Conflict, Climate and Cells: A disaggregated analysis*

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Abstract

We conduct a disaggregated empirical analysis of civil conflict at the subnational level in Africa over 1997-2011 using a new gridded dataset. We construct an original measure of agriculture-relevant weather shocks exploiting within-year variation in weather and in crop growing season, and spatial variation in crop cover. Temporal and spatial spillovers in conflict are addressed through spatial econometric techniques. Negative shocks occurring during the growing season of local crops affect conflict incidence persistently, and local conflict spills over to neighboring cells. We use our estimates to trace the dynamic response to shocks and predict how future warming may affect violence.

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1 Introduction

A vivid debate has emerged in recent years on the consequences that global warming and the increased frequency of extreme weather events have on aggregate scenarios. There is concern that the adverse impact of climatic changes may be more strongly felt in poorer and more politically unstable countries, such as those in Sub-Saharan Africa, where the majority of the population is dependent on rainfed agriculture. The correlation between vulnerability to weather shocks and propensity to conflict has spurred a growing amount of research trying to establish a causal link. This literature has traditionally employed cross-country panel data on precipitation and temperature to estimate how they affect the occurrence of civil war, defined based on predetermined thresholds in casualties.

In this paper we attempt to take a step further in understanding the relationship between climate and conflict by taking the analysis to a different scale. We conduct a geographically disaggregated analysis taking as units of observation 110 $\times$ 110 km subnational "cells," and we estimate the incidence of conflict as a function of weather shocks and a number of other covariates both in the cell and in neighboring areas, plus a "lag" in space and time of the endogenous variable.

Our approach contributes to the literature in two main directions. The first and most important is methodological. We construct a cell/year panel with a rich set of geo-referenced covariates. We model spatial and temporal dependence thorough state-of-the-art spatial econometrics techniques that have seldom been applied in economics. In particular, our model includes spatially and temporally autoregressive terms to account for the fact that conflict may be persistent over time, and that both the covariates and the presence of conflict may be correlated across space. This poses a number of challenges for estimation and constitutes an original contribution to the empirical conflict literature. This approach allows us to produce two novel sets of results. The first is the assessment of how persistent the effects are in space and time: persistence implies that even temporary shocks may have long-lasting effects on political instability. The second is the ability to better detect conflict spillovers across locations compared to the existing cross-country literature (e.g., Buhaug & Gleditsch, 2008).

A second contribution of our paper is that we look at climate indexed *within the year*. Because the main hypothesized (but not yet proven) channel linking weather shocks to conflict operates through shocks to agricultural incomes, we attempt to isolate the component of climate variability that is relevant for agriculture. Instead of using yearly averages, we measure climatic conditions during the growing season, which is when crops are most sensitive to unfavorable conditions. This is a data-intensive process that involves both within-year variation in the timing of shocks and spatial variation in crop cover.

An additional contribution relates to the climate indicator we employ. Most of the conflict literature has focused on precipitation or temperature.[1] We instead use a drought index, the Standardized Precipitation-Evapotranspiration Index (SPEI), that considers the joint effects of precipitation, potential evaporation, and temperature. This accounts for the fact that the impact of rainfall on the growing cycle of a plant depends on the extent to which water can be retained by the soil.

Our methodology and results can be summarized as follows. We assemble a panel dataset

[1]Recent exceptions include Hsiang, Meng, and Cane (2011), who employ El Niño-Southern Oscillation (ENSO); Couttenier & Soubeyran (2014), who employ the Palmer Drought Severity Index (PDSI); and Almer, Laurent-Lucchetti, and Oechslin (2017), who employ the Standardized Precipitation-Evapotranspiration Index (SPEI) as we do.

covering about 2,700 cells in 46 African countries from 1997 to 2011. We combine data from the Armed Conflict Location and Event Dataset (ACLED) with an original measure of growing season SPEI. Using maximum likelihood we estimate the probability that a cell experiences at least one conflict event during the year as a function of contemporaneous and lagged SPEI and spatial and temporal lags of conflict. In our benchmark specification this is conditional on cell fixed effects and country-specific year fixed effects, so that we identify changes in conflict propensity relative to a cell's historic mean and country-specific trends. We find that:

(i) There is a significant local-level relationship between agriculture-relevant shocks and conflict. According to our most conservative specification, a one standard deviation shock to SPEI during the growing season is associated with a 1.3 percentage point increase in conflict likelihood in the subsequent year, relative to the cell's historic mean. This is roughly 8 percent of the unconditional mean of the dependent variable. As a reference, a shock of such magnitude corresponds to the cell experiencing SPEI below its long-term mean by one standard deviation throughout four growing season months in a given year.

(ii) Conflict exhibits high persistence in time and space. When a cell experiences conflict, the cell itself has a 12 percentage point higher probability of experiencing it the following year, and each of its neighboring cells has a 2.3 percentage point higher probability of experiencing it during the same year.

(iii) Climate outside the growing season has no effect on conflict. This suggests that the mechanism operates through low agricultural yields.

(iv) Conflict spillovers are particularly pronounced across countries. For conflicts at the border, spillovers appear stronger across ethnicities.

(v) Among the channels through which our effect may operate, the "opportunity cost" one seems most consistent with our data, as indicated by significant effects of weather shocks on rebel recruitment. We also find that ethnic cleavages and low state capacity exacerbate the impacts of weather shocks.

Before proceeding, two caveats are in order. The first is that by focusing on the role of local shocks our paper has little to say about long-term institutional causes of conflict. This does not reflect a judgment on the relative importance of the two sets of causes; it is a consequence of the scale at which we conduct our analysis. The second caveat relates to the extent to which our results can speak to the effects of climate change. The main indicator we use is based on the deviation of weather from its historical average and can to some extent capture global trends. At the same time, our analysis holds constant economic and political variables that endogenously evolve over the long run: we should thus refrain from extrapolating the results too far into the future or to contexts with ample possibilities for adaptation.

With these caveats in mind, we use cell-level projections of future temperature and precipitation in 2016 through 2050 to construct a SPEI forecast. We predict that negative SPEI shocks during the growing season will become 5.4 times more pronounced over the next 35 years. Based on our estimates, this implies that the marginal contribution of future SPEI shocks to conflict in an average cell and year during 2016 through 2050 is 1.2 percentage points, or about 7 percent of the unconditional mean.

Our work is related to three strands of literature. The first is the literature on climate and violent conflict (e.g., Miguel, Satyanath, and Foley, 2004; Ciccone, 2013). We conduct the analysis at a more disaggregated level, and we isolate the component of weather variation that occurs during the growing season. Also, differently from the above authors, who adopt an instrumental variables strategy, we estimate a reduced-form relationship - there is no reliable data that captures yearly variation in income or GDP in rural areas at the level of disaggregation that we employ.[2] Other authors have expanded the cross-country coverage (Couttenier & Soubeyran, 2014) or investigated the link between conflict and global warming (Burke et al., 2009; Buhaug, 2010; Hsiang et al., 2013). We share with this literature the acknowledgment that temperature is crucial, and indeed our SPEI measure combines data on temperature with data on precipitation. Our focus on within-country variation is shared by recent studies linking weather shocks to insurgency and protests, including Dell (2012), Vanden Eynde (2017), Jia (2014), and Madestam et al. (2013). O'Loughlin et al. (2012) also share the "grid" approach with us.[3]

A second strand of literature focuses on climate and development. Recent studies have investigated the impact of climate on economic growth (Dell, Jones, & Olken, 2012), mortality (Burgess et al., 2013; Kudamatsu, Persson & Strömberg, 2017), health (Maccini & Yang, 2009) and political institutions (Brückner & Ciccone, 2011).

[2]We have experimented with nighttime luminosity as a proxy for income, finding a negative and significant effect of climate shocks on luminosity. However, we prefer not to rely on luminosity as we are mostly interested in rural incomes, which are poorly proxied by nighttime lights.

[3]Our geographic resolution and the conflict data sources are similar to O'Loughlin et al. (2012). However, our approach departs in several respects: (i) we disaggregate climate indicators by local growing season, defined based on the local main crop; O'Loughlin et al. conduct the analysis at the monthly level and control for growing season, which is defined ex post based on climatic characteristics; (ii) we employ cell and country $\times$ year fixed effects; (iii) we address spatial and temporal autocorrelation through spatial econometric techniques; (iv) we rely on satellite and not on station data; and (v) our geographic coverage is the entire African continent.

The third strand of literature related to our work is that on the determinants of civil conflict.[4] Recent papers by Bazzi & Blattman (2014) and by Berman & Couttenier (2015) explore the role of external economic shocks on conflict. While we share with these authors the interest in local variation in economic shocks, we focus on internal climatic shocks as opposed to external income shocks. This difference becomes relevant when we think of policy implications to mitigate the role of shocks (e.g., weather-indexed insurance).

