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ORIGINAL PAPER

Climate change and armed conflicts in Africa: temporal persistence, non-linear climate impact and geographical spillovers

Federica Cappelli[1] · Caterina Conigliani[1] · Davide Consoli[2] · Valeria Costantini[1] · Elena Paglialunga[3]

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Abstract
The paper focuses on the nexus between climate change and armed conflicts with an empirical analysis based on a panel of 2653 georeferenced cells for the African continent between 1990 and 2016. Our econometric approach addresses unobservable heterogeneity in predicting the probability of violent events and the persistency of conflicting behaviour over time. The proposed strategy also accounts for both changes in climatic conditions and spatial dynamics. The two main findings carry policy-relevant implications. First, changes in climatic conditions influence the probability of conflicts over large spatial ranges, thus suggesting that the design of adaptation policies to reduce climate vulnerability should account for multiple spatial interrelations. Second, the persistency of violence calls for planning adaptation strategies for climate resilience jointly designed with measures in support of peacekeeping.

Keywords Africa · Armed conflicts · Climate change · Geographical spillovers · Spatial econometrics

✉ Valeria Costantini
valeria.costantini@uniroma3.it

Federica Cappelli
federica.cappelli@uniroma3.it

Caterina Conigliani
caterina.conigliani@uniroma3.it

Davide Consoli
davide.consoli@ingenio.upv.es

Elena Paglialunga
elena.paglialunga@uniurb.it

[1] Roma Tre University, Rome, Italy

[2] INGENIO CSIC-UPV, Valencia, Spain

[3] University of Urbino “Carlo Bò”, Urbino, Italy

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1 Introduction

The deterioration of living conditions due to climate change is the trigger of a vicious cycle that imperils individual well-being and, ultimately, social order. Violent events are hard to predict and difficult to counter as they propagate in unforeseeable directions. One major concern is the prospect of conflicts in regions of the world that are vulnerable to climate events and, also, prone to social instability. The goal of the present paper is to develop an empirical strategy that allows addressing unobservable sources of heterogeneity in the climate-conflict nexus. This allows better disclosing temporal and spatial mechanisms that are relevant for integrating climate adaptation policies with peacekeeping actions to fruitfully exploit potential ancillary benefits or to mitigate negative side-effects.

We focus on Africa, a continent that is home to some of the most conflict-ridden regions in the world according to Croicu and Sundberg (2017). Empirical evidence suggests a correlation between changes in temperature and rainfall patterns, that have the effect of worsening living conditions of African populations in vulnerable areas, and the breakout of violence (Dell et al., 2014). The acceleration of climate change in such a precarious context exacerbates tensions and gives way to repeated armed conflicts as well as massive migratory movements (Daccache et al., 2015; Hendrix & Glaser, 2007; Marchiori et al., 2012; Maystadt et al., 2015).

At the general level, changes in weather conditions present both direct and indirect impacts on human beings (Buhaug, 2015; Burke et al., 2015). Direct effects can be envisaged in the increase of violent behaviours associated to higher temperatures given that people become more nervous, or in the conflicts for access to water when extreme drought conditions directly harm human livelihood. Indirect effects are explained by the impacts on anthropogenic activities as in the case of agriculture, or reduction in land fertility or diseases diffusion, which in turns foster competition over scarce resources and at the end cause battles and wars.

In the context of developing countries, agriculture is unquestionably the sector most exposed to climate variability (Raleigh et al., 2015). Together with agriculture, the joint increase in temperature and changes in precipitation patterns often leads to more severe drought conditions, also influencing the livestock sector by inducing changes in prices or pastoralism displacement with a consequent increase in competition on land-use (Maystadt & Ecker, 2014). Water access is another channel responsible for linkages between conflicts and weather-induced water scarcity since the control over water resources is an instrument of war for both offensive and defensive purposes (Gizelis & Wooden, 2010). The occurrence of climate-related shocks increases the risk of armed-conflict outbreak under certain socio-economic conditions, as for instance a high degree of ethnic fractionalisation (Schleussner et al., 2016), or the cultural specialisation of the affected ethnic group into activities that are particularly vulnerable to climate risks (van Uexküll et al., 2016).

A recent and comprehensive literature review by Koubi (2019) points out that the debate on whether changes in climatic conditions systematically increases risk of conflict or magnitude is still open. Some studies point to a link between increasing temperature, or decreasing precipitation, and armed conflicts (Fjelde & von Uexkull, 2012; Hendrix & Salehyan, 2012; Hsiang et al., 2011; Raleigh & Kniveton, 2012) while others find no significant (or direct) impact (Adams et al., 2018; Buhaug, 2010; O'Loughlin et al., 2012; Theisen et al., 2013). Empirical analyses on Africa conversely find that excess precipitation is responsible for rising violence (Klomp & Bulte, 2013; Salehyan & Hendrix, 2014; Theisen, 2012; Witsenburg & Adano, 2009). A contentious, and to some extent unexplored, issue is whether location-specific conditions amplify the effects of changing weather conditions. Scholars concur that resilient communities experience lower risks of violence in certain climate conditions (Buhaug, 2015; Burke et al., 2015; Hsiang, 2016) but empirical research is still inconclusive on the sources of local resilience, partly due to methodological uncertainties (Ide, 2017).

The present paper adds to the foregoing debate a novel methodology and empirical evidence on the existence and magnitude of the climate-conflict nexus in Africa with three contributions.

First, we propose an econometric approach that overcomes some shortcomings of prior research. Empirical analysis of climate-induced conflicts based on large-N quantitative analysis (Busby et al., 2014) relies on count data that are operationalised in one of two ways: (i) binary information—i.e., whether a territory experiences peace ($Y=0$) or conflict ($Y=1$)—or (ii) a discrete non-negative variable measuring the number of recorded conflicts in a territory in a time period. Depending on the measure, empirical studies yield contradictory findings even when the same explanatory variables are used. This is because socio-economic, territorial and climate conditions interact in non-linear ways and minor variations in one, or more, of the attendant characteristics can lead to extremely different outcomes. Recent work using linear and non-linear probability models applied to large-N quantitative geo-referenced databases focuses on specific aspects, such as the political status of ethnic groups (Basedau & Pierskalla, 2014; Chica-Olmo et al., 2019), water scarcity (Almer et al, 2017), vulnerability to extreme events (Breckner & Sunde, 2019), short-term impacts of climate change via the agriculture sector (Harari & La Ferrara, 2018) or via the conflict trap (Cappelli et al., 2021), but does not specifically address the potential bias deriving from overdispersion of structural zeros in a large territory. One interesting contribution in this direction is the transition analysis carried by Mack et al. (2021) wherein a logistic regression approach reveals that changes in rainfalls affect the probability that a cell faces above average conflicts in Sub-Saharan Africa. In order to control for differences in structural characteristics (i.e., season, geographical position), they apply different models to four regional aggregates. Along with this intuition on the role of structural features in shaping the transition from peace to war, we propose a zero-inflated negative binomial (ZINB) regression model to estimate the influence of local climate conditions and other geographical and socio-economic features both on structural zeros affecting the probability of conflicts and on the magnitude of violence. This empirical framework better accounts for the propensity of violence in small areas even if they have not experienced any conflicts in the past. Additionally, the empirical strategy allows accounting for structural features that might explain conflicts' outbreak independently from changes in climatic conditions, for instance related to the social instability or institutional failures. In turn, this has the potential of informing policy, both in terms of adaptation strategies as well as peacekeeping actions, by focusing not only on areas that are commonly known as prone to climate-related social disruptions but, also, on peaceful places that would be at risk of violence if climatic conditions worsen.

Second, we explore non-linear relationships between the vulnerability of the agricultural sector to climate-related events and the magnitude of violent conflicts. Such an exercise generates useful insights into the pivotal role of territorial characteristics (Ang & Gupta, 2018; Wischnath & Buhaug, 2014). The connection between climate and natural resource environment is far from trivial because the vulnerability of a territory depends on intervening context-specific features such as the degree of mechanisation in agricultural activities, the quality and quantity of chemical products used or the degree of diffusion of irrigation systems (Bates et al., 2008). The seminal study by Harari and La Ferrara (2018) finds a linear positive correlation between short-term climate shocks during the growing season and the probability of conflict breakouts. Likewise, Almer et al. (2017) report a similar association by analysing the impact of water scarcity on the number of days in which a riot occurs in Sub-Saharan Africa, thus addressing the magnitude of violence as well as its incidence. We build on and extend the above by: (i) measuring climate shocks determined by weather conditions with diversified time scales; (ii) explicitly accounting for local geographical features—as suggested by Anselin (1995)—by distinguishing the impact associated to the direction and to the magnitude of weather variations (Papaioannou, 2016). Our results suggest that the pressure on food availability related to water scarcity increases the number of conflicts only if the drought condition has persisted at least for 3 years prior. On the other hand, excess in rainfalls triggers larger and immediate reactions. This leads us to suggest that such non-linearity should be carefully accounted for when punctual actions for improving the resilience of the agricultural sector are planned.

Third, we assess the role of cross-area spillovers on local conflicts. In particular, we estimate for each cell the impact on the magnitude of violence of changes in climate conditions, agricultural yield, and socio-economic features such as income per capita, income inequality and demographic change in neighbouring cells. In so doing, we capture indirect conflict pathways that are difficult to identify in the absence of large-N scale spatial data. The main findings are that long-term growth in temperature and precipitations in the surrounding areas leads to an increase of violent events within the cell by 4–5 times, with a threshold distance of up to 550 km radius. On the opposite, short-term events as floods trigger conflicts only at a narrow local scale with negligible geographical spillovers. This points to a broader approach towards the design of adaptation strategies, namely by accounting for potential ancillary benefits due to the propagation over space of the positive effects of higher climate resilience.

The rest of the paper is structured as follows. In Sect. 2 we describe the empirical strategy, in Sect. 3 we present the main empirical results, and in Sect. 4 we present a discussion on policy implications.

2 Empirical strategy

The empirical analysis of the nexus between climate change and armed conflicts has grown remarkably over the last decade (Ide, 2017). Three types of studies dominate this strand. The first includes case studies on selected regions or countries based on micro-data at household level (Meierding, 2013; Salick & Ross, 2009). A second group of studies with greater spatial coverage uses artificially designed geographical scale based on administrative borders (counties or countries), cells with equal territorial dimension (Almer et al., 2017; Maystadt et al., 2015), or georeferenced socio-economic characteristics such as, for instance, ethnic groups as units of analysis (Schleussner et al., 2016; von Uexküll et al., 2016). The third and more recent literature strand resorts to a multi-method approach that combines statistical inference with qualitative comparative analysis and case studies (Ide et al., 2020).

Each of the foregoing approaches carries benefits and shortcomings, and the selection of one or another ultimately depends on the research questions. Since the present paper deals with the impact of long-term changes in climate conditions and the role of geographical spillovers, we opt for the large-N scale approach based on an artificial grid. Accordingly, we build a georeferenced NxT panel database with $N=2653$ cells—each with $1^\circ \times 1^\circ$ spatial resolution (approximately 110×110 km)—covering the entire (gridded) African continent over the period 1990–2016 ($T=27$). The rationale for this spatial scale is threefold. The first reason is the spatial availability of data on gross per-capita income at the level of individual cells. Second, robustness checks on different scales reveal that the $1^\circ \times 1^\circ$ grid provides the best model fit when the climate-conflict nexus for the whole African continent is under investigation (Harari & La Ferrara, 2018). Third, this allows working with a balanced panel that covers the whole African continent, thus avoiding sample selection bias and allowing for a dynamic assessment.

2.1 The dependent variable

The dependent variable is the total number of conflicts per cell/year. To build this, we extract information on armed conflicts between 1989 and 2016 from the UCDP-GED (Uppsala Conflict Data Project—Georeferenced Event Dataset, Global version 17.1 at 2016) for all African countries (Sundberg & Melander, 2013). Conflict events are defined as "incidents where armed force was used by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date" (Croicu & Sundberg, 2017, p. 2). Organized actors include the government of an independent state and both formally and informally organized groups, while a death is labelled as 'direct' if resulting from either infighting between warring parties or violence against civilians.

We consider the total number of violent events, excluding conflicts between two or more states, in order to estimate the effects of explanatory variables not only on the probability of a cell to experience at least one conflict (as in the case of binary information) but, also, on the relative magnitude of violence in the case of several episodes occurring over one year/cell.[1] This is a standard approach in the analysis of the climate-conflict nexus as the inter-states conflicts usually pertain to tensions regarding transboundary waters, where climate stress impacts are indistinctly related to property rights regimes (GCA, 2021). Given the nature of the dependent variable, we implement a dynamic spatial regression model for count data that accounts jointly for the drivers of a conflict outbreak and the magnitude of violence.

