too much water or by too little (e.g., Hendrix and Salehyan, 2012; Raleigh and Kniveton, 2012; Salehyan and Hendrix, 2014). Water abundance can come from multiple sources and have various consequences. For instance, if ice melt in the Antarctic and Greenland generated predicted increases in sea levels, migration patterns from coastal regions to inland areas have the potential to increase social tension (Raleigh et al., 2008). Moreover, the migration of various animal species, including disease bearing insects (e.g., Zika virus), are linked to climatic pressures (Sala et al., 2000; Staudinger et al., 2013). Evidence suggests these physical dislocations are taking place on a broad scale (Lenton et al., 2008; Sala et al., 2000; Staudinger et al., 2013).

Data demonstrate considerable regional variation in global temperature and precipitation anomalies, and expectations for social or political consequences should be attentive to region or geospatial grids (e.g., O'Loughin et al., 2012). The mean temperature anomaly on the African continent during the 1980-2012 period was .54°C and the mean anomaly for the tropical regions (-10 to 10 latitude) was .46°C (National Ocean and Atmospheric Administration, NOAA, 2014). However, those mean temperature anomalies change dramatically across time, with the African mean rising to .87°C for the period in the 21st century and the tropical region rising to .68°C. The mean temperature changes in Rwanda in the 19 years from 1980 through 1999 (.09°C) versus the 12 years in the 21st century (.38°C) increased by a factor of four.

2.3 Sensitivity and adaptive capacity

How actors respond in the face of stress on their ability to produce is a critical component in understanding the relationship between climate pressures and armed conflict. Climate change may impose pressures on soil productivity and crop yields though individuals, communities and countries can adapt to these changing climatic pressures (COP21, Paris, 2015; Potts, 2012). Not

all will be equally capable of doing so, but observed behavioral outcomes will be affected by the steps taken to adapt to these changes. In effect, models of the climate drivers of armed conflict are underspecified if that relationship is mediated by social adaptation.

Brooks et al. (2005) argue that identifying vulnerability to climate change can provide leverage points for intervening between the climatic drivers and social responses. Outcomes tied to climate change are in part of function of the sensitivity and capacity to adapt to climate hazards, such that high sensitivity and low capacity leaves a country more vulnerable to climate change. Definitions of sensitivity and adaptive capacity differ but the IPCC (2001) defines overall vulnerability with regard to system-wide exposure to climate pressures through its sensitivity and adaptive capacity. Brooks et al. (2005) define vulnerability in terms of state level susceptibility to injury or damage from climate events (p.152). Moreover, they see in the aggregate that vulnerability to climate variation is a "state variable determined by the internal properties of a system" (p. 152).

The level of observed adaptation is a function of the underlying resources and ability to adapt. At the community or regional level adaptation is made more efficient to the extent that national level preparedness is in place (Brooks et al., 2005). Preparedness is driven by the values at risk and the structural ability to adapt. We view the risks from climate change in terms of national level sensitivity, that is, what is at risk and in what sectors, and the underlying capacity to adapt to those changing conditions that put value at risk. Comparing two countries facing the same climate stressors we would expect the one least able to adapt to suffer greater consequences, whether that be lower crop yields or a greater propensity for armed conflict. Put differently, absent outside support to ward off the effects of climate pressures, individual, regional and national level adaptation will be constrained by the resources committed to the task.

When the outcome involves armed conflict the national government has a strong interest in providing these resources, if it is able to do so.

3. Climate change and armed conflict: Theoretical links and hypotheses

There are multiple pathways from changing patterns of resource availability to armed conflict. Studies have linked water boundaries to armed conflict and have shown that agreements that generate institutional arrangements for addressing disputes are less likely to be volatile (Tir and Stinnet, 2012). The curse of diamonds and oil has been linked to armed conflict (Ross, 2004), as has climate driven water scarcity (Hsiang et al., 2013; Yang and Choi, 2007). The theoretical mechanisms that translate climate pressures to the incentives for groups to take up arms against their state work through the effect of climate on hydrology and ecology (Nijssen et al., 2001; Sala et al., 2000; Theisen et al., 2011/12).

As climate restricts access by some to resources required for production or subsistence we would anticipate that those denied access have increased incentives to demand changes to the patterns of distribution (Bernauer et al., 2012; Brown and Funk, 2008; Exenberger and Pondorfer, 2013; Regan, 2009; Regan and Norton, 2005; Scheffran et al., 2012). We know from prior empirical studies that riparian conflict provides a frequent explanation for war even during periods of relative resource stability (Tir and Stinnet, 2012), so as these resources become increasingly scarce we would expect pressures on the distribution mechanism to increase, and along with that, tensions that can lead to armed conflict. The Department of Defense sees this as a critical threat on the African Continent (US DoD, 2011).

