Violent conflicts, climate conditions and socio-economic vulnerability in Africa

Abstract

We propose an analysis of the multiple linkages between armed conflicts and climate-related variables based on an original geo-referenced database covering the entire African continent with a grid resolution of 1°x 1° for the period 1990-2016. A dynamic spatial panel Durbin model is applied to detect both short and medium-term impacts of changes in climate-related variables as well the role played by spatial spillovers. Different channels explaining violent conflicts at the local scale level are jointly included, as resource abundance, socio-economic conditions and institutional quality. A conflict trap mechanism is empirically found through the dynamic econometric estimation that control for persistence over time of conflicts. The spatial specification allows to quantify also the contagious effect across space, that persists in a radius of more than 300 km. Socio-economic conditions at the local level play a significant role in shaping the magnitude of conflicting events, as more populated places characterised by slow economic growth path are those suffering the higher probability to experience violent circumstances. Climate-related variables play a significant role in determining the strength and duration of armed conflicts, with different effects depending on the temporal horizon. We find a strong link between an increase in temperature and conflict through both direct and indirect pathways by which temperature affects conflict levels in a given area. The increase in temperature particularly over a medium-term horizon seems to give impulse to conflicting actions, and this nexus is strongly reinforced by what occurs in neighbouring cells. We finally find that a constant reduction in rainfalls with respect to a medium-term benchmark reinforces the occurrence of conflicting events. This phenomenon seems to be more confined at the geographical scale since spillover effects are negligible.

Keywords: Climate conditions; armed conflicts; Africa; geographical spillovers; drought; socio-economic vulnerability

J.E.L. code: D74; O13; O55; Q54

1.   Introduction

Armed conflicts wreak disorder on economies and have devastating effects on development. According to Gates et al. (2012), about a quarter of the population of the developing world lives in conflict and post-conflict countries. These countries are characterised by very low levels of human development, a wide portion of the world's undernourished people, and more than half of the illiterate population.

During last decades, especially African countries have experienced many conflicts and civil wars. In addition, the continent also suffers from several challenges as poverty, limited education and health systems, food insecurity, and last but not least the negative impacts of severe changes in climate conditions. Although climate change is a global threat, developing countries (DCs) and especially the African ones suffer the most due to their greater vulnerability to climatic factors (Moore and Diaz, 2015).

For these reasons, the African continent has been continuously put under the lens of empirical investigation. Changes in temperature and rainfall patterns are estimated to affect a large share of population, influencing their lives and creating further incentives for violent attacks and armed conflicts in the next future (Dell et al., 2014; Miguel et al., 2004).

As for the causes of this high vulnerability, geographical and climate characteristics are not the only explanations. A key role is also played by the economic structure of countries, their poor institutional capacity, unequal income distribution, the scarcity of financial resources to implement adaptation measures and the consequent low resilience to extreme events and disasters causing unsustainable pressure on natural resources (Burke et al., 2015; Hsiang et al., 2011). This complexity is well explained by the comprehensive concept of social vulnerability to climate change (Otto et al., 2017). Moreover, the negative impacts of climate change hit crucial aspects of human life, such as agriculture and food security, as well as access to water and other natural resources, worsening the already critical conditions characterizing poor economies, with the risk that the resulting tensions might become armed conflicts (Weir and Virani, 2011).

Although the debate on the causes of conflicts, riots and violence is increasing and the relevance of climate-related features in shaping conflicts is highly investigated, there is still no consensus on direction and strength of the causal linkages. Our analysis contributes to the current debate in the following ways.

First, according to recent empirical developments (Auffhammer et al., 2013; Busby et al., 2014; Devlin and Hendrix, 2014; Fjelde and von Uexkull, 2012; Harari and La Ferrara, 2018; Maystadt et al., 2015) we adopt a cell-based analysis mapping the whole African continent at a sub-national scale with a geographic detail corresponding to a grid of 3,402 units of observation of 1°x 1° corresponding to an area around 110x110 km (from now on referred to as cells). To the best of our knowledge, this database constitutes the widest informative source for geographical coverage and temporal span (1990-2016) jointly considered.

Second, the dependent variable we build for representing armed conflicts reports the number of conflicting events occurring each year in each cell. Differently from previous analyses, this allows one to detect the role of analysed co-variates in driving not only the probability of a cell to experience at least one conflict (as in the case of binary information) but also the relative strength of violence if several episodes occur in the same place and year.[1]

Third, we test several different variables representing climatic conditions and changes over the short and the medium-term, also detecting if spatial spillover effects occur. The combination of information on medium-term climate changes and the geographical scale of these events allows indirect effects to be captured, as for instance migration and consequent over- pressure on scarce

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[1] In what follows, according to Sundberg and Melander (2013), one event is defined as the incidence of the use of armed force by an organized actor against another organized actor, or against civilians, resulting in at least one death at a specific location and for a specific temporal duration. Studies based on binary information rely on the definition of a selected area as conflicting if there are one or more events determining a threshold of 25 deaths per year, but above that threshold the conflict variable always assumes value 1 independently of the number of events or their intensity. On the contrary, by quantifying the events for each year we can move from the analysis of conjunctural causes of conflicts as detected in previous contributions while focusing on more structural features influencing the occurrence and repetition of conflictual events over each year and persisting over different years.

resources, which are not deeply investigated at a continent scale level.

Large migrations might be a consequence of structural (at least medium-term) changes in climate conditions and people forced to move to other areas might exacerbate pressures on already scarce natural resources, leading to the likelihood of increasing violent conflicts (Brzoska and Fröhlich, 2016; Burrows and Kinney, 2016). Nonetheless, existing analysis are based on international migration flows (Cai et al., 2016; Cattaneo and Bosetti, 2017; Marchiori et al., 2012) while internal migration effects are less investigated given the unavailability of precise information on internal migration flows. In particular, climate-induced migration, especially due to severe drought conditions and subsequent soil barrenness has increasingly been recognized as a form of adaptation to climate change and environmental degradation (Gray and Mueller, 2012). Following Buhaug (2015), we contribute in underpinning how changes in climatic conditions occurred within a reasonable time lag (past five years) in surrounding areas might impact on conflicting propensity of one territory by assuming that one of the channels is migration.

Fourth, we include a wide range of cell-based and country-based socio-economic variables that allows us to consider a set of driving forces that might explain the climate-conflict nexus by also controlling for the social vulnerability to climate change.

Fifth, we look at contagious and spillover effects across space by investigating different cut-off distances according to the source of spatial correlation under investigation.

The remainder of the article is organised as follows: Section 2 provides a review of main contributions in the literature on climate change and conflicts; Section 3 describes the econometric methodology and the dataset; Section 4 comments on main results; Section 5 discusses concluding remarks and future research lines.

2.   Channels and links between climate conditions and armed conflicts

The linkages between change in climate conditions and conflicts have been increasingly investigated during recent years under different perspectives (Bosetti et al., 2018; Buhaug, 2010; Burke et al., 2009; Hendrix and Glaser, 2007; Nordås and Gleditsch, 2007; Raleigh and Urdal, 2007). Although selected common issues can be derived in support of a link between climate change and violent conflicts ranging across regions, time intervals and spatial scales, there are many alternative explanations demonstrating a lack of consensus (Hsiang et al., 2013; Hsiang and Burke, 2014) that leaves space for additional investigation. The main channels investigated in this field of analysis are the following.

Dealing with climate-related variables is a complex issue since different aspects need to be disentangled. The first distinction is between structural changes in climatic conditions as expressed

by a persistent increase in average temperatures and change in precipitation levels over years, and increased variability in climatic phenomena that might bring higher frequency and magnitude of extreme events (e.g. floods, heatwaves, typhoons). The second issue is the direct or indirect impact on human being. Changes in climatic conditions might directly affect people as in the case of damages provoked by extreme events, or might indirectly impact anthropic activities as in the case of agriculture, or reduction in land fertility or water availability or diseases diffusion, just to mention a few.

The third distinction refers to the causal linkages between changes in climatic variables and armed conflicts that vary according to the chosen variable (temperature, precipitation, drought indices), time frame, the geographical scale and the specific channel investigated.

With respect to the choice of the climatic variable and the time frame, Burke et al. (2015) focus on the relevance of short-term climatic variables and on the relative impact of higher temperature on economic development motivated by a non-linear relationship. As another example, while Adano et al. (2012) find that armed conflicts are positively related to an increase in rainfall in a short horizon, Fijelde and von Uexküll (2012) suggest that, in a longer horizon, large negative deviations in rainfall from normal values are associated with an increased risk of violent conflicts.

With respect to the specific channel through which changes in climatic conditions might influence anthropic activities, several studies focus on the role of agriculture, which is unquestionably the sector most exposed to climate variability (Crost et al., 2018; Harari and La Ferrara, 2018; Raleigh et al., 2015; Wischnath and Buhaug, 2014).[2] 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 as for instance inducing changes in livestock prices (Maystadt and Ecker, 2014) or pastoralism displacement (Meier et al., 2007) with a consequent increase in competition on land-use (Benjaminsen et al., 2012).

Water access is another channel responsible for linkages between conflicts and climate-induced water scarcity since the control over water resources is an instrument of war for both offensive and defensive purposes (Brochmann and Gleditsch, 2012; Gleick, 1993, 2014).

Together with climate-related events, it is also necessary to account for other features that might directly constitute a source of conflict or that might reinforce (or reverse) the climate-conflict causality nexus. We list the most relevant ones.

The first is the existence of a conflict trap as emphasised in Collier (2003). According to Hegre et

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[2] More than 80 percent of world food production mainly located in DCs relies on rain-fed irrigation, which depends critically on the variation of the spatial and temporal distribution of both climate dimensions of precipitation and temperature (Bates et al., 2008; FAO, 2008). This explains why those regions without an irrigation system and more exposed to dry conditions are found to be the most exposed to the risk of conflicts because of climatic variations (Daccache et al., 2015; von Uexküll, 2014).

al. (2016), the conflict trap is empirically verified by taking into account the four pathways through which it works, namely the conflict-induced increase in the likelihood of continuation, recurrence, escalation and diffusion of armed conflicts. They find that in previous studies both the intensity and the duration over time of the conflict trap have been underestimated.