2.2 Regression models for count data with excess zeros and spatial correlation

Count data regression analyses are characterized by discrete response variables with a distribution that places probability mass at positive integer values. Data are usually skewed to the left and intrinsically heteroskedastic, with variance increasing with the mean (Cameron & Trivedi, 1998a, 1998b, 2005). Our response, in particular, exhibits overdispersion and an excess number of zeros, which leads us to use a zero-inflated negative binomial (ZINB) count model. Based on the canonical log link for the negative binomial component, the regression equation for the conditional mean can be written as:

$$E(Y_{it}|X_{it}, Z_{it}) = (1 - \pi_{it})exp(\alpha + X_{it}^{'}\beta) \tag{1}$$

while the probability of structural zeros (i.e. the probability of not being eligible for a non-zero count) can be expressed as a function of a set of covariates using the inverse logit function:

$$\pi_{it} = \frac{exp(\delta_i + Z_{it}^{'}\gamma)}{1 + exp(\delta_i + Z_{it}^{'}\gamma)} \tag{2}$$

In what follows we refer to Eqs. (1) and (2) as the Count model and the *Zero* model respectively. Notice that the occurrence of zero outcomes under the ZINB model rests on two premises. First, some cells will not experience conflicts for structural reasons, for instance because the corresponding territory is covered by desert or by water that prevents anthropic activities. On the other hand, other cells may experience or not violent breakouts depending on factors that are best captured by additional explanatory variables. According to Bagozzi (2015), the ZINB model is particularly useful to study the issue at hand (Clare, 2007; Hegre et al., 2009) because the event of a conflict is rare, and it is unclear whether the preponderance of peace cases typically observed in conflict datasets is due to inherent rarity of the phenomenon or, rather, to heterogeneous mix of actual and inflated peace observations (Price & Elu, 2017). Moreover, relative to logistic regression, the ZINB specification allows assessing the intensity of the phenomenon, rather than merely its occurrence (Mack et al., 2021).

[1] We prefer the UCDP database to ACLED because the latter covers a shorter time span (from 1997 onwards) relative to UCDP (1989 onwards).

Together with unobservable heterogeneity due to structural features, also spatial dynamics might influence our response variable. Notice that different types of interaction effects can explain why an observation at a specific location may depend on observations at other locations (Elhorst, 2014). First, due to endogenous interaction effects, the response variable Y of a particular unit depends on the response variable of neighbouring units. Second, due to exogenous interaction effects, the response variable of a particular unit depends on the explanatory variables X of neighbouring units. A third mechanism concerns interaction effects among the error terms, for instance in presence of spatial autocorrelation between the determinants of the response variable omitted from the model. These effects can be included in a spatial econometric model by means of a non-negative matrix W that describes the spatial configuration of the units in the sample. Thus, in a normal setting a full general model for panel data with all types of interaction effects can be written as:

$$Y_{it} = \alpha + \rho WY_{it} + X_{it}^{'}\beta + WX_{it}^{'}\theta + u_{it} \tag{3}$$

$$u_{it} = \lambda Wu_{it} + \varepsilon_{it} \tag{4}$$

where WY, WX, Wu represent respectively the endogenous interaction effects, the exogenous interaction effects, the interaction effects among the disturbance terms, and ε is the normal disturbance term. It is worth mentioning that this full model is usually overparametrized (Elhorst, 2014), so that most empirical studies resort to simpler models derived from (3) and (4) by imposing restrictions on one or more of its parameters (Anselin, 1988; LeSage & Pace, 2009).

Turning to the inclusion of spatial interaction effects in a regression model for count data, as for instance the ZINB in Eqs. (1)–(2), one major difference between a classical linear regression model and the specification for the conditional mean in a count regression model is that the latter does not include a random error term. Thus, accounting for the spatial structure in the unexplained part of the dependent variable is not as straightforward as in the continuous case. In fact, spatial error models can be defined also for count data by introducing in the regression equation spatial random effects following for instance the conditional autoregressive scheme (Besag, 1974; Pettitt et al., 2002), and are typically estimated using Bayesian Markov chain Monte Carlo methods. However, the introduction of random effects allows to account for spatial heterogeneity, which is a rather different point with respect to spatial autocorrelation (Simoes & Natário, 2016).

Further, the introduction of endogenous interaction effects is controversial in classical count data models. This is because there is no direct functional relationship between the regressors and the dependent variable but, rather, a relationship between the regressors and the conditional expectation of the response. One strategy to overcome this issue is the auto-Poisson model proposed by Besag (1974), which includes the spatially lagged dependent variable in the intensity equation of a Poisson regression model, but it suffers from various limitations. Another option is to include the spatially lagged dependent variable into the intensity equation using an exponential spatial autoregressive coefficient (Beger, 2012). Yet another possibility is the addition of the spatially lagged conditional expectation—rather than the spatially lagged dependent variable—to the intensity equation (Lambert et al., 2010). However, none of these different proposals have found broad application.

In contrast, the introduction of exogenous interaction effects in regression models for count data is straightforward and raises no particular issues since spatially lagged regressors can be computed before the actual regression is performed and treated in the same way as the non-spatial ones (Glaser, 2017). In particular, introducing exogenous spatial interaction effects in Eqs. (1)–(2) leads to a ZINB spatial model with $\rho, \lambda = 0$ *and* $\theta \neq 0$:

$$E(Y_{it}|X_{it}, WX_{it}, Z_{it}, WZ_{it}) = (1 - \pi_{it})exp(\alpha + X_{it}^{'}\beta + WX_{it}^{'}\theta) \tag{5}$$

$$\pi_{it} = \frac{exp(\delta_i + Z_{it}^{'}\gamma + WZ_{it}^{'}\eta)}{1 + exp(\delta_i + Z_{it}^{'}\gamma + WZ_{it}^{'}\eta)} \tag{6}$$

Another relevant issue in spatial econometrics concerns the choice of the spatial weight matrix *W*. Three elements are worthy of attention: (i) the method for computing distances between geographical units; (ii) the adoption of a normalisation procedure; (iii) the choice of a cut-off point. With respect to the first issue, we apply the Mercator's projection map accounting for the spheroidal form of the Earth and compute inverse great circle distances via the so-called Harversine formula between the centroids of cells.[2] Regarding the second issue, although it is common to normalize *W* such that the elements of each row sum to unity, following Ord (1975) we use an alternative procedure that normalizes *W* by $D^{1/2}WD^{1/2}$, where *D* is a diagonal matrix containing the row sums of *W*. This procedure, unlike row normalization, leads to a weight matrix that is symmetric, thus still allowing for an economic interpretation of distances, and that maintains the mutual proportions between the elements of *W* (Elhorst, 2014). With respect to the third issue, we explore the behaviour of different cut-offs calculated by combining the pure inverse distance with the queen contiguity approach. Since all cells in our dataset have the same spatial dimension, this is the only way to account for cut-offs that include all the cells belonging to the buffer whose radius is the cut-off measure. This brings to select 11 ideal cut-offs that include all cells whose centroid is in the area with radius of 178, 266, 355, 444, 533, 622, 710, 797, 887, 976, 1065 km, respectively (hereafter referred to from W1 to W11). For a discussion on the cut-off choices in the econometric estimation see Sect. 3.3.

[2] We are aware that the Harversine formula yields valid measures for short distances but underestimates long distances, especially in places far from the Equator line for which the Rhumb lines approach is more appropriate. Nonetheless, given that the maximum cut-off distance that is selected according to the two criteria described in Sect. 3.3 is around 533 km of radius, difference between the two approaches is negligible (Weintrit and Kopacz, 2012).

Table 1 List of base variables, main statistics and data source

Variable acronym	Variable description	Obs	Mean	Std.dev	Source
Dependent variable					
No $Confl_{i,t}$	Number of conflicting events per year in all coordinates belonging to each cell in each year	71,631	0.48	4.31	Authors' elab on UCDP-GED
Climatic conditions					
$Temp\_var_{i,t\ wrt\ t0}$	Temperature change w.r.t. to the base period	71,631	0.75	1.01	Authors' elab on AFDM (African Flood and Drought Monitor)
$Temp\_av\_var_{i,t\ wrt\ t0}$	Long-term trend of temp ch w.r.t. to the base period	71,631	0.44	0.26	
$Prec\_var_{i,t\ wrt\ t0}$	Precipitation change w.r.t. to the base period	71,631	0.04	0.45	
$Prec\_av\_var_{i,t\ wrt\ t0}$	Long-term trend of prec ch w.r.t. to the base period	71,631	0	0.19	
Agriculture					
$Sh\_grsSPEI6>1.49_{i,t}$	Sh of months of grow season with SPEI-6 > 1.49	71,631	0.02	0.12	Authors' elab on AFDM (African Flood and Drought Monitor), HYDE, and R code by Beguería and Vicente-Serrano (2017)
$Sh\_grsSPEI6<-1.49_{i,t}$	Sh of months of grow season with SPEI-6 < -1.49	71,631	0.07	0.22	
$Sh\_grsSPEI12>1.49_{i,t}$	Sh of months of grow season with SPEI-12 > 1.49	71,631	0.02	0.12	
$Sh\_grsSPEI12<-1.49_{i,t}$	Sh of months of grow season with SPEI-12 < -1.49	71,631	0.07	0.23	
$Sh\_grsSPEI36>1.49_{i,t}$	Sh of months of grow season with SPEI-36 > 1.49	71,631	0.02	0.11	
$Sh\_grsSPEI36<-1.49_{i,t}$	Sh of months of grow season with SPEI-36 < -1.49	71,631	0.08	0.25	
Socio-economic conditions					
$GCP_{i,t}$	Total cell GDP (PPP) constant international 2011 US$	71,631	17.82	4.44	Authors' elab on Kummu et al. (2018), HYDE and WDI World Bank
$GCPpc\_var_{i,t}$	Cell GDP per capita growth w.r.t. to t-1	68,978	0.01	0.08	
$Gini_{i,t}$	Gini index (cell level)	71,631	0.62	0.24	
$POP_{i,t}$	Population number	71,631	10.21	3.51	Authors' elab on HYDE
$POP\_var5_{i,t\ wrt\ t-5}$	Population growth in year t w.r.t to t-5	55,713	0.09	0.08	
$Ethnic\_fract_{i}$	Number of ethnic groups	71,631	1.97	1.18	Authors' elab on GREG
$Inst\_Quality_{c,t}$	Institutional quality index excluding conflicting tensions, country level	71,631	2.74	0.89	PRS Group database

Table 1 (continued)

Variable acronym	Variable description	Obs	Mean	Std.dev	Source
$NatResVal_{c,t}$	Value of foss fuel and min res exp w.r.t. total exp (%)	71,631	10.13	26.03	Authors' elab on WDI World Bank, NASA and PRS group database
$NatRes_{i,t}$	Interaction between $Resource\_d_i$ and $NatResVal_{c,t}$				
$Inst\_NatRes_{i,t}$	Interaction between Inst_Quality and $NatRes_{i,t}$	71,631	29.06	73.74	
Geographical characteristics					
$Border\_d_i$	Presence of country border (dummy)	71,631	0.25	0.43	Authors' elab on Natural Earth Database
$Water\_d_i$	Presence of water basins (dummy)	71,631	0.45	0.50	SEDAC and RCMRD
$Desert\_d_i$	Presence of desert areas (dummy)	71,631	0.35	0.46	USGS database
$Forest\_d_i$	Presence of forest areas (dummy)	71,631	0.08	0.24	USGS database
$Resource\_d_i$	Presence of exhaustible resource (dummy)	71,631	0.22	0.41	NASA database
$Slope\_sd_i$	Slope, standard deviation (time invariant index)	71,631	2.01	1.81	NASA SRTM
$Drought_i$	Risk of drought (time invariant index)	71,631	2.51	1.48	Aqueduct Water Risk Atlas

2.3 Explanatory variables

The key explanatory variables of our analysis cover four dimensions. (i) climatic conditions; (ii) agriculture vulnerability; (iii) socioeconomic variables; (iv) geographical features. The list of variables is provided in Table 1 while further details on the way the indicators have been computed are provided as Supplementary material.[3]

The main data source for climatic conditions is the African Flood and Drought Monitor (AFDM) database, developed by Princeton University in collaboration with ICIWaRM and UNESCO-IHP. We gather monthly data for Africa at 0.25° grid resolution about precipitations (mm per month), minimum and maximum temperatures (degree Celsius) for the time span ranging from 1971 to 2016. The decades 1971–1989 are excluded from the econometric estimation and serve as a benchmark for computing long-term changes in climatic conditions. Starting from monthly information, we compute the long-term trend of variation for precipitation and temperature by calculating for each year the average variation of the difference between the yearly change in the climate recorded in a given month (from 1990 onwards) and that registered in the same month of the previous year and, the corresponding average variations of that month recorded in the base period (1971–1989). The use of such long-term information better accounts for general hydrological conditions affecting human activities (Breckner & Sunde, 2019; Dubrovsky et al., 2009; IPCC, 2007; Papaioannou, 2016).

The second group of variables captures a widely established trigger of social tensions, namely vulnerability of agricultural activities due to climate change (Harari & La Ferrara, 2018; von Uexküll et al., 2016). The proposed vulnerability index combines information on monthly climate conditions with the UCDP-PRIO (Peace Research Institute Oslo) data on the growing season at the local level (Gleditsch et al., 2002) in four steps.

