Drought Perceptions, Local Institutional Contexts, and Support foViolence in Kenya[1]

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Abstract:
We address two questions of interest to those who study climate change effects on social stability. First, do droughts and their associated environmental impacts affect levels of violent conflict? Second, do local level formal (governmental) and informal (traditional) institutions moderate the risk of violence where droughts are reported to be worse than they were in that past? To answer these questions, we recently conducted a national survey of 1,400 Kenyans and asked them about the frequency, severity, and timing of rainfall, as well as the presence of rules regulating natural resource use and access. We analyze reports of precipitation change together with a series of endorsement experiments designed to elicit honest responses about support for the use of violence among the Kenyan population. In addition to relying on survey data, we join sampling locations to observed remote sensing images of vegetation health and spatially-interpolated rain station records of precipitation. We find no evidence of a direct link between drought and violent attitudes. In line with our theoretical expectations, however, we find that reported *increases* over time in the number of rules regulating natural resource use (informal and formal) have conditional and dampening effects on support for violence. Meanwhile, the mere presence of such rules (rather than change in the number of them) has no statistically significant impact on support for violence. We find that observed changes in precipitation have no effects consistent with reports of worsening drought, an observation that warrants further investigation in our ongoing research and fieldwork.

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I. Introduction

Much of the research investigating climate change impacts on violent conflict has been carried out using coarse geographical resolutions, such as countries or large regions, and similarly analyzes crude weather variability and conflict measures. For example, Burke et al. (2009) use the occurrence of civil war (yes/no) within a year for every African country as their outcome variable for violence and average temperature across entire countries as their key predictor that captures climate change. In countries as large as Sudan or Democratic Republic of Congo, for example, the assumption that either of these measurements capture the localized nuances of environmental variability and conflict dynamics is deeply problematic (for similar country-level analyses see Hsiang, Meng, and Cane, 2011; Landis, 2014; Saleyhan and Hendrix, 2014, among others).

Some research in high profile journals such as *Science* has broadened the definition of what forms conflict can take (Hsiang, Burke, and Miguel, 2013; Hsiang and Burke, 2013), but arguably goes a step too far in mixing many diverse manifestations of violence and combining the possible effects of a multitude of distinct weather and climate indicators (Buhaug, et al. 2014).[2] There has in fact been lively debate about the modeling of climate-conflict relationships (O'Loughlin, Linke, and Witmer, 2014a; Hsiang and Meng, 2014) and the assumptions underlying the data and methods that researchers use to understand them. Most importantly, however, the limitations of many

[2] Hsiang, Burke, and Miguel (2013) combine interpersonal violence, civil war, and civilizational collapse on dramatically different time scales into a single measure of "human conflict."

studies on this topic are conceptual and not only technical in character. Hsiang, Burke, and Miguel (2013), for instance, conduct a meta-analysis of dozens of research articles that is not designed to *explain why* observed associations are found, though the authors can isolate statistical correlations. Ideally, of course, such a causative explanation is the gold standard of social science research and increasingly those who study the impacts of climate change are directing their efforts accordingly (Buhaug, 2015). Building new and better datasets using novel research designs and methodological techniques that focus on the possible explanatory linkages is the most productive path forward in the study of climate-conflict effects. By following such an analysis framework, our Kenyan study makes a substantial contribution to the existing literature on this crucially important topic.

Scholarly efforts to substantially incorporate explanatory mechanisms for relationships between environmental change and violent conflict are increasingly common, and we review some examples of this research below (e.g. Detges, 2014; De Juan, 2015; Maystadt and Ecker, 2014; Böhmelt et al. 2014; Fetzer, 2014; Ide et al. 2015; Maystadt, Calderone, and You, 2015; Linke et al. 2015). The conceptual framework for many of these studies, as we will show, is closely in line with the methodological and epistemological dedications of human geographers and anthropologists (e.g. McCabe 2004; Bollig 1993; Turner 2004), where nuances of local level power dynamics and social structures are considered to be central to thorough understandings of violence as a social processes. Our article is structured as follows. We outline the state of existing research in the following section. Sections three through seven describe our theory and specific propositions, data, methods, results, and conclusions, respectively.

II. Existing literature

Contemporary studies of environmental change and conflict strive for detailed understandings of multiple forms of violence as well as the spatial and temporal resolutions at which any associations emerge. Some environmental crisis effects are manifested immediately, while others may not be felt for a year or more. Similarly, not all conflict is identical; cattle-raiding violence varies fundamentally in aims and scope from attacks of rebel organizations against government forces that are designed to take over a country's capital city. The temporal variation in types of fighting, actor motivating influences, and expected outcomes varies based on the cause of grievances. As such, distinctions among forms of violence can reveal important information about its underlying drivers. By understanding such different forms of conflict, Raleigh and Kniveton (2012) present evidence that rainier periods are more likely to experience inter-communal violence and that drought might relate more closely to cohesive rebel group attacks. In a similar fashion, O'Loughlin, Linke, and Witmer (2014b) separate a continental sub-Saharan Africa analysis of drought, temperature, and violence by types of conflict incidents; violence against civilians, battles between two armed groups, and rioting are not similarly influenced by environmental stresses and variability. Maystadt, Calderone, and You (2015) find that high temperature extremes are associated with local conflict in North and South Sudan, but are able to illustrate that a single type of conflict - competition over water - dominates the general relationships.

Temporal sequencing is the focus of Nardulli, Peyton, and Bajjalieh (2015), who move beyond contemporaneous overlap of weather related disasters and conflict at an annual scale. While this work has clear merits for testing the timing of intra-state conflict, the authors nevertheless rely on coarse country-level data in their study. Using a comparatively fine geographical scale of analysis, von Uexkull (2014) distinguishes between sub-national regions classified as rainfed agriculture zones and compares conflict trends in these areas to others (such a designation is impossible with country-level data). A conditional relationship linking weather variability to conflict via rainfed agricultural classification points toward an economic mechanism operating in sub-Saharan Africa conflicts. De Juan (2015) blends attention to spatial and temporal resolutions in his study of Sudan's civil war and finds that migration in response to ecological change is a key component of a causal chain that raises the risk of violence. According to De Juan (2015), it is resource scarcity and inter-ethnic tensions in migrants' arrival areas that have the strongest effects on the likelihood of conflict. Similar spatial disaggregation is found in Ide et al. (2014), who use a 0.5 degree grid cell resolution to study climate change vulnerability and conflict in Uganda and Kenya (see also Theisen, Holterman, and Buhaug, 2012; O'Loughlin et al. 2012; Fjelde and von Uexkull, 2012; Yeeles, 2015).

Our intention in this study is to understand which *conditional social contexts* may shape attitudes toward violence when droughts become worse. In this effort to identify intermediate, moderating, or conditional mechanisms in conflict analysis we are not alone. Wischnath and Buhaug (2014), for example, find that harvest loss in India raises the level of political violence observed year-on-year (also for food prices see Adger, et al. 2014). Investigating civil war in Somalia, Maystadt and Ecker (2014) have shown that livestock markets are the primary channel for a relationship between droughts and violent conflict. At the onset of drought, herders sell off livestock (usually the weakest first) to avoid incurring costs of a severe slow onset disaster that kills a large section of the herd. This practice floods the market and results in reduced livestock incomes that can affect purchasing power dramatically (FSNAU, 2011). By distinguishing between demand- and supply-side theoretical explanations for why water shortages lead to conflict, Böhmelt, et al. (2014) also undermine the thrust of overly-simplistic scarcity narratives of violence erupting. In India, Fetzer (2014) finds that insurance providing farmers with employment opportunities during periods of drought mediates and reduces the risk of social strife. While it is not modeled as a mediating variable in panel time-series analysis, Ide et al. (2015) consider climate change vulnerability to be a set of multiple social conditions that amplify the chances of conflict during times of environmental stress. Building on one another, it is low education rates, poor health, population density, and existing soil degradation that characterize the authors' "vulnerability to climate change index." Communities exposed to rainfall shortages and extreme temperatures are more likely to experience conflict when the index defining vulnerability is high than when vulnerability is low.

Other non-monetary social forces have been shown to condition the effects of environmental change in sub-Saharan Africa as well. Fieldwork in Ethiopia by Kassahun, Snyman, and Smit (2008) shows that failing traditional coping mechanisms for drought management has had harmful effects on physical security. Where cultural institutions in the Somali region of Eastern Ethiopia previously managed inter- and intragroup relations during periods of scarcity, these forums for risk mitigation are disappearing and survey respondents in their research reported greater levels of conflict as a result of this unfortunate development. This finding is closely in line with that of Bogale and Korf (2008), who also found that traditional practices of sharing among households (e.g. access to pasture or water) contributed substantially to peace during times of drought. Inter-ethnic community dialogue in three counties of Kenya has also been found to condition any link between changes in drought recurrence and support for the use of violence (Linke, et al. 2015). The particular format or design of these and other social forums and practices may vary by region or country but all of them are part of the broadly defined “coping mechanisms” that scholars strive to understand.