The second issue connected with the nature of conflicts is the probability of contagion. According to Silve and Verdier (2018), from a theoretical point of view there are at least two channels to be considered jointly. From the one side, regional clusters of civil wars result from the clustering of similar internal features (geographical or social characteristics, resource endowments, and climatic conditions). From the other, spatial spillovers between neighbouring regions should be considered as a crucial determinant of the geographical distribution of civil wars. Regional interactions and feedback effects should be included in a broader analysis where feedback and spillovers effects associated to the existence of the phenomenon and the driving factors influencing conflict explosion need to be jointly considered.

The third aspect is related to natural (exhaustible and renewable) resource endowment. Scholars argue that armed conflicts are triggered by (especially non-renewable) resource abundance as it represents a key economic source, the competition for control of which may increase the risk of conflict (Cilliers, 2009; Holmberg, 2008). Especially when governments are unable to ensure fair distribution of returns from resources and provide basic public goods, resource abundance stimulates violence caused by rebel groups, and even civil war (Mehlum et al., 2006; Ross, 2004). Also in the case of renewable natural resources, a relatively higher endowment might lead to an increase in conflict.[3]

All the aspects described can be aggravated by the absence of a proper institutional setting, which is the third issue to be included among the non-climate related factors. Good institutions are essential for an effective use of resources as well as for coping with adverse socio-economic conditions and implementing adaptation policies that limit vulnerability to climate change. The more a country is vulnerable to climate change, the more is its exposure to these risks, especially if the focus of the economy is on climate-dependent sectors, as in the case for many DCs (Castells-Quintana et al., 2017; Gizelis and Wooden, 2010). Strong institutions are also recognised as a source of protection from conflict contagious (Braithwaite, 2010; McBride et al., 2011) in the case of cross-borders spillovers of armed conflicts.

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[3] As a good example of water-related conflict, Onuoha (2010) describes the effects of climate change on Lake Chad, which represents the main source of freshwater for drinking and sanitation, as well as for economic activities (agriculture, fishing and pastoralism) for four African countries. Owing to climate change, the lake has lost over 50 per cent of its water during the last 40 years, leading to a reduction of fish stock, water availability and a loss of vegetation and land. The reduction of Lake Chad has contributed to the eruption of violent conflicts over competition for diminishing water resources, by intensifying the pattern of migration and the contact between major livelihood systems.

Together with the quality of institutions a fourth element that might prevent a climate-conflict vicious cycle is the reduction in socio-economic vulnerability. Sustained economic growth combined with a well-suited property rights regime (Butler and Gates, 2012) and a resilience strategy are key elements for reducing damages provoked by changes in climatic conditions and extreme events to anthropic activities as well as to ecosystem services (Busby et al., 2014).

From the methodological point of view, the adoption of wide scale geo-referenced approaches seems to be the most promising way to account for large divergences in causes of local conflicts that might be linked with climate change. Within the African continent, most of the studies based on geo-referenced analysis have focused on East Africa with the literature largely accounting for variations in the precipitation patterns and, more recently, temperature change (Ember et al., 2012; Hsiang et al., 2011; Maystadt and Ecker, 2014; Raleigh and Kniveton, 2012). According to Ide and Scheffran (2014), this scale of analysis better captures micro-level phenomena (e.g. intrastate migration and resource distribution at the local level), which depend on geographical and landscape characteristics, rather than on administrative boundaries, as in country-based analyses. To this purpose, the contribution by Harari and La Ferrara (2018) shows that a sub-national analysis helps in discovering fine-grained events as the role played by rainfall changes during the crop growing season in reinforcing the possibility of conflict. More importantly, they suggest the role played by geographical spillovers in such kind of analyses, thus disclosing indirect effects that might complete the overall picture.

3. Methods and data

3.1. Methods

We adopt a dynamic panel spatial approach in order to fully account for the geographical scale and the temporal dimension of the linkages between changes in climate-related variables and armed conflicts.

Notice that from the point of view of the spatial configuration, different types of interaction effects can explain why an observation at a specific location may depend on observations at other locations (Elhorst, 2014). The first are endogenous interaction effects, where the response variable Y of a particular unit depends on the response variable Y of neighbouring units. The second are exogenous interaction effects, where the response variable of a particular unit depends on explanatory variables X of neighbouring units. The third are interaction effects among the error term, that represent, for instance, a situation where the determinants of the response variable omitted from the model are spatially correlated. All these interaction effects can be introduced in a spatial econometric model by means of a nonnegative (and usually symmetric) weights matrix that describes the spatial

configuration of the units in the sample.

From the point of view of the panel structure of our data, both spatial and temporal heterogeneity can be accounted for. In fact, units are likely to differ in their background variables, such as the distance from the sea or from the border, or the degree of urbanization, which are usually space-specific and time-invariant. Similarly, units are likely to differ over time, due, for instance, to time points marked by an economic recession, by a boom, or by a change in legislation. Failing to account for these spatial and temporal effects can lead to biased estimation results due to serial correlation of the residual term. In particular, spatial and temporal heterogeneity could be considered within a fixed or a random effects approach. However, random effects models require the assumption of zero correlation between the random effects and the explanatory variables; moreover, they also require that the number of units should potentially be unbounded and that the units of observation are representative of a larger population. On the contrary, in several spatial econometric analyses the data are generally relative to adjacent spatial units located in an unbroken area (such as all regions in a country), so that they cover the whole population and each unit represents itself (Elhorst, 2014). For this reason in what follows we will concentrate on fixed effects models.

Finally, given the focus on persistence over time of the conflictual propensity and intensity of cells and the potential mutual correlation between conflicts and some explanatory variables representing social vulnerability, our models also allows for temporal lags of order *p*. Its general form can be written as:

$$Y_{it} = \alpha Y_{it-p} + \rho W Y_{it} + \beta X_{it-p} + \vartheta D X_{it-p} + \gamma_i + \delta_t + u_{it} \qquad (1)$$

$$u_{it} = \lambda M u_{jt} + \varepsilon_{it} \qquad (2)$$

where α is the coefficient associated with persistence over time, ρ is the spatial autoregressive coefficient representing the endogenous interaction effect (introduced by means of the spatial weight matrix *W*), β is the vector of parameters associated with the explanatory variables, ϑ is the vector of parameters associated with the spatial exogenous interaction effects (introduced by means of the spatial weight matrix *D*), γ_i are cell-specific fixed effects, δ_t are year-specific fixed effects, λ is the spatial autocorrelation coefficient representing the interaction effects among the disturbance term of the different units (introduced by means of the spatial weight matrix *M*), and ε_{it} is an *N×1* vector of independent and identically distributed (i.i.d.) homoscedastic normal disturbance terms. It is worth mentioning that the model allows the weighting matrices associated with the spatial autoregressive

term, the spatial exogenous effects and the spatial autocorrelation coefficient (*W, D, M* respectively) to be different.

Notice that, as pointed out for instance in Elhorst (2014), the full model specified in (1) and (2) is usually over-parametrised, so that the significance levels of the explanatory variables tend to decrease and in empirical studies it does not appear to outperform simpler models. In particular, in order to choose the best model not affected by this over-parametrisation bias, we have compared a spatial autoregressive model (SAR) with $\rho \neq 0 \ and \ \vartheta, \lambda = 0$, a SAR model with spatial autocorrelation (SAC) with $\rho, \lambda \neq 0 \ and \ \vartheta = 0$, and a SAR model with Durbin effects (SDM) with $\rho, \vartheta \neq 0 \ and \ \lambda = 0$ (Anselin, 1988, Anselin et al., 1996, Le Sage and Pace, 2009)comparison is particularly interesting with respect to both the SAR and the SAC as it imposes no restrictions on the magnitude of both the direct and indirect effects (Elhorst, 2014).

Final model selection has been based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). According to both AIC and BIC values, the SDM in our case is the most appropriate way to perform the analysis accounting for temporal dynamics and spatial spillovers. The same approach has been also adopted for selecting temporal lags of order p, with a final SDM with lag 1 for both the persistence term associated to parameter α and the indirect effects associated to parameter ϑ.

With respect to the choice of the spatial resolution, given that the selection of the geographical scale is not a priori determined on a theoretical basis but it is mainly driven by empirical findings, we adopt units of observation of 1°x 1° (approximately 110x110 km^2) relying on the most recent analysis of the climate-conflict nexus in Africa with a cell-based approach, represented by the contribution of Harari and La Ferrara (2018) where robustness checks on alternative resolution scales (both lower and higher) confirm the 1°x 1° as the most appropriate.

Another aspect to consider carefully is the spatial spillover effect. First, recall that if an explanatory variable X_k changes in a particular unit, not only will the response variable in that unit change (which is the direct eff ect), but also the response variable in other units (which is the indirect or spillover eff ect). Because of these feedback eff ects, that arise due to the impacts passing through neighbouring units and back to the units themselves, conclusions about spatial spillovers cannot in general cannot be drawn by simply looking at the parameters of the model but require the computation of a partial derivative (LeSage and Pace, 2009). In particular, the diagonal elements of the partial derivative of *E(Y)* with respect to X_k, which for the full model without constraints to spatial coefficients equal to

$$(I - \rho W)^{-1} = (\beta_k I_N + \vartheta_k D) \tag{3}$$

represent the direct eff ects of X_k, while the off -diagonal elements of the same matrix represent the

indirect eff ects. Such elements represent proportional marginal effects and can thus be considered as elasticities. More specifically, direct effects describe the impact that a percentage change in an independent variable in cell *i* has on conflicts in the same cell (with respect to other cells). Indirect effects are interpreted as the impact that a percentage change in an independent variable in the other cells has on conflicts in cell *i*. Accordingly, empirical results reported in the main text and related comments on linkages strength and direction refer to direct and indirect effects calculated as eq. (3), while coefficient estimates (β_k, ϑ_k) are reported in Appendix B.[4] Finally, in a dynamic SDM (where the lagged dependent variable is introduced among the covariates) there is a further distinction to make, between short- and long-term direct and indirect effects. Specifically, the short-term effects are given by the matrix of partial derivatives of *Y* with respect to the *k-th* explanatory variable in unit 1 up to unit *N*:

$$\left[\frac{\partial Y}{\partial x_{1k}} \cdots \frac{\partial Y}{\partial x_{Nk}}\right] = (1 - \rho W)^{-1}[\beta_k I_N + \vartheta_k D] \tag{4}$$

Likewise, the long-term effects are given by:

$$\left[\frac{\partial Y}{\partial x_{1k}} \cdots \frac{\partial Y}{\partial x_{Nk}}\right] = [(1 - \tau)I - (\rho + \eta)W]^{-1}[\beta_k I_N + \vartheta_k D] \tag{5}$$

where τ and η are the time lags of the variables Y_t and WY_t, respectively.