First, we compute the Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010) using the R package developed by Beguería and Vicente-Serrano (2017), which is considered the most accurate to jointly include variations in precipitations and temperature-related effects, and it has the advantage to be standardized, thus comparable and applicable for all climate regimes (WMO & GWP, 2016). The SPEI is calculated for three timescales, 6, 12 and 36 months to consider different types of impacts (Pandey & Ramasastri, 2001). Second, we build a monthly dummy variable equal to 1 if a month is in the main crop's growth season of each cell according to UCDP-PRIO data. Third, according to the classification system defined in McKee et al. (1993), we divide the monthly SPEI in six classes, three denoting drought conditions (d1, d2, d3) and three indicating flood occurrence (f1, f2, f3). For each class of the various timescale SPEIs, we create a dummy variable equal to 1 if the index exceeds the underlying threshold for each cell, and we interact it with the dummy variable reflecting the months of

[3] The Supplementary material is available at: https://www.dropbox.com/sh/8w3vhkd891agnnc/AACdk10GCgi1i5bBOCuGMsZpa?dl=0.

growing season. Fourth, we sum the resulting variable by year and cell obtaining a measure of the number of months in each year in each cell in which a drought or a flood event occurs during the growing season. Given that the length of the growing season is different across cell, we standardize the information by dividing for the total number of months forming the growing season in each cell. In doing so, we account for the impact of climate change on resource availability, in particular, for the possibility of social unrest in case of scarcity (Brochmann & Gleditsch, 2012; Daccache et al., 2015; von Uexküll, 2014).

The third class of variables captures economic and institutional conditions as well as social vulnerability, here represented by income distribution, horizontal inequality, institutional quality and the endowment of exhaustible resources. Indeed, Buhaug (2015) and Ide et al. (2014) acknowledge that the economic structure of countries, their poor institutional capacity, the scarcity of financial resources for implementing adaptation measures weaken resilience to changes in climatic condition, thus further reinforcing the vicious climate-conflict nexus (Burke et al., 2015; Hsiang et al., 2011).

In particular, we have time-variant data at cell level on gross cell product ($GCP_{i,t}$), population, and income distribution represented by a cell Gini index (*Gini*), obtained by the dataset by Kummu et al. (2018). GCP and population are used also to build composite indices as the per capita GCP and growth rates over time ($GCPpc\_var_{i,t}$). Following Salehyan (2014), we also control for the potential linkage between migration movements and conflicts by computing a variation rate in cell-specific population w.r.t. the previous 5 years. Horizontal inequality is represented by a time-invariant count variable that gathers information about the number of distinct ethnic groups coexisting within a single cell ($Ethnic\_fract_i$), taken from the Geo-referenced of ethnic groups (GREG) dataset provided by Weidmann et al. (2010). Indeed, according to Basedau and Pierskalla (2014), political exclusion of ethnic groups in Africa is found to magnify the probability of conflicts breakout in those areas where there is an unequal access to resources due to the monopolistic power of the dominant group.

Institutional quality and the endowment of resources also belong to this group of explanatory variables. In fact, institutional and structural capabilities of national government, including the effectiveness of property right regimes, play a key role in reducing the risk that climate-induced resource scarcity (e.g., water and food insecurity) translates into conflict (Di Falco et al., 2020; Jones et al., 2017). Moreover, countries relying on the exploitation of natural resources are more exposed to the risk of armed conflicts (Bodea et al., 2016; Ross, 2004). Accordingly, to account for the quality of institutions we rely on the synthetic Political Risk Services Index (PRI) of the PRS Group, an index that encompasses several aspects of governance (including the respect of property rights) and is the most complete source both in terms of temporal and spatial coverage ($Inst\_Quality_{c,t}$). On the other hand, we measure exhaustible natural resource endowment by combining two data sources. First, we compute the time-variant share of mineral and fossil fuel exports on total merchandise exports at the country level, using the World Bank World Development Indicators (WDI) database ($NatResVal_{c,t}$). Second, we account for the presence of mineral and fossil fuel resources by creating a georeferenced dummy variable assuming the value of 1 whether an exhaustible resource (i.e., coal, oil, natural gas, minerals) is exploited within the cell and 0 otherwise (*Resource_d*$_i$). The final time-variant cell-specific regressor is given by the interaction between the two variables ($NatRes_{i,t}$). Finally, by combining the information on institutional quality with that on resource exploitation, we can follow the suggestions provided by Koubi et al. (2012) and Sarmidi et al. (2014) where resource endowment is not a curse per se, since it may help economic growth, but it reinforces competition, corruption and violence if local governance is favourable to rent-seeking behaviours especially when economic conditions are deteriorating ($Inst\_NatRes_{i,t}$).

The fourth group includes time-invariant cell-specific controls related to geographical and location-specific features which may influence the onset of armed conflicts. We compute a dummy variable assuming value 1 if the cell is located at the national border and 0 otherwise (*Border_d*$_i$). Another dummy variable proxies the presence of a water basin in the cell (*Water d*$_i$), since it has been found that drought-related local violence is more likely in areas where a large share of the population lacks access to water sources (Detgesm, 2016). This is obtained by combining different georeferenced sources: the Africa water bodies information provided by the RCMRD GeoPortal database (i.e., lagoons, lakes and reservoirs); the Africa waterways database provided also by the RCMRD GeoPortal database (i.e., drains, streams, rivers, canals, dams, docks, rapids, aqueducts, weirs, boatyards, lakes, jetties and riverbanks); the Reservoirs v1.01 (2011) database provided by the Socioeconomic Data and Applications Center (SEDAC); the data centre in NASA's Earth Observing System Data and Information System (EOSDIS).

Also included in the fourth group are two dummies that refer to the main coverage of the land area, specifying if the cell is mainly occupied by the desert (*Desert_d*$_i$) or by forests (*Forest_d*$_i$), and they rely on the History Database of the Global Environment (HYDE) for land coverage (Klein Goldewijk et al., 2017). Together with land coverage, we also control for the geomorphology of the cell in being specifically vulnerable to the risk of drought conditions with a time-variant continuous variable from the Aqueduct Water Risk Atlas ($Drought_i$).

Finally, we capture the role of cell characteristics in influencing the facility to hide and hence the propensity to the onset of guerrilla warfare as suggested by Nunn and Puga (2012). The ruggedness characterizing the African terrain is measured by the standard deviation of the slope computed in each cell by using information on elevation (meters above sea level) and slope (degrees) from NASA Shuttle Radar Topography Mission (SRTM) Version 4.0 Global (*Slope_sd*$_i$), that provides data on a 1 arc second spatial resolution (approximately 30 m on the line of the Equator).[4]

[4] All time-invariant variables are built on the basis of multiple layers both by the original data sources and by collecting different sources from the authors. The resulting variables must be taken as geographical controls without the possibility to distinguish the specific point in the temporal profile when they are taken. Accordingly, they can be interpreted as cell-based fixed effects proxying omitted variables specifically related to territorial features.

2.4 Base model choice

Two characteristics of our data call for reflection as regards the choice of the model. First, the frequency distribution of the count dependent variable reveals that the coefficient of dispersion (i.e. the variance-to-mean ratio) is equal to 38.69. Second, the number of zeros corresponds to 92% of our observations. In order to deal with both overdispersion and excess of zeros, a ZINB regression model is highly recommended (Hilbe, 2014), and this holds in particular for analysing civil conflicts as they are rare events but, at the same time, the roots of (in)stability can be manifold (Bagozzi, 2015).

Accordingly, there are specific features that can explain why an area is structurally free from violence, and other characteristics that influence the number of events occurring in each statistical unit. The former features are included in the logistic part of the model and are selected on the basis of prior literature on the probability of conflict, while the other characteristics are included in the count part to capture the magnitude of the phenomenon.

In particular, our base model includes the following variables to explain structural zeros.

First, the lagged number of conflicts accounts for the persistency of the phenomenon, since the probability of a cell to experience at least one conflict is highly influenced by past violent events as the population is less shocked by violence and guns and weapons are already available in that area (Collier, 2003; Hegre et al., 2016).

Second, the presence of anthropic activities (or their absence), captures the high probability of peaceful living conditions of scarcely populated (or exploited) areas based on neo-Malthusian assumptions concerning competition for resources (Homer-Dixon, 1999). We use different variables to reflect living conditions in addition to the standard demographic density. First, we include a dummy variable representing the main desertic coverage (more than 50%) of the cell, as living conditions are substantially reduced in places with extreme drought conditions forcing people to migrate in other areas and reducing the risk of emerging conflicts (Bosetti et al., 2021; Reuveny, 2007). Moreover, we include a dummy for the presence of a water basin in the area that represents a reservoir of a natural resource that can help reducing the incidence of competition on scarce endowments in the case of diminishing rainfalls (Daccache et al., 2015). Then, we control for the forest coverage of the cell (Corrales et al., 2019) with a dummy variable assuming value equal to one if the area covered by forest is more than 50% of cell's surface, with resulting low anthropic activity. Finally, we control for the presence of fossil fuel and mineral resources that are widely acknowledged as potential trigger for rent-seeking behaviour, corruption and violence, especially in weak institutional settings (Parker & Vadheim, 2017; Ross, 2004; Shields et al., 1999). The presence of a resource basin is expected to (negatively) influence the probability of structural zeros while, on the other hand, effective institutions help turning resource rents into development opportunities that increase the probability of long-lasting peace (Clare, 2007).[5]

[5] Robustness tests for temporal lag structure are discussed in the Appendix.

All the other explanatory variables illustrated in Sect. 2.3 are included in the negative binomial component for capturing the magnitude of the phenomenon. The *Count* model also incorporates a vector of fixed effects (FE), leading to a FE model specification. This is grounded by the fact that in spatial analysis data are generally relative to adjacent units located in an uninterrupted area (i.e. all regions in a country), so each unit represents itself (Elhorst, 2014). Notice that recent contributions in climate-conflict literature using similar small-scale georeferenced information suggest adopting linear probability models with cell-specific FE (Almer et al., 2017; Breckner & Sunde, 2019), due to the potential bias deriving from including a large number of FE into non-linear estimations with large N and T (Fernández-Val & Weidner, 2016; King & Zeng, 2001). However, the properties of our count dependent variable suggest that a mixture model specification is preferable to a linear one. Following Witmer et al. (2017), in order to avoid the potential bias due to an excess in number of FE, we introduce country rather than cell-specific FE in the count part of the model to account for heterogeneity, and we include the lagged dependent variable in the logistic part to account for persistency. In addition, we include time-specific FE in the form of year dummies in order to correct for potential overestimation of coefficients related to spatially lagged variables as emphasised by Lee and Yu (2010).

Notice that the use of country-specific FE brings two additional advantages with respect to cell-specific ones. First, they allow including among the covariates those time-invariant cell-specific variables that the literature has found to be relevant in understanding the source of violence independently from climatic conditions, related to the morphological and social structure. Second, they capture the influence of high conflict diffusion at the country level when violence and disorders are widespread across the whole country and not strictly local.[6]

Thus, in what follows we model the number of conflicts with the following ZINB specification:

$$E(Y_{it}|\boldsymbol{X}_{it}, \boldsymbol{C}_c, \boldsymbol{T}_t, \boldsymbol{Z}_{it}, Y_{it-1}) = (1 - \pi_{it})exp(\alpha + \boldsymbol{X}'_{it}\beta + \boldsymbol{C}'_c\varphi + \boldsymbol{T}'_t\tau) \tag{7}$$

$$\pi_{it} = \frac{exp(\delta_i + \boldsymbol{Z}'_{it}\gamma + Y_{it-1}\omega)}{1 + exp(\delta_i + \boldsymbol{Z}'_{it}\gamma + Y_{it-1}\omega)} \tag{8}$$

where $\boldsymbol{Z}_{it}$ represents the set of covariates that explain the structural zeros and $\boldsymbol{X}_{it}$ is the set of covariates that capture the magnitude of the phenomenon and includes the aforementioned four dimensions of interest: i) socio-economic conditions (SE); ii) climate change measures; iii) impacts of climate change on land use and agricultural activities associated to the seasonal information on crop yields; iv) other controls including geographical features. The baseline model also includes country-specific ($\boldsymbol{C}_c$) and time-specific ($\boldsymbol{T}_t$) FE in the count equation and the lagged dependent

[6] Robustness tests and discussion over the choice of the ZINB estimator as preferred to the NB are provided in the Appendix.

variable $\left(Y_{it-1}\right)$ in the logistic equation for controlling for unobserved heterogeneity and autocorrelation of residuals.[7]

3 Results

The description of the empirical results is organised in three steps. First, in Sect. 3.1, we present results of the baseline model that accounts only for geographical and socio-economic features. This is followed in Sect. 3.2 by a cell-specific analysis that adds to the above the effect of short and long-term climate change. Finally, in Sect. 3.3, we focus on spatial interactions and spillover effects across cells.

To interpret the results of a ZINB regression, it is convenient to compute exponentiated coefficients as $e^{\hat{\beta}}$ or $e^{0.01*\hat{\beta}}$ in the case of log-transformed covariates. If lower (higher) than 1, the exponentiated coefficient indicates a negative (positive) variation. In particular, in the *Zero model* the exponentiated coefficients represent the multiplicative effect of a one-unit (or for a log-transformed covariate of a 1%) variation of a predictor on the odds ratios associated to structural zeros (the event that $Y=0$), all else being equal. Hence, the higher the exponentiated coefficient, the higher the probability that the *i-th* cell will not experience a conflict. Instead, in the *Count* model the exponentiated coefficients represent the multiplicative effect of a one-unit (or a 1%) variation of a predictor, *ceteris paribus*, on the expected number of conflicts. In particular, Tables 2, 3 and 4 report the exponentiated coefficients only for regressors with p-values lower than 10%; when the coefficient is not statistically significant and, therefore, has no effect on the magnitude or the probability of violence, it is reported as *n.s.*[8]

As a general remark, the use of controls in a regression analysis of the climate-conflict nexus might lead to biased results if the covariates are endogenously determined by the measure of conflict used as the dependent variable, or if they are affected by changes in climate conditions, leading to collinearity issues (Burke et al., 2015). Accordingly, collinearity is controlled by the Mean Variance Inflation Factor (Mean VIF), that is always lower than 5.00 and thus allows rejecting any risk of misinterpretation of coefficients. Given that the dependent variable is the sum of all conflicting events occurred over one year, all time variant covariates whose effect on conflict probability and magnitude is likely to be delayed over time are included with one-year lag. Finally, we use robust standard errors clustered on the panel id because default standard errors can greatly overstate estimator precision (Wooldridge, 2010).