Our contextualized research design is guided by fundamental tenets of the disciplines of human geography, political ecology, political science, and anthropology. We bridge the divisions between these disciplines in several ways that result in a more comprehensive understanding of Kenyan conflicts. By honing in on the specifics of an individual case (Kenya) our work represents a departure from cross-national studies on the topic cited above, including von Uexkull (2014), Theisen et al. (2014), O’Louglin, Linke, and Witmer (2014b), among others. As a country case study, our research is more similar to those of de Juan (2015) in Sudan, Bogale, and Korf (2008) in Ethiopia, or Maystadt and Ecker (2014) in Somalia. Despite focusing on a single society, there are four main reasons that Kenya represents an ideal case for sound generalization to other regions of sub-Saharan Africa. First, Kenya has an ethnically diverse population, which facilitates comparison to other countries that are not homogenous demographically and are instead dominated by only one or two groups. Second, from the arid north to the rainy west and tropical coast, Kenya has a diverse set of underlying climatic and environmental conditions. Third, Kenya is not a site of complete breakdown of social institutions or outright civil war, as is the case in Somalia and Sudan. Generalizing conclusions from research carried out in such settings to other regions of Africa can be difficult. Fourth, Kenya is a democracy with problems, but it is still fundamentally an open regime and not a total autocracy, which would also make generalizations outward difficult (e.g. if the work were based in Zimbabwe).

We examine the influences of official (governmental) and also unofficial (traditional or customary) rules dealing with the use and governance of natural resources. Both are likely to be influential, but they matter for Kenyans to different degrees across various regions of the country. With regard to formal institutions, research suggests that institutional management of resources has a moderating influence on the potential linkages between water availability and conflict among countries (Dinar et al. 2015; Tir and Stinnett, 2011). Within countries there is also evidence of such a relationship. Lecoutere, et al. (2010) use a lab-in-the-field experimental game and find that the quality of governmental institutions (as inclusive and representative versus exclusionary) determines whether resource scarcity translates into conflict in Tanzania. But the rules governing resource use are of course not only governmental and official. In rural areas of many countries, the formal rule of law is weak relative to the customary practices that guide inter- and intra-community politics. In Ethiopia, sharing of pasture, for instance, contributes to peace during times of scarcity, but is not common practice only because of governmental decree (Bogale and Korf, 2008). In Kenya, nearly all ethnic communities have some history of negotiating access to resources with nearby groups (even if the agreements sometimes fail; see McCabe 1990). For example, in the boundaries between Borana and Somali communities the traditional *dehda* structure for negotiating pasture access contributed to peace when the 2015 rains ended early. “Embedded in *dedha* are rules related to use and access of pastures, water and other resources and that elders are always on standby to arbitrate in case of simmering conflict,” reports Mbaria (2015) in the Kenyan *Daily Nation*. As an example of the kind of social forces we test in our study Daudi Tari, who directs the Resource Advocacy Program, explained *dedha* in clear terms: “although each of the 25 wells have ‘owners’ who organize other community members to dig them, no pastoralist is ever denied access.” Adherence to these informal institutions of dialogue does not exist only because of governmental enforcement of official law and must be considered a distinct non-official realm of Kenyan society.

III. Theory and specific propositions

Our conceptual framework has the following elements (see Figure 1). The scarcity of water represents a condition that individuals and communities must manage (e.g. Maystadt, Calderone, and You, 2015). The responses for managing changes in a baseline condition are clearly determined by characteristics of any individual (e.g. age, wealth, community membership, or social status) but are *additionally* shaped by social setting. In following classical political geography research that focuses on the “politics of place,” to use Agnew’s (1987) terminology, we understand that interactions between individuals take place within sets of cultural norms, institutional traditions, and economic realities. Given some change in baseline environmental conditions, the possibilities that exist for managing scarcity must take place within and through the formal and informal social structures present in an area. Some of those social structures may be conducive to peace, but others may make tensions more severe or otherwise constrain the options for nonviolent resolution of disputes. Cultural traditions of sharing pasture and access to water are one example, rather than treating water and land access as a zero-sum game.

< FIGURE ONE HERE >

Specifically, we argue that any link between drought and support for the use of violence should be moderated according to the relationship shown in Figure 1. We believe that the setting of regulatory mechanisms would dampen the risk of conflict associated with freshwater shortages and scarcity if we compare this context to one where no accepted rules exist. Consider, for example, that villages *a* and *b* in Figure 1 would be more likely to experience conflict under circumstances of drought becoming worse than towns *c*, *d*, or *e,* where rules for sharing and resource management exist. Even where communities are mobile, as in a pastoralist setting, the broader social influences of context should define conflict risk within some limited range of mobility.

Corresponding with Figure 1 and our review of the literature above, we test four hypotheses. We expect that the following social conditions (e.g. contexts I versus II) will have moderating effects on support for the use of violence when drought becomes worse:

> <u>First</u>, the presence of official government rules regulating natural resources;
>
> <u>Second</u>, a greater number of government rules than there were in the past;

Third, the presence of non-governmental traditional rules regulating natural resources;

Fourth, a greater number of non-governmental traditional rules regulating resources than there were in the past;

To test these expectations in regression analyses, we use interaction terms combining two dichotomous variables measuring the characteristics of rules and the presence of drought conditions (reported or observed). Support for the use of violence is always the outcome of interest. By reporting the estimates of these interaction terms – one for each of the four expectations separately – we capture the influences of different social circumstances that translate into violence support, given the effects of drought for society. Details of the methodology are described in section five.

IV. Data

We use a combination of population-based survey data and remotely collected data in the form of satellite images (vegetation conditions) and gridded precipitation data based on spatially interpolated rainfall station information (Standard Precipitation Index deviations). The following sub-sections describe each in turn. Survey data for precipitation, violence, and the presence of resource rules are discussed separately, followed by vegetation health and precipitation. Descriptive statistics for all of our data are presented in Table 1 below.

IVa. Surveys – precipitation change

Our survey data were collected between 6 June and 5 July 2014. The distribution of sampling enumeration areas is country-wide (as seen in figures 5 and 6 below). Our team of 40 enumerators was trained in Nairobi for one week before being deployed to conduct their personal interviews. The survey instrument was tested during training in Nairobi to gauge the average length of the interviews and to familiarize the enumerators with the order and structure of the questions. We based these surveys on a large (*N* = 500) field pilot of the instrument in Nakuru, Uasin Gishu, and Vihiga counties in late 2013. The strategy for respondent sampling was a standard stratified probability sample for Enumeration Areas (EAs) within counties. The EA maps are the same as those used by the Kenyan National Bureau of Statistics for their census data collection. Across survey EAs (175 locations), members of our team identified the pre-determined Survey Sampling Point (SSP) and began a random walk pattern directed in four separate directions (north, south, east, and west). From the SSP, enumerators selected individual respondents of voting age from within the fifth and tenth house. The final sample population size is 1,400 respondents and is nationally representative.

Our key independent variable measuring drought is the perceived change in precipitation over time as viewed by each survey respondent. Other researchers have asked similar survey questions to understand the social implications of changing environmental and ecological conditions (Kassahun, Snyman, and Smit, 2008; Solomon, Snyman, and Smit, 2006; Abule, Snyman, and Smit, 2007; Kaimba et al. 2011). Kassahun, Snyman, and Smit (2008) ask about changes in environmental conditions and also incidents of violence in Ethiopia, which include cattle raiding activity and land seizures. Their environmental degradation questions of Kassahun, Snyman, and Smit (2008) cover an extensive time period (dating back to 1944) and they intentionally select older respondents to characterize changes in two thirty-year time periods before and after a severe and widespread drought in 1974. We select survey respondents who are 18 years old or older but also control for the age of respondents in our modeling, which should ease concerns that our findings are biased by inaccurate recollections of drought by younger respondents.

< FIGURE TWO HERE >

We ask respondents about both the frequency and the duration of droughts since we want to capture multiple dimensions of temporal change in rainfall scarcity. Specifically, we ask respondents whether “droughts are more frequent than they were approximately 10 years ago (they happen more often)”. Respondents who replied, “yes, droughts are more frequent than they were in the past” are coded as reporting more frequent drought. We also posed the following question to each participant in the project: “Are droughts more severe than they were approximately 10 years ago (when they happen did they last longer)?” Those who claimed that, “droughts are more severe than they were in the past” are coded as reporting more severe drought. In Figure 2 we map the distribution of respondents who reported drought becoming worse (either more severe or more frequent than it was in the past). Our reason for combining drought frequency and severity measures is to capture multiple dimensions of drought, as noted above, but also to accommodate the differences in ways that respondents may remember changes in drought conditions compared with 10 years ago. [3]

IVb. Surveys – violent conflict

[3] With drought and violence related questions (below) we asked survey enumerators to record whether or not a respondent seemed intentionally dishonest about certain questions. This is considered a technical control in our models, rather than a substantive individual-level variable like age or education (see descriptive statistics Table 1).