Yang and Choi (2007) demonstrate that rainfall serves as a proxy for local wealth – through the mechanism of crop yields -- in the Philippines and when wealth is constrained conflict increases. Moreover, Benjaminsen et al. (2012), Hendrix and Salehyan (2012), Raleigh

and Kniveton (2012), and Theisen et al. (2011/12) and others use rainfall patterns in Africa to model conflict at the local level. Water deficits in regions with low levels of irrigation have an immediate impact on the production of crops, altering the ability of many regions to provide sustenance and tradable goods.

The climate-driven deficit in crop yields results from a complex set of hydrological dynamics (Lesk et al., 2016). Put differently, observed patterns of water scarcity on crop production, industrial capacity, or personal consumption can be driven by a number of different geological factors. For example, irrigation and farming in the Ganges delta in Bangladesh are impacted by glacial melt in the mountains, rainfall over the basin, and broader issues of river discharge rates that are affected by factors such as evaporation rates (Mote et al., 2005; Nijssen et al., 2001). Some of this takes place far from the locus of scarcity concerns. But importantly, scarcity is also affected by human efforts to address deficits via irrigation or collection and retention mechanisms, such that adaptation can influence measures of water scarcity.

A common metric for describing climate change is the change in global temperature, or the anomaly, from a baseline (Hsiang et al., 2013; NOAA, 2014). The effect of temperature on hydrological cycles is driven, at least partially, by the temperature's effect on evapotranspiration. Higher temperatures can increase the rate at which soil loses its moisture, and with the loss of moisture comes a reduction in crop yield productivity (Lesk et al., 2016; Ochsner et al., 2013). The temperature's influence on soil moisture is not necessarily immediate. This interaction between temperature and precipitation as they work through soil moisture levels suggests that the effects of climate on conflict are spatially and temporally dependent.

Important for our understanding of the relationship between climate pressures and conflict is that contemporary change can be quite small yet aggregate over time. Precipitation or

temperature anomalies in any given month would be unlikely to act as a catalytic condition for armed conflict. This temporal effect can be moderated by the social ability to adapt to reductions in precipitation or soil moisture, for example, by irrigation systems. Evidence suggests that in the short term adaptive strategies could be more efficient than conflictual ones (Richerson et al., 2003; Wilson, 2002). If the rate of change in climatically driven pressures is slower than the ability to adapt, communities may adapt in ways that minimize the effect of climate pressures on resources. This would suggest that even in the face of declining resources, scarcity would be muted. Adaptation tends to be local but the capacity to adapt by committing necessary resources to stressed locales is facilitated by country-level resources. To the extent that states have developed their adaptive capacity, social resilience will be strengthened and conflict minimized. Functionally this suggests that models of climate-induced armed conflict should include capacities to offset the effects of climate through adaptive responses.

We frame hydrologic processes relating to local water scarcity in terms of multi-year patterns, focusing on physical changes rather than immediate triggers such as weather (Gleditsch, 2012). Contemporary scholarship sometimes argues that climate change – often proxied by temperature anomalies– must work through intervening processes (e.g., Exenberger and Pondorfer, 2013). We expect that the effects of climate will, over time, impact soil moisture and/or drought conditions. Low or declining levels of soil moisture can reflect systematic patterns in climatic variability and over temporal ranges of years can lead to conditions of water insecurity. The contemporary example of note is the climate-induced conflict in Sudan where pastoralists and sedentary farmers shared a common resource for generations. As drought reduced the productivity of the land to the point where only one group could thrive, the

motivation for conflict increased (UNEP, 2007). A similar argument was recently made with regard to the conflict in Syria (Kelley et al., 2015).

When soil moisture in specific regions drop to levels that are unsustainable there will be direct impacts on ground and subterranean water access, as well as reductions in river discharge rates (Nijssen et al., 2001; Lesk et al., 2016; Ochsner et al., 2013). Although we cannot focus on the complete complexity of soil hydrology, we argue that increasing temperatures and declining precipitation decrease soil moisture content, which in turn affects the ability to produce crop yields consistent with population needs. This impact on soil moisture also reflects declining access to water for drinking and industrial production, such that many sectors of society are challenged by the effects of climatic changes. As water in a community becomes increasingly scarce and the adaptive capacity strained, we are more likely to observed armed conflict.

Our expectations are that the physical changes in conditions related to hydrology through climate change will increase the risk of armed conflict when those changes are in the direction of hotter and dryer conditions. That is, as temperatures systematically increase, soil moisture and precipitation decrease and as drought conditions increase we expect to observe a greater likelihood of armed conflict.

