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HEAT AND HATE
Climate Security and Farmer-Herder Conflicts in Africa

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ABSTRACT

This paper investigates the impact of climate shocks on violence between herders and farmers by using geolocalized data on conflict events for all African countries over the 1997-2014 period. We find that a +1℃ increase in temperature leads to a +54% increase in conflict probability in mixed areas populated by both farmers and herders, compared to +17% increase in non-mixed areas. This result is robust to controlling for the interaction between temperature and ethnic polarization, alternative estimation techniques, disaggregation levels, and coding options of the climatic/conflict/ethnic variables. When quantifying at the continental level the impact on conflict of projected climate change in 2040, we find that, in absence of mixed population areas, global warming is predicted to increase total annual conflicts by about a quarter in whole Africa; when factoring in the magnifying effect of mixed settlements, total annual conflicts are predicted to rise by as much as a third. We also provide two pieces of evidence that resource competition is a major driver of farmer-herder violence. Firstly, conflicts are much more prevalent at the fringe between rangeland and farmland - a geographic buffer of mixed usage that is suitable for both cattle herding and farming but is particularly vulnerable to climate shocks. Secondly, information on groups' mobility reveals that temperature spikes in the ethnic homeland of a nomadic group tend to diffuse its fighting operations outside its homeland, with a magnified spatial spread in the case of conflicts over resources. Finally, we show that violence is substantially reduced in the presence of policies that empower local communities, foster participatory democracy, enforce property rights and regulate land dispute resolution.

Keywords: Conflict, civil war, violence, climate change, weather, heat, temperature, nomadic, ethnicity, resource competition, farmer-herder conflict, Sahel.

JEL Classifications***: D74, N47, O13, Q34, Z13.***

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1 Introduction

Abel became a herder of sheep while Cain was a tiller of the soil. (...) And Cain said to Abel his brother, "Let us go out to the field," and when they were in the field Cain rose against Abel his brother and killed him. Bible, Genesis 4:1-18.

Many conflicts around the world have their roots in clashes between farmers and herders.[1] In recent years, these conflicts have flamed up with intensity and scope, leading observers to point out that the "Sahel is on fire" –both in terms of heat waves and armed fighting– as illustrated by the Tuareg rebellions for over five decades in Mali, the Mauritania-Senegal Border War, the recent fighting in Darfur, or the violence between nomadic herders from northern Nigeria and sedentary agrarian communities in the central and southern zones. A multitude of recent NGO reports and newspaper articles provide anecdotal evidence that climatic stress magnifies competition over resources between farmers and herders, accounting for a very substantial share of climate-related violence.[2,3] A typical pattern is the one of nomadic groups experiencing their economic base threatened by drought and having to move beyond the borders of their traditional homelands, and thereby infringing in territories of other ethnic groups, resulting in often very violent clashes.

Beyond case study evidence, this gloomy observation of the salience of farmer-herder conflict is also supported by large-scale data. As described in detail below, roughly a third of fatalities (30.6%) observed over the 1997-2014 period in Africa happen in areas populated by both nomadic and sedentary groups, despite they represent only slightly above a tenth of areas (13.4%). Given these magnitudes it is very surprising that hardly any quantitative evidence exists on farmer-herder violence and that the related channels and policy responses remain mostly unexplored.

In this paper we investigate the impact of climate shocks on violence between herders and farmers by using geolocalized data on conflict events for all African countries over the 1997-2014 period. Our empirical analysis is based on the combination of newly merged ethnic groups' historic mode of settlement with the Armed Conflict Location Events Data (ACLED), containing information on the location and type of conflict events and the involved actors. The units of analysis are cells of 0.5×0.5 degree latitude and longitude (approximately 55 km $\times$ 55 km at the equator). The core of the analysis consists in estimating a model of conflict occurrence at the local level and showing

[1]Conflicts between sedentary groups and herders are as old as mankind, and even appear in the Old Testament of the Bible in the account of Cain the settler killing his brother Abel the herder. Historical examples are as diverse as the conquests of settlements by the nomadic Akkadians in ancient Mesopotamia, the invasions of the nomadic White Huns into the Indian Gupta empire (featuring complex agriculture and manufacture), the clashes between Attila's nomadic Huns and the settlers of the Roman Empire, or the centuries lasting conflict between Han Chinese and nomadic groups such as the Xiongnu, Mongols and Tartars (culminating in the famous attacks led by Genghis Khan, and triggering the building of the Great Wall of China) (see e.g. Bai and Kung, 2011).

[2]See Olsson and Siba (2013), International Crisis Group (2017) and also the coverage by CNN [Link], as well other articles in The Economist including [Link] and [Link]. For example, as related by The Economist of the 28th April 2018, "An attack on a church in Nigeria left at least 19 people dead, including two priests, in the latest incident of violence between nomadic herders and farmers in the country's volatile middle belt. The escalating conflict is now claiming more lives than an insurgency in the north-east of the country by jihadist groups, including Boko Haram".

[3]See e.g. Middle East Eye [Link].

how the impact of temperature shocks on violence are magnified in cells with mixed settlements (i.e. populated by herders and farmers). The use of georeferenced information enables causal identification. Including country-year fixed effects and cell fixed effects, we exploit in most of our econometric specifications within-cell panel variations in violence due to exogenous changes in local temperature.

Our baseline result is that a one degree increase in temperature leads to a 54% higher conflict frequency in cells with mixed settlement, compared to 17% in non-mixed cells. The effect is present even when controlling for the interaction between temperature and ethnic polarization at the local level. Hence this piece of evidence uncovers a specific logic of the herder-farmer interaction that goes beyond the standard ethnic polarization channel. This finding is robust to alternative estimation techniques, disaggregation levels, and coding options of the climatic, conflict and ethnic variables. We then perform a quantification exercise to gauge the magnitude of the effect. To this purpose, we forecast future conflict likelihoods, drawing on cell-level projections of global warming until 2040. When aggregated at the continental level, we find that, in absence of mixed settlements, climate-induced conflicts increase by 26 percent; this number goes up to 33 percent when factoring in the magnifying effect of mixed settlements. Zooming in on the Sahel zone, these numbers become even larger, namely 40 percent (when ignoring settlement patterns) and 54 percent (when taking them into account). To sum up, both for Africa and Sahel, the quantification results show that the presence of mixed cells with nomads and settlers magnifies climate-induced conflict risk by roughly one third (from 26 to 33 percent and 40 to 54 percent respectively).

In the second part of the paper we show that conflicts between herders and farmers are much more prevalent at the *fringe* between rangeland and farmland –a geographic buffer of mixed usage that is suitable for both cattle herding and farming but is particularly vulnerable to climate shocks. Our interpretation is that violence tends to be driven by economic competition over resources rather than being solely due to a clash of cultural norms leading to ethnic hostility and raids, driven by coordination problems, difficulty of communication and ancient hatred. Next, we look at the diffusion over space of climate-induced violence, a question of central importance for understanding how climate shocks drive the escalation of violence from local into regional or national conflicts. More specifically, we show that spikes in temperature in the ethnic homeland of a nomadic group tend to increase the spatial distance between its fighting operations and its homeland. We also show that this spatial spread of violence is magnified in the case of events (i) being reported in the ACLED dataset as linked to disputes over resources; (ii) taking place in cells with water supply or suitable for agriculture. All in all, this evidence is compatible with the view that heat shocks trigger mobility of nomadic groups leading to violent competition for the remaining fertile lands.

In the last part of the paper we investigate how formal institutions are able to mitigate climate-induced conflicts. The idea is that, in many places, informal arrangements between ethnic groups traditionally regulate the management of common resources and settle disputes over property rights. In times of disruptions, climate-induced migrations perturb these fragile arrangements, harm cooperation and lead to an escalation of violence. By contrast, formal institutions can provide a greater resilience to climate and migration shocks. We find evidence that coherent democratic institutions, and in particular the protection of property rights and land dispute resolution mechanisms are key factors attenuating the conflict-fuelling effect of heat shocks. These results are in line with the Coasian logic of property rights' attribution eliminating externalities, and thereby curbing the scope for conflict.

Our findings speak to the fast-growing literature on climate security and the effects of global warming on political stability which has documented a strong causal link between temperature and conflict (see the surveys in Dell, Jones and Olken, 2014; Burke, Hsiang and Miguel, 2015). Worries about the adverse effects of climate change appear with increasing frequency on title pages of major newspapers, and in recent years research on climate change and armed conflict has multiplied and received increasing public attention.[4] However, there is a substantial gap in our understanding of the underlying mechanisms linking heat to hate or of the remedies available to reduce the political footprint of global warming. Unsurprisingly, Burke, Hsiang and Miguel (2015, p. 577) in their recent survey and meta-analysis piece listed as first research priority the "better understanding of the mechanisms linking climate to conflict", while the review article of Dell, Jones and Olken (2014, p. 790) stresses that "there are plausibly important channels that have, to date, received comparatively little study" and that "carefully understanding the specific mechanism would help target potential intervention". These are exactly the issues we investigate in the current paper.

Some candidate mechanisms have been emphasized in the literature. First of all, in an important and recent contribution, McGuirk and Burke (2017) provide compelling empirical evidence on the prominent role played by the opportunity cost of fighting. Hence, it is highly plausible that at least part of the impact of adverse weather shocks is transmitted through lower agricultural productivity and a reduced opportunity cost of soldiering for producers (see e.g. Miguel, Satyanath and Sergenti, 2004; Hidalgo et al., 2010; Fetzer, 2019). While our analysis is consistent with the role played by agricultural productivity, we will emphasize the major magnifying effect of a particular type of ethnic cleavage driving much of the role of agricultural productivity in our sample.

A second proposed channel of transmission in the literature relates to adverse weather shocks shrinking the economy, hence reducing the fiscal capacity of the government and eventually its state capacity. This results in weaker governments that are more likely to be swept aside in a coup in the event of adverse weather shocks (see Burke and Leigh, 2010; Brückner and Ciccone, 2011; Chaney, 2013). While this channel of transmission is not at odds with our findings, we control for it through the inclusion of country-year fixed effects. In fact, our coefficient of interest is barely affected when accounting for country-year fixed effects, which may indicate that country-level shocks such as regime change are not be the dominant force at work for our sample.

Further, a third potential mechanism concerns psychological channels of transmission of heat fuelling crime, which may partly be linked to biological processes in the body (see e.g. Jacob, Lefgren and Moretti, 2007; Ranson, 2014; Burke, Hsiang and Miguel, 2015). Again, while it is plausible

[4] See for example the survey of Burke, Hsiang and Miguel (2015) and the recent overview piece in The Economist [Link].

that part of the effects of climate shocks can indeed by attributed to such psychological factors, we would expect such processes rooted in human biology to be universally present throughout the sample, and hence picked up by our batteries of fixed effects.

While the above mechanisms can surely explain part of the impact of climate on conflict, another channel has received very little attention: The role of ethnic group migration and ensuing clashes between different ethnic groups.[5] International medias have at length discussed climate-related movements of nomadic groups and violent massacres between farmers and herders, but it has oddly received only dismal attention in academia. This is surprising, as indeed there is a sizeable literature having shown that adverse climate shocks lead to population movements (Barrios, Bertinelli and Strobl, 2006; Feng, Krueger and Oppenheimer, 2010; Marchiori, Maystadt and Schumacher, 2012; Bohra-Mishra, Oppenheimer and Hsiang, 2014), and one would intuitively expect that nomadic and settler ethnic groups disputing the same plot of land may lead to tensions and violent disputes.

The existing literature on settler-nomad conflicts consists, to a large extent of the findings, in anthropology and most contributions focus on case study evidence (see the survey of Fratkin, 1997). An example is the seminal work of Scott (2017). There is only very limited quantitative evidence such as Bai and Kung (2011) on China, Theisen (2012) on Kenya, Olsson and Siba (2013) on Darfur and Ralston (2013) and Meier, Bond and Bond (2007) on the Karamoja border region between Uganda and Kenya.[6] Recent work-in-progress by McGuirk and Nunn (2020) – carried out independently – links rainfall to herder-farmer conflicts. Overall, and in contrast to this existing literature, our study systematically assesses the impact of heat shocks over the whole African continent, with a focus on the modulating impact of mixed settlements by settler-nomad groups and an emphasis on mechanisms and policy recommendations.

Given that our channel studies resource competition between rival production methods (crop farming versus cattle herding), recent empirical work on agriculture and conflict is also relevant (Harari and La Ferrara, 2018; Grosfeld, Sakalli and Zhuravskaya, 2020; Berman, Couttenier and Soubeyran, 2019; Iyigun, Nunn and Qian, 2017), as well as theoretical work on production technology, capital and labor-intensiveness and conflict (Grossman, 1991; Dal Bó and Dal Bó, 2011; Botticini and Eckstein, 2014). Last but not least, our work is also embedded in the growing literature linking ethnic cultural norms and local institutions to conflict (Michalopoulos and Papaioannou, 2013; Grosjean, 2014; Moscona, Nunn and Robinson, 2018).

[5]See also the literature studying conflict between ethnic groups (which does not focus on climate-related issues) (see e.g. Montalvo and Reynal-Querol, 2005*a*; Esteban, Mayoral and Ray, 2012; Rohner, Thoenig and Zilibotti, 2013; Esteban, Morelli and Rohner, 2015).

[6]Somewhat related is also the paper of Schleussner et al. (2016) that studies whether disasters coincide with armed conflict in ethnically fractionalized areas. Their data and methodology are very different from ours: They focus on disasters (the magnitude of which may depend endogenously on a series of country characteristics, such as e.g. state capacity) while we focus on (arguably more exogenous) temperature shocks. Further, contrary to Schleussner et al. (2016), who compare the coincidence rate of conflict after a disaster with the pooled baseline risk for a group of several countries and years, we control for time-invariant local characteristics using cell fixed effects and for any shocks hitting a country in a given year through the inclusion of country-year fixed effects. Their work is complementary to ours, and we find, consistently with them, some (small) impact of ethnic diversity in general, but uncover very strong effects of heat shocks for the particular context of areas with mixed settler-nomad population which is the novel angle we examine.

In a nutshell, our contribution to the literature is manifold: It is the first study of ethno-economic conflict that simultaneously i) studies farmer-herder conflicts, ii) covers a whole continent (Africa) and iii) provides evidence on the mechanisms at work. In particular, we provide evidence of an important understudied channel, namely migration under climate stress leading to violent competition on resources. We find that this configuration can account for roughly a third of Africa's fatal conflicts and magnifies the impact of temperature shocks threefold. Finally, our analysis permits to formulate a series of policy recommendations: Stepping up formal institutions for property rights protection and land dispute resolution can substantially attenuate the risk of farmer-herder tensions in times of heat stress where economic disruption puts at risk traditional arrangements.

The remainder of the paper is organized as follows. Section 2 presents the data. Section 3 explains our identification strategy, and displays our baseline results, as well as a battery of robustness checks. The mechanism driving the results is investigated in Section 4 and policies mitigating the conflict are addressed in Section 5. Finally, Section 6 concludes.

2 Data

We organize our empirical analysis around a geo-referenced, annual panel dividing Africa into equally-sized grid cells of $.5 \times .5$ decimal degrees (corresponding to 55×55 km around the equator).[7] Relying on cells rather than on administrative boundaries may attenuate endogeneity concerns, and yields the further advantage that cells can be matched exactly to the spatial unit of the weather data, which is our main source of variation across time.[8] The unit of observation in most of our analysis is cell × year.

2.1 Data sources

Conflict data. The Armed Conflict Location and Event dataset (ACLED) by Raleigh et al. (2010) is used to generate the main dependent variable for our analysis. ACLED collects conflict event data from multiple accounts commonly published by regional and national media, NGOs and humanitarian organizations. The data is available for the years since 1997 for the African continent, which determines the starting point of our panel. The date and geographic location (longitude and latitude) of each event are reported, which allows us to assign each event to a cell-year pair. We

[7]This approach has become increasingly popular in recent years. Examples of recent papers employing a similar methodology include, among others, Michalopoulos and Papaioannou (2013), Harari and La Ferrara (2018), Berman et al. (2017), Iyigun, Nunn and Qian (2017) and McGuirk and Burke (2017).

[8]This is ideal for two reasons: First, using exactly overlapping spatial units reinforces data precision, because there is no need to average multiple cells for large administrative units that potentially could smooth extreme weather events. Second, the temporal variation in temperature remains comparable across cells, whereas differently sized administrative units may smooth the within standard deviation for larger units. For example, calculating the average temperature for two countries that vastly vary in size (e.g. large Algeria vs. small Togo) may smooth the data for Algeria, resulting in a smaller within-cell standard deviation. This may be misinterpreted as differences in sensitivity to variations of temperature. Put differently, if large Algeria were to display a lower impact of temperature on conflict this could be spuriously due to variation being smoothed out.

build CONFLICT, a binary variable coding for conflict incidences that is equal to 1 when at least one ACLED event has occurred in a given cell and year. Since information on events is based on media report, some regions may receive a larger (lower) coverage than others, and consequently are over- (under-)represented in ACLED. Our empirical design accounts for this issue with the inclusion of cell-fixed effects, absorbing systematic coverage bias. Moreover, we show that our results are similar when focusing on major, violent types of events for which over- or under- reporting is unlikely.

A desirable feature of ACLED is the availability of information on the type of conflict. We exploit this information and only consider events categorized as "battles", "violence against civilians" or "riots", excluding thereby less violent events. We prefer to restrict conflict events by type rather than by a fatality threshold, as the latter is subject to substantial missing observations and is generally less reliable. The fighting actors are also identified for each conflict event in ACLED. We exploit this information by matching actors to their ethnic origins, hence allowing us to trace back rebel groups' ethnic affiliations. As a robustness exercise, we also carry out our baseline analysis using an alternative data source for georeferenced conflict events, the UCDP Georeferenced Event Dataset (GED) (Sundberg and Melander, 2013).

Settlement mobility, herders, farmers. We measure ethnicities' settlement mobility with the variable "Settlement Patterns" (v30) from the Ethnographic Atlas (Murdock, 1967).[9] The Ethnographic Atlas comprises over 100 variables on historic ethnic traits and cultural norms. While the data was published over 60 years ago, they are still considered an accurate record of ethnic traits and have been used frequently in recent research.[10] The variable "Settlement Patterns" is categorically ordered with values ranging from 1 to 8, with decreasing mobility in settlement as values increase.[11] We assign to a group the status NOMAD equal to 1 if Settlement Patters are in category 1 or 2 ("Nomadic or fully migratory" or "Seminomadic"), otherwise 0. In contrast, groups of lesser mobility in their settlement within the categories 3 to 8 ("Semisendentary" to "Complex settlements") are assigned the status SETTLER equal 1, otherwise 0. We investigate alternative coding options in the sensitivity analysis (Section 3.4).

In the rest of the paper, we consider these historical mobility characteristics, NOMAD and SETTLER, as proxies for "herder" and "farmer" groups, respectively. As shown below in Figure 2, being classified as a historical settler group is strongly associated with living in areas suitable for crop farming, while having been historically nomadic correlates strongly with inhabiting soils that are infertile for farming, but suitable for herding.

Pre-sample location of ethnic groups. We exploit information on the geolocation of the ethnic groups listed in the "Geo-referencing of Ethnic Groups" (GREG) dataset (Weidmann, Rod and Cederman, 2010). GREG is the geo-referenced version of the 1964 "Soviet Atlas Narodov Mira",

[9] The dataset was later digitalized by Gray (1999).

[10] Recent examples include Nunn (2008); Nunn and Wantchekon (2011); Michalopoulos and Papaioannou (2013).

[11] In particular, a score of 1 = Nomadic or fully migratory; 2 = Seminomadic; 3 = Semisendentary; 4 = Compact but impermanent settlements; 5 = Neighborhoods of dispersed family homesteads; 6 = Separated hamlets, forming a single community; 7= Compact and relatively permanent settlements; 8 = Complex settlements.

and covers 929 ethnic groups world wide, out of which 221 are located in Africa. We match its African sub-sample with the 401 ethnic groups retrieved from of the Ethnograhic Atlas, which leaves us with 216 groups after the data cleaning process. For all these groups, we assemble information on their mobility patterns and location.[12] In particular, we generate a dummy MIXED SETTLEMENT that codes for the coexistence of nomads *and* settlers in a given cell. In other words, if at least one nomadic group and at least one settler group are located in a cell, then MIXED SETTLEMENT equals 1, otherwise 0. Our results are shown to be robust to selecting alternative thresholds for distinguishing nomads and settlers, as well as to controlling for population density. Since the settlement dummies are cross-sectional and pre-date our sample, they are taken as constant throughout our sample period. We focus on pre-sample data and do not account for potential changes in settlements caused by migration, since migration is potentially endogenous to conflict. Note that ignoring changes in settlements introduces some imprecision, which may lead to attenuation bias, making our results appear weaker than they are. As shown below, comparing data on settlements and historical homelands of ethnic groups at different points in time reveals a high persistence in group location patterns. Little has changed over time and transhumant pastoralism remains the most common cattle husbandry practice in the Sahel, with 70-90 percent of herds being moved in line with the seasonal availability of grazings and water (Toure et al., 2012). Cattle herds tend to be moved northward (southward) during rain (dry) season, usually operating within a 100 to 200 kilometers radius. For example in Guinea, internal migratory routes can cover distances from as little as 20 kilometers up to 100 kilometers and more across localities (Higazi and Abubakar Ali, 2018).