The quantification of the contagious effect, represented by the spatial lag, and of the direct and indirect marginal effects, which hereafter we refer to as spillovers, is strongly influenced by the choice of the weighting distance system. Given that the whole African continent is here artificially gridded with a 1°x 1° resolution, by computing distance matrices on the basis of a pure contiguity criterion might bring to biased results if we account for what is happening outside the first ring of cells, corresponding to an inverse distance between centroids by around 180 km. Accordingly, 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 calculated between the centroids of cells. The inverse distance has also been combined with the queen contiguity approach when choosing the cut-off, in order to consider all cells being included or even also tangent for a single point with respect to the buffer computed with the radius equal to the cut-off distance expressed in km.[5]

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[4] Direct, indirect and total eff ects as well as their standard errors are computed by using Monte Carlo simulations. Given the dynamic specification of our models, we report both short and long-term marginal eff ects computed applying the bias-corrected quasi-maximum likelihood approach suggested by Yu et al. (2008). Standard errors for marginal effects reported in Tables in the main text are available upon request from the authors.

[5] We are aware of drawbacks of the Harversine formula that provides valid measures for short distances, but underestimated values for long distances especially if calculated in places far from the Equator line where the Rhumb lines approach is more appropriate.

Notice that although it is common practice to normalize distance weight matrices such that the elements of each row sum to unity, so that the weighting operation can be interpreted as an averaging of neighbouring values, according to Harari and La Ferrara (2018) we do not make use of row normalization.[6]

In order to choose the cut-off for the three weight matrices (respectively W, D, M) we used two criteria. First, we compute global Moran's I in order to detect for each variable the maximum distance where spatial correlation is significantly different from zero. Second, we adopt different cut-off values for the same econometric model in order to choose those estimations that perform best in terms of AIC and BIC values. Results described in Section 4 are thus based on optimal cut-offs of 250 km for the contagious effect and of 500 km for spillover effects. By relying on the combination of great circle distances with the queen contiguity criterion, the actual size of buffers projected on a bi-dimensional space corresponds to radius equal to around 311 and 568 km, respectively. For the sake of simplicity in the rest of the text we call them as 250 and 500 km.

It is worth mentioning that the optimal cut-off for spillover effects is heterogeneous with respect to different dimensions. In particular, for those variables representing social vulnerability such as income and population the cut-off obtained with the global Moran's I corresponds to the 500 km distance while for climate-related variables as temperature and precipitation the spatial correlation is significantly different from zero with a cut-off of 1,000 km (around 1,111 km radius of the actual buffer). Given that a common weight matrix should be adopted for all covariates (D), we consider the 500 km cut-off in order to account for spillover effects also for social vulnerability.[7]

3.2. Data

The empirical analysis is conducted on an original georeferenced database that combines conflict data

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Nonetheless, given that our maximum cut-off distance is around 568 km of radius, difference between the two approaches is negligible (Weintrit and Kopacz, 2011).

[6] The reasons for this are several. First, LeSage and Pace (2014) argue that in some situations it is the economic behaviour of individuals that leads to row normalization. Consider for instance the case of an individual that estimates the price of his house using local prices, i.e. the average of neighbouring house prices; in this case WY reflects an average of nearby observations and therefore requires scaling. Our problem, however, does not seem to fall into this category. Second, row normalization alters the internal weighting structure of W, in the sense that it has the effect of understating the weights of a unit with many neighbours with respect to those of a unit that is located near the boundary: pairs with the same distance can have different weights depending on the number of nearby observations. Third, as pointed out in Kelejian and Prucha (2010), normalising the elements of a spatial weight matrix by a different factor for each row (as it is the case in the aforementioned row normalisation) is likely to lead to misspecification problems, especially when an inverse distance matrix is assumed. It is important to acknowledge that in order to overcome this problem, various alternative normalization procedures have been proposed (Elhorst, 2001; Kelejian and Prucha, 2010; Ord, 1975); these, unlike row normalization, lead to a weight matrix that is symmetric (so that it does not lose its economic interpretation in terms of distances) and such that the mutual proportions between the elements of W remain unchanged (Elhorst, 2014). Nonetheless, in our case we consider the W without any normalisation procedure because it is the only way to account for the fact that if a cell is surrounded by several other units characterised by a high number of conflicts, the contagious effect is higher and the actual distance is crucial in shaping it. If whatever normalisation criterion is applied, the high numerosity of cells will automatically reduce the value of distance.

[7] Details related to the choice of cut-offs, global Moran's I values for main variables and representation of the radius computation for different buffers are provided in Appendix A. Values for global Moran's I for all variables as well as values for local Moran's I are available upon request from the authors.

with climate and socio-economic information resulting in a panel dataset for the entire African continent divided into 3,402 georeferenced cells covering the period from 1990 to 2016.[8]

Differently from previous grid-based analyses on the African case that rely on the ACLED database, we build the dependent variable by taking raw data from the UPPSALA-UCDP database that provides information on conflicting events with geographical coordinates at a very detailed level. We define our dependent variable (hereafter called as number of conflicts) as the sum of any conflicting event occurred in a specific year — where armed force is used and results in the death of at least one person — whose geographical coordinates are included in the area covered by the cell itself.[9]

The explanatory variables related to climatic conditions represent both weather conditions related to the geo-localisation of each cell as well as changes occurring in the short and medium-term elaborated from the African Flood and Drought Monitor developed by Princeton University in collaboration with ICIWaRM and UNESCO-IHP. It provides information at a 0.25° resolution.

Concerning temperature, we consider temperature measured at two meters above the surface and calculated from averaging monthly data. Data from 1990 to 2008 rely on the Princeton Global forcing methodology while from 2009 to 2016 they are taken from the Global Forecasting System Analysis. Original data expressed in the Kelvin scale have been converted in Celsius (centigrade) degrees. We compute temperature change rates w.r.t. the previous year in order to account for short-term variations, that can be interpreted as temporary anomalies. By also calculating the average yearly temperature change rates over the past five years we control for persistency of increasing (or decreasing) temperature over time as an indication of medium-term change in climate conditions.

With respect to precipitation, annual average precipitation values expressed as daily total surface precipitation in mm/day are computed by using monthly data from the Princeton Global forcing methodology for the period 1990-2008 and from Satellite Precipitation (3B42RT) for the period 2009-2016. Also in this case, we compute changes occurring with a one-year lag in order to account for short-term variations (anomalies) and average precipitation changes over the past five years as a

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[8] The 48 countries included are: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Cote d'Ivoire, Democratic Republic of Congo, Djibouti, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe. Benin, Equatorial Guinea, Gabon, Gambia and Malawi have been included even if no conflicts have been registered for these countries in the UPPSALA-UCDP, while we excluded island countries (Cape Verde, Comoros, Mauritius, São Tomé and Príncipe, Seychelles). South Sudan has been classified as Sudan for combining country-based information.

[9] Our dependent variable corresponds to the sum of all events defined as incidents where armed force is used by a government or by any organised actor against another organised actor, or against civilians, resulting in at least one direct death at a specific location and a specific date (Croicu and Sundberg, 2017). Interstate armed conflicts fought between two or more states are excluded. The total amount of events for the African continent in the time span 1990-2016 used for building the dependent variable corresponds to 34,605 observations. This choice presents several positive aspects. First, ACLED has a limited time span starting from 1997 while UCDP starts from 1989. Second, ACLED does not allow distinguishing conflicts on the basis of the number of deaths. Third the quality of UCDP geocoding and precision information if the scale of the analysis is at the subnational level is far superior to ACLED (Eck, 2012). This is particularly important when examining geographic dimensions of conflicts.

measure of medium-term changing conditions. We also compute an annual average Standard Precipitation Index (SPI-12) that is a comparison in terms of standard deviation of the precipitation for 12 consecutive months with that recorded in the same 12 consecutive months in all previous years of available data and it can be interpreted as an index of meteorological drought where negative values represent dry conditions.[10] With respect to the other meteorological composite indices, SPI is recommended since it is considered as computationally feasible and homogeneously available for all regions (WMO, 2017). In addition, in this analysis we choose to include climatic conditions such as precipitation and temperature as distinguished variables. Accordingly, we have considered the SPI as it is based only on precipitation values, leaving temperature outside. As emphasised in recent contributions (Burke et al., 2015; Eckstein et al., 2017) temperature should be considered as a separate variable in such kind of analyses especially if the African continent is under scrutiny, because rainfalls and temperature present quite divergent trends and deserve to be considered simultaneously but separately. Coherently with the other climatic variables, we also compute an average SPI-12 over the past five years that may be interpreted as a measure of drought persistency over a medium-term horizon.

