Conflict, Climate and Cells: A disaggregated analysis*

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Abstract

We conduct a geographically and temporally disaggregated empirical analysis of civil conflict at the sub-national level in Africa over the period 1997-2006. Our units of observation are cells of 1 degree of latitude by 1 degree of longitude. 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 shocks that are relevant for agricultural production. Employing a new draught index we show that negative climate shocks which occur during the growing season of the main crops cultivated in the cell have a sizeable effect on conflict incidence. This effect is persistent over time and to a lesser extent in space. We also 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 sizeable and highly statistically significant. Exploiting variation in the type of conflict episode, we find that the impact of climate shocks on conflict is particularly significant when focusing on outcomes such a rebel recruitment.

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1 Introduction

Sub- Saharian Africa is both the world's poorest region and the region which has experienced, in the past 60 years, the most armed conflicts, the majority of which are civil conflicts (Blattman and Miguel, 2010). Poverty and internal conflict appear to be tightly linked throughout the world: the correlation between low per capita incomes and higher propensities for internal war is one of the most robust empirical relationships in the literature. In the past decade, it has become increasingly clear that understanding the causes and consequences of civil conflict should have a prominent place in the development economics agenda. A major focus in the empirical research on conflict has been the role of economic fluctuations in shaping conflict risk. The relationship between weather shocks and civil conflict was first highlighted by Miguel et al. (2004), who detected a reduced form negative relationship between rainfall shocks and conflict incidence. The link between climate and conflict has attracted considerable attention ever since, further motivated by accumulating evidence on the potentially disruptive effects of climate change.

We attempt at making a step further in understanding the relationship between climate shocks and civil conflict by taking the analysis to a different scale. We conduct a geographically disaggregated analysis which takes as units of observation 100 x 100 km subnational "cells", and we estimate the incidence of conflict in a cell as a function of climate 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 existing literature in three directions.

The first is methodological. We disaggregate the level of analysis both in space and time, constructing a cell-year panel with a rich set of georeferenced covariates. This disaggregated level of observation allows us to take a closer look at a number of geographic covariates, which have been claimed to be predictors of conflict but which have so far been measured at an arguably wrong scale. More importantly, it enables us to detect previously neglected within-year and within-country patterns. Our disaggregated approach is accompanied by a careful modelling of spatial dependence and thorough state-of-the-art spatial econometrics techniques which have seldom been applied in economics. In particular, we estimate a model that 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. As we explain in the next section, this poses a number of challenges for estimation and constitutes an original contribution to the empirical conflict literature, and one which is particularly crucial when dealing with highly disaggregated data.

The second contribution is that we look at climate indexed *within* the year. Because the main channel linking climate shocks and conflict operates through shocks to agricultural incomes, we attempt to isolate the component of annual climate variability which is relevant for agriculture. In other words, instead of using climate indicators aggregated over the whole year (e.g., average yearly rainfall), we construct specific indicators for climatic conditions during the growing season, which is when crops are most sensitive to unfavorable conditions. This is a data intensive process as it requires a number of steps: identifying the main crops cultivated in each cell; finding the growing season of this crops (which varies across cells); and matching this information with high frequency climate data. In other words, we exploit both within-year variation in the timing of weather shocks as well as spatial variation in crop cover to construct an original measure of agriculture-relevant weather shocks. Once we isolate the impact of the weather shock component which effectively affects local agriculture, we find evidence that this is what drives the overall observed local negative relationship between conflict episodes and weather.

A third contribution relates to the climate indicator we employ. While most of the conflict literature so far has focused on precipitation, we use a multiscalar drought index that 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. This in turn depends on the characteristics of the soil and on the extent to which sunshine induces evaporation. The climate indicator we use in our benchmark specification, the Standardized Precipitation-Evapotranspiration Index (SPEI) , has been recently developed by Vicente-Serrano et al. (2010) and considers the joint effects of precipitation, potential evaporation and temperature. We also explore robustness to using traditional measures of precipitation and temperature.

Our main results can be summarized as follows. We find evidence of a local-level negative relationship between civil conflict episodes and agriculture-relevant weather shocks. In particular, we consider a new draught index (the Standardized Precipitation-Evapotranspiration Index, SPEI) which improves upon crude rainfall measures and provides a better measure of the effective amount of moisture received by the soil. We show that "effective rainfall" as captured by SPEI has a negative impact on conflict incidence only when occurring in the growing season months of the main crops cultivated in the area. This effect is sizeable: a one standard deviation negative shock in SPEI induces an approximate 5 percentage point increase in local conflict incidence in the subsequent year and a 3 percentage point in the year after that.

We show that crude, individually taken weather indicators such as precipitation and temperature are not strong predictors of conflict at such high spatial resolution. Moreover, even controlling for rainfall and temperature as such, SPEI retains significance, suggesting that location-specific geographic factors interact in crucial ways with climatological phenomena.

Our innovative econometric approach allows us to investigate also patterns of propagation of conflict in time and space. Conflict appears very clustered in space, and our estimation results suggest that this is partly driven by direct spillovers. The magnitude of the effect of conflict in another cell is found to decrease with the distance of the cell from the one under consideration, as one would expect. Conflict persistence in time appears to be even more relevant, as highlighted by a large, robust autoregressive component. Overall this seems to suggest that small, one-time shocks can have potential far-reaching effects through conflict's propensity to propagate.

Drawing upon the rich disaggregation of conflict events of the ACLED dataset, we can also look at individual types of conflict episodes to have a better understanding of the channels of causation. We find that agriculture-relevant weather shocks impact mostly non-violent activities carried out by rebels, which include recruitment and the establishment of headquarters. This is consistent with theories which emphasize fluctuations in the "opportunity cost" of joining a civil conflict as important predictors of conflict onset. Finally, the scale of our study also allows us to take a closer look at the relationship between time-invariant local characteristics – such as mineral endowments and terrain ruggedness – without encountering in the "ecological fallacy" most of the cross country literature runs into.[1] We find that terrain ruggedness and the presence of mineral resources are strong local conflict predictors.

Our work is mostly related to two strands of the literature: that on civil conflict determinants and that on climate and development.

The idea that economic shocks affect civil conflict dates back to the "greed" ad "grievance" models of Collier and Hoeffler (1998). Based on Herschell and Grossman's (1991) theoretical model of insurrections, Collier and Hoeffler emphasized an opportunity cost channel linking economic conditions with conflict onset: when income is low, the opportunity cost of joining a rebellion is lower, leading to increased likelihood of conflict. However, there could also be a "greed" effect positively linking conflict likelihood and economic conditions, as the potential benefits from insurgency also increase during economic upturns. The relative effectiveness of fighting technology for rebels vs. the government is also believed to affect the cost of insurgency; this leads to the prediction that conflict should be more prevalent in areas characterized by the presence of closed terrain to provide "safe havens" for insurgents. More recently, Dal Bo & Dal Bo (2004) develop a model in which positive shocks to labor intensive industries diminish conflict, while positive shocks to capital intensive industries increase it. Chassang and Padro-i-Miquel (2009) develop a theoretical model which predicts higher conflict likelihood following an economic shock, through the channel of lower opportunity cost of fighting; the key is that transient economic shocks increase the immediate incentives to fight but not the discounted present value of victory.

[1] The so called "ecological fallacy" derives from the fact that inference about the nature of individual or local level relationships is drawn only from aggregate statistics for the countries to which those individuals or localities belong.

Based on these theoretical channels, a vast empirical literature has blossomed, focusing on factors such as natural resources, terrain ruggedness, ethnic fractionalization and economic shocks as conflict catalysts. Most first generation quantitative studies consisted of cross country regressions focusing on explanatory variables related to "greed" and "grievance" (Fearon and Laitin, 2003), whereas recent contributions have started to look at more local factors (Buhaug et al., 2011; Besley and Reynal-Querol, 2012). A large body of literature has focused on weather driven economic shocks and civil conflict. Miguel et al. (2004) were the first to highlight a relationship between rainfall driven economic shocks and conflict incidence in Sub Saharan Africa. Recently, a number of papers (Ciccone, 2011; Jensen, Sandholt and Gleditsch, 2009) have reconsidered the link between rainfall and conflict, indicating that mean-reverting properties and the spatial correlation in rainfall have not been taken into account. This suggests that the relationship between conflict and weather shocks deserves to be more carefully evaluated, in particular it has been argued that "uncovering an effect of rainfall on civil conflict will require using more disaggregated data" (Ciccone, 2011).

A second strand of the literature related to our work is that on climate and development. Motivated by the debate on the economic consequences of global warming, recent studies have looked at the impact of temperature on economic activity. Dell, Jones and Olken (2012) find that higher temperatures substantially reduce economic growth in poor countries, while Schlenker and Lobell (2010) highlight the negative impact of climate change on African agriculture. Some of these studies have also moved beyond the conventional country-year framework by looking at within-year weather fluctuations: Burgess et al. (2011) study how weather shocks impact mortality in India by looking at high frequency variations in rainfall and temperature and conclude that only shocks occurring after the monsoon are relevant. Kudamatsu, Persson and Strömberg (2011) explore a similar question with African data and conclude that weather shocks had a significant impact on child mortality through the channels of malaria and malnutrition.

The remainder of the paper is organized as follows. In section 2 we present our econometric methodology. In section 3 we document our data sources and dataset construction, and we provide some descriptive statistics on the variables of interest. In Section 4 we discuss the econometric evidence at the cross-sectional (cross-cell) level; while in section 5 we conduct the main analysis exploiting both cross-sectional and time variation, and focusing on climatic shocks.

2 Methodology

We construct a dataset which has the structure of a raster grid: the cross-sectional units of observations are subnational "cells" of 1 degree of latitude x 1 degree of longitude, whose sides are placed in correspondence of integer values of latitude and longitude.

At these latitudes, 1 degree corresponds on average to approximately 110 km. This "grid" approach is followed, among others, by Buhaug and Rød (2006), Dell (2011) and Alesina, Michalopoulos and Papaioannou (2012). An alternative way to conduct a subnational analysis would be to consider administrative units. However, the way in which a country is split into administrative units is in itself the outcome of a political decision: it may take into account both geographical and demographic features of the territory which could all be arguably determinants of conflict themselves, or jointly determined with it. The supposed advantage of using administrative units is that data on income, population or inequality are often available at the administrative level; however, such variables are almost inevitably endogenous to conflict and incorporating them in a conflict regression is at least problematic. Our approach is one which takes as unit of observation an entity whose borders are truly exogenous to conflict, by ideally superimposing a grid of equally-sized cells on the territory of interest.[2]

The bulk of our empirical analysis is conducted at the cell/year level. Our main dependent variable is *ANY EVENT*, a binary measure of conflict incidence indicating whether the cell has experienced a conflict-related episode - of any of the categories included in the ACLED dataset - over the course of the year. In order to investigate the local level relationship between climate and conflict incidence we estimate three models. Consider a panel of N cells *indexed by c,* and T years indexed by t. Denote with C a generic climate indicator (e.g., precipitation) and with GS_C the climate indicator measured in the cell-specific growing season (see below). Let X be a vector of controls with no time variation - such as terrain characteristics, and γ and μ denote year and country fixed effects, respectively. Model I takes the following form:

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

where c denotes the cell, i the country and t the year. This specification is essentially the transposition of state-of-the-art cross country conflict regression equations - à la Ciccone (2011) - at a high spatial resolution.

Our dependent variable is binary and several conflict regressions in the literature using a binary dependent variable resort to logit estimators. However, we prefer to conduct the estimation by OLS, thus fitting an unrestricted linear probability model. The reason is twofold. On the one hand, this can be easily integrated with state-of-the-art spatial econometrics techniques, which so far have not been explicitly developed for

[2] One potential difficulty arising when such units of observations are used is the so-called "Modifiable Aeral Unit Problem" (MAUP). We address this issue in section 5.

limited dependent variables. On the other hand, it has been argued that when dealing with "rare events", such as wars, logit and probit may yield biased estimates (King and Zeng, 2001).

One key feature of our data is spatial correlation. Most empirical work in the conflict literature implicitly assumes that observations are independent across space, and thus does not take spatial correlation nor spatial dependence into account. When dealing with georeferenced, cross-sectional data with potential spatial dependence the majority of the development literature conducts OLS estimation with Conley (1999) standard errors, which are robust to spatial dependence of unknown form in the error term (e.g., Dell, 2010). We estimate model I by OLS and we apply such a correction to our standard errors, following the procedure of Hsiang (2010) and adjusting standard errors for both spatial and serial correlation.

This is appropriate in cases in which spatial correlation is present in the error term ("spatial error model"), however it does not address the issue of how to explicitly model spatial dependence in the process itself. We expect spatial correlation to be present both in the georeferenced covariates – for example, mineral deposit presence or climatological events – and in conflict itself, through direct cross-cell spillovers. A simple way of controlling for spatial correlation in the covariates is to include spatial lags of the variables of interest, just as in time series it is common to include temporal lags. In spatial econometrics the structure of spatial dependence between observations is defined through a symmetric weighting matrix W, and the spatial lag of a given variable is obtained 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 Model II:

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

$$+ \sum_{k=0}^{2} \theta_{1k} W \cdot C_{t-k} + \sum_{k=0}^{2} \theta_{2k} W \cdot GS\_C_{t-k} + \lambda W \cdot X + W \cdot \mu + \gamma_t + \varepsilon_{c,i,t}$$

This is a spatial Durbin model (Anselin, 1998) in which we let conflict in one cell depend on covariates observed not only in the cell itself, but also in the neighboring cells. Since the structure of spatial dependence cannot be directly estimated but can only be assumed, the choice of the weighting matrix is always a crucial issue. Spatial econometricians recommend to base one's decision on the underlying context and to conduct a sensitivity analysis to different choices of matrices (Pluember and Neumayer, 2010). A popular choice is that of a binary contiguity matrix in which a weight of 1 is assigned to cells surrounding the cell of interest - within a given distance cutoff -, and a weight of 0 to other cells. Our benchmark connectivity matrix is a binary matrix with distance cutoff set to 290 km. Because 290 km is the radius of the circle drawn around the cell's center, and each cell is a square with sides of approximately 110 km, this connectivity matrix implies that we effectively consider as neighbors of a given cell the 8 bordering cells plus those immediately adjacent to them. In section 5 we discuss our choice of the weighting matrix and we conduct a sensitivity analysis to different spatial matrices.

Following a common procedure in the spatial econometrics literature, we row-standardize the connectivity matrix W . The coefficients on the spatial lags should thus be interpreted as the effect of the average of a given variable in the neighborhood of each cell. This model has the advantage of simplicity, since including spatial lags of the independent variables is straightforward and poses no particular econometric concerns. Standard errors are corrected for spatial and temporal correlation à la Hsiang (2010).

However, we expect spatial correlation to be present not only in the covariates, but also in conflict itself. Allowing for spatial autocorrelation in the dependent variable, in order to capture direct conflict spillovers, is more problematic than allowing for spatial correlation in the controls due to an obvious simultaneity problem. Part of the observed spatial correlation in conflict location is to be attributed to the fact that conflict determinants are spatially correlated themselves; part of it, on the other hand, is to be attributed to direct contagion effects. Disentangling these two effects is in general difficult, as it is a version of the well-known reflection problem (Manski, 1993). Models allowing for spatial dependence in the dependent variable are known as spatial autoregressive models. They have been mostly developed for cross-sectional models, and have only recently been extended to panel data (LeSage & Pace, 2009; Elhorst, 2010 among others). These models are estimated with maximum likelihood or GMM techniques and tend to be computationally intensive.

A further complication arises in our context, since in addition to spatial autocorrelation we expect the process of conflict to be autocorrelated in time as well. To fully incorporate both sources of autocorrelation we estimate Model III:

$$ANY\ EVENT_{c,i,t} = \phi ANY\ EVENT_{c,i,t-1} + \rho W \cdot ANY\ EVENT_t + \tag{3}$$

$$\alpha + \sum_{k=0}^{2} \beta_{1k} C_{c,t-k} + \sum_{k=0}^{2} \beta_{2k} GS\_C_{c,t-k} + \delta X_c + \mu_i +$$

$$+\sum_{k=0}^{2}\theta_{1k}W\cdot C_{t-k}+\sum_{k=0}^{2}\theta_{2k}W\cdot GS\_C_{t-k}+\lambda W\cdot X+W\cdot\mu$$

$$+\gamma_t+\varepsilon_{c,i,t}.$$

This is a dynamic, spatially autoregressive Durbin model (Elhorst, 2010) in which we let conflict in one cell depend on lagged conflict in the cell itself, on contemporaneous conflict in the neighboring cells, on covariates in the cell itself and on covariates in the neighboring cells. To our knowledge, this is the first time a spatio-temporal autoregressive model is applied in the empirical conflict literature.

An obvious identification challenge is posed by the endogeneity of the first two regressors, which requires these models to be estimated either by GMM or maximum likelihood. We use the routines developed by Hughes (2012), which are based on quasi-maximum likelihood techniques described in Elhorst (2009) and Parent and LeSage (2009). In particular, we fit a random effects model estimated applying the full maximum likelihood method described in Parent and Le Sage (2009), which treats the value of the dependent variable for the initial time period as exogenous and uses the data for *t=2*... T in the estimation (see appendix note 1 for details). Standard errors are clustered by cell.

Note that the impact of a covariate X in a given cell on the independent variable Y in that same cell is not entirely captured by the β parameter estimates in equation (3): there is also an additional feedback effect due to the fact that each X affects through λ the Y's of neighboring cells too, which in turn affect the Y of the cell itself through the spatially autoregressive term. The impact as estimated by the coefficient plus this feedback effect compose what is known as the "direct effect". On the other hand, indirect effects estimates measure the impact of changing an independent variable in a particular unit on the dependent variable of all other units (LeSage and Pace, 2009). Total effects are the sum of direct and indirect effects. Both these effects can be computed rearranging the equation for Model III (see appendix note 2 for details*).* We report direct and total effects in all of our main specifications.