Weather data. We focus on temperature shocks for two reasons. First, according to the existing literature, temperature has a particularly strong impact on conflict and is –if anything– measured more precisely than other weather variables (see the surveys of Dell, Jones and Olken, 2014; Burke, Hsiang and Miguel, 2015). Second, and more substantially, temperature is an input factor for both crop farmers and livestock herders, because heat shocks reduce crop and plant yields (Grosfeld, Sakalli and Zhuravskaya, 2020) and increase evaporation in seasonal floodplains, hence hitting crop farmers and herders alike and fueling resource competition between them.[13] Various publicly available weather datasets have been constructed using a variety of underlying methods, each one

[12]The aforementioned Ethnograhic Atlas can be linked to the ethnic groups in "The Tribal Map of Africa" (Murdock, 1959). The map is generally considered as a record of historic homelands and was geo-referenced by Nunn (2008) and later matched to the Ethnograhic Atlas by Michalopoulos and Papaioannou (2013). Nunn and Wantchekon (2011) show that the map is still fairly accurate today with a .55 correlation between the location of ethnicities in the Tribal Map and geo-referenced individual ethnicity data in 2005 from Afrobarometer. Nevertheless, to minimize attenuation bias due to potential migration, we prefer to retain a more recent map of Africa's ethnic groups: This is the reason why we focus on the (pre-sample) spatial projection of the African sub-sample of GREG. Unlike in Murdock's map, the geographic extent of groups in GREG can overlap (i.e. more than one group in a location) and ethnic groups can occur in more than one location.

[13]Another option could have been to focus on rainfall variation. One reason for which we prefer to use temperature shocks is that the impact of rainfall has been found in the literature to be less universally clear-cut than temperature with rain mattering more for some countries than for others and its data quality being more often challenged. Also, the impact of rainfall is typically non-monotonic (absence of rain causes drought, whereas a lot of rain causes flooding), while for our African sample heat shocks have been found to have a monotonically detrimental impact.

with its strengths and weaknesses (an assessment of the different methods can be found in the two aforementioned surveys). We retain monthly temperature data from the Climate Research Unit at the University of East Anglia (Jones and Harris, 2008). This dataset records monthly temperature per grid cell, which we then average across time to achieve annual observations. The data belong to the class of "gridded" weather data sets, which means that missing values in areas without ground station coverage are interpolated based on a statistical procedure. This results in a balanced panel and makes the data set a popular choice among economists. A first potential issue could be a lack of spatial precision caused by interpolation. However, the spatial variation of temperature is relatively low, attenuating concerns about data precision (Mitchell and Jones, 2005). Another potential issue could be a spurious correlation between the interpolation scheme of the temperature data and conflict. To minimize this risk, we cross-validate our analysis with other temperature data.

Data on agriculture and pastoralist production. We rely on crop suitability data from the Globcover dataset version 2.3 built by the European Space Agency (Bontemps et al., 2011). We define a variable capturing agricultural suitability that includes land-use classes 11, 14, 20 and 30. Soil infertility (bare land) is defined by the land-use class 200 of Globcover. For each variable, the cell share is calculated. To measure livestock production, we use data from the Gridded Livestock of the World (GLW) by FAO (Robinson, Franceschini and Wint, 2007), which rely on sub-national censuses for several types of livestock for the year 2005. Second, the Harmonized world soil database (HWSD) (Nachtergaele et al., 2008) provides us with information on a range of inherent and dynamic soil properties that are relevant for crop production.

Other data. For the analysis of heterogeneous effects and policy implications, we also include country-level data on institutional features from the Database of Political Institutions (DPI) (Beck et al., 2001) and the Polity IV project (Marshall, Gurr and Jaggers, 2012). Information on land dispute resolution is derived from the Ease of Doing Business Report (World Bank, 2018) and information on political corruption is from the Varieties of Democracy (V-Dem) Project (Coppedge et al., 2018). Information on federal systems is based on data from Pippa Norris' Democracy Time-series Dataset (Norris, 2009).

2.2 Descriptive statistics

Figure 1, left panel, displays the spatial distribution of the different settlement characteristics. Out of a total of 9,687 sample cells, 3,579 (36.8%) are inhabited only by nomads and 4,854 (49.8%) only by settlers and 1,308 (13.4%) are subject to mixed settlement. Mixed cells are spatially clustered at the transitional outskirts of deserts. The line of mixed settlement cells runs horizontally along the semi-arid Sahel zone that divides the Southern border of the Sahara desert from increasingly humid areas towards the continent's center. At the aggregate level, twenty-seven African countries contain cells with settler-nomadic coexistence.

Figure 2 further provides insights into the geographic/agricultural characteristics facilitating each mobility mode. This log-scaled figure shows that agricultural suitability, NDVI (remotely-sensed measure of vegetation strength, average of monthly data from 1997-2014) and soil infertility (agricultural suitability and soil fertility based on the average of six two-month observations throughout 2009), are powerful predictors of mobility modes: Barren lands tend to by populated by nomads while settlers are located in fertile areas with high crop suitability. Interestingly, for each geographical feature, mixed cells lie in the intermediate range between nomadic and settler areas. This observation shows that most mixed settlement cells correspond to transition zones, at the fringe between geographical units –a pattern that we exploit for the purpose of our empirical analysis in Section 4.2. Finally, these findings inform us on the accuracy of the procedure building our main variable of interest, Mixed settlement, that is based on pre-1970 historical data on ethnic groups and the matching of two different datasets (settlement patterns and location). With this respect, the high correlation between characteristics related to physical geography and human geography is a reassuring validity check.

The spatial distribution of violence in Africa is depicted in the right panel of Figure 1, with darker shadings indicating cells with a higher share of sample years with conflict incidence. Conflict events are spread throughout the continent, with particularly important incidence around the Sahel and in the Great Lakes region. Across all countries in our sample, 83,724 conflict events had been reported between 1997 and 2014, which we aggregate to 13,929 cell-year conflict incidents. Strikingly, the 13.4% of cells that have mixed settlement account for 17.6% of conflicts events and 30.6% of fatalities.

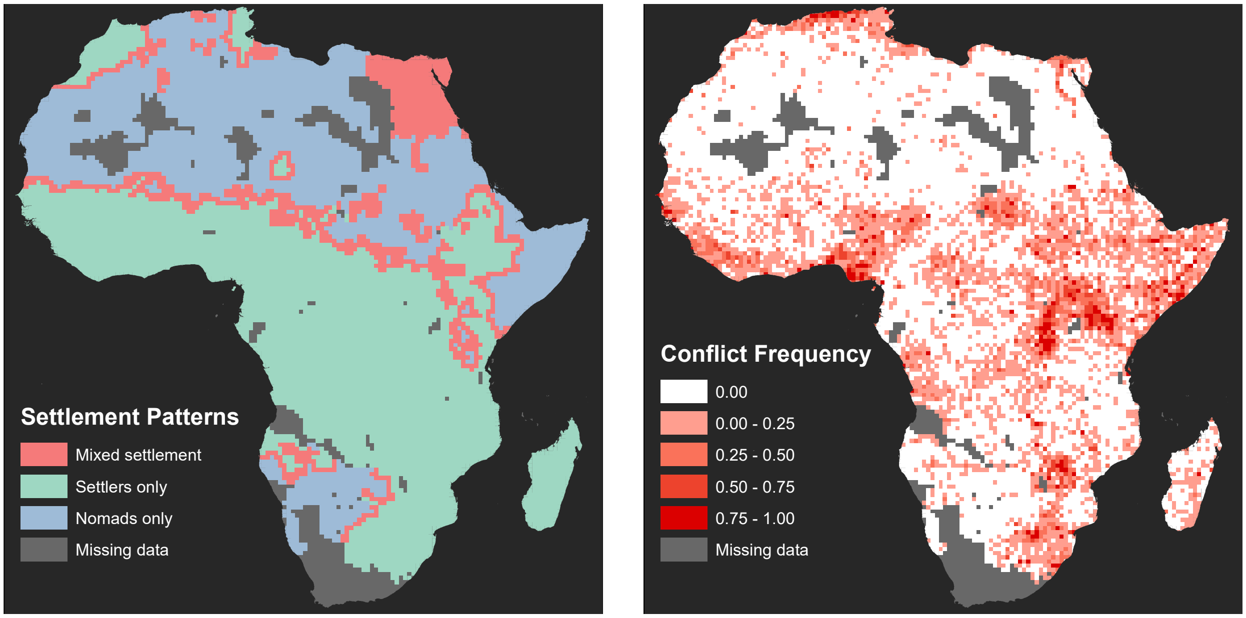
Figure 3 presents both between- and within- cell evidence on temperature variations in Africa. The left panel shows large spatial variations in average temperatures across cells in Africa. However, in our empirical design, the sources of identification are residual spatio-temporal variations in temperatures after filtering out cell-level fixed effects. With this respect, visual inspection of the right panel reassuringly suggests that within-cell variations in temperatures are also substantial.

We supplement the previous graphical analysis with some descriptive statistics of our main variables of interest in Table 1. Contrasting cells with mixed settlement and those inhabited by either nomads or settlers only (No mix) indicates that mixed settlement cells are significantly more prone to conflict, experience higher average temperatures and are populated by a larger number of ethnic groups.

3 Empirical Analysis

In this section we discuss our identification strategy and present the baseline results. Then, we provide a series of alternative specifications assessing the robustness of the results.

Figure 1: Spatial and temporal Heterogeneity of Violence and Settlement



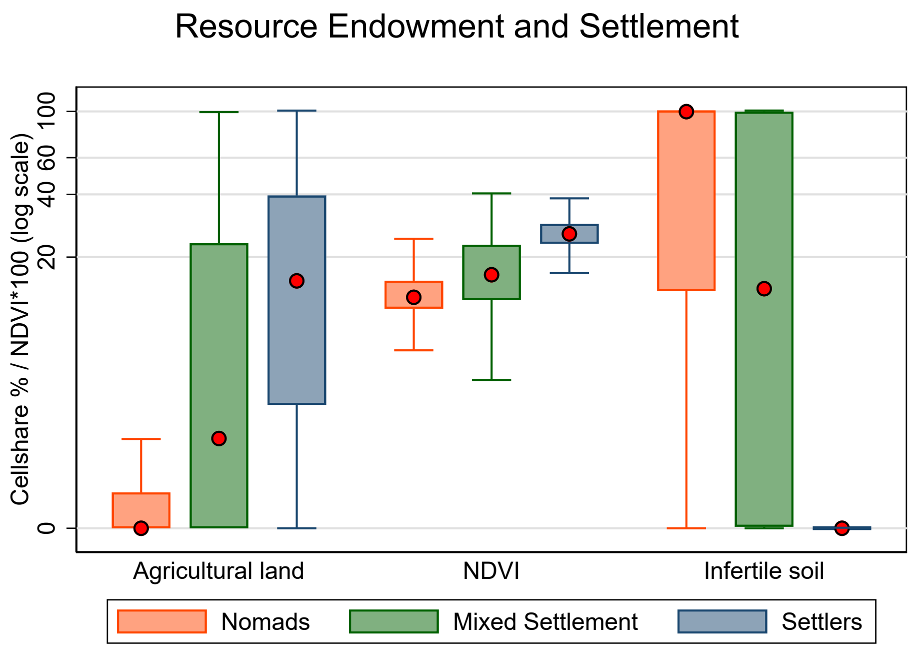
Notes: Left Panel: Spatial distribution of settlement patterns, based on settlement mobility data from Murdock's Ethnographic Atlas matched on to geolocation information from the Geo-referencing of Ethnic Groups dataset (GREG). Green (blue) cells represent regions inhabited by sedentary (nomadic) ethnic groups only. Red cells represent regions in which settlers and nomads coexist. Grey areas indicate missing data. Right Panel: Spatial distribution of conflict, 1997-2014. Darker shadings indicate cells with a higher proportion of years with at least one conflict incident, based on data from the Armed Conflict Location and Event Data Project (ACLED).

3.1 Identification strategy

Assessing the causal impact of mixed settlement on violence involves a range of methodological challenges. The most obvious one relates to omitted factors that drive a long-run correlation between population admixture and latent proneness to conflict. Likely candidates are terrain characteristic (soil quality, mining area, etc.). This is not a minor concern, as the direction of this bias is most likely positive: Fertile and valuable lands tend to be historically more contested between ethnic groups in the long run, leading to contemporaneous conflict and potentially spatial co-existence of nomads and settlers. To address these endogeneity concerns, our empirical design follows the identification strategy developed in the recent conflict literature that exploits spatial variations in rainfall shocks or commodity price shocks (Miguel, Satyanath and Sergenti, 2004; Dube and Vargas, 2013; Berman et al., 2017). While we instead consider temperature shocks, the basic idea remains similar, as we interact those shocks with local characteristics of the cell to identify our main effects. The potential confounders and omitted variables are absorbed by a rich structure of fixed effects (notably cell fixed effects). Many methodological aspects of the estimation procedure are discussed in Berman et al. (2017).

To abstract from local determinants of violence and guarantee exogeneity, we exploit the variations in local temperatures and estimate a specification of the following form:

Figure 2: Resource Availability and Mobility Determine Settlement Style



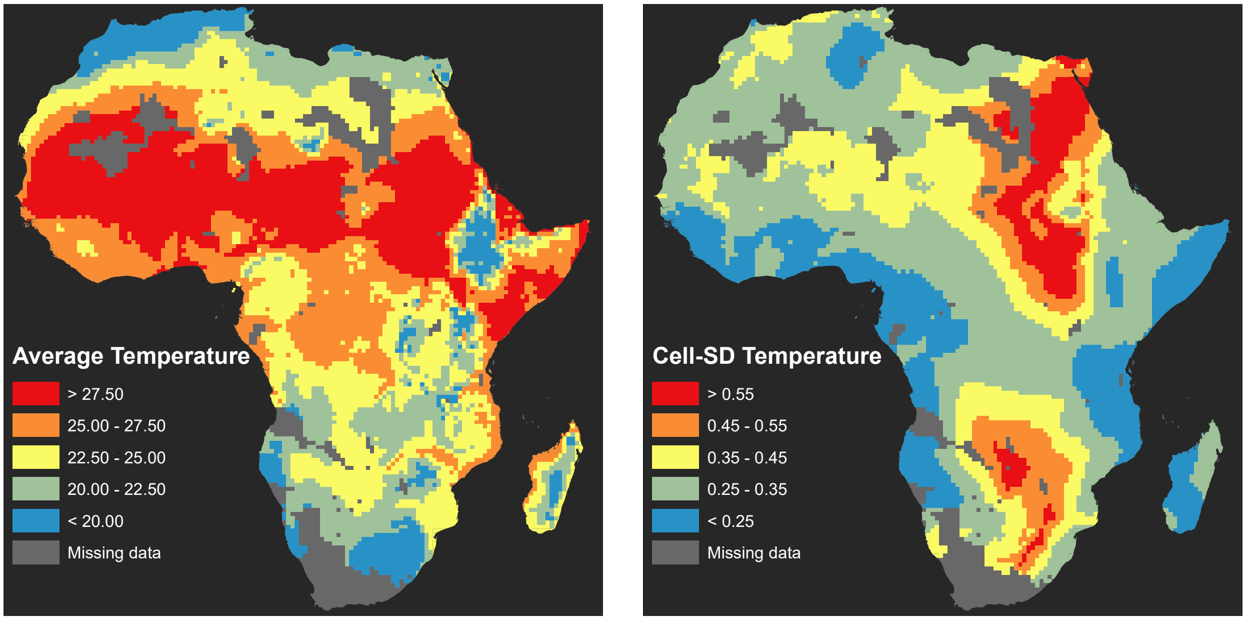
Notes: The sample includes 9,687 cells and considers average values over the period 1997-2014. This figure depicts box plots, dividing the data into three mobility categories: Cells with nomads only, mixed settlement and settlers only. The vertical axis measures the cell average (agricultural suitability and infertile soil) / Value multiplied by 100 (NDVI) in each category in a logarithmic scale for presentation purposes. The median is indicated by the red dot; the 25^{th} (75^{th}) percentile is indicated by the lower (upper) bound of the box; the lower (upper) adjacent value is indicated by the limits of the lower (upper) whisker. The first set of box plots uses land cover data by Globcover to depict the average land share suitable for agriculture. The second set of box plots uses the Normalized Difference Vegetation Index (NDVI), derived from data by NOAA (Vermote et al., 2014) to approximate the average vegetational strength in cells. The third set of box plots uses land cover data by Globcover to depict the average land share of bare soil.

$$\textsc{conflict}_{kt} = \alpha \times T_{kt} + \beta \times T_{kt} \times \textsc{Mixed settlement}_k + \mathbf{FE}_k + \mathbf{FE}_{it} + \mathbf{C_{kt}}'\delta + \varepsilon_{kt}, \qquad (1)$$

where (k, t, i) denote respectively cell, year, and country. The dependent variable, $\textsc{conflict}_{kt}$ is a variable measuring the incidence of conflict events at the cell-year level, i.e., a binary variable coding for non-zero events in the ACLED dataset on civil conflicts. Alternative measures of violence are considered in the sensitivity analysis. $\mathbf{FE}_k$ are cell fixed effects, $\mathbf{FE}_{it}$ are country×year fixed effects, and $\mathbf{C}_{kt}$ is a vector of other potential determinants of conflicts. The vector of cell fixed effects picks up all time-invariant unobserved heterogeneity, such as land quality, ethnic polarization, mountainous terrain or being in a mining region. Country-year fixed effects filter out all country-wide shocks affecting violence such as a recession, an election year, a collapse of the rule of law or property rights.

The main explanatory variable, $\textsc{Mixed settlement}_k$ is a binary variable coding for mixed settlement in cell k. The variable T_{kt} corresponds to the average temperature in degree Celsius in cell

Figure 3: Spatial and Temporal Heterogeneity of Temperature



Notes: Left Panel: Cell-level average in temperature in degree Celsius, over the sample period 1997-2014. Blue (red) color indicates areas with low (high) average temperature. Grey areas indicate missing data. Right Panel: Cell-level standard deviation in annual temperature in degree Celsius, over the sample period 1997-2014. Blue (red) color indicates areas with low (high) variability in temperature over time. Temperature data is from the Climatic Research United (CRU).

k and year t. Our sensitivity analysis investigates alternative coding rule for $\text{Mixed settlement}_k$ and T_{kt} (Section 3.4). In equation (1) we focus primarily on the estimates of β, the coefficient of the interaction term between temperature and the mixed settlement dummy. This coefficient can be interpreted as the impact on local violence of an exogenous local *heat shock* (i.e. increase in local temperature with respect to its long-run average) in cells where nomads and settlers co-exist. Given the inclusion of cell fixed effects, the identifying variations stem from within-cell across-year changes in temperature.[14] Our identification assumption relies on the exogeneity of the interaction term, $T_{kt} \times \text{Mixed settlement}_k$ with respect to the local determinants of conflict. As for temperature, this assumption is natural; as for mixed settlement, it is guaranteed by the inclusion of the cell fixed-effect.

Due to the high-dimensional battery of fixed effects (i.e. more than 880 country×year fixed effects and 9000 cell fixed effects in most specifications), we estimate equation (1) using a Linear Probability Model in our baseline specifications. Spatial correlation must be taken into account, given the high spatial resolution of the data. In all specifications we estimate standard errors with a spatial HAC correction allowing for both cross-sectional spatial correlation and location-specific serial correlation, drawing on the method developed by Conley (1999) and recently applied in König et al. (2017). We use the acreg command developed by Colella et al. (2019). No constraint is

[14] In other words, equation (1) is equivalent to a model where T_{kt} is de-trended by its cell-specific time-average $\bar{T}_k$ in both the linear and interaction terms.