Asking survey respondents about personal experiences with violence and/or indirect exposure to violence in their area is not uncommon (e.g. in Kenya, Finkel, Horowitz, and Rojo-Mendoza, 2012). Asking directly about attitudinal support for the use of violence is less common because it may be difficult (e.g. putting enumerators at risk) and less reliable (e.g. responses may not be honest). Nevertheless, Oyefusi (2008) asked Nigerians about support for the MEND rebel group in the Niger delta region of Southern Nigeria. In Kenya, Schilling, Opiyo, and Scheffran (2012), asked questionnaire respondents about taking part in cattle-raiding activities. Much of the large-N survey research asking about support for the use of violence is found in political science (and especially in the study of counterinsurgency). In Pakistan, for example, Blair et al. (2013) asked survey respondents about support for militancy and use endorsement experiments, which we also use, to elicit honest levels of support for groups such as the Taliban. The survey experiment method is viewed by many as an improvement upon direct questioning of violent attitudes, and has been used successfully in many politically volatile and dangerous field research settings (e.g. Lyall, Blair, and Imai, 2013; Blair, Imai, and Lyall, 2014).

Endorsement experiments rely on a policy cue (e.g. in Pakistan the policy may be teaching girls in elementary school). Our endorsement experiments are based on three policy cues: budgetary spending, police practices and location of stations, and language policies in schools. The exact wording of each cue is presented in the appendix to the article but we have one example presented in Figure 3 below. Levels of support for the cues are averaged across the whole set. In one version of the question, a group is said to also support the policy listed in the question and this group is one that is known to be violent (e.g. in Pakistan the group could be the Taliban). Identifying an endorsing party suitable for Kenya (and for our research question) is difficult because of the great number of ethnic communities in the country (over 40). In order for the endorsing party to be relevant to a respondent's experiences there should be agreement between his/her ethnic community and the group named in the survey experiment. For example, that a Samburu respondent would support a "Pokot ethnic militia" in their endorsement of a policy (no matter what it is) is highly unlikely and would even raise suspicion during the interview. Also, with such a diversity of ethnic communities in Kenya randomization of treatment versions of questions across the sample to ensure that appropriate versions are sent to ethnically-homogenous areas would be prohibitively difficult.

Instead of referring to a specific ethnic community in the endorsement of a policy, we rely instead on a generic reference to ethnic community militias. With great regularity in Kenya, violence is perpetrated by members of an ethnic community against members of a historically rival community. The reasons for the grievances are variable and the temporal dimension changes dramatically, whether from historical injustices committed against one community by another since independence (e.g. narratives of disenfranchised Kalenjin by the Kikuyu first president Jomo Kenyatta) or dynamics of reprisal attacks between pastoralists (Pokot and Turkana cyclical raiding designed for the theft of livestock). We ask a control version of a question where we present respondents with the following statement: "It has been proposed that young school children learn only in their home (vernacular/tribal) language," to which they state whether they "strongly agree", "agree", "disagree", or "strongly disagree." Respondents may also state that they “don’t know.” In the treatment version of this policy cue question (which is randomized throughout the sample), we ask participants how much they support the same policy with an additional clause. In the treatment question, we modify the text to include, “in the past and generally speaking, violent youth from your ethnic/tribal community have expressed support for this policy.” After testing these phrases with our Kenyan survey enumerators and in 75 pilot tests of the survey instrument in and near Nairobi, we decided that the generic references included in the description of endorsing parties were suitable. After averaging policy support across the three separate cues, our outcome of interest is a single variable that is scaled 0 – 1. When treatment status is used as an indicator in a regression model testing respondent-level variables that predict support for the policy, the estimate of the binary treatment assignment indicators tells us the level of support for policies *given the endorsement of a violent actor*. Details of the method are explained in greater detail in section five.

IVc. Surveys – rules of resource use

We measure the presence of rules governing resource use at sub-national levels using several survey questions. Baybeck and McClurg (2005) similarly used subjective questioning (perceptions) for measuring social context. Especially where data reliably characterizing such rules at local levels is rare, we believe that we have a valuable measurement of the contexts that could moderate links between drought and conflict. If a comprehensive and comparative dataset of regulations across Kenya were available, we would test the survey responses against these data. However no such information exists or is publically accessible. Furthermore, by relying on individuals’ familiarity with rules we are capturing the extent to which they should even be expected to influence

Kenyans' lives (if Kenyans in an area are not aware of rules, they are not likely to be effective). In fact, we probe the quality of local governance in a manner similar to Kassahun, Snyman, and Smit (2008, 1267) who asked Ethiopian respondents a series of questions about "the indigenous management practices in rangeland and water resources in terms of coping mechanism.

< FIGURE THREE HERE >

Our questions about resource management rules are multi-faceted, capturing each of the four theoretical expectations that we have listed above. First, we ask respondents whether traditional non-governmental rules exist in their area for the management of natural resources, including the use of water and access to land. The specific wording of the question is presented in the appendix. We also ask whether or not there are more of these rules than there were approximately 10 years ago (matching the drought question in temporal reference). Respondents are provided with the option of saying that they don't know (whether because they just moved into the area, because they are uninformed, or because they were reluctant to answer). As a corollary to these questions, we ask respondents whether or not there are governmental/official rules for managing resources in their area. The distribution of the survey responses to all four of these questions are presented in Figure 3.

Clearly there is great variation in the distribution of responses within Kenya. Some areas have a great number of traditional rules (e.g. Pokot and Marsabit) and in others, they are rare (Uasin Gishu and Trans Nzoia). Substantial variation in the type or form of the rules also exists and we believe that this variation may reveal telling patterns with regard to conflict risks during times of droughts. Pokot county, for example - which lies just south of Turkana (the largest county, by area) along the northwestern border of Kenya with Uganda - has very few local official rules for resource management (top left panel). In contrast, Pokot has many traditional non-governmental rules (bottom left). In Laikipia and in Marsabit, we find the greatest reported change in the presence of customary non-governmental rules from ten years ago.

IVd. Vegetation condition index

We use changes in vegetation health as an important control for potential bias in the reporting of drought. Our concern is whether or not a survey respondent accurately remembers changes in his or her area. If a respondent recollects a time 10 years prior when a lush field existed immediately across the fence from her property and a large farm operated across the dirt road, she may be disappointed with the conditions today *even if the changes had nothing to do with rainfall*. For example, perhaps now the road in front of this respondent's house now has tarmac and the farm across the street became a two-story apartment complex with 20 families living inside. Imagine that the road is busy now and a dusty and a hectic *matatu* stage (public transportation stop) lies at the edge of her property. In responding to our survey it may be difficult for the respondent to separate a memory of drought and farming (or livestock) activities from the current, comparatively poor, conditions. This is not just an illustrative vignette. East African research has shown that "drying precipitation patterns only partially statistically explain the vegetation browning trends, indicating that other factors such as population pressures and land use change might be responsible for the observed declining vegetation condition" (Pricope et al. 2013, p 1525). We believe that controlling for browning trends in our analysis should eliminate a chief potential source of biases in drought perceptions that could be based on population movement, infrastructure development, or changes in forestry practices (clearing land) that *are not a result of precipitation alone*.

< FIGURE FOUR HERE >

To control for browning trends that could bias respondent answers, we use a Vegetation Condition Index (VCI) based on the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (AVHRR) sensor. Our data were processed at a 16km by 16km grid cell resolution and are mapped along with survey sample EAs in Figure 4. The map shows VCI for a sample week of 1 January – 7 January, 2005. High values (maximum 100; in green) represent very good vegetation health and low values (minimum 0; in red) indicate poor health during the given time period. We merge the time-series VCI data to survey sampling locations and average the value for the period 10 years ago (2003-2004) and calculate the change to 2013-2014, when the survey was completed. The resulting value measures whether the vegetation health is better or worse than it was a decade ago.

IVe. Standard Precipitation Index (3-month average)

To compare our results using reported drought to the measured precipitation changes in each EA, we join survey locations to a Standard Precipitation Index (SPI) based on the TAMSAT ~4km high resolution data (Maidment, et al. 2014). These data are derived from archived Meteosat infrared imagery calibrated with historical rain gauge data from numerous international and African agencies. Figure 5 shows our survey enumeration areas mapped above the raw rainfall estimate image for an example month (January 2003). The three-month average SPI (SPI3) compares rainfall in a given month and the two preceding it to the long-term average of the same months since 1945. In other words, September, August, and July of 2006 are compared to all previous Septembers, Augusts, and Julys. The three-month average is better at capturing precipitation variability in areas with high seasonality than longer averages such as six or nine month periods, where the seasons of long and short rains might be averaged into a longer period resulting in a single SPI3 deviation value that eclipses dynamic monthly variability.

< FIGURE FIVE HERE >

The temporal trend in SPI3 values for each EA is shown in Figure 6. Dramatic sub-national variation exists in the line graphs, even though there is greater precipitation overall during this period than during the long term (mean SPI3 is .204). Looking at 2010 as an example year, it is evident that some locations experienced negative deviations, while others are positive and greater than one standard deviation above the long-term average. Differences such as these are completely lost in aggregated national statistics, illustrating the value of the geographical and localized lens that we have adopted for this research. To make our SPI3 results comparable with reported drought, we create a dichotomous indicator of whether or not an EA SPI3 value is drier than 90 percent of the other EAs.[4]

< FIGURE SIX HERE >

[4] Varying this threshold (e.g. to 75%) does not fundamentally change the results. If drought effects are not observed using an extremely dry threshold it is not surprising that less restrictive cutoffs also reveal no effect. Using a different source of precipitation data (Climate Research Unit at University of East Anglia with a similar SPI3 metric also does not change the result; see the appendix and Figure A1).