[7] We acknowledge that the inclusion of a lagged dependent variable might be a source of endogeneity by construction, but the large T in the panel reduces the problem. An alternative could be to substitute the lagged dependent variable with the pre-sample (or initial) mean of the number of conflicts, approximating a fixed effect estimator with non-linear models. Nonetheless, in this way the impact of persistency is not controlled along with the mechanisms under the conflict trap theory. Indeed, the conflict trap occurs only if the past conflicts refer to a reasonable temporal lag, otherwise the mechanisms explaining the persistency are no longer valid.

[8] The standard model output with coefficient estimates and the corresponding statistics (robust standard errors and p-values) is available for each model in the Supplementary material, Appendix D.

Table 2 Base model with geographical and socio-economic features

	(1)	(2)	(3)	(4)
Count model				
$POP_{i,t-1}$	1.003	1.003	1.003	1.003
$GCPpc\_var_{i,t-1}$	0.161	0.163	0.138	0.135
$Gini_{i,t-1}$		2.186	2.303	2.319
$Ethnic\_fract_{i}$			1.130	1.115
$Border\_d_{i}$			1.292	1.245
$Slope\_sd_{i}$				1.058
$Drought_{i}$				1.240
Zero model				
No $Confl_{i,t}$	0.081	0.082	0.082	0.082
$POP_{i,t}$	0.998	0.998	0.998	0.998
$Inst\_Quality_{i,t}$	1.301	1.310	1.334	1.346
$NatRes_{i,t}$	0.976	0.976	0.976	0.977
$Inst\_NatRes_{i,t}$	1.006	1.006	1.006	1.006
$Desert\_d_{i}$	1.446	1.543	1.528	1.660
$Water\_d_{i}$	1.158	1.171	1.169	1.172
$Forest\_d_{i}$	1.908	1.952	1.850	1.744
No Obs	66,325	66,325	66,325	66,325
Year fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
AIC	48,954	48,918	48,845	48,771
BIC	49,718	49,691	49,637	49,581
Mean VIF	1.00	1.00	1.12	1.30
No Conflicts (predict)	31,378	31,594	31,616	32,323
No Zeros (predict_round)	55,184	55,145	55,180	55,017
No Conflicts (UCDP)	32,326			
No Zeros (UCDP)	61,023 (92%)			

Exponentiated coefficients reported, full estimates in Supplementary material, Appendix D, Table D2

3.1 Cell-specific analysis: no climate change

Table 2 shows the exponentiated coefficients for the baseline model that does not take into account climate change or spatial interactions; the covariates representing the four dimensions that might influence conflicts are introduced gradually into the *Count* model. Two main results emerge from this estimation round: (i) the persistency of conflicts over time strongly affects the probability to experience additional conflicts; (ii) the resource curse is a powerful driver of conflicts but it is mitigated by the quality of the institutions.

By looking at the significant variables included in the *Zero* model, we can identify the factors that influence the probability of an area not being eligible for a non-zero count. As a general remark, the absence of conflicts in the previous

Table 3 Climate change short and long-term horizon

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Count model							
$POP_{i,t-1}$	1.003	1.003	1.003	1.003	1.003	1.003	
$POP\_var5_{i,t-1}$							25.739
$GCPpc\_var_{i,t-1}$	0.150	0.142	0.157	0.140	0.143	0.148	0.188
$Gini_{i,t-1}$	2.411	2.303	2.397	2.401	2.344	2.425	3.171
$Temp\_var_{i,t-1\ wrt\ t0}$	1.139		1.135				
$Prec\_var_{i,t-1\ wrt\ t0}$		0.912	0.922				
$Temp\_av\_var_{i,t-1\ wrt\ t0}$				2.147		2.121	1.699
$Prec\_av\_var_{i,t-1\ wrt\ t0}$					0.656	0.670	0.651
$Ethnic\_fract_{i}$	1.112	1.115	1.113	1.091	1.116	1.092	1.141
$Border\_d_{i}$	1.240	1.246	1.242	1.244	1.251	1.250	1.363
Slope sd_{i}	1.051	1.057	1.050	n.s	n.s	n.s	1.113
$Drought_{i}$	1.213	1.237	1.212	1.231	1.231	1.224	n.s
Zero model							
No $Confl_{i,t-1}$	0.082	0.082	0.082	0.083	0.082	0.083	0.086
$POP_{i,t-1}$	0.998	0.998	0.998	0.998	0.998	0.998	0.997
$Inst\_Quality_{c,t-1}$	1.340	1.343	1.339	1.331	1.338	1.325	1.412
$NatRes_{i,t-1}$	0.976	0.977	0.977	0.976	0.977	0.976	n.s
$Inst\_NatRes_{i,t-1}$	1.006	1.006	1.006	1.006	1.006	1.006	n.s
$Desert\_d_{i}$	1.667	1.657	1.664	1.691	1.654	1.684	1.984
$Water\_d_{i}$	1.168	1.174	1.168	1.170	1.175	1.172	1.175
$Forest\_d_{i}$	1.765	1.742	1.763	1.718	1.747	1.719	2.024
No Obs	66,325	66,325	66,325	66,325	66,325	66,325	55,713
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	48,755	48,768	48,753	48,733	48,762	48,724	41,459
BIC	49,574	49,588	49,581	49,552	49,581	49,553	42,236
Mean VIF	1.27	1.27	1.25	1.29	1.28	1.27	1.13
No Conflicts (predict)	27,288	27,426	27,270	27,195	27,181	26,930	47,900
No of Zeros (predict_round)	55,171	55,025	55,169	55,300	55,062	55,390	46,131
No Conflicts (UCDP) year > 1995							26,755
No Zeros (UCDP) year > 1995							51,185

Note: exponentiated coefficients reported, full estimates in Supplementary material, Appendix D, Table D3

year substantially increases the probability of structural zeros in all model settings, revealing the dynamic nature of the response variable. In other words, peaceful cells are more likely to remain at peace while conflictive areas suffer from persistence. More importantly, this resonates with the conflict trap theory (Collier, 2003) whereby the probability of continuation, recurrence, escalation or diffusion of armed conflicts depends on prior occurrences. Given that weapon availability reduces opportunity costs to engage aggressive behaviour, we can

Table 4 Climate change long-term horizon and agriculture

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Count model							
$POP_{i,t-1}$	1.003	1.003	1.003	1.003	1.003	1.003	
$POP\_var5_{i,t-1}$							21.137
$GCPpc\_var_{i,t-1}$	0.148	0.155	0.163	0.142	0.147	0.158	0.214
$Gini_{i,t-1}$	2.440	2.447	2.474	2.354	2.316	2.347	2.983
$Temp\_av\_var_{i,t-1\ wrt\ t0}$	2.063	2.081	1.970	2.330	2.438	2.223	1.872
$Prec\_av\_var_{i,t-1\ wrt\ t0}$	0.671	0.672	0.682	0.682	0.689	0.695	n.s
$Sh\_grsSPEI6 < -1.49_{i,t-1}$	n.s			1.267			
$Sh\_grsSPEI12 < -1.49_{i,t-1}$		n.s			n.s		
$Sh\_grsSPEI36 < -1.49_{i,t-1}$			1.307			1.315	1.359
$Sh\_grsSPEI6 > 1.49_{i,t-1}$				1.684			
$Sh\_grsSPEI12 > 1.49_{i,t-1}$					1.958		
$Sh\_grsSPEI36 > 1.49_{i,t-1}$						1.598	1.893
$Ethnic\_fract_i$	1.092	1.091	1.090	1.086	1.086	1.087	1.131
$Border\_d_i$	1.251	1.250	1.241	1.261	1.261	1.254	1.369
Slope sd_i	n.s	n.s	n.s	n.s	n.s	n.s	1.105
$Drought_i$	1.218	1.223	1.214	1.221	1.228	1.217	n.s
Zero model							
No $Confl_{i,t-1}$	0.083	0.083	0.083	0.084	0.084	0.083	0.087
$POP_{i,t-1}$	0.998	0.998	0.998	0.998	0.998	0.998	0.997
$Inst\_Quality_{c,t-1}$	1.323	1.325	1.325	1.326	1.325	1.325	1.415
$NatRes_{i,t-1}$	0.976	0.976	0.976	0.976	0.976	0.976	n.s
$Inst\text{-}NatRes_{i,t-1}$	1.006	1.006	1.006	1.006	1.006	1.006	n.s
$Desert\_d_i$	1.682	1.684	1.679	1.677	1.679	1.670	1.968
$Water\_d_i$	1.171	1.172	1.172	1.174	1.176	1.174	1.177
$Forest\_d_i$	1.718	1.718	1.723	1.697	1.692	1.702	1.994
No Obs	66,325	66,325	66,325	66,325	66,325	66,325	55,713
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	48,722	48,724	48,715	48,711	48,706	48,706	41,430
BIC	49,560	49,562	49,552	49,558	49,552	49,553	42,224
Mean VIF	1.26	1.26	1.26	1.24	1.24	1.24	1.13
No Conflicts (predict)	26,897	26,904	26,922	26,866	26,957	26,892	144,000
No of Zeros (predict_round)	55,403	55,405	55,396	55,446	55,418	55,387	46,191

Exponentiated coefficients reported, full estimates in Supplementary material, Appendix D, Table D4

interpret the conflict trap result as follows: if one cell hosts at least one (organised or non-organised) group with military equipment, the cost of a new conflict is lower than it would be in locations with no prior history of violence. It is interesting to notice that by applying this mixture non-linear probability model like with a dynamic structure on a long enough panel dataset, we correct the common underestimation of both the intensity and the duration of the conflict trap, as emphasised by Hegre et al. (2016).

Different additional factors are found to affect the probability of structural zeros. The size of the population ($POP_{i,t}$) has a negative effect but this is interpreted as a control, given that in low populated areas the probability of unrest is structurally lower than in crowded places. Country-level quality of institutions ($Inst\_Quality_{c,t}$), on the other hand, has a positive effect and it contributes to reduce the potential conflicts associated to the endowment of exhaustible resources. In fact, the location of oil wells and/or mines producing large revenues is quantified by the interaction between country-level revenues from mining and fossil fuels extraction and transformation per year and the georeferenced cell-based location of wells or mines ($NatRes_{i,t}$).

The weight of exhaustible resources on local economy has a negative effect on structural zeros since it reduces the probability of a cell to be structurally peaceful by around 2%. This is in line with studies showing a positive correlation between abundant resource endowment and conflicts (Ross, 2004). Resource (especially oil) extraction and export increase the probability of (the onset of) conflicts due to the rent-seeking behaviour that could give further financial incentives to engage in conflicts, where the state and extraction firms gain more benefits than local unskilled workers. Although these activities per se negatively influence the probability of peace (Auty, 2001), we take an additional step by controlling for the influence of institutional quality in managing profit making from extractive activities (Bodea et al., 2016; Parker & Vadheim, 2017). According to our estimates, exhaustible resources operate in the opposite direction in cells located in countries with well-functioning institutions (here represented by the interaction term $Inst\_NatRes_{i,t}$) slightly increasing (by 1.006 times) the probability of structural zeros.

Additional controls for geographical features that may affect the structural probability of violence are land coverage by desert, forests and water. While the incidence of violence in a desertic area is negligible, abundance of essential resources (i.e., products from harvesting in forest areas or freshwater for daily needs and agriculture) reduces competition on using commons that are not protected by legal property rights (Brochmann & Gleditsch, 2012).

Looking at the results for the *Count* model, cell-level lagged growth rate of income per capita ($GCPpc\_var_{i,t}$) indicates lower cell exposure to conflicts. Following Chassang and Padro-i-Miquel (2009), intra-state battles are more likely the lower the opportunity cost of fighting, which in turn is strongly related to income shocks. In other words, if poor areas experience a negative shock in per capita income availability, the probability of conflicts increases due to low opportunity costs.

Another important socio-economic aspect is income distribution. Our results confirm that income inequality, measured by cell-level Gini index, more than doubles the number of conflicts. Moreover, according to Hillesund et al. (2018), horizontal inequality, defined on the basis of heterogeneous opportunities available to different groups identified by their ethnicity, region, religion, or social classes, is also a powerful source of instability. By following recent contributions on the climate-conflict nexus (Manotas-Hidalgo et al., 2021; Schleussner et al., 2016; von Uexküll et al., 2016) we find that places that host a higher number of different ethnic groups

(*Ethnic_fract*$_i$) are more prone to host violence given the higher number of agents (groups) competing for the same (scarce) resource.

Favourable socio-economic conditions in terms of income availability, combined with an equal distribution of resources, are key elements for preventing competition on scarce resources and, eventually, conflicts for survival. Given that the decision of engaging a conflict is directly related to the pay-off from comparing the net gains of peace relative to conflict, if the available resources are lower than those of the opponent (net of the military cost), the opportunity cost to attack will be lower (or even negative).