Table 1: Averages and Differences of the Types of Settlement

	Mixed settlement	No mix	Total	Mean difference (Mix - No mix)
P(Conflict > 0)	0.090	0.078	0.080	0.011^a
	(0.286)	(0.269)	(0.271)	(0.002)
Battles	0.056	0.041	0.043	0.015^a
	(0.229)	(0.197)	(0.202)	(0.001)
Riots	0.031	0.029	0.029	0.002^c
	(0.172)	(0.167)	(0.167)	(0.001)
Violence against civilians	0.048	0.044	0.044	0.005^a
	(0.214)	(0.204)	(0.206)	(0.001)
Temperature ($°C$)	24.972	24.740	24.771	0.232^a
	(3.654)	(3.418)	(3.451)	(0.024)
Number of tribes	4.210	3.628	3.706	0.582^a
	(2.825)	(3.143)	(3.108)	(0.022)
Share - Mixed settlement			0.134	
Share - Nomads only			0.367	
	(sd)	(sd)	(sd)	(se)

Notes: The sample includes 9,687 cells for the years 1997-2014. Columns 1-3: Summary statistics. Columns 1-2 divide cells along mobility patterns, based on settlement mobility data from Murdock's Ethnographic Atlas matched onto geolocation information from the Geo-referencing of Ethnic Groups dataset (GREG). Column 1 depicts the average (standard deviation) of cells inhabited by at least one settled and at least one nomadic group ("Mixed settlement"); column 2 identifies cells inhabited by either settlers or nomads ("No mix"). Column 3 considers the complete sample. Column 4 performs a difference of mean test between mixed and non-mixed settlement cells, with the following significant levels: ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conflict indices are based on data by the Armed Conflict Location and Event dataset (ACLED); annual temperature averages are derived from monthly temperature data by the Climatic Research United (CRU).

imposed on the temporal decay for the Newey-West/Bartlett kernel that weights serial correlation across time periods. In the spatial dimension we retain a radius of 500 km for the spatial kernel, close to the median internal distance in our sample of African countries according to the CEPII geodist dataset.

3.2 Baseline results

Table 2 reports the baseline estimation results of equation (1). In column 1 we first assess the impact of temperature shocks on conflict and then compare our results to the existing evidence. To this purpose we estimate a partial version of the model where only the linear term of temperature is included. We find that a local heat shock (average temperature being filtered out by cell fixed effects) increases the likelihood of local conflict incidence. Reassuringly for the quality of our data and scrutinized sample of countries, this is in line with the literature, both qualitatively and quantitatively: Our point estimate implies that a 1 degree (1σ within) increase in temperature translates into a 25% (8.7%) increase in conflict probability, while the meta-analysis by Burke, Hsiang and Miguel (2015) finds an average effect of 13.2% per 1σ increase in temperature. Note that temperature could have a non-monotonic effect on conflict, as extremely cold regions may economically

Table 2: Mixed Settlement and Conflict

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	ln(Events+1) (5)
T	0.020[a]	0.014[c]	0.013	0.010	0.016
	(0.007)	(0.007)	(0.009)	(0.008)	(0.015)
T × Mixed settlement		0.029[a]		0.028[a]	0.058[a]
		(0.010)		(0.010)	(0.021)
T × Polarization			0.013	0.007	0.024
			(0.009)	(0.009)	(0.018)
Cells	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). [c] significant at 10%; [b] significant at 5%; [a] significant at 1%.

benefit from years with milder temperatures. However, modern Africa is highly unlikely to benefit from heat shocks, with an average temperature of 24.7 degree Celsius throughout our sample. And with respect to hot regions, the existing literature finds that heat shocks fuel violence (see Dell, Jones and Olken, 2014; Burke, Hsiang and Miguel, 2015).

In column 2 we turn to the estimation of the full version of the model. The interaction term between temperature and population mixture, our coefficient of interest, is positive and significant at the 1 percent level. Thus, a spike in temperature increases conflict risk in cells where nomads and settlers co-exist. This difference is quantitatively large. A 1 degree Celsius increase in temperature leads to a 17.5% higher conflict frequency in non-mixed cells, versus 53.8% in mixed cells.

A candidate mechanism for explaining this finding is ethnic polarization (e.g. Montalvo and Reynal-Querol, 2005*b*; Esteban, Mayoral and Ray, 2012). As previously mentioned, in mixed settlement cells inhabit two or more ethnic groups (i.e. at least one nomad and one settler group), hence such cells are more likely to be polarized, which could potentially be a driver of violence. We investigate this question in the next two columns with the aim of showing that there is a specificity of the farmer-herder interaction that goes beyond the standard polarization channel. In column 3 we replicate the previous specification with ethnic polarization substituting to mixed settlements in the interaction term. In line with the existing literature we find that polarization magnifies the conflict risk. However, when in column 4 we include both the interaction terms with mixed settlements and with polarization simultaneously, we see that our coefficient of interest (i.e. temperature shocks interacted with mixed settlements) continues to have a highly statistically significant effect with a magnitude that is comparable to the one of column 2 (while the interaction with ethnic polarization is not statistically significant). This confirms that the conflict-proneness of farmer-herder admixture has a logic that is different from the one of ethnically polarized areas. Column 4 is our preferred specification.

In column 5 we extend the analysis by looking at the intensive margin. To this purpose we replicate column 4 with an alternative measurement of the dependent variable, namely the log(number of conflict events + 1) rather than a binary incidence variable. The additive shifter +1 is a standard procedure to cope with the very large number of zeros on the left-hand side (92% of observations). The benefit is that non-violent cells are not dropped from the estimation sample, a desirable feature given the very large number of fixed-effects to be estimated. However, this functional form is distorting the distribution of the variable and this potentially affects the point estimates. We investigate alternative coding options and specifications in our robustness analysis. Generally, we find a positive and statistically significant coefficient of the interaction term. This shows that heat shocks magnify not only the incidence (column 4) but also the intensity of violence (column 5) in areas where nomads and settlers co-exist.

3.3 Quantification: Climate change and future farmer-herder conflicts

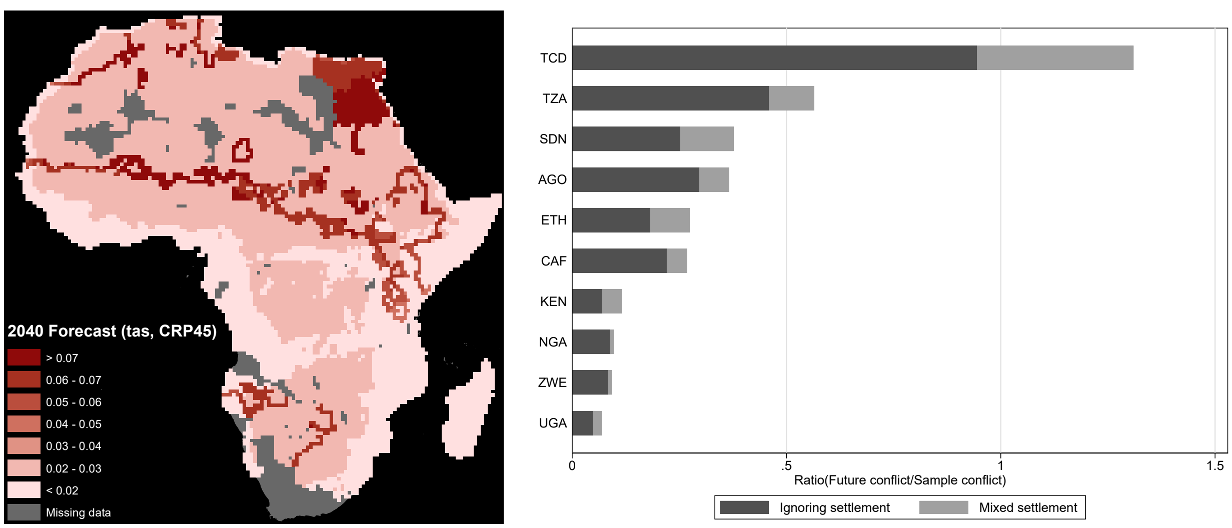
Relying on the baseline estimates of Table 2, column 2, we now report a quantification exercise of how climate change until 2040 may exacerbate the risk of conflict. Data and methodology are discussed in greater details in Appendix A.

Our procedure draws on existing projections of expected global warming at the cell level. We use forecasting data on monthly surface air temperature at the 50km spatial resolution from the Coordinated Regional Downscaling Experiment (CORDEX) (Gutowski et al., 2016); this multi-institutional project endorsed by the World Climate Research Programme produces data and studies that are regularly reported by the Intergovernmental Panel on Climate Change (IPCC). In line with existing work (see e.g. Burke et al. (2009)), we do not rely on a single projection, but instead perform a multi model ensemble by calculating the arithmetic mean across four climate model temperature outputs. There remains of course much uncertainty for every forecast given the wide range of policy choices available to governments that will impact on global warming. We focus on the intermediate emission scenario RCP4.5, which assumes the stabilization of the radiative forcing level and is considered as one of the more likely outcomes (Thomson et al., 2011; Pachauri et al., 2014).

For each cell, we compute the prospective temperature in 2040 as the cross-model arithmetic mean averaged over the 2030-2049 period (to limit weight on a potential "outlier" year). For making valid comparisons, retrospective temperature in 1995 must also be model-generated and is computed as the cross-model arithmetic mean averaged over the 1985-2004 period. Note that 1995 has been chosen as reference year because it is close to the starting year of our sample period (1997) and the CORDEX data are available only up to 2005. The cell-level change in temperature between 1995 and 2040 is simply built as the difference between prospective and retrospective temperatures. Finally, this cell-level temperature change is multiplied by the estimated coefficient of 0.14 for non-mixed cells and 0.043 (=0.014 + 0.029) for mixed cells (Table 2 and col.2). We then obtain for each cell the projected change in violent incident likelihood associated with climate change.

The projected conflict increases due to global warming are depicted below in Figure 4, both at the local and national levels. The left panel displays for each cell the surge in conflict scaled as a change in violent incident likelihood. Strikingly, particularly large numbers are found in the Sahel region. Two factors drive this pattern: First of all, this region is estimated to experience particularly large temperature increases, and second, the presence of many mixed settlements magnifies the effect. In the right panel, climate-induced increase in conflict incidents is reported for the ten most violent Sub-Saharan countries over 1997-2014 and with at least 1% share of mixed cells. Our quantification procedure allows us to disentangle the purely "meteorological" effect of rising temperatures from its interaction with the "political" magnifying effect of mixed settlements. We accordingly report on the right panel the share of the overall impact that is due to the temperature shock only (dark gray) and its interaction with the presence of mixed settlements (light gray). The complete results at the country level for all African countries are reported in the Appendix Table A1.

Figure 4: Climate Change and Projected Violence



Notes: Left Panel: For each cell, the map depicts the projected change in conflict probability associated with climate change by 2040 (based on estimates in Table 2, col. 2). Temperature forecast data come from CORDEX. Right Panel: For each country, the bar represents climate-driven projected change in conflict incidents in 2040 with respect to its 1997-2014 average. Dark gray section of the bar depicts the change that is attributable to temperature variations only (ignoring mixed settlement patterns) and light gray section is the additional effect resulting from the interaction of temperature variations and mixed settlement patterns. The list of countries shown is restricted to the ten most violent Sub-Saharan countries between 1997-2014, with at least 1% share of mixed cells.

Aggregating over all cells, we are able to compute a projected number of conflicts for the whole of Africa. We find that, when ignoring the effect of mixed settlements, conflicts are predicted to increase by 26 percent due to global warming, while this number goes up to 33 percent when taking into account the magnifying effect of mixed settlements.[15] When zooming in on the Sahel zone – which is an area often pinpointed in policy debates – these numbers become even larger. Global warming is projected to increase conflicts in Sahel by 40 percent when ignoring settlement patterns, and by even 54 percent when taking the magnifying effect of mixed settlements into account. To sum up, both for Africa and Sahel, the quantification results show that the presence of mixed cells with nomads and settlers magnifies climate-induced conflict risk by roughly one third (from 26 to 33 percent and 40 to 54 percent respectively).

3.4 Sensitivity analysis

In this section, we perform a battery of sensitivity checks to test for the robustness of the baseline estimates of column 4, Table 2. In what follows, we report only a summary of the main results; all tables and a detailed discussion are relegated to the Online Appendix section B.

Types, intensity and persistence of conflicts. In Table B1 we study the impact of temperature shocks in mixed settlements on different types and intensity of conflict events. This serves the purpose of assessing whether the baseline findings are driven by particular conflict types, and if they also hold when focusing on battles and high-intensity events, for which reporting bias is least likely. We find that our baseline results continue to hold for all conflict types considered, i.e. for battles, riots and violence against civilians, and that the effect of temperature shocks in mixed settlements is stronger for large-scale events. This analysis attenuates concerns about reporting bias and highlights the great policy relevance of tackling such conflicts. In Table B2 we take into account the potential persistence of violence, by controlling for conflict in the past. In such a dynamic panel setup, however, it is well-known (Nickell, 1981) that the results need to be interpreted with caution. This being said, our coefficient of interest retains statistically significance and remains of a similar magnitude.

Interpretation of the mixed settlement variable. Table B3 aims at controlling for the influence of nomadic presence, addressing potential concerns that, in the baseline analysis, the variable mixed settlement could simply pick up the impact on violence of groups with greater geographical mobility. It is found in this table that temperature shocks interacted with nomadic presence –if anything– reduces the conflict risk, and that it is indeed the co-existence of nomadic and sedentary groups in the same location that magnifies the violent impact of temperature shocks. Related, in Table B4 we control for the presence of a series of possible confounders (interacted with temperature shocks) that may correlate with mixed settlements. With respect to its baseline counterpart, the point estimate is unaffected when controlling for population density, the number of ethnic groups, and ethnic fractionalization.

[15] In an average year during our sample period there are 773 incidences of conflict, which is projected to increase by 200 events on average when ignoring the magnifying effect of mixed cells (i.e. applying the estimated coefficient of 0.014 from Table 2, col.2, for all cells), while it increases by 259 events when taking into account the magnifying effect (applying the augmented coefficient of 0.014 + 0.029 = 0.043 for mixed cells).

Definition of settlement patterns. In Table B5 we investigate how sensitive our results are to using alternative coding rules for categorizing ethnic groups into nomads and settlers. We continue to detect strong and robust effects– no matter which definition we apply. Furthermore, we look at whether the results are driven by a specific subset of countries. As detailed in the Online Appendix Section B, one stark feature of our group matching algorithm is that Egypt is coded as having mixed cells across the whole country. In Table B6 we show that our results go through when we drop Egypt from the estimation sample. Next, in the second half of the same table, we restrict the sample to countries bordering the Sahel zone, which is motivated by the casual observation that farmer-herder conflicts appear to be particularly pronounced in this region. Our baseline results prove to be robust to all of these sensitivity exercises.

Country borders. In Table B7 we investigate whether the presence of a country border in a given cell could represent a confounding factor. It is found that neither excluding border cells from the sample, nor controlling for the distance to the closest border affect our baseline results.

Measurement of weather shocks. We also explore alternative options for measuring of our main source of exogenous variations, namely weather shocks. We start in Table B8 with investigating alternative functional forms and weighting of temperature shocks. It is found that our baseline results are not sensitive to how a temperature shock is defined. Next, we control in Table B9 for the role of precipitation (rain) and its interaction with temperature shocks. While we do not detect an effect of rain fall shocks, we continue to find a strong and robust effect of the explanatory variable of interest, temperature shocks in mixed settlement cells.

Climate zones, biomes and soil properties. In Tables B11 an B10 we exclude the possibility that our results are driven by underlying climate zones or areas with particular vegetation (so-called biomes). We also check in Table B12 that our results are robust to controlling for underlying soil stress.

Further robustness exercises. We also replicate our baseline analysis using alternative conflict data from the UCDP georeferenced Event Dataset (Sundberg and Melander, 2013) that focuses on violence perpetrated by larger-scale and more structured groups. Given that part of farmer-herder violence corresponds to localized fighting by informal (non-structured) actors, we expect weaker results for such a more restrictive actor definition (that leads to a drop in observed fighting events by 50 percent). This is what we find in Table B13: While the results are qualitatively consistent, the coefficients are less precisely estimated. Another sensitivity check focuses on an alternative temperature source issued by the University of Delaware (UDEL) (Matsuura and Willmott, 2012). As depicted in Table B14, the coefficient of interest remains positive and highly significant, although of smaller magnitude. Further, in Table B15 we study whether we also find an association between mixed settlements and conflict in a cross-sectional setting (refraining from using temperature shocks). Our findings indeed document a positive association between mixed settlement and conflict. Last but not least, in Table B16 we control for basin-specific trends and Table B17 allows for spatial and serial correlation in standard errors. For both exercises, the coefficient of interest retains its statistical significance.

4 Mechanisms at work

As mentioned in the introduction, several mechanisms may be at work for explaining our findings: Economic competition for access to resources (land), long-run grievances, or differences in social norms and informal institutions. In this section, we focus specifically on the economic competition channel, and provide various pieces of evidence suggesting that it is empirically relevant. The main objective of this section is to test for this mechanism by exploiting the various dimensions of our data (i.e. time-series, geolocation, and the identity of the perpetrators). We first provide a verbal theory highlighting how climate-induced mobility of nomads harms local social arrangements on the management of common land and resources and can trigger conflicts. We then revisit our main findings in the spirit of disentangling the competition channel from other channels of transmission. Finally, we document climate-induced mobility of nomadic groups.

4.1 Conceptual framework

Competition channel. Nomads and settlers differ in a variety of dimensions. The main difference is in terms of production technology, as they typically operate in areas with different soil characteristics. Nomads make an extensive use of low quality open rangeland for cattle herding, while settlers focus on cultivating enclosed tracts of better quality farmland for both crop farming and grazing.[16] Hence, in most instances, they do not compete for the same land. However, as documented in many case studies (see e.g. Benjaminsen, Maganga and Abdallah, 2009; Olsson and Siba, 2013; Olaniyan and Okeke-Uzodike, 2015; International Crisis Group, 2017), conflicts arise in areas of mixed usage, typically at the fringe between rangelands and farmlands. There, nomads may be tempted to bring their cattle on cultivated lands and competition on scarce resources leads to conflicts. In a nutshell, this economic "Competition" channel states that heat shocks lead to property right disputes between nomads and settlers over the remaining fertile land at the fringe between rangeland and farmland. This tragedy of the commons results in conflicts being driven both by the motivation to grab a scarce resource and the lower opportunity costs resulting from a lower productivity in droughts.

Institutions regulating the commons. The problem is magnified by the lack of formal institutions aiming at establishing and enforcing property rights (see the classic argument by Coase (1960) which he incidentally illustrates with conflicts between herders and crop farmers). In these

[16]In modern times, almost all nomadic tribes operate cattle herding, only few of them are hunter/gatherers (see Dyson-Hudson and Dyson-Hudson, 1980); by contrast, crop farming leads to sedentary life because the time horizon of the investment in farming is long (Goldstein and Udry, 2008). This said, settlers also practice cattle herding but in that case it is mostly operated in enclosed pastures.

(often) remote territories, state capacity is weak and regulation by central authorities is absent. However, as shown e.g. Ostrom (1990, 2009), Williamson (2009) or Nyborg et al. (2016), informal institutions and social norms may emerge in the long-run and substitute to the lack of formal institutions. The idea is that repeated interactions between nomads and settlers at the fringe between rangeland and farmland enable users of this territory to establish rules for how the commons (e.g water) and land (e.g. pastures) have to be cared for and used in a way that is both economically and ecologically sustainable.

From a game-theoretic standpoint, these arrangements rely on the perspective that future interactions discipline current compliance to the rule and cooperation. Hence, they are naturally vulnerable to short-run changes in population composition: migration inflows of individuals originating from far-distant groups, with different habits and norms, reduce information and memory of the game; migration outflows mechanically reduce the time horizon of the game and unravel cooperation (see e.g. the experimental evidence of Duffy and Ochs (2009), that cooperation is easier to sustain in repeated games with fixed pairs than with random matching).

Finally, the last element of our argument is that the portability of the productive asset of nomads and settlers differs. Transhumant pastoralism follows the seasonal availability of fodder. For instance in Mali, cattle herds move North during the rain season and return South when resources shrink during dry season (Toure et al., 2012). In time of climatic hardship farmers cannot relocate their asset (land) but herders can move their cattle to more fertile areas. The larger the temperature shock is, the more likely nomads are to move to new areas far from their traditional territory of transhumance. And this comes at the risk of being confronted to new ethnic/social groups and *destabilized local social arrangements* in the management of the commons. In other words, when climate change forces nomads to migrate, this tends to erode informal institutions and trigger conflict on land and resources both at destination and origin.