< TABLE ONE HERE >

V. Methods

We follow the conventional approach for analysis of endorsement experiments in survey research (see Blair, et al. 2013). With the continuous measure of support for the policy cues averaged, we use an Ordinary Least Squares estimation of individual-level variables. Policy support (P_i) is modeled most simplistically as a function of variation across treatment (T_i) group status in:

$$P_i = \beta T_i + \boldsymbol{\eta}\mathrm{x}_i + \boldsymbol{\gamma}T_i\mathrm{x}_i + \varepsilon_i$$

where individual level characteristics are x_i and support for the policy is $\boldsymbol{\eta}$. Variation in treatment effects (of violence support) by respondent characteristics such as drought or existence of local rules is captured in the estimated value of $\boldsymbol{\gamma}$. Random error is represented by ε_i. We report $\boldsymbol{\gamma}$ in the results section with standard errors and also as a treatment effect in percentages. We experiment with including and systematically dropping fixed effects terms at EA and County scales and also with dropping our individual level demographic controls.

VI. Results

The main results of our analysis are presented in Table 2 below. First, we present the findings with reported drought as the key indicator of interest across support for violence in several social contexts (e.g. of government rules for resources use). All model estimates include our individual level controls for age, gender, education, socioeconomic status, and other characteristics listed in Table 1. After presenting these estimates, we test the statistically significant results using the observed precipitation measured in the SPI3 data described above. Models one, two, three, and four in the table correspond to our hypothesized relationships above, respectively. The key estimates in the table appear in italics, representing the change in support for the use of violence in percentages.

< TABLE TWO HERE >

Following much of the academic and policy discussion of climate change effects, we might expect drought to directly increase support for the use of violence. However, Table 2 shows that we find no such effect in Kenya (the interactive term ‘violence cue x drought worse’ across all models). Additionally, there is no effect at all of drought on support for violence where local level official rules exist. The estimated drought treatment effects in this context is -.03 percent, which matches our prediction for the sign of the relationship but is not statistically significant. We therefore find no support for our first proposition. As with the results of model one, there is no conditional or moderating influence of traditional rules on drought effects in model two, indicating that our third expectation about changes in the number of rules is also not met.

While our theoretical intuitions for the effects of official and unofficial rules are not supported, we find evidence that an increase in the number of rules over time (informal and formal) has a dampening effect on support for the use of violence when drought is reported to be worse than in the past (see models three and four in Table 2). Drought treatment effects in settings with more local rules than there were in the past result in a 7.1 percent reduction in support for the use of violence. Where drought has become worse, a greater number of traditional rules is associated with a 8.0 percent reduction in support for the use of violence. Our second and fourth expectations are therefore verified. The differences between presence of rules and changes in the number of rules suggests that social adaptation to changing environmental conditions may be taking place. This is a difficult proposition to formally test with cross-sectional data but we will further investigate this dynamic explanation in our ongoing research.

< TABLE THREE HERE >

In Table 3, we present a replication of our main Table 2 analysis using observed precipitation instead of reported changes in drought. Low SPI3 (drier conditions than the long term average) is measured as a dichotomous variable for each survey EA. We model SPI3 effects following the same steps as we follow for reported drought. Interestingly, the statistically significant effects for a greater number of local official and unofficial rules over time are no longer found. The general conclusion from the Table 3 analysis does not change fundamentally with regard to the role of drought alone raising or reducing support for the use of violence; where we found that reported drought does not correlate with support for violence directly in Table 2, the finding is confirmed for observed drought in Table 3. However, the fact that our context-level expectations for the dampening influences of rules exists only in models of reported drought (and not observed drought) warrants further reflection in our ongoing research and fieldwork. There is a generally weak correlation between perceived and observed drought at the EA scale (~0.4) and one would expect perceived drought impacts to be greater than the measured precipitation since people reflect on and perhaps act on their perceptions.

A straightforward set of robustness checks presented in the appendix confirm that our findings hold under several modeling configurations. Excluding EA fixed effects

(Tables A1-A2), excluding individual level controls as well as EA and county fixed effects (Tables A3-A4), and replacing county fixed effects with regional violent events recorded in the media (Tables A5-A6) all result in similar assessments of the four key article propositions. The purpose of the last analysis in the appendix is to account for endogenous effects of prior conflict on current levels of support for violence.

VII. Conclusion

We set out to understand how drought might lead to support for the use of violence. Our operating assumption, based on research in the field of conflict studies, is that conflict will be most likely when a large segment of a population believes that physical violence is a legitimate expression of grievances. In general and across several models, we find no evidence that reported drought increases the level support for violence among Kenyans. This is also true if we use an observed measurement of rainfall deviations in a region instead of our individual-level survey-based indicator. As our discussion of the literature above suggests, this conclusion is in line with some scholarship on the topic of climate change impacts. However, it does not align with the message of one segment of the climate-security research community who hold that drought will lead to increased risks of violence. We believe that testing such a direct link is just one piece of a much larger puzzle. The most valuable cutting-edge research is designed to understand the varying conditions that explain this association.

As a significant contribution to literature on the topic of climate change impacts for societies, we have tested several specific theoretical expectations of the role that conflict-mitigating social forces play within Kenya. While many researchers claim that environmental changes translate into conflict as a result of some social and economic perturbations to usual conditions (or “shocks” to status quo), such mechanisms are rarely tested in empirical analysis. We remedy this gap in the literature by proposing that support for the use of violence would be lower where informal and official rules for the use of natural resources exist. We find support for our expectation that an increasing number of rules over time reduces support for violence when drought is reported to be worse than in the past but, there is not a corresponding statistically significant link between only the presence of rules. There are several interesting caveats to our study that will guide our ongoing research.

First of all, the fact that our results for observed and reported drought do not line up directly is cause for reflection. While drought is arguably an objective condition when it is measured by millimeters of rainfall, we have found that a perception of changing drought patterns leads to support for violence in Kenya and that measured precipitation deviations do not. It is critically important that this distinction exists after controlling for a suite of individual level variables such as age, education, and socioeconomic status. A pastoralist might be more likely to remember the conditions of drought than someone employed in non-agricultural sectors, for example, but we have controlled for this potential source of bias. A younger Kenyan may have a poorer recollection of drought conditions ten years ago than an older farmworker, though we have also controlled for age differences in our analysis. Even after controlling for perceived relative deprivation vis-à-vis other ethnic communities in Kenya, this difference between reported and observed drought effects remains.

Secondly, another goal of our ongoing Kenyan fieldwork will be to identify why the trend in certain towns and counties deviates from the overall pattern. While traditional or customary rules may moderate conflict risk in some contexts, we know that this is not true in all places. We hope to understand why some customary practices are influential at some locations and not at others, which will complement the nationally-representative and generalizable findings of this article. Further analysis of our survey data can direct us toward a multi-faceted understanding of conditions that moderate conflict risk at multiple geographical resolutions.

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Article Figures

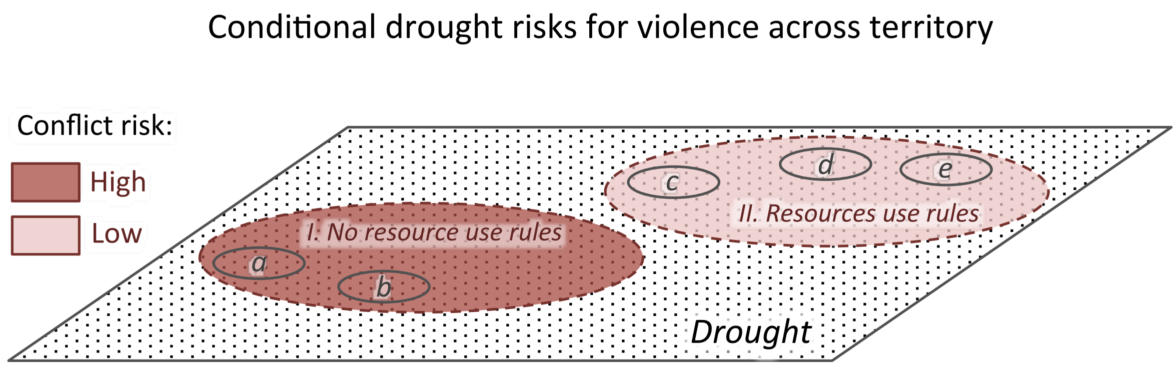

Figure 1: *Graphical representation of the conceptual framework for our research and the specific propositions tested in this analysis. Locations a, b, c, d, and e experience drought commonly. Social/political context I and II condition the likelihood of observing conflict given the underlying stress introduced by the rainfall deficit and freshwater scarcity.*