The explicit inclusion of spatially and temporally autoregressive terms represents an innovation of our paper in the empirical literature on conflict, and one which is particularly crucial when dealing with highly disaggregated data. Neglecting spatial patterns has the potential of introducing a serious bias in one's estimates. A detailed review of the problems posed by spatial dependence and the possible approaches to solve them is provided by Franzese and Hays (2004, 2006). One possibility is to simply ignore the explicit spatial autoregressive component and estimate the model via plain, non-spatial OLS. This leads to omitted variable bias: the impact of location-specific factors tends to be overestimated as interdependency effects are neglected. Thus, if we limited our analysis to model I, we might worry that the local impact of climate is driven simply by the fact that conflict is clustered in space and so are climate shocks. A possibility is to explicitly include the spatial autoregressive component and estimate the model via OLS: estimates will suffer simultaneity bias, as the spatial lag will be endogenous. The analyses will be biased in the opposite direction: in the typical case of positive interdependence and positive covariance of spatial lag and exogenous regressors, one would overestimate the interdependence effects and underestimate contextual (cell-specific) effects. This discussion suggests that inference from studies which do not address spatial dependence at all should be taken with caution, especially when considering data at higher geographic resolutions.

Since our focus is on within-country variation in the incidence of conflict, our specification of choice includes country fixed effects[3], so as to account for long-run aspects of the political, economic or social structure of the states in our sample, as well as for state-level geographic features (e.g. country size). According to Besley and Persson (2008) "this gets around one of the key worries in the literature, namely that it is unobserved characteristics of institutions, culture and economic structure that are primarily responsible for civil war" and ensures that estimation results are not driven by unmeasured features of states. Through the inclusion of year fixed effects we control for global trends in conflict incidence as well as climate.

As a preliminary step to our panel analysis, we collapse our cell-year panel to create a time-invariant measure of conflict prevalence in a given cell. Our aim is that of investigating cross-sectional relationships with various local terrain characteristics. Our dependent variable capturing average conflict incidence over time is the fraction of years in the sample in which the cell has experienced at least one conflict event. The aim of the cross-sectional analysis is to highlight geographic correlates of conflict exploiting the high spatial resolution of the dataset to detect these patterns at the appropriate scale. Again, we estimate three models:

$$\overline{ANY\ EVENT}_{c,i} = \alpha + \delta X_c + \mu_i + \varepsilon_{c,i} \tag{4}$$

$$\overline{ANY\ EVENT}_{c,i} = \alpha + \delta X_c + \lambda W \cdot X + W \cdot \mu + \varepsilon_{c,i} \tag{5}$$

which are estimated by OLS with Conley errors, and

$$\overline{ANY\ EVENT}_{c,i} = \alpha + \varphi W \cdot \overline{ANY\ EVENT} + \delta X_c + \lambda W \cdot X + W \cdot \mu + \varepsilon_{c,i} \tag{6}$$

estimated by maximum likelihood with errors clustered by cell.

[3] For the purposes of defining country fixed effects, each cell in the dataset is uniquely assigned to a country. Cells shared among more than one country are assigned to the country which has the largest share of the cell's territory; a "shared" dummy for those cells is also included among the controls.

3 Data

3.1 Sources and dataset construction

We bring together high-frequency, georeferenced data from a variety of sources and construct a dataset which covers 36 African countries over the period 1960-2006, including information on individual conflict episodes and on a large number of geo-climatic characteristics. In particular, we collect detailed data on agricultural land cover, ethnic groups distribution, terrain characteristics and the location of mineral resources, and match it with data on crop calendars as well as climate indicators like precipitation and temperature. The structure of the dataset is that of a raster grid: the cross-sectional units of observations are subnational "cells" of 1 degree of latitude x 1 degree of longitude, whose sides are placed in correspondence of integer values of latitude and longitude.

In our panel analysis we focus on a smaller, balanced panel of 33 countries[4] over the period 1997-2006. The reason is manifold: first, this panel includes only the more recent and presumably more accurate conflict events coded in ACLED - see below. Second, this sample does not include civil conflicts related to independence from colonial powers, which are much less likely to be driven by local economic shocks. Finally, and most importantly, this is the largest balanced panel possible with our data. Spatial econometrics techniques have been developed for balanced panels only[5] (Elhorst, 2009; Hughes, 2012). A map of the cells included in the balanced panel is provided in the appendix (figure A1). Appendix table A1 shows that our benchmark model I and model II specifications yield similar results in the full sample versus the balanced panel, thus limiting the concern of selection.

Conflict events

Data on civil conflict episodes over the period 1960-2010 are drawn from the PRIO/Uppsala Armed Conflict Location and Event (ACLED) dataset in its fall 2010 version. We combine the first version of ACLED released in 2008, which covered 8 Central African countries (Angola, Burundi, Congo, DRC, Liberia, Rwanda, Sierra Leone and Uganda) over the period 1960-2006, with the new version (released in fall 2010) which covers almost the whole continent over the period 1997-2010.

This is the most recent and detailed conflict dataset developed by PRIO/Uppsala. It codes exact locations, in terms of latitude and longitude, dates, and additional

[4]These countries are: Algeria, Angola, Benin, Burkina Faso, Cameroon, Central African Republic, Chad, Congo, Cote d'Ivoire, Rep. Dem. of the Congo, Equitorial Guinea, Ethiopia, Gabon, Ghana, Guinea, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Sudan, Tanzania, Togo, Zambia, Zimbabwe.

[5]The main conceptual difficulty is that with unbalanced panels the spatial weighting matrix would no longer be time invariant, and there would be a degrees of freedom problem.

characteristics of a wide range of conflict-related events in states affected by civil war. Civil conflict episodes are defined broadly, to include not only battles with more than 25 casualties (the standard PRIO threshold) but all kinds of activity involving rebels, such as recruitment or the establishment of headquarters.

In most of our analysis we use a broad indicator of conflict incidence, that is, a dummy equal to one if at least one conflict event of any type occurred in a given cell in a given year ($ANY\ EVENT$). We also consider a breakdown of conflict events into different types, i.e. battles, violence against civilians, riots and rebel recruitment, to test if our explanatory variables have a differential impact on these different outcomes.

Note that not all of the cells within the African grid correspond to countries which are coded in the ACLED dataset; many cells do not even correspond to land, but to the ocean. The criterion for including a cell in our dataset is the following: we include only those cells which contain a portion of territory of a country ever included in the ACLED dataset, i.e. included either in the "old ACLED" or in the "new ACLED".

Crop cover data

Data on the geographical distribution of agricultural crops is drawn from the M3-Crops Data by Monfreda et al. (2008), a detailed raster dataset at the 5 arc minutes x 5 arc minutes resolution (about 9.2 km by 9.2 km at the equator) including 137 crops. For each 5"x5" cell in the raster and each of the 137 crops included, Monfreda et al. report harvested area in hectars. We aggregate the harvested area variable at the lower resolution of our dataset, i.e. 1 degree x 1 degree, and we employ it to rank the crops cultivated in each cell. We identify the main crop for each cell of our dataset as the crop with the largest harvested area in the cell; we thus obtain 30 different "main crops" in our full sample. In a similar way, we identify the second and third most cultivated crop.

Natural resources

In an effort to collect georeferenced data on as many natural resources as possible, data on the location of mineral resources are drawn from a combination of the Mineral Resource Data System (MRDS) prepared by the United States Geological Survey (USGS) and of the PRIO/Uppsala datasets Gemdata, Petrodata and Diadata. We have identified 85 types of mineral commodities present in the countries of our dataset, including precious metals, industrial metals, oil and gems.[6]

[6] Specifically, the list includes: aluminum, amber, aquamarine, asbestos, barium, barite, bentonite, beryl, beryllium, bismuth, bromine, calcium, chromium, clay, cobalt, coltan, copper, diamond, diatomite, emerald, feldspar, fluorine, and, fluorite, fuller's, earth, garnet, garnet, gold, goshenite, graphite, halite, heliodor, iridium, iron, jadeite, lapis-lazu, lead, lithium, magnesite, manganese, marble, metal, mica, moganite, molybdenum, nephrite, nickel, oil, opal, osmium, palladium, pearl, periodit, PGE, phosphates, platinum, potassium, quartz, REE, rhodium, ruby, ruthenium, sapphire, silica, silver, sodium, spinel, stone, strontium, sulfur, talc, tantalum, thorium, tin, titanium, topaz, tourmaline, tungsten, uranium, vanadium, vermiculite, zinc, zirconium.

PRIO natural resources datasets were compiled through an intensive literature search of academic databases and journals, national geological survey reports and industry databases and reports, and as a result they tend to be more comprehensive and reliable than USGS. However, although likely to underreport mineral occurrences, USGS data are the only comprehensive, georeferenced data source for mineral commodities available to the general public.

In the present analysis we employ a coarse indicator for the presence of any mineral in the cell. In ongoing work we are exploring the differential impact of gemstones, oil and other types of minerals, as well as the time-varying impact of these resources in relation to changes in their prices.

Ethnic groups

Data on ethnic groups are drawn from the new University of Zurich "Geo-referencing of Ethnic Groups" (GREG) dataset. The latter relies on maps and data drawn from the classical Soviet Atlas Narodov Mira and employs geographic information systems to represent group territories as polygons. We used the maps available in the GREG data and combined them with our raster grid to measure the extent of ethnic diversity in each cell. As a proxy for ethnic grievances, we compute a cell-level Ethno-Linguistic Fractionalization (ELF) index, based on the shares of inhabited territory attributed to different ethnic groups in each cell.

Infrastructure and geography

Data on the location of roads are drawn from the Global GIS Atlas Developed by the U.S. Geological Survey, a digital atlas of the world at a nominal scale of 1:1 million. These data have no time variation and report only the roads known in year 2000. To mitigate measurement error and selection concerns, we use as a proxy for road density a dummy for the presence in the cell of at least one road of primary use.

The remaining cross-sectional geographic information are coded from the Yale G-Econ Gridded Output dataset, from which our dataset inherits the "grid" structure and the 1 degree by 1 degree resolution.

To investigate at the disaggregated scale the relationship between mountainous terrain and conflict, wee include two different measures: one is the average elevation in the cell and one is the standard deviation of elevation, denoted as "roughness"; both are measured in meters. In the conflict literature terrain ruggedness has received considerable attention, starting from Fearon and Laitin (2003); their proxy for elevation is the share of "mountainous" terrain over a country's surface. This is a poor measure for various reasons: first, it is a measure of elevation, and not of slope: as a result, according to this measure, a plateau would count as "rugged" terrain due to its elevation, even though it does not display characteristics favorable to rebel warfare. Secondly, and perhaps most importantly, being expressed as a proportion of the country's territory, it is arguably measured at the wrong scale: unless the rebels indeed operate on the mountainous share of the country, the magnitude of this share should not matter. Our measure should be an improvement on both grounds.

We also include the distance from the closest navigable river - measured in km from the cell's midpoint - to capture the strategic importance of the location.

Climate data

Our main climate indicator is the Standardized Precipitation-Evapotranspiration Index (*SPEI*), a recently developed multiscalar drought index (Vicente-Serrano et al., 2010). This is a departure from most conflict literature, which so far has focused on precipitation as the main climate indicator. One of the concerns with precipitation as such is that it might not be an accurate measure of climate shocks impacting agriculture, since the impact of rainfall on the growing cycle of a plant depends also on the extent to which water can be retained by the soil. This in turn depends on a variety of factors: the characteristics of the soil itself, the slope, the extent to which sunshine induces evaporation, wind exposure. This information is incorporated in Potential Evapotranspiration (PET), which is defined as the amount of water that could be evaporated and transpired if there were sufficient water available. A way to take into account the different soil's ability to retain rainfall moisture is to consider a measure of precipitation corrected by PET. The Standardized Precipitation-Evapotranspiration Index (SPEI) considers the joint effects of precipitation, PET and temperature, thus representing an improved alternative to the widely used Palmer Draught Index. SPEI is available at a monthly frequency and at a spatial resolution of 0.5 degrees x 0.5 degrees, providing temporal coverage for the period 1901-2006. SPEI will be our main explanatory variable of interest for what concerns climate, because it encompasses all the above mentioned features of climate and of the terrain which are relevant for agricultural production.

The SPEI index is expressed in units of standard deviation from the average based on the available period (1901-2006). The data is fitted to a normal distribution and normalized to a flexible multiple time scale such as 1, 4-,6-,12-,24- 48- months etc. A short - say 4 months - time scale reflects short- and medium-term moisture conditions and thus provides a seasonal estimation of precipitation as it is relevant for agriculture. For this reason we use SPEI at a 4 months time scale.[7]

We also consider precipitation and temperature individually. We draw monthly precipitation data at a resolution of 1 degree by 1 degree for years 1960-2007 from the Global Precipitation Climatology Project (GPCP). We employ the World Climate Research Programme Global Climate Observing System GPCP Total Precipitation dataset, at the resolution of our grid, 1 degree x 1 degree. The dataset is available through the International Research Institute for Climate and Society at Columbia University.

[7] Our results are robust to different time scales too - available upon request.

Temperature data are drawn from the CRU TS3.0 dataset prepared by the Climatic Research Unit at the University of East Anglia. CRU TS3.0 is a high-resolution gridded dataset reporting monthly temperatures at a resolution of 0.5x0.5 for the period 1901-2006. In order to capture the relevance of the most extreme temperature values (see e.g. Burgess et al. 2011), we construct a "temperature deviation" variable as follows: for each cell we compute the historic average over the sample 1960-2006 of the monthly daily mean temperature; then for each month we take the absolute deviation of the monthly daily mean temperature from this historic average; finally we average this monthly measure over the year.

Crop calendars and crop-specific climate shocks

A key feature of our analysis is that we do not confine our measurement of climate indicators to aggregates over the year, but we try to identify periods during the year during which climatic conditions impact agricultural production the most. In particular, we construct specific indicators for climatic conditions during the growing season, which is when crops are most sensitive to unfavorable conditions. To retrieve the growing season of the first three crops (ranked by harvested area) cultivated in each cell we rely on crop calendars drawn from a variety of sources.

As a primary source we use the Global Monthly Irrigated and Rainfed Crop Areas around the year 2000 (MIRCA 2000), prepared by the Physical Geography Department of the Goethe Universität Frankfurt am Main. This is a dataset of monthly growing seasons of 26 irrigated and rainfed crops at different latitudes and longitudes, with a spatial resolution of 5 arc-minutes by 5 arc-minutes. It is our preferred source given that it disaggregates by irrigated and rainfed crops - which we focus on - , and given its high spatial resolution.

For the crops and cells not covered by MIRCA, we turn to two complementary sources, which both report crop calendars at the country level. The first are those generated with the FAO Food security and Early warning Network for Information eXchange Workstation (FENIX) Crop Calendar tool. The FENIX tool indicates for various crops and countries the planting and harvesting season. We define the growing season as the months comprised between planting and harvesting. Our second source are the FAO Seeds and Plant Genetic Resources Crop Calendars.

We construct measures of crop-specific climate shocks by matching our monthly climate data with the calendars of the main crops cultivated in each cell, thus creating cell-specific measures of "relevant" climatic conditions.

Our benchmark indicator of climate shock, denoted as *SPEI Shock Growing Season*, captures low SPEI episodes occurring during the growing season of the main crop of a given cell. It is defined at the cell-year level as follows: in a given year, consider the growing season months of the main crop; take the number of consecutive growing season months in which SPEI was below its mean by more than one standard deviation;

express this measure as a fraction of the number of growing season months.[8] The value of *SPEI Shock Growing Season* thus ranges between 0 and 1, with 0 denoting a "good" year in which never during the growing season of the main crop SPEI assumed abnormally low values, and 1 denoting a "bad" year in which the entire growing season witnessed abnormally low values of SPEI. We also consider a more extreme version of this measure in which the relevant spells are ones in which SPEI is below its mean by 2 standard deviations.

For different climate indicators - rainfall, SPEI and temperature absolute deviation - we also define "Growing Season-adjusted indicators" constructed as follows: we compute monthly interactions between a "growing season" dummy and the monthly climate indicator, and we average these monthly interactions over the year. This amounts to computing a weighted average of monthly rainfall, SPEI or temperature absolute deviation assigning a weight 0 to months outside the growing season of the main crop.

Finally, we construct a version of the above interaction measures using information not only on the main crop, but on the three first crops present in each cell. The monthly interactions between the climate indicator and growing season dummies are computed as above, separately for each of the three first crops present in the cell; then for each month a weighted average of the three interactions is computed, weighting each crop by its share of harvested area in the cell; and finally these monthly weighted interactions are averaged over the year.

3.2 Descriptive statistics

Descriptive statistics are reported in table 1. Panel A reports statistics at the cell level for the cross-sectional estimates we will perform in table 2; Panel B instead reports statistics at the cell/year level for the balanced panel used in the rest of the analysis.

[Insert Table 1]

Cell level incidence of conflict is very high: the average cell in our sample has experienced conflict episodes for 17% of the years in our full panel, which means 1.7 years for countries covered throughout 1960-2006. The territory in our sample appears to be mineral rich, as about 20% of the cells have at least one mineral deposit, and on average moderately elevated, with an average elevation of about 300 meters. Ethnic fractionalization also appears to be high, with an average cell-level ELF index of 23%. We include among our cross-sectional controls a "shared" dummy for cells which do

[8] In case there are more than one consecutive spell of low SPEI during the growing season in a given year, we consider the longest spell. Our results are robust to considering instead the first spell in the year. Note that SPEI is already expressed as standard deviations form the cell's historic mean over the whole available period 1901-2006. For the purposes of defining our variable, we re-normalize it based on the mean over our sample period, which is slightly lower than the historic mean.

not belong entirely to one country, but contain a country border; these cells are about 29% of our sample. The dummy "border", on the other hand, identifies cells whose edge coincides with a state border (about 4% of our sample).