The remainder of the paper is organized as follows. In section 2 we present our conceptual framework and econometric methodology. In section 3 we discuss our data and provide descriptive statistics. In section 4 we present our main results and in section 5 we examine mechanisms and heterogeneous effects. Section 6 contains robustness checks, and section 7 concludes.

2 Conceptual framework and methodology

2.1 Conceptual framework

The literature on the effects of economic shocks on conflict has traditionally stressed two channels (e.g., Collier & Hoeffler, 1998). On one hand, there is an "opportunity cost" effect: a negative shock to the local economy decreases the returns from labor market participation relative to fighting, making it more attractive to join a rebellion. On the other hand, the same negative shock implies that the size of the "pie" to be appropriated is lower, thus reducing the incentives to fight. The net effect is thus ambiguous, depending on, among other things, whether the shock occurs to

[4] For a comprehensive review, see Blattman & Miguel (2010). Among more recent contributions, Berman et al. (2017) share with us the disaggregated level of analysis but focus on mineral extraction.

a labor-intensive or capital-intensive sector. In our case, because African agriculture is typically labor intensive, based on Dal Bó & Dal Bó (2011) the opportunity cost effect would be predicted to prevail: negative agricultural shocks should lead to more conflict. Economic shocks may also have an additional effect, namely worsening the extent of poverty and exacerbating existing inequalities, thus fueling conflict in response to "grievances."

Fearon & Laitin (2003) propose different channels, stressing the role of state capacity and infrastructure. Economic shocks may reduce a government's tax base, weakening its ability to fight rebellion and leading to more conflict. Moreover, if shocks affect the quality of infrastructure (e.g., roads), an increase in conflict may be the result of logistical difficulties in repressing insurgents.

The way in which we construct our climate shock variable, namely focusing on weather during the agricultural growing season, allows us to isolate effects that are specific to agricultural yields and opportunity cost: if other channels were involved, we would expect to find an effect of weather throughout the year. As for tax revenues, our benchmark specification includes the interaction of country and year dummies, which capture aggregate shocks to state revenues. In section 5 we propose a discussion of competing mechanisms in light of our results.

2.2 Empirical strategy

We construct a dataset that has the structure of a raster grid: the units of observation are subnational "cells" of 1 degree of latitude $\times$ 1 degree of longitude (approximately 110 km). As for the resolution of the grid, theory is of limited help in selecting it a priori: the degree of localization of agricultural shocks and the spatial extent of conflict spillovers are ultimately empirical objects. We validate our choice of 1 degree resolution by conducting the analysis at higher and lower spatial scales (see section 6.1).

Our analysis is at the cell/year level. Our main dependent variable is *ANY EVENT*, a binary indicator for whether the cell has experienced a conflict-related episode in a given year. This variable is coded based on the ACLED dataset, discussed in section 3.1 below. We estimate three models: the first contains only exogenous regressors specific to the cell; the second includes a "spatial lag" of the exogenous regressors; the third (preferred) model also includes lags of the endogenous variable in time and space.

We focus on conflict incidence as opposed to onset or termination for two reasons. First, our specification with spatial and temporal lags of the dependent variable requires a balanced panel. Onset and termination regressions imply the loss of a large number of observations, and the resulting balanced sample would be small and hardly representative. Second, we are interested in how conflict in a cell spills over to neighbors and how such effects persist over time, something that is more naturally assessed with incidence. Nevertheless, in section 5.5 we discuss results for onset and termination. We now turn to the empirical specifications of the three models we estimate.

Model I

Consider a panel of N cells and T years. Denote with C a generic climate indicator (e.g., precipitation) and with GS_C the climate indicator measured in the cell-specific growing season. Let X be a vector of time-invariant controls (e.g., terrain characteristics) and γ and μ denote year and country fixed effects, respectively. Model I takes the form:

$$\textit{ANY EVENT}_{c,i,t} = \alpha + \sum_{k=0}^{2} \beta_{1k} C_{c,t-k} + \sum_{k=0}^{2} \beta_{2k} GS\_C_{c,t-k} + \delta X_c + \gamma_t + \mu_i \tau + \varepsilon_{c,i,t} \qquad (1)$$

where c denotes the cell, i the country, and t the year, and τ is a linear time trend.[5] We fit a linear

[5]For defining country fixed effects each cell is assigned to one country. Cells shared among more than one country are assigned to the country that has the largest share of the cell's territory.

probability model and estimate (1) via OLS, as it can be easily integrated with spatial econometrics techniques.

Most empirical work on conflict assumes that observations are independent across space. We instead estimate Model I following the procedure of Hsiang (2010) to adjust standard errors for both spatial and serial correlation.[6] This is appropriate in cases in which spatial correlation is present in the error term ("spatial error model") but it does not model spatial dependence in the process itself. However, we expect spatial correlation both in the covariates - e.g., weather - and in conflict, through direct cross-cell spillovers.

Model II

To control for spatial correlation in the covariates, we include spatial lags of the variables of interest. The structure of spatial dependence is defined by a symmetric weighting matrix W, and the spatial lag of a variable is obtained by multiplying the matrix W by the vector of observations. Let C_t and GS_C_t be N-dimensional vectors of climate observations in year t, and let X be the matrix of cell-level controls. We estimate the following spatial Durbin model (Anselin, 1988):

$$\begin{aligned} \mathit{ANY\ EVENT}_{c,i,t} &= \alpha + \sum_{k=0}^{2} \beta_{1k} C_{c,t-k} + \sum_{k=0}^{2} \beta_{2k} GS\_C_{c,t-k} + \delta X_c + \mu_i \tau + \\ &+ \sum_{k=0}^{2} \theta_{1k} W \cdot C_{t-k} + \sum_{k=0}^{2} \theta_{2k} W \cdot GS\_C_{t-k} + \lambda W \cdot X + W \cdot \mu \tau + \gamma_t + \varepsilon_{c,i,t} \end{aligned} \tag{2}$$

Our benchmark W is a binary contiguity matrix in which a weight of 1 is assigned to cells sur-

A "shared" dummy is included among the controls.

[6]Hsiang (2010) extends to panel data the correction originally proposed by Conley (1999) for the cross-section. We are thankful to Nicolas Berman, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig for sharing the amended version of the code in Hsiang (2010).

rounding the cell of interest - within a 180 km distance cutoff - and a weight of 0 to other cells. This implies that we effectively consider as neighbors the eight bordering cells. In section 6.1 we conduct a sensitivity analysis to different spatial matrices. For ease of interpretation we do not row-standardize W, so the coefficients on the spatial lags, θ_{1k}, θ_{2k}, and λ, should be interpreted as the effect of a marginal change in a given variable in *one* of the neighbors.

We estimate (2) by OLS, with standard errors corrected à la Hsiang (2010).

Model III

Part of the observed spatial correlation in conflict is due to the fact that conflict determinants are correlated; part is due to direct contagion. Disentangling these two effects is, in general, difficult. Models allowing for spatial dependence in the dependent variable are known as spatial autoregressive models and are estimated with maximum likelihood or GMM techniques. A further complication arises in our context, since in addition to spatial autocorrelation we expect the process of conflict to be autocorrelated in time. We thus estimate Model III:

$$\begin{aligned} &\mathit{ANY\ EVENT}_{c,i,t} = \phi \mathit{ANY\ EVENT}_{c,i,t-1} + \rho W \cdot \mathit{ANY\ EVENT}_{t} + \\ &+ \alpha_c + \sum_{k=0}^{2} \beta_{1k} C_{c,t-k} + \sum_{k=0}^{2} \beta_{2k} GS\_C_{c,t-k} + \mu_{it} + \\ &+ \sum_{k=0}^{2} \theta_{1k} W \cdot C_{t-k} + \sum_{k=0}^{2} \theta_{2k} W \cdot GS\_C_{t-k} + W \cdot \mu_t + \varepsilon_{c,i,t} \end{aligned} \tag{3}$$

where μ_{it} denote country $\times$ year fixed effects and α_c cell fixed effects. We also explore different sets of fixed effects and trends. The model in (3) is a dynamic, spatially autoregressive Durbin model that we estimate by maximum likelihood following Parent & LeSage (2012) and Yu, de Jong, and Lee (2008), clustering standard errors by cell. The likelihood is derived in the Online Appendix, Section C.