Cultural channel. An alternative explanation for farmer and herder clashes could be the differences in social norms between different ethnic groups, which may make communication and dispute resolution harder. As Marxists would put it, the infrastructure (production technology) influences the superstructure (community politics and social norms). Thus, over centuries, differences in social organization and norms of behavior may have emerged between nomadic and sedentary groups and within these categories. In a nutshell, according to this "persistent culture" explanation (see the recent survey by Voth et al. (2020)), clashing cultural norms lead to ethnic hostility and raids, driven by coordination problems, difficulty of communication and ancient hatred.

4.2 Competition vs Culture

We now aim at disentangling the economic competition channel from the cultural persistence channel. Our empirical strategy exploits the long-run spatial evolution (potentially driven by climate change) of the fringe between rangeland and farmland. Places that are not located at the fringe anymore, but used to be in the past, tend to be populated nowadays by descendants of former settlers and former nomads. In these places, culture-driven conflicts may potentially keep on bursting; by contrast, the competition motive is likely to exert no influence anymore (because the fringe has moved).

The main challenge consists in tracing the time evolution of the fringe. With this respect, we build FRINGE, a binary variable coding for cells *currently* located at the fringe between rangeland and farmland. By contrast, we interpret MIXED SETTLEMENT, that is based on pre-1970 data on settlement patterns, as a variable coding for cells that were *historically* located at the fringe. In detail, we define FRINGE as cells featuring an above-median share of agricultural land and at the same time an above median share of bare land, based on data issued by Globcover for the year 2009. The combination of cropland, farmland and infertile soil in close proximity to each other allows us to identify the agricultural frontier, i.e. farm land facing open range land. Indeed, fringe cells following our definition scatter along the Southern border of the Sahara, as shown in Figure C6 in the Appendix.

Our verbal theory predicts that a heat shock in cell k in year t tends to: (i) increase the likelihood of conflict in k [various channels discussed in the survey literature]; (ii) even more so in cells historically populated by nomads and settlers [Culture Channel]; (iii) and even more so in cells populated by nomads and settlers *and* currently located at the fringe of rangeland and farmland [Competition Channel]. Note that we also expect to observe more conflicts in cells at the fringe in general, whatever the population composition [Vulnerability Channel]. The reason is that agricultural productivity may be more vulnerable to temperature shocks in these areas. According to USGS (2020) (Link), "these transition zones have very fragile, delicately balanced ecosystems. Desert fringes often are a mosaic of microclimates". We accordingly estimate our baseline model after including the triple interaction between FRINGE and our variable of interest $T_{kt} \times \text{MIXED SETTLEMENT}_k$ (note that for completion, the double interaction $T_{kt} \times \text{FRINGE}_k$ is also included). We interpret the coefficient of $T_{kt} \times \text{MIXED SETTLEMENT}_k$ as an indication of the cultural channel and the coefficient of the triple interaction as capturing the competition channel. For example, if we find that temperature shocks in mixed settlements are statistically significant but not the triple interaction, this could be interpreted as an indication that farmer-herder conflict may be mostly due to cultural differences, while if we find a strong impact of the triple interaction term, we can conclude that not only the historical group presence matters but also the actual resource competition of these two modes of production today.

This empirical strategy is sensitive to measurement errors on both current population composition at the cell-level and on the exact location of the fringe between rangeland and farmland. When studying whether nomadic-settler production technology competition may be partly responsible for clashes between ethnic groups, one of course has to first investigate whether historical group locations and methods of production are still relevant today. It turns out they are. First, the ethnic group homeland borders are quite stable (as shown in Figure C7). Second, the use of production technologies is very persistent, as shown in Figure 2 above. In fact, 65 percent of the African labor force is still in agriculture and it represents 32 percent of the GDP (Al-Amin et al., 2008), and in the Sahel region, livestock accounts for 40 percent of the agriculture (Kamuanga et al., 2008). Table C1 shows that nomadic homelands are still linked to production features associated with nomadic cattle herding, while areas settled by sedentary groups feature much more agriculture and more fertile soils today.

Table 3 below displays the main results on the mechanisms at work. While the variable $T \times$ Mixed settlement captures, as before, the impact of temperature shocks in historically mixed settlements, the variable $T \times$ fringe picks up the heat shock effect in areas that are today both suitable for agriculture and for cattle herding and where current resource competition should be greatest. In column 2, we find that both variables are statistically significant and of expected sign. In column 3 we then include the interaction $T \times$ Mixed settlement $\times$ fringe. While this interaction is highly statistically significant, the variable $T \times$ Mixed settlement ceases to be statistically significant. This is consistent with the interpretation that historical cultural differences in ethnic groups do only matter today when economic competition in production is still present. Our findings do not imply that culture does not matter, but highlights the fact that the impact of cultural differences is greatly magnified in contexts in which actual economic competition for scarce resources is present. Column 4 shows that this result prevails when controlling for polarization, while column 5 reveals robustness to focusing on the intensive rather than extensive margin of conflict.

Tables C2, C3 and C4 in the Appendix show that these results are robust to alternative definitions of resource competition and the joint presence of both production technologies. Table C2 is based on alternative data sources from different reference years for the construction of fringe cells. Solely relying on land cover data from a single reference year potentially runs the risk to induce measurement error, as land cover may have changed over time, e.g. due to desertification and climate change. Panel A consults land use data for the year 1992 by the Center for Sustainability and the Global Environment (SAGE) and Panel B uses data for the year 2014 by Fao (GLC-SHARE). Results in both cases are robust and in line with Table 3. In Table C3 we focus on cattle output as proxy for the nomadic production technology, which leads to a similar picture: conflict concentrates at the conjunction of both production technologies (crop farming and cattle herding).[17] While cattle output is arguably less exogenous to conflict than our fringe variable, the results at hand emphasize the central role of competing production functions for the occurrence of farmer-herder conflicts. Table C4 uses alternative definitions of fringe. Unlike in the main specification, here the agricultural frontier does not rely on remotely-sensed information, but on soil properties that are considered crucial for growing capacities of vegetation.[18] We find similarly-sized coefficients of the triple interaction, whereas the initial interaction of mixed settlement and temperature remains. This might be due to the fact that a soil's properties are one of many input factors neces-

[17] Here, fringe is defined as cells with an above-median share of crop and bare land and an above-median cattle density, measured with data from the Gridded Livestock of the World (GLW3) dataset by Fao for the year 2005 and available for Sub-Saharan Africa.

[18] To construct our fringe variable in this setting, remotely-sensed data on bare soil is exchanged for soil property data. In detail, fringe is defined as cells with an above-median share of crop and grass land and an above-median share of constrained soil.

Table 3: Channels: Competition Versus Culture

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	ln(1+Conflicts) (5)
T	0.014^{c}	0.008	0.011	0.007	0.010
	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)
T × Mixed settlement	0.029^{a}	0.024^{a}	0.010	0.008	0.011
	(0.010)	(0.009)	(0.008)	(0.009)	(0.018)
T × Fringe		0.045^{a}	0.024^{b}	0.024^{b}	0.051^{a}
		(0.011)	(0.010)	(0.010)	(0.018)
T × Mixed set. × Fringe			0.064^{a}	0.064^{a}	0.163^{b}
			(0.022)	(0.022)	(0.069)
T × Polarization				0.007	0.024
				(0.009)	(0.017)
Cells	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. Fringe indicates cells with an above median share of agricultural land (total of crop and grass land) and an above-median share of bare soil; data is derived from Globcover 2009, and correspond to categories 11, 14 ,20, 30 and 200, respectively. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

sary for agricultural production, thus being less precise in predicting production functions correctly (e.g. a poor nutrient endowment may be compensated for with fertilizers or effective crop rotation scheme, hence not necessarily result in bare land). Finally, Table C5 confirms that conflicts are limited to cells with both agricultural and bare land (i.e. fringe cells). Neither agriculture, nor bare soil on their own drive our results, underlining that conflict only occurs if both production functions are feasible (i.e. herding and farming).

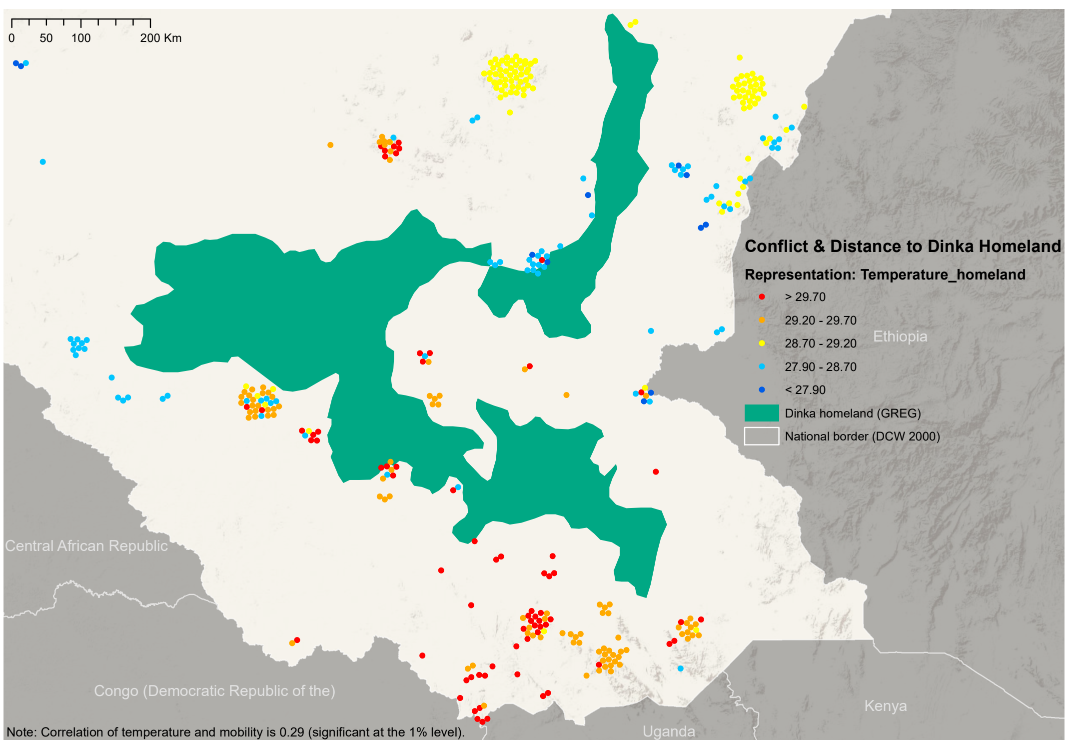
4.3 Climate-induced spread of violence

So far our empirical analysis has focused on local violence, i.e. in the immediate surroundings of mixed-settlement areas. We now investigate another element of our conceptual framework, namely that heat shocks trigger mobility of nomadic groups leading to competition and conflict for more fertile lands. Addressing this question is important because it informs on how climate shocks drive the spatial spread of violence.

The main empirical challenge consists in retrieving information on the effective presence and influence of certain groups in particular territories. We assume that groups react primarily to heat shocks affecting their ethnic homeland. If heat shocks negatively impact the productivity of grasslands in their homeland, we expect groups to move elsewhere in search of more fertile lands and consequently to be potentially involved in violent events further away from their homeland.

To illustrate the patterns of mobility that we have in mind, consider Figure 5 that displays mobility patterns of the Dinka ethnic group in Sudan. The homelands of this traditionally nomadic group are represented by green polygons, and each dot represent the geolocalisation of one given fighting event involving this group and taking place outside their traditional homelands. Warmer colors (i.e. red and orange) depict events occurring in years with high temperatures measured in the Dinka homelands, while colder colors (i.e. blue) correspond to colder years. Visual inspection suggests a positive correlation between heat and the range of mobility – in hotter years the Dinka are involved in conflict events taking place further away from their homelands. This is confirmed by a correlation analysis between temperature and distance yielding a coefficient of 0.29 that is significant at the 1 percent level.

Figure 5: Conflict and Distance to Dinka Homeland, Sudan



Notes: The unit of observation: ACLED conflict events, matched to GREG for Dinka affiliated groups. The green polygon depicts Dinka ethnic homeland according top GREG. Points indicate ACLED conflict event location. Temperate in a given homeland centroid and year is indicated by different colors. For illustrative purposes, events in the same location are dispersed locally.

Moving beyond this example of a single group, we now investigate systematically such mobility patterns for various ethnic groups. To this purpose, we extend our dataset in a new dimension, namely to the fighting group operating in each location. We focus on active rebel groups involved in at least one violent conflict event over the sample period, ignoring other types of fighting groups.

ACLED considers as rebel groups "political organizations whose goal is to counter an established national governing regime by violent acts". Further, we restrict the analysis to Sahel countries.[19] With the Sahara desert to the north and relatively fertile biomes to the south, the semi-arid Sahel zones has been subject to numerous violent incidents between settlers and nomads in recent years, as discussed earlier.

We test whether heat shocks in the ethnic homeland of a rebel group boost its fighting operations far from its homeland. Following the methodology of Berman et al. (2017), we exploit ACLED information on the identity of the rebel groups and assign to each group its main ethnic affiliation, based on the ethnicity of the group's leaders and troops. This allows us to link rebel groups in ACLED to settlement information from Murdock's Ethnographic Atlas and to information in a group's ethnic homeland from GREG. We do not include events for which none of the involved actors has distinguishable ethnic affiliations. Of the 538 rebel groups in our sample, we are able to match the ethnic affiliation for 145 groups, whereby the remaining groups are dropped. Matched groups account for 4,406 of 9,290 events. The majority of excluded groups are local, and contrary to rebel groups, their objective is not to replace or change the political regime in power. As a next step, we then retrieve from the GREG dataset the geocoordinates of the ethnic homelands to compute the average yearly temperature in their centroid.

We obtain a dataset containing, for each rebel group, all violent events where the group is involved. Our unit of analysis is a rebel group × location × year triplet (i, k, t). In this setting, a location is defined as 1 × 1 km cells, to fully exploit the spatial nature of this exercise and to be able to track profound changes in nomadic migration patterns. Table C6 in the Appendix contains descriptive statistics on the sample used in this section. Unconditional evidence shows that nomadic groups tend to fight further away from their homeland than settlers.

We now study how distance to ethnic homeland of conflict events is affected by heat shocks in the ethnic homeland of the group, and we estimate the following specification:

$$\text{DISTANCE}_{ikt} = \beta_1 \times \mathrm{T}_{it}^{\text{HOMELAND}} + \mathbf{FE}_i + \mathbf{FE}_{ct} + \epsilon_{ikt} \tag{2}$$

where DISTANCE_{ikt} is the distance between the geolocation of the fighting event k and the homeland centroid the involved group i and $\mathrm{T}_{it}^{\text{HOMELAND}}$ measures temperature in the homeland centroid of the group.[20] Conditional on rebel group fixed effects (i.e. $\mathbf{FE}_i$), the coefficient β_1 captures the impact of temperature on the spatial spread of violence. Given the data structure we cluster standard errors in the actor-location dimension.[21]

The estimation results of equation 2 are reported in Table 4. In column 1, all events and groups

[19]Sahel countries include Algeria, Burkina Faso, Cameroon, Central African Republic, Chad, Eritrea, Ethiopia, Mali, Mauritania, Niger, Senegal, South Sudan, Sudan.

[20]In GREG, a single ethnic group can be scattered across multiple locations. Therefore, we assign to each rebel group-location pair the geographically closest homeland centroid. We allow a maximal distance of 1000 km, although results are robust to alternative choices as shown in Appendix Table C7.

[21]Nomadic homelands frequently span across wide geographies. Hence, far apart events fought by the same group may be very different in their type and intensity.

are included in the sample. The coefficient of interest is positive and significant at the 1% threshold confirming that groups tend to fight further away from their traditional area of operation when heat shocks impact their ethnic homeland. We restrict the estimation to the subsamples of settlers and nomadic groups only in columns 2 and 3 respectively. Clearly, the effect is limited to nomadic groups only: The coefficient of interest is 3 times larger and highly significant in the subsample of nomadic groups while both its magnitude and statistical significance collapse for settlers. In other words, the climate-induced spatial spread of violence is driven by nomadic groups only. In the remaining columns we consequently restrict the estimation to this subsample.

We now investigate how the spread of violence relates to the search of new resources and competition. In Column (4) we make use of fine-grained information on the nature of each violent event, a unique feature of the ACLED dataset. More precisely, we code as "fighting over resources" all events whose description in ACLED contains at least one word from a list of key words that pertain to resources and competition.[22] Then, we replicate column (3) for the subsample of events that correspond to fighting over resources. This specification is very demanding as it leads to a drastic reduction in sample size. Yet, statistical significance is still very high. And, more importantly, we observe a threefold increase in the coefficient of interest. A natural interpretation is that the spatial spread of violence is magnified when it turns to search of new resources. The next two columns follow the same logic but with a different approach. There, we look at soil quality in the cells where violence takes place and highlight respectively cells containing water and cells suited for agriculture. In detail, only cells with an above-median share of cropland and water among all cells with nomadic conflicts are considered in columns (5) and (6), respectively. Information on land cover is derived from the Global Land Cover SHARE database by FAO. In each case, the estimation sample is restricted to these cells. Again, we observe that the magnitude of the coefficient of interest increases substantially with respect to the benchmark in column (3). This confirms that the spatial spread of violence is more pronounced when nomadic groups move to fertile areas.

In terms of quantification, focusing on the (lower-bound) specification of column 3, we can see that the effect is quantitatively sizeable. A one SD increase in homeland temperature (+ 3.2 degrees) leads to a distance from homeland increase of 47 km (representing 0.13 SD). When focusing on the (upper-bound) estimate of column 4, the effect is almost three times larger, i.e. a one SD increase in homeland temperature translates into an increase in the distance from homeland by 134 km (0.37 SD).

Next, the robustness of these findings is investigated. The baseline imposes a maximal distance between an event and the centroid of a associated ethnic homeland (DISTANCE_{ikt}) of 1000 km. Panel A in Table C7 limits this distance to maximally 500 km, which omits events further apart from their homelands. Reducing maximal distance yields smaller coefficient magnitudes, although the results remain comparable to the baseline. Panel B returns to the full sample, but clusters the standard errors spatially, allowing for a spatial correlation within a 500 km radius of a cell's

[22] The list of key phrases is: land dispute, dispute over land, control of land, over land, clash over land, land grab, farm land, land invaders, land invasion, land redistribution, land battle, over cattle and land, invade land, over disputed land, over a piece of land, herd, pastoral, livestock, cattle, grazing, pasture, cow, cattle, farm, crop, harvest.

centroid and infinite serial correlation. Finally, Panel C changes the unit of observation from the location-actor-year level to the event level. In this setting, frequently-fought regions receive more weight, as several events may occur in a single cell and year by a single rebel group. Overall, the estimation results withstand these robustness exercises.

Table 4: Climate-Induced Mobility and Conflict

Dependent variable:	Distance to homeland (centroid, km)					
Fighting group:	All	Settlers	Nomads			
	(1)	(2)	(3)	(4)	(5)	(6)
T in homeland (centroid)	5.873^{a}	0.839	14.840^{a}	41.879^{a}	24.372^{a}	27.351^{a}
	(2.008)	(1.821)	(4.583)	(11.492)	(6.746)	(8.235)
Events	1904	895	1009	98	509	488
Groups	127	41	86	30	63	63
Group FE	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓
Fight over resources only				✓		
Conflict location: Agri. (M)					✓	
Conflict location: Water (M)						✓

Notes: An observation is a rebel group × location × year. The sample is limited to Sahel countries. Information on conflict participants is derived from ACLED and matched on the ethnic group level to settlement mobility information from Murdock's Ethnographic Atlas. As a result, conflict participants' mode of settlement can be identified. Multiple events of the same group within the same 1 × 1 kilometer cell and year are coded as a single observation. T in homeland (centroid) measures temperature in degree Celsius in the geographic center of a fighting group's nearest homeland. A group's homeland is defined according to the specified ethnic group location in GREG. Column 1 considers all conflict events, column 2 only considers conflict events involving a settler group and columns 3-6 only considers conflict events involving a nomadic group. Column 4 restricts the subsample of nomadic event further to events including at least one of the following key words: land dispute, dispute over land, control of land, over land, clash over land, land grab, farm land, land invaders, land invasion, land redistribution, land battle, over cattle and land, invade land, over disputed land, over a piece of land, herd, pastoral, livestock, cattle, grazing, pasture, cow, cattle, farm, crop, harvest. Column 5 (6) restricts the subsample of nomadic events further to events taking place in cells with an above-median share of farm land (water), with data from Global Land Cover SHARE by Fao. The dependent variable measures the distance between a conflict event and the center of a participating group's homeland. The regressions control for group and country-year fixed effects. Coefficients are reported with standard errors clustered at the actor-location level in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

5 Resilience through Formal Institutions and Policies

As discussed above, heat shocks may perturb fragile informal arrangements of cooperation between groups. While relying on social norms and informal institutions works well in environments that are characterised by stability and repeated interactions, in times of disruptions (e.g. due to climate shocks), coherent formal institutions can provide greater resilience to shocks (see the discussion in Besley and Persson, 2011). In particular, democratic governance and rule of law guarantee property rights protection, contract enforcement and dispute resolution mechanisms, which we expect to limit the potential for conflict escalation after adverse shocks, in line with the logic of the

Coase Theorem (Coase, 1960). We also hypothesize that decentralization and institutions fostering local-level cooperation and conflict resolution imply that rulings and political decisions are taken based on detailed knowledge of local conditions and hence may have the potential to curb the scope for dispute. Thus, in line with this logic, we expect federalism to potentially reduce the conflict-fueling effect of adverse climatic shocks.