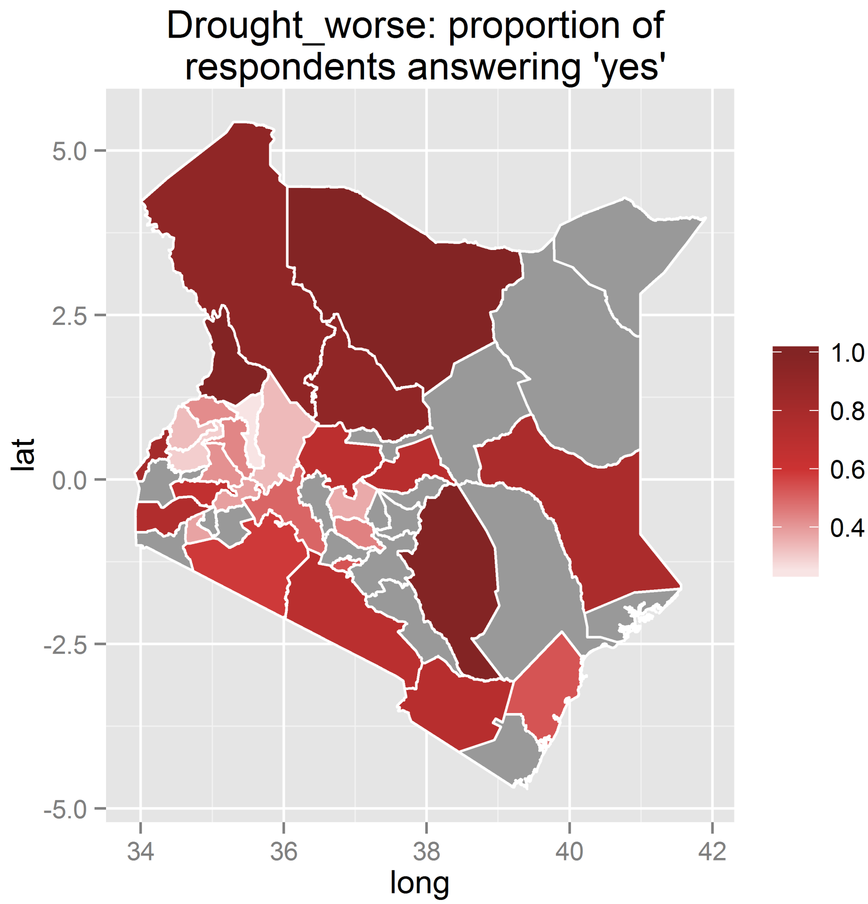

Figure 2: *Reported change in drought conditions from approximately 10 years ago, by Kenyan county. Darker counties are areas where many or all respondents reported that drought is worse than it was in the past and lighter counties had comparatively fewer respondents reporting worsening drought. Grey counties were not included in our survey sample.*

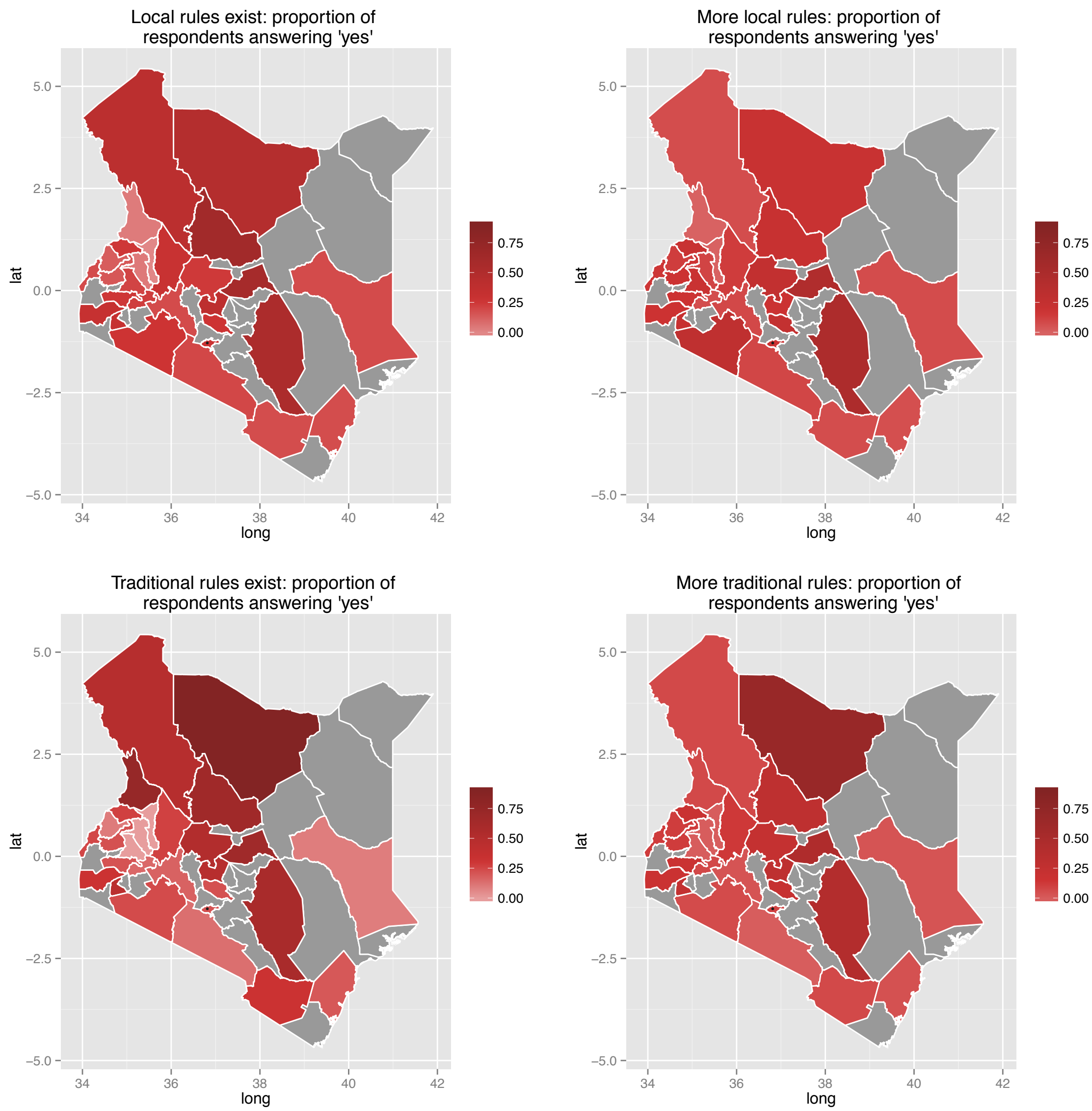

Figure 3: *Survey responses, by county, of four indicators that characterize the presence of rules governing natural resource use in a respondent's region. From left to right in the top row of maps, we measure whether local governmental rules exist and whether there are more local governmental rules than there were in the past. In the bottom row from left to right we measure if traditional rules exist and whether there are more traditional rules than there were in the past. Darker counties are areas where more or all respondents reported that rules existed or that there are more of them than there was in the past. Lighter counties had comparatively fewer respondents reporting the existence or increase in the number of rules. Grey counties were not included in our survey sample.*

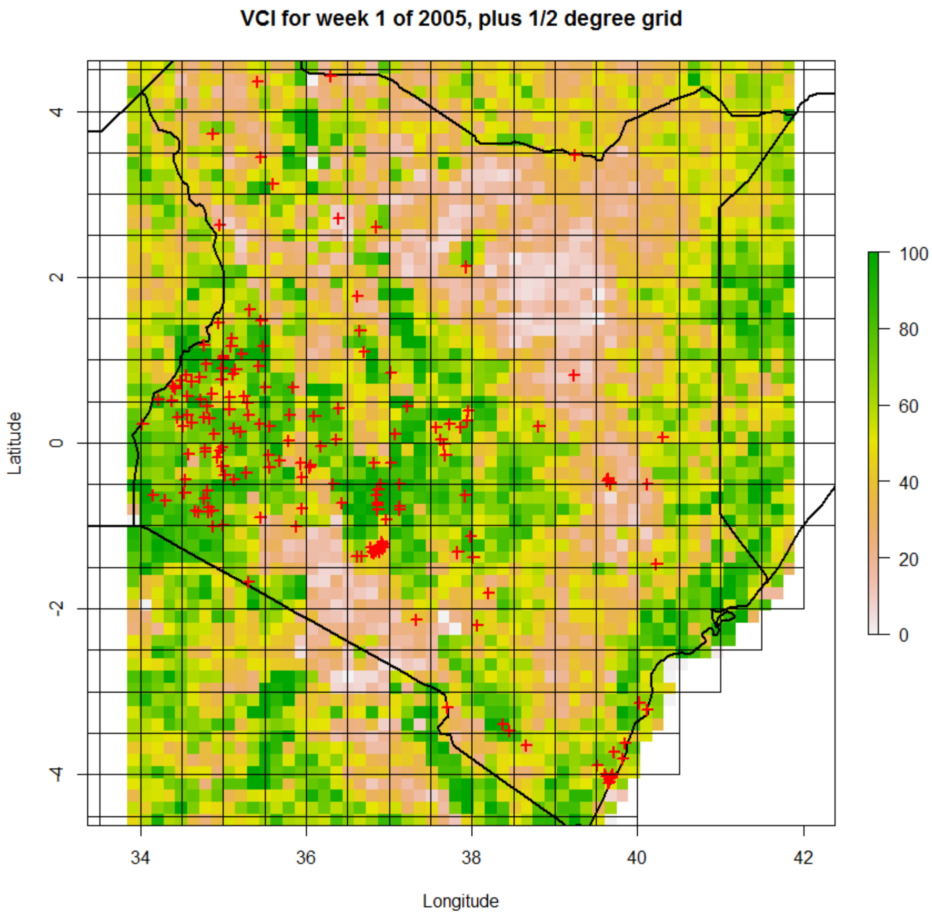

Figure 4: *Survey sample locations (in red, N = 175) and vegetation health (VCI) for a sample week in 2005. The full times series VCI values for each EA are joined with survey responses using the same steps as for observed precipitation records. Green areas represent good vegetative health and brown areas have comparatively poor health.*