[Insert Figures 1 to 5]

In figures 1-5 we map some of our key variables, to have a sense of the within-country variation in our covariates. Figure 1 shows cell-level conflict prevalence. Conflict appears to be clustered in space, and in particular the Rwanda – Burundi conflict cluster is very apparent. Overall, areas in the tropical belt appear to have experienced more conflict, which could induce a positive spurious correlation between rainfall levels and conflict incidence. Figure 2 plots average rainfall levels, which as expected are higher at the tropics and display a strong spatial correlation. Figure 3 plots the average SPEI index. Although it also appears to be spatially clustered, it displays much more local variation than rainfall, suggesting it might be a better explanatory variable. The plot substantiates the claim that, although correlated with rainfall, SPEI is indeed a richer indicator. Figure 4 shows the historic mean of the absolute temperature deviation. Temperature variability appears to be either very high or very low; areas around the equator appear as the most stable ones temperature wise.[9] Finally, in figure 5 each cell is associated to a color corresponding to the main crop cultivated in the cell. The map shows that a wide range of crops are cultivated in our sample, and there seems to be considerable variation in their spatial distribution. This suggests that focusing on the growing season of one crop "representative" of the whole Sub-Saharan African continent would provide a very limited picture of the true cultivation pattern. Indeed we can derive significant variation across cells and across months in climate measures thanks to variation in the growing seasons of different crops.

4 Empirical results: cross section

In this section we explore the empirical determinants of civil conflict starting with time invariant characteristics such as geography and location of mineral deposits. Our interest in conducting this type of analysis hinges on two factors. First, despite the limitations of cross-sectional inference, the high level of spatial resolution of our data limits the concerns related to state-wide unobservable determinants of conflict and allow us to pin down the relationship between each factor and the location in which conflict occurs with more confidence. Second, the data exhibits spatial dependence, in the sense that geographic features in a given cell will likely not only affect the cell itself

[9] In the Appendix we report, for comparison, figures 2, 3, and 4 constructed considering climate indicators in a given year (2000) rather than their sample average.

but also neighboring cells. This is something that we can test and that potentially yields interesting insights on the interdependence among neighboring locations in the diffusion of conflict.

[Insert Table 2]

Our cross-sectional evidence is presented in table 2. The table reports OLS coefficients and standard errors in parentheses corrected for spatial dependence following Conley (1999). The dependent variable captures average conflict incidence and is the fraction of years during the sample period in which the cell has experienced at least one conflict event. The mean and standard deviation of this variable are, respectively, .17 and .25.

In columns 1 and 2 we consider "own" characteristics of the cell (Model I), in columns 3 and 4 we also include characteristics of the neighboring cells (Model II) and in columns 5 and 6 (Model III) we estimate a spatial lag model in which we further include a spatially autoregressive component to capture direct conflict spillovers across neighbors. Neighbors are defined according to our benchmark weight matrix as cells whose midpoints lie within 290 km from the midpoint of the own cell. Columns 1, 3 and 5 report the coefficients of a purely cross-sectional regression without area fixed effects. In columns 2, 4 and 6 we instead include country fixed effects (and their spatial lags, for columns 4 and 6). The specifications that include country fixed effects are our preferred ones because our focus is on within-country variation in the incidence of conflict, and by including country fixed effects we account for time-invariant aspects of the political, economic or social structure of the states in our sample, as well as for state-level geographic features, e.g. country size.

Let us consider first own characteristics of the cell. The first set of controls we include measure geo-administrative characteristics: *Shared* is a dummy for whether a cell belongs to more than one country, and *Border* is a dummy for whether a cell's side is tangent to a country border (the two are mutually exclusive). The idea is that cells which are at the border with other countries may be more likely to experience conflict. The coefficient for *Shared* is positive and consistent with this hypothesis in all specifications, and significant in models II and III. The *Border* coefficient on the other hand is statistically indistinguishable from 0. The third control listed in the table, *Area*, measures the area of the cell corresponding to land, to account for coastal cells which correspond mostly to sea. The coefficient of this variable is zero in virtually all specifications. We next move to geographic characteristics of the terrain. The first, *Elevation*, measures the average altitude of the cell (in mt.). Its coefficient is negative but mostly statistically insignificant. More interesting is the variable *Rough*, which is the standard deviation of elevation in the cell, and thus captures the roughness of the terrain. This variable is strongly and significantly correlated with conflict incidence.

A one-standard deviation increase in roughness increases conflict incidence by .04 in column 6 - our preferred specification, that is approximately 1/4 of the mean of the dependent variable. This confirms a relationship which has been previously highlighted in cross country studies, starting with Fearon and Laitin (2003), and which is usually attributed to the fact that impervious areas provide safe havens for rebels.

We next consider the variable *Distance from river.* This is the minimum distance (in km) of the centroid of the cell from a navigable river. The negative coefficient of this variable in columns 1 and 2 suggests that areas further away from navigable rivers tend to experience less conflict. This could depend on the fact that these areas are more controlled by local governments or simply less prosperous in the long run, so that they are less appealing for predation purposes. This is also consistent with findings by Gleditsch et al.(2006), who note that the presence of a shared river basin is associated to higher conflict risk. Notice however that this variable is no longer significant when we include neighbors' characteristics.

Transport infrastructure plays a significant role, as confirmed by the coefficient of the variable *Road*, which is a dummy equal to one if the cell contains at least one road of "primary use" (as defined by the Global GIS Atlas). The coefficient of this variable is around .10 across the various specifications, remaining highly significant in all cases. The magnitude of the effect suggests that the presence of a road in the cell increases the fraction of years with conflict by about one fourth of a standard deviation. One possible interpretation is that areas served by main roads are easier to reach for the purpose of attacks. Another interpretation is again that the long terms benefits of capturing those areas are higher compared to areas not covered by main roads.

We next turn to some of the channels more widely explored in the cross country literature. The first is linked to the literature on ethnic fractionalization. We compute an equivalent of the ELF index in which we use, rather than population shares of different ethnic groups, the relative territory shares occupied by each group as reported by the GREG dataset, after having normalized these shares by the total inhabited land in each cell. This is a proxy for the degree of ethnic diversity in the cell, which may be associated with "grievance" motives for conflict. The average cell in our sample has 2 ethnic groups, with an ELF of 0.23. The coefficient of this variable is positive and significant at the 10 percent level in the first two columns, but this effect is no longer distinguishable from 0 once spatial covariates are included.

The second channel is linked to the natural resource curse. The variable *Minerals* is a dummy equal to one if the cell contains at least one mineral deposit (20 percent of the cells in our sample have at least one such deposit). Ceteris paribus, the presence of minerals in the cell is associated with a significantly higher incidence of conflict, in the order of about 30% of the mean of the dependent variable. This coefficient is very stable in terms of size and significance across specifications. The effect of this variable can be explained in two (non-mutually exclusive) ways. On the one hand, there can be "greed" motives, as competing forces may try to capture territory that promises high revenue from mineral extraction. On the other hand, control over mineral resources yields a flow of cash revenue that rebels and government can use to finance their military activities.[10]

Let us now turn to the neighbor's characteristics, represented by the spatial lags of the covariates considered above. Most neighbors' characteristics are statistically insignificant, suggesting, in general, that the impact of the geographic characteristics discussed above is a strictly local one. However the impact of neighboring Roads and Shared cells appears to have the opposite sign compared to their impact in the own cell. This is probably driven by the fact that these two variables are negatively correlated in space, so that own road or border presence is negatively correlated with the presence of a major road or a border in the neighborhood.

Finally, let us consider conflict spillovers. The autoregressive term in columns 5 and 6 appears highly significant and large. To gauge the magnitude of the effects consider the following. Because we row-standardize the weighting matrix, the regressor $W \cdot Y$ goes from 0 to 1 when *each and every* neighboring cell experiences a conflict event. If the number of neighbors is N, then the effect of conflict in *one* neighboring cell is given by the estimated coefficient $\widehat{\varphi}$ reported in the table multiplied by $1/N$. Based on this, our estimates in column 6 imply that after controlling for own and neighbor's characteristics, conflict in *all* neighboring cells makes it 53 percentage points more likely to observe conflict in the cell itself. Given that each cell has on average 17 neighbors according to our benchmark weighting matrix, this amounts to roughly 3 percentage points higher conflict prevalence for each neighbor in conflict. Note that, however, this analysis employs a definition of conflict prevalence with no time variation: this should only be taken as suggestive evidence that conflict spillovers in space are relevant, as only the panel analysis can provide adequate estimates of both temporal and spatial spillovers.

It is however interesting to note that the addition of the spatial autoregressive term does not radically modify the significance or magnitude of the covariates estimated in the non-autoregressive model. This indicates that there is indeed some spatial correlation in conflict prevalence which is explained by spatial correlation in covariates alone. A comparison between direct effects and parameter estimates in Model III seems to suggest that feedback effects - from own cell's characteristics to neighboring conflict and back to own conflict - are limited.

[10] According to the theoretical literature there is a third, indirect channel through which mineral-wealth can fuel conflict, i.e., by increasing rent-seeking and corruption phenomena, which weaken states and their ability to effectively govern and maintain security. This third effect, though, is not captured at the scale of our study, as it is mediated through a country's institutions (which in our study are partly controlled for by the inclusion of country dummies).

Overall, our cross-sectional analysis suggests that geography characteristics have a strictly local effect, especially terrain ruggedness and presence of mineral endowments, and that cross-cells conflict spillovers are potentially very relevant.

5 Empirical results: panel

We next turn to the analysis of climatic factors as determinants of conflict. For this purpose we exploit the rich temporal dimension of the data and conduct the analysis at the cell/year level. Our dependent variable becomes $ANY\ EVENT_{\mathrm{t}}$, a dummy equal to one if the cell experienced at least one conflict event during year *t*. We consider three models: a non-spatial, static model (Model I), in which we include climate shocks in the own cell only; a non-autoregressive, spatial static model (Model II), in which we consider climate shocks both in the own and neighboring cells; and a fully spatial, dynamic Durbin model (Model III) in which we also include two autoregressive terms: a spatial lag of the dependent variable, to capture contemporaneous conflict spillovers over space, and a temporal lag, capturing temporal conflict persistence in the own cell. The first two models are estimated by OLS, with standard errors corrected for spatial and temporal correlation, while the third model is estimated by MLE. All regressions include country and year fixed effects, plus the controls listed in table 2; models II and III include the spatial lags of controls and country fixed effects; these coefficients are not reported for ease of exposition.

We will first present our benchmark specification, in which we highlight the relationship between cell specific weather shocks and conflict, accounting for spatial dependence. We then consider two critical issues arising in spatial econometrics: the choice of the weighting matrix and the choice of scale. We then turn to alternative climate indicators, and finally we attempt an analysis disaggregated by type of conflict event.

[Insert Table 3]

Table 3 contains our main results on the effects of climate on civil conflict. The regressor of interest is *SPEI Shock Growing Season*, defined as the fraction of the main crop's growing season during which SPEI was below its cell-level mean by one standard deviation. As explained in section 4, the SPEI index considers the joint effects of precipitation, potential evapotranspiration and temperature, higher values of this index corresponding to higher levels of "effective"rainfall. In our specifications 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.

In column I *SPEI Shock Growing Season* displays a strong, highly significant correlation with conflict, both contemporaneous and in its two temporal lags, indicating that spells of low SPEI during the growing season are associated to more conflict. The impact of the standalone SPEI variable is also positive and significant. This is likely to be driven by the fact that high levels of SPEI outside the growing season are not beneficial for crops, which for example might rot. The specification in column 1, however, fails to take into account spatial and temporal correlation; this could create omitted variable bias. We then turn to model II (column 2), which addresses the issue of spatial correlation in the covariates by including spatial lags of all the independent variables. In this specification, the only own cell climate indicator which remains significant is *SPEI Shock Growing Season*, in its first and second temporal lag. This is consistent with the idea that climatic conditions during the growing season are those which matter the most for agriculture. Conflict responds with a one and two year lag, which is consistent with the kind of temporal persistence highlighted in cross country studies. Contemporaneous *SPEI Shock Growing Season* in the neighborhood is also significantly associated with more conflict.

Although Model II controls for climatic conditions in the surrounding cells, it might still suffer omitted variable bias from not including autoregressive components of the dependent variable. We address this issue in column 3 (Model III). First note that, as expected, including autoregressive components tends to reduce the magnitude and significance of the coefficients estimated in Model II. However, the coefficients of the first and second lag of *SPEI Shock Growing Season* in the own cell retain significance. A spell of SPEI below one standard deviation throughout the whole growing season is associated to a 6% increase in conflict likelihood in the subsequent year, and 4% in the year following that; this is roughly 1/3 and 1/4 of the dependent variable's mean. Put in other terms, a one standard deviation increase in our measure of "relevant rainfall" induces an increase in conflict likelihood of 5% and 3% in the first and second subsequent years - a sizeable effect.

Direct conflict spillovers, both in time and space, appear to be very significant. Conflict in the own cell is associated to a 31% increase in the probability of experiencing conflict the following year. Contemporaneous conflict in all of the neighboring cells induces a 45% increase in the probability of experiencing conflict in the cell itself. Given that according to our definition of contiguity matrix the average cell in our sample has 17 neighbors, this means that conflict in each of these neighbors induces a 2.5% increase in the probability of conflict in the average cell itself. Overall it seems that temporal persistence within cell is more relevant than contemporaneous spatial spillovers across cells. We will be able to address this more comprehensively in the next section, in which we explore the sensitivity of these estimates to different choices of spatial weighting matrix.

[Insert Table 4]

Just as in time series the structure of temporal dependence is assumed by the researcher and cannot be estimated, so is the structure of spatial dependence - encompassed by the spatial weighting matrix - in spatial econometrics. Plumper and Neumayer (2010) warn that some datasets are very sensitive to functional form specification of the weighting matrix, and recommend that a sensitivity analysis be included in empirical work using spatial econometrics. The most popular choices for spatial weighting matrix are binary contiguity matrices, as our benchmark, or matrices based on the inverse geographic distance, typically squared. Table 4 reproposes the specification of column 3 in table 3, estimated using different kinds of spatial matrix. In columns 1, 2 and 3 we estimate our model using binary contiguity matrices with different distance cutoffs: 190, 450 and 600 km. A 190 km distance cutoff implies that we are potentially considering as a cell's neighbors the 8 adjacent cells. Increasing the distance cutoff to 290 km we add another circle of adjacent cells, and increasing it further to 450 we add yet another circle. Finally, with a cutoff of 600 km, we are considering a large, approximately circular area around the reference cell. With distance cutoffs of 190, 450 and 600 km the average number of neighbors for each cell is respectively 7, 41 and 74. In columns 4, 5 and 6 we turn to inverse quadratic distance matrices, again specifying different cutoffs past which the spatial dependence is assumed to be 0. The main difference with respect to binary weight matrices is that observations lying further away are weighted less than observations closer to the reference cell. We include distance cutoffs of 290, 450 and 600 km.[11] We have also repeated the analysis with linear distance based matrices, and found that results are very similar to those obtained with squared distance (results available upon request). All of our matrices are row standardized.

It is interesting to note that using different weighting matrices the magnitude and significance of our covariates of interest is minimally altered. In particular the coefficient of *SPEI Growing Season Main Crop* in its first temporal lag appears to be remarkably stable across specifications, and so does the temporal autoregressive coefficient. This is an important robustness check for our main result. On the other hand, as expected, the choice of weighting matrix does affect the coefficients of the spatially lagged variables. In particular, the spatial autoregressive coefficient is most significantly affected by changes in the definition of neighborhoods, increasing in magnitude as we increase the distance cutoff. This is partly driven by a mechanical effect: as we increase the size of neighborhoods, we increase the number of neighbors. Recall that the regressor $W \cdot Y$ goes from 0 to 1 only when *all* neighboring cells experience a conflict event. For a cell with N neighbors, the effect of conflict in *one* neighboring cell is given by the estimated coefficient on $W \cdot Y$ reported in the table multiplied by $1/N$.

[11] We do not include the 190 km cutoff since at this cutoff all neighboring cells are roughly at the same distance from the reference cell.

Consider the coefficients of the spatially autoregressive term in the case of binary weight matrices, i.e. columns 1 to 3. If we normalize them by the average number of neighbors under each weighting scheme, we obtain respectively 0.05 (190 km), 0.01 (450 km) and 0.008 (600 km). This reveals that as we broaden the definition of neighbors, the contribution of each individual neighbor becomes smaller. This is intuitive: as we add neighbors further away from the cell, and presumably with a smaller absolute impact on conflict in the reference cell, the impact of the average neighbor is driven down. The calculation of the effect per neighbor in the case of inverse distance based weighting matrices is less straightforward but the same intuition applies.

Overall this analysis seems to suggest that own effects are considerably stable as we change the definition of weighting matrix. Since our focus is on the local dimensions of conflict, we choose as our benchmark matrix one with a reasonably restrictive definition of neighbors. Moreover, we prefer the simplicity of a binary weighting matrix, which makes the coefficient of spatial lags easier to interpret.

Another critical specification issue arising when dealing with spatial data is the so-called Modifiable Aeral Unit Problem (MAUP), a well-know phenomenon in spatial analysis. It is defined as "a problem arising from the imposition of artificial units of spatial reporting on continuous geographical phenomenon resulting in the generation of artificial spatial patterns" (Heywood et al., 1998). The MAUP consists of two components: one is a scale problem, which is the variation in numerical results occurring due to number of zones used in analysis, and hence the possibility of obtaining different results for different resolutions; the other is an aggregation problem or zonation effect, which refers to which zoning scheme is used at a given level of aggregation. Although not eliminable, this problem is mitigated when the units of observations are equal-sized cells rather than administrative units of different sizes: at that point, the zonation effect will be minimal, even though a scale effect nevertheless exists. Despite the lack of general solutions, a simple strategy to deal with the problem, is to undertake the analysis at multiple scales or zones. In table 5 we repeat our analysis for larger scales of aggregation: 2 by 2 and 3 by 3 degrees cells.

[Insert Table 5]

First we construct "macro-cells" of 2 by 2 degrees composed by aggregating 4 of our 1 by 1 original cells. This new, lower-resolution grid can be constructed in 4 different ways depending on where the "macro-cells" are centered. We run our benchmark table 3 specification in each of these 4 possible grids. We use a binary contiguity matrix with a 390 km cutoff, so that each macro-cell's neighborhood is formed by the 8 adjacent macro-cells. In table 5a we report the average coefficients and average standard errors obtained from running our Model I and Model III benchmark in the four different grids. We also report the standard deviation of each estimated coefficient across the four grids, to have a sense of how sensitive the results are to the centering of the macro-cells. We repeat this kind of analysis for an even lower resolution, by constructing a panel of 3 by 3 degrees cells. In this case the new grid can be centered in 9 possible ways. Table 5b reports the results of the analysis in those 9 panels. The binary contiguity matrix in this case has a cutoff of 490 km, so that each macro-cell's neighborhood is formed by the 8 adjacent macro-cells.