Lastly, we assess the role of territorial features in shaping conflicts and peace. Cells near the borders (*Border_d*$_i$) have 1.2 more conflicts than others, and so do areas at risk of drought (*Drought*$_i$). Cells characterised by rugged terrain (*Slope_sd*$_i$), that facilitates hiding during attacks (Nunn & Puga, 2012), risk an increasing number of fights by around 1.05.

3.2 Cell-specific analysis: changes in climate conditions

We include in our models different covariates related to changes in climatic conditions in the short and the long-term in order to verify how they affect the probability and the magnitude of conflicts. Herein short-term changes ($Temp\_var_{i,t\text{-}1\ wrt\ to\ t0}$ and $Prec\_var_{i,t\text{-}1\ wrt\ to\ t0}$) are computed as the difference between previous year temperature and precipitations and the relative average of the base period (1971–1989) calculated on a monthly basis. Instead, long-term changes are average differences across all years from 1990 to the year of observation of both temperature and precipitations relative to the base year ($Temp\_av\_var_{i,t\text{-}1\ wrt\ to\ t0}$ and $Prec\_av\_var_{i,t\text{-}1\ wrt\ t0}$). In so doing, we control for the trend and not for punctual events.

The results are shown in Table 3 for different combinations of covariates. Two main results emerge from this estimation round: (i) both short and long-term changes in temperature and precipitations play a key role in directly impacting the magnitude of conflicts; (ii) non-linear impacts of changes in climatic conditions emerge when indirect effects driven by the agricultural vulnerability are accounted.

More in detail, with respect to short-term variations, the *Count* model indicates that a one-degree temperature change from the base period increases the expected number of conflicts by 1.14 times, while a one-millimetre per day precipitation change relative to the base period reduces conflicts by 0.92 times. The findings are similar for long-term changes, with stronger impact. In particular, a one-degree increase in long-term average temperatures more than doubles the expected number of conflicts. On the contrary, a one-millimetre per day increase in long-term precipitations reduces the expected number of conflicts by 0.35 on average.

To determine whether and to what extent climate-induced pressure on agriculture explain the climate-conflict nexus, we also control for weather variations during crop cultivation periods within each cell. In particular, we use the SPEI index to account for the impact of temperatures on hydrological conditions and evapotranspiration of soils (Vicente-Serrano et al., 2010). Timescales of 6 months are used to evaluate the short-term effects on the agricultural sector while timescales equal to

12 and 36 months allow the identification of persistent stress conditions. We define a drought condition when the SPEI, whatever the timescale examined, is < -1.49, while on the opposite precipitations and soil humidity higher than expectations based on past observation are defined as floods if SPEI is > 1.49 (WMO & GWP, 2016).[9]

Two novelties with respect to prior studies are worth highlighting. First, we consider both short- (represented by SPEIs for a maximum of 6-month horizon) and long-term effects. Second, we introduce a non-linear effect of SPEI by differentiating its value with respect to the flood and drought thresholds. The last variables are the shares of months during the growing season of the main crop in each cell facing a climate stress (von Uexküll, 2014; von Uexküll et al., 2016).

Results in Table 4 indicate that both extreme abundance and scarcity of water negatively impact harvest and food production, and this is a source of competition leading to more violence. The non-linear modelling approach allows to jointly account for both aspects, thus adding to prior studies that instead considers them separately (Adano et al., 2012; Almer et al., 2017; Chassang & Padro-i-Miquel, 2009; Ghimire et al., 2015; Harari & La Ferrara, 2018).

The use of positive and negative threshold levels for the SPEI reveals intrinsically non-linear effects associated to climate stress that have a different effect on conflicts depending on both the temporal horizon and the stress type. In sum, extremely dry conditions cause harvest loss that turns into more violent events only in the case of a prolonged drought conditions, since only the SPEI36 < -1.49 is statistically significant, increasing the number of conflicts by 1.3 times. On the contrary, excess of humidity determined by flood conditions during the growing season has an immediate and larger impact on the magnitude of violence as revealed by the three temporal horizons in SPEI computation, all statistically significant with higher impact relative to drought and with a peak value of around 1.9 times corresponding to 12 months. Relative to prior findings on the U-shaped relation between water availability in the agricultural sector and the probability of conflicts (van Weezel, 2019), our results underline the role of the temporal dimension of the climatic events.

3.3 Cross-cell analysis: spatial spillover effects

Besides studying whether a conflict occurs and to which extent violence spreads out, we also focus on the spatial nature of the phenomenon. A simple graphical illustration that shows the climate-conflict nexus across the African continent can be obtained by combining two criteria (Fig. 1). First, we distinguish between cells that in the entire time span experience no conflicts and those that experience at least one conflict. Secondly, each cell is classified as affected by climate change if on average along the time span it has witnessed an increase in temperature relative to the benchmark period (1971–1989) above the mean (computed on all cells) and a reduction in precipitations, relative to the same benchmark, below the mean. If, on the contrary,

9 For full details on formulas used for calculating changes in climate conditions and climatic composite indices see Supplementary material, Appendix A-B-C.

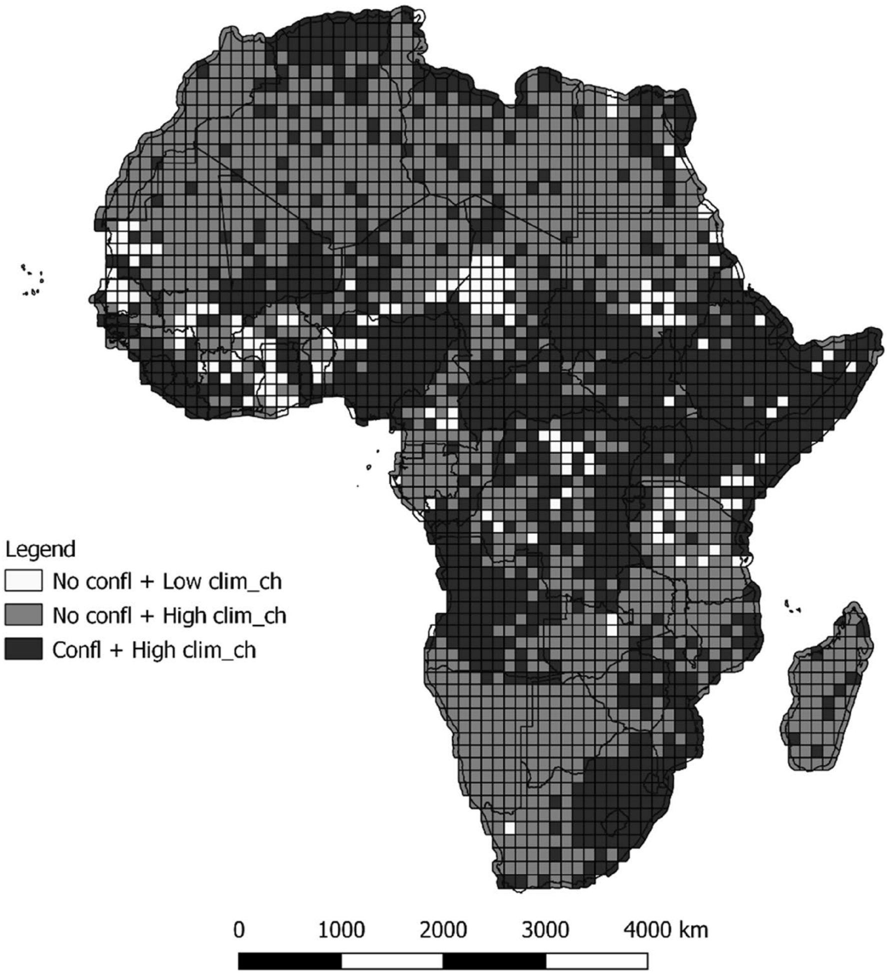


Fig. 1 Cell classes for the climate-conflict nexus. Source: own elab. on UCDP-GED (version 17.1) and AFDM

the cell presents changes in climatic conditions that are below the average, it is classified as climate neutral. By combining the two criteria, we find that there are no cells experiencing conflicts classified as climate neutral, while more than 42% of the areas under analysis suffer from the co-occurrence of climate change and conflicts (dark grey colour), and they are geographically dispersed not coinciding only to cells located at the country boundaries. Such a pattern motivates an analysis of cross-cells effects across neighbouring areas that confront similar climatic conditions and hazards.

In particular, the spillover effects associated with climate, economic and social conditions in neighbouring areas, can be analysed by adding into Eqs. (7)–(8) exogenous interaction effects and by estimating the following model specification:

Table 5 Spatial spillovers of socio-economic and long-term climate conditions

	(1)	(2)	(3)	(4)	(5)	(6)
Count model						
$POP_{i,t-1}$	1.004	1.003	1.003	1.003	1.003	1.004
$W3\_POP_{i,t-1}$	0.998					0.998
$GCPpc\_var_{i,t-1}$	0.188	0.046	0.161	0.166	0.134	0.066
$W5\_GCPpc\_var_{i,t-1}$		8.093				n.s
$Gini_{i,t-1}$	n.s	2.382	2.974	2.291	2.323	1.919
$W5\_Gini_{i,t-1}$			0.000			0.000
$Temp\_av\_var_{i,t-1\ wrt\ t0}$	2.289	2.217	2.155	n.s	2.300	n.s
$W5\_Temp\_av\_var_{i,t-1\ wrt\ t0}$				n.s		4.059
$Prec\_av\_var_{i,t-1\ wrt\ t0}$	n.s	0.695	n.s	0.705	0.417	0.465
$W5\_Prec\_av\_var_{i,t-1\ wrt\ t0}$					4.545	5.249
$Sh\_grsSPEI36 < -1.49_{i,t-1}$	1.340	1.323	1.214	1.302	1.289	1.200
$Sh\_grsSPEI36 > 1.49_{i,t-1}$	n.s	1.581	1.522	1.498	1.647	n.s
$Ethnic\_fract_i$	1.106	1.084	1.060	1.076	1.077	n.s
$Border\_d_i$	1.281	1.251	1.200	1.242	1.254	1.202
Slope sd_i	1.048	1.034	n.s	n.s	n.s	n.s
$Drought_i$	1.202	1.210	1.428	1.209	1.226	1.391
Zero model						
No $Confl_{i,t-1}$	0.084	0.083	0.085	0.084	0.083	0.085
$POP_{i,t-1}$	0.998	0.998	0.998	0.998	0.998	0.998
$Inst\_Quality_{c,t-1}$	1.323	1.320	1.302	1.318	1.335	1.297
NatRes $Val_{i,t-1}$	0.976	0.976	0.974	0.975	0.976	0.975
$Inst\text{-}NatRes_{i,t-1}$	1.006	1.006	1.006	1.006	1.006	1.006
$Desert\_d_i$	1.817	1.672	1.448	1.692	1.647	1.579
$Water\_d_i$	1.170	1.172	1.142	1.170	1.166	n.s
$Forest\_d_i$	1.744	1.694	1.528	1.701	1.692	1.547
No Obs	66,325	66,325	66,325	66,325	66,325	66,325
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AIC	48,604	48,721	48,431	48,674	48,707	48,701
BIC	49,451	49,567	49,277	49,530	49,562	49,556
Mean VIF	1.87	1.97	1.39	2.60	1.66	3.66
No Conflicts (predict)	32,116	31,904	30,840	31,793	31,763	31,731
No of Zeros (predict_round)	55,370	55,448	56,311	55,437	55,434	56,372

Exponentiated coefficients reported, full estimates in Supplementary material, Appendix D, Table D5