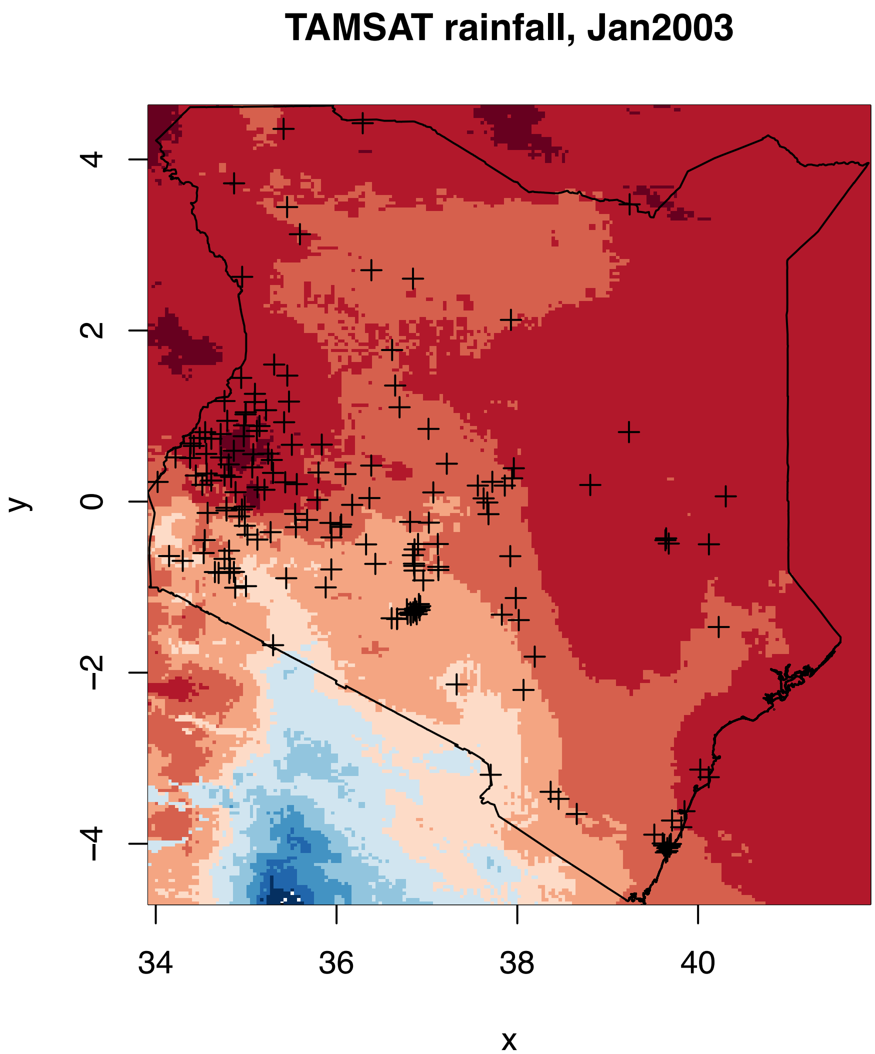

Figure 5: *Rainfall estimates at ~4km resolution across Kenya. Survey enumeration area locations (N=175) are shown as black crosses. Red areas were dry during January 2003 (a sample month for illustration) and blue areas were comparatively wet. Survey EA locations are joined to the TAMSAT time-series data. For comparability with our survey question about drought we create an annual average of the monthly values.*

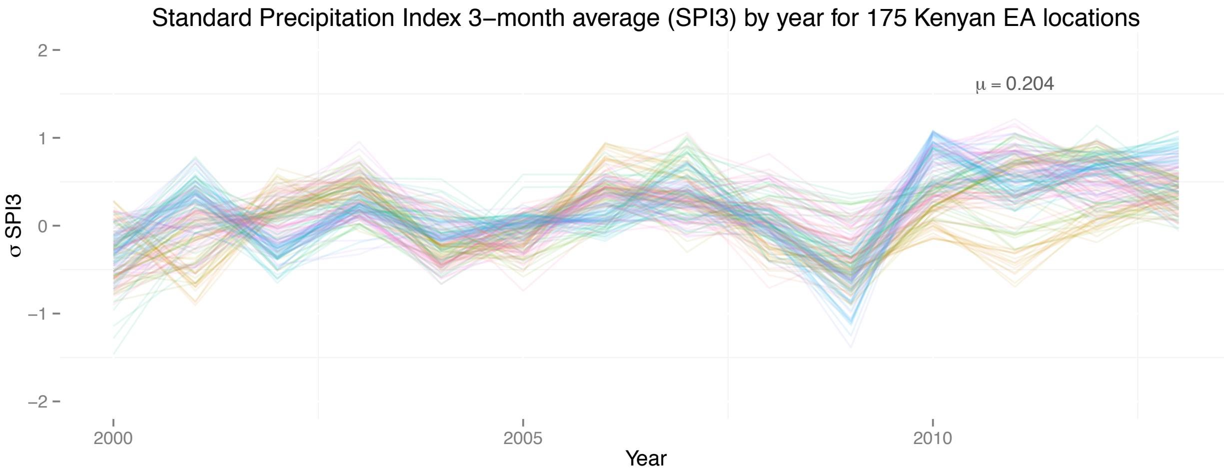

Figure 6: *Standard Precipitation Index 3-month average (SPI3) deviations from long term rainfall for Kenyan EA locations (N = 175). The times series is derived from data mapped in Figure 6. We display the average SPI3 value for all locations in the figure. To match the drought question in the survey we convert SPI3 values into a binary variable measuring extreme rainfall deficits.*

Article Tables

Variable	Max	Mean	SD	Min
Either drought worse (reported)	1	0.575	0.495	0
TAMSAT very dry (SPI3 <= 90%ile)	1	0.105	0.307	0
Veg. condition change (VCI)	1.202	-0.467	0.470	-1.430
Local rules exist	1	0.260	0.439	0
More local rules exist than past	1	0.177	0.382	0
Traditional rules exist	1	0.284	0.451	0
More traditional rules than past	1	0.145	0.353	0
Age	90	36.367	13.210	18
Gender	1	0.507	0.500	0
Employed	1	0.543	0.498	0
Formal eduction	1	0.332	0.471	0
Pastoralist	1	0.373	0.484	0
Low socioeconomic status	1	0.246	0.431	0
Included in governing regimes	1	0.729	0.445	0
Attacked one year prior	1	0.170	0.376	0
Ethnic match	1	0.300	0.458	0
Gender match	1	0.500	0.500	0
Not-forthcoming (weather)	1	0.046	0.210	0

Table notes: VCI = vegetation condition index value; 'Ethnic match', 'gender match', and 'not-forthcoming (weather)' are technical controls for survey interview dynamics (see main text).

***Table 1:** Independent and control (substantial and technical) variable descriptive statistics for our analysis. The bottom control is measured by the enumerator and indicates whether or not the respondent appeared dishonest or hesitant in answering questions about changing precipitation.*

	Model 1			Model 2			Model 3			Model 4		
	Est	StdEr		Est	StdEr		Est	StdEr		Est	StdEr	
(Intercept)	0.411	0.066	***	0.400	0.066	***	0.407	0.066	***	0.404	0.066	**
Violence cue	0.003	0.019		0.003	0.019		0.000	0.019		0.001	0.018	
Violence cue x drought worse	-0.011	0.026										
Violence cue x local rules	0.033	0.039										
Violence cue x drought worse x local rules	-0.055	0.050										
Drought treatment effect (local rules)	*-0.030*											
Violence cue x drought worse				0.004	0.026							
Violence cue x traditional rules				0.022	0.039							
Violence cue x drought worse x traditional rules				-0.079	0.049							
Drought treatment effect (traditional rules)				*-0.050*								
Violence cue x drought worse							-0.007	0.025				
Violence cue x more local rules							0.081	0.044				
Violence cue x drought worse x more local rules							-0.144	0.055	**			
Drought treatment effect (more local rules)							*-0.071*					
Violence cue x drought worse										-0.007	0.024	
Violence cue x More traditional rules										0.072	0.049	
Violence cue x drought worse x more traditional rules										-0.146	0.061	*
Drought treatment effect (more traditional rules)										*-0.080*		
Analysis N	1121			1156			1091			1130		
R-Squared	0.243			0.236			0.256			0.246		
County fixed effects ?	TRUE			TRUE			TRUE			TRUE		
EA fixed effects ?	TRUE			TRUE			TRUE			TRUE		

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

Table 2: *The effects of reported drought on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