The analysis highlights the following patters. First, the centering of the grid does not seem to affect the results in a very significant way, as shown by the low standard deviation of the estimated coefficients across grids. This indicates that the zonation effect is limited when using the "grid" approach. This is an important robustness check which we can conduct at these lower resolutions and not with our original 1 by 1 cells - in that case the grid cannot be re-centered due to constraints in data availability. Secondly, changing the resolution does not affect the sign of the relevant parameter estimates, but affects the magnitude: the coefficients of own cell covariates appear to increase in magnitude as the resolution decreases. This effect is documented in the MAUP literature (Fotheringham and Wong, 1991; Amrhein, 1995): the correlation coefficient for variables of absolute measurement typically increases when areal units are aggregated contiguously. The reason is that the aggregation process involves a smoothing effect, by averaging the relevant variables, so that the variation of a variable tends to decrease as aggregation increases. When the variances of X and Y variables decrease, the correlation coefficient will increase if the covariance between X and Y is relatively stable. Finally, the statistical significance of the relevant covariates tends to decrease at lower resolutions - this is especially apparent in Model III estimates. This is likely driven by lack of power, as the number of observations decreases.

We next turn to other potential indicators of climate conditions that have been employed in the cross country literature.

[Insert tables 6a and 6b]

The first is a crude measure of rainfall, measured in logs, and the second is *Temperature Absolute Deviation*, which is the absolute deviation of the temperature from the historical mean for the cell. For each of these two climate indicators, we compute a "Growing Season Indicator" obtained by averaging the monthly values of the variable only over the growing season of the main crop. Table 6a reports Model I, II and III specifications in which we include both the standalone climate measure and the corresponding growing season indicator for rainfall (cols. 1 to 3) and temperature (cols. 4 to 6).

In column 1 the coefficients on rainfall are actually positive, which runs against the findings in the cross country literature. While apparently surprising, this result is easily understood when considering the pattern of rainfall in figure 2 and the pattern of conflict in figure 1. Average rainfall is in fact high at the tropics and exhibits relatively less within country variation compared to *SPEI* (see, e.g. figure 3). Furthermore, simply measuring rainfall fails to take into account differences in temperature, soil, and other conditions that may be crucial in terms of effects of climate on agricultural production. Virtually all coefficients on rainfall, however, become insignificant once we account for spatial spillovers in Models II and III (cols. 2 and 3). Turning to temperature, there is some evidence from column 1 that temperature shocks during the growing season increase the likelihood of conflict, consistent with Burke et al. (2009). However this effect appears non significant once we account for spillovers in Models II and III (cols. 5 and 6).

This seems to suggest that neither rainfall alone nor temperature alone adequately capture the local level relationship between conflict and climate. In table 6b we include the climate indicators above - rainfall and temperature - together with our benchmark SPEI variables. Recall that SPEI is based on precipitation and temperature but also on potential evotranspiration, which in turn depends on things like latitude, month of the year, number of sun hours, etc. Table 6b shows that even controlling for temperature and rainfall, both standalone and in the growing season, in the own as well as in the neighboring cells, the own cell coefficient of *SPEI Shock Growing Season* retains significance, thus confirming that SPEI indeed captures the most agriculturally relevant components of climatic phenomena.

In appendix table A2 we show some alternative SPEI based indicators. In columns 1, 2 and 3 we show that standalone SPEI is not a significant conflict predictor once spatial lags are included, suggesting that indeed what matter most are climatic conditions during the relevant growing season. In columns 4, 5 and 6 we show an alternative indicator of SPEI over the growing season, computed by averaging monthly SPEI over growing season months for the main crop. Unlike our benchmark indicator, this measure is not confined to severe SPEI negative shocks. Our estimation results indicate that low SPEI over the growing season is associated to more conflict, but the predictive power of this indicator is inferior to our benchmark one. In columns 7, 8 and 9 we propose a SPEI-based growing season indicator which incorporates the growing season of the three main crops in the cell, each weighted by its relative harvested area. The estimation results indicate that low SPEI during the growing season of the three main crops is associated to higher conflict, both in the own and in neighboring cells, but the estimates are very noisy, possibly due to the lower number of observations available for this specification. Finally in columns 10, 11 and 12 we consider a version of our benchmark indicator in which we consider more extreme SPEI shocks occurring during the main crop's growing season. We compute the fraction of the main crop's growing season during which SPEI was below its mean by 2 standard deviations. Although the effect is large in magnitude - roughly twice the effect of our benchmark indicator - and significant in model I, these results do not survive the inclusion of spatial lags.

6 Different types of conflict events

We now turn to a disaggregation of conflict events into four different types, based on the ACLED classification. The dummy *BATTLE* is equal to 1 when a cell/year has experienced a battle of any kind, either one where control of the contested location does not change, or one where the government or the rebels take control of a location previously occupied by the other contestant. 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. A third type of event is riots and protests (dummy *RIOT*), i.e. instances in which "a group is involved in a public meeting against a government institution." Finally, ACLED also codes rebel activities such as the establishment of a base or headquarter (which can be non-violent) as well as recruitment drives and incursions (dummy *REBEL*). This is the variable where we should expect to find effects according to theories that stress rebel recruitment and the opportunity cost of fighting as an underlying rationale for the link between rainfall shocks and conflict. Summary statistics for these dependent variables - table 1 - indicate that these are all rare events individually taken, especially the last class of events. This limits the power of the specifications we estimate in this section, which yield relstively noisy estimates.

[Insert Table 7]

In table 7 we estimate a series of cross-sectional regressions (Models I, II and III) along the lines of what we did in table 2, but the dependent variable is now disaggregated according to the type of conflict event: battles in cols. 1-3, violence against civilians in cols. 4-6, riots in cols. 7-9 and rebel recruitment in cols. 10-12. The following patterns can be detected.

First, the coefficient of spatial autoregressive term (Model III) is positive and highly significant for all dependent variables, suggesting that spatial spillovers exist for all types of events. Second, characteristics such as rough terrain positively correlate with all types of events. Third, other characteristics impact differentially the different types of events. One example is the variable *Shared*, which identifies cells that contain a country border. This variable has a positive and significant impact on rebel recruitment, on the occurrence of battles (likely for the control of territory) and to some extent on violence against civilians, but no impact on riots. The presence of minerals, on the other hand, affects the variables BATTLE, CIVILIAN and RIOT – as one would expect if the goal is to take control of the cell where minerals are located – but not so much rebel recruitment (at least not significantly in Model 3).

[Insert Table 8, part I and II]

We next turn to the effect of climate shocks on different conflict events using panel data. In table 8 the coefficients of the autoregressive terms, both in space and time, appear to be larger for battles and violence against civilians than for riots or rebel recruitment. Violent episodes thus appear to be more likely to persist in time and to spill over in space compared to non-violent ones. This is not surprising, since battles and violence against civilians seem intuitively more likely to propagate by retaliation. The coefficient on the temporal lag, in particular, is smallest for rebel recruitment, which indeed we expect to consist of relatively independent episodes. The coefficients on own climate shocks point in the same direction as the results we obtained for the aggregate dependent variable, i.e. years with long spells of low SPEI during the growing season are associated to more battles (column 1), more violence against civilians (column 4), more riots (column 7) and more rebel recruitment (column 10). However, when we account for temporal and spatial correlation in the dependent variable by estimating Model III, the coefficients on the *SPEI Shock* variables are noisily estimated in all specifications, except for rebel recruitment. This could be taken as evidence in favor of theories on the opportunity cost of rebel recruitment, although caution should be exerted as the coding of this variable in ACLED is subject to intrinsic limitations (e.g., higher difficulty of detecting recruitment activities compared to violent episodes).

7 Conclusions

In this paper we conducted a spatially disaggregated analysis of the empirical determinants of conflict in Africa over the period 1997-2006. We exploited 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 shocks that are relevant for agricultural production. We found that negative climate shocks which occur during the growing season of the main crops cultivated in the cell have a sizeable effect on conflict incidence. We also used state of the art spatial econometric techniques to test for the presence of temporal and spatial spillovers in conflict, and we found both to be sizeable and highly statistically significant. These results indicate that caution should be exerted when interpreting results of studies which do not incorporate spatial dynamics at all.

Our findings indicate that conflict risk does not affect all the territory of a state in the same way: the correlates of civil conflict have a strong local dimension, and the likelihood of conflict likelihood is not constant in time nor in space, even within the same country. This seems to suggest that policy interventions, be them in the form of monitoring, prevention or peacekeeping efforts, could be and should be targeted both in space and time.

Finally, given the increasing availability of high resolution data (e.g., gridded datasets) and the growing number of research contributions that employ this data to address important development questions, our study can hopefully provide a number of insights and methodological indications that are useful for future work.

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8 Appendix

8.1 Derivation of the likelihood for dynamic spatial panels[12]

Consider the following dynamic, spatial, random effects model with N cross-sectional units and T time periods:

$$y_t = \phi y_{t-1} + \rho W y_t + i_N \alpha + x_t \beta + \eta_t \tag{1}$$

with $\eta_t = \mu_t + \varepsilon_t$., where $y_t = (y_{1t}, ..., y_{Nt})'$ is the $N \times 1$ vector of observations for the t-th time period, α is the intercept, i_N is an $N \times 1$ column vector of ones, x_t is the $N \times k$ matrix of non-stochastic regressors and μ is an $N \times 1$ vector of random effects, with $\mu_i \sim N(0, \sigma_\mu^2)$. The random terms ε_t are i.i.d. with zero mean and a variance $\sigma_\varepsilon^2 I_N$, and μ is assumed to be uncorrelated with ε_t. W is a row-normalized, symmetric $N \times N$ spatial weighting matrix with zeros on the diagonal, whose eigenvalues are denoted as $\varpi_i, i = 1, ..., N$. For simplicity spatial lags of the covariates are not explicitly included in (1), but they could be part of matrix x_t .

The basic idea is to remove the two sources of autocorrelation by combining two transformations: a space filter to remove the spatally autorgressive term and a time filter à la Prais-Winsten to remove the temporal autoregressive one.

Define first the space filter as the $N \times N$ matrix

$$B = I_N - \rho W \tag{2}$$

To see how this transformation removes the spatial autoregressive term, suppose that $\phi = 0$ and apply this filter to equation (1):

$$B y_t = i_N \alpha + x_t \beta + \eta_t \tag{3}$$

Now define the time filter as the $T \times (T + 1)$ matrix

[12] This subsection draws upon Parent and Le Sage (2009).

$$C = \begin{bmatrix} -\phi & 1 & 0 & ... & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & ... & ... & -\phi & 1 \end{bmatrix} \tag{4}$$

To see how this transformation removes the temporal autoregressive term, consider the $(T+1) \times 1$ vector of observations for the i-th cross-sectional unit $y_i = (y_{i0,}\ ...,\ y_{iT})'$. Similarly, let $x_i = (x_{i1,}\ ...,\ x_{iT})'$ be the $T \times k$ vector of covariates observed in the i-th cross-sectional unit and $\eta_i = (\eta_{i0,}\ ...,\ \eta_{iT})'$ a vector of errors. Further assume that $\rho = 0$. Applying the filter to y_i one obtains:

$$Cy_i = i_T\alpha + x_i\beta + \eta_i \tag{5}$$

Note that we are assuming that y_0 is given. This considerably simplifies the computational complexity of the estimation and has been shown to have little effect on the estimates when T is not too small.

The space-time filter proposed by Parent and LeSage is given by the Kronecker product of matrices C and B. Set $Y = (y'_0, ..., y'_T)'$ and $X = (x'_1, ..., x'_T)'$ and apply the filter to the entire vector of observatios. One obtains*:*

$$(C \otimes B)Y = X\beta + i_{NT}\alpha + \eta \tag{6}$$

with $\eta \sim N(0, \Omega)$.

Since the random effects are integrated out, the $NT \times NT$ variance-covariance matrix can be shown to be equivalent to

$$\Omega = \sigma^2_\mu(J_T \otimes I_N) + \sigma^2_\varepsilon[I_T \otimes I_N] \tag{7}$$

with $J_{T+1} = i_{T+1}i'_{T+1}$.

This allows to write down the log-likelihood for the complete sample size of T for the model defined in (1) as

$$\ln L_T(\xi) = -\frac{NT}{2}\ln(2\pi) - \frac{1}{2}\ln|\Omega| + T\sum_{i=1}^{N}\ln[(1-\rho\varpi_i)] - \frac{1}{2}\eta'\Omega^{-1}\eta \tag{8}$$

where $\xi = (\beta', \alpha, \sigma^2_\varepsilon, \sigma^2_\mu, \phi, \rho)$.

8.2 Derivation of direct vs. indirect effects[13]

Consider again the spatial model in (1). For simplicity of exposition let us neglect the temporal autoregressive component and explicitly include spatial lags of the covariates x_t.

$$y_t = \rho W y_t + i_N \alpha + x_t \beta + W x_t \theta + \eta_t \tag{9}$$

Applying the space filter defined in (2), this model can be rewritten as

$$y_t = B^{-1} i_N \alpha + B^{-1} x_t \beta + B^{-1} W x_t \theta + B^{-1} \eta_t \tag{10}$$

The matrix of partial derivatives of the dependent variable in the different cross-sectional units with respect to the k-th explanatory variable in the different units (say, x_{ik} for i=1,...,N) at a particular point in time t is

$$\left[\frac{\partial Y}{\partial x_{1k}} \cdots \frac{\partial Y}{\partial x_{Nk}}\right]_t = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \vdots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix}_t = \tag{11}$$

$$= B^{-1} \begin{bmatrix} \beta_k & W_{12}\theta_k & \cdots & W_{1N}\theta_k \\ W_{21}\theta_k & \beta_k & \cdots & W_{2N}\theta_k \\ \vdots & \vdots & \vdots & \vdots \\ W_{N1}\theta_k & W_{N2}\theta_k & \cdots & \beta_k \end{bmatrix} \tag{12}$$

The direct effect of the k-th covariate is defined as the average of the diagonal elements of matrix (12). The indirect effect is defined as the average of either the row sums or, equivalently, the column sums of the non-diagonal elements of matrix (12).

[13] This subsection draws upon Elhorst (forthcoming).