In order to account for specific geographical features that may help in detecting vulnerability to climate change we have also included some time invariant variables: i) a dummy variable assuming value 1 if land cover is classified as cropland according to MODIS-based Global Land Cover Climatology dataset; ii) the water stress of each cell described in terms of drought severity and flood occurrence indices taken from the Aqueduct Water Risk Atlas. With respect to the information related to rural coverage, we have calculated a time variant cell-based variable by interacting the rural coverage at the cell level with the percentage of value added coming from the agriculture sector for each year at the country level taken from the World Development Indicator (WDI) database from the World Bank. In this way, we are able to consider the relative relevance of land use while also accounting for how much the whole country depends on the primary sector. Given that this is the most affected sector in Africa from changes in climatic conditions, by assigning an economic value to this geographical feature allows us to account for vulnerability also from a socio-economic point of view. All these variables have been used for computing interaction effects in order to better shape differentiated vulnerability to changes in climatic conditions.

In particular, we interact short and medium-term changes in temperatures with drought-risk level, short and medium-term changes in precipitations with the time variant rural-related interacted variable, and with drought-risk and flood-risk levels. The same is applied by interacting the SPI-12

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[10] The SPI-12 is the Standard Precipitation Index indicating deviations from long-term normal rainfall during the 12 preceding months for each month (ranging from -3.719 to +3.719). If positive, it represents that the level of actual precipitation was higher than what expected or, in other word, it has been less dry.

and its average value over five years with rural, drought-risk and flood-risk features.

Social vulnerability is represented by the value of gross domestic product (GDP) and population level provided by SEDAC-Socioeconomic Data and Applications Center at the 1°x 1° grid level for the period 1990-2005. Population data for the period 2006-2016 have been integrated with information coming from the History Database of the Global Environment (HYDE, version 3.2.1). Data for GDP in the period 2006-2016 have been interpolated at the cell level and calibrated with the annual GDP growth rate at the country level taken from WDI. Within the category of social vulnerability, we also include the presence of mineral and fossil resources by first computing a dummy variable assuming value 1 if an exhaustible resource (coal, oil, natural gas, mineral) is exploited in an area located within the cell. Differently from previous analyses (Adano et al., 2012; Bodea et al., 2016) we consider not only the presence of fields and mines but also the localisation of power plants, mills and refineries. All these data come from the Data Basin Dataset. In addition, as for the case of rural land cover, we compute a time-variant variable that results from interacting the cell-based resource dummy with a time variant country-based variable representing the share of fossil fuels and minerals on total merchandise exports at the country level taken from WDI. Finally, we consider the quality of institutions at the country level provided by the PRS Group as the most complete database covering the entire time span and all countries included in our analysis. By combining information on institutional quality with resource endowment and exploitation we can address the potential impact of a resource curse while also controlling for the quality of institutions, according to most recent advancement in resource curse hypothesis contributions (Sarmidi et al., 2014).[11]

In order to provide a broad descriptive picture of the addressed issues we present three maps directly derived from our database. By looking at Figure (1) it emerges that during the last decades the African continent has been characterized by a high number of conflicts, from the last years of Apartheid in South Africa and the Rwandan Civil War in the early '90s to the Arab Spring of the recent years. The most violent region has been, on average, the Horn of Africa, while Algeria registers the highest number of conflicts at the country level. As illustrated in Figure 1, the distribution of conflicts overlaps with two interesting features, the presence of exploitable resources and water bodies. While there is a clear overlap of conflict zones with the presence of energy and mineral resources, thus confirming the necessity to include the resource channel in the analysis of the climate-conflict nexus, the frequency of conflictual events is more heterogeneously located with respect to the presence of water bodies.[12] As for climate dynamics, during last years temperature has increased

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[11] A complete list of variables with main statistics and correlation matrix are provided in Appendix A.
[12] Selected statistics and Figures representing the quantification and distribution over space and time of the number of conflicts are provided in Appendix A.

all over the continent, especially in North-West and South-West Africa (Figure 2).

Figure 1 - Number of conflicts (1990-2016), resources and water bodies
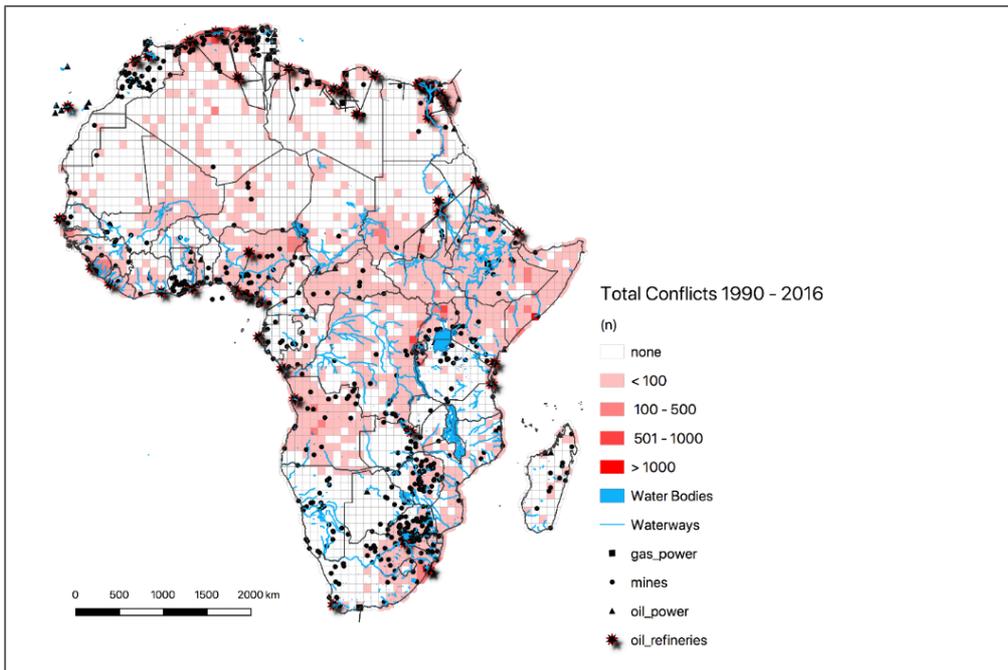
As for precipitation, the average year values for rainfall levels have also changed dramatically and with substantial heterogeneity across the continent, increasing in the Tropical Bell and substantially decreasing in Sub-Saharan Africa (Figure 3).

Figure 2 - Change in temperature (av. 2014−2016 w.r.t. av. 1990-1992)
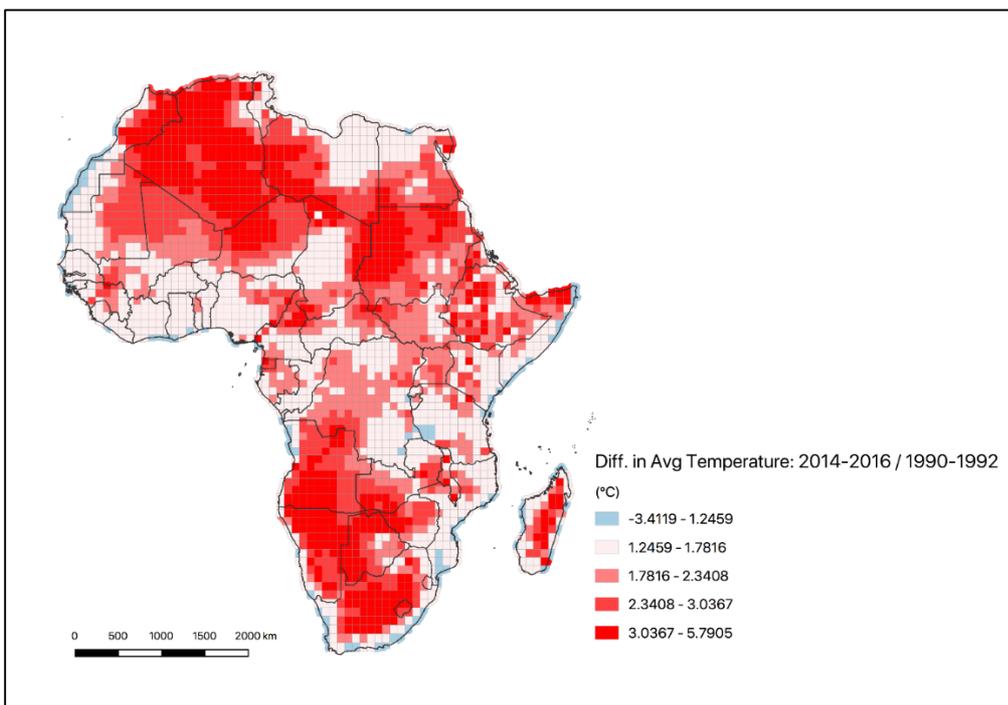
Figure 3 - Change in precipitation (av. 2014−2016 w.r.t. av. 1990-1992)
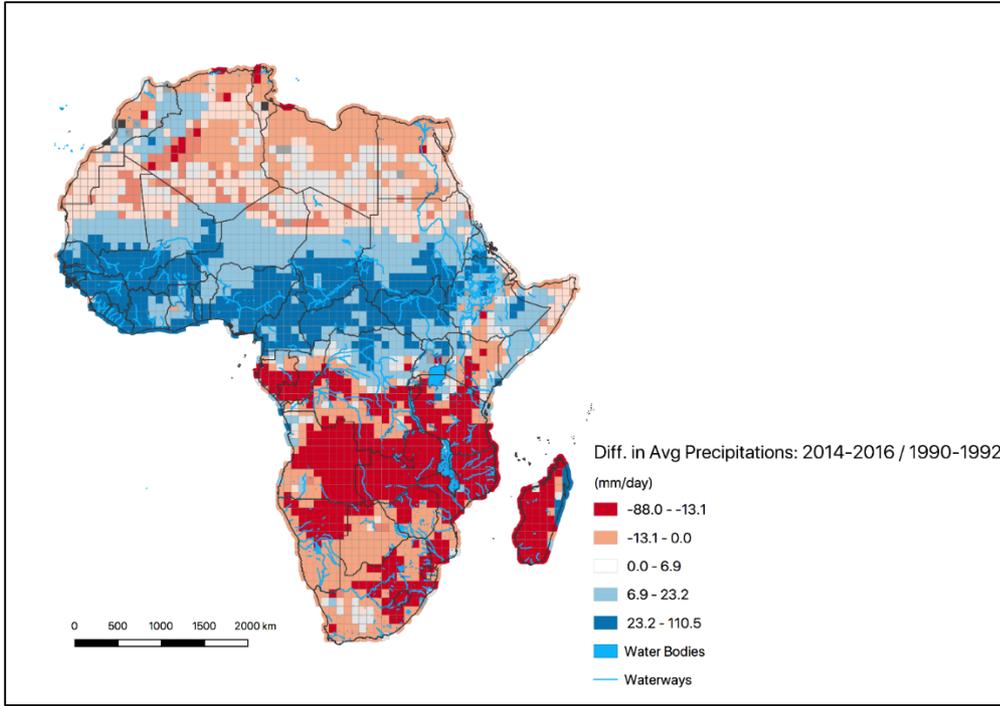
4.   Results