Drawing inferences on the impact of local climate shocks on conflict, accounting for spatial spillovers, presents challenges comparable to the estimation of peer effects. As discussed in Gibbons, Overman, and Patacchini (2015), disentangling contextual effects (in our case, local weather shocks that are clustered in space) from direct spillovers (in our case, conflict contagion) requires imposing some structure on the spatial dependence in the process. Such structure is embedded in the spatial matrix. Intuitively, the MLE estimator exploits climate shocks occurring beyond 180 km (among the "second-degree neighbors") as a source of variation in conflict incidence in the immediate neighbors (within 180 km). This is similar in spirit to an instrumental variables approach such that shocks occurring among second-degree neighbors instrument for conflict occurring among the immediate neighbors. We discuss an instrumental variable version of our estimates in section 4.1. Our implicit identifying assumption is thus that rainfall beyond 180 km is not affecting conflict in the own cell, other than by inducing more local conflict that then spills over in space. While this is by definition not testable, in section 6.1 we discuss robustness to various distance cutoffs.

The estimation of spatially and temporally autoregressive terms is an innovation of our paper and is particularly relevant when the data are highly disaggregated, and hence highly spatially correlated. Ignoring the term $W \cdot Y$ can lead to omitted variable bias: all of the observed spatial clustering in conflict would be attributed to conflict determinants that happen to be clustered spatially, and the contemporaneous impact of climate shocks would tend to be overestimated.[7] On the other hand, if one included $W \cdot Y$ but estimated the model via OLS, estimates would suffer from simultaneity bias in the opposite direction, overestimating spillover effects and underestimating

[7] An alternative way to frame this is to note that Models I and II are the reduced form version of Model III: the coefficients of climate variables capture the equilibrium effect of local and neighboring shocks, gross of direct conflict spillovers that they may have induced.

the local impact of shocks.

3 Data

3.1 Sources and dataset construction

We bring together high-frequency, geo-referenced data from a variety of sources and construct a dataset covering 46 African countries over the period 1997 through 2011. Details on countries and sources can be found in the Online Appendix, section A.

Conflict data

Data on conflict come from the PRIO/ Uppsala ACLED dataset, covering 1997 through 2011. ACLED codes the latitude, longitude, and date of a wide range of conflict-related events, including battles and activities involving rebels, such as recruitment or the establishment of headquarters. Event data are derived from reports from war zones, humanitarian agencies, and research publications. While there may be selection in reporting, it is unclear that such bias would be systematically correlated with our measure of cell-specific growing season weather shocks. We also explore robustness to using the alternative Uppsala Conflict Data Program Georeferenced Event Dataset (UPCDP-GED), which follows a different coding strategy (see Online Appendix, section A).

Climate data

Our main climate indicator is the Standardized Precipitation-Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2010). While most of the conflict literature has focused on precipitation, the impact of rainfall on the growing cycle of a plant depends also on the ability of the soil to retain water. This is captured by "potential evapotranspiration," which in turn depends on temperature, latitude, sunshine exposure, and wind speed. SPEI reflects this and has been found to generally outperform other indexes in predicting crop yields (Vicente-Serrano et al., 2012).

The climate inputs we employ to compute SPEI are drawn from a high-quality re-analysis dataset (ECMWF ERA-Interim), which relies on weather stations, satellites, and sondes. SPEI is expressed in units of standard deviation from the cell's historical average and thus has mean 0 by construction in the historical sample (1979-2011 in our case). Sections A and B of the Online Appendix include further details on the inputs and computation of SPEI.

Crop calendars and crop-specific climate shocks

Our analysis exploits periods within the year during which climatic conditions affect agricultural production the most. We identify the main crop, by harvested area, cultivated in each cell as of the year 2000, drawing on Monfreda, Ramankutty, and Foley (2008). We then retrieve its cell-specific growing season, based primarily on the MIRCA 2000 crop calendars dataset (Portmann, Siebert, & Döll, 2010). We then match our monthly climate data with the calendars of the crops cultivated in each cell, thus creating cell-specific measures of "relevant" climatic conditions.

Our key climate indicator, denoted as *SPEI Growing Season*, is computed by averaging monthly SPEI over the growing season months of a cell's main crop in a given year. Higher values of this variable correspond to more favorable conditions for local agriculture. For the sensitivity analysis in Table A10, we consider alternative functional forms and widely used indicators such as rainfall and temperature.

Other data

We complement our dataset with a number of cell-level characteristics related to geography, infrastructure, and ethnic fractionalization that we employ as control variables or sources of heterogeneity. These variables are described in the Online Appendix, section A, and summary statistics are reported in Appendix Table A1. Section D in the Appendix also discusses cross-sectional estimates relating cell-level characteristics to conflict propensity.

3.2 Descriptive statistics

Table 1 reports descriptive statistics. The average cell in our sample has experienced conflict episodes for 17 percent of the years, which means 2.5 years. The mean of SPEI in our sample is -0.11, indicating that weather conditions throughout 1997-2011 have been less favorable to agriculture compared to the 1979-2011 historical sample over which SPEI is computed.

In Figure 1 we map our key variables, to get a sense of their within-country variation. Figure 1A shows conflict prevalence, reporting the fraction of years during 1997 through 2011 in which each cell experienced at least one conflict event. Conflict appears to be clustered in space, and in particular in the Great Lakes region and in West Africa. Figure 1B plots average SPEI (for comparison, Appendix Figure A1 plots average rainfall). Although SPEI appears to be spatially correlated, it displays more local variation than rainfall. Appendix Figure A3 maps the distribution of crops, showing that a wide range of crops are cultivated in our sample, which gives us significant variation in climate across cells and months thanks to variation in the growing season of different crops.

4 Empirical results

Our dependent variable is $\textit{ANY EVENT}_t$, a dummy equal to 1 if the cell experienced at least one conflict event during year t. As discussed in section 2.2, we consider three models: a non-spatial, static model (Model I), a non-autoregressive spatial static model (Model II), and a spatial autoregressive dynamic model (Model III). All specifications include the following cell-level controls: elevation, roughness, area, presence of roads, distance to river, shared cell, border, presence of minerals, and ethno-linguistic fractionalization (ELF). Models II and III also include the spatial lags of controls and of the relevant fixed effects (these coefficients are not reported for ease of exposition).

4.1 Benchmark estimates

Table 2 contains our main results. The regressor of interest is *SPEI Growing Season*, defined as the average level of SPEI during the main crop's growing season. Higher values of this variable correspond to higher "effective" rainfall. We also control for standalone SPEI, which in this specification captures the impact of SPEI in months outside the growing season of the main crop. The first and second temporal lag are included for all climate indicators.

Column 1 shows that the contemporaneous effects of SPEI inside and outside the growing season essentially offset one another. However, high values of *SPEI Growing Season* reduce conflict likelihood in the following year and the year after that, whereas lagged SPEI outside of the growing season has no significant impact. When we introduce the spatial lag of our climate variables (column 2), standalone SPEI becomes insignificant also contemporaneously and only the first lag of *SPEI Growing Season* remains negative and significant. This is consistent with the idea that conditions during the growing season are those which matter the most for agriculture. The fact that conflict responds with a one-year lag parallels the temporal persistence highlighted in cross-country studies (e.g., Ciccone, 2013). If this variable affects conflict through rural incomes, it could plausibly take one full agricultural season for these seasonal weather patterns to translate into an economic shock. The coefficients on the spatial lags of the SPEI variables are generally small and do not display a consistent pattern, suggesting that the direct effects of weather shocks are strictly local. We nevertheless include the spatial lags of the regressors in all of our specifications, in order to correctly estimate the coefficient on $W \cdot Y$.

In column 3 we introduce our full spatially and temporally autoregressive model. The coefficient of the first lag of *SPEI Growing Season* in the own cell maintains its negative sign, magnitude, and significance level. A one standard deviation increase in this variable is associated with a 1.5 percentage point reduction in conflict likelihood in the subsequent year, relative to the cell's long-term mean. This is roughly 9 percent of the unconditional mean of the dependent variable.

Conflict spillovers are significant both in time and space. Conflict in a cell in a given year is associated with a 33 percentage point higher probability of conflict the following year. Contemporaneous conflict in one of the neighbors induces a 4 percentage point increase in the probability of conflict in the cell itself. Given that the average cell in our sample has 7.4 neighbors, this means that conflict in *all* of the neighbors induces a 30 percentage point increase in the probability of conflict in the average cell.

As discussed in section 2.2, we estimate Model III by maximum likelihood using spatial econometric techniques. As a validation exercise, in Appendix Table A4 we propose two instrumental variables versions of Model III. In column 4 of Table A4 we instrument for conflict in the immediate neighbors using conflict in the second-order neighbors, an approach similar to those used in time series to address autocorrelation in the dependent variable. In column 7 our instrument is the growing season SPEI of second-order neighbors –an approach similar to that of Bramoullé, Djebbari, and Fortin (2009). In both cases we instrument lagged conflict in the own cell using the second lag of conflict, following the time series literature. Both approaches yield estimates that are comparable, in sign and significance, to those found in Table 2.