Figure 1 – Fraction of sample years with at least one conflict event, 1997-2006

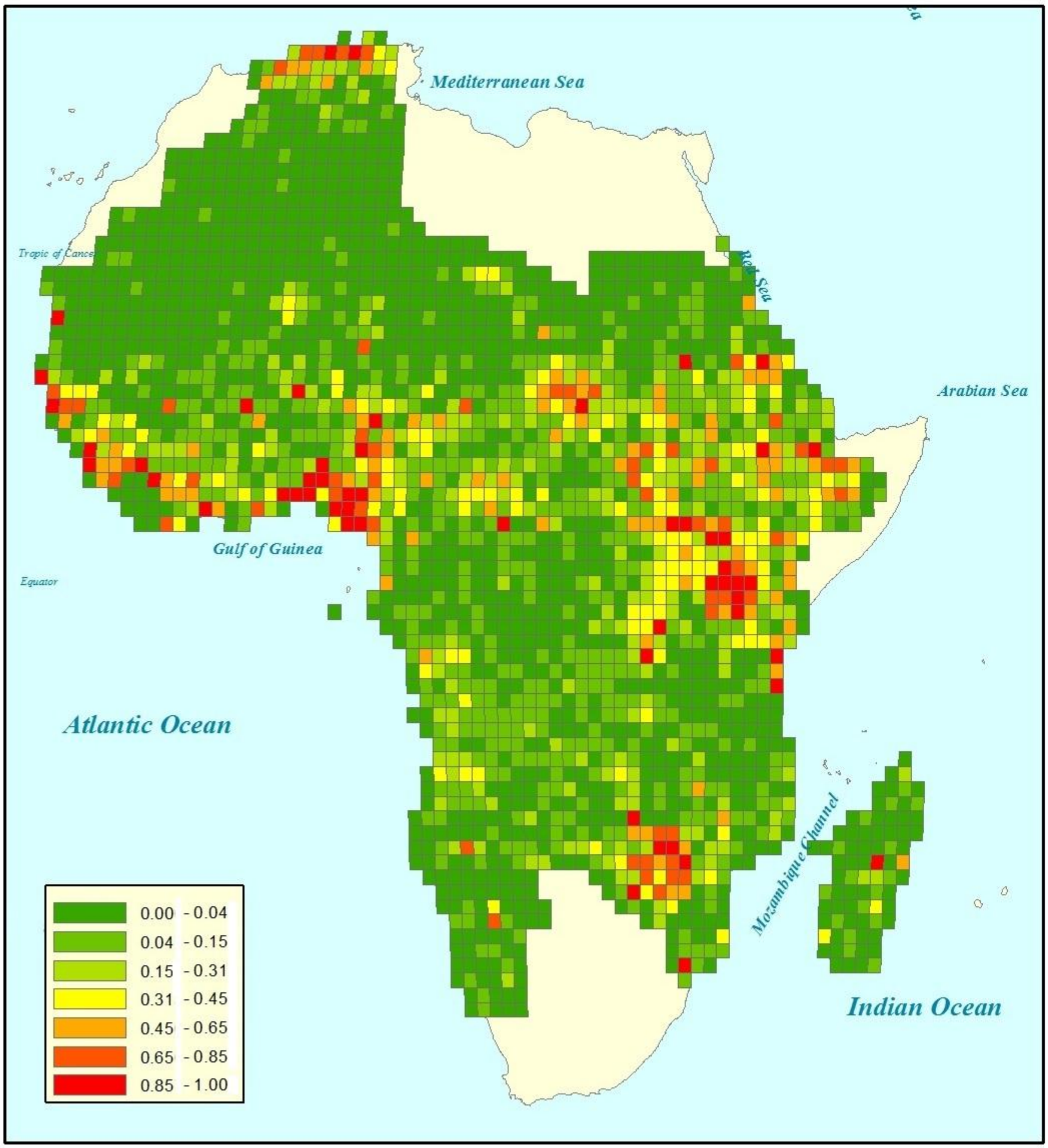

Figure 2 - Log Rain, average 1997-2006

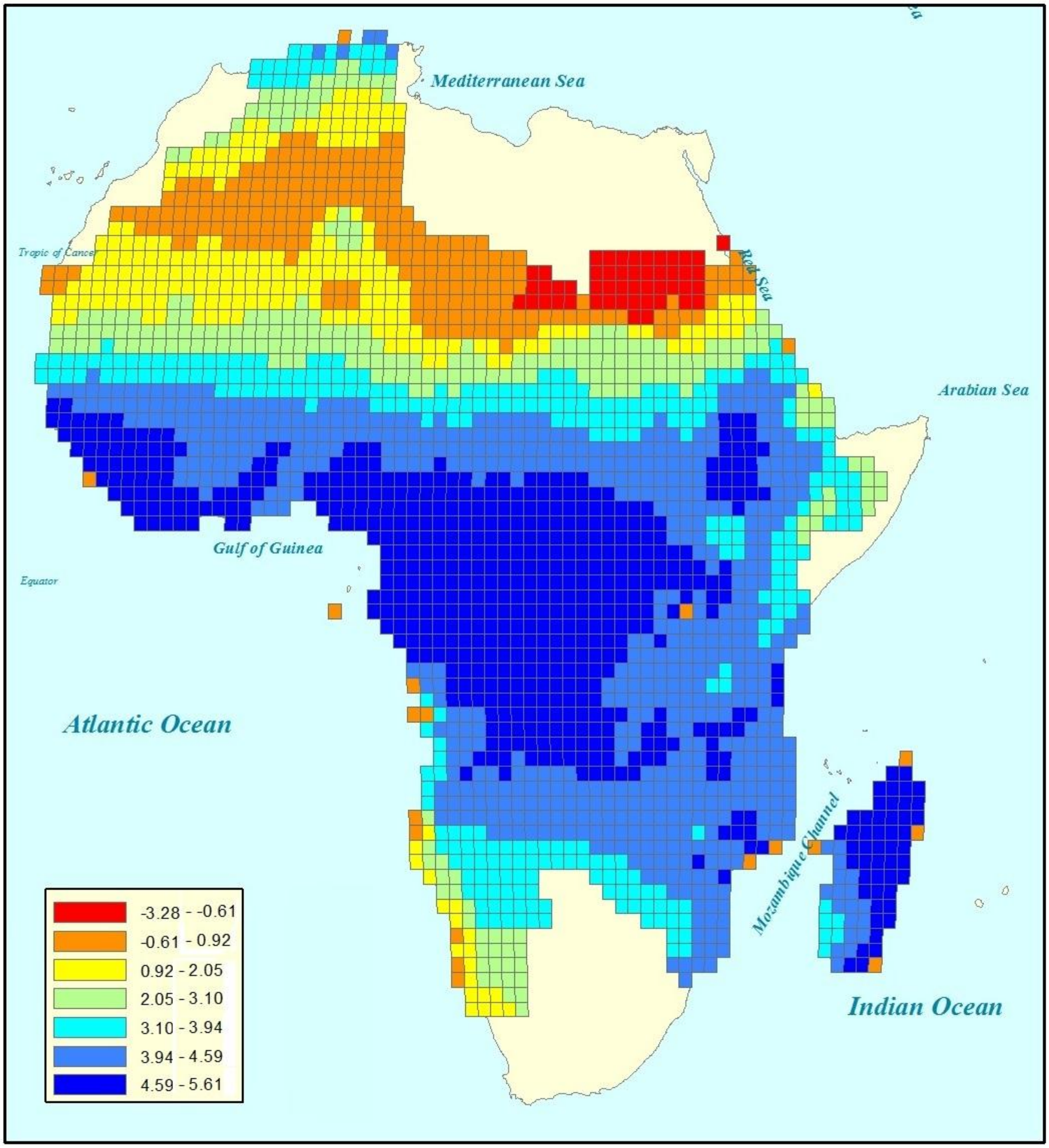

Figure 3 - SPEI , average 1997 – 2006

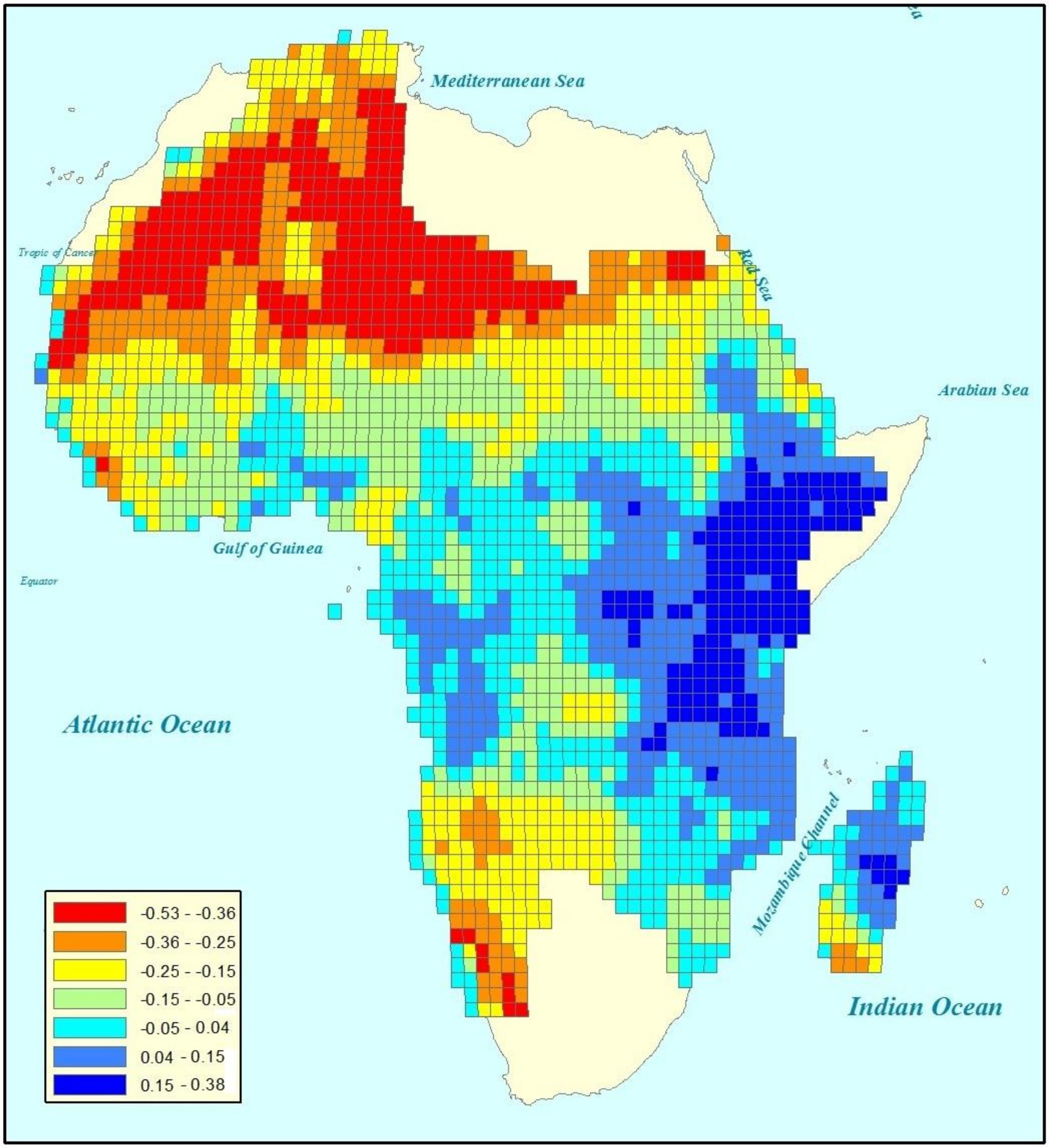

Figure 4 – Temperature Absolute Deviation, average 1997 - 2006

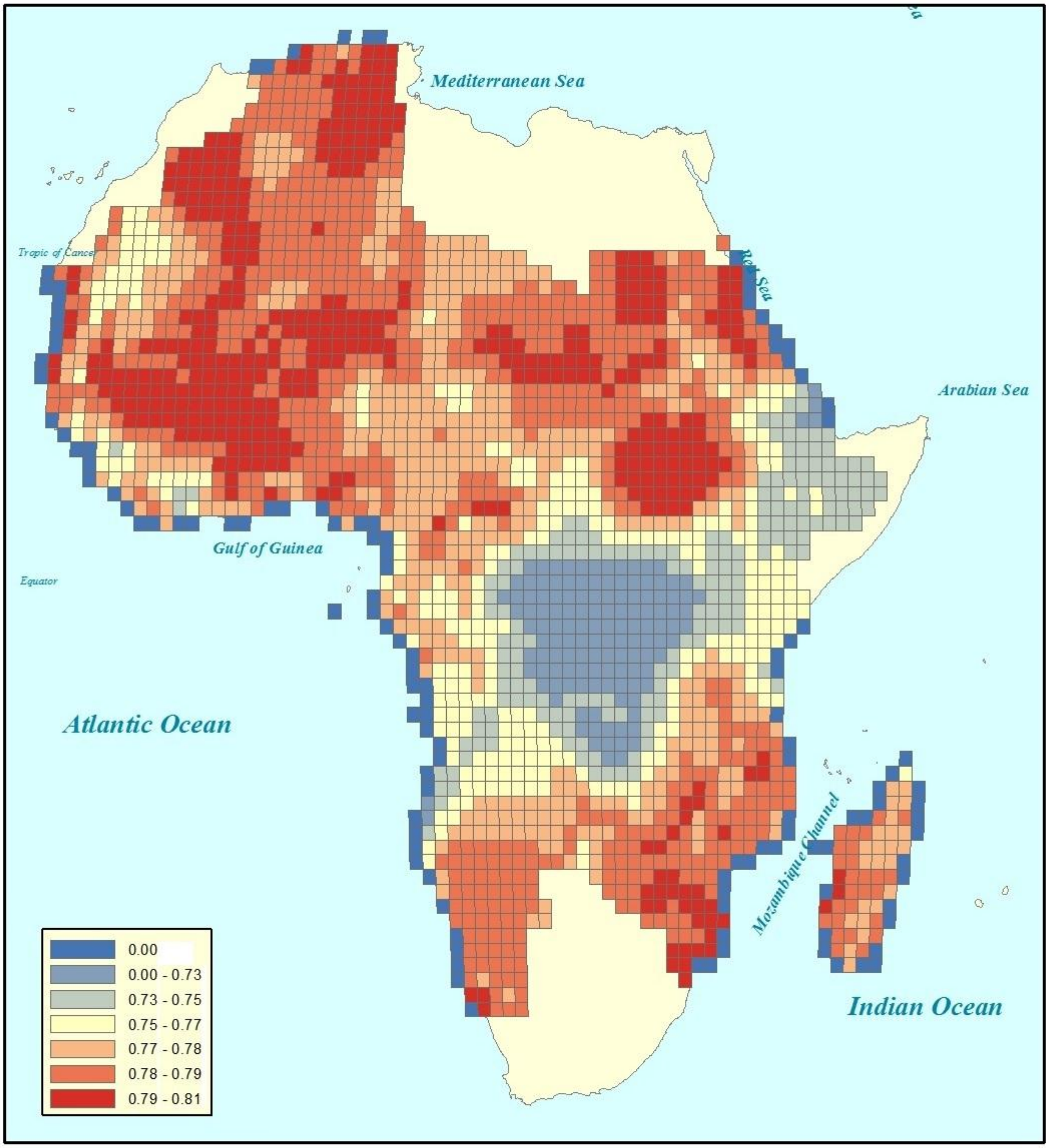

Figure 5 - Main crop by harvested area, year 2000

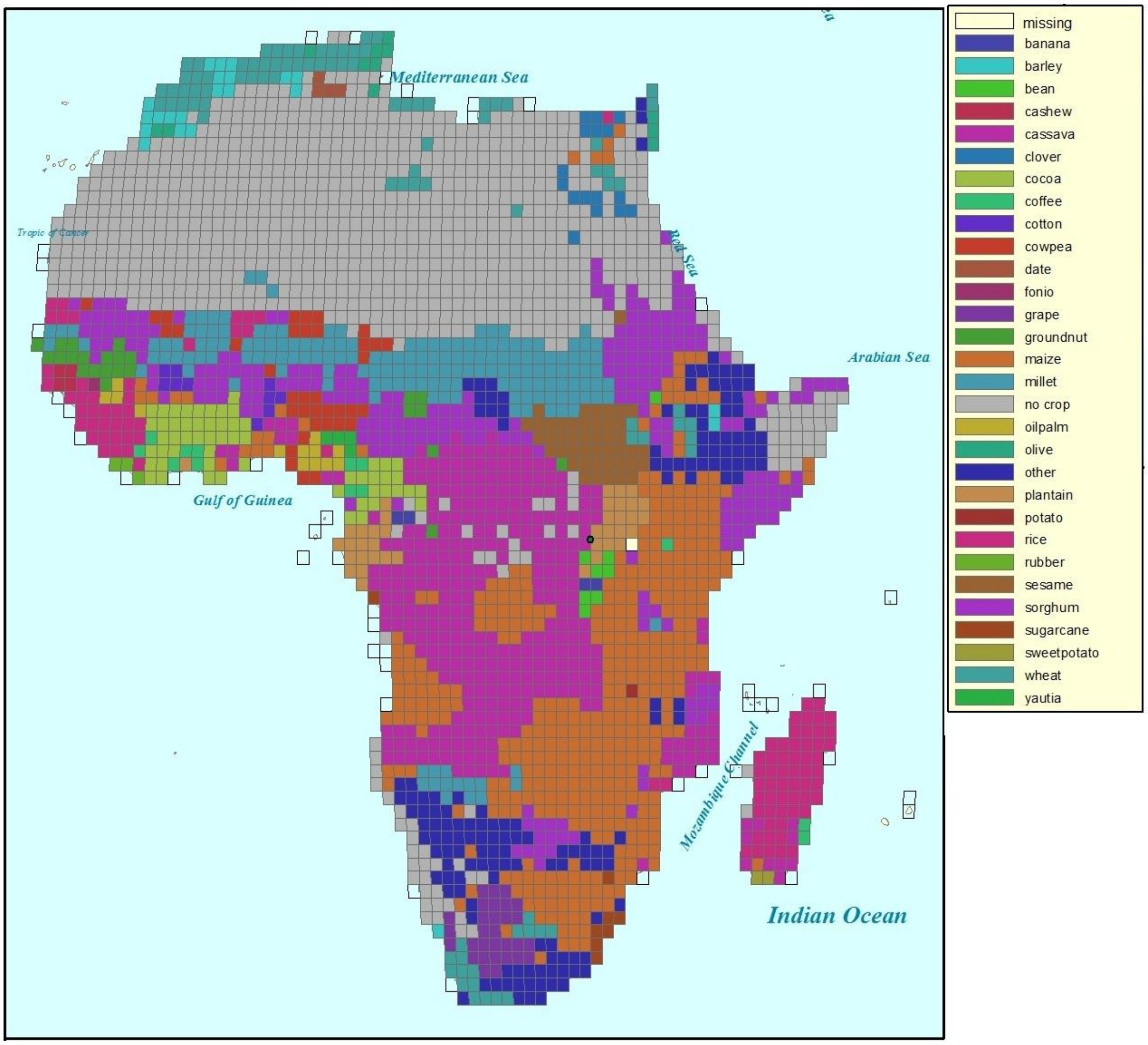

Figure A1 – Cells in full vs. balanced panel

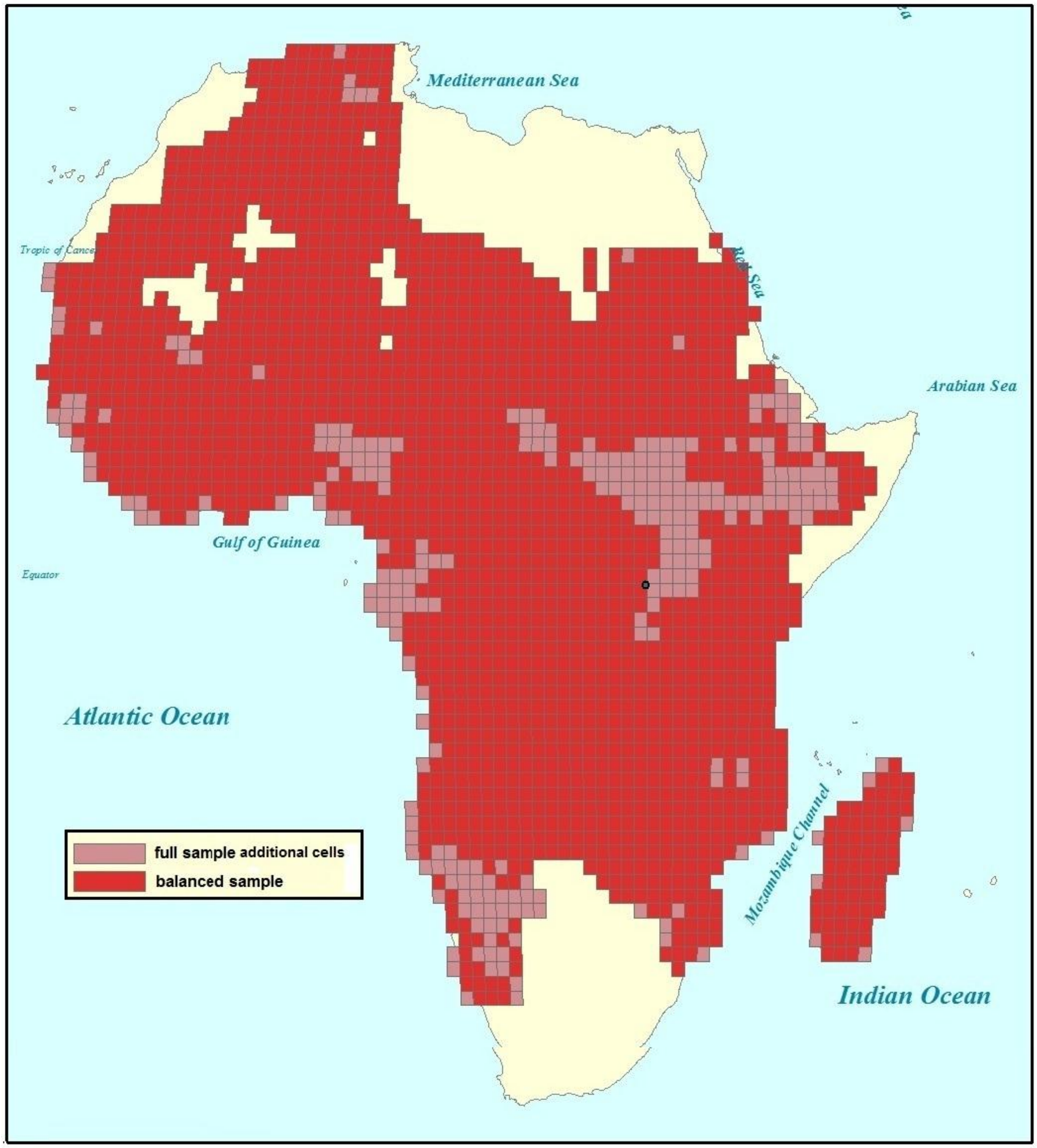

Figure A2 - Log Rain, year 2000

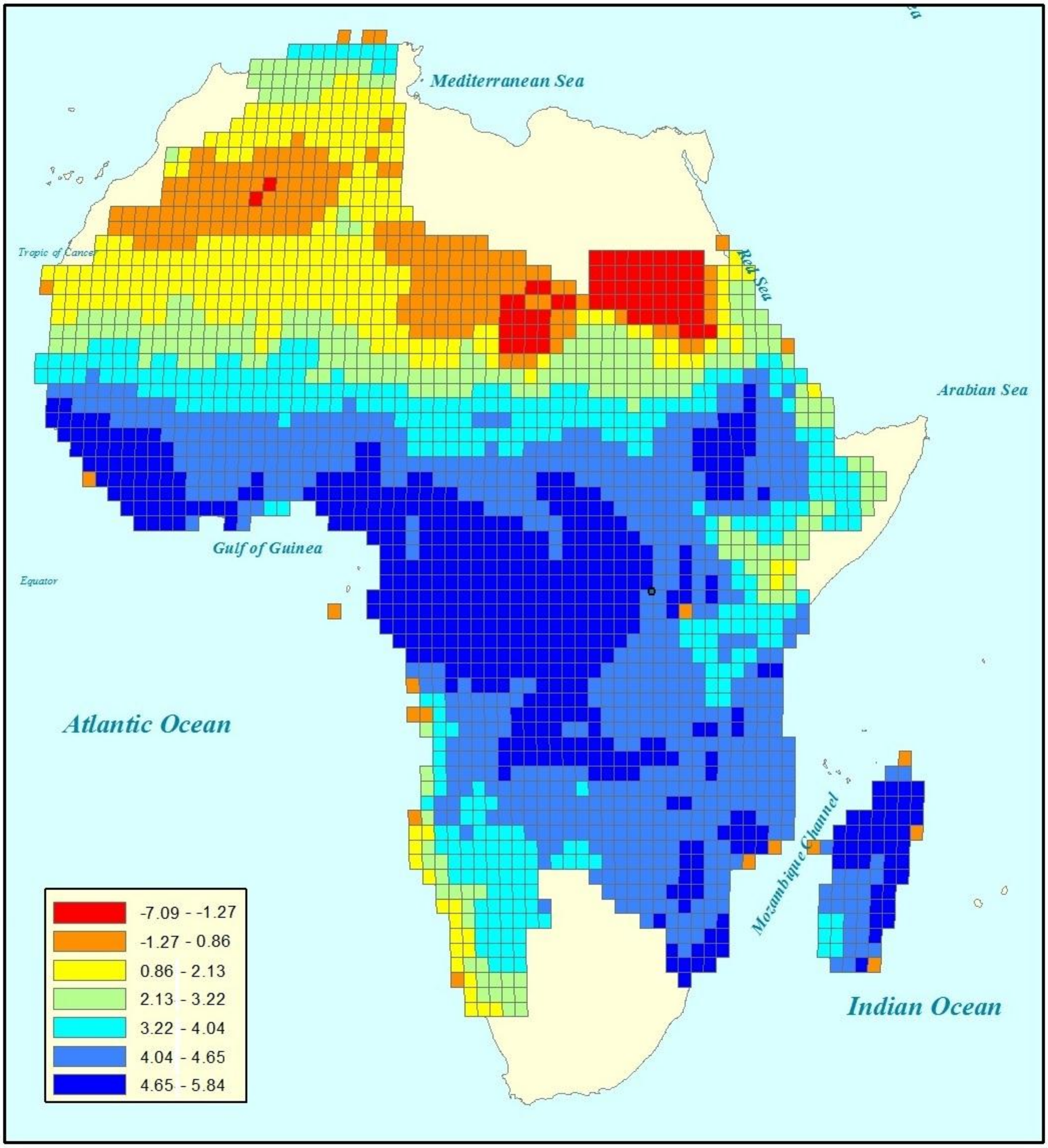

Figure A3 - SPEI , year 2000

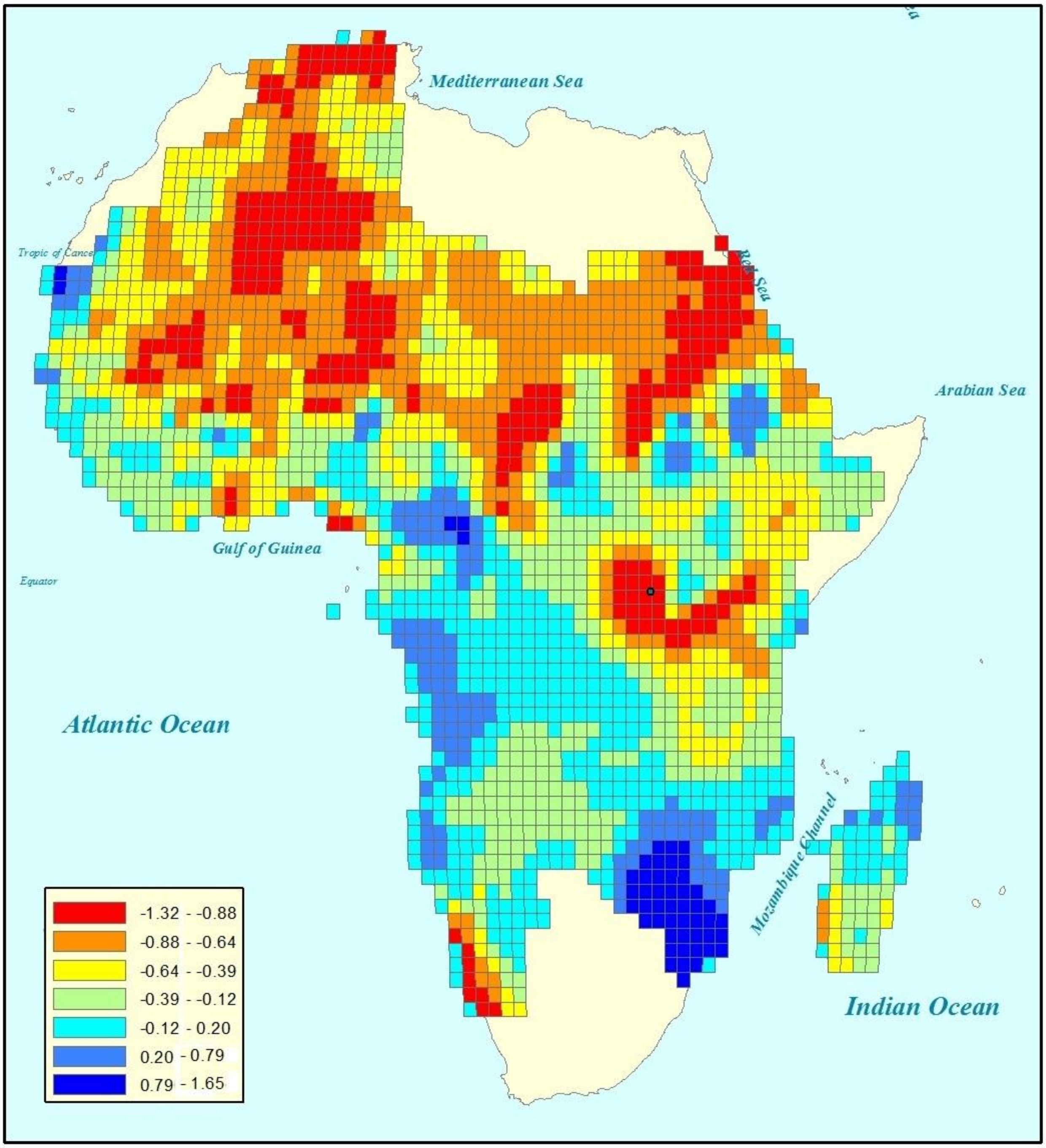

Figure A4 – Temperature Absolute Deviation, year 2000

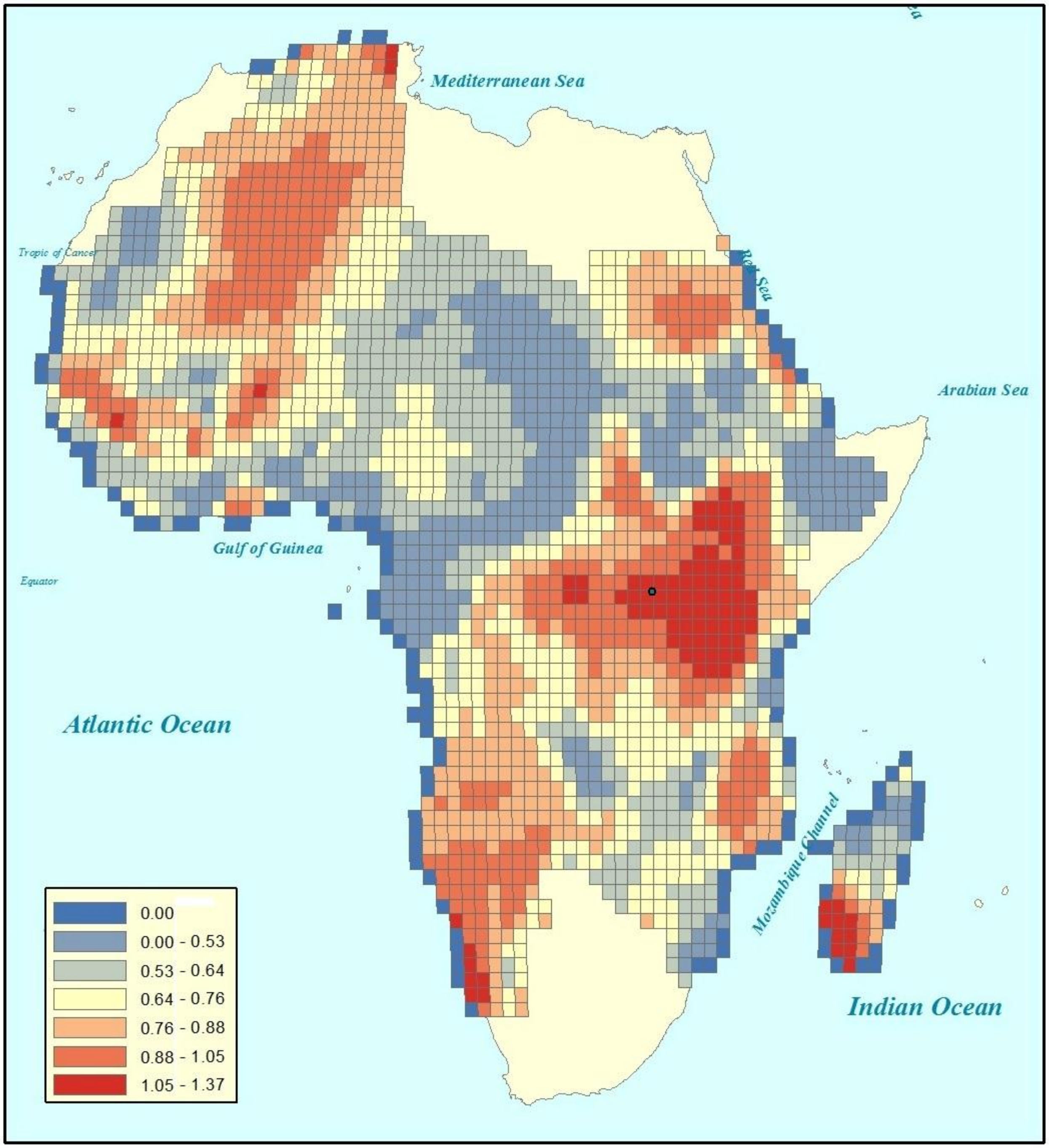

Table 1: Summary statistics

A: Cross sectional sample	No. Obs.	Mean	Std Dev
Fraction of years with conflict	2149	0.171	0.257
Shared	2149	0.289	0.453
Border	2149	0.043	0.204
Area, in km^2	2149	11260.880	2288.834
Elevation, in m	2149	328.500	270.684
Rough	2149	0.089	0.099
Distance to river, in km	2149	560.663	439.596
Road	2149	0.213	0.410
Minerals	2149	0.202	0.402
ELF	2149	0.227	0.245
B: Panel sample			
ANY EVENT	18790	0.161	0.367
BATTLE	18790	0.095	0.293
CIVILIAN	18790	0.088	0.283
RIOT	18790	0.050	0.217
REBEL	18790	0.021	0.144
SPEI	18790	-0.324	0.458
SPEI Shock, Growing Season	18790	0.087	0.189
SPEI 2 stdev Shock, Growing Season	18790	0.004	0.040
SPEI Growing Season, Main Crop	18790	-0.060	0.252
SPEI Growing Season, Weighted	13750	-0.001	0.008
Rain	18774	3.372	1.691
Rain Growing Season, Main Crop	18774	1.738	1.370
Temperature, abs dev	18210	0.914	0.320
Temperature abs dev, Growing Season, Main Crop	18210	0.360	0.344

Table 2: Conflict incidence, cross section

Dependent variable: fraction of years over sample period with at least one conflict event

	(1)	(2)	(3)	(4)	(5)			(6)		
	Model I OLS		Model II OLS		Model III MLE					
						direct effects	*total effects*		*direct effects*	*total effects*
W · Y					0.782***			0.561***		
					(0.0252)			(0.0389)		
Shared	0.0149	0.0145	0.0273*	0.0220*	0.0329***	0.0284	-0.172	0.0272**	0.0239	-0.1247
	(0.0188)	(0.0110)	(0.0152)	(0.0132)	(0.0120)			(0.0114)		
Border	-0.00196	-0.00526	-0.0134	-0.0105	-0.0173	-0.0139	0.1367	-0.0118	-0.01	0.0694