Hypothesis 1: *Local increases in temperature and decreases in precipitation will increase the likelihood of observing armed conflict in the local area.*

Climatic pressures on a local environment provide incentives for both conflict and cooperation. When structural conditions make easier the avenue for cooperation through social adaptation, the likelihood of conflict will decline, given the pressures on local resources. That is, if the national level capacity to adapt to climatic pressures is greater there will be reduced pressures generated by climate at the local level and the likely onset of conflict will decrease.

Hypothesis 2: *National level sensitivity to climatic pressures and adaptive capacity will mediate between local level stressors and armed conflict, reducing the likelihood of armed conflict when the state is more structurally capable of supporting adaptation.*

4. Research design and methods

4.1 Variables and data

We test expectations on a spatial and temporal domain that incorporates the African continent 1980-2013. The temporal period changes to 1995-2013 when we include country level adaptive capacity and sensitivity attributes to the model. We divide our geographical sample into 2.5° X 2.5° grids within 53 African countries. Our outcome variable is the grid-month based, binary indicator, of an ongoing armed conflict[1].

Our primary predictor variables capture climate conditions at the grid level and national level adaptive capacity and sensitivity. We rely on NOAA for data on temperature, soil moisture, and precipitation anomalies. Soil moisture and precipitation data are recorded in terms of the contemporary values and then we generate an anomaly from a 1948-1980 baseline. This approach makes the anomalies consistent across the various data sets. Each data series is normalized to zero and negative or positive values express the month-on-month changes. The climate data for this project required processing to standardized temporal and spatial resolutions. In all cases, the spatial processing was done first. The final spatial grid of data points was set at a 2.5° interval. Soil moisture and temperature anomalies required down-sampling the original data to a lower resolution. To obtain temperature anomalies, we used a nearest neighbor algorithm except in those cases where the central points of more than one of the original 2° grid cells fell within a single new 2.5° cell. In these cases, the average value was assigned to the new cell. All

[1] We test robustness with a count indicator of the number of armed battles in proximity to the initial onset of an armed conflict. The battle count data comes from the UCDP data.

of the variables were already at a monthly interval, so temporal aggregation was not necessary. In all of the down-sampled data, maximum and minimum values were maintained along with the mean value.

After the data were processed to a temporal and spatial resolution with an average value for each month/grid cell, these grid cells were then coordinated with georeferenced conflict data and country codes to generate a database with a dichotomous coding for whether or not there was an armed conflict in a particular cell for a particular month. Political boundaries often cross the boarders of individual grid cells. In these cases, climate data are duplicated for each specific country code, although the country code for each conflict is also retained. Data preparation was done primarily in R using bindings for the Geospatial Data Abstraction Library with some additional processing and visualization in ESRI ArcGIS. All code is available upon request.

NOAA data on temperature anomalies reflect a monthly average (or maximum and minimum) anomaly per grid; the data on soil moisture content also allow for the average along with maximum and minimum values per cell. Because we have no expectation that climate anomalies have an instantaneous influence on conflict we create 30 month moving averages for each of our climate conditions. 30 months is somewhat arbitrary but certainly not capricious. Two and a half years of increasingly hotter temperatures or declining precipitation would generate cumulative stress on a community. Whether that break point is 25, 30 or 60 months is an empirical question; we test alternatives by way of checking the robustness of our results. We use the mean values for each grid-month to create our moving averages (see Appendix 3).

The temperature models created by NOAA are based on individual readings and generally unrelated to geopolitical boundaries, leaving some locations with data that are counted in cells that cover parts of two (or more) countries. For example, a recording station within a

short distance of a political border can cover a cell in two countries and there is no expectation that the temperature variation is a function of those political boundaries. In these instances, we count the cell as part of both adjoining countries. The number of monthly observations per grid cell is 408 if a grid is contained within one country. If a grid crosses national boundaries there will be multiples of 408 observations for that grid. In the extreme one grid encompasses five different countries.

We are aware that duplicating grid cell data to include all relevant data at the state level could lead to two potential problems. First, there are issues with artificially increasing the sample size with inaccurate data and potentially obscuring viable patterns. Second, because the boundaries of an individual grid can contain data from multiple states, there also remains the potential for patterns to be driven by the modifiable areal unit problem (Jelinsky and Wu, 1996). To overcome this, we also ran our models without those grids that overlap multiple states (264 grids cross country boundaries, 231 are solely within one country). The results show a similar substantive pattern (see Appendix 2). We run our analyses using hierarchical modeling which allows for controls at grid and national levels.