Next, we explore robustness to different types of fixed effects. Column 3 includes year fixed effects and a country-specific linear time trend, column 4 includes country $\times$ year fixed effects, and column 5 includes cell and country $\times$ year fixed effects. The coefficient on *SPEI Growing Season*$_{t-1}$ is remarkably stable in sign and magnitude.

As expected, temporal spillovers are greatly attenuated once we include cell fixed effects, as some of the persistence is attributed to unobserved cell-level long-run characteristics. Nevertheless, relative to a cell's historical conflict propensity, conflict in a given year increases the likelihood of conflict in the subsequent year by 12 percentage points. Spatial spillovers are mildly attenuated once we focus on within-cell conflict variation, possibly because being part of a persistent conflict cluster is one of the time-invariant characteristics picked up by the cell fixed effects. According to column 5 estimates, when a cell experiences conflict each of its neighbors faces a 2.3 percentage point increased conflict likelihood. In the subsequent analysis we adopt the conservative specification of column 5 as our benchmark.

4.2 Impact magnitude and projections

In Model III, the impact of a covariate X on Y in a given cell is not entirely captured by the estimated regression coefficient of that covariate. For instance, the coefficient -0.037 from column 5 of Table 2 should be interpreted as the direct impact of *SPEI Growing Season* on next period's conflict in the own cell. However, a shock in the own cell also affects conflict in neighboring cells, which in turn affect conflict in the own cell through the spatial lag term. As a result, current conflict in the own cell may be amplified. Moreover, the effects of a one-time shock will persist in time, and these impacts will further propagate in space.

To quantify the total effects of a one-time shock we conduct an exercise similar in spirit to the evaluation of an impulse response. We consider Model III and start by setting all explanatory variables and prior conflict to 0; we then provide a hypothetical cell with a one-time negative shock to *SPEI Growing Season* equal to minus one standard deviation; finally, we use the estimates in Table 2, column 5, to track the marginal impact of this shock on the dependent variable in subsequent periods, leaving all other covariates at 0, in the own as well as the neighboring cells. In Figure 2 we report the results of this exercise.

Figure 2a plots the marginal impacts of the one-time decrease in *SPEI Growing Season* on conflict incidence in the five subsequent periods. The solid line refers to the own cell, the dashed to the average neighbor. At $t = 0$ the shock occurs. Conflict in the own cell does not react immediately: the point estimate of the contemporaneous response is slightly negative but insignificant; the neighbor's response is more precisely estimated and is a modest conflict increase, which will feed back in the own cell's response through the term $W \cdot Y$. In the first period after the shock, although no additional shocks occur, conflict in the own cell increases by a total of 1.3 percentage points, close to the point estimate of the first lag of *SPEI Growing Season* (Table 2, column 5) rescaled to the standard deviation of the covariate. After period 3 the marginal effects start fading away. The response of neighbors in Figure 2a roughly mirrors that of the own cell at a much smaller scale, but appears to be more persistent in time.

Figure 2b reports the results of the same exercise, but focusing on space instead of time. For time periods 0, 1, 2, and 4 we map on a grid the marginal impacts of the shock on different cells, representing larger impacts with darker shades. The cell that receives the one-time shock is at the center of the grid and is marked by an x. The definition of neighbors allows only the eight adjacent cells to be directly affected by cell x through their spatial lag terms. However, conflict induced by the one-time shock to cell x does propagate to cells beyond those immediately adjacent, due to spillovers from their own adjacent cells.

The above exercises are also useful to assess the bias from ignoring spillovers. We make this assessment in two ways. First, we have directly compared estimates from Model I with those of Model II and Model III when commenting Table 2. Second, the values in Figure 2a can be compared to the coefficients of Model I. Taken together, these results suggest that neglecting spatial spillovers leads to lower estimated impacts of lagged SPEI on conflict.

While in Figure 2 we employ a one-time, artificial shock, the same method can be used to feed into the process actual projected shocks. We repeat the above procedure feeding into the process forecast values of *SPEI Growing Season* for 2016 through 2050, to get a sense of how climate change will affect conflict likelihood, all else being equal and under the assumption that the responsiveness of conflict to SPEI remains constant in the future.

The first step involves computing projections of future SPEI shocks. We draw on cell-level precipitation and temperature projections obtained from a variety of climate models and under a range of emissions scenarios, all belonging to the World Climate Research Programme's Coupled Model Intercomparison Project phase 5 (CMIP5). Our benchmark model is FGOALS-g2, under a RCP 2.6 emissions scenario - a conservative one that assumes a peak in greenhouse gas emissions between 2010 and 2020 followed by a decline throughout the rest of the 21st century. A description of our sources and forecasting methodology is provided in the Online Appendix, sections A and B. The average of *SPEI Growing Season* (which is -0.025 in our 1997-2011 sample) becomes -0.135 in the 2016-2050 projected sample, indicating that the average cell experiences shortages of rainfall relative to its historic mean. Average projected values of *SPEI Growing Season* over 2016 through 2050 are reported in Figure A4. Next, we obtain for each cell and year the marginal change in conflict incidence induced by *SPEI Growing Season* shocks, according to Model III (Table 2, column 5). This marginal change reflects current and past shocks, among neighbors and in the own cell, due to the mechanisms discussed in Figure 2. Figure A5 maps these marginal changes in each cell, averaged over 2016 through 2050. The pattern clearly overlaps with that in Figure A4.

In an average year, conflict increases by 1.2 percentage points relative to a cell's historic mean (approximately a 7 percent increase) due to SPEI shocks. Note that this reflects averages over cells that experience negative shocks and also cells that experience positive ones. The peak marginal increase in conflict is over 4 percentage points, or about 23 percent of the 1997-2012 average conflict incidence. As a comparison, Burke et al. (2009) predict an increase in conflict incidence between 43% and 56% by 2030, though the larger magnitude may depend on the fact that they include country and not cell fixed effects. In Appendix Table A5 we perform a sensitivity analysis of these results to different climate models and emissions scenarios, as recommended by Burke, Hsiang, and Miguel (2015). Our estimates are remarkably stable. We must however be cautious in taking these estimates literally, as they do not account for crop mix adaptation (Costinot, Donaldson, & Smith, 2016), and we hold constant a number of socioeconomic and political variables that may evolve endogenously over the long run.

5 Mechanisms and heterogeneous effects

Our benchmark estimates indicate that favorable weather during the growing season decreases the likelihood of conflict, while outside the growing season it does not. This is consistent with an "opportunity cost" mechanism related to local agricultural incomes and rules out direct effects through channels such as violence due to extremely hot weather. It also rules out a predation mechanism, by which cells experiencing agricultural booms would be *more* likely to experience conflict. In this section we further explore competing mechanisms using multiple approaches.

5.1 Channels

In Table 3 we examine heterogeneous effects in the impact of cell-level weather conditions. We revisit our benchmark specification (Table 2, column 5), augmenting it with interactions between

SPEI Growing Season and cell-level characteristics capturing alternative channels. Spatial lags of the SPEI regressors are included in all specifications, but not reported in the table for brevity. The first channel relates to the logistics of warfare: precipitation might affect conflict directly by causing floods and hindering the movement of troops. Given that this should not be systematically correlated with the timing of the growing season, our benchmark estimates do not lend support to this interpretation. However, to further investigate this hypothesis, in column 1 we interact growing season weather with a proxy for road infrastructure in the cell: the presence of at least one road of primary use. The coefficient on the first lag of this interaction is negative and significant at the 10% level. This could indicate that seasonal weather interacts with the logistics of troop movements, but could also reflect the greater strategic importance of locations near a major road.

The second channel relates to state capacity. Fearon & Laitin (2003) argue that civil conflict is more prevalent in countries with poor state capacity, which have limited resources for counterinsurgency or for redistribution. This explanation emphasizes state capacity at the national level, whose fluctuations are captured in our specification by country $\times$ year dummies. Nevertheless, local dimensions of state capacity may be correlated with cell-level weather. In column 2 we interact our weather variables with the tax-to-GDP ratio, drawn from Cagé and Gadenne (2014). The coefficient on the interaction with *SPEI Growing Season*$_{t-1}$ is positive and significant, suggesting that the local effects of weather on conflict are attenuated in countries with better state capacity.