	Model 1			Model 2			Model 3			Model 4		
	Est	StdEr		Est	StdEr		Est	StdEr		Est	StdEr	
(Intercept)	0.419	0.066	***	0.397	0.066	***	0.407	0.067	***	0.410	0.066	**
Violence cue	-0.001	0.014		0.008	0.014		-0.004	0.013		-0.003	0.013	
Violence cue x drought worse	-0.012	0.039										
Violence cue x local rules	-0.010	0.025										
Violence cue x drought worse x local rules	0.056	0.088										
Drought treatment effect (local rules)	*0.033*											
Violence cue x drought worse				-0.017	0.037							
Violence cue x traditional rules				-0.034	0.024							
Violence cue x drought worse x traditional rules				-0.015	0.098							
Drought treatment effect (traditional rules)				*-0.059*								
Violence cue x drought worse							0.009	0.036				
Violence cue x more local rules							-0.008	0.028				
Violence cue x drought worse x more local rules							-0.049	0.166				
Drought treatment effect (more local rules)							*-0.052*					
Violence cue x drought worse										0.007	0.037	
Violence cue x More traditional rules										-0.020	0.031	
Violence cue x drought worse x more traditional rules										-0.067	0.138	
Drought treatment effect (more traditional rules)										*-0.083*		
Analysis N	1121			1156			1091			1130		
R-Squared	0.234			0.229			0.239			0.233		
County fixed effects ?	TRUE			TRUE			TRUE			TRUE		
EA fixed effects ?	TRUE			TRUE			TRUE			TRUE		

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

Table 3: *The effects of observed drought (TAMSAT) on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

Appendix

In the appendix we present supporting analyses that accompany our main results. In Tables A1-A2 we present replications of Tables 2 and 3 in the main text but we exclude the EA fixed effects term from the model. As the results show, model fit is comparatively poor. However, our main findings for the moderating contextual effects remain consistent.

	Model 1			Model 2			Model 3			Model 4		
	Est	StdEr		Est	StdEr		Est	StdEr		Est	StdEr	
(Intercept)	0.442	0.036	***	0.442	0.037	***	0.444	0.037	***	0.451	0.036	**
Violence cue	-0.007	0.018		-0.008	0.017		-0.008	0.018		-0.007	0.017	
Violence cue x drought worse	-0.001	0.024										
Violence cue x local rules	0.033	0.036										
Violence cue x drought worse x local rules	-0.045	0.046										
Drought treatment effect (local rules)	*-0.021*											
Violence cue x drought worse				0.007	0.024							
Violence cue x traditional rules				0.039	0.036							
Violence cue x drought worse x traditional rules				-0.073	0.045							
Drought treatment effect (traditional rules)				*-0.035*								
Violence cue x drought worse							-0.001	0.023				
Violence cue x more local rules							0.078	0.040				
Violence cue x drought worse x more local rules							-0.135	0.051	**			
Drought treatment effect (more local rules)							*-0.066*					
Violence cue x drought worse										0.001	0.022	
Violence cue x More traditional rules										0.089	0.045	*
Violence cue x drought worse x more traditional rules										-0.153	0.057	**
Drought treatment effect (more traditional rules)										*-0.070*		
Analysis N	1121			1156			1091			1130		
R-Squared	0.142			0.138			0.150			0.148		
County fixed effects ?	TRUE			TRUE			TRUE			TRUE		
EA fixed effects ?	FALSE			FALSE			FALSE			FALSE		

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

TABLE A1: *Without including an EA fixed effects term, the influences of reported drought on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

	Model 1			Model 2			Model 3			Model 4		
	Est	StdEr		Est	StdEr		Est	StdEr		Est	StdEr	
(Intercept)	0.452	0.036	***	0.439	0.036	***	0.449	0.036	***	0.451	0.036	***
Violence cue	-0.002	0.013		0.000	0.013		-0.006	0.012		-0.005	0.012	
Violence cue x drought worse	-0.035	0.035										
Violence cue x local rules	-0.005	0.023										
Violence cue x drought worse x local rules	0.089	0.081										
Drought treatment effect (local rules)	*0.047*											
Violence cue x drought worse				-0.036	0.034							
Violence cue x traditional rules				-0.015	0.022							
Violence cue x drought worse x traditional rules				0.053	0.090							
Drought treatment effect (traditional rules)				*0.003*								
Violence cue x drought worse							-0.013	0.033				
Violence cue x more local rules							-0.008	0.026				
Violence cue x drought worse x more local rules							-0.009	0.141				
Drought treatment effect (more local rules)							*-0.035*					
Violence cue x drought worse										-0.015	0.034	
Violence cue x More traditional rules										-0.014	0.028	
Violence cue x drought worse x more traditional rules										-0.020	0.134	
Drought treatment effect (more traditional rules)										*-0.053*		
Analysis N	1121			1156			1091			1130		
R-Squared	0.132			0.130			0.133			0.134		
County fixed effects ?	TRUE			TRUE			TRUE			TRUE		
EA fixed effects ?	FALSE			FALSE			FALSE			FALSE		

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

TABLE A2: *Without including an EA fixed effects term, the influences of observed (TAMSAT) drought on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

Tables A3-A4 we estimate similar models to the main text but drop all fixed effects (EA and county) and all individual level controls. Predictably, the model fit is poor relative to the values in main text Tables 2 and 3. Our main conclusions for the influence of moderating contextual level variables hold.

	Model 1			Model 2			Model 3			Model 4		
	Est	StdEr		Est	StdEr		Est	StdEr		Est	StdEr	
(Intercept)	0.446	0.013	***	0.455	0.013	***	0.443	0.013	***	0.456	0.012	***
Violence cue	-0.006	0.018		-0.011	0.018		-0.002	0.018		-0.004	0.017	
Violence cue x drought worse	0.001	0.025										
Violence cue x local rules	0.019	0.037										
Violence cue x drought worse x local rules	-0.045	0.047										
Drought treatment effect (local rules)	*-0.031*											
Violence cue x drought worse				0.016	0.024							
Violence cue x traditional rules				0.058	0.037							
Violence cue x drought worse x traditional rules				-0.117	0.046	**						
Drought treatment effect (traditional rules)				*-0.055*								
Violence cue x drought worse							-0.006	0.024				
Violence cue x more local rules							0.070	0.041				
Violence cue x drought worse x more local rules							-0.133	0.053	*			
Drought treatment effect (more local rules)							*-0.071*					
Violence cue x drought worse										0.002	0.022	
Violence cue x More traditional rules										0.085	0.047	
Violence cue x drought worse x more traditional rules										-0.179	0.058	**
Drought treatment effect (more traditional rules)										*-0.097*		
Analysis N	1121			1156			1091			1130		
R-Squared	0.023			0.036			0.034			0.042		
County fixed effects ?	FALSE			FALSE			FALSE			FALSE		
EA fixed effects ?	FALSE			FALSE			FALSE			FALSE		

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

TABLE A3: *Without including an EA or county fixed effects term and without any individual level controls, the influences of reported drought on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

	Model 1			Model 2			Model 3			Model 4		
	Est	StdEr		Est	StdEr		Est	StdEr		Est	StdEr	
(Intercept)	0.479	0.011	***	0.466	0.011	***	0.477	0.010	***	0.477	0.010	***
Violence cue	-0.002	0.013		0.001	0.013		-0.006	0.013		-0.002	0.012	
Violence cue x drought worse	-0.017	0.036										
Violence cue x local rules	-0.015	0.024										
Violence cue x drought worse x local rules	0.052	0.083										
Drought treatment effect (local rules)	*0.017*											
Violence cue x drought worse				-0.025	0.035							
Violence cue x traditional rules				-0.027	0.023							
Violence cue x drought worse x traditional rules				-0.013	0.092							
Drought treatment effect (traditional rules)				*-0.064*								
Violence cue x drought worse							0.007	0.034				
Violence cue x more local rules							-0.009	0.027				
Violence cue x drought worse x more local rules							-0.132	0.143				
Drought treatment effect (more local rules)							*-0.140*					
Violence cue x drought worse										0.000	0.035	
Violence cue x More traditional rules										-0.039	0.029	
Violence cue x drought worse x more traditional rules										-0.026	0.138	
Drought treatment effect (more traditional rules)										*0.412*		
Analysis N	1121			1156			1091			1130		
R-Squared	0.002			0.021			0.006			0.018		
County fixed effects ?	FALSE			FALSE			FALSE			FALSE		
EA fixed effects ?	FALSE			FALSE			FALSE			FALSE		

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

TABLE A4: *Without including an EA or county fixed effects term and without any individual level controls, the influences of observed drought*

(TAMSAT) on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.

Most conflict analysts are concerned about the endogenous effects of past violence upon current levels of support for violence or the observed level of violence in an area. Table A5 and A6 show that controlling for violent events in a county does not change our results. There are two reasons for this. First, each model already controls for individual exposure to violence, which we ask about in the survey. Additionally, including county violent events from the Armed Conflict Location Event Data (Raleigh, et al. 2010) for two years preceding the survey has no impact on the results because our main models already include location specific fixed effects terms. Comparing these appendix tables to the main text shows that the only difference is in the model intercept.