We use data from the Uppsala Conflict Data Project (UCDP) to record the existence of an armed conflict in a country-grid. UCDP records three types of armed conflict that start with an individual battle: 1) those involving the state, 2) those between groups, and 3) mass killings. To be included a conflict event must meet the conditions for an armed conflict, which requires having at least 25 battle fatalities within a given year. The data are recorded at the level of the battle, and by the geo-coordinates of the location of a battle. We use these geo-located battles to aggregate to conflict months within our 2.5° square grids (Sundberg and Melander, 2013). Functionally our outcome variable reflects the existence of an armed action within a grid which

forms all or part of a broader armed conflict that kills at least 25 people. Twenty-five battle fatalities provide a threshold that is low enough to capture armed conflict in localized areas but also high enough to require organized efforts to achieve this threshold.

Because our grids impose artificial boundaries over the political and social dynamics of a potential armed conflict we account for conflicts in immediately adjoining grids that could be part of the same conflict process across our artificial grids. If there is a conflict in the same country in an adjacent grid that starts within one year of the neighboring grid and if the conflict in a grid does not have a battle, then both grids are coded *Ongoing*. For example, if a grid has a conflict that starts in January and ends in March (three months coded *Ongoing*) but a contiguous grid has a conflict that starts in March and runs through July (five months coded *Ongoing*) then both are considered to have eight months of *Ongoing* conflict. If the two grids have a gap between *Ongoing* conflicts of less than one year, both are considered one conflict for that entire duration, but if the conflict in a grid stops in March and the conflict in another grid starts the following April, they are two separate onsets with the appropriate coding for *Ongoing* durations. This is consistent with the UCDP criterion for inclusion of a battle within the context of an armed conflict and it minimizes our breaking up of cultural groups based on a climate-determined grid structure. To help ensure that our coding scheme does not bias results we also test our models using the number of battles (*Battles*) generated from every five-grid unit around each conflict onset.

Table 1 describes our control variables, including the percentage of rural population (*Rural population*), life expectancy (*Mortality rate*), political regime type (*Polity*), and economic wealth (*per capita GDP*) as country level non-climatic conditions. Those variables were derived from the UN and World Bank, and the POLITY IV project. Each variable is based on annual

observations at country level. In order to control for the underlying environmental conditions in each locale we generate a climate classification as a structural indicator of the amount of rainfall in each grid. This climate classification for each grid cell was created from a digitized version of a standard Arid Zones of Africa Map (McCarthy et al., 2001, p.518). Grid cells containing multiple zones were given a characterization of the dominant value. We generate six categories reflecting arid and hyperarid, semi-arid and dry-subhumid, and most-subhumid and humid conditions; we collapse these six categories into three that reflect the degree of aridity in a country-grid (*Arid effect*, *Moderate or mixed*, *Humid effect*), with arid and hyperarid, semi-arid and dry sub-humid, and most subhumid and humid comprising the three categories.

To capture country-level adaptive capacity (*Adaptive capacity*) and climate sensitivity (*Sensitivity*), we rely on data from the Notre Dame Global Adaptation Index (ND-GAIN) project (http://index.gain.org) which generates sensitivity and adaptive capacity indices constructed from a diverse set of indicators. The *Sensitivity* variable represents social, political and physical risks posed by climate pressures and the *Adaptive capacity* variable reflects social, political, and economic infrastructure that can respond to the physical and social consequences of climate change (Chen et al., 2016).

4.2 Methods

We specify empirical models that include country level non-climatic variables, grid level climatic variables, and a grid level indicator of armed conflict (see Table 1). To formulate the different spatial levels, we use multi-stage panel logistic regression with *ongoing* conflict as our outcome variable (Models I (1) and (2) of Table 2). The models are specified to "take account of the variability concerned about each level of nesting" (Snijders and Bosker, 1999, p.1) and adjust for the lack of independence within the spatial clusters (Rabe-Hesketh and Skrondal, 2012;

Raudenbush and Bryk, 2002). A multi-level panel logistic regression model is appropriate to estimate the spatial cross-level effects of country-level non-climatic conditions and grid-level climatic conditions on the likelihood of armed conflicts. Additionally, we use a multilevel negative binomial regression to test the effect of climate and adaptation on the number of battles (*Battles*) associated with a conflict in each five-grid unit (see Model II of Table 2).[2]

Next we use an instrumental variable estimation with two-step probit endogenous regressors to account for an underlying process by which water scarcity persists. This accounts for unobserved effects and endogeneity in one or more time-varying explanatory variables (Wooldridge, 2006, p.538). We treat *Soil moisture anomaly* as endogenous and set several variables including four month lagged climatic conditions (*Lagged Temperature anomaly, Lagged Precipitation anomaly, Lagged Soil moisture anomaly*), other climatic conditions (*Arid effect* and *Humid effect*), and components of country level sensitivity and adaptive capacity conditions (*Water dependency* and *Drinking water access*) as instruments variables (see Model III, Table 2).