In what follows we discuss econometric results in terms of marginal effects obtained by three different models based on a dynamic SDM estimated with Maximum Likelihood, assuming $\rho, \vartheta \neq 0 \ and \ \lambda = 0$ and calculated by eqs. (4)-(5) for direct and indirect effects, respectively. In eqs. (6)-(7)-(8) all variables in level are log-linearized while variation rates are expressed in the form of natural logarithm of the ratio between the final and the initial level. All models include cell specific (γ_i) and year (δ_t) fixed effects in order to capture potential omitted variables effect.[13] All variables with subscript i refer to cell-specific measures while sub-script c refers to country-specific covariates. The first model setting considers the relation between number of conflicts and the geographical and social

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[13] Tests for model fitting for comparison with other spatial model specifications, test for choosing the cut-off distance for W and D, punctual estimates for SDM results with robustness tests, Hausman test for random vs. fixed effects, collinearity robustness with Condition numbers, AIC and BIC values are all reported in Appendix B. Controls for potential influence of outlier values have been performed by applying the multivariate blocked adaptive computationally efficient outlier nominators (BACON) algorithm proposed by Billor et al. (2000). By applying the default percentile (0.15) of the chi-squared distribution to be used as a threshold to separate outliers from non-outliers, we obtain 28 outliers. By performing the same regression dropping out these observations results remain stable. In addition, for the sake of simplicity we report estimates with the temporal lag structure of one year as the most appropriate in terms of model fitting performed by comparing AIC and BIC values. Results for models with alterative time lags are available upon request from the authors. In Appendix B, Tables B.1A, B.1B and B.1C have been used to select the best distance threshold in the spatial matrix for the effects of cell-based climate and socio-economic features on conflicts number (250 km); we then used results from Table B.2 for selecting the SDM as the best spatial model specification. Punctual estimates of coefficients $\beta^{x,z,k}$, $\vartheta^{x,z,k}$ reported in Appendix B have the following correspondence to marginal effects reported in the main text: Table B.3 corresponds to Tables 2A-2B; Table B.4 corresponds to Tables 3A-3B; Table B.5 corresponds to Tables 4A-4B.

characteristics of each cell in the form:[14]

$$NC_{it} = \alpha NC_{it-1} + \rho W_{250km} NC_{it} + \beta^x X_{it} + \vartheta^x D_{500km} X_{it} + \beta^z Z_{it-1}$$
$$+ \vartheta^z D_{500km} Z_{it-1} + \beta^k K_{ct} + \vartheta^k D_{500km} K_{ct} + \gamma_i + \delta_t + \varepsilon_{it} \tag{6}$$

The second model setting considers the relation between number of conflicts and the geographical and social characteristics of each cell as well as changes occurring in the short-term for social dimension (represented by the GDP per capita growth rate) and climate variables. In both cases the optimal lag structure for variables is one year. Accordingly, the short-term change is calculated as the variation occurring at time *t-1* w.r.t. the previous year (hereafter referred as 1y). Model equation results as follows:

$$NC_{it} = \alpha NC_{it-1} + \rho W_{250km} NC_{it} + \beta^x X_{it} + \vartheta^x D_{500km} X_{it} + \beta^z Z_{it-1}$$
$$+ \vartheta^z D_{500km} Z_{it-1} + \beta^z \Delta^{1y} Z_{it-1} + \vartheta^z D_{500km} \Delta^{1y} Z_{it-1} + \beta^k K_{ct} \tag{7}$$
$$+ \vartheta^k D_{500km} K_{ct} + \gamma_i + \delta_t + \varepsilon_{it}$$

The third model setting considers the relation between number of conflicts and the geographical and social characteristics of each cell as well as changes occurring in the 1y for social dimension and in the medium-term for climate variables (calculated as the average value of yearly changes over the past five years starting from time *t-1*, hereafter referred as 5y) in the form:

$$NC_{it} = \alpha NC_{it-1} + \rho W_{250km} NC_{it} + \beta^x X_{it} + \vartheta^x D_{500km} X_{it} + \beta^z Z_{it-1}$$
$$+ \vartheta^z D_{500km} Z_{it-1} + \beta^z \Delta^{1y} Z_{it-1} + \vartheta^z D_{500km} \Delta^{1y} Z_{it-1} + \beta^z \Delta^{5y} Z_{it-1} \tag{8}$$
$$+ \vartheta^z D_{500km} \Delta^{5y} Z_{it-1} + \beta^k K_{ct} + \vartheta^k D_{500km} K_{ct} + \gamma_i + \delta_t + \varepsilon_{it}$$

Table 1 summarizes variable description and data source used for econometric estimations of models expressed in eqs. (6)-(7)-(8). Tables 2A-2B contain marginal effects estimated by eq. (6); while Tables 3A-3B and 4A-4B report, respectively, effects for eqs. (7)-(8). When commenting on short and long-term direct and indirect effects we define as short-term effects the impact on conflicts at time *t*, and as long-term ones the impact on conflicts at time *t-1*. Accordingly long-term marginal effects can provide a measure of persistency of the phenomenon over time. In order to simplify the interpretation of results, we provide an overall picture in Figure 4 summarizing the effects of the main

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[14] In eqs. (6)-(8) we refer to a set of *X* variables when they are not temporally lagged and a set of *Z* variables if they are one-year lagged, while set of *K* variables are those country and not cell-based.

variables reporting the sign of the corresponding effect and visualizing the specific climate change condition under scrutiny.

Before commenting on marginal effects, we focus on two main results that are not reported in Tables for marginal effects but are available in Appendix B in all Tables reporting punctual estimates of coefficients.

First, we find evidence on the key role played by contagion, as the estimated spatial ρ (associated with the number of conflicts in neighbouring cells) is always positive and statistically significant.[15] Secondly, we find that persistency over time (represented by coefficient α) according to the conflict trap hypothesis (Ide et al., 2014; Maystadt et al., 2015) is a key element explaining the number of conflicts, confirming that once a region has experienced violent events, *ceteris paribus* it is more at risk of further conflicts.

Let us start the discussion on marginal effects by examining the role of socio-economic vulnerability conditions. Looking at the impact of GDP, the direct effect always has a negative sign meaning that areas with higher income are less likely to be involved in conflicting episodes, confirming findings in Busby et al. (2014). On the contrary, a relatively higher population count has a positive direct effect on number of conflicts. This may be expected, since *ceteris paribus* conflicts are more likely to occur in highly populated places. The only exceptions where the effect is negative are associated with the indirect effects when considering 5y changes in climate conditions. In this case, the long-term indirect effect associated to population is negative meaning that a percentage increase in the population of the neighbouring cells seems to determine a reduction in the probability of having a large number of conflicts in the cell i. According to Reuveny (2007), this could be interpreted as follows: if population in neighbouring cells is increasing due to medium-term changes in climate conditions, it could be a sign of internal migration flows from cells experiencing harder conditions toward more favourable areas, thus reducing the population count of cell i and consequently the likelihood of violent conflicts. Given that data on internal migration are not yet available at a large-scale level, investigating the nexus between climate change, migration and conflicts will constitute the first point in the future research agenda.

The indirect effect of GDP level is significant in the short-term (Table 2A) but it is not stable since the sign changes depending on the specification for the institutional quality index. The indirect effect of the GDP level is never significant in the case of 1y variation (Tables 3A-B), and when considering the 5y variation of climatic conditions, the indirect effect of GDP is negative and robust only in the short-term (Tables 4A).

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[15] By focusing on the number of events we differentiate with respect to Harari and La Ferrara (2018) whose analysis is on the occurrence of at least one event per year. This explains why the cut-off distance for contagion in our case is larger measuring a maximum of 311 km instead of 180 km.

In order to better capture the role of income, in Tables 3A-B and 4A-B we also account for the impact of changes in the growth rate of GDP per capita and, conversely to what happens in terms of GDP in level, the direct effect is always positive. The indirect effect is mainly negative in the short-term, with exception of Column (2) which reports the 5y variation (Table 4A), in which case the effect is positive. When significant, the indirect effects are positive in the long-term (Table 4B), meaning that an increase in the GDP per capita in the neighbouring cells occurred in the previous year increases the probability of conflicts in the cell itself. This result together with those described for the indirect effects associated with GDP in levels could be interpreted as a sign of the negative impact associated with increasing inequality in income distribution. A higher GDP level in cell i is a sign of reduced socio-economic vulnerability and is negatively correlated with conflicts. On the contrary, if neighbouring cells are experiencing a higher increase in income per capita growth w.r.t. to cell i, this would imply an increase in income inequality that in turn could cause grievance leading to revenge and potential violent actions to reduce inequality (Barnett and Adger, 2007; Koubi et al., 2012). This effect is also persistent over time since long-term indirect effects associated to models accounting for 5y climate variations are the most relevant ones.

Another element in the overall picture of the role of socio-economic vulnerability is the quality of institutions. Good institutions are generally responsible for a reduction of conflicts as emphasised in Adano et al. (2012).

Moving to the impact of agriculture, the direct effect is always negative meaning that *ceteris paribus* those areas with a higher specialisation in agricultural activities are well equipped with resources able to ensure human livelihood. At the same time, as shown in Fjelde and von Uexkullis (2012) these areas are also the most vulnerable to changes in climate conditions. As revealed by the positive signs associated with marginal effects when accounting for the 1y and 5y climate variation, if anomalies in precipitation levels (with respect to short and even more to average medium-term conditions) occur in cells with large agriculture activities the probability of increasing number of conflicts arises with also a strong spillover effects in the 5y case (Table 4B).