The third mechanism is related to grievances: weather shocks might exacerbate (perceived) inequalities between groups. Democracy and civil liberties should be associated with a lower risk of grievance-induced conflict, as they provide room for requesting redistribution peacefully. In column 3 we interact our weather variables with the Polity IV combined polity score (Marshall, Jaggers, & Gurr), and do not find significant effects.[8] Finally, we turn to ethnic cleavages as a potential source of grievances. In column 4 we consider the number of discriminated groups in a cell as a proxy for latent ethnic conflict. This is drawn from the GeoEPR-ETH dataset (see Online Appendix, section A). We consider groups classified as "subjected to active, intentional, and targeted discrimination, with the intent of excluding them from both regional and national power" at the beginning of our sample. The interaction with the first lag of *SPEI Growing Season* is negative and significant, suggesting that preexisting grievances are more likely to turn into violent conflict following an agricultural shock. We pursue this idea further by considering ethnicities that are partitioned across country borders and that may advance secessionist demands or seek military assistance from coethnics across the border (Michalopoulos and Papaioannou, 2016). We construct an indicator for whether a cell contains a border that cuts through an ethnic homeland ("Partition" in column 5) and interact it with *SPEI Growing Season*. Homelands are defined based on the GREG dataset (see Online Appendix, section A). We do not find significant effects, although the interaction with *SPEI Growing Season*$_{t-1}$ has the expected negative sign and is quite large in magnitude.

5.2 Heterogeneous spatial spillovers

In this section we investigate heterogeneous effects in spatial persistence, which can be informative of conflict spillover channels. The literature has proposed a number of mechanisms (see, e.g., Buhaug and Gleditsch, 2008). First, conflict may disrupt the local economy, reducing the opportunity cost of fighting in neighboring areas. It may also induce an inflow of arms or attract

[8]This index, measured at the country-year level, ranges from -10 (strongly autocratic) to $+10$ (strongly democratic).

mercenaries who move across the territory. Finally, rebellion may induce emulation. Additional mechanisms are specific to cross-country spillovers (e.g. Gleditsch, 2007). Refugee flows across countries may induce tensions leading to conflict; arms trading may be particularly pronounced near the border; irredentist demands may involve territory across two nations.

To shed light on the pass-through of conflict across cells, we vary the definition of what constitutes a neighbor and estimate specifications analogous to our benchmark but differing in the spatial weighting matrix used to define $W \cdot Y$. The results are reported in Table 4. Each column reports the coefficient on $W \cdot Y$ from a different regression, with the column header indicating how W is defined in that specification.[9]

In columns 1 and 2 we investigate whether spillovers are stronger across national borders. We consider two sets of neighbors: adjacent cells that belong (column 1) or not (column 2) to the same country. We detect positive spillovers in both cases, stronger when considering neighbors from a different country.

We next examine spillovers across ethnicities and country boundaries.[10] Coethnics residing across the border can provide rebels with resources and protection (Bosker and de Ree, 2014). Columns 3 and 4 consider the role of coethnics alone: we consider as neighbors adjacent cells that share (column 3) or do not share (column 4) the same main group.[11] The size of the spillover

[9]We continue to employ our benchmark weighting matrix when defining spatial lags in the covariates, so as to make the specifications comparable across columns.

[10]For a network analysis of rebel behavior that incorporates rainfall patterns in ethnic homelands, see König et al. (2017).

[11]We rank ethnic groups based on their share of the territory according to the GREG dataset.

effect is comparable across the two sets of neighbors. Interesting differences emerge, however, when we consider the interaction of ethnicity and borders. Within the same country, spillovers are not differential across ethnic homelands (column 5 versus column 6); cross-country spillovers are instead more pronounced across ethnic boundaries (column 7 versus column 8). These findings could reflect differences in the nature of conflicts occurring in the interior of a country versus in bordering areas. For example, conflicts occurring near boundaries may be separatist in nature and may spill over to areas occupied by different ethnic groups. They may also be more likely to generate refugee flows that fuel interethnic tensions. On the other hand, conflicts occurring in the interior are likely to have (non-separatist) objectives and follow a different diffusion process. Besides direct conflict spillovers, our data present an additional source of spatial dependence: spatial decay in the effects of agricultural shocks . The coefficients of the spatial lags of *SPEI Growing Season* are generally small, indicating that the direct effects of local shocks dissipate rapidly in space. However, this could also result from heterogeneous effects across neighbors operating in opposite directions. We explore this in the Appendix, section E. Appendix Table A6 shows that only shocks occurring among coethnic neighbors and among neighbors cultivating the same main crop increase conflict in the own cell. This provides suggestive evidence that coinsurance within the ethnic group may not be effective in the presence of uniform crop patterns across space.

5.3 Different types of conflict events

We next turn to a disaggregation of conflict events into four types, based on the ACLED classification. The dummy BATTLE equals 1 when a cell/year has experienced a battle of any kind, regardless of whether control of the contested location changes. The dummy CIVILIAN captures violence against civilians, defined in ACLED as instances where "any armed group attacks unarmed civilians within a larger conflict." This is the type of event most closely related to possible predation motives. Riots and protests (dummy RIOT) are instances in which "a group is involved in a public meeting against a government institution." ACLED also codes non-violent rebel activities, such as the establishment of a base or headquarters and recruitment drives.[12] These are particularly interesting to test theories that stress the opportunity cost of fighting, and we aggregate them in the binary variable REBEL. Summary statistics in Table 1 indicate that the average frequency of these events in the cell/years in our sample is $.10$ for battles, $.10$ for violence against civilians, $.06$ for riots, and $.03$ for rebel recruitment.

In Table 5 we examine the effects of climate on different types of events.[13] The coefficients of the temporal autoregressive terms are in the $0.07 - 0.14$ range. Battles and rebel recruitment have the highest degree of temporal persistence, whereas riots appear less persistent in time, possibly due to the intermittent nature of these episodes. The coefficients on the spatial autoregressive terms range from 0.004 for riots to 0.02 for battles and violence against civilians, suggesting that more violent episodes are more likely to spill over in space. The coefficients on own climate shocks point in the same direction as in the aggregate results, with the first lag of *SPEI Growing Season* associated with lower incidence of conflict events (albeit insignificant for riots). The effect sizes are largest for rebel recruitment, followed by violence against civilians: for a one standard deviation shock to *SPEI Growing Season*, the standardized point estimates are 24 percent and 17 percent of

[12]In the ACLED codebook, these correspond to events of type 4 ("headquarters or base established") or 5 ("non-violent activity," which includes recruitment drives, incursions, and rallies).

[13]The Appendix also reports cross-sectional estimates for the impact of cell-level geographic covariates on different types of conflict events (section D and Table A3).

the mean of the dependent variable. This points toward theories based on the opportunity cost of rebel recruitment.

5.4 Different conflict actors

We next exploit the breakdown of conflict by type of actor. For each event, ACLED reports the identity of the perpetrator and the victim and classifies them as government, rebel force, or civilians. By investigating which actors initiate conflict or are attacked following a SPEI shock, we can shed more light on mechanisms. We focus on three sets of actors: the government, politically violent actors (rebels, political militias, ethnic militias), and non-organized actors (a category in which we pool civilians, rioters, and protesters).[14]

About 32 percent of the events are initiated by the government, 21 percent by rebels, and 27 percent by political militias. Rioters, protesters, and civilians are the most common victims (38 percent of events), followed by rebels (23 percent). We start by disaggregating our dependent variable by perpetrator-victim pairs. For example, we can construct a dummy equal to 1 if a cell experienced at least one event involving the government as perpetrator and a rebel force as victim. For each actor-pair we estimate our benchmark specification (Table 2, column 5) and focus on the coefficient of *SPEI Growing Season*$_{t-1}$. We report these coefficients in Table 6. Each cell in the matrix shows the coefficient from a different regression, corresponding to a different perpetrator-victim pair. Rows correspond to perpetrators and columns to victims. A number of interesting

[14]As per ACLED, rebel groups are violent actors with a stated political agenda for national power. Political militias are actors with a political purpose who do not seek the removal of a national power. Ethnic militias are violent groups who claim to operate on behalf of a larger identity community (Raleigh & Dowd, 2016).

patterns arise. The main perpetrators of attacks induced by SPEI shocks are political militias and rioters attacking mostly the government and rebel forces. This supports the opportunity cost interpretation, but is also compatible with a state capacity effect. Rioters, protesters, and civilians are also victimized, consistent with our finding that SPEI shocks lead to violence against civilians. Of the non-government victims, ethnic and political militias seem unaffected by SPEI shocks, possibly because their recruiting strategies may be more identity-based.

5.5 Conflict onset and termination

Our analysis so far has focused on conflict incidence. We now briefly discuss the results for conflict onset and termination, which we report in Appendix Table A7. Conflict onset is a binary indicator that takes value 0 in years of peace and 1 in the first year in which a cell experiences conflict, and is missing in subsequent conflict years. Conflict termination equals 0 in years of conflict and 1 in the first year with no conflict after a spell of conflict, and is missing in subsequent peace years.[15] In Table A7 we present estimates of Model II for onset and termination. As explained in section 2.2, we cannot estimate Model III with these dependent variables because the estimation of autoregressive Durbin models requires a balanced panel. Table A7 should thus be taken cautiously, as Model II does not account for direct conflict spillovers.