5. Results

We analyze our data sequentially, presenting several multilevel and longitudinal empirical models on the effects of climatic conditions on the probability of armed conflict in Africa. The most basic specification, a fixed panel logit includes only three grid-level climatic anomalies measured as 30 month moving averages: temperature, soil moisture, and precipitation (Table 2, Model I (1)). Results suggest that increases in temperature and precipitation at the grid level increase the likelihood of observing armed conflicts in that grid (β=.168, σ=.01; β=.009, σ=.001); increases in soil moisture are associated with a decrease in the likelihood of observing

[2] We test for the impact of the modifiable areal unit problem on our results (see Appendix 1).

conflict (β=-.003, σ=.001). When we control for the general aridity of the grid (*Arid* and *Humid*), results remain functionally the same, though arid regions are less likely to have armed conflict (β=-1.81, σ =.38, Model I (2)).

We expand these grid-based models to include country level non-climatic attributes such as socio-economic and political conditions, adaptive capacity and climate sensitivity attributes using a two-stage panel logistic regression (Table 2, Model I (3)). The results continue to support the argument that warmer and drier conditions are associated with an increased observation of armed conflict (β=.087, σ=.01; β=-.001, σ=.0001), and increased precipitation remains a predictor of increased conflict at the grid level (β=.004, σ=.002). Country level adaptive capacity is associated with a decrease in the likelihood of observing an armed conflict in a country-grid (β=-4.29, σ= .74), but climate sensitivity at country level lacks statistical significance (see also Model I, Appendix 1).[3]

Following the specification in Model I, we examine the relationship to the number of monthly battles associated with an armed conflict. The core results hold with an increase in temperature and a decline in soil moisture being associated with an increased likelihood of conflict in a country-grid (β=.22, σ=.03; β=-.001, σ=.0002; Model II (1)). Humid climates are significantly related to the observed likelihood of armed conflict if a grid (β=.45, σ=.05; Model II (3)). We see the results for individual battles as a confirmation that the general results of a dichotomous coding of an ongoing conflict are not a function of coding rules or estimation technique, however we have no theoretical foundation to think that climate anomalies directly affect the number of individual battles.

[3] In Appendix 2 we present a check of the robustness of our results to the modified aerial unit. These results confirm general trends.

Our instrumental variable model confirms the results of our multilevel models. Our instrumental specification directly tests the underlying argument about water scarcity on conflict by treating long term trends in soil moisture (*Soil moisture anomaly*) as endogenous, the core results follow the significant impact of temperature, soil moisture, and precipitation on the observation of armed conflict in a country-grid. The overall climatic conditions are also influential in the location of armed conflict (*Arid effect*, β=-.28, σ=.01; *Humid effect*, β=.23, σ=.01), while adaptive capacity remain significant and in the expected direction (β=-.14, σ=.05; Model III (2)).

To further describe the effects of national level adaptive capacity on armed conflict within a grid we present several graphs generated from Model I (3). As illustrated in Figure 1, each graph reflects the impact of high or low national level adaptive capacity under different climatic conditions. High and low conditions of adaptive capacity are determined relative to the global mean level of adaptive capacity. For example, in Figure 1(a) as the temperature increases the likelihood of armed conflict in a grid increases in high capacity countries, but declines in low capacity countries. The underlying probability of observing a conflict, given climate driven stress, is higher and the slope is greater in low capacity countries. When controlling for country level characteristics, as the soil moisture content increases the probability of observing an armed conflict decreases, but does so from a higher initial position in low capacity countries relative to high capacity ones (Figure 1(b)).

6. Conclusions and discussion

Considerable debate about the role of climate change in armed conflict has generated divergent outcomes (e.g., Buhaug et al., 2014; Burke et al., 2015; Salehyan and Hendrix, 2014), with specific cases presenting hard to refute evidence (Kelley et al., 2015) and with confounding

conditions accelerating the influence of climate drivers (Schleussner et al., 2016). Our results help to clarify and extend this debate in important ways. By narrowing the spatial focus to a 2.5° square grid we isolate more local climatic conditions and link them more closely to local conflict events. Furthermore, our methodology changes climate drivers from short term fluctuations over a month into a longer term trends that reflect the cumulative influence of climate on conflict. There should be little expectation that short term variation in climate (averaged at the year or recorded at the month) would compel something as complex as armed conflict.