An interesting case is represented by the role of resource endowments. Results show that the presence of resources in an area generally increases the number of conflicts. On the contrary, when interacted with the quality of institutions, the sign associated to direct effects, when significant, is negative. This confirms that the abundance of resources can be a source of conflict but, if institutions are effective, it becomes a blessing.

Table 1 – Variable description and original source

Variable	Description	Source
Cell-based/time variant		
NC it	Number of conflicting events	UPPSALA-UCDP
Temp it-1	Temperature (yearly average value, °C)	AFDM
Prec it-1	Precipitation (yearly average value, mm/day)	AFDM
SPI it-1	SPI-12 (yearly average value, index)	AFDM
GDP it-1	Gross Domestic Product (Th. US$ PPP constant 2005)	SEDAC-WDI
Pop it-1	Population (number)	SEDAC-HYDE
D1y-GDP-PC it-1	One-year var of GDP per capita w.r.t. t-1 (%)	Authors' elaboration
D1y-Temp it-1	One-year var of temperature w.r.t. t-1 (%)	Authors' elaboration
D1y-Prec it-1	One-year var of precipitation w.r.t. t-1 (%)	Authors' elaboration
D5y-Temp it-1	Average 5y var of temperature in t-1 (%)	Authors' elaboration
D5y-Prec it-1	Average 5y var of precipitation in t-1 (%)	Authors' elaboration
Av5y-SPI it-1	Average SPI-12 in the past 5y at t-1 (index)	Authors' elaboration
Cell-based/time invariant		
Resource-D i	Presence of mineral and fossil fuel resources (dummy)	Data Basin Dataset
Rural-D i	Presence of rural areas (dummy)	Global Land Cover
Drought i	Drought Severity (index)	Aqueduct Water Risk
Flood i	Flood Occurrence (index)	Aqueduct Water Risk
Country-based/time variant		
Agri VA ct	Value Added in Agriculture w.r.t. total VA (%)	WDI-World Bank
FF-Min exp ct	Export Value for exhaustible resources w.r.t. Merch Exp (%)	WDI-World Bank
Inst-PRS ct	PRS synthetic institutional quality (index)	PRS Group Dataset
Inst-Gov-Eff ct	Government effectiveness (index)	PRS Group Dataset
Inst-Law ct	Law and order (index)	PRS Group Dataset
No. y indep ct	Number of years from colonial independence (number)	CIA
Cell-based/time variant interaction terms		
Agricult it	Rural-D x Agri VA	Authors' elaboration
Resources it	Resource-D x FF-Min exp	Authors' elaboration
Int-Resources it	Resources it x Institutional quality indices	Authors' elaboration
D1y-Temp it-1 dr	One-year var of temp w.r.t. t-1* in drought risk cell	Authors' elaboration
D1y-Prec $_{it-1}$ rur	D1y-Prec it-1 x Rural-D i	Authors' elaboration
D1y-Prec $_{it-1}$ dr	D1y-Prec it-1 x Drought i	Authors' elaboration
D1y-Prec $_{it-1}$ fl	D1y-Prec it-1 x Flood i	Authors' elaboration
SPI $_{it-1}$ rur	SPI-12 x Rural-D i	Authors' elaboration
SPI $_{it-1}$ dr	SPI-12 x Drought i	Authors' elaboration
SPI $_{it-1}$ fl	SPI-12 x Flood i	Authors' elaboration
D5y-Temp it-1 dr	D5y-Temp it-1 x Drought i	Authors' elaboration
D5y-Prec it-1 rur	D5y-Prec it-1 x Rural-D i	Authors' elaboration
D5y-Prec it-1 dr	D5y-Prec it-1 x Drought i	Authors' elaboration
D5y-Prec it-1 fl	D5y-Prec it-1 x Flood i	Authors' elaboration
Av5y-SPI it-1 rur	Av5y-SPI it-1 x Rural-D i	Authors' elaboration
Av5y-SPI it-1 dr	Av5y-SPI it-1 x Drought i	Authors' elaboration
Av5y-SPI it-1 fl	Av5y-SPI it-1 x Flood i	Authors' elaboration

Table 2A - Impact of climate and socio-economic conditions (short-term marginal effects)

	(1)	(2)	(3)	(4)	(5)
Short-term Direct					
GDP $_{it-1}$	-0.005	-0.038***	-0.035	-0.006	-0.007
Pop $_{it-1}$	0.033***	0.053***	0.046	0.033***	0.034
Temp $_{it-1}$	2.304***	2.357***	2.022	2.337***	1.165***
Prec $_{it-1}$	0.041***	0.039***	0.029	0.042***	0.038***
SPI$_{it-1}$	-0.012**	-0.010**	-0.018	-0.011**	-0.022**
Resources $_{it}$	-0.000	-0.000***	-0.000**	0.000**	0.001**
Int-Resources $_{it}$				-0.000***	-0.000
Agricult $_{it}$	-0.002***	-0.002***	-0.003	-0.002***	-0.001
Nr year from indep$_{ct}$	0.044***	0.013	0.013	0.048***	0.094
Inst-Law $_{ct}$	-0.000				
Inst-Gov-Eff $_{ct}$		-0.003***		-0.003***	
Inst-PRS $_{ct}$			-0.017**		-0.004**
Short-term Indirect					
GDP $_{it-1}$	0.137***	-0.153***	1.144	0.084***	0.031
Pop $_{it-1}$	-0.021	0.081	-1.751	-0.001	-0.150
Temp $_{it-1}$	-1.397***	1.123***	-4.740	-0.885***	0.267
Prec $_{it-1}$	-0.419***	0.294***	-1.048	-0.264***	0.151
SPI$_{it-1}$	-0.074**	0.077**	-1.125	-0.040*	0.003
Resources $_{it}$	-0.000	0.001**	-0.007	0.001**	-0.004
Int-Resources $_{it}$				-0.000***	0.001
Agricult $_{it}$	-0.006***	0.010***	0.002	-0.004***	0.005
Nr year from indep $_{ct}$	0.174***	-0.050	0.862	0.115***	-0.439
Inst-Law $_{ct}$	-0.001				
Inst-Gov-Eff $_{ct}$		0.012***		-0.007***	
Inst-PRS $_{ct}$			-0.408		0.007

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 2B - Impacts of climate and socio-economic conditions (long-term marginal effects)

	(1)	(2)	(3)	(4)	(5)
Long-term Direct					
GDP $_{it-1}$	-0.024	-0.067***	-0.091*	-0.023	-0.008
Pop $_{it-1}$	0.091***	0.087*	0.132*	0.075**	0.044
Temp $_{it-1}$	7.419***	4.206***	5.135**	6.356***	1.841**
Prec $_{it-1}$	0.146***	0.074***	0.076***	0.126***	0.062**
SPI$_{it-1}$	-0.026*	-0.014	-0.028	-0.020	-0.033*
Resources $_{it}$	-0.000	-0.000	-0.001	0.001*	0.001**
Int-Resources $_{it}$				-0.000**	-0.001
Agricult $_{it}$	-0.004***	-0.004	-0.007	-0.003**	-0.001
Nr year from indep $_{ct}$	0.109***	0.020	0.010	0.098**	0.131
Inst-Law $_{ct}$	-0.000				
Inst-Gov-Eff $_{ct}$		-0.004		-0.006**	
Inst-PRS $_{ct}$			-0.032		-0.005**
Long-term Indirect					
GDP $_{it-1}$	-0.020	-0.084	0.001	-0.020	0.025
Pop $_{it-1}$	-0.102**	0.403	0.039	-0.095**	-0.101**
Temp $_{it-1}$	-3.938***	1.144	0.792	-2.837*	-0.323
Prec $_{it-1}$	-0.026	-0.219*	-0.022	-0.004	0.015
SPI $_{it-1}$	0.059***	-0.275***	-0.020	0.049***	0.029
Resources $_{it}$	0.000	-0.007**	-0.002	-0.002**	-0.003**
Int-Resources $_{it}$				0.000***	0.001**
Agricult $_{it}$	0.007***	-0.047***	-0.002	0.007***	0.003
Nr year from indep $_{ct}$	-0.194***	0.254	-0.070	-0.192***	-0.276***
Inst-Law $_{ct}$	0.001				
Inst-Gov-Eff $_{ct}$		-0.060***		0.012***	
Inst-PRS $_{ct}$			0.001		0.010

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Let us now focus on the role of changes in climate conditions in explaining conflicts. To this end, Figure 4 shows a summary of the main effects (in terms of temperature and precipitation variations)

in the case of short (1y) and medium-term (5y), as from Tables 3A-B and 4A-B, respectively. As a general remark, we can interpret 1y variations as conjunctural anomalies in climate conditions (a heat wave, an extreme drought or an excess in rainfall confined to one single year) and 5y variations as more persistent changes in conditions (a prolonged drought or a stable increase in temperature levels).

Let us first examine the role of temperature changes. The direct effect is always positive in line with O'Loughlin et al. (2012). More precisely, a 1% increase in temperature change in a cell produces an increase of 1.8% of the number of conflicts. Differently from previous studies, when considering spatial spillovers we find that when temperature increases in areas already facing drought, there is a reduction in number of events by around 0.5%. This specific result might capture different mechanisms. First, very drought-prone areas are generally characterised by low population density. Second, a temperature increase in already dry regions might force people to move, reducing internal source of conflicts. Third, according to Adano et al. (2012), in environmentally fragile areas farmers and shepards do not engage in violent conflict during a time of scarcity but during periods of plenty. We will turn on this point when commenting on the role of precipitation.