In Table 5 we focus on four dimensions of formal institutions that represent promising ways of absorbing shocks. In particular, in column 1 we interact our benchmark variable of $T_{kt} \times$ MIXED SETTLEMENT$_k$ with a binary measure of democracy, HIGH POLITY: This variable takes a value of 1 in cells with an above-median value in the Polity variable of the Polity 4 Project in 1996 (pre-sample), and 0 otherwise.[23] As expected, we find that in democratic environments there is a greater resilience to temperature shocks in mixed cells, and the adverse effects of heat waves on political stability are attenuated. This is in line with the aforementioned logic that democracies on average do a better job at protecting property rights, enforcing contracts and providing fair resolutions of disputes.

Democracy has some features, like e.g. free elections, that may be less relevant for our question of coping with climate shocks than those closely linked to the resolution of land disputes. Hence, in column 2, we dig deeper into the most relevant features (for our purpose) of democratic rule of law, namely we interact our benchmark variable of $T_{kt} \times$ MIX$_k$ with a binary measure of LAND DISPUTE RESOLUTION, which takes a value of 1 for cells with an above-median degree of immovable property rights and access to land dispute resolution mechanism (from the World Bank's Ease of Doing Business Report), and 0 otherwise. As expected, we find that the coefficient of interest has a statistically significant negative sign, indicating that indeed sound property rights protection and land dispute resolution strongly reduces the scope for harmful conflict effects of heat shocks in cells with mixed settlement.[24]

While the indicators included in these first two columns are in our view the most important policy parameters for our purpose, we also provide results for two further governance and institutional variables below. First of all, we interact $T_{kt} \times$ MIXED SETTLEMENT$_k$ with a measure of good governance. In particular, we rely on the variable LOW CORRUPTION (from the Varieties of Democracy (V-Dem) Project) which takes a value of 1 for cells with a below-median degree of political corruption in 1996 (pre-sample). The underlying idea is that efficient property rights protection and land dispute resolution require a reliable administration respecting the rule of law and putting in place high-quality governance, which is linked, among others, to an environment without endemic corruption. As expected, we find that LOW CORRUPTION environments are more

[23] In all columns we obviously also always control for all combinations of the variables included in the triple interaction of interest. In particular, we have in column 1 as control variable the interaction of temperature with HIGH POLITY, as well as the baseline effect of $T_{kt} \times$ MIX SETTLEMENT$_k$. Note that both HIGH POLITY and MIXED SETTLEMENT$_k$ are time invariant, hence their interaction is captured by the battery of cell fixed effects.

[24] The land dispute variable is a composite of property rights and judicial resolution mechanisms. In Table D1, we further disentangle which of the two dimensions drives the negative coefficient. Columns 1 and 2 of Table D1 find a negative association between settler-nomad conflict and both stable property rights and judicial systems, respectively. Including both dimensions in the same regression however shows that property rights appear to play a more pronounced role than judicial resolution mechanisms, as depicted in column 3 of Table D1.

resilient to adverse stability effects of heat shocks.

In column 4, we focus on a final institutional feature that we expect to matter in our context: Federalism. Our binary variable FEDERALISM takes a value of 1 in cells located in countries with federal systems in 1996 (pre-sample); the indicator is based on data from Pippa Norris's Democracy Time-series Dataset.[25] Federalist organization leads to power devolved to the local level, which may favor decision-making that appropriately takes into account local conditions. We hence expect federalist states to be better at solving local land disputes. Our coefficient of interest, i.e. the interaction of the baseline variable of $T_{kt} \times$ MIXED SETTLEMENT$_k$ with federalism, has indeed the expected negative sign, implying that the heat-turned-hate nexus is less strong in federalist countries.

Column 5 includes all the four aforementioned interactions simultaneously. We continue to find for all four policy variables the negative sign of the coefficient of interest, albeit only statistically significant for our two main policy variables, namely HIGH POLITY and HIGH LAND DISPUTE RESOLUTION.

One limitation to our analysis is that countries are rather large entities spread over a huge continent (Africa). Hence, comparing heterogenous effects across different countries involves comparing places that are potentially thousands of kilometers apart, and may differ in various other dimensions than just the policy variables we are interested in. To address such concerns, we have built in the appendix two Tables (D2 and D3) where we limit comparisons to places that are in the same local environment but on two opposite sides of a border. In particular, in Table D2 we continue to study the interaction of $T_{kt} \times$ MIXED SETTLEMENT$_k$ with the same battery of institutional and policy characteristics as in Table 5, but restricting the sample to areas within 75 kilometers of borders (panel A) and in addition include border-year specific fixed effects (panel B). This amounts to compare places in the same border area (e.g. a location in Nigeria next to the Niger-Nigeria border with another location on the other side of this same border), sharing the same local characteristics, but belonging to distinct countries, and hence being exposed to a different institutional and policy setting. This very demanding exercise is based on a much more homogeneous sample; yet, we continue to find that institutional features matter. In particular, land dispute resolutions and federalism continue to tend to mitigate adverse effects of temperature shocks in mixed cells. Table D3 performs the analogous analysis, but for a wider buffer of 120 kilometers, yielding similar results as for Table D2.

Overall, we take the results of Table 5 (and the corresponding robustness results in the Appendix) as evidence that formal democratic institutions with property rights protection and land dispute resolution contribute to building up resilience in the face of adverse climate shocks.

[25]We prefer the data source of "Pippa Noris's Democracy Time Series Data" over available alternatives for several reasons: First, the data covers all African nations for the year 1996. Second, the data not only defines federal and unitary states, but also identifies hybrid (confederate) states. This distinction is important, as we are interested in capturing the effect of fully federal systems.

Table 5: Resilience Through Formal Institutions and Policies

	(1) Incident	(2) Incident	(3) Incident	(4) Incident	(5) Incident
T	0.009	0.008	0.021^{c}	0.014^{c}	0.035^{b}
	(0.010)	(0.008)	(0.012)	(0.008)	(0.016)
T × Mixed settlement	0.046^{a}	0.041^{a}	0.039^{a}	0.034^{a}	0.059^{a}
	(0.012)	(0.013)	(0.014)	(0.010)	(0.022)
T × High polity	0.002				0.008
	(0.012)				(0.013)
T × Mixed set. × High polity	-0.059^{a}				-0.048^{a}
	(0.015)				(0.017)
T × High land dispute resolution		0.019			0.024^{c}
		(0.014)			(0.013)
T × Mixed set. × High land dispute resolution		-0.066^{a}			-0.050^{b}
		(0.019)			(0.020)
T × Low corruption			-0.018		-0.049^{a}
			(0.013)		(0.015)
T × Mixed set. × Low corruption			-0.036^{b}		-0.011
			(0.016)		(0.018)
T × Federal sates				-0.003	0.005
				(0.019)	(0.019)
T × Mixed set. × Federal sates				-0.082^{a}	-0.021
				(0.028)	(0.032)
Constant	0.000	0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cells	8200	8050	9588	9588	6894
Observations	147600	144900	172584	172584	124092
Sample share - interaction group	.44	.42	.51	.1	.92
Mix share - interaction group	.1	.1	.1	.11	.11
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The table tests heterogeneity across relevant country-wide institutional features that have been argued to potentially mitigate settler-nomad conflict. The sample includes the years 1997-2014 and the number of included cells in each column varies with the data availability of the test heterogeneity. High polity indicates cells with an above-median value in the Polity variable of the Polity 4 Project in 1996 (pre-sample); the indicator is derived from country-level data. High land dispute resolution indicates cells with an above-median degree of immovable property rights and access to land dispute resolution mechanism in 2014 (post-sample, since no pre-sample data available); the indicator is derived from country-level data of the World Bank's Ease of Doing Business Report, variable Land Dispute Resolution index accessed via the Quality of Government data collection. Low corruption indicates cells with a below-median degree of political corruption in 1996 (pre-sample); the indicator is derived from country-level data of the Varieties of Democracy (V-Dem) Project, variable Political Corruption Index accessed via the Quality of Government data collection. Federalism indicates cells located in countries with federal systems in 1996 (pre-sample); the indicator is based on data from Pippa Norris's Democracy Time-series Dataset, variable Unitary or Federal State, accessed via the Quality of Government data collection. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads. Dependent variable: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

6 Conclusion

The growing literature on the climate-conflict nexus lacks an in-depth analysis of the underlying mechanisms and channels of transmission. This knowledge gap represents a dangerous pitfall in our understanding of this prominent issue and impacts our ability to formulate policy lessons. In the current contribution we have aimed at addressing this shortcoming. Motivated by anecdotal evidence and journalistic reports, the current study has analyzed how heat waves translate into surges of farmer-herder violence in a fine grained dataset covering all of Africa over the 1997-2014 period. In particular, we find that the greatest effects are found at the *fringe* between rangeland and farmland where the land is suitable for both cattle herding and farming. Relying on a specification that aims to disentangle a pure clash of cultural norms from economic competition over resources, we conclude that –beyond coordination and communication failure and ancient hatreds– actual resource competition plays a quantitatively important role for explaining the heat-turned-hate nexus. We also uncover evidence that nomadic groups engage into more widespread mobility patterns in the face of heat waves that result in violent competition for the remaining fertile lands. We complete the investigation by assessing the role of formal institutions and polices to foster resilience against adverse shocks, concluding that democratic governance, protection of property rights and sound institutions guaranteeing dispute resolution, are key ramparts against heat melting away traditional arrangements and boiling inter-group hate.

One key implication of the current paper pertains to climate security and the necessity of assessing the political vulnerability of subnational territories. Our findings highlight how the deleterious impact of global warming is likely to be magnified by population admixture and mobility patterns at the local level. Indeed, within Africa, we observe great differences across space, with impacts of heat shocks on political violence being three times larger in mixed areas populated by both nomadic and sedentary ethnic groups.

Related to this, taking into account settlements patterns also matters heavily when projecting the impact of climate change on future fighting: When aggregated at the continental level for all of Africa, it is found that when ignoring the impact of mixed settlements, conflicts are predicted to surge by 26 percent, while this number goes up to 33 percent when taking into account the magnifying effect of mixed settlements. When zooming in on the Sahel region, these numbers become even larger, namely 40 percent (when ignoring settlement patterns) and 54 percent (when taking mixed settlements into account).

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Heat and Hate: Climate Security and Farmer-Herder Conflicts in Africa

– Online Appendix –

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A Future climate

Data and quality. The quantification exercise of Section 3 is based on temperature forecasting data from the Coordinated Regional Downscaling Experiment (CORDEX) (Gutowski et al., 2016). Like the Coupled Model Intercomparison Project (CMIP), CORDEX is a multi-institutional effort endorsed by the World Climate Research Programme and the findings are reported by the Intergovernmental Panel on Climate Change (IPCC). While CMIP is deeply embedded in the assessment of climate change (e.g. the Paris Agreements), the spatial resolution of the data– ranging from 100 to 200km– is relatively low and hence less suitable for local impact studies. For that reason, CORDEX has emerged with the last iteration of CMIP and offers data at a spatial resolution of at least 50km. Unlike CMIP, CORDEX factors regional characteristics such as local topography into the modeling to improve the local precision of models. Generally speaking, temperature forecasting precision is relatively high (Masson-Delmotte et al., 2018). CORDEX provides both historic and forecasting data at different temporal resolutions. We focus on monthly surface air temperature (tas) at the 50km spatial resolution.

Model ensemble and emission scenarios. Multiple climate institutes around the world participate in CORDEX with their own climate models. Each institute performs forecasts for a wide range of climate variables, following a standardized experimental framework that allows to draw comparisons across models. To avoid relying on a single climate model, similar to Burke et al. (2009), we perform a multi model ensemble by calculating the arithmetic mean across four climate model temperature outputs.[4]

Any forecast is subject to uncertainty. In the case of climate models a major source of uncertainty stems from green house gas emissions associated to human activity in the future. To account for different trajectories in the anthropogenic impact on climate change, the climate forecasting literature developed a set of emissions scenarios, so-called Representative Concentration Pathways (RCP). Scenarios simulate the climate under a set of green house gas emission concentrations, ranging from substantial cuts to stark increases in global future emissions. We choose the intermediate emission scenario RCP4.5, which assumes the stabilization of the radiative forcing level and is considered as one of the more likely outcomes (Thomson et al., 2011; Pachauri et al., 2014). Provided our relatively short forecasting horizon (2040), our results are unlikely to be sensitive to the choice of emission scenario, because the trajectories of the main scenarios (RCP 26, 45 and 85) mostly diverge in the second half of the century.

Data processing. For the quantification exercise of Section 3, the cell-level changes in temperature by 2040 are constructed by subtracting the 1995 historic mean (1985-2004) from the 2040

[4]We consider only CORDEX models for which the three main RCP emission scenarios 26, 45 and 85 are available. Calculating multi model ensembles is a common practice that can improve hindcast skill (Kim et al., 2014).

forecast mean (2030-2049).[5] 1995 is chosen as reference year, as it allows to construct the 20-year average (ten-year before and after 1995), taking into account that historic model data in CORDEX is available up to 2005. Further, 1995 appears to be a suitable reference year, as it is close to the start of the analysis data sample period, 1997. Our final data records temperature for 1995 and 2040, based on the same underlying data, allowing us to calculate cell-level changes in temperature over time.

[5] Climate models are calibrated to a long time horizon (2100 and beyond), and tend to perform poorly in modeling year-to-year changes. A common practice is to take at least 20 years of data and derive the average to identify difference in temperature trends. Alternatively, a class of models with time horizon of usually up to ten years, so-called "near-term" or decadal models, have recently gained popularity among policy makers and researchers to assess climatic trends over a short period of year. Although these models have become more precise in recent years, they tend to be less vetted than the long-term models participating in CMIP. Further, so-called seasonal climate models have an even shorten time span of six month to one year.

Table A1: Climate Forecast - Country Overview

Country Name	ISO 3	$\sum \beta_1 \times \Delta^{Temp}_{Future}$	$\sum \tilde{\beta}_2 \times \Delta^{Temp}_{Future}$	$\sum Incidents$	$\frac{\sum \tilde{\beta}_2 \times \Delta^{Temp}_{Future}}{\sum Incidents}$	Share-mixed cells
Angola	AGO	6.821	8.404	22.944	.366	.106
Benin	BEN	.802	.802	1.444	.555	0
Botswana	BWA	4.342	5.992	1.611	3.719	.182
Burkina Faso	BFA	1.935	2.226	5.611	.397	.069
Burundi	BDI	.209	.209	8.111	.026	0
Cameroon	CMR	3.046	3.28	6.5	.505	.032
Central African Rep.	CAF	4.275	5.195	19.389	.268	.103
Chad	TCD	9.71	13.464	10.278	1.31	.191
Congo (DRC)	COD	15.468	15.468	71.333	.217	0
Cote D'Ivoire	CIV	2.106	2.106	13.944	.151	0
Djibouti	DJI	.116	.116	1.333	.087	0
Equatorial Guinea	GNQ	.135	.135	1.167	.116	0
Eritrea	ERI	.941	1.532	4.167	.368	.255
Ethiopia	ETH	7.737	11.594	42.333	.274	.237
Gabon	GAB	1.263	1.263	1.333	.947	0
Ghana	GHA	1.579	1.579	6.5	.243	0
Guinea	GIN	1.5	1.5	7.889	.19	0
Guinea-Bissau	GNB	.188	.188	2.667	.071	0
Kenya	KEN	3.47	5.843	50.389	.116	.319
Lesotho	LSO	.236	.236	.667	.354	0
Liberia	LBR	.503	.503	8.389	.06	0
Libya	LBY	10.974	12.278	10.611	1.157	.06
Madagascar	MDG	3.514	3.514	9.722	.361	0
Malawi	MWI	.724	.724	4.944	.146	0
Mali	MLI	8.76	11.238	9.056	1.241	.134
Mauritania	MRT	7.02	8.255	3.944	2.093	.092
Morocco	MAR	3.68	5.026	8.056	.624	.165
Mozambique	MOZ	4.896	4.896	11.389	.43	0
Namibia	NAM	4.078	5.195	4.556	1.14	.126
Niger	NER	8.734	13.355	6.556	2.037	.255
Nigeria	NGA	6.441	7.018	72.111	.097	.039
Republic of Congo	COG	2.027	2.027	4.889	.415	0
Rwanda	RWA	.189	.189	4.333	.044	0
Senegal	SEN	1.382	1.625	8.5	.191	.095
Sierra Leone	SLE	.484	.484	8.722	.056	0
Somalia	SOM	3.752	3.752	54.667	.069	.004
South Africa	ZAF	4.866	4.911	38.722	.127	.004
Sudan	SDN	18.281	27.338	72.556	.377	.245
Swaziland	SWZ	.084	.084	1.556	.054	0
Tanzania	TZA	5.407	6.648	11.778	.564	.117
The Gambia	GMB	.035	.035	1.5	.024	0
Togo	TGO	.364	.364	2.111	.172	0
Tunisia	TUN	1.292	1.749	8.889	.197	.143
Uganda	UGA	1.462	2.055	29.556	.07	.197
Zambia	ZMB	5.018	5.018	9.444	.531	0
Zimbabwe	ZWE	2.72	2.995	32.389	.092	.046

Notes: $\sum \beta_1 \times \Delta^{Temp}_{Future}$ is the projected change conflict probability by 2040 due to climate change and equals the sum of forecasted change in temperature Δ^{Temp}_{Future}, multiplied by β_1 and summed across a the cells of a country, with β_1 referring to the top coefficient (0.014) of Table 2, column 2 (i.e. ignoring settlement). $\sum \beta_2 \times \Delta^{Temp}_{Future}$ additionally takes settlement pattern into account, with $\tilde{\beta}_2$ equal the sum the coefficients $(0.014 + 0.029)$ in Table 2, column 2. $\sum Incidents$ is the sum of conflict incidents per country and year in our sample, averaged across 1997-2014. $\frac{\sum \tilde{\beta}_2 \times \Delta^{Temp}_{Future}}{\sum Incidents}$ is the ratio between projected events and past events. "Share-mixed cell" is the share of mixed cell in a country.

B Sensitivity analysis

In this Online Appendix section we present in depth all robustness checks that we summarized very briefly in the main text under subsection 3.4.

B.1 Types, intensity and persistence of conflicts.

We start by shedding light on the exact type, scale and intensity of farmer-herder disputes. According to the aforementioned case studies and policy reports, farmer-herder conflict can range from disputes between local farmers and herders to high-intensity combats between rebels and military forces. To uncover the most relevant types of violence, we exploit the richness of ACLED dataset and breakdown events into three categories: Battles, Riots and Violence against civilians. We then replicate column 4, Table 2 with a dummy variable coding for each event category as dependent variable.[6] Results are reported in columns 1 to 3 of Table B1. In all specifications our coefficient of interest (temperature interacted with mixed settlement) retains its positive sign and statistical significance. There are two ways to assess its magnitude. In absolute terms, it is smaller than its baseline counterpart, a direct consequence of the low sample means of battle events, riots and violence against civilians (respectively 0.04, 0.03 and 0.04, see Table 1). More relevant is its magnitude relative to the sample mean; there we see that it is comparable to the baseline one. Finally it is worth noting that battles are events easily reported by external observers and media sources; thus, they are often the most precisely measured in ACLED. Hence, focusing on battles alone serves also the purpose of addressing concerns about reporting bias and non-classical measurement errors.