Our results demonstrate that at the country-grid level of observation, climate drivers of water scarcity are associated with an increased likelihood of armed conflict, and that national level adaptive capacity under conditions of climate stress can reduce that probability. The role of adaptive capacity in moderating armed conflict under conditions of climate driven scarcity provides policy suggestions. In our theoretical framework, national level adaptive capacity can act in a way to moderate the effect of climate on the choice sets of people facing increasingly harsh conditions. In this sense the state can take steps that reduce the marginal impact of climatic changes and in doing so provide local level respite from the conditions that nature is envisaging on a local region. Although we have yet to see this in the literature, facilitating – or bolstering – a country's adaptive capacity may be a form of external intervention into countries that are potentially at risk of armed conflict (Regan and Meachum, 2014). The US DoD (2011) estimates that by 2060 nearly 600,000 square kilometers of currently arable land in Africa will become non-productive because of climate imposed scarcity. Our evidence suggests that investing in the adaptive capacity of African countries can reduce the propensity for people to take up arms as they confront recurring water scarcity. Governments and aid agencies may be well placed to facilitate movements toward more prepared countries.

In general, our models support the inference that 2.5 year moving averages of temperature, precipitation, and soil moisture are strong predictors of an observation of armed conflict within country-grids. These results confirm much of the findings in the literature, albeit with nuances. Increases in temperatures within a grid that are sustained over a 30 month period are associated with increases in armed conflict; increases in soil moisture decreases conflict. At the same time, increases in precipitation over a 30 month period is associated with increased in observed armed conflict in the grid, which is consistent with the results of Salehyan and Hendrix (2014), but seems to run counter to others (e.g., Fjelde and von Uxekull, 2012). Given that our evidence points to rather strong links between climate drivers and armed conflict, our results also suggest that the greater the level of adaptive capacity of a country, the less likely they are to observe conflict in one of their grids. This result remains robust to model specification.

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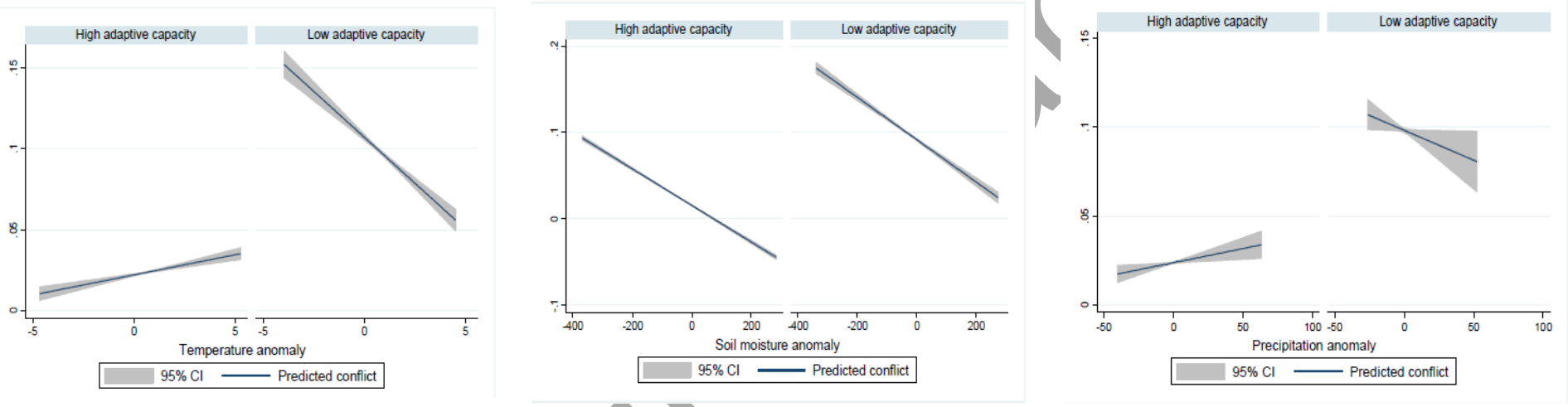

Temperature anomaly **Soil moisture anomaly** **Precipitation anomaly**

Figure 1. Predicted armed conflict and climatic conditions by adaptive capacity level