Turning to the indirect effect of temperature change, the most statistically significant effects correspond to 5y average variations. If temperature increases in neighbouring cells, conflicts in cell i will increase by around 4.7%, and this is a persistent phenomenon over time. In the case of drought risk cells, the indirect effect of an increase in temperature in other cells is negative (i.e., in line with the direct effect), suggesting a decrease of conflicts in cell i at risk of drought by 1.7% when the temperature of neighbouring areas increase by 1%.

As a general remark, temperature changes strongly influence the number of conflicts and the spatial dimension plays a key role, since the magnitude of both direct and indirect effects is higher w.r.t. the other explanatory variables. This confirms the need for distinguishing temperature from precipitation as climate-related variables when focusing on violent conflicts in Africa.

On the contrary, changes in precipitation levels seem to be less relevant in shaping violence, since marginal effects are lower and more confined to a local level. The only significant effect is in the case of 1y change where an increase by 1% in rainfall produces a reduction in number of conflicts at the local level by around 0.02%. This is valid except for those cells where rural activities are predominant. In this case, an increase in precipitations over the last year is positively correlated with violent events, with an elasticity equal to 0.07%. Two motivations might explain these findings. First, if a precipitation increase corresponds to a large anomaly, rainfalls may provoke loss in crop yields rather than help agricultural activities. Second, according to previous results on temperature, if the rural area is particularly fragile, propensity to fight increases in wet periods rather than in dry ones.

Table 3A - Impacts of 1y changes in climate and socio-economic conditions (short-term effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short-term Direct								
GDP $_{it-1}$	-0.038***	-0.038***	-0.039***	-0.038***	-0.036***	-0.036***	-0.036***	-0.036***
D1y-GDP-PC $_{it-1}$	0.154***	0.149**	0.154***	0.091	0.220	0.193***	0.159	0.191***
Pop $_{it-1}$	0.047***	0.052***	0.048***	0.053***	0.047***	0.048***	0.051**	0.049***
Temp $_{it-1}$	0.303***	0.285***	0.298***	0.224	0.409*	0.371***	0.324	0.369***
D1y-Temp $_{it-1}$	1.809***	1.781***	1.811***	1.714***	1.858***	1.826***	1.784***	1.821***
D1y-Temp $_{it-1}$ dr	-0.479***	-0.471***	-0.479***	-0.445***	-0.506***	-0.497***	-0.476***	-0.492***
Prec $_{it-1}$	0.027***	0.026***	0.026***	0.024*	0.049***	0.046***	0.042	0.046***
D1y-Prec $_{it-1}$					-0.017**	-0.023***	-0.017	-0.015
D1y-Prec $_{it-1}$ rur						0.070***		
D1y-Prec $_{it-1}$ dr							0.001	
D1y-Prec $_{it-1}$ fl								0.001
SPI $_{it-1}$	-0.020***	-0.018***	-0.028***	-0.032**	-0.027***	-0.028***	-0.028***	-0.029***
SPI $_{it-1}$ rur		-0.035*						
SPI $_{it-1}$ dr			0.004					
SPI $_{it-1}$ fl				0.007				
Resources $_{it}$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
Int-Resources $_{it}$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001**	-0.001***
Agricult $_{it}$	-0.002***	-0.003***	-0.002***	-0.003***	-0.002***	-0.002***	-0.002***	-0.002***
Nr year from indep $_{ct}$	0.028**	0.029*	0.025*	0.028*	0.036**	0.037**	0.037	0.035**
Inst-PRS $_{ct}$	-0.006**	-0.007**	-0.007**	-0.007*	-0.005*	-0.005	-0.005	-0.005

Table 3A - Impacts of 1y changes in climate and socio-economic conditions (short-term effects) - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short-term Indirect								
GDP $_{it-1}$	0.073	0.082	0.074	0.259	-0.067	-0.023	0.069	-0.015
D1y –GDP-PC $_{it-1}$	-0.458***	-0.599	-0.467***	-0.153	0.542	0.167	-0.353	0.123
Pop $_{it-1}$	0.195***	0.305	0.206***	0.737	-0.287	-0.084	0.187	-0.064
Temp $_{it-1}$	-0.544***	-0.769	-0.571***	-1.959	0.761	0.221	-0.477	1.628
D1y-Temp $_{it-1}$	-0.805***	-1.011	-0.833***	-0.266	0.836	0.239	-0.661	1.681
D1y-Temp $_{it-1}$ dr	0.276***	0.363	0.288***	0.960	-0.320	-0.925	0.222	-0.671
Prec $_{it-1}$	-0.291***	-0.439	-0.312***	-1.001	0.493	0.152	-0.480	0.116
D1y-Prec $_{it-1}$					-0.125	-0.075	-0.099	0.026
D1y-Prec $_{it-1}$ rur						0.483		
D1y-Prec $_{it-1}$ dr							0.079	
D1y-Prec $_{it-1}$ fl								-0.026
SPI $_{it-1}$	0.069*	0.301	-0.057	-0.545	-0.129	-0.024	0.147	-0.028
SPI $_{it-1}$ rur		-0.237						
SPI $_{it-1}$ dr			0.055*					
SPI $_{it-1}$ fl				0.299				
Resources $_{it}$	0.009***	0.011	0.008***	0.026	-0.012	-0.004	0.007	-0.003
Int-Resources $_{it}$	-0.004***	-0.006	-0.004***	-0.013	0.006	0.002	-0.004	0.001
Agricult $_{it}$	-0.010***	-0.016	-0.011***	-0.034	0.015	0.005	-0.007	0.004
Nr year from indep $_{ct}$	0.116**	0.162	0.106*	0.385	-0.132	-0.092	0.202	-0.066
Inst-PRS $_{ct}$	-0.026**	-0.041	-0.031**	-0.105	0.030	0.012	-0.033	0.009

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3B - Impacts of 1y changes in climate and socio-economic conditions (long-term effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-term Direct								
GDP $_{it-1}$	-0.088	-0.076***	0.002	-0.070	-0.084	-0.123	-0.072	-0.073**
D1y-GDP-PC $_{it-1}$	0.295	0.436**	0.994	0.435*	0.434**	0.235	0.432	0.442***
Pop $_{it-1}$	0.111	0.093**	-0.076	0.075	0.109	0.172	0.097	0.093
Temp $_{it-1}$	0.625	0.744***	0.949	0.722*	0.821**	0.786***	0.784**	0.830***
D1y-Temp $_{it-1}$	4.005**	3.674***	1.623	3.630*	3.895	5.591	3.859	3.715***
D1y-Temp $_{it-1}$ dr	-1.060***	-0.997***	-0.557	-0.984**	-1.056	-1.495	-1.046*	-1.015***
Prec $_{it-1}$	0.057***	0.061***	0.054*	0.062***	0.102*	0.130	0.095***	0.099***
D1y-Prec $_{it-1}$					-0.036	-0.066	-0.035	-0.031
D1y-Prec $_{it-1}$ rur						0.161*		
D1y-Prec $_{it-1}$ dr							0.001	
D1y-Prec $_{it-1}$ fl								0.001
SPI $_{it-1}$	-0.046	-0.043***	-0.018	-0.053	-0.059	-0.085	-0.057	-0.060**
SPI $_{it-1}$ rur		-0.011						
SPI $_{it-1}$ dr			0.003					
SPI $_{it-1}$ fl				0.008				
Resources $_{it}$	0.005	0.003**	-0.002	0.004	0.004	0.008	0.004	0.004
Int-Resources $_{it}$	-0.003	-0.002**	0.001	-0.002	-0.002	-0.004	-0.002	-0.002
Agricult $_{it}$	-0.006	-0.005**	0.003	-0.004	-0.004	-0.008	-0.005	-0.004
Nr year from indep $_{ct}$	0.072	0.053	0.022	0.051	0.062	0.169	0.078	0.071
Inst-PRS $_{ct}$	-0.016	-0.013*	0.007	-0.011	-0.014	-0.014	-0.013	-0.010

Table 3B - Impacts of 1y changes in climate and socio-economic conditions (long-term effects) - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long-term Indirect								
GDP $_{it-1}$	0.063	0.035	0.169	0.040	0.062	0.070	0.053	0.040
D1y-GDP-PC $_{it-1}$	0.359	0.354	0.669	1.043	1.118	0.989	1.384***	0.743
Pop $_{it-1}$	-0.123	-0.335	-0.657	-0.146	-0.187	-0.182	-0.196	-0.121
Temp $_{it-1}$	0.255	0.388	0.649	1.159	1.369	1.056	1.719***	0.840
D1y-Temp $_{it-1}$	-0.260	0.188	0.294	-0.633	-1.427	-0.226	-1.185	-1.251
D1y-Temp $_{it-1}$ dr	0.564	-0.673	-1.620	-0.040	0.112	0.396	0.011	0.157
Prec $_{it-1}$	-0.016	0.207	0.317	0.043	0.050	0.018	0.081*	0.030
D1y-Prec $_{it-1}$					-0.007	-0.011	0.012	0.041
D1y-Prec $_{it-1}$ rur						0.252		
D1y-Prec $_{it-1}$ dr							-0.009	
D1y-Prec $_{it-1}$ fl								-0.020
SPI $_{it-1}$	0.034	-0.135	0.163	0.093	0.023	0.042	0.014	0.016
SPI $_{it-1}$ rur		0.162						
SPI $_{it-1}$ dr			-0.065					
SPI $_{it-1}$ fl				-0.036				
Resources $_{it}$	-0.005	-0.014	-0.022	-0.005	-0.007	-0.008	-0.008	-0.005
Int-Resources $_{it}$	0.003	0.007	0.011	0.003	0.003	0.004	0.004	0.003
Agricult $_{it}$	0.006	0.020	0.030	0.007	0.008**	0.009	0.010	0.006
Nr year from indep $_{ct}$	-0.054	-0.268	-0.163	-0.082	-0.132	-0.164	-0.152	-0.100
Inst-PRS $_{ct}$	0.012	0.048	0.089	0.020	0.022	0.019	0.024	0.016