Table 6 Spatial spillovers through the agricultural channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Count model									
$POP_{i,t-1}$	1.003	1.003	1.003	1.003	1.003	1.003	1.003	1.003	1.003
$W5\_POP\_var5_{i,t-1}$									0.914
$GCPpc\_var_{i,t-1}$	0.151	0.171	0.192	0.170	0.185	0.199	0.226	0.193	0.406
$Gini_{i,t-1}$	2.455	2.430	2.440	2.248	2.214	2.275	2.298	2.261	n.s
$Temp\_av\_var_{i,t-1\ wrt\ t0}$	2.054	2.094	1.935	2.246	2.181	2.130	2.000	n.s	n.s
$W5\_Temp\_av\_var_{i,t-1\ wrt\ t0}$								n.s	n.s
$Prec\_av\ var_{i,t-1\ wrt\ t0}$	0.675	0.680	0.684	0.679	0.688	0.680	0.694	0.438	0.344
$W5\_Prec\_av\_var_{i,t-1\ wrt\ t0}$								4.015	7.877
$Sh\_grsSPEI6 < -1.49_{i,t-1}$	n.s								
$W4\_Sh\_grsSPEI6 < -1.49_{i,t-1}$	2.102								
$Sh\_grsSPEI12 < -1.49_{i,t-1}$		0.775							
$W4\_Sh\_grsSPEI12 < -1.49_{i,t-1}$		2.565							
$Sh\_grsSPEI36 < -1.49_{i,t-1}$			n.s				n.s	n.s	n.s
$W5\_Sh\_grsSPEI36 < -1.49_{i,t-1}$			2.835				2.504	2.335	2.289
$Sh\_grsSPEI6 > 1.49_{i,t-1}$				2.601					
$W7\_Sh\_grsSPEI6 > 1.49_{i,t-1}$				0.094					
$Sh\_grsSPEI12 > 1.49_{i,t-1}$					3.130				
$W7\_Sh\_grsSPEI12 > 1.49_{i,t-1}$					0.037				
$Sh\_grsSPEI36 > 1.49_{i,t-1}$						2.423	2.280	2.255	2.054
$W5\_Sh\_grsSPEI36 > 1.49_{i,t-1}$							0.138	0.160	0.326
$W7\_Sh\_grsSPEI36 > 1.49_{i,t-1}$						0.049			
$Ethnic\_fract_i$	1.090	1.089	1.087	1.081	1.083	1.083	1.080	1.068	1.074
$Border\_d_i$	1.241	1.241	1.223	1.247	1.244	1.245	1.226	1.226	1.285
$Slope\ sd_i$	n.s	n.s	n.s	n.s	n.s	n.s	n.s	n.s	1.062
$Drought_i$	1.218	1.221	1.214	1.219	1.218	1.218	1.210	1.218	1.219
Zero model									
$No\ Confl_{i,t-1}$	0.083	0.083	0.083	0.083	0.083	0.082	0.083	0.082	0.089
$POP_{i,t-1}$	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998
$Inst\_Quality_{c,t-1}$	1.324	1.326	1.324	1.319	1.318	1.315	1.320	1.327	1.381
$NatRes\ Val_{i,t-1}$	0.976	0.976	0.975	0.976	0.976	0.976	0.975	0.975	n.s
$Inst\text{-}NatRes_{i,t-1}$	1.006	1.006	1.006	1.006	1.006	1.006	1.006	1.006	n.s
$Desert\_d_i$	1.679	1.677	1.664	1.696	1.694	1.697	1.667	1.652	2.175
$Water\_d_i$	1.174	1.174	1.171	1.168	1.166	1.166	1.168	1.160	n.s

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Forest_d$_i$	1.726	1.730	1.749	1.742	1.770	1.782	1.786	1.768	1.837
No Obs	66,325	66,325	66,325	66,325	66,325	66,325	66,325	66,325	55,713
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AIC	48,715	48,709	48,688	48,686	48,662	48,671	48,656	48,643	41,008
BIC	49,561	49,555	49,535	49,532	49,509	49,518	49,521	49,526	41,848
Mean VIF	1.58	1.45	1.49	1.41	1.42	1.40	1.59	2.96	2.81
No Conflicts (predict)	26,828	26,758	26,807	26,764	26,671	26,477	26,502	26,492	25,885
No of Zeros (predict_ round)	55,443	55,452	55,447	55,510	55,533	55,545	55,565	46,713	46,586

Note: exponentiated coefficients reported, full estimates in Appendix D, Table D5

$$E\left(Y_{it}|\boldsymbol{X}_{it}, W_d\boldsymbol{X}_{it}, \boldsymbol{C}_i, \boldsymbol{T}_t, \boldsymbol{Z}_{it}, W_d\boldsymbol{Z}_{it}, Y_{it-1}\right) = (1-\pi_{it})exp(\alpha + \boldsymbol{X}^{'}_{it}\beta + W_d\boldsymbol{X}^{'}_{it}\theta + \boldsymbol{C}^{'}_i\varphi + \boldsymbol{T}^{'}_t\tau) \tag{9}$$

$$\pi_{it} = \frac{exp(\delta_i + \left[\boldsymbol{Z}^{'}_{it}\right]\gamma + \left[W_d\boldsymbol{Z}^{'}_{it}\right]\eta + Y_{it-1}\omega)}{1 + exp(\delta_i + \left[\boldsymbol{Z}^{'}_i t\right]\gamma + \left[W_d\boldsymbol{Z}^{'}_{it}\right]\eta + Y_{it-1}\omega)} \tag{10}$$

Notice that in estimating Eqs. (9)–(10) we explore the behaviour of 11 inverse distance normalised matrices W_d, each corresponding to a different cut-off d. This allows considering all cells as well as neighbouring ones included in the buffer computed with the radius equal to the cut-off distance expressed in km. Moreover, we allow the spatial weight matrices in the count and zero model equations to be different.

The results, in terms of the exponentiated coefficients of the dynamic panel spatial ZINB, are shown in Tables 5 and 6 for different combinations of covariates and specific cut-offs that were selected according to two criteria. First, for each covariate we identified the cut-off that corresponds to the stronger effect on the response, in the sense that beyond such value the estimated coefficients for the spatially-lagged explanatory variable starts losing its significance. Moreover, given that for several regressors we find similar estimates for two contiguous cut-offs, as a second criterion we select the combination of cut offs that leads to the lowest Akaike Information Criterion (AIC).[10]

Two main results emerge from this estimation round: (i) local conflicts are strongly impacted by the relative vulnerability of neighbouring areas to climate shocks; (ii) non-linear impacts of changes in climatic conditions are also found in spatial interactions with a prevailing effect caused by geographically diffused drought conditions.

Starting with the impact of spatial spillovers of socio-economic conditions, we find that an increase in income growth rates of neighbouring cells corresponds

[10] Results for all different cut-offs combinations are available upon request from the authors.

to an increase in the number of conflicts for those cells at risk of violence with a radius of around 500 km (W5 = 533 km). This is in contrast with the positive impact at the local level associated to better living opportunities, but it might be explained by the positive correlation between income per capita growth rate and distribution inequality in poor economies (Stewart et al., 2018), i.e. rapid increases in income per capita are often associated to greater inequality. However, while the Gini index is sufficient to capture cell-specific distributional features, the same cannot be expected for neighbouring areas because the detrimental effect of social disorder due to inequality may undermine the benefits stemming from the increase of economic opportunities for the few.

Looking at the influence of population changes in the short- (over one year, in Table 5) and the medium-term (over five years, in Table 6) in the surrounding cells allows us to approximate the effects of migration on conflicts. Empirical literature on migration is mostly based on case studies due to lack of comprehensive data on either domestic movement of population (Burrows & Kinney, 2016) or on international migration flows (Cai et al., 2016; Marchiori et al., 2012). Buhaug (2015) suggests that sudden sharp decreases in population may, at least partly, signal significant migration movements that can affect the probability of conflict in adjacent territories. Following on this, for each cell we estimate the effect of demographic movements in the neighbouring cells and find that negative variations in population levels, both in the short and in the medium-term, are associated with a higher frequency of conflicts, reaching around 8% in the five-year case with a cut-off corresponding to a radius of around 533 km. Quite intriguingly, the spillover effect associated to demographic movement in the short-term is lower in intensity and with a reduced spatial influence with a cut-off distance of around 355 km (W3). While this cannot be taken as direct evidence of the effect of migratory movements on resource competition, and consequently on conflicts, we believe our findings call attention to the relevance of spillovers due to demographic changes in adjacent areas.

Further, we find that long-term temperature and precipitation changes in surrounding areas in a radius of around 533 km increase by 4 and 5 times the number of conflicts, respectively.

Once the indirect impact of agriculture is included (Table 6), we find some non-linearities also in the spillover effects. On the one hand, if dry conditions affect the harvesting potential in a radius of around 444 km, lack of food experienced by the surrounding areas triggers a vicious cycle of violent competition for scarce resources at the local level. On the other hand, a persistent increase in rainfalls experienced by neighbours directly impacts local conflicts, but the indirect impact through the agricultural channel is opposite to that of drought. Indeed, the disruptive effects of floods go beyond rural activities in that they impinge upon communication and transportation channels, availability of basic resources like food and clean water for a vast portion of population, with evident risks for social stability. The indirect impact channelled via the agricultural sector has exactly the reverse behaviour, as it is more localised while the spillover effects are negligible.

Two interrelated explanations can reconcile this apparent contradiction. First, the African continent has historically faced a larger number of droughts with respect to floods, resulting in a higher geographical and temporal coverage (number of cells and years in our panel) of drought events which may force parts of the population that rely directly on agriculture for subsistence to migrate to more favourable places, thus altering the social equilibria in the destination places. Second, given that floods are localised phenomena in the continent, they destroy the crop yields only for that season, thus fuelling conflicts mainly where the event occurs.

4 Conclusions

Our empirical study disentangles whether and to what extent changes in climatic conditions have affected the number of conflicts, both in the short and in the long-term, by accounting for structural features independent from weather-related variables and introducing the role played by spatial spillovers.

First, the dynamic setting of the econometric method allows finding that the occurrence of conflicting events is persistent over time. This means that past experiences might reinforce the causal loop independently from actions devoted to improving the resilience of the area, since the cost of new unrest in conflict areas is lower than in locations that experience peaceful conditions. The policy implication is that even if adaptation strategies effectively reduce vulnerability to adverse climatic conditions, lower competition over scarce resources might still be insufficient to mitigate violence.

Second, non-linearities in the climate-conflict nexus are particularly relevant when agriculture is under pressure as both water excess and scarcity reduce crop yields, thus increasing competition for resources. The spatial diffusion of these impacts is much larger for drought conditions, while flood-type impacts remain localised. Such a non-linearity should be carefully accounted for when designing targeted actions to improve agricultural resilience, given that spatial specific features limit the efficacy of one-size fits all approaches to adaptation.

Third, changes in climatic conditions are important factors for risk and propensity of conflict, and their influence stretches over large spatial ranges. Long-term temperature and precipitation changes in surrounding areas in a radius of around 500 km increase by 4 and 5 times the number of conflicts, respectively. Consequently, even if specific territorial features must be a key ingredient to inform policy, neglecting spatial effects might significantly hamper the long-term effectiveness of adaptation measures.

All in all, our findings point to two main policy implications. First, the results on geographical spillovers indicate that planning of adaptation policies to reduce climate vulnerability should account for multiple spatial interrelations. A well-designed adaptation action might improve resilience at the local scale but vulnerability in neighbouring areas may substantially reduce those benefits. Second, the results on persistency of violence call for the explicit inclusion of peacekeeping measures in the design and implementation of adaptation strategies for climate resilience. Indeed, poorly designed adaptation interventions can compound existing inequalities and exacerbate the risk of conflicts instead of improving the socio-economic resilience to external shocks. This is for instance explicitly recognised by the African Union (AU) that is employing an innovative discourse on the adaptation strategy to coper with climate security risks, which should fully include also socioeconomic development, peace, security and stability. The AU is placing particular emphasis on the importance of comprehensively assessing the climate, peace, and security nexus, and consequently to link early warning systems and adaptation measures with violent conflict prevention.

Appendix—Econometric details

The distribution of the count dependent variable, the number of conflicts, is shown in Fig. 2 and reveals a high number of zeros (92%) as well as high overdispersion, with variance-to-mean ratio equal to 18.57/0.48 = 38.69. Prior literature (Cameron & Trivedi, 1998a, 1998b; Hilbe 2014) recommends the ZINB regression model to deal with the joint effect of overdispersion and excess of zeros.

On the one hand, the key critical issue of many event-count datasets is precisely the large proportion of zeros, so that the selection of a model that help detecting the process that inflates the probability of zeros is crucial. On the other hand, the selection of a non-linear mixture model with an additional equation and parameters must be based on both theoretical grounds and on empirical testing of whether the increased complexity of the ZINB improves significantly upon the fit of the standard non-linear count model.

To this purpose we compare the ZINB with alternative regression models considering the specification in Column (3) of Table 2 in the main text, which is the regression with the most desirable AIC and BIC values, prediction capacity and with variables that remain statistically significant in all specifications.[11] Notice that, while the variables included in the baseline model are selected on the basis of prior empirical work on violent conflicts, the selection of the variables that explain the structural zeros deserves particular attention, since these must explain the reasons behind the specific data generation process.

In particular, we select the lagged number of conflicts due to persistency following the indications of the conflict trap theory, namely that the probability of a cell experiencing a conflict is highly influenced by past outbreaks since the population has already experienced violence and weapons are plausibly already available (Collier, 2003; Hegre et al., 2016). Population density is usually a good indicator for the presence of anthropic activities, or lack of thereof, following the neo-Malthusian tenet that scarcely populated areas are more likely to experience peaceful living conditions owing to low competition for resources (Ehrlich, 1969; Cilliers, 2009; Homer-Dixon, 1999). Related to this, we include variables that capture structural features of cells that are strictly related with anthropic activities. First, we add a dummy variable equal to one if desertic areas cover more than half the territory, to capture significant constraints to living conditions that may force out migration, thus reducing the risk of conflict breakouts (Bosetti et al., 2021; Reuveny, 2007). Second, we include a dummy variable to account for the presence of a water basin in the area, following the findings of Daccache

[11] For details on estimated coefficient values see Tables D2–D6in Supplementary material.