Table 1. Descriptive statistics

Variable name		Number of observations	Mean	SD	Range
Grid-level climatic condition variables					
Temperature anomaly		305,125	0.567	0.689	-4.662-5.264
Soil moisture anomaly		300,627	-23.004	61.853	-461.22-663.44
Precipitation anomaly		284,340	-0.395	3.423	-40.466-79.453
Arid effect		359,032	0.397	0.489	0-1
Moderate or mixed		359,032	0.308	0.461	0-1
Humid effect		359,032	0.293	0.455	0-1
Country-level non-climatic condition variables					
Polity		332,200	-1.587	5.659	-10 – 10
Per capita GDP		311,212	1,354.04	2,017.92	64.81-24,035.71
Mortality rate		335,404	133.358	69.188	13.10-334.50
Rural population		335,956	63.425	17.099	13.542-95.661
Water dependency		185,636	0.461	0.394	0-1
Drinking water access		185,612	0.728	0.322	0.002-1
Sensitivity		193,353	0.414	0.101	0.101-0.656
Adaptive capacity		193,353	0.270	0.150	0.042-0.703
Grid-level armed conflict variables					
Ongoing	1 =yes	40,889	0.111	0.314	0-1
	0=no	325,973			
Battles		366,862	0.503	4.371	0-279

Table 2. The effect of climatic and non-climatic conditions on armed conflict

	Multilevel model						Instrumental model	
	Model I : Ongoing conflict			Model II : Number of battles			Model III : Ongoing conflict	
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)
Grid-level climatic conditions								
Temperature anomaly	0.168*** (0.010)	0.168*** (0.010)	0.087*** (0.013)	0.221*** (0.028)	0.268*** (0.027)	0.010 (0.033)	0.032*** (0.006)	0.070*** (0.007)
Soil moisture anomaly	-0.003 *** (0.001)	-0.003*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0002)	-0.0004* (0.0002)	-0.0002 (0.0003)	-0.001*** (0.000)	-0.0007*** (0.000)
Precipitation anomaly	0.009*** (0.001)	0.009*** (0.001)	0.004** (0.002)	0.003 (0.004)	0.006 (0.005)	0.011** (0.005)	0.006*** (0.001)	0.005*** (0.001)
Arid effect		-1.818*** (0.380)	-1.054*** (0.028)		-0.699*** (0.041)	-1.805*** (0.060)	-0.005 (0.010)	-0.282*** (0.013)
Humid effect		-0.215 (0.404)	0.059** (0.028)		0.339*** (0.042)	0.452*** (0.059)	0.218*** (0.010)	0.232*** (0.011)
Country-level non-climatic conditions								
Polity			0.004 (0.003)			-0.056*** (0.006)		-0.044*** (0.001)
Per capita GDP			-0.0002*** (0.000)			-0.0003*** (0.000)		-0.00007*** (0.000)
Mortality rate			0.007*** (0.005)			-0.011*** (0.0006)		-0.001*** (0.0001)
Rural population			0.035*** (0.005)			0.048*** (0.003)		0.001*** (0.0005)
Sensitivity			-0.318 (0.438)			-2.289*** (0.485)		-0.200** (0.078)
Adaptive capacity			-4.293*** (0.740)			1.928*** (0.308)		-0.140** (0.048)
Constant	-4.064*** (0.169)	-3.207*** (0.281)	-3.616*** (0.585)	-0.769*** (0.023)	-0.685*** (0.034)	-0.749** (0.227)	-1.000*** (0.009)	-0.792*** (0.043)
Country characteristic level			2.285 (0.283)			11.950 (4.054)		
N of observations	284,068	281,968	129,611	284,068	281,968	129,611	123,700	112,481
N of ongoing conflict	35,308	35,301	19,341				23,312	19,272
Log likelihood	-78552.0	-78495.7	-44399.04	-100,446.7	-100,016.2	-53404.1		
Wald Chi-square	1,198.5***	1,223.7**	3,459.1***	120.2***	795.3***	2,379.3***	1015.3***	4361.4***