Our explanatory variable of interest, *SPEI Growing Season*$_{t-1}$, is significantly correlated with the onset of conflict broadly defined (column 1) and especially the onset of battles (column 2), violence against civilians (column 3), and non-violent rebel activities (column 5). Relative to the

[15]Since the majority of cell/years in the sample experiences no conflict events, conflict termination is non-missing in a very small sample. This prevents us from disaggregating by type of event when analyzing conflict termination.

mean of the dependent variable, the impacts are largest for rebel activities, followed by violence against civilians, mirroring our findings for conflict incidence. This suggests that agriculture-relevant shocks might be especially important as local triggers of new conflict spells, particularly through the opportunity cost channel. The effect is negative but insignificant for conflict termination (column 6).

6 Robustness

In this section we explore the sensitivity of our estimates to different grid resolutions, different choices of spatial weighting matrix, and alternative climate indicators.

6.1 Sensitivity to spatial resolution and distance

Just as in time series the structure of temporal dependence is assumed by the researcher and is not estimated, so is the structure of spatial dependence implied by the choice of grid resolution and spatial weighting matrix. In Appendix Table A8 we present our benchmark specification (Table 2, column 5) estimated on gridded datasets of different spatial scales.[16] In column 1 we consider a higher-resolution 0.5×0.5-degree grid, placed in such a way that four 0.5-degree cells are contained in one of our benchmark 1-degree cells. In columns 2 to 5 we consider a lower-resolution 2×2 grid, obtained aggregating four of our 1×1 original cells in a single "macro-cell." This coarser grid can be constructed in four different ways, depending on where such "macro-cells" are centered; hence we report estimates obtained with each of these four grids.[17] The 1-degree grid

[16]This exercise addresses the Modifiable Areal Unit Problem (MAUP) that commonly arises with spatial data (Heywood, Cornelius, & Carver, 1998).

[17]When estimating our specification for the 0.5- and the 2-degree grids, we employ binary contiguity matrices with cutoffs of 90 and 390 km respectively, so that each cell's neighborhood is

we used throughout the paper appears to provide more precise estimates than those obtained with higher or lower resolutions, validating our choice. The effects of SPEI may not be captured at very high resolutions because a drought in a limited area may not have enough of an impact on local incomes when there is smoothing across agricultural markets; at the same time, the effects may be washed out at lower resolutions because fixed effects at the macro-cell level may absorb too much of the variation.

In Appendix Table A9 we turn to the choice of spatial weighting matrix. The latter is particularly relevant as the exclusion restriction on which our MLE estimates are based is that shocks occurring in second-order neighbors do not directly affect conflict in the own cell. The most popular choices in the literature are binary contiguity matrices, that we consider in columns 1 to 3, and matrices based on the inverse geographic distance, which we examine in columns 4 to 6. In columns 1 to 3 we estimate our model using binary contiguity matrices with different distance cutoffs: 290, 450 and 600 km.[18] When we increase the radius of our distance matrix, the coefficient on *SPEI Growing Season*$_{t-1}$ becomes increasingly smaller and eventually loses significance. The temporal autoregressive coefficient is very stable around the value of .12 and is significant at the 1 percent level in all specifications. On the other hand, as expected, the choice of weighting matrix does affect the spatial autoregressive coefficient (the coefficient on $W \cdot Y$), which decreases in magnitude as we increase the distance cutoff. This is intuitive: as we add neighbors farther away from the cell, the impact of the average neighbor is driven down. These patterns are confirmed in

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formed by the eight adjacent cells at both resolutions.

[18]With distance cutoffs of 290, 450, and 600 km the average number of neighbors for each cell is respectively 18, 44, and 81.

columns 4, 5, and 7, in which we employ an inverse distance-based weighting matrix.

6.2 Other climate indicators

In Appendix Table A10 we turn to other potential climate indicators and functional forms, including stand-alone SPEI averaged over the entire year (column 1), a measure of drought spells (column 2), nonlinear effects of *SPEI Growing Season* (column 3), and an extended version of this variable that includes the three main crops instead of just the main one (column 4). Details are provided in the Online Appendix, section E. Results obtained with SPEI-based indicators are qualitatively consistent with our benchmark, although only the first lag of our main variable of interest remains significant in column 3. The coefficients on plain measures of rainfall and temperature, averaged over the growing season, have the expected signs but are mostly insignificant.

The contrast with the existing literature, which finds significant effects of rainfall and temperature, may be rationalized by observing that our specification with both spatial and temporal lags of the dependent variable absorbs a lot of the variation in conflict, which is already reduced by the inclusion of cell fixed effects. The richness of SPEI, which embeds information on precipitation and temperature but also on latitude, month of the year, number of sunlight hours, etc., allows us to obtain more precise estimates when we use our benchmark variable.

6.3 Alternative data sources and specifications

In Appendix Table A11 we explore robustness to the choice of conflict dataset by reestimating Table 2 employing the UPCDP-GED dataset, described in the Online Appendix, section A. The qualitative patterns are similar to those obtained with ACLED, although the coefficient on *SPEI Growing Season*$_{t-1}$ becomes smaller and insignificant as we add autoregressive terms, arguably because GED data features less variation in the dependent variable.[19] In terms of magnitudes, according to Model III estimates in columns 3 to 5, the impact of a one standard deviation increase in *SPEI Growing Season* reduces GED-based conflict incidence in the following year by 5% to 7% of the mean of the dependent variable, in line with our ACLED-based estimates.

In Appendix Table A12 we consider different temporal lag structures and find that the significance of the first lag is consistent across specifications. As a placebo, in column 3 we also include a specification with four lags and four leads in *SPEI Growing Season*. Reassuringly, we find leads not to be significant conflict predictors.

7 Conclusions

In this paper we conduct a spatially disaggregated analysis of the determinants of conflict in Africa over the period 1997 through 2011. We exploit within-year variation in the timing of weather shocks and in the growing season of different crops, as well as spatial variation in crop cover, to construct an original measure of weather that is relevant for agricultural production. We find that improved weather during the growing season of the main crops cultivated in the cell significantly reduces conflict incidence. We use state-of-the-art spatial econometric techniques to test for the presence of temporal and spatial spillovers in conflict, and we find both to be sizable and highly significant. These results indicate that caution should be exercised when interpreting results of studies that do not incorporate spatial dynamics. Finally, we use our estimates to predict potential future conflict scenarios induced by climate change, under the assumption that the responsiveness of conflict to weather shocks remains constant in the next decades. Using a variety of models

[19]Another potential explanation is that GED records only events involving casualties, within conflicts that involve at least 25 battle-related deaths per year, whereas ACLED also codes low-intensity conflict episodes.

and emissions scenarios, we predict that shocks occurring during the growing season, as per the definition of our main explanatory variable, should become 5.4 times more pronounced during the next 35 years. This in turn leads to an increase in average conflict incidence of 7 percent. Our findings indicate that the correlates of civil conflict have a strong local dimension and that the likelihood of conflict is not constant in time or in space, even within the same country. This suggests that policy interventions, be they in the form of monitoring, prevention, or peacekeeping efforts, should be targeted in space and time. Our results may be especially relevant when assessing appropriate policy responses to global warming scenarios. Given the link we trace between shocks affecting agricultural yields and conflict risk, policies aimed at mitigating the effects of climate change on agriculture may be particularly desirable. These include the development of drought-resistant crop varieties, investments in irrigation, and schemes to improve soil water retention. On the other hand, complementary measures to reduce the adverse impacts on incomes, such as weather-indexed crop insurance, also constitute a valuable policy option. Finally, given the increasing availability of high-resolution data (e.g., gridded datasets) and the growing number of research contributions that employ these data to address important development questions, we hope our study can provide a number of insights and methodological indications that are useful for future work.

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Table 1: Summary Statistics

	No. Obs.	Mean	Std. Dev.
ANY EVENT	35042	0.170	0.376
BATTLE	35042	0.097	0.295
CIVILIAN	35042	0.099	0.299
RIOT	35042	0.056	0.231
REBEL	35042	0.030	0.170
SPEI	35042	-0.114	0.571
SPEI Growing Season	35042	-0.025	0.365

Notes: Each observation is a cell/year.