	Model 1		Model 2		Model 3		Model 4	
	Est	StdEr	Est	StdEr	Est	StdEr	Est	StdEr
(Intercept)	0.160	0.241	0.109	0.241	0.102	0.272	0.048	0.260
Violence cue	0.003	0.019	0.003	0.019	0.000	0.019	0.001	0.018
Violence cue x drought worse	-0.011	0.026						
Violence cue x local rules	0.033	0.039						
Violence cue x drought worse x local rules	-0.055	0.050						
Drought treatment effect (local rules)	*-0.030*							
Violence cue x drought worse			0.004	0.026				
Violence cue x traditional rules			0.022	0.039				
Violence cue x drought worse x traditional rules			-0.079	0.049				
Drought treatment effect (traditional rules)			*-0.050*					
Violence cue x drought worse					-0.007	0.025		
Violence cue x more local rules					0.081	0.044		
Violence cue x drought worse x more local rules					-0.144	0.055 **		
Drought treatment effect (more local rules)					*-0.071*			
Violence cue x drought worse							-0.007	0.024
Violence cue x More traditional rules							0.072	0.049
Violence cue x drought worse x more traditional rules							-0.146	0.061 *
Drought treatment effect (more traditional rules)							*-0.080*	
Analysis N	1121		1156		1091		1130	
R-Squared	0.243		0.236		0.256		0.246	
FE County ?	FALSE		FALSE		FALSE		FALSE	
FE EA ?	TRUE		TRUE		TRUE		TRUE	

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

TABLE A5: *Replacing a county fixed effects term with the violent event count for two years preceding the survey date, the influences of reported* *drought on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

	Model 1		Model 2		Model 3		Model 4	
	Est	StdEr	Est	StdEr	Est	StdEr	Est	StdEr
(Intercept)	0.172	0.242	0.140	0.241	0.107	0.274	0.055	0.262
Violence cue	-0.001	0.014	0.008	0.014	-0.004	0.013	-0.003	0.013
Violence cue x drought worse	-0.012	0.039						
Violence cue x local rules	-0.010	0.025						
Violence cue x drought worse x local rules	0.056	0.088						
Drought treatment effect (local rules)	*0.033*							
Violence cue x drought worse			-0.017	0.037				
Violence cue x traditional rules			-0.034	0.024				
Violence cue x drought worse x traditional rules			-0.015	0.098				
Drought treatment effect (traditional rules)			*-0.059*					
Violence cue x drought worse					0.009	0.036		
Violence cue x more local rules					-0.008	0.028		
Violence cue x drought worse x more local rules					-0.049	0.166		
Drought treatment effect (more local rules)					*-0.052*			
Violence cue x drought worse							0.007	0.037
Violence cue x More traditional rules							-0.020	0.031
Violence cue x drought worse x more traditional rules							-0.067	0.138
Drought treatment effect (more traditional rules)							*-0.083*	
Analysis N	1121		1156		1091		1130	
R-Squared	0.234		0.229		0.239		0.233	
County fixed effects ?	TRUE		TRUE		TRUE		TRUE	
EA fixed effects ?	TRUE		TRUE		TRUE		TRUE	

*Table notes: ***, **, * represents p <= .001, .01 , .05, respectively; "Don't know" moderating variables responses dropped from each respective model; EA = survey enumeration area; Drought treatment effects measured as percent change support for violence; OLS estimates.*

TABLE A6: *Replacing a county fixed effects term with the violent event count for two years preceding the survey date, the influences of observed drought (TAMSAT) on support for violence. Treatment effects (italics) of droughts in contexts of rules (and changes in rules) are shown as change in support for violence by percentage points.*

Alternative precipitation data to TAMSAT exist for measuring deviations for a given three-month period. One source of such data is the Climate Research Unit of the University of East Anglia, who have interpolated precipitation data at a 50km resolution based on rain gauge measurements from 1949 to 2012 (see Figure A2). These data have a comparatively poor spatial resolution to TAMSAT, which is deeply problematic for our research goals and analysis. Nevertheless, our main conclusions for the observed precipitation record are the same when we use the CRU SPI3 data instead of the preferred TAMSAT metric.

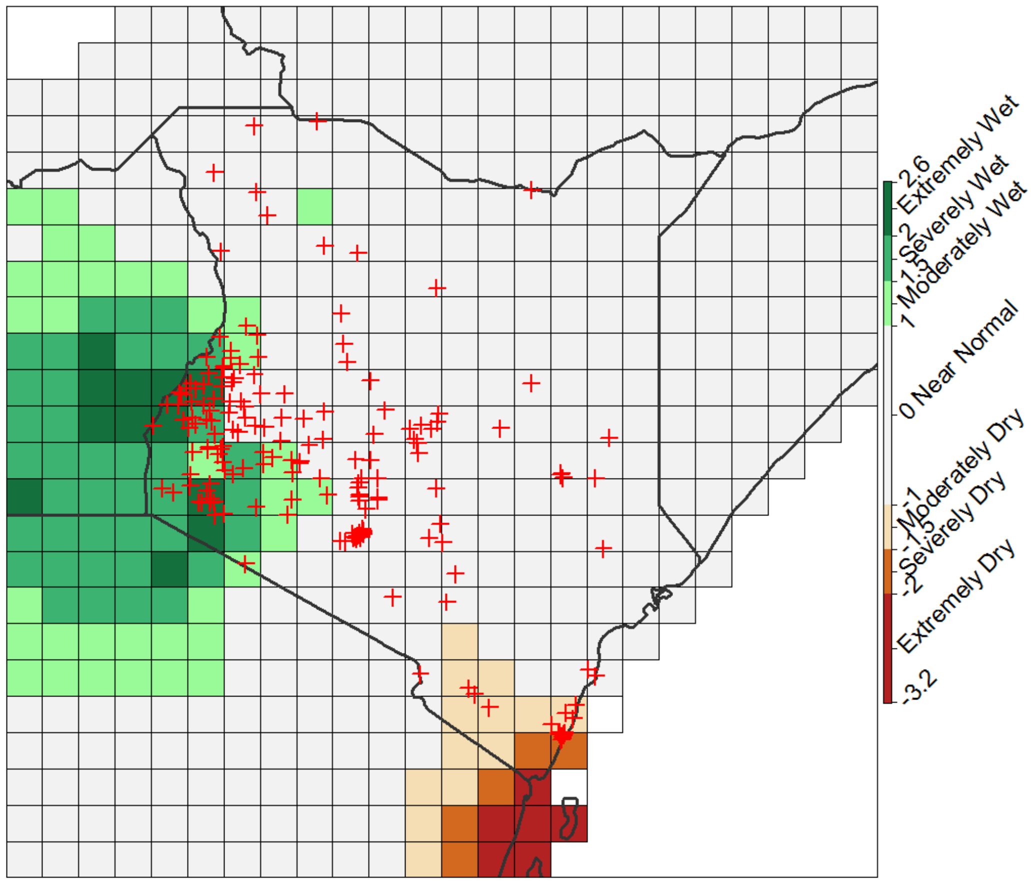

Figure A2: *SPI3 precipitation deviation data for an example month (September 2012) at a comparatively coarse spatial resolution (50km at the equator). These data are from the Climate Research Unit at the University of East Anglia. EA locations (N = 175) are shown in red. Green areas are wetter and brown areas are drier, respectively, than the long-term average measured in standard deviations.*

The specific wording of our survey questions for resource use rules is presented below. In order, the questions measure the presence of local official rules, the presence of local traditional rules, whether or not there are more local official rules than in the past, and whether or not there are more local traditional rules than there were in the past.

Q ##: Do LOCAL OFFICIAL/COUNTY (GOVERNMENTAL) rules regulate the use of water or pasture resources in your area? *(Choose all that apply)*	
Yes (land for grazing)	1
Yes (water for livestock)	2
Yes (land for farming)	3
Yes (water for farming)	4
There are no LOCAL OFFICIAL/COUNTY (GOVERNMENTAL) rules in place in this area	5
I don't know	6
Refused to answer *[DNR]*	98

Q ##: Do LOCAL TRADITIONAL/CUSTOMARY (NON-GOVERNAMENTAL) rules regulate the use of water or pasture in your area? *(Choose all that apply)*	
Yes (land for grazing)	1
Yes (water for livestock)	2
Yes (land for farming)	3
Yes (water for farming)	4
There are no LOCAL TRADITIONAL/CUSTOMARY (NON-GOVERNMENTAL) rules in place in this area	5
I don't know	6
Refused to answer *[DNR]*	98

Q ##: Compared with 10 years ago, how has the number of LOCAL OFFICIAL (GOVERNMENTAL) rules regulating the use of water or pasture in your area changed? *[Interviewer: probe respondents about this if they are young – e.g. do they remember differences]*	
There are many more rules	1
There are more rules	2
There has been no change in the number of rules	3
There are fewer rules	4
There are much fewer rules	5
There have never been LOCAL OFFICIAL (GOVERNMENTAL) rules in place in this area	6
I don't know	7
Refused to answer *[DNR]*	98

Q ##: Compared with 10 years ago, how has the number of LOCAL TRADITIONAL/CUSTOMARY (NON-GOVERNAMENTAL) rules regulating the use of water or pasture in your area changed? *[Interviewer: probe respondents about this if they are young – e.g. do they remember differences]*	
There are many more rules	1
There are more rules	2
There has been no change in the number of rules	3
There are fewer rules	4
There are much fewer rules	5
There have never been LOCAL TRADITIONAL/CUSTOMARY (NON-GOVERNMENTAL) rules in place in this area	6
I don't know	7
Refused to answer *[DNR]*	98