	(0.0187)	(0.0191)	(0.0116)	(0.0154)	(0.0185)			(0.0183)		
Area[a]	0.00166	-0.000634	0.000894	0.00195	0.00203	0.0018	-0.01	0.00191	0.0021	0.0107
	(0.00347)	(0.00277)	(0.00429)	(0.00431)	(0.00317)			(0.00327)		
Elevation[a]	-0.0251	-0.0558**	-0.180	0.0271	-0.0395	-0.0373	0.0625	0.0307	0.0271	-0.1371
	(0.0392)	(0.0258)	(0.184)	(0.141)	(0.0940)			(0.0990)		
Rough	0.719***	0.623***	0.345**	0.424***	0.373***	0.3906	1.1682	0.407***	0.4193	0.9963
	(0.156)	(0.0707)	(0.137)	(0.0999)	(0.0796)			(0.0744)		
Distance to river[b]	-0.0154***	-0.00762***	0.00458	-0.00288	0.000385	-0.0002	-0.025	-0.00127	-0.0012	0.0016
	(0.00282)	(0.00187)	(0.00699)	(0.00521)	(0.00415)			(0.00378)		
Road	0.127***	0.0995***	0.106***	0.100***	0.108***	0.109	0.1443	0.105***	0.1034	0.0505
	(0.0259)	(0.0154)	(0.0174)	(0.0169)	(0.0165)			(0.0159)		
ELF	0.0606*	0.0407*	0.0141	0.0151	0.0128	0.0175	0.2283	0.0150	0.0183	0.1693
	(0.0365)	(0.0223)	(0.0252)	(0.0248)	(0.0235)			(0.0228)		
Minerals	0.0654***	0.0632***	0.0531***	0.0565***	0.0507***	0.0536	0.1844	0.0531***	0.0579	0.2792
	(0.0174)	(0.0136)	(0.0127)	(0.0139)	(0.0126)			(0.0123)		
W·Shared			-0.0862*	-0.0758*	-0.0703***			-0.0818***		
			(0.0508)	(0.0410)	(0.0258)			(0.0294)		
W·Border			0.204	0.0910	0.0470			0.0422		
			(0.132)	(0.106)	(0.0578)			(0.0660)		
W·Area[a]			0.00727	0.00441	-0.00426			0.00276		
			(0.0174)	(0.0160)	(0.00745)			(0.00868)		
W·Elevation[a]			0.198	-0.107	0.0531			-0.0909		
			(0.202)	(0.171)	(0.102)			(0.116)		
W·Rough			0.647***	0.315	-0.119			0.0303		
			(0.186)	(0.209)	(0.121)			(0.154)		
W·Distance to river[b]			-0.0230***	-0.000335	-0.00576			0.00196		
			(0.00815)	(0.00725)	(0.00473)			(0.00491)		
W·Road			0.0382	-0.0220	-0.0768***			-0.0825**		
			(0.0460)	(0.0616)	(0.0290)			(0.0394)		
W·ELF			0.145	0.118	0.0368			0.0592		
			(0.111)	(0.0978)	(0.0469)			(0.0528)		
W·Minerals			0.0706	0.148***	-0.0106			0.0694		
			(0.0717)	(0.0550)	(0.0338)			(0.0450)		
Country FE		X		X				X		
Observations	2,149	2,149	2,149	2,149	2,149			2,149		
R-squared	0.467	0.400	0.485	0.624	0.260			0.462		

(a) Coefficient and std error multiplied by 10^3 (b) Coefficient and std error multiplied by 10^2

Standard errors in parenthesis corrected for spatial dependence, following Conley (1999). * p<0.01, ** p<0.05, * p<0.1

W = binary contiguity matrix, cutoff 290 km.