Note: *: $P<0.1$, **: $P<0.05$, ***: $P<0.001$, standard error in parentheses

Appendix 1. The effect of climatic and non-climatic conditions on armed conflict

	Model I : Ongoing conflict	Model II : Number of battles	Model III : Ongoing conflict
	(1)	(2)	(3)
Grid-level climatic conditions			
Temperature anomaly	0.064***	-0.022	0.034***
	(0.013)	(0.034)	(0.007)
Soil moisture anomaly	-0.002***	-0.0004	-0.001***
	(0.0001)	(0.0003)	(0.000)
Precipitation anomaly	0.003	0.005	0.003**
	(0.002)	(0.005)	(0.001)
Country-level non-climatic conditions			
Polity	0.005	-0.037***	-0.040***
	(0.003)	(0.006)	(0.001)
Per capita GDP	-0.0002***	-0.0002***	-0.00008***
	(0.000)	(0.000)	(0.000)
Mortality rate	0.007***	-0.004***	-0.00009
	(0.0005)	(0.0007)	(0.0001)
Rural population	0.039***	0.031***	0.002***
	(0.005)	(0.003)	(0.0005)
Sensitivity	-0.413	-1.633**	-0.992***
	(0.434)	(0.548)	(0.074)
Adaptive capacity	-4.393***	0.587*	-0.483***
	(0.721)	(0.350)	(0.047)
Constant	-4.077***	-0.578**	-0.481***
	(0.571)	(0.244)	(0.041)
Country characteristic level	2.204	13.202	
	(0.275)	(4.447)	
N of observations	130,475	130,475	112,481
N of ongoing conflict	19,346		19,272
Log likelihood	-45188.71	-53841.54	
Wald Chi-square	2,131.3***	1171.7***	2905.9***

Note: *: $P<0.1$, **: $P<0.05$, ***: $P<0.001$, standard error in parentheses

Appendix 2. The effect of climatic and non-climatic conditions on armed conflict

	Model I : Ongoing conflict		
	(1)	(2)	(3)
Grid-level climatic conditions			
Temperature anomaly	0.258***	0.259***	0.023
	(0.020)	(0.020)	(0.027)
Soil moisture anomaly	-0.002***	-0.002***	-0.0006*
	(0.0002)	(0.0002)	(0.0003)
Precipitation anomaly	0.007*	0.007*	0.009
	(0.003)	(0.004)	(0.005)
Arid effect		-1.784**	-1.653***
		(0.568)	(0.071)
Humid effect		-0.771	0.071
		(0.634)	(0.082)
Country-level non-climatic conditions			
Polity			0.045***
			(0.009)
Per capita GDP			-0.0006***
			(0.000)
Mortality rate			-0.005***
			(0.001)
Rural population			-0.013
			(0.011)
Sensitivity			-1.450
			(1.165)
Adaptive capacity			-17.489***
			(1.805)
Constant	-4.256***	-3.115***	4.038**
	(0.254)	(0.447)	(1.357)
Country characteristic level			4.005
			(0.731)
N of observations	77,662	75,982	34,908
N of ongoing conflict	8,797	8,790	4,832
Log likelihood	-20073.76	-20,028.03	-10359.66
Wald Chi-square	360.1***	367.3***	1205.4***

Note: *: $P<0.1$, **: $P<0.05$, ***: $P<0.001$, standard error in parentheses

Appendix 3. The effect of climatic and non-climatic conditions on armed conflict (moving average 25 months and 60 months)

	Model I : Ongoing conflict					
	25 months			60 months		
	(1)	(2)	(3)	(4)	(5)	(6)
Grid-level climatic conditions						
Temperature anomaly	0.132***	0.133***	0.355***	-0.072**	-0.070**	0.592***
	(0.018)	(0.018)	(0.029)	(0.023)	(0.023)	(0.041)
Soil moisture anomaly	-0.003***	-0.003***	-0.0008***	-0.003***	-0.003***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.0001)	(0.0002)
Precipitation anomaly	0.058***	0.059***	0.006	0.123***	0.127***	0.050***
	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.010)
Arid effect		-1.770***	-1.075***		-1.741***	-1.074***
		(0.374)	(0.029)		(0.378)	(0.029)
Humid effect		-0.210	0.062**		-0.139	0.077**
		(0.397)	(0.028)		(0.402)	(0.028)
Country-level non-climatic conditions						
Polity			0.004			0.003
			(0.003)			(0.003)
Per capita GDP			-0.0002***			-0.0002***
			(0.000)			(0.000)
Mortality rate			0.008***			0.009***
			(0.0005)			(0.0005)
Rural population			0.037***			0.042***
			(0.005)			(0.005)
Sensitivity			-0.086			0.034
			(0.438)			(0.437)
Adaptive capacity			-3.921***			-3.426***
			(0.742)			(0.744)
Constant	-4.161***	-3.309***	-4.220***	-4.129***	-3.285***	-4.995***
	(0.168)	(0.276)	(0.591)	(0.171)	(0.279)	(0.605)
Country characteristic level			2.313			2.386
			(0.286)			(0.295)
N of observations	292,284	290,073	129,876	295,552	293,172	129,876
N of ongoing conflict	35,347	35,340	19,380	35,347	35,340	19,380
Log likelihood	-79971.8	-79911.15	-44463.6	-80521.6	-80458.1	-44411.4
Wald Chi-square	809.2***	839.0***	3535.9***	488.7***	519.0***	3627.8***

Note: *: $P<0.1$, **: $P<0.05$, ***: $P<0.001$, standard error in parentheses