In the rest of Table B1, we scrutinize violence intensity and return to the baseline approach where all conflict events are pooled together. Column 4 considers the logarithm of the number of fatalities plus 1 and finds that temperature drives conflict intensity, as the death toll rises with the severity of heat shocks. Note that data on the fatalities have to be interpreted with caution, as counts of battle-related deaths may be inaccurate. As an alternative approach we split conflict incidents into two groups according to their degree of violence: In column 5, "large incidents" report an above-median number of deaths (> 7) per cell and year, whereas in column 6 "small incidents" report a below or equal median number of deaths (≤ 7). Results show that violence in mixed cells is clearly driven by larger incidents, with a positive coefficient significant at the 5% level. By contrast, in column 6, no statistically relevant relationship between temperature shocks in mixed cells and small conflict incidents is detected. Quite interestingly, polarization seems to be rather associated with small-scale events. Overall, these pieces of evidence consistently suggest that farmer-herder conflicts are associated with large scale, high-intensity violence, highlighting the policy importance of tackling this type of violence.

[6] Thus far, the dependent variable has been based on events classified as battles, riots and violence against civilians, without considering each subtype in isolation.

We study time persistence of violence in Table B2. To this purpose, we replicate the full baseline Table 2 in a dynamic panel setup that controls for one-year lag in conflicts (the dependent variable) at the cell-level. This specification could suffer from Nickell bias (Nickell, 1981) which is why we have decided not to opt for this type of design in our baseline analysis. Although we observe some persistence in the effect of past conflicts, it is reassuring to see that our main coefficient of interest is robust and comparable to its baseline point estimate.

Table B1: Alternative Conflict Definitions

Dep. var.:	Battle	Riot	Vs. civilians	ln(Deaths+1)	Large incid.	Small incid.
	(1)	(2)	(3)	(4)	(5)	(6)
T	0.002	-0.001	0.008	0.033	0.008	-0.002
	(0.007)	(0.004)	(0.007)	(0.023)	(0.005)	(0.003)
T × Mixed set.	0.019^{b}	0.016^{a}	0.019^{b}	0.073^{b}	0.015^{b}	0.006
	(0.008)	(0.006)	(0.007)	(0.029)	(0.006)	(0.003)
T × Polarization	0.009	0.005	0.008	0.032	0.005	0.010^{a}
	(0.006)	(0.004)	(0.008)	(0.025)	(0.006)	(0.003)
Cells	9687	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T indicates temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Battle indicates battles and is equal one if at least one battle event occurs in a cell and year; Riot indicates riots and is equal one if at least one riot event occurs in a cell and year; Vs. civilians indicates violence against civilians and is equal one if at least one event involving violence against civilians occurs in a cell and year; ln(Deaths+1) is the logarithm of the number of fatalities plus 1 per cell and year; Large incidents only considers the sub-sample of conflict incidents with an above-median number of fatalities involved (i.e. more than 7 fatalities); Small incidents only considers the sub-sample of conflict incidents with a below-median number of fatalities involved (i.e. less or equal 7 fatalities). Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B2: Controlling for Lagged Dependent Variable

Dep. var.:	Incident	Incident	Incident	Incident	ln(Events+1)
	(1)	(2)	(3)	(4)	(5)
Lagged dependent variable	0.098^{a}	0.098^{a}	0.098^{a}	0.098^{a}	0.310^{a}
	(0.009)	(0.009)	(0.009)	(0.009)	(0.019)
T	0.020^{a}	0.015^{b}	0.014^{c}	0.012	0.017
	(0.008)	(0.007)	(0.009)	(0.008)	(0.014)
T × Mixed settlement		0.024^{a}		0.022^{b}	0.039^{b}
		(0.009)		(0.009)	(0.017)
T × Polarization			0.011	0.007	0.024
			(0.008)	(0.008)	(0.015)
Cells	9687	9687	9687	9687	9687
Observations	164679	164679	164679	164679	164679
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. This table performs a dynamic regression and controls for the lagged dependent variable; T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

B.2 Interpretation of the mixed settlement variable.

The analysis so far has focused on identifying the effect of temperature on conflict in cells with mixed settlement (i.e. the interaction term in Equation 1) relative to a reference group composed of cells with either nomads or settlers (the linear term T). We look at the consequences of breaking down this reference group in Table B3. We start with investigating whether nomads on their own are differently exposed to conflict than settled groups; column 1 of Table B3 controls for cells with NOMADS ONLY, interacted with temperature. In this setting the reference group is made of mixed cells together with settlers-only cells. With a negative coefficient significant at the 5% level, the result shows that the presence of nomads per se does not appear to drive conflict. Column 2 augments the previous specification with our main variable of interest (temperature interacted with mixed settlement); there, the linear term T captures the effect of temperature on conflict for a reference group consisting of cells exclusively inhabited by sedentary groups. We first see that heat shocks increase conflict in cells with settlers only, with a weakly significant coefficient of 0.016. Second, nomads on their own do not appear to be differently exposed to conflict than settlers. Third, the main coefficient of interest capturing the effect of MIXED SETTLEMENT remains comparable in magnitude to the baseline and is significant at the 5% level. Columns (3) follows the same logic after controlling for polarization. Column (4) investigates the intensive margin. Overall, our coefficient of interest remains statistically significant throughout all specifications.

As pointed out throughout this paper, nomadic lifestyles differ from sedentary ones in various dimensions. Hence, several population features are specific to regions of mixed settlement and could therefore act as confounders. For example, scattered, seasonal and erratic availability of pastures facilitates a mobile living arrangement, which directly impacts nomadic agglomeration patterns. Further, mixed cells represent the gateway to urban areas and historically served as trading posts across the Sahara. Among them are local economic and cultural centers such as Timbuktu in Mali, that have been subject to terrorist attacks in recent years. This raises the question whether population density drives our main coefficient. We therefore control for population density with data from the Gridded Population of the World (GPW) for the year 2000 (CIESIN, 2015), in column 1 of Table B4. Results show that the effect of temperature on conflict in mixed cells remains unaffected and highly significant. Moreover, summary statistics in Table 1 show that cells of mixed settlement have by construction a higher number of groups, because they form upon the borders of ethnic territories. In column 2, we additionally control for the number and squared number of ethnic groups per cell. In column 3, we control for fractionalization, a commonly-applied index to approximate ethnic diversity. The indicator is calculated at the cell level following the definition in Montalvo and Reynal-Querol (2005*b*) and based on population counts from GPW.[7] Column 4 considers the intensive margin. Note that any time-varying country-wide variation in ethnic composition (e.g. induced by large-scale migration waves) is absorbed by the country-year fixed effects. All in all, the effect of fractionalization on conflict is statistically indistinguishable from zero. Overall, our main coefficient of interest retains its significance and is of similar magnitude as in the baseline throughout all specifications.

Table B3: Nomads' Exposure to Conflict

Dep. var.:	Incident	Incident	Incident	ln(Events+1)
	(1)	(2)	(3)	(4)
T	0.027^a	0.016^c	0.013	0.026
	(0.009)	(0.009)	(0.009)	(0.017)
T × Nomads only	-0.018^b	-0.005	-0.005	-0.018
	(0.008)	(0.011)	(0.011)	(0.020)
T × Mixed settlement		0.026^b	0.024^c	0.047^c
		(0.012)	(0.013)	(0.027)
T × Polarization			0.007	0.025
			(0.009)	(0.018)
Cells	9687	9687	9687	9687
Observations	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T indicates temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Nomads only indicates cells with nomadic groups, but no sedentary groups; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

[7] GREG does not contain information on groups' population shares in cases where ethnic territories overlap. In such cases, we assign equal population shares to the groups on site. Further, the number of groups and all ethnicity indices are based on the group definition of Murdock, rather than GREG (i.e. we only use Murdock for group location). First, this is consistent with how we assign settlement patterns to groups. Second, while GREG provides more recent group location information, the data is more aggregated (e.g. the Murdock groups Ahaggaren, Asben, Antessar, Azjer and Ifora all belong to the Tuareg cluster in GREG). If we were to calculate ethnicity indices based on GREG, we may miss to capture intra-group tensions among sub-groups of a larger cluster (e.g. Ahaggaren fighting Asben in the above example).

Table B4: Correlation with Population Variables

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	ln(Events+1) (4)
T	0.008	0.017^c	0.017^c	0.031^c
	(0.008)	(0.010)	(0.010)	(0.017)
T × Mixed settlement	0.026^a	0.030^a	0.030^a	0.063^a
	(0.009)	(0.010)	(0.010)	(0.022)
T × Polarization	0.007	0.013	0.011	0.037^c
	(0.009)	(0.009)	(0.011)	(0.021)
T × Population density	0.000^b	0.000^b	0.000^b	0.000^b
	(0.000)	(0.000)	(0.000)	(0.000)
T × # Tribes		-0.005^b	-0.006	-0.015^a
		(0.002)	(0.003)	(0.006)
T × (# Tribes)^2		0.000	0.000	0.001^b
		(0.000)	(0.000)	(0.000)
T × Fractionalization			0.006	0.010
			(0.016)	(0.026)
Cells	9687	9687	9687	9687
Observations	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T indicates temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization; Population density measures the population per km^2 with data from the Gridded Population of the World (GPW), version 4 for the year 2000; # Tribes ((# Tribes)^2) accounts for the (squared) number of tribes per cell; Fractionalization measures cell-level fractionalization; Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

B.3 Definition of settlement patterns

We now investigate alternative constructions of the mixed settlement indicator. In the baseline specifications, the variable is defined by first assigning a settlement status to groups, before identifying regions in which both settlement modes overlap (c.f. Section 2.1). Although we believe our assignment rule is a sensible one, there exist plausible alternatives to dividing ethnic groups into nomads and settlers. Column 1 of Table B5 replicates column 4 of the Table 2 with nomads being defined as "nomadic or fully migratory" and "seminomadic" groups, whereas "semisedentary" and less mobile groups receiving settler status (threshold 2).[8] Column 2 now assigns "semisedentary" groups nomad status, whereas groups with "compact but impermanent settlements" or less mobility are considered as settlers (threshold 3). Columns 3 and 4 keep on shifting the threshold further by assigning relatively settled groups to the status nomadic, until in column 5 only "compact and relatively permanent settlements" and "complex settlements groups" receive settler status. The coefficients in columns 2-5 are throughout highly significant, although smaller in magnitude than the baseline. This attenuation pattern is likely attributable to measurement errors as these definitions may be less precise measures of mobility modes.

As outlined above, we match ethnic groups from Murdock's Ethnographic Atlas to the more recent, but more aggregate, GREG map. As a result, several Murdock groups may be matched to a single GREG group. In most of those cases, multiple Murdock groups within the same GREG group have the same settlement mode. One exception is Egypt, which has mixed cells across the whole country (see Figure 1).[9] While from a data matching point of view this appears to be reasonable, it may be rather unlikely to find larger settlements in the southern regions of Egypt. In other words, our matching procedure could induce some measurement error in this particular context of Egypt. Columns 1 to 3 of Table B6 exclude Egypt from the sample and the results show that the effect of mixed settlement on conflict is less strong, but remains positive and significant at the 5% and 10% level. Next, we only include countries bordering the Sahel zone in the sample. This exercise is motivated by the casual observation that farmer-herder conflicts seem most pronounced in this region. Further, the mobility analysis of Section 4.3 focuses on the Sahelian subsample. Again, the results presented in columns 4-6 of Table B6 are less precisely estimated, but remain in line with the baseline.

[8] For details on threshold definitions, please consult the footnote of Table B5.

[9] "Arabs of UAR (Egyptians)" in GREG cover all of Egypt and merge with 2 groups in Murdock, "Eqyptians" (settlers) and "Saadi" (seminomadic). Cross-checking with sources such as Encyclopedia Britannica confirms that the merge between groups, settlement patterns and geographic extent appears indeed correct.

Table B5: Alternative Settlement Definitions

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)
T	0.010	0.010	0.010	0.010	0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
T × Mixed settlement	0.028^a	0.021^a	0.018^a	0.018^a	0.014^b
	(0.010)	(0.008)	(0.007)	(0.006)	(0.007)
T × Polarization	0.007	0.008	0.008	0.007	0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Cells	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓
Nomad-settler threshold (v30)	2	3	4	5	6

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T indicates temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year. Ethnic groups' settlement characteristics are defined according to the settlement patterns (variable 30) information in George Murdock's Ethnographic Atlas. Seven different settlement modes are defined: i) nomadic or fully migratory, ii) semi-nomadic, iii) semi-sedentary, iv) compact but impermanent settlements, v) neighbourhoods of dispersed family homesteads vi) separated hamlets, forming a single community and vii) compact and relatively permanent settlements. In our baseline setting, we define nomads as groups in categories i) or ii) and settlers as groups in categories iii) to vii) (threshold 2). This tables tests alternative thresholds to divide nomads and settlers, by assigning up to six mobility modes to nomadism (in that case settlers only consists of group in category vii)). Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B6: Exclude Egypt and Sahel Countries Only

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)	Incident (6)
T	0.014^{c}	0.011	0.010	0.011	0.007	0.004
	(0.007)	(0.007)	(0.008)	(0.011)	(0.010)	(0.013)
T × Mixed settlement		0.019^{b}	0.018^{c}		0.019^{c}	0.018^{c}
		(0.009)	(0.010)		(0.011)	(0.011)
T × Polarization			0.002			0.005
			(0.009)			(0.012)
Sample	No Egypt	No Egypt	No Egypt	Sahel only	Sahel only	Sahel only
Cells	9366	9366	9366	4012	4012	4012
Observations	168588	168588	168588	72216	72216	72216
Cell FE	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes data for the years 1997-2014. Columns 1-3: Sub-sample of Sahel countries (Algeria, Burkina Faso, Cameroon, Central African Republic, Chad, Eritrea, Ethiopia, Mali, Mauritania, Niger, Senegal, South Sudan and Sudan); columns 4-6: excludes Egypt from the sample. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

B.4 Country borders

We explore the role of national borders in shaping disputes between farmers and herders. It is possible that conflict is amplified along national boundaries when local issues over land rights coincide with national interests. For instance, the Mauritania–Senegal Border War during the late 1980s was initiated by disputes over grazing rights between herders and farmers along the Senegal River dividing both countries. The conflict escalated into a crisis between the two nations and resulted in large-scale displacement (Parker, 1991). To determine whether national borders act as a confounding factor of violence in mixed settlement cells, we first omit cells ranging across national borders. The coefficient of interest in column 1 of Table B7 remains unaffected. We then return to the full sample and control for the distance between cells' centroids and the closest border in columns 2 to 4. Each of the columns uses a different methodology to calculate border distance, as described in the table notes. Finally, we control for border cells in column 5. Overall, we observe that farmer-herder conflict does not appear to be driven by tensions along national borders.

Table B7: Exclude Border Cells and Control for Border Distance

Dep. var.:	Incident	Incident	Incident	Incident	Incident
	(1)	(2)	(3)	(4)	(5)
T	0.006	0.016^{b}	0.015^{c}	0.015^{c}	0.010
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
T × Mixed set.	0.030^{a}	0.026^{a}	0.026^{a}	0.026^{a}	0.027^{a}
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
T × Polarization	0.009	0.006	0.006	0.005	0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T × Border dist. 1		-0.000^{a}			
		(0.000)			
T × Border dist. 2			-0.000^{a}		
			(0.000)		
T × Border dist. 3				-0.000^{a}	
				(0.000)	
T × Border cell					0.005
					(0.007)
Sample	Exclude border cells	All	All	All	All
Cells	8221	9436	9687	9687	9687
Observations	147978	169848	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. Column 1: excludes cells coinciding with national borders; columns 2-4: controls for the distance in kilometer from a cell's centroid to national boarders, calculated in three different ways based on bdist measures from PRIO-GRID version 2.0; column 2: distance to the nearest neighbouring nation connected via land; column 3: distance to nearest border, irrespective if two countries are divided by water; column 4: distance to the territorial outline a cell belongs to. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

B.5 Measurement of weather shocks

This section investigates the measurement of our main source of variations, namely weather shocks. We consider alternative measures of temperature and also look at precipitations.[10] We have used in the baseline specification the yearly average level of temperature (in degree Celsius) at the cell-level; conditional on cell fixed effects, this variable captures the effect of deviations in temperature from a cell's long-term trend (see equation 1). As a first alternative, the logarithm of temperature is considered and interacted with the mixed settlement dummy. Results in columns 1 and 2 of Table B8 are in line with the baseline in terms of magnitude and significance. The coefficient of mixed settlement in column 2 suggests that a +5% increase in temperature (or about 1.25 degree Celsius) translates into a +42.1% increase in the likelihood of conflict, relative to the sample mean, which is quantitatively comparable to the baseline effect (36.3%).
The African continent has a variety of climatic zones and the variation in local temperature across years differs from one region to another (see right panel, Figure 3). A potential issue in measuring temperature in levels pertains to assuming a linear impact of temperature on violence, ignoring that the effect might differ between regions, as some of them may be better adapted to erratic climate or extreme temperature swings. While any permanent difference across space in the adaptation to climate is absorbed by the cell fixed effect, explicitly accounting for such local sensitiveness to temperature is a valuable and complementary approach. With this respect, we consider locally re-scaled temperature shocks in columns 3 and 4 of Table B8 where each temperature level is divided by its cell-specific (time series) standard deviation. This approach puts less weight on cells with extreme temperature anomalies. The main coefficient is positive and significant at the 5% level. In degree Celsius units, the coefficient equals 0.02, which is smaller than the baseline, but remains quantitatively substantial. Overall, our results are robust to alternative temperature indices. We do prefer temperature in levels, as it fits the African context (heat shocks only) and allows a straightforward interpretation of regressions coefficients.

Observed precipitation is an alternative candidate for measuring exogenous weather variations at the local level. However, while the existing literature widely agrees on a positive association between heat shocks and conflict, the picture is less clear-cut for precipitation. This could be due to various reasons, including measurement error and a non-monotonic effect of rainfall on conflict. With this caveat in mind, we test in Table B9 for the role of rainfall and study whether there is a relationship to temperature in the data, by interacting both indices with each other. The correlation between average temperature and the sum rainfall per year is -0.06. We first measure rainfall in levels and as natural logarithm and columns 1 to 4 of Table B9 show that neither rainfall itself affects conflict, nor does it change the effect of temperature in mixed cells. The remaining columns adopt alternative measures of rainfall. Columns 5 and 6 consider rainfall anomalies and keep detecting

[10] Dell, Jones and Olken (2014) provide an overview of the most common weather indices in the literature. The ones used in this section are (i) relevant in the African context and (ii) address potential concerns about the identification strategy.

no effect. Columns 7 and 8 focus on absolute anomalies. The rationale is that both extreme high (floods) and extreme low (droughts) precipitation may cause economic damage and thus conflict. Again, the results suggest that rainfall neither drives the effect of temperature on conflict, nor is relevant on its own. To summarize, while there appears to be no relevant relationship between precipitation and conflict in the data, the effect of temperature on conflict in mixed cells remains robust.