Table 2: Conflict incidence and climate, panel

Dependent variable (Y)=1 if conflict event in year t (ANY EVENT)

	(1)	(2)	(3)	(4)	(5)
	Model I	Model II	Model III	Model III	Model III
	OLS	OLS	MLE	MLE	MLE
Y_{t-1}			0.333***	0.342***	0.121***
			(0.00759)	(0.00769)	(0.00849)
$W{\cdot}Y$			0.0449***	0.0291***	0.0229***
			(0.00116)	(0.00127)	(0.00150)
SPEI	0.0334***	0.0150	0.00458	0.00216	-0.00491
	(0.00690)	(0.0144)	(0.0127)	(0.0131)	(0.0132)
SPEI, $_{t-1}$	0.00112	0.0199	0.0107	0.0252*	0.0148
	(0.00698)	(0.0141)	(0.0136)	(0.0142)	(0.0130)
SPEI, $_{t-2}$	0.00883	0.00659	-0.00190	-0.00990	-0.0145
	(0.00701)	(0.0151)	(0.0132)	(0.0138)	(0.0126)
SPEI Growing Season	-0.0329***	-0.00217	0.00122	0.00430	0.0207
	(0.0121)	(0.0149)	(0.0135)	(0.0136)	(0.0129)
SPEI Growing Season, $_{t-1}$	-0.0300**	-0.0399***	-0.0400***	-0.0498***	-0.0367***
	(0.0118)	(0.0148)	(0.0153)	(0.0152)	(0.0139)
SPEI Growing Season, $_{t-2}$	-0.0335***	-0.0238	-0.0145	-0.00523	-0.00925
	(0.0121)	(0.0156)	(0.0144)	(0.0146)	(0.0140)
W·SPEI		0.00379	0.00187	0.00202	5.88e-06
		(0.00234)	(0.00194)	(0.00222)	(0.00220)
W·SPEI, $_{t-1}$		-0.00287	-0.00235	-0.00376	-0.00451**
		(0.00230)	(0.00210)	(0.00239)	(0.00219)
W·SPEI, $_{t-2}$		0.00101	0.00139	0.00453**	0.00329
			(0.00201)	(0.00228)	(0.00211)
W·SPEI Growing Season			-0.00284	-0.00427*	-0.00420*
			(0.00226)	(0.00252)	(0.00248)
W·SPEI Growing Season, $_{t-1}$			0.00464*	0.00621**	0.00648**
		(0.00279)	(0.00250)	(0.00267)	(0.00257)
W·SPEI Growing Season, $_{t-2}$		-0.00260	5.54e-05	-0.00167	0.000522
		(0.00288)	(0.00234)	(0.00261)	(0.00260)
Observations	35,042	35,042	35,042	35,042	35,042
Controls	X	X	X	X	
Year FE	X	X	X		
Country-specific time trend	X	X	X		
Country x Year FE				X	X
Cell FE					X

Notes: Each observation is a cell/year. Standard errors in parenthesis. Columns 1 and 2 corrected for spatial and serial correlation following Hsiang (2010). Columns 3 through 5 corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1. W = binary contiguity matrix, cutoff 180 km.

Table 3: Channels of Impact

Dependent variable (Y)=1 if conflict event in year t (ANY EVENT)

	(1)	(2)	(3)	(4)	(5)
Variable Z is:	Roads	Tax to GDP ratio	Polity Score	Number of Discriminated Groups	Partition
Y_{t-1}	0.121***	0.0209	0.121***	0.121***	0.121***
	(0.00850)	(0.0192)	(0.00848)	(0.00849)	(0.00849)
$W \cdot Y$	0.0228***	0.0108***	0.0228***	0.0227***	0.0227***
	(0.00150)	(0.00349)	(0.00150)	(0.00151)	(0.00150)
SPEI Growing Season	0.0150	0.0774	0.0202	0.0239*	0.0197
	(0.0137)	(0.0612)	(0.0128)	(0.0135)	(0.0129)
SPEI Growing Season, $_{t-1}$	-0.0264*	-0.176***	-0.0372***	-0.0297**	-0.0339**
	(0.0149)	(0.0634)	(0.0138)	(0.0146)	(0.0140)
SPEI Growing Season, $_{t-2}$	-0.0165	-0.0357	-0.00942	-0.0102	-0.0117
	(0.0151)	(0.0704)	(0.0140)	(0.0143)	(0.0140)
SPEI Growing Season × Z	0.0133	-0.00258	-0.00141	-0.00431	0.00902
	(0.0135)	(0.00349)	(0.00196)	(0.00526)	(0.0174)
SPEI Growing Season, $_{t-1}$ *× Z*	-0.0244*	0.00906**	-0.000115	-0.00943**	-0.0254
	(0.0133)	(0.00371)	(0.00213)	(0.00448)	(0.0167)
SPEI Growing Season, $_{t-2}$ *× Z*	0.0180	0.00269	-0.00119	0.00175	0.0141
	(0.0141)	(0.00420)	(0.00210)	(0.00540)	(0.0165)
Observations	35,042	6,822	35,042	35,042	35,042
W· SPEI variables	X	X	X	X	X
Country x Year FE	X	X	X	X	X
Cell FE	X	X	X	X	X

Notes: Each observation is a cell/year. Estimation by MLE. Standard errors in parenthesis corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1. W = binary contiguity matrix, cutoff 180 km.

Table 4: Heterogeneous Conflict Spillovers, Panel

Dependent variable (Y)=1 if conflict event in year t (ANY EVENT)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Same country		Different country	
Neighbors included in W	Same Country	Different Country	Same Main Group	Different Main Group	Same Main Group	Different Main Group	Same Main Group	Different Main Group
W·Y	0.0217***	0.0308***	0.0222***	0.0248***	0.0217***	0.0219***	0.0275***	0.0340***
	(0.00168)	(0.00372)	(0.00186)	(0.00281)	(0.00199)	(0.00339)	(0.00561)	(0.00475)
Observations	35,042	35,042	35,042	35,042	35,042	35,042	35,042	35,042
Country x Year FE	X	X	X	X	X	X	X	X
Cell FE	X	X	X	X	X	X	X	X

Notes: Each observation is a cell/year. Estimation by MLE. Standard errors in parenthesis corrected for clustering at the cell level.

*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Different Types of Conflict Events, Panel

Dependent variable:	*Battle*	*Civilian*	*Riot*	*Rebel*
	(1)	(2)	(3)	(4)
Y_{t-1}	0.131***	0.109***	0.0705***	0.138***
	(0.0106)	(0.0101)	(0.0119)	(0.0165)
W·Y	0.0233***	0.0236***	0.00438**	0.0104***
	(0.00174)	(0.00177)	(0.00200)	(0.00230)
SPEI	0.00620	-0.0190*	-0.00502	-0.0133**
	(0.0108)	(0.0109)	(0.00876)	(0.00672)
SPEI, $_{t-1}$	-0.000270	0.0134	0.0180*	0.0127*
	(0.0107)	(0.0106)	(0.00927)	(0.00707)
SPEI, $_{t-2}$	0.00154	-0.000397	-0.0149	-0.0107
	(0.0103)	(0.0101)	(0.00930)	(0.00653)
SPEI Growing Season	0.0133	0.0230**	0.0180**	0.0108
	(0.0109)	(0.0113)	(0.00903)	(0.00738)
SPEI Growing Season, $_{t-1}$	-0.0289**	-0.0454***	-0.0148	-0.0193**
	(0.0116)	(0.0120)	(0.00972)	(0.00783)
SPEI Growing Season, $_{t-2}$	-0.0203*	-0.00800	0.0198**	0.00979
	(0.0122)	(0.0109)	(0.00928)	(0.00764)
W·SPEI	-0.00227	0.00292	0.000648	0.00156
	(0.00179)	(0.00179)	(0.00139)	(0.00108)
W·SPEI, $_{t-1}$	-0.00211	-0.00334*	-0.00169	-0.00216*
	(0.00187)	(0.00174)	(0.00150)	(0.00113)
W·SPEI, $_{t-2}$	-0.000699	0.000674	0.00319**	0.00177*
	(0.00181)	(0.00171)	(0.00146)	(0.00107)
W·SPEI Growing Season			-0.000539	-0.000973
			(0.00152)	(0.00130)
W·SPEI Growing Season, $_{t-1}$			0.00127	0.00252*
			(0.00166)	(0.00138)
W·SPEI Growing Season, $_{t-2}$	0.00446**	0.00171	-0.00444***	-0.00249*
	(0.00224)	(0.00199)	(0.00159)	(0.00135)
Observations	35,042	35,042	35,042	35,042
Country x Year FE	X	X	X	X
Cell FE	X	X	X	X