Table 3: Conflict incidence and climate, panel

Dependent variable (Y) = 1 if conflict event in year t (ANY EVENT)	(1)	(2)	(3)		
	Model I	Model II	Model III		
	OLS	OLS	MLE		
				direct effects	*total effects*
Y, t-1			0.311***		
			(0.00700)		
W · Y			0.446***		
			(0.0137)		
SPEI	0.0401***	0.0211	0.0123	0.0129	0.0535
	(0.0132)	(0.0233)	(0.0208)		
SPEI, t-1	0.0336***	0.0171	0.0137	0.0136	0.0050
	(0.0129)	(0.0224)	(0.0199)		
SPEI, t-2	0.0119	0.0170	0.00693	0.0067	-0.0057
	(0.0116)	(0.0205)	(0.0181)		
SPEI Shock Growing Season	0.0938***	0.0214	0.00342	0.0053	0.1187
	(0.0245)	(0.0261)	(0.0234)		
SPEI Shock Growing Season, t-1	0.106***	0.0756***	0.0619**	0.0611	0.0129
	(0.0257)	(0.0242)	(0.0246)		
SPEI Shock Growing Season, t-2	0.0658***	0.0488**	0.0401*	0.0398	0.0195
	(0.0243)	(0.0239)	(0.0225)		
W · SPEI		0.0300	0.0246		
		(0.0309)	(0.0252)		
W · SPEI, t-1		0.0222	-0.0103		
		(0.0311)	(0.0245)		
W · SPEI, t-2		-0.0115	-0.0108		
		(0.0278)	(0.0226)		
W · SPEI Shock Growing Season		0.145***	0.0784**		
		(0.0497)	(0.0367)		
W · SPEI Shock Growing Season, t-1		0.0650	-0.0530		
		(0.0475)	(0.0385)		
W · SPEI Shock Growing Season, t-1		0.0349	-0.0267		
		(0.0452)	(0.0367)		
Observations	18,790	18,790	18,790		
R-squared	0.315	0.333	0.317		

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects. W = binary contiguity matrix, cutoff 290 km.
Standard errors in parenthesis. Cols. 1-2-4-5 corrected for spatial and serial correlation. Cols. 3-6 corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Sensitivity to different spatial matrices

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

	(1)	(2)	(3)	(4)	(5)	(6)
	Binary contiguity matrix			Inverse quadratic distance matrix		
	190 km	450 km	600 km	290 km	450 km	600 km
Y, t-1	0.313***	0.312***	0.321***	0.307***	0.302***	0.302***
	(0.00703)	(0.00704)	(0.00710)	(0.00702)	(0.00700)	(0.00710)
W · Y	0.327***	0.554***	0.608***	0.405***	0.486***	0.530***
	(0.0107)	(0.0179)	(0.0218)	(0.0121)	(0.0140)	(0.0156)
SPEI	0.0134	0.0185	0.0254**	0.00812	0.0148	0.0104
	(0.0280)	(0.0145)	(0.0118)	(0.0257)	(0.0218)	(0.0199)
SPEI, t-1	0.0257	0.00910	0.00692	0.0202	0.0129	0.00847
	(0.0274)	(0.0142)	(0.0121)	(0.0250)	(0.0213)	(0.0199)
SPEI, t-2	-0.0113	0.00769	0.0134	-0.00129	0.00114	0.00717
	(0.0242)	(0.0134)	(0.0115)	(0.0222)	(0.0192)	(0.0179)
SPEI Shock Growing Season	0.00897	0.00934	0.0304	0.00319	0.00245	-0.000410
	(0.0263)	(0.0203)	(0.0187)	(0.0262)	(0.0248)	(0.0243)
SPEI Shock Growing Season, t-1	0.0548**	0.0541**	0.0519**	0.0591**	0.0552**	0.0508**
	(0.0267)	(0.0219)	(0.0203)	(0.0268)	(0.0258)	(0.0257)
SPEI Shock Growing Season, t-2	0.0318	0.0336	0.0441**	0.0405*	0.0383	0.0400*
	(0.0238)	-0.0205	(0.0191)	(0.0240)	(0.0236)	(0.0234)
W · SPEI	0.0217	0.0157	0.0103	0.0272	0.0190	0.0289
	(0.0310)	(0.0207)	(0.0202)	(0.0296)	(0.0270)	(0.0262)
W · SPEI, t-1	-0.0176	-0.00630	-0.00162	-0.0137	-0.00940	-0.00133
	(0.0307)	(0.0204)	(0.0207)	(0.0292)	(0.0268)	(0.0267)
W · SPEI, t-2	0.0126	-0.0145	-0.0282	0.000102	-0.00445	-0.0139
	(0.0275)	(0.0195)	(0.0199)	(0.0263)	(0.0244)	(0.0241)
W · SPEI Shock Growing Season	0.0597*	0.0811**	0.0622	0.0682*	0.0720*	0.0878**
	(0.0353)	(0.0403)	(0.0455)	(0.0377)	(0.0402)	(0.0434)
W · SPEI Shock Growing Season, t-1	-0.0271	-0.0553	-0.0631	-0.0406	-0.0469	-0.0429
	(0.0355)	(0.0423)	(0.0477)	(0.0387)	(0.0420)	(0.0455)
W · SPEI Shock Growing Season, t-2	-0.00812	-0.0320	-0.0588	-0.0251	-0.0302	-0.0323
	(0.0322)	(0.0413)	(0.0462)	(0.0355)	(0.0391)	(0.0420)
Observations	18,790	18,790	18,790	18,790	18,790	18,790
R-squared	0.313	0.313	0.301	0.314	0.319	0.301

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects. Estimation by MLE. Standard errors corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1

Table 5a: Sensitivity to different spatial resolutions, 2x2 cells

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

	Model I - OLS				Model III - MLE			
	avg. coefficient	coefficient std. dev.	avg. std. error	nr of panels in which 10% significant	avg. coefficient	coefficient std. dev.	avg. std. error	nr of panels in which 10% significant
Y, t-1					0.3703	0.0126	0.0135	4/4
W · Y					0.3883	0.0098	0.0192	4/4
SPEI	0.0601	0.0040	0.0116	4/4	0.0102	0.0073	0.0225	0/4
SPEI, t-1	0.0576	0.0057	0.0119	4/4	0.0019	0.0138	0.0222	0/4
SPEI, t-2	0.0312	0.0064	0.0105	4/4	0.0043	0.0064	0.0196	0/4
SPEI Shock Growing Season	0.1655	0.0145	0.0275	4/4	-0.0064	0.0362	0.0332	0/4
SPEI Shock Growing Season, t-1	0.1720	0.0164	0.0315	4/4	0.0547	0.0152	0.0356	2/4
SPEI Shock Growing Season, t-2	0.1189	0.0164	0.0279	4/4	0.0178	0.0201	0.0333	0/4
W · SPEI					0.0320	0.0151	0.0278	1/4
W · SPEI, t-1					-0.0018	0.0101	0.0270	0.4
W · SPEI, t-2					-0.0185	0.0113	0.0253	0/4
W · SPEI Shock Growing Season					0.1053	0.0472	0.0506	3/4
W · SPEI Shock Growing Season, t-1					-0.0728	0.0026	0.0558	0/4
W · SPEI Shock Growing Season, t-1					-0.0318	0.0352	0.0516	0/4
Average nr of obs	4698				4698			
Average R squared	0.2803				0.4978			

Results of the estimation of models I and III in 4 possible panels of 2x2 cells. All regressions include controls listed in table 2, country and year fixed effects. W = binary contiguity matrix, cutoff 390 km.
OLS standard errors corrected by spatial and serial correlation. MLE standard errors corrected for clustering at the cell level. *** p<0.01, **

Table 5b: Sensitivity to different spatial resolution, 3x3 cells

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

	Model I - OLS				Model III - MLE			
	avg. coefficient	coefficient std. dev.	avg. std. error	nr of panels in which 10% significant	avg. coefficient	coefficient std. dev.	avg. std. error	nr of panels in which 10% significant
Y, t-1					0.3723	0.0352	0.0197	9/9
W · Y					0.4267	0.0409	0.0269	9/9
SPEI	0.0663	0.0101	0.0190	9/9	0.0396	0.0143	0.0182	7/9
SPEI, t-1	0.0619	0.0125	0.0177	9/9	0.0086	0.0167	0.0191	0/9
SPEI, t-2	0.0265	0.0037	0.0167	5/9	0.0161	0.0118	0.0170	2/9
SPEI Shock Growing Season	0.1962	0.0311	0.0418	9/9	0.0553	0.0260	0.0380	4/9
SPEI Shock Growing Season, t-1	0.1927	0.0489	0.0393	9/9	0.0382	0.0356	0.0399	1/9
SPEI Shock Growing Season, t-2	0.1243	0.0211	0.0387	9/9	0.0346	0.0251	0.0354	1/9
W · SPEI					-0.0008	0.0205	0.0260	0/9
W · SPEI, t-1					-0.0157	0.0302	0.0279	2/9
W · SPEI, t-2					-0.0479	0.0144	0.0243	4/9
W · SPEI Shock Growing Season					0.0451	0.0490	0.0635	5/9
W · SPEI Shock Growing Season, t-1					-0.0635	0.0527	0.0646	6/9
W · SPEI Shock Growing Season, t-1					-0.0809	0.0386	0.0585	2/9
Average nr of obs	2088				2088			
Average R squared	0.6001				0.6084			

Results of the estimation of models I and III in 9 possible panels of 3x3 cells. All regressions include controls listed in table 2, country and year fixed effects. W = binary contiguity matrix, cutoff 490 km.
OLS standard errors corrected by spatial and serial correlation. MLE standard errors corrected for clustering at the cell level. *** p<0.01, **

Table 6a: Conflict incidence and other climate indicators

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

	(1)	(2)	(3)	(4)	(5)	(6)
		Log rain			**Temperature absolute deviation**	
	Model I	Model II	Model III	Model I	Model II	Model III
Y, t-1			0.294***			0.295***
			(0.00726)			(0.00726)
W · Y			0.445***			0.446***
			(0.0143)			(0.0142)
Climate	0.0199***	0.00215	-0.00176	0.0297	0.0687	0.0244
	(0.00500)	(0.00782)	(0.00712)	(0.0240)	(0.0547)	(0.0419)
Climate, t-1	0.00934**	-0.00911	-0.00979	-0.0177	0.106*	0.0891**
	(0.00474)	(0.00754)	(0.00800)	(0.0268)	(0.0544)	(0.0444)
Climate, t-2	0.000968	0.00707	0.00439	0.00754	0.0397	0.0152
	(0.00461)	(0.00694)	(0.00666)	(0.0263)	(0.0538)	(0.0439)
Climate, Growing Season Indicator	0.00648	0.0144	0.00988	0.0807**	0.0189	0.0411
	(0.0143)	(0.0119)	(0.0111)	(0.0319)	(0.0432)	(0.0328)
Climate, Growing Season Indicator, t-1	0.0130	0.00523	0.000730	0.0495	0.0227	0.00903
	(0.0151)	(0.0122)	(0.0125)	(0.0341)	(0.0393)	(0.0355)
Climate, Growing Season Indicator, t-2	0.0240*	0.00108	0.00202	0.0541	0.0554	0.0200
	(0.0139)	(0.0116)	(0.0110)	(0.0334)	(0.0425)	(0.0316)
W · Climate		0.0221*	0.0153*		-0.0763	-0.0195
		(0.0116)	(0.00895)		(0.0657)	(0.0476)
W · Climate, t-1		0.0253**	0.0110		-0.163**	-0.121**
		(0.0115)	(0.00984)		(0.0661)	(0.0497)
W · Climate, t-2		-0.0142	-0.0122		-0.0497	-0.00333
		(0.0106)	(0.00907)		(0.0683)	(0.0506)
W · Climate, Growing Season Indicator		-0.0333	-0.0132		0.118*	-0.000392
		(0.0337)	(0.0206)		(0.0607)	(0.0447)
W · Climate, Growing Season Indicator, t-1		9.98e-05	0.00426		0.0690	0.00727
		(0.0334)	(0.0244)		(0.0592)	(0.0465)
W · Climate, Growing Season Indicator, t-2		0.0522	0.0145			0.000421
		(0.0331)	(0.0212)			(0.0416)
Observations	17,670	17,670	17,670	17,670	17,670	17,670
R squared	0.295	0.334	0.320	0.329	0.348	0.321

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects. W = binary contiguity matrix, cutoff 290 km.

Standard errors in parenthesis. Cols. 1-2-4-5 corrected for spatial and serial correlation. Cols. 3-6 corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1

Table 6b: Conflict incidence and other climate indicators

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

	(1)	(2)		(3)	
	Model I	Model II		Model III	
Y, t-1				0.295***	
				(0.00730)	
W · Y				0.437***	
				(0.0144)	
		X	W · X	X	W · X
SPEI	0.0290**	0.0283	0.00492	0.0142	0.0199
	(0.0143)	(0.0244)	(0.0335)	(0.0216)	(0.0270)
SPEI, t-1	0.0159	0.0325	-0.0282	0.0236	-0.0302
	(0.0137)	(0.0226)	(0.0325)	(0.0211)	(0.0262)
SPEI, t-2	-0.00140	0.0223	-0.0452	0.00724	-0.0239
	(0.0123)	(0.0206)	(0.0286)	(0.0195)	(0.0247)
SPEI Shock Growing Season	0.0517**	0.0165	0.0709	0.00322	0.0564
	(0.0251)	(0.0274)	(0.0537)	(0.0250)	(0.0395)
SPEI Shock Growing Season, t-1	0.0689***	0.0614**	0.00600	0.0481*	-0.0524
	(0.0256)	(0.0253)	(0.0513)	(0.0255)	(0.0394)
SPEI Shock Growing Season, t-1	0.0236	0.0480*	-0.0531	0.0434*	-0.0594
	(0.0257)	(0.0254)	(0.0495)	(0.0242)	(0.0391)
Rain	0.0158***	-0.00619	0.0318***	-0.00109	0.0118
	(0.00479)	(0.00751)	(0.0114)	(0.00732)	(0.00917)
Rain t-1	0.00474	-0.0135*	0.0262**	-0.00818	0.00712
	(0.00439)	(0.00734)	(0.0112)	(0.00838)	(0.0104)
Rain t-2	-0.000602	0.00317	-0.00682	0.00616	-0.0119
	(0.00438)	(0.00667)	(0.0104)	(0.00673)	(0.00915)
Rain Growing Season Main Crop	0.00325	0.00959	-0.0278	0.00471	-0.0166
	(0.0132)	(0.0117)	(0.0334)	(0.0112)	(0.0216)
Rain Growing Season Main Crop t-1	0.00104	0.000706	-0.0141	-0.00349	0.00197
	(0.0139)	(0.0120)	(0.0347)	(0.0126)	(0.0258)
Rain Growing Season Main Crop t-2	0.0174	-0.00574	0.0629*	-0.000634	0.0313
	(0.0127)	(0.0115)	(0.0335)	(0.0113)	(0.0222)
Temperature, abs dev	0.0490**	0.0692	-0.0297	0.0176	0.0123
	(0.0242)	(0.0542)	(0.0660)	(0.0422)	(0.0490)
Temperature, abs dev, t-1	0.00242	0.109**	-0.124*	0.0954**	-0.110**
	(0.0270)	(0.0540)	(0.0661)	(0.0444)	(0.0505)
Temperature, abs dev, t-2	0.0384	0.0375	0.00641	0.0185	0.00968
	(0.0267)	(0.0527)	(0.0675)	(0.0441)	(0.0510)
Temperature abs dev, Growing Season Main Crop	0.0401	0.00955	0.0405	0.0414	-0.0308
	(0.0320)	(0.0421)	(0.0625)	(0.0336)	(0.0463)
Temperature abs dev, Growing Season Main Crop t-1	0.00141	0.0145	-0.0139	-0.00155	-0.01712
	(0.0346)	(0.0390)	(0.0610)	(0.0369)	(0.04995)
Temperature abs dev, Growing Season Main Crop t-2	0.00121	0.0428	-0.0506	0.0155	-0.03151
	(0.0342)	(0.0424)	(0.0696)	(0.0325)	(0.04254)
Observations	17,670	17,670		17,670	
R-squared	0.336	0.354		0.319	

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects.
W = binary contiguity matrix, cutoff 290 km. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1
Cols 1-2: corrected for spatial and serial correlation. Col. 3: corrected for clustering at the cell level.