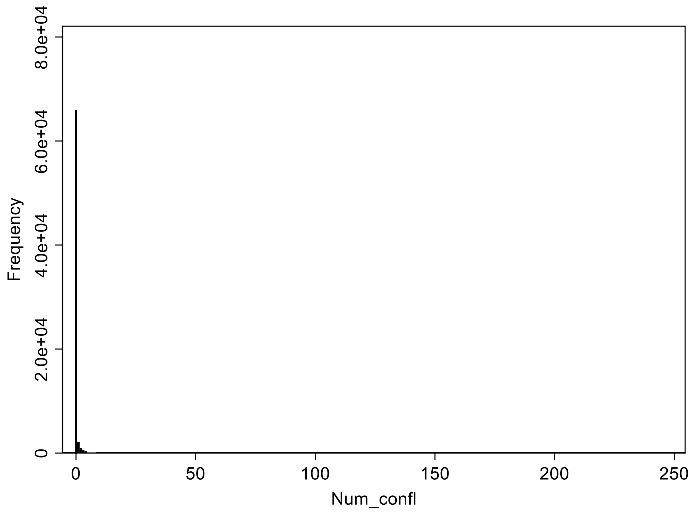


Fig. 2 Frequency distribution of the dependent variable (number of conflicts)

et al. (2015) that agricultural activities in Africa are based on rain-fed crops, and basin reservoirs are crucial to avoid water shortages in case of low rainfall. Third, we include a dummy variable equal to one if more than 50% of cell's surface is covered by forest, again a barrier to anthropic activity. Finally, we control for the presence of fossil fuel and mineral resources amenable to extraction and commercial use as prior studies establish an association between availability of exhaustible resources and rent-seeking behaviour, corruption and violence. In particular, Parker and Vadheim (2017) and Ross (2004) find a strict connection between resource extraction and civil wars, which is only smoothed by proper governmental institutions. In our case, the presence of a resource basin is expected to (negatively) influence the probability of structural zeros while, on the opposite, well-functioning institutions can turn resource rents into development opportunities, thus increasing the probability of long-lasting peace.

Notice that we used the Sargan-test (Baum et al., 2003) to check for endogeneity issues of the socio-economic explanatory variables in the base model that are not related only to geographical features and of weather conditions. According to the test, we included in the base model only those socio-economic variables that have been defined as relevant within the climate-conflict nexus literature and that are not endogenously related with the response.

Another important issue related to the model specification is the introduction of the fixed effects in the count part of the model. In fact, the panel structure of the dataset calls for particular attention due to the risk of spurious correlations from unobserved heterogeneity. To overcome this problem, as we already pointed out in the paper, in the count part of the model we could include cell-specific fixed effects or country specific fixed effects.

In Table 7 we compare the following model specifications: a ZINB with country-specific (ZINB_CE, corresponding to the model in Column 3 of Table 2, which is

Table 7 Different estimators for the base model (Column 3 Table 2)

	ZINB_CE	NB_CE	ZINB_FE	NB_FE	LM_FE	LM_FE_nl
	Count model	*Count model*	*Count model*	*Count model*	*Linear model*	*Linear model*
$POP_{i,t-1}$	0.288*** (0.06)	0.407*** (0.04)	0.787 (0.70)	1.412*** (0.54)	0.024 (0.02)	0.042* (0.02)
GCPpc $var_{i,t-1}$	– 1.982*** (0.36)	– 2.054*** (0.34)	– 2.012*** (0.37)	– 3.314*** (0.41)	– 0.138*** (0.02)	– 0.204*** (0.02)
$Gini_{i,t-1}$	0.834* (0.45)	0.716** (0.30)	3.224 (2.37)	4.325* (2.55)	0.743*** (0.25)	0.851*** (0.31)
Ethnic_fract i	0.122*** (0.04)	0.086*** (0.03)	– 0.945 (0.95)	0.456 (5.49)	– 0.041 (0.05)	– 0.077** (0.03)
Border_d i	0.256** (0.11)	0.116 (0.08)	18.077*** (1.31)	0.828 (4.59)	0.273* (0.16)	0.292** (0.11)
Constant	– 5.481*** (0.85)	– 8.445*** (0.54)				
	Zero model		*Zero model*			
No $Confl_{i,t-1}$	– 2.503*** (0.13)	0.296*** (0.03)	– 1.630*** (0.13)	0.079*** (0.01)	0.039*** (0.01)	
$POP_{i,t-1}$	– 0.227*** (0.04)		– 0.039 (0.03)			
$Inst\_Quality_{c,t-1}$	0.288*** (0.04)	– 0.153*** (0.05)	0.166*** (0.04)	– 0.237*** (0.05)	– 0.014*** (0.00)	– 0.017** (0.01)
NatRes $Val_{i,t-1}$	– 0.024*** (0.01)	0.008 (0.01)	– 0.036*** (0.01)	0.020*** (0.01)	0.004*** (0.00)	0.006*** (0.00)
$Inst\_NatRes_{i,t-1}$	0.006*** (0.00)	– 0.001 (0.00)	0.010*** (0.00)	– 0.010*** (0.00)	– 0.001*** (0.00)	– 0.002*** (0.00)
Desert_d i	0.424*** (0.13)	– 0.612*** (0.18)	– 0.209 (0.15)	2.592 (18.33)	– 0.439** (0.17)	0.908*** (0.29)
Water_d i	0.156** (0.08)	– 0.073 (0.08)	0.148* (0.08)	– 0.072 (5.62)	0.333** (0.14)	0.396** (0.20)
Forest_d i	0.615*** (0.14)	– 0.222 (0.21)	0.484*** (0.15)	– 0.887 (6.30)	– 0.062 (0.19)	– 0.453*** (0.17)
Constant	3.434*** (0.44)		0.640* (0.35)		– 0.014***	
No Obs	66,325	66,325	66,325	66,325	66,325	66,325
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes				
Cell fixed effects			Yes	Yes	Yes	Yes
AIC	48,845	51,630	44,926	46,982	38,557	49,181
BIC	49,637	52,404	59,799	62,119	38,840	49,454
LogAlpha	0.830***	2.082***	0.136***	1.234***		
Vuong test ZINB vs NB	30.441***					
Alpha test ZINB vs. ZIP	49,000***					

Table 7 (continued)

	ZINB_CE	NB_CE	ZINB_FE	NB_FE	LM_FE	LM_FE_nl
Serial Correlation test on res	0.076		0.041			
No Conflicts (predict)	31,616	61,640	34,807	48,932	75,389	13,823
No of Zeros (predict_round)	55,180	58,571	57,680	57,532	60,695	60,464
Prob of Structural Zeros (av)	92%		92%			
Residuals (abs)$^{++}$	15,552	21,889	12,388	15,013	86,835	33,367
No Conflicts (UCDP)	32,326	32,326	32,326	32,326	32,326	32,326
No Zeros (UCDP)	61,023 (92%)	61,023 (92%)	61,023 (92%)	61,023 (92%)	61,023 (92%)	61,023 (92%)

Robust clustered (panel id) standard errors in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01

$^{++}$Residuals are computed as Pearson residuals in ZINB and NB and as raw residuals for LM as the difference between the observed number of conflicts and the exponentiated linear prediction of the dependent variable

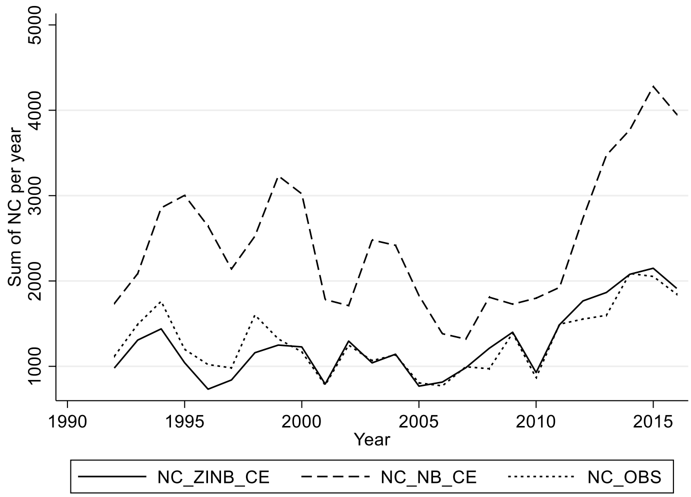
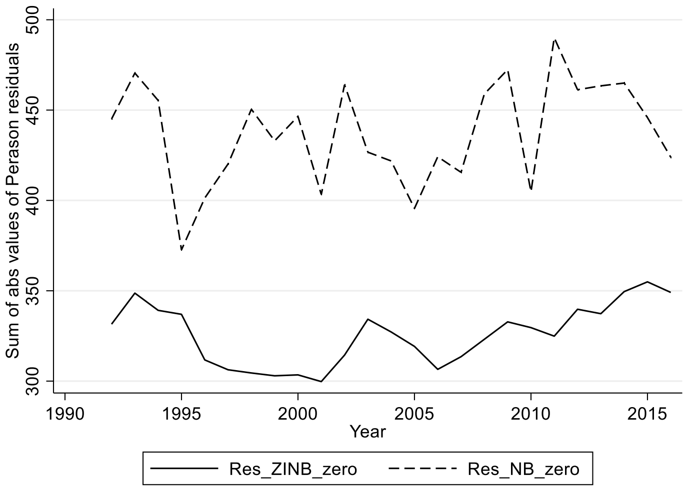


Fig. 3 Observed and predicted total number of conflicts over time under the ZINB and the NB (with country-specific fixed effects)

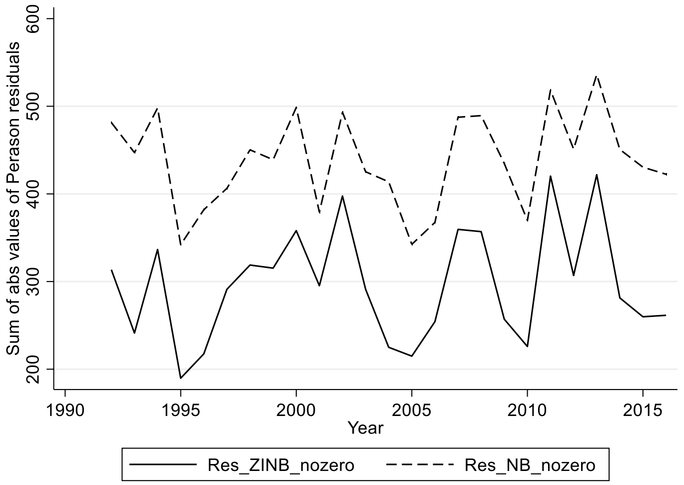
the benchmark,); a NB with country-specific fixed effects (NB_CE); a ZINB with cell-specific fixed effects (ZINB_FE); a NB with cell-specific fixed effects (NB_FE); a linear model with cell-specific fixed effects, that includes the lagged number of conflicts among the explanatory variables (LM_FE); a linear model with cell-specific fixed effects that does not include the lagged dependent variable (LM_FE_nl) as a control. All the above model specifications include also year-specific fixed effects.

Consider first the comparison between the zero inflated model and the corresponding negative binomial model with country-specific fixed effects. Looking at the first two columns of Table 7 we see that the former is preferable both in terms of the AIC and BIC and in terms of the total number of conflicts predicted (31,616 and 61,640 under the ZINB_CE and the NB_CE, respectively), the actual figure being 32,326. These findings are confirmed by the following two figures. Figure 3 shows the plot of the observed and predicted total number of conflicts under both models over time, confirming that the ZINB_CE model yields more accurate predictions while the NB overestimates the number of conflicts. Figure 4 shows the sum of the (absolute) Pearson residuals[12] under both models over time, and confirms that ZINB_CE leads to greater predictive accuracy for both the cells that experience no conflicts (panel a in Fig. 4) and for those with at least one violent event (panel b). In fact, despite the fact that the estimated number of total zeros (rounded at < 0.5) is closer to the actual figuer (61,023) under the NB_CE

[12] Pearson residuals are defined as raw residuals scaled by the square root of the variance function, and are commonly used in regression models for count data.



(a) cells with no conflicts



(b) cells with conflicts

Fig. 4 Total absolute Pearson residuals over time under the ZINB and the NB (with country-specific fixed effects)

than under the ZINB_CE, the latter specification leads to a sum of (absolute) Pearson residuals constantly lower over time.