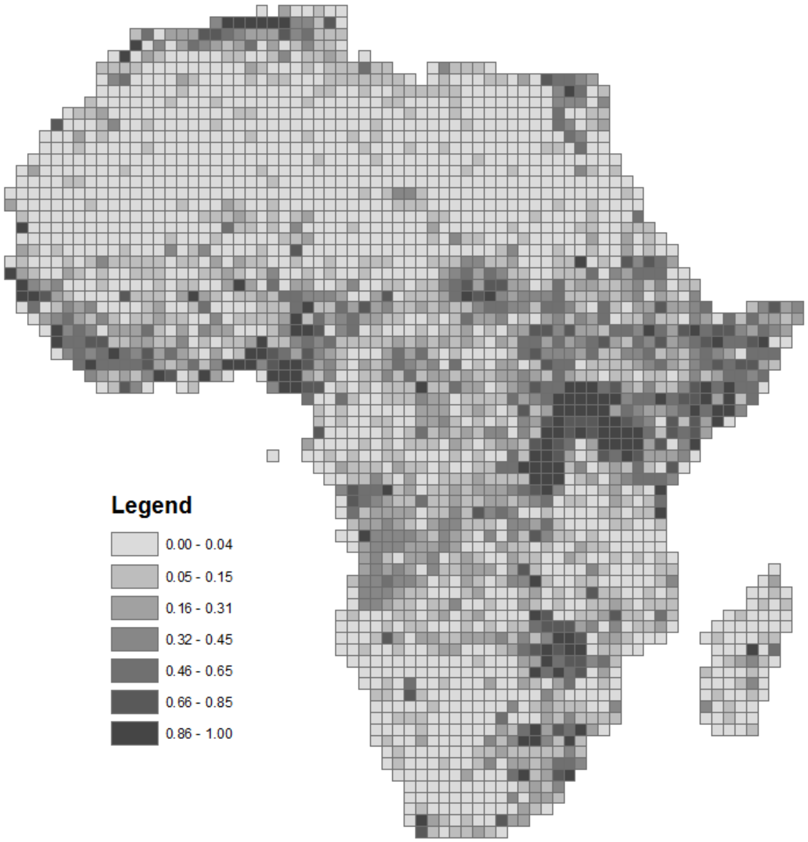
Notes: Each observation is a cell/year. Estimation by MLE. Standard errors in parenthesis corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1. W = binary contiguity matrix, cutoff 180 km.

Table 6: Perpetrators and Victims, Panel

Dependent variable (Y)=1 if conflict event in year t (ANY EVENT)

		Coefficients of SPEI Growing Season, $_{t-1}$				
		ACTOR 2 (Victim)				
		Government	Rebel force	Political militia	Ethnic militia	Rioters, protesters, and civilians
ACTOR 1 (Perpetrator)	Government	-0.0185**	-0.0221**	-0.00625	-0.00428	-0.0267***
	Rebel force	-0.0102	-0.0134*	-0.00365	-0.00276	-0.0144**
	Political militia	-0.0274***	-0.0259***	-0.00626	-0.00352	-0.0300***
	Ethnic militia	-0.0127**	-0.00456	-0.00600	-0.00634	-0.00914
	Rioters, protesters, and civilians	-0.0236***	-0.0127*	-0.0127*	-0.00246	-0.0175**

Notes: Each observation is a cell/year. Estimation by MLE. Standard errors in parenthesis corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1. W = binary contiguity matrix, cutoff 180 km.



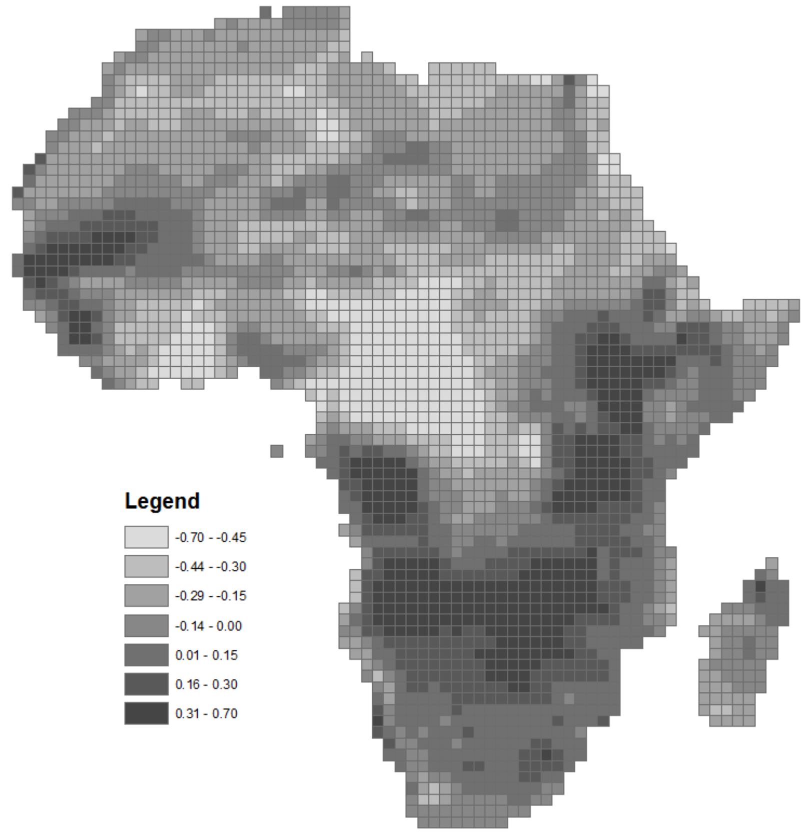


Figure 1A:

Fraction of years with at least one conflict event (1997-2011)

Figure 1B:

Average SPEI, 1997-2011

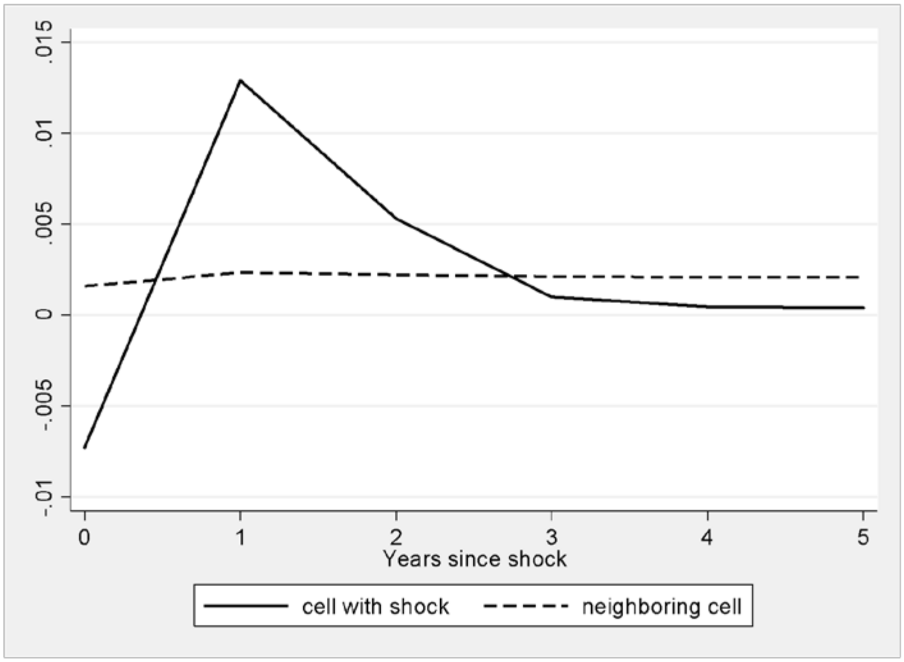


Figure 2a:

Dynamic impact of a one-time SPEI Growing Season shock on conflict incidence

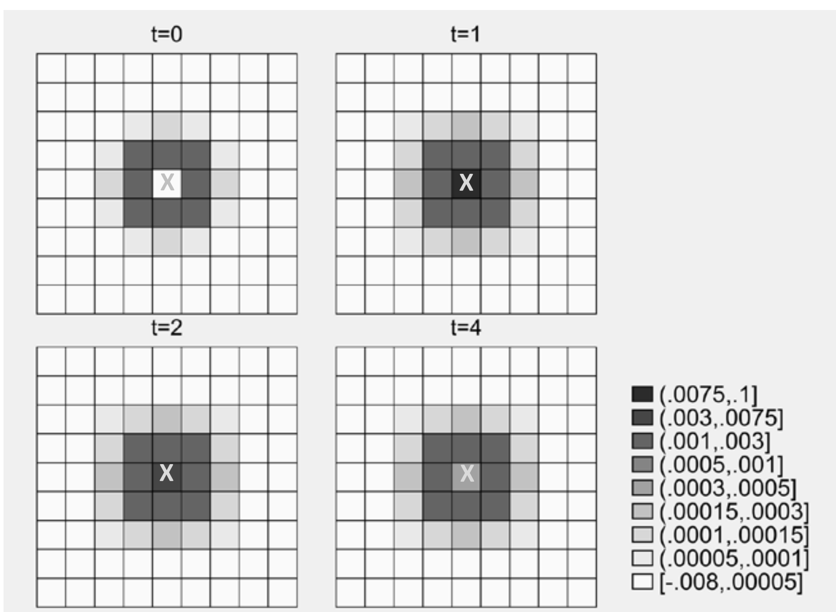


Figure 2b:

Spatial impact of a one-time SPEI Growing Season shock on conflict incidence