Table 7: Different types of conflict events, cross section

	Y = BATTLE			*Y = CIVILIAN*			*Y = RIOT*			*Y = REBEL*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III
W · Y			0.689***			0.728***			0.304***			0.589***
			(0.0314)			(0.0299)			(0.0528)			(0.0373)
Shared	0.0129	0.0176*	0.0205**	0.0114	0.0175	0.0213**	-0.00767	-0.00465	-0.00363	0.0138***	0.0123**	0.0131***
	(0.00810)	(0.0100)	(0.00824)	(0.00828)	(0.0107)	(0.00828)	(0.00657)	(0.00762)	(0.00769)	(0.00419)	(0.00494)	(0.00452)
Border	-0.0122	-0.0165	-0.0126	0.00314	0.00265	0.00759	-0.00662	-0.00791	-0.00816	-0.000637	-0.00334	-0.00204
	(0.0146)	(0.0121)	(0.0146)	(0.0143)	(0.0139)	(0.0135)	(0.00986)	(0.00719)	(0.0102)	(0.00602)	(0.00706)	(0.00700)
Area[(a)]	0.00247	0.00419	0.00450**	-0.000798	0.00160	0.00215	-0.00450**	-0.00153	-0.00128	-0.000638	-5.36e-05	-0.000214
	(0.00169)	(0.00295)	(0.00195)	(0.00194)	(0.00316)	(0.00221)	(0.00207)	(0.00289)	(0.00234)	(0.000788)	(0.000971)	(0.000913)
Elevation[(a)]	-0.0147	0.166	0.0780	-0.0232	-0.0824	-0.161**	-0.0303**	-0.0984	-0.137**	-0.00310	-0.00787	-0.0532
	(0.0184)	(0.114)	(0.0758)	(0.0192)	(0.0984)	(0.0722)	(0.0149)	(0.0681)	(0.0617)	(0.00644)	(0.0318)	(0.0356)
Rough	0.431***	0.316***	0.301***	0.536***	0.352***	0.330***	0.245***	0.214***	0.210***	0.161***	0.140**	0.134***
	(0.0642)	(0.0956)	(0.0668)	(0.0626)	(0.103)	(0.0690)	(0.0420)	(0.0705)	(0.0519)	(0.0376)	(0.0675)	(0.0348)
Distance to river[(b)]	-0.00585***	-0.00592	-0.00357	-0.00579***	0.000560	0.00185	-0.00203*	0.00183	0.00244	-0.000227	-0.000202	0.00107
	(0.00132)	(0.00371)	(0.00243)	(0.00140)	(0.00398)	(0.00302)	(0.00107)	(0.00333)	(0.00282)	(0.000490)	(0.00198)	(0.00144)
Road	0.0450***	0.0543***	0.0607***	0.0596***	0.0629***	0.0674***	0.0698***	0.0640***	0.0656***	0.00394	0.00847*	0.0115**
	(0.0109)	(0.0124)	(0.0114)	(0.0118)	(0.0135)	(0.0121)	(0.0113)	(0.0121)	(0.0114)	(0.00499)	(0.00470)	(0.00546)
ELF	0.0376**	0.0215	0.0207	0.0279*	0.00809	0.00669	0.00943	0.00177	0.00272	0.0129*	0.00638	0.00700
	(0.0162)	(0.0185)	(0.0163)	(0.0168)	(0.0189)	(0.0170)	(0.0133)	(0.0137)	(0.0152)	(0.00735)	(0.00788)	(0.00795)
Minerals	0.0302***	0.0276***	0.0231***	0.0309***	0.0287***	0.0238***	0.0317***	0.0237**	0.0223**	0.00820*	0.00805**	0.00572
	(0.00972)	(0.00991)	(0.00859)	(0.0100)	(0.0101)	(0.00907)	(0.00916)	(0.00971)	(0.00882)	(0.00449)	(0.00354)	(0.00396)
W·Shared		-0.0415	-0.0311		-0.0547*	-0.0357*		-0.0436**	-0.0281		-0.000931	-0.000118
		(0.0299)	(0.0218)		(0.0309)	(0.0215)		(0.0197)	(0.0182)		(0.0118)	(0.0116)
W·Border		-0.00639	0.0199		-0.0293	-0.0266		0.0662	0.0684		-0.0426	-0.0148
		(0.0777)	(0.0471)		(0.0775)	(0.0433)		(0.0570)	(0.0464)		(0.0277)	(0.0227)
W·Area[(a)]		-0.000765	-0.00421		0.00221	0.000852		-0.00656	-0.00529		0.000874	0.00200
		(0.0117)	(0.00595)		(0.0129)	(0.00670)		(0.00930)	(0.00630)		(0.00467)	(0.00318)
W·Elevation[(a)]		-0.236*	-0.105		0.0697	0.172**		0.102	0.164**		-0.00932	0.0501
		(0.139)	(0.0839)		(0.120)	(0.0810)		(0.0754)	(0.0718)		(0.0391)	(0.0378)
W·Rough		0.153	-0.0595		0.320**	-0.0439		-0.00303	-0.0741		-0.0333	-0.0785
		(0.164)	(0.119)		(0.154)	(0.120)		(0.102)	(0.0853)		(0.0652)	(0.0578)
W·Distance to river[(b)]		0.00504	0.000907		-0.00304	-0.00468		-0.00496	-0.00663*		0.00206	-0.00179
		(0.00556)	(0.00309)		(0.00520)	(0.00391)		(0.00424)	(0.00386)		(0.00274)	(0.00180)
W·Road		-0.0610	-0.0771***		-0.0224	-0.0458*		-0.0115	-0.0137		-0.0270**	-0.0136
		(0.0416)	(0.0216)		(0.0508)	(0.0277)		(0.0302)	(0.0229)		(0.0120)	(0.00904)
W·ELF		0.0700	0.0734*		0.0867	0.0557		0.0153	0.0296		0.00146	0.0193
		(0.0674)	(0.0400)		(0.0788)	(0.0409)		(0.0370)	(0.0322)		(0.0223)	(0.0212)
W·Minerals		0.104**	0.00346		0.0865**	0.0148		0.0926***	0.0597*		0.0321*	0.000364
		(0.0439)	(0.0288)		(0.0427)	(0.0309)		(0.0296)	(0.0306)		(0.0181)	(0.0151)
Country FE	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149	2,149
Observations	0.415	0.606	0.432	0.405	0.569	0.402	0.223	0.350	0.255	0.400	0.515	0.413
R-squared	X	X	X	X	X	X	X	X	X	X	X	X

Notes: Each observation is a cell. All regressions include country fixed effects. W = binary contiguity matrix, cutoff 290 km.

Standard errors in parenthesis corrected for spatial dependence, following Conley (1999). * p<0.01, ** p<0.05, * p<0.1

Table 8: Different types of conflict events, panel - to be continued

	Y = BATTLE					*Y = CIVILIAN*				
	(1)	(2)	(3)			(4)	(5)	(6)		
	Model I	Model II	Model III			Model I	Model II	Model III		
				direct effects	*total effects*				*direct effects*	*total effects*
Y, t-1			0.2335***					0.270***		
			(0.0072)					(0.00715)		
W · Y			0.4943***					0.450***		
			(0.0132)					(0.0142)		
SPEI	0.0139	-0.0122	-0.0139	-0.014	0.019	0.0180*	0.0193	0.00741	0.0076	0.0184
	(0.0104)	(0.0199)	(0.0177)			(0.0106)	(0.0174)	(0.0166)		
SPEI, t-1	0.0130	0.0240	0.0176	0.0174	0.0002	0.0296**	0.0204	0.0259	0.0255	0.0022
	(0.0101)	(0.0187)	(0.0171)			(0.0116)	(0.0183)	(0.0164)		
SPEI, t-2	-5.77e-05	0.00853	0.0024	0.0023	-0.004	0.0148	0.00208	-0.00848	-0.0084	-0.0014
	(0.00932)	(0.0168)	(0.0206)			(0.00970)	(0.0152)	(0.0146)		
SPEI Shock Growing Season	0.0415**	0.00144	0.0178	0.0183	0.0582	0.0754***	0.0141	-0.00324	-0.0021	0.0767
	(0.0199)	(0.0228)	(0.0206)			(0.0214)	(0.0218)	(0.0192)		
SPEI Shock Growing Season, t-1	0.0629***	0.0432**	0.0317	0.0318	0.0399	0.0636***	0.0304	0.0219	0.0217	0.0026
	(0.0198)	(0.0194)	(0.0213)			(0.0210)	(0.0192)	(0.0196)		
SPEI Shock Growing Season, t-2	0.0436**	0.0301	0.0316	0.0313	0.0125	0.0461**	0.0347*	0.0286	0.0285	0.019
	(0.0183)	(0.0190)	(0.0196)			(0.0198)	(0.0188)	(0.0177)		
W · SPEI		0.0331	0.0285				0.00594	0.00606		
		(0.0257)	(0.021)				(0.0238)	(0.0202)		
W · SPEI, t-1		-0.0167	-0.0174				0.0174	-0.0242		
		(0.0233)	(0.0209)				(0.0273)	(0.0202)		
W · SPEI, t-2		-0.0157	-0.0051				0.0142	0.00748		
		(0.0225)	(0.0191)				(0.0224)	(0.0180)		
W · SPEI Shock Growing Season		0.0733*	0.0268				0.130***	0.0592*		
		(0.0406)	(0.0308)				(0.0418)	(0.0302)		
W · SPEI Shock Growing Season, t-		0.0373	-0.0012				0.0816**	-0.0201		
		(0.0361)	(0.0333)				(0.0401)	(0.0308)		
W · SPEI Shock Growing Season, t-		0.0250	-0.022				0.0299	-0.0147		
		(0.0345)	(0.0316)				(0.0394)	(0.0268)		
Observations	18,790	18,790	18,790			18,790	18,790	18,790		
R-squared	0.230	0.253	0.236			0.230	0.249	0.276		

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects.
W = binary contiguity matrix, cutoff 290 km. Standard errors in parenthesis.

Table 8 - continued: Different types of conflict events, panel

	Y = RIOT					Y = REBEL				
	(7)	(8)	(9)			(10)	(11)	(12)		
	Model I	Model II	Model III			Model I	Model II	Model III		
				direct effects	*total effects*				*direct effects*	*total effects*
Y, t-1			0.277***					0.175***		
			(0.00707)					(0.00731)		
W · Y			0.329***					0.362***		
			(0.0165)					(0.0164)		
SPEI	0.0190**	0.00427	0.000238	0.0005	0.0211	0.0199***	0.0170*	0.0236***	0.0235	0.0171
	(0.00876)	(0.0150)	(0.0150)			(0.00647)	(0.00973)	(0.00900)		
SPEI, t-1	0.0144**	0.00542	0.00693	0.0071	0.0158	0.00722	-0.000759	-0.00821	-0.0081	0.0015
	(0.00735)	(0.0148)	(0.0141)			(0.00520)	(0.00959)	(0.00951)		
SPEI, t-2	0.00777	0.0392***	0.0266**	0.026	-0.013	0.00419	0.00374	0.00619	0.0061	0.0013
	(0.00641)	(0.0134)	(0.0124)			(0.00597)	(0.00967)	(0.00958)		
SPEI Shock Growing Season	0.0377***	0.0378**	0.0209	0.021	0.0284	0.0282***	0.0196**	0.0246**	0.0246	0.022
	(0.0137)	(0.0165)	(0.0154)			(0.0106)	(0.00992)	(0.0101)		
SPEI Shock Growing Season, t-1	0.0395***	0.0387**	0.0203	0.0203	0.0143	0.0144*	0.0261***	0.0180	0.0177	-0.0138
	(0.0133)	(0.0159)	(0.0147)			(0.00870)	(0.00988)	(0.0117)		
SPEI Shock Growing Season, t-2	0.0207*	0.0178	0.0145	0.0142	-0.008	0.00282	0.00650	0.00264	0.0025	-0.0073
	(0.0112)	(0.0129)	(0.0154)			(0.00997)	(0.0115)	(0.0107)		
W · SPEI		0.0151	0.0150				0.00491	-0.00950		
		(0.0204)	(0.0185)				(0.0126)	(0.0107)		
W · SPEI, t-1		0.00879	0.00447				0.00704	0.00946		
		(0.0187)	(0.0168)				(0.0109)	(0.0109)		
W · SPEI, t-2		-0.0440**	-0.0363**				-0.00153	-0.00515		
		(0.0175)	(0.0157)				(0.0128)	(0.0113)		
W · SPEI Shock Growing Season		-0.00948	-0.000336				0.0164	-0.00645		
		(0.0290)	(0.0241)				(0.0194)	(0.0144)		
W · SPEI Shock Growing Season, t-		-0.00803	-0.0100				-0.0255	-0.0294*		
		(0.0282)	(0.0222)				(0.0161)	(0.0170)		
W · SPEI Shock Growing Season, t-		-0.00165	-0.0204				-0.00691	-0.00863		
		(0.0261)	(0.0226)				(0.0161)	(0.0144)		
Observations	18,790	18,790	18,790			18,790	18,790	18,790		
R-squared	0.140	0.154	0.190			0.099	0.122	0.136		

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects.
W = binary contiguity matrix, cutoff 290 km. Standard errors in parenthesis.

Table A1: Conflict incidence and climate, full vs. balanced panel

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

	(1)	(2)	(3)	(4)
	Balanced panel		Full panel	
	Model I	Model II	Model I	Model II
	OLS	OLS	OLS	OLS
SPEI	0.0401***	0.0211	0.0358***	0.0353***
	(0.0132)	(0.0233)	(0.00720)	(0.00811)
SPEI, t-1	0.0336***	0.0171	0.0316***	0.0308***
	(0.0129)	(0.0224)	(0.00759)	(0.00852)
SPEI, t-2	0.0119	0.0170	0.0206***	0.0180**
	(0.0116)	(0.0205)	(0.00683)	(0.00764)
SPEI Shock Growing Season	0.0938***	0.0214	0.0828***	0.0886***
	(0.0245)	(0.0261)	(0.0165)	(0.0174)
SPEI Shock Growing Season, t-1	0.106***	0.0756***	0.0910***	0.0914***
	(0.0257)	(0.0242)	(0.0173)	(0.0181)
SPEI Shock Growing Season, t-2	0.0658***	0.0488**	0.0745***	0.0750***
	(0.0243)	(0.0239)	(0.0167)	(0.0174)
W · SPEI		0.0300		-0.00440***
		(0.0309)		(0.000962)
W · SPEI, t-1		0.0222		-0.00236**
		(0.0311)		(0.00102)
W · SPEI, t-2		-0.0115		-0.00164*
		(0.0278)		(0.000900)
W · SPEI Shock Growing Season		0.145***		-0.0128***
		(0.0497)		(0.00246)
W · SPEI Shock Growing Season, t-1		0.0650		-0.00347
		(0.0475)		(0.00336)
W · SPEI Shock Growing Season, t-1		0.0349		-0.00798***
		(0.0452)		(0.00271)
Observations	18,790	18,790	29,532	29,532
R-squared	0.315	0.333	0.252	0.274

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects. W = binary contiguity matrix, cutoff 290 km.

Standard errors corrected for spatial and serial correlation in parenthesis.

Table A2: Conflict incidence and other SPEI based climate indicators, panel

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Standalone			**Growing Season Maincrop**			**Growing Season Weighted**			**Growing Season 2 St Dev Shock**		
	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III
Y, t-1			0.311***			0.310***			0.306***			0.313***
			(0.00699)			(0.00700)			(0.00821)			(0.00699)
W · Y			0.452***			0.445***			0.388***			0.452***
			(0.0136)			(0.0138)			(0.0154)			(0.0136)
SPEI	0.0257**	0.0219	0.0139	0.0558***	0.0316	0.0114	0.0275*	0.0292	0.00440	0.0302**	0.0223	0.0126
	(0.0127)	(0.0229)	(0.0206)	(0.0158)	(0.0268)	(0.0219)	(0.0143)	(0.0249)	(0.0222)	(0.0127)	(0.0229)	(0.0208)
SPEI, t-1	0.0114	0.00374	0.00282	0.0454***	0.0208	0.0286	0.00440	0.0279	0.0183	0.0161	0.00615	0.00177
	(0.0122)	-0.0218	(0.0192)	(0.0151)	(0.0273)	(0.0214)	(0.0131)	(0.0246)	(0.0213)	(0.0125)	(0.0220)	(0.0192)
SPEI, t-2	0.000516	0.00754	-0.000680	0.0156	0.0235	0.00936	-0.00444	0.0325	-0.00232	0.00104	0.00846	-0.000600
	(0.0110)	(0.0201)	(0.0174)	(0.0155)	(0.0250)	(0.0203)	(0.0126)	(0.0220)	(0.0203)	(0.0111)	(0.0203)	(0.0177)
SPEI, Growing Season Indicator				-0.0685***	-0.0171	0.00685	-0.897	-0.486	-0.623	0.216***	0.0540	0.0460
				(0.0264)	(0.0299)	(0.0231)	(0.764)	(0.732)	(0.637)	(0.0808)	(0.0729)	(0.0879)
SPEI, Growing Season Indicator, t-1				-0.0738***	-0.0279	-0.0454*	-0.189	-0.171	0.424	0.141**	0.0903	0.117
				(0.0255)	(0.0296)	(0.0254)	(0.802)	(0.809)	(0.755)	(0.0676)	(0.0750)	(0.0912)
SPEI, Growing Season Indicator, t-2				-0.0399	-0.0235	-0.0189	-0.155	0.520	0.776	0.0387	0.0201	-0.0152
				(0.0256)	(0.0268)	(0.0224)	(0.767)	(0.812)	(0.665)	(0.0761)	(0.0671)	(0.0679)
W · SPEI		-0.00423	0.00523		0.0383	0.0402		-0.0123	0.0251		0.00390	0.0123
		(0.0292)	(0.0246)		(0.0350)	(0.0271)		(0.0327)	(0.0270)		(0.0295)	(0.0249)
W · SPEI, t-1		0.00167	-0.00143		0.0419	-0.0173		-0.0354	-0.0270		0.00489	0.00508
		(0.0290)	(0.0229)		(0.0361)	(0.0263)		(0.0312)	(0.0246)		(0.0297)	(0.0231)
W · SPEI, t-2		-0.0177	-0.00278		-0.00698	-0.0115		-0.0465	-0.00122		-0.0194	-0.00382
		(0.0263)	(0.0207)		(0.0334)	(0.0248)		(0.0295)	(0.0243)		(0.0267)	(0.0210)
W · SPEI, Growing Season Indicator					-0.102**	-0.0800**		-1.019	-0.490		0.297	0.185
					(0.0475)	(0.0346)		(1.061)	(0.959)		(0.194)	(0.135)
W · SPEI, Growing Season Indicator, t-1					-0.0997**	0.0229		-0.517	-0.216		0.0646	-0.117
					(0.0447)	(0.0366)		(1.001)	(1.062)		(0.169)	(0.139)
W · SPEI, Growing Season Indicator, t-2					-0.0503	0.00864		-2.541**	-2.115**		-0.00123	0.00538
					(0.0452)	(0.0315)		(1.107)	(0.965)		(0.154)	(0.110)
Observations	18,790	18,790	18,790	18,790	18,790	18,790	13,750	13,750	13,750	18,790	18,790	18,790
R squared	0.310	0.328	0.315	0.314	0.314	0.317	0.305	0.306	0.312	0.311	0.328	0.312

Notes: Each observation is a cell/year. All regressions include controls listed in table 2, country and year fixed effects. W = binary contiguity matrix, cutoff 290 km.

Standard errors in parenthesis. Cols. 1-2-4-5-7-8-10-11 corrected for spatial and serial correlation. Cols. 3-6-9-12 corrected for clustering at the cell level. *** p<0.01, ** p<0.05, * p<0.1