Table B8: Alternative Temperature Definitions

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)
ln(T)	0.511^a	0.293		
	(0.172)	(0.193)		
ln(T) × Mixed settlement		0.757^a		
		(0.252)		
ln(T) × Polarization		0.140		
		(0.205)		
T_{it}/SD_i			0.005^b	0.003
			(0.002)	(0.003)
$T_{it}/SD_i\times$ Mixed settlement				0.007^b
				(0.003)
$T_{it}/SD_i\times$ Polarization				0.001
				(0.003)
Cells	9687	9687	9687	9687
Observations	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. ln(T) measures the logarithm of temperature; T_{it}/SD_i is temperature normalized by cell standard deviation; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B9: Controlling for Precipitation

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)	Incident (6)	Incident (7)	Incident (8)
T		0.012		0.010		0.010		0.010
		(0.008)		(0.008)		(0.008)		(0.008)
T $\times$ Mixed set.		0.027^{a}		0.028^{a}		0.028^{a}		0.028^{a}
		(0.010)		(0.010)		(0.010)		(0.010)
T $\times$ Polar.		0.007		0.008		0.007		0.007
		(0.009)		(0.009)		(0.009)		(0.009)
Rain	0.001	0.005						
	(0.001)	(0.007)						
T $\times$ Rain		-0.000						
		(0.000)						
ln(Rain)			-0.003	-0.016				
			(0.003)	(0.020)				
T $\times$ ln(Rain)				0.001				
				(0.001)				
$\frac{Rain_{it}-Mean_i}{SD_i}$					0.000	0.010		
					(0.001)	(0.007)		
T $\times \frac{Rain_{it}-Mean_i}{SD_i}$						-0.000		
						(0.000)		
$\frac{\lvert Rain_{it}-Mean_i\rvert}{SD_i}$							-0.004^{b}	-0.006
							(0.001)	(0.010)
T $\times \frac{\lvert Rain_{it}-Mean_i\rvert}{SD_i}$								0.000
								(0.000)
Cells	9687	9687	9516	9516	9492	9492	9492	9492
Observations	174366	174366	171119	171119	170856	170856	170856	170856
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓
Country $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T measures temperature in degree Celsius; Rain measures total annual precipitation per cell in decimeter with data from the Climatic Research Unit; ln(rain) measures the logarithm annual precipitation; $\frac{Rain_{it}-Mean_i}{SD_i}$ measures the mean deviation in precipitation, divided by a cell's standard deviation in precipitation (anomaly); $\frac{\lvert Rain_{it}-Mean_i\rvert}{SD_i}$ measures the absolute mean deviation in precipitation, divided by a cell's standard deviation in precipitation (absolute anomaly); Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

B.6 Climate zones, biomes and soil properties

The purpose of this section is to understand whether conflicts in mixed cells can be driven by climatic and vegetation conditions. It is important to distinguish between "climate" and "weather", with the first being the long term pattern (distribution) and the latter (in our case temperature) being a temporal condition (observation) (Dell, Jones and Olken, 2014). Local climatic conditions are undoubtedly related to resource availability and to whether people pursue a nomadic lifestyle. To address the role played by climatic conditions, we retrieve information from the ERSI data that map climate zones according to the Köppen-Geiger classification system. In this system, climate zones define regions of similar long-term temperature and precipitation patterns. The Sahel zone for instance is classified as a "semi-arid" band horizontally crossing Africa below the Sahara desert. In Table B10 we control for climate zone-specific dummy variables, interacted with temperature. The results show that none of the climate zones appear to be more prone to conflict than others. Further, the main coefficient in mixed settlement remains unaffected. One limit of this definition of climate zone is its focus on long-term temperature and rainfall patterns, without considering other important factors such as soil properties or actual vegetation.

Hence, to draw a clearer picture of the role of actual vegetation, we consult data on biomes. Biomes are based on the definition of Olson et al. (2001) and issued by the World Wildlife Fund. Biomes define regions sharing the same predominant vegetation.[11] Biome-specific dummy variables are interacted with temperature of each cell-year pair and results are reported in Table B11. While some biomes appear reactive to temperature-induced violence, the main coefficient of interest remains comparable to the baseline. In other words, we do not find that vegetative patterns drive conflict in mixed cells.

One important input factor for vegetation is soil. We derive data on soil properties from the Harmonized World Soil Database (Nachtergaele et al., 2008). To identify regions subject to soil stress, cells with an above-median share of poor soil are interacted with temperature.[12] Table B12 neither finds a general pattern of soil stress and temperature shocks, nor does controlling for poor soil affect the main coefficient of interest.

[11] We follow Henderson et al. (2017) and combine biomes 2 and 3 and biomes 7 and 9, due to their similarity and because categories 3 and 9 represent very minor shares on a global scale.

[12] Details on the construction of the variable can be found in the table description and in the channel section.

Table B10: Correlation with Climate Zones

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)	Incident (6)	Incident (7)	Incident (8)	Incident (9)	Incident (10)	Incident (11)	Incident (12)	Incident (13)	Incident (14)
T	0.010	0.010	0.011	0.012	0.010	0.009	0.010	0.010	0.010	0.011	0.010	0.010	0.010	0.007
	(0.008)	(0.008)	(0.009)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.073)
T × Mixed settlement	0.027^a	0.027^a	0.028^a	0.027^a	0.027^a	0.026^a	0.027^a	0.028^a	0.027^a	0.027^a	0.027^a	0.027^a	0.027^a	0.027^a
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
T × Polarization	0.007	0.007	0.008	0.008	0.007	0.008	0.007	0.007	0.007	0.007	0.008	0.007	0.007	0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T × Climate zone Af	-0.009													-0.009
	(0.023)													(0.076)
T × Climate zone Am		-0.004												-0.004
		(0.018)												(0.075)
T × Climate zone Aw			-0.005											-0.001
			(0.011)											(0.073)
T × Climate zone BWh				-0.005										0.002
				(0.008)										(0.073)
T × Climate zone BWk					0.010									0.015
					(0.015)									(0.074)
T × Climate zone BSh						0.010								0.012
						(0.010)								(0.073)
T × Climate zone BSk							0.009							0.015
							(0.017)							(0.074)
T × Climate zone Csa								0.031						0.035
								(0.031)						(0.079)
T × Climate zone Csb									0.006					0.012
									(0.038)					(0.082)
T × Climate zone Cwa										-0.009				-0.004
										(0.010)				(0.074)
T × Climate zone Cwb											0.008			0.011
											(0.016)			(0.073)
T × Climate zone Cfa												-0.005		0.000
												(0.072)		(.)
T × Climate zone Cfb													0.055	0.061
													(0.053)	(0.082)
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cells	9657	9657	9657	9657	9657	9657	9657	9657	9657	9657	9657	9657	9657	9657
Observations	173826	173826	173826	173826	173826	173826	173826	173826	173826	173826	173826	173826	173826	173826
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. The regressions control for temperature interacted with different climate zones according to the Köppen-Geiger climate classification, downloaded via ESRI. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B11: Correlation with Biomes

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)	Incident (6)	Incident (7)	Incident (8)	Incident (9)	Incident (10)
T	0.011	0.010	0.010	0.001	0.010	0.009	0.017^c	0.010	0.010	-0.045
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.066)
T × Mixed set.	0.027^a	0.027^a	0.028^a	0.025^a	0.028^a	0.028^a	0.025^a	0.027^a	0.028^a	0.026^a
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)
T × Polarization	0.007	0.007	0.007	0.009	0.007	0.007	0.009	0.007	0.007	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T × Biome 1	-0.014									0.044
	(0.013)									(0.065)
T × Biomes 2 + 3		-0.026^b								0.027
		(0.013)								(0.066)
T × Biome 5			-0.011							0.052
			(0.141)							(0.158)
T × Biomes 7 + 9				0.016^b						0.061
				(0.007)						(0.066)
T × Biome 10					0.026					0.080
					(0.021)					(0.069)
T × Biome 12						0.042^c				0.090
						(0.024)				(0.070)
T × Biome 13							-0.024^a			0.039
							(0.007)			(0.066)
T × Biome 14								-0.055		0.000
								(0.065)		(.)
T × Biome 99									0.010	0.068
									(0.028)	(0.071)
Cells	9687	9687	9687	9687	9687	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. The regressions control for temperature interacted with biomes, with data from the Terrestrial Ecoregions of the World data set by the WWF. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B12: Correlation with Soil Stress

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)	Incident (6)
T	0.008	0.008	0.007	0.013	0.009	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T × Mixed settlement	0.028[a]	0.028[a]	0.028[a]	0.028[a]	0.028[a]	0.028[a]
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
T × Polarization	0.007	0.007	0.007	0.008	0.006	0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T × Poor nutrient availability	0.005					
	(0.005)					
T × Poor nutrient retention cap.		0.005				
		(0.005)				
T × Poor rooting conditions			0.006			
			(0.005)			
T × Poor oxygen availability				-0.010		
				(0.006)		
T × High excess salts					0.008	
					(0.006)	
T × High toxicity						0.005
						(0.007)
Cells	9655	9655	9655	9655	9655	9655
Observations	173790	173790	173790	173790	173790	173790
Cell FE	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9655 cells for the years 1997-2014. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization; interacted soil indices indicate cells with relative poor soil fertility, with data from the Harmonized World Soil Database, version 1.2. In detail, an indicator variable takes a value of one if a cell has an above-median combined land share in classes 4 and 5 in the respective soil quality category (soil classes of 4 and 5 correspond to soil with very severe limitations and non-soil, such as desert sand). Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). [c] significant at 10%; [b] significant at 5%; [a] significant at 1%.

B.7 Further robustness exercises

In what follows, we draw on alternative conflict data from the UCDP georeferenced Event Dataset (Sundberg and Melander, 2013). Unlike ACLED, a death threshold of at least 1 fatality per event is imposed. Further, only events of active groups are considered, i.e. a group has to be associated in at least one year with 25 deaths or more. In other words, this dataset focuses on events involving larger-scale, and possibly more structured actors. Given that part of the farmer-herder violence may be quite localized and may possibly not involve structured and organized militias, we expect a weaker effect for the more restrictive UCDP data, for which the sample is downsized to 6,960 incidents. This results in a reduction of the variation in the dependent variable by 50%, compared to ACLED. Results in Table B13 report positive, although no longer statistically significant coefficients for mixed settlement cells. The lower variation in the dependent variable is likely to account for the less precise estimates. Only the last column, the only non-binary (and hence less coarse) specification, features a highly significant coefficient similar to the baseline.

Further, to demonstrate robustness across data sources with respect to the independent variable, we next consult temperature data issued by the University of Delaware (UDEL) (Matsuura and Willmott, 2012). The correlation coefficient between temperature data from CRU (baseline) and UDEL is 0.93 and significant at the 1% level. The results in Table B14 show a positive and highly significant coefficient for mixed cells, although less than half the magnitude of the baseline.

The panel analysis so far has relied on exogenous variations in temperature shocks. While desirable from an identification point of view, the external validity of our findings may be limited, because farmer-herder violence could be partly rooted in other causes than climatic stress. One way to test whether farmer-herder conflict can be identified in the absence of weather shocks is to perform a cross-sectional analysis. We therefore construct a time-invariant dependent variable measuring the share of sample years with conflict incidence for each cell. Results reported in Table B15 document a positive association between mixed settlement and conflict, significant at the 5% level. The econometric specification exploits variation across cells and controls for country fixed effects. Note that we can no longer control for cell fixed effects which bears the risk of cell-specific, constant omitted variable bias. Although statistically less well identified, the results of the cross-section are in line with the baseline, which reinforces the external validity of our findings.

Another potential worry is that time trends across cells may differ, which could affect the results in a non-trivial way. We address this concern by replacing cell fixed effects with cell-specific time trends. Table B16 reports the findings of this sensitivity check. It turns out that our baseline results continue to hold for this specification.

Last but not least, several regressions with alternative spatial and serial clustering are performed. In detail, columns 1 to 4 of Panel A in Table B17 allow for a spatial correlation within 50, 100, 250 and 750 km from a cell's centroid, respectively, while maintaining infinite serial correlation. Columns 1 to 4 of Panel B of the same table allow for a serial correlation across 0, 1, 5 and 10 periods, respectively, while maintaining a spatial correlation of 500 km from a cell's centroid. The results remain statistically significant in all specifications.

Table B13: Alternative Conflict Data: UCDP GED

Dep. var.:	Incident	Incident	Incident	Incident	ln(Events+1)
	(1)	(2)	(3)	(4)	(5)
T	0.018^{a}	0.016^{b}	0.016^{b}	0.015^{b}	0.016
	(0.007)	(0.006)	(0.007)	(0.007)	(0.015)
T × Mixed settlement		0.013		0.013	0.058^{a}
		(0.009)		(0.009)	(0.021)
T × Polarization			0.003	0.001	0.024
			(0.008)	(0.009)	(0.018)
Cells	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T indicates temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables are based on data from the UCDP Georeferenced Event Dataset (GED): Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). [c] significant at 10%; [b] significant at 5%; [a] significant at 1%.

Table B14: Alternative Weather Data: UDEL

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	ln(Events+1) (4)
T (UDEL)	0.003^{c}	0.001	-0.000	0.000
	(0.001)	(0.004)	(0.004)	(0.006)
T (UDEL) × Mixed settlement	0.013^{a}		0.013^{a}	0.027^{a}
	(0.005)		(0.005)	(0.009)
T (UDEL) × Polarization		0.004	0.004	0.008
		(0.004)	(0.004)	(0.007)
Cells	7872	7872	7872	7872
Observations	141696	141696	141696	141696
Cell FE	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T (UDEL) measures temperature in degree Celsius with data from Willmott, Matsuura, and Legates (2010) at the University of Delaware (UDEL); Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B15: Cross-Sectional Specification

Dep. var.:	Conflict share (1)	Conflict share (2)	Conflict share (3)	Conflict share (4)
Mixed settlement	0.030^{b}	0.030^{b}	0.031^{b}	0.032^{a}
	(0.012)	(0.012)	(0.012)	(0.012)
Polarization		-0.003	0.022	0.022
		(0.013)	(0.020)	(0.018)
Fractionalization			-0.044^{c}	-0.036^{c}
			(0.024)	(0.021)
Population density				0.000^{a}
				(0.000)
Observations	9687	9687	9687	9687
Country FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell. The sample consists of 9687 cells. Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization; Fractionalization measures cell-level fractionalization; Population density measures the population per km^2 with data from the Gridded Population of the World (GPW), version 4 for the year 2000. Dependent variable: Conflict share measures the share of years (1997-2014) in which at least one conflict incident occurred in a cell. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B16: Controlling for Cell-Specific Time Trends

Dep. var.	Incident (1)	Incident (2)	Incident (3)	ln(Events+1) (4)
T	0.014^a	0.013^a	0.010^b	0.016^b
	(0.003)	(0.004)	(0.004)	(0.007)
T × Mixed settlement	0.029^a		0.028^a	0.058^a
	(0.007)		(0.006)	(0.013)
T × Polarization		0.013^b	0.007	0.024^b
		(0.006)	(0.006)	(0.010)
Cells	9687	9687	9687	9687
Observations	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell-specific time trends and country-year fixed effects. Coefficients are reported with standard errors clustered at the cell level in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table B17: Alternative Spatial and Serial Clustering

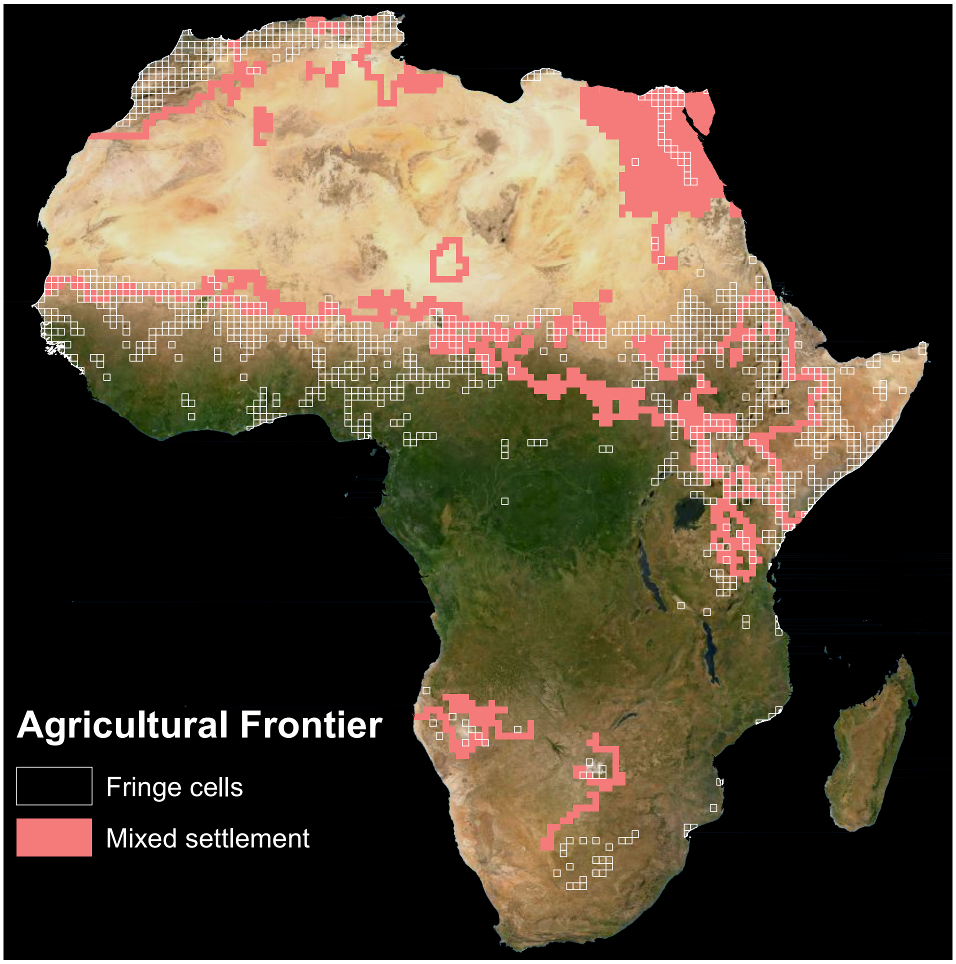
Dep. var.:	Incident	Incident	Incident	Incident
	(1)	(2)	(3)	(4)
Panel A. Alternative spatial clustering				
T	0.014^{a}	0.014^{a}	0.014^{b}	0.014^{c}
	(0.003)	(0.004)	(0.006)	(0.007)
T × Mixed settlement	0.029^{a}	0.029^{a}	0.029^{a}	0.029^{a}
	(0.007)	(0.008)	(0.009)	(0.010)
Spatial clustering	50 km	100 km	250 km	750 km
Panel B. Alternative serial clustering				
T	0.014^{b}	0.014^{b}	0.014^{b}	0.014^{b}
	(0.007)	(0.007)	(0.007)	(0.007)
T × Mixed settlement	0.029^{a}	0.029^{a}	0.029^{a}	0.029^{a}
	(0.008)	(0.009)	(0.009)	(0.009)
Serial clustering	0 periods	1 period	5 periods	10 periods
Cells	9687	9687	9687	9687
Observations	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses. Panel A tests alternative spatial clustering specifications, while maintaining infinite serial correlation. Colum1-4 allow for a spatial correlation within a 50, 100, 250 and 750 km radius of a cell's centroid, respectively. Panel B tests alternative serial clustering specifications, while maintaining a spatial correlation within a 500 km radius of a cell's centroid. Colum1-4 allow for a serial correlation of 0, 1, 5 and 10 years, respectively. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

C Mechanisms at work

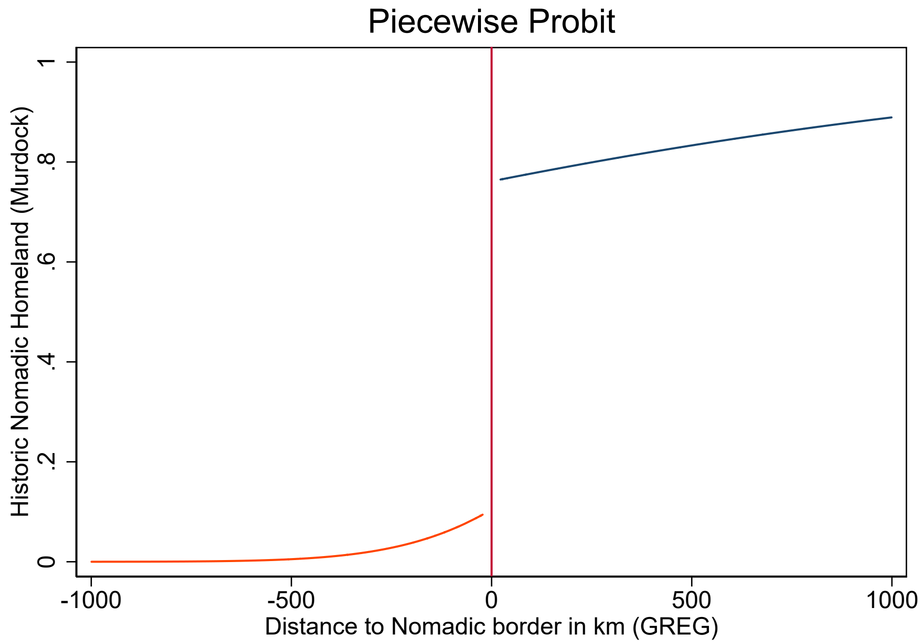
Below are depicted a series of Figures and Tables investigating mechanisms at work and channels of transmission. They are all discussed in detail in the main text under section 4.

Figure C6: The Agricultural Frontier: Fringe Cells



Notes: This graph depicts "Fringe" cells, defined as regions with an above-median share of agricultural land and an above-median degree of infertile land.

Figure C7: Overlap between GREG and Murdock ethnic group boarder data



Notes: The graph predicts the location of the historic ethnic homeland of nomads (Murdock), dating back up to 5,000 years, from the location of nomads in the 1960s (GREG). The red vertical line indicates the border between nomadic and sedentary groups, based on data from GREG. Negative values on the horizontal axis measure the distance to nomadic homeland (as seen from settler homeland).