We also performed a likelihood test to determine whether the mixture model is more appropriate than the single-equation count model (Vuong, 1989). The Vuong test, based on the Stata command developed by Desmarais and Harden (2013),

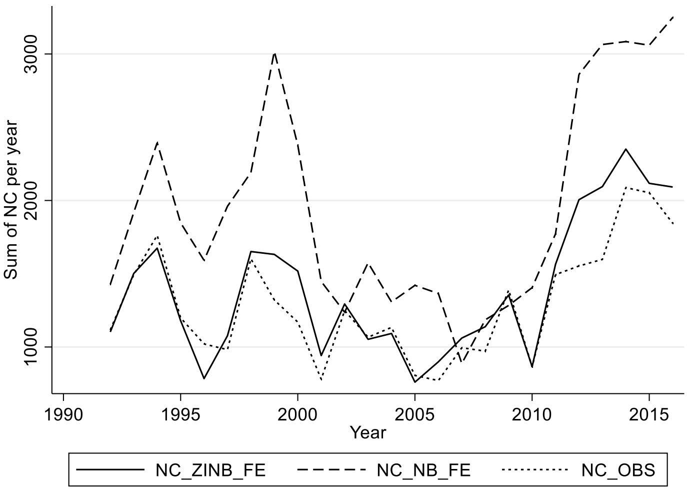
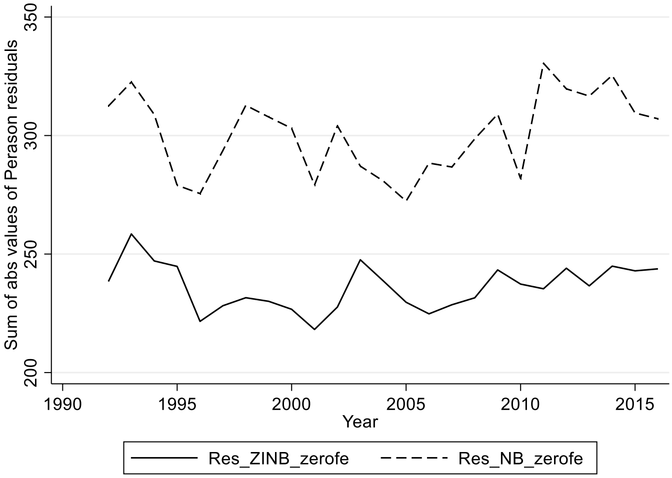


Fig. 5 Observed and predicted number of conflicts over time under the ZINB and the NB (with cell-specific fixed effects)

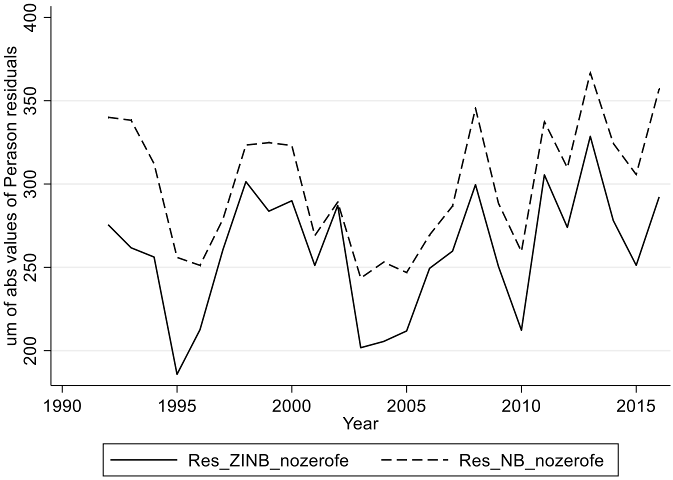
computes a statistic with corrections based on the AIC and BIC due to different number of parameters in the two models. The Vuong test rejects the null hypothesis that the two models are equally close to the true data generating process, and the ZINB_CE model is preferred to the NB_CE one. It is also interesting to notice that a likelihood ratio test for comparing the ZINB_CE with the corresponding zero-inflated Poisson model rejects the null hypothesis, so that again the ZINB_CE is the preferred model.

Similarly, the comparison between the zero inflated model and the corresponding negative binomial model with cell-specific fixed effects favours the former. In fact, looking at the third and fourth columns of Table 7, we notice that the ZINB_FE specification estimates the total number of conflicts more accurately than the corresponding NB_FE one, with lower Pearson residuals and lower AIC and BIC values.[13] Again, these findings are confirmed by Fig. 5, that shows the total number of conflicts predicted under the two models over time compared to the observed data, and Fig. 6, that shows the behaviour over time of Pearson residuals distinguishing between cells with no observed conflicts and those with at least one conflict over the entire time span (panel a and b, respectively). As in the case of country-specific fixed effects, these graphical results confirm the higher prediction capacity of the inflated model – especially for observations corresponding to zero conflicts, pointing out once again that overdispersion and excess of zeros might lead to biased results if not taken into account correctly.

[13] Given that our dependent variable is a discrete count, in order to obtain comparable results with the non-linear probability models in terms of number of observations and number of zeros, it is transformed into $y = ln(nc + 1)$.



(a) cells with no conflicts



(b) cells with conflicts

Fig. 6 Total absolute Pearson residuals over time under the ZINB and the NB (with cell-specific fixed effects)

It is also interesting to compare the results obtained under the inflated model with those of a linear normal model, shown in last two columns of Table A1. In fact, while the AIC and BIC of the two linear models are lower and the predicted number of cells with zero conflicts is closer to the observed data, the predicted total number of conflicts is significantly different from the actual figure (32,326). In particular, the LM_FE leads to overestimating the total number of conflicts, with a value (75,389) that is more than double the observed one, while the LM_FE_nl (that does

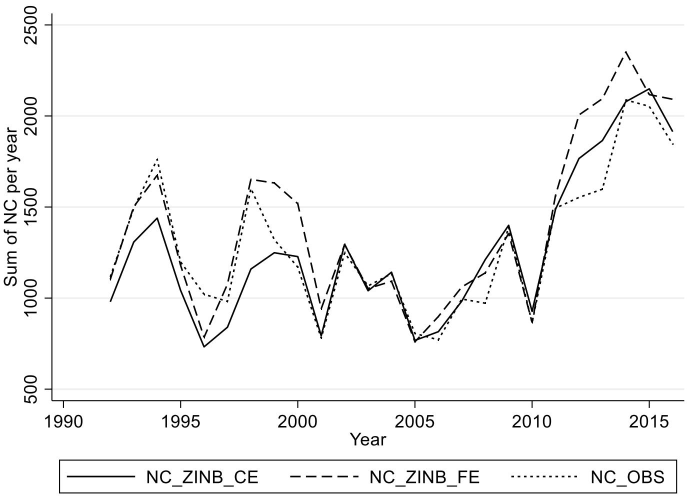


Fig. 7 Observed and predicted number of conflicts over time under the ZINB with country-specific and cell-specific fixed effects

not include the lagged dependent variable) leads to a value (13,823) that significantly underestimates the total number of conflicts. This lends further support to our rationale of relying on a mixture ZINB model rather than a NB or a linear model.

Finally, we ought to compare the two inflated models with country-specific and cell-specific fixed effects. Preliminarily, it is important to point out that in order to fully account for individual heterogeneity, individual fixed effects should be introduced also in the logistic equation of the ZINB. A zero-inflated Poisson model with fixed effects in both the component that models the probability of structural zeros and the count component has been considered for instance in Majo and van Soest (2011). However, in order to limit the parameter dimensionality of our models while still acknowledging for autocorrelation of errors within clusters, we took an alternative approach and made use of robust standard errors clustered on the panel id (Arellano, 1987; Wooldridge, 2010). Moreover, as we will see, the presence of the lagged number of conflicts in the logistic component, that characterizes each cell considerably, substantially reduces the serial correlation of the residual term, thus making individual fixed effects in the Zero model not necessary.

Moving to the actual comparison of the ZINB_CE and the ZINB_FE in terms of control for the serial dependence in the data, consider first a very simple ZINB model with only a regression constant in both equations and no explanatory variables (the so-called *empty* model). Computing and correlating the Pearson residuals of this simple model leads to an average correlation coefficient equal to 0.24.[14] It is interesting to note that if we introduce cell-specific fixed effects solely in the

[14] Notice that, since some of the correlations are positive and some are negative, here the average correlation coefficients are computed by taking the average of the absolute values of the correlations.

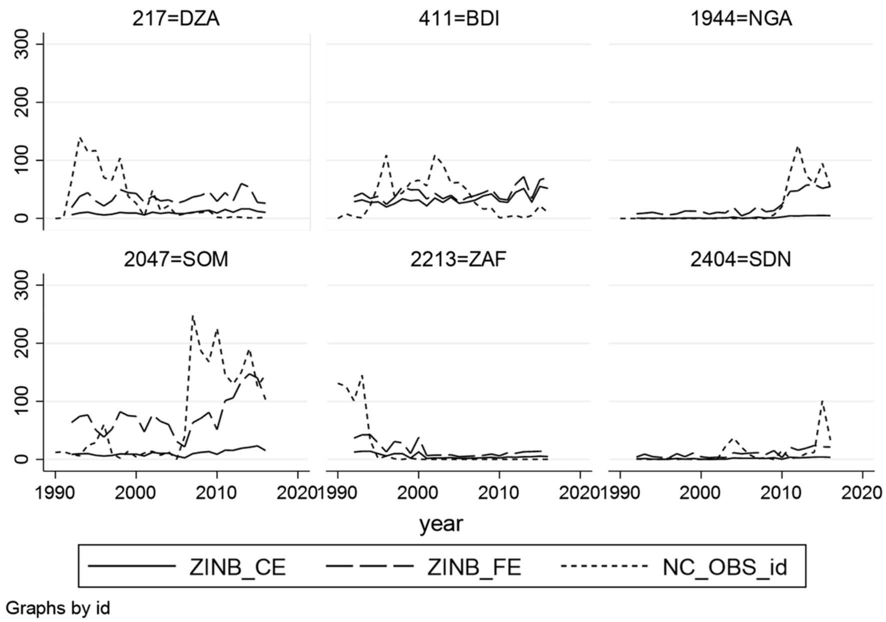


Fig. 8 Observed and predicted number of conflicts per cell under the ZINB with country-specific and cell-specific fixed effects (cells belonging to different countries with a high peak, i.e. at least one year with conflicts > 100)

negative binomial component of the *empty* model we can indeed control for most of this (observed and unobserved) heterogeneity at the unit level, with an average residuals correlation coefficient of 0.06. If on one hand estimating this model is computationally very expensive, since it includes 2653 individual fixed effects, on the other hand replacing cell-specific fixed effects with country-specific fixed effects appear to be less effective in terms of controlling for the causes of serial correlation, as it leads to an average correlation coefficient for residuals of 0.15. Nevertheless, if in addition to country-specific fixed effects in the negative binomial component we also include the lagged number of conflicts in the logistic component, the above average correlation coefficient reduces to 0.07, which is more or less equivalent to that of the ZINB model with cell-specific effects (equal to 0.04).

Going back to the comparison of the ZINB_FE and the ZINB_CE in Table 7, we can see that the former is preferrable to the latter in terms of the AIC but not of the BIC, that clearly identifies the ZINB_FE as being overparametrized. Furthermore, if we look at the number of zeros and at the total number of conflicts predicted by the two models (the observed values being 61,023 and 32,326 respectively) we see that the ZINB_FE yields a more accurate result in terms of the number of zeros, while the ZINB_CE is preferrable in terms of the predicted total number of conflicts. In this sense it is interesting to look at Fig. 7, that shows a graphical comparison of the two specifications with respect to the predicted total number of conflicts over time. In fact, the main differences between the two curves correspond to those periods with peaks, and while the ZINB_CE usually underestimates the predicted number

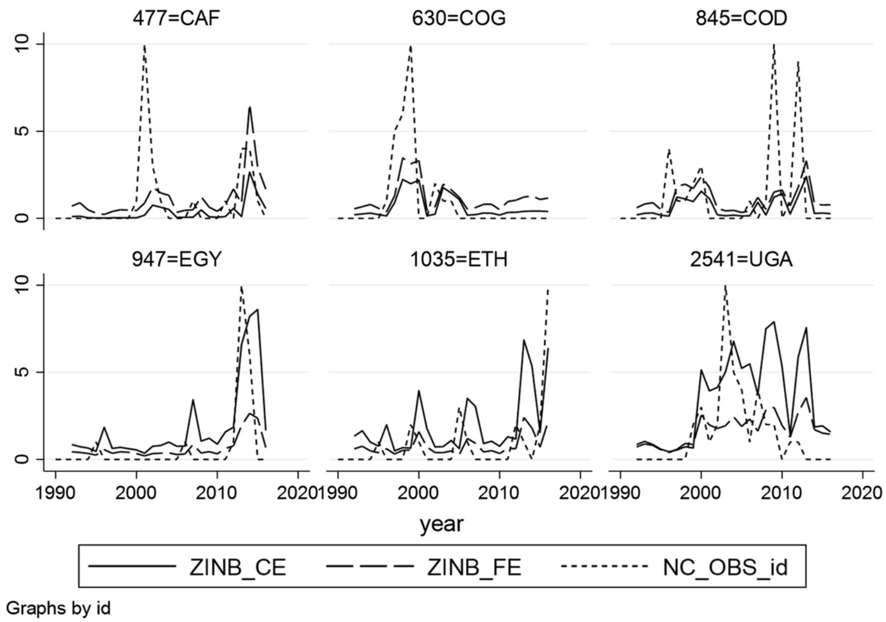


Fig. 9 Observed and predicted number of conflicts per cell under the ZINB with country-specific and cell-specific fixed effects (cells belonging to different countries with a low peak, i.e. with max conflicts = 10 in one year)

of conflicts at a peak, the ZINB_FE often present a persistent overestimation for the years following the peak.

One final point is worth considering, namely the fact that looking at the total number of predicted conflicts per year can be misleading when comparing different models, as overestimations in some cells could compensate with underestimations in others, giving a false sense of goodness of fit. Thus, we randomly selected two groups of six cells each belonging to different countries: the first group represents cells that in the time span 1992–2016 experienced in a specific year a peak equal or higher than 100 conflicting events (Fig. 8); the second group is formed by cells that in the same time span experienced maximum 10 conflicting events (Fig. 9). We drop the first two years due to the lag structure of the estimation.

Notice that the plots in Figs. 8 and 9 do not seem to favour neither the model with country-specific nor the model with cell-specific fixed effects, since they both under/over-estimate the observed number of conflicts depending on the specific cell and year. However, this is an important point, as it shows that including cell-specific effects (i.e. 2653 parameters into the count part of the model) does not substantially improve the prediction ability of the model with respect to including country-specific effects. Because of this, and given both the fact that the BIC suggests that the ZINB_FE is over-parametrized and the concerns on potential biased results in non-linear panel models due to an excessive number of fixed effects, in the paper we choose to evaluate the relative influence of our covariates on the magnitude of violence while taking into account driving factors explaining structural zeros by means of the ZINB specification with country fixed effects.

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