Table C1: Persistence of Production Technologies

	Nomads	Mixed settlement	Settlers	Total
Crop suitability (cell sh./human per km^2)	5.974	17.042	24.887	16.865
	(16.439)	(24.029)	(27.146)	(24.900)
Infertile land (cell share)	66.799	34.304	2.390	30.331
	(42.605)	(42.322)	(12.620)	(43.238)
Cattle (# animals/person)	12.413	353.163	36.433	62.142
	(170.572)	(6087.183)	(849.829)	(2100.291)
Goat	17.668	274.962	23.102	48.382
	(226.908)	(3790.582)	(419.822)	(1292.721)
Sheep	29.775	219.382	17.537	43.669
	(594.322)	(3255.092)	(262.105)	(1144.596)

Notes: The unit of observation is a cell. The table provides summary statistics on the underlying production technologies. Columns 1-3 divide cells along mobility patterns, based on settlement mobility data from Murdock's Ethnographic Atlas matched onto geolocation information from the Geo-referencing of Ethnic Groups dataset (GREG). Column 1 depicts the average (standard deviation) of cells inhabited by nomads only; column 2 identifies cells inhabited by at least one settled and at least one nomadic group (”Mixed settlement”); column 3 cells inhabited by settlers only. Column 4 considers the complete sample. Data on crop suitability and on infertile land are derived from Globcover categories 11, 14, 20 30 and 200, respectively; population data is derived from the Gridded Population of the World (GPW), version 4; data on cattle density is derived from the Gridded Livestock of the World (GLW3) dataset by Fao for the year 2005 and available for Sub-Saharan Africa; data is accessed via HarvestChoice.

Table C2: Competition versus Culture, Alternative Data and Reference Years

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	ln(Events+1) (5)
Panel A. GLC-SHARE data for 2014					
T	0.013^a	0.008^b	0.010^a	0.006	0.010
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)
T × Mixed settlement	0.027^a	0.023^a	0.009	0.008	0.006
	(0.007)	(0.006)	(0.007)	(0.007)	(0.014)
T × Fringe (1992)		0.031^a	0.019^a	0.019^a	0.034^a
		(0.006)	(0.006)	(0.006)	(0.010)
T × Mixed set. × Fringe (1992)			0.046^a	0.046^a	0.129^a
			(0.017)	(0.016)	(0.035)
T × Polarization				0.007	0.024^b
				(0.006)	(0.010)
Cells	9353	9353	9353	9353	9353
Observations	168354	168354	168354	168354	168354
Panel A. SAGE data for 1992					
T	0.014^a	0.008^b	0.010^a	0.006	0.012
	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
T × Mixed settlement	0.029^a	0.026^a	0.013^b	0.011^c	0.015
	(0.007)	(0.006)	(0.006)	(0.006)	(0.013)
T × Fringe (2014)		0.036^a	0.023^a	0.023^a	0.030^a
		(0.006)	(0.006)	(0.006)	(0.009)
T × Mixed set. × Fringe (2014)			0.052^a	0.052^a	0.148^a
			(0.017)	(0.017)	(0.037)
T × Polarization				0.008	0.026^b
				(0.006)	(0.010)
Cells	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. Fringe indicates cells with an above median share of agricultural land (total of crop and grass land) and an above-median share of bare soil. This table defines Fringe with alternative data sources for different reference years. Panel A: data on the agricultural extent in 1992 is derived from the SAGE data set by the Center for Sustainability and the Global Environment at the University of Wisconsin-Madison. Panel B: data on the agricultural extent and on bare soil extent in 2014 is derived from the Global Land Cover SHARE (GLC-SHARE) database by Fao. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table C3: Competition versus Culture, Cattle Data

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	ln(Events+1) (5)
T	0.008	0.005	0.006	0.004	0.003
	(0.008)	(0.008)	(0.008)	(0.010)	(0.016)
T × Mixed settlement	0.023^{b}	0.019^{b}	0.008	0.007	0.013
	(0.010)	(0.009)	(0.008)	(0.009)	(0.018)
T × Fringe (Cattle)		0.028^{b}	0.014	0.015	0.024
		(0.012)	(0.011)	(0.011)	(0.018)
T × Mixed set. × Fringe (Cattle)			0.048^{b}	0.047^{b}	0.074^{b}
			(0.023)	(0.023)	(0.036)
T × Polarization				0.006	0.018
				(0.010)	(0.019)
Cells	7705	7705	7705	7705	7705
Observations	138690	138690	138690	138690	138690
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. Fringe indicates cells with an above-median share of crop and bare land and above-median cattle density. Data on cattle density is derived from the Gridded Livestock of the World (GLW3) dataset by Fao for the year 2005 and available for Sub-Saharan Africa; data is accessed via HarvestChoice. Data on crop and bare land cover is derived from Globcover 2009, categories 11 and 14. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table C4: Competition versus Culture, Soil Qualities

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)	Incident (6)
T	0.008	0.009	0.008	0.014	0.011	0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
T × Mixed settlement	0.022^{b}	0.018^{c}	0.012	0.026^{b}	0.018^{c}	0.023^{b}
	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)
T × Polarization	0.008	0.008	0.007	0.007	0.007	0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
T × Fringe (Poor nutrient av.)	0.009					
	(0.008)					
T × Mix × Fringe (Poor nutrient av.)	0.039					
	(0.026)					
T × Fringe (Poor nutrient retention)		0.006				
		(0.007)				
T × Mix × Fringe (Poor nutrient ret.)		0.053^{b}				
		(0.022)				
T × Fringe (Poor rooting conditions)			0.012			
			(0.008)			
T × Mix × Fringe (Poor rooting cond.)			0.060^{a}			
			(0.019)			
T × Fringe (Poor oxygen to roots)				-0.018^{b}		
				(0.007)		
T × Mix × Fringe (Poor oxygen to roots)				0.014		
				(0.021)		
T × Fringe (High excess salts)					-0.009	
					(0.010)	
T × Mix × Fringe (High excess salts)					0.087^{a}	
					(0.032)	
T × Fringe (High toxicity)						-0.014
						(0.012)
T × Mix × Fringe (High toxicity)						0.079^{c}
						(0.043)
Constant	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cells	9655	9655	9655	9655	9655	9655
Observations	173790	173790	173790	173790	173790	173790
Cell FE	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. Fringe indicates cells with an above-median share of agricultural land and constrained soil qualities. Data on agricultural land is from Globcover 2009. Data on soil qualities is from the Harmonized World Soil Database, version 1.2. Constrained soil quality indicates cells with an above-median combined land share in classes 4 and 5 in the respective soil quality category (soil classes of 4 and 5 correspond to soil with very severe limitations and non-soil, such as desert sand). T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization; Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table C5: Competition versus Culture, Extended Version

Dep. var.:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	ln(Events+1) (5)
T	0.014[a]	0.008	0.010[c]	0.006	0.011
	(0.003)	(0.005)	(0.005)	(0.006)	(0.009)
T × Mixed settlement	0.029[a]	0.023[a]	0.010	0.009	0.026[c]
	(0.007)	(0.006)	(0.012)	(0.012)	(0.014)
T × Agriculture		0.005	0.005	0.006	0.009
		(0.005)	(0.005)	(0.005)	(0.007)
T × Barren		-0.004	-0.004	-0.004	-0.012
		(0.006)	(0.006)	(0.006)	(0.008)
T × Fringe		0.044[a]	0.023[b]	0.023[b]	0.052[a]
		(0.010)	(0.010)	(0.010)	(0.016)
T × Mix set. × Agric.			-0.007	-0.006	-0.027
			(0.015)	(0.015)	(0.025)
T × Mix set. × Barren			0.004	0.003	-0.011
			(0.015)	(0.015)	(0.023)
T × Mixed set. × Fringe			0.066[a]	0.066[a]	0.183[a]
			(0.025)	(0.025)	(0.048)
T × Polarization				0.008	0.024[b]
				(0.006)	(0.010)
Cells	9687	9687	9687	9687	9687
Observations	174366	174366	174366	174366	174366
Cell FE	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The sample includes 9687 cells for the years 1997-2014. Fringe indicates cells with an above median share of agricultural land (total of crop and grass land) and an above-median share of bare soil; data is derived from Globcover 2009, and correspond to categories 11, 14 ,20, 30 and 200, respectively. Agriculture indicates cells with an above-median share of agricultural land; Barren indicates cells with an above-median share of bare land. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads; Polarization measures cell-level polarization. Dependent variables: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year; ln(Events+1) is the logarithm of the number of conflict events plus 1 per cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). [c] significant at 10%; [b] significant at 5%; [a] significant at 1%.

Table C6: Climate-induced Mobility and Conflict, Descriptive Statistics

	Nomad	Settler	Total	Mean difference (Nomad - Settler)
T in homeland (centroid)	28.687	27.308	28.242	1.379^a
	(1.457)	(2.925)	(2.137)	(0.388)
Distance to homeland	233.643	419.632	293.687	-185.989^b
	(293.170)	(632.131)	(438.699)	(81.919)
Event in other settlement cat.	0.528	0.119	0.396	0.408^a
	(0.404)	(0.302)	(0.419)	(0.071)
Event in own homeland	0.768	0.345	0.631	0.423^a
	(0.334)	(0.425)	(0.415)	(0.069)

Notes: The unit of observation is an actor. Columns 1-3: Summary statistics. Columns 1-2 divide cells along mobility patterns. Column 1 and 2 depict the average (standard deviation) nomadic and settled rebel groups, respectively. Column 3 considers the complete sample. Column 4 performs a difference of mean test between nomads and settler, with the following significant levels: ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table C7: Climate-induced Mobility and Conflict, Alternative Specifications

Dependent variable:	Distance to homeland (centroid, km)					
Fighting group:	All	Settlers	Nomads			
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Restricting dependent variable to < 500 km						
T in homeland (centroid)	2.715^{b}	1.489	9.537^{a}	34.745^{a}	19.910^{a}	22.962^{a}
	(1.371)	(1.471)	(3.654)	(9.460)	(5.911)	(6.557)
Events	1615	698	917	96	478	448
Groups	120	35	85	30	61	60
Panel B. Spatially clustered standard errors						
T in homeland (centroid)	5.873^{b}	0.839	14.840^{a}	41.879^{a}	24.372^{a}	27.351^{a}
	(2.444)	(2.381)	(5.608)	(7.952)	(6.579)	(7.987)
Events	1904	895	1009	98	509	488
Groups	127	41	86	30	63	63
Panel C. Event level regressions						
T in homeland (centroid)	2.172	-3.175	18.234^{a}	45.535^{a}	29.348^{a}	31.166^{a}
	(2.326)	(2.286)	(5.466)	(8.879)	(7.212)	(9.107)
Events	4406	2148	2258	127	1134	1102
Groups	127	41	86	30	63	63
Group FE	✓	✓	✓	✓	✓	✓
Country × Year FE	✓	✓	✓	✓	✓	✓
Fight over resources only				✓		
Conflict location: Agri. (M)					✓	
Conflict location: Water (M)						✓

Notes: Panel A: as baseline table, with the difference that the maximal distance between conflict event and rebel groups' homeland is restricted to 500 km (instead of 1000km). Panel B: as baseline table, with the difference that the standard errors are spatially clustered, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). Panel C: as baseline table, with the difference that the unit of observation is a conflict event. As a results, a single actor potentially could be involved in multiple conflict events in the same location and year. The sample is limited to Sahel countries. Information on conflict participants is derived from ACLED and matched on the ethnic group level to settlement mobility information from Murdock's Ethnographic Atlas. As a result, conflict participants' mode of settlement can be identified. Multiple events of the same group within the same 1 × 1 kilometer cell and year are coded as a single observation. T in homeland (centroid) measures temperature in degree Celsius in the geographic center of a fighting group's nearest homeland. A group's homeland is defined according to the specified ethnic group location in GREG. Column 1 considers all conflict events, column 2 only considers conflict events involving a settler group and columns 3-6 only consider conflict events involving a nomadic group. Column 4 restricts the subsample of nomadic event further to events including at least one of the following key words: land dispute, dispute over land, control of land, over land, clash over land, land grab, farm land, land invaders, land invasion, land redistribution, land battle, over cattle and land, invade land, over disputed land, over a piece of land, herd, pastoral, livestock, cattle, grazing, pasture, cow, cattle, farm, crop, harvest. Column 5 (6) restricts the subsample of nomadic events further to events taking place in cells with an above-median share of agricultural (water), with data from Global Land Cover SHARE by Fao. The dependent variable measures the distance between a conflict event and the center of a participating group's homeland. The regressions control for group and country-year fixed effects. Standard errors are reported in parentheses. ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

D Resilience through Formal Institutions and Policies

Below are presented a several Tables studying the impact of policies. They are all discussed in detail in the main text under section 5.

Table D1: Resilience Through Formal Institutions and Policies, Alternative Variables

	(1) Incident	(2) Incident	(3) Incident
T	0.033^{a}	0.016^{c}	0.036^{a}
	(0.012)	(0.008)	(0.013)
T × Mixed settlement	0.032^{b}	0.031^{a}	0.035^{b}
	(0.016)	(0.010)	(0.017)
T × Property rights	-0.023		-0.024
	(0.015)		(0.016)
T × Mixed set. × Property rights	-0.034^{c}		-0.037^{c}
	(0.020)		(0.021)
T × Independent Judiciary		-0.010	-0.009
		(0.014)	(0.014)
T × Mixed set. × Independent Judiciary		-0.023	-0.002
Cells	8479	9230	8134
Observations	152622	166140	146412
Sample share - interaction group	.51	.12	.55
Mix share - interaction group	.11	.07	.11
Cell FE	✓	✓	✓
Country × Year FE	✓	✓	✓

Notes: LPM estimated with OLS. An observation is a cell and a year. The table tests heterogeneity across relevant country-wide institutional features The sample includes the years 1997-2014 and the number of included cells in each column varies with the data availability of the test heterogeneity. Column 1 tests the role of property rights with data from the Economic Freedom of the World Dataset (only post sample data available) and column 2 considers judiciary independence (pre-sample) with data from Political Constraints Database. In both cases, data is accessed via the Quality of Government data collection and a binary variable is coded indicating above-median levels in the respective variable. T measures temperature in degree Celsius; Mixed settlement indicates cells with both settlers and nomads. Dependent variable: Incident indicates conflict incidence and is equal one if at least one conflict event occurs in a cell and year. The regressions control for cell and country-year fixed effects. Coefficients are reported with spatially clustered standard errors in parentheses, allowing for a spatial correlation within a 500 km radius of a cell's centroid and infinite serial correlation (Conley, 1999). ^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%.

Table D2: Resilience Through Formal Institutions and Policies, Border Analysis

Dependent variable:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)
Panel A. 75 km buffer around national borders					
T	0.013	0.006	0.053^a	0.024^b	0.036^c
	(0.012)	(0.009)	(0.015)	(0.009)	(0.020)
T × Mixed settlement	0.034^b	0.027^b	0.018	0.024^b	0.044^c
	(0.014)	(0.012)	(0.018)	(0.011)	(0.025)
T × High polity	-0.005				0.019
	(0.015)				(0.017)
T × Mixed set. × High polity	-0.050^b				-0.033
	(0.021)				(0.022)
T × High land dispute resolution		0.029			0.021
		(0.019)			(0.017)
T × Mixed set. × High land dispute resolution		-0.057^b			-0.034
		(0.022)			(0.024)
T × Low corruption			-0.061^a		-0.062^a
			(0.017)		(0.019)
T × Mixed set. × Low corruption			-0.007		0.007
			(0.022)		(0.025)
T × Federal states				-0.026	-0.008
				(0.021)	(0.020)
T × Mixed set. × Federal sates				-0.099^b	-0.078^c
				(0.039)	(0.043)
Cell FE / Country × Year FE	✓	✓	✓	✓	✓
Panel B. 75 km buffer around national borders, including border × year fixed effects					
T	-0.021	-0.002	0.007	-0.006	-0.011
	(0.014)	(0.011)	(0.013)	(0.010)	(0.024)
T × Mixed settlement	0.033^a	0.021^c	0.036^b	0.031^a	0.042^c
	(0.012)	(0.012)	(0.015)	(0.010)	(0.023)
T × High polity	0.019				0.027
	(0.016)				(0.019)
T × Mixed set. × High polity	-0.041^b				-0.018
	(0.019)				(0.022)
T × High land dispute resolution		0.001			-0.000
		(0.017)			(0.019)
T × Mixed set. × High land dispute resolution		-0.026			0.001
		(0.020)			(0.023)
T × Low corruption			-0.021		-0.016
			(0.016)		(0.021)
T × Mixed set. × Low corruption			-0.030^c		-0.019
			(0.018)		(0.024)
T × Federal states				0.007	0.004
				(0.025)	(0.025)
T × Mixed set. × Federal sates				-0.100^a	-0.082^b
				(0.036)	(0.040)
Cell FE / Country × Year FE / Border × Year FE	✓	✓	✓	✓	✓
Cells	2897	2997	3319	3319	2638
Observations	52146	53946	59742	59742	47484
Sample share - interaction group	.44	.42	.51	.1	.93
Mix share - interaction group	.1	.1	.1	.11	.14

Notes: For details, consult the notes of Table 5. The sample is limited to cells within a 75 km buffer around national borders. The distance is measured between the centroid of a cell and a border. Panel B additionally controls for border-year specific fixed effects. In cases where cells contain multiple borders, a cell is assigned to the border closest to its centroid.

Table D3: Resilience Through Formal Institutions and Policies, Border Analysis, Larger Buffer

Dependent variable:	Incident (1)	Incident (2)	Incident (3)	Incident (4)	Incident (5)
Panel A. 120 km buffer around national borders					
T	0.014	0.005	0.045[a]	0.021[a]	0.040[b]
	(0.010)	(0.008)	(0.013)	(0.008)	(0.019)
T × Mixed settlement	0.037[a]	0.025[b]	0.022	0.026[a]	0.043[c]
	(0.012)	(0.010)	(0.017)	(0.010)	(0.023)
T × High polity	-0.007				0.010
	(0.012)				(0.015)
T × Mixed set. × High polity	-0.053[a]				-0.038[b]
	(0.018)				(0.019)
T × High land dispute resolution		0.027[c]			0.024[c]
		(0.016)			(0.014)
T × Mixed set. × High land dispute resolution		-0.046[b]			-0.031
		(0.019)			(0.021)
T × Low corruption			-0.050[a]		-0.061[a]
			(0.015)		(0.017)
T × Mixed set. × Low corruption			-0.010		0.006
			(0.020)		(0.022)
T × Federal states				-0.023	-0.005
				(0.019)	(0.019)
T × Mixed set. × Federal sates				-0.085[b]	-0.059
				(0.033)	(0.036)
Cell FE / Country × Year FE	✓	✓	✓	✓	✓
Panel B. 120 km buffer around national borders, including border × year fixed effects					
T	-0.013	0.003	0.009	-0.001	0.002
	(0.013)	(0.010)	(0.012)	(0.009)	(0.022)
T × Mixed settlement	0.035[a]	0.020[b]	0.035[b]	0.029[a]	0.041[c]
	(0.011)	(0.009)	(0.014)	(0.009)	(0.021)
T × High polity	0.012				0.011
	(0.014)				(0.018)
T × Mixed set. × High polity	-0.046[a]				-0.027
	(0.016)				(0.019)
T × High land dispute resolution		-0.002			-0.006
		(0.015)			(0.017)
T × Mixed set. × High land dispute resolution		-0.026			-0.010
		(0.018)			(0.020)
T × Low corruption			-0.016		-0.010
			(0.014)		(0.018)
T × Mixed set. × Low corruption			-0.028[c]		-0.013
			(0.017)		(0.022)
T × Federal states				0.007	0.004
				(0.023)	(0.024)
T × Mixed set. × Federal sates				-0.081[a]	-0.052
				(0.031)	(0.034)
Cell FE / Country × Year FE / Border × Year FE	✓	✓	✓	✓	✓
Cells	2897	2997	3319	3319	2638
Observations	52146	53946	59742	59742	47484
Sample share - interaction group	.44	.42	.51	.1	.93
Mix share - interaction group	.1	.1	.1	.11	.14

Notes: For details, consult the notes of Table 5. The sample is limited to cells within a 120 km buffer around national borders. The distance is measured between the centroid of a cell and a border. Panel B additionally controls for border-year specific fixed effects. In cases where cells contain multiple borders, a cell is assigned to the border closest to its centroid.