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4A - Impacts of 5y changes in climate conditions (short-term marginal effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-term Direct										
GDP $_{it-1}$	-0.044	-0.044***	-0.025	0.008	-0.031***	-0.032***	-0.031***	-0.028***	-0.020	0.045
D1y-GDP-PC $_{it-1}$	-0.354	0.928***	0.245***	0.315	0.208***	0.235	0.210**	0.287	0.269***	0.336
Pop $_{it-1}$	0.073	0.041***	0.059*	0.067	0.048***	0.044***	0.042***	0.039*	0.050**	0.117
Temp $_{it-1}$	-0.267	0.822***	0.392	1.169***	0.219	0.277	0.210	0.425	0.514	2.174
D5y-Temp $_{it-1}$	1.360	3.421***	1.120***	0.544	1.209***	1.255***	1.223***	1.166***	1.077***	-0.269
D5y-Temp $_{it-1}$ dr		-1.001***	-0.350***	-0.379	-0.331***	-0.350***	-0.330***	-0.372***	-0.359***	-0.403
Prec $_{it-1}$	-0.001	0.048***	0.015	0.032***	0.011*	0.013	0.017	0.022	0.023	0.048
D5y-Prec $_{it-1}$							0.002	-0.008	0.022	0.028*
D5y-Prec $_{it-1}$ rur								0.116		
D5y-Prec $_{it-1}$ dr									-0.006	
D5y-Prec $_{it-1}$ fl										-0.003
SPI $_{it-1}$	-0.017	-0.016**					-0.017**	-0.020***	-0.024***	-0.032
Av5y-SPI $_{it-1}$			-0.005	-0.018	-0.058**	-0.074**				
Av5y-SPI $_{it-1}$ rur				0.045						
Av5y-SPI $_{it-1}$ dr					0.022**					
Av5y-SPI $_{it-1}$ fl						0.040***				
Resources $_{it}$	0.003	0.001***	0.002*	0.001	0.002***	0.002**	0.002***	0.001*	0.001*	-0.000
Int-Resource $_{it}$	-0.001	-0.001***	-0.001**	-0.000	-0.001***	-0.001***	-0.001***	-0.001*	-0.001*	0.000
Agricult $_{it}$	-0.005	-0.002***	-0.002*	-0.001	-0.002***	-0.002***	-0.002***	-0.002*	-0.002*	-0.001
No. year from indep $_{ct}$	0.042	0.015	0.112*	0.232	0.046**	0.032	0.031	0.054*	0.083	0.438
PRS $_{ct}$	-0.014	-0.003	0.001	0.019	-0.008**	-0.008*	-0.009***	-0.007	-0.001	0.048

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 4A - Impacts of 5y changes in climate conditions (short-term marginal effects) - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Short-term Indirect										
GDP $_{it-1}$	0.427	-0.343*	-0.111	0.046	-0.033	0.017	0.006	0.068	0.248	0.020
D1y-GDP-PC $_{it-1}$	-1.712	3.504***	-0.802	-0.446	-1.396	1.984	-2.396	4.589	1.892	-0.852***
Pop $_{it-1}$	0.382	-0.759***	0.118	-0.120	0.104	-0.171	0.092	-0.317	-0.282	-0.174**
Temp $_{it-1}$	-1.426	3.163***	-3.675	1.030	-3.071	5.213	-3.443	1.048	0.945	-0.080
D5y-Temp $_{it-1}$	-4.745	4.689***	-0.097	-1.152	-1.397	2.597	-2.432	2.679	-1.160	-0.680*
D5y-Temp $_{it-1}$ dr		-1.711***	0.723	0.117	0.902	-1.503	1.207	-2.577	-1.460	0.242
Prec $_{it-1}$	-0.618	1.401***	-0.085	0.026	-0.089	0.178	-0.167	0.300	0.016	-0.114***
D5y-Prec $_{it-1}$							0.024	-0.226	0.584	0.090
D5y-Prec $_{it-1}$ rur								3.860		
D5y-Prec $_{it-1}$ dr									-0.095	
D5y-Prec $_{it-1}$ fl										0.006
SPI $_{it-1}$	-0.102	-0.061					0.060	-0.008	-0.042	0.029
Av5y-SPI $_{it-1}$			0.108	-0.113	-0.021	0.198				
Av5y-SPI $_{it-1}$ rur				0.109						
Av5y-SPI $_{it-1}$ dr					-0.002					
Av5y-SPI $_{it-1}$ fl						0.001				
Resources $_{it}$	0.150	-0.024***	0.003	-0.001	0.003	-0.003	0.004	-0.013	-0.012	0.000
Int-Resource $_{it}$	-0.074	0.014***	-0.001	0.000	-0.002	0.003	-0.002	0.007	0.006	-0.000
Agricult $_{it}$	-0.261	0.045***	-0.004	0.002	-0.005	0.012	-0.006	0.021	0.018	0.001
No. year from indep $_{ct}$	0.248	-0.271	0.220	-0.399	0.091	-0.130	0.006	-0.392	-0.680	-0.653**
PRS $_{ct}$	-0.668	0.065	0.006	-0.033	-0.017	0.013	-0.016	0.052	0.016	-0.071**

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4B - Impacts of 5y changes in climate conditions (long-term marginal effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Long-term Direct										
GDP $_{it-1}$	-0.079***	-0.083***	-0.032	0.021	-0.041	-0.822	-0.055	0.045	-0.024	0.090
D1y-GDP-PC $_{it-1}$	1.538***	1.597***	0.523**	0.577	0.562	-0.201	0.470***	0.512	0.418	0.765
Pop $_{it-1}$	0.071***	0.085***	0.094	0.105	0.044	1.309	0.065	-0.132	0.066	0.244
Temp $_{it-1}$	1.350***	1.410***	1.086***	2.053	0.797	-3.486	0.585*	1.005	0.896	4.444
D5y-Temp $_{it-1}$	2.798***	6.365***	2.045	0.910	1.909	2.304	2.241***	-0.369	1.656	-0.545
D5y-Temp $_{it-1}$ dr		-1.843***	-0.706	-0.649	-0.624	-4.404	-0.647***	-0.033	-0.575	-0.819
Prec $_{it-1}$	0.074***	0.084***	0.036***	0.061	0.034	-0.057	0.040	0.040	0.040	0.102
D5y-Prec $_{it-1}$							-0.001	-0.048	0.038	0.046
D5y-Prec $_{it-1}$ rur								0.501		
D5y-Prec $_{it-1}$ dr									-0.011	
D5y-Prec $_{it-1}$ fl										-0.004
SPI $_{it-1}$	-0.028**	-0.030**					-0.030*	0.027	-0.036	-0.065
Av5y-SPI $_{it-1}$			-0.019	-0.038	-0.078	-2.312				
Av5y-SPI $_{it-1}$ rur				0.069						
Av5y-SPI $_{it-1}$ dr					0.026					
Av5y-SPI $_{it-1}$ fl						0.925				
Resources $_{it}$	0.003***	0.003***	0.003	0.001	0.003	0.045	0.003	-0.002	0.002	-0.000
Int-Resource $_{it}$	-0.001***	-0.002***	-0.001	-0.000	-0.001	-0.024	-0.001	0.001	-0.001	0.000
Agricult $_{it}$	-0.005***	-0.005***	-0.004	-0.002	-0.003	-0.061	-0.004	0.009	-0.003	-0.001
No. year from indep $_{ct}$	0.037	0.030	0.190	0.378	0.065	1.011	0.050	-0.198	0.125	0.910
PRS $_{ct}$	-0.014***	-0.007	0.001	0.033	-0.014	-0.235	-0.015	0.011	0.000	0.094

Table 4B - Impacts of 5y changes in climate conditions (long-term marginal effects) - continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Long-term Indirect										
GDP $_{it-1}$	0.011	0.073	0.097***	0.022	0.232	-1.847	0.051	-0.064	0.100	-0.038
D1y-GDP-PC $_{it-1}$	1.784***	1.256***	-0.050	-0.722	2.221	-5.126	0.745	0.331	0.146	-1.201
Pop $_{it-1}$	-0.102***	-0.619***	-0.199***	-0.151	-0.594	7.461	-0.124	0.152	-0.193	-0.295
Temp $_{it-1}$	1.553***	1.143***	1.533**	-0.541	5.136	-1.036	1.577	0.707	2.009**	-2.758
D5y-Temp $_{it-1}$	-1.052***	4.509***	-2.266*	-1.367	-4.287	0.223	-0.708	2.207	-1.989	-0.258
D5y-Temp $_{it-1}$ dr		-3.040***	0.282	0.485	0.081	2.077	-0.124	-0.709	0.130	0.701
Prec $_{it-1}$	0.052***	0.442***	0.037	-0.020	0.188	-2.675	0.057	0.027	-0.017	-0.159
D5y-Prec $_{it-1}$							-0.022	0.023	0.098	0.052
D5y-Prec $_{it-1}$ rur								0.070		
D5y-Prec $_{it-1}$ dr									-0.015	
D5y-Prec $_{it-1}$ fl										0.006
SPI $_{it-1}$	0.007	0.059					0.022	-0.073	0.036	0.063
Av5y-SPI $_{it-1}$			-0.050	-0.060	0.416	-5.329				
Av5y-SPI $_{it-1}$ rur				0.057						
Av5y-SPI $_{it-1}$ dr					-0.173					
Av5y-SPI $_{it-1}$ fl						2.165				
Resources $_{it}$	-0.004***	-0.020***	-0.006**	-0.002	-0.008	0.162	-0.005	0.003	-0.006	0.000
Int-Resource $_{it}$	0.002***	0.011***	0.003***	0.001	0.006	-0.092	0.002	-0.002	0.003	-0.001
Agricult $_{it}$	0.008***	0.037***	0.008**	0.003	0.021	-0.235	0.007	-0.010	0.008	0.001
No. year from indep $_{ct}$	-0.053	-0.221	-0.392**	-0.516	-0.343	4.356	-0.094	0.251	-0.345*	-1.104
PRS $_{ct}$	0.020***	0.053	-0.003	-0.044	0.040	-1.108	0.026	-0.008	0.002	-0.116

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 4 - The role of changes in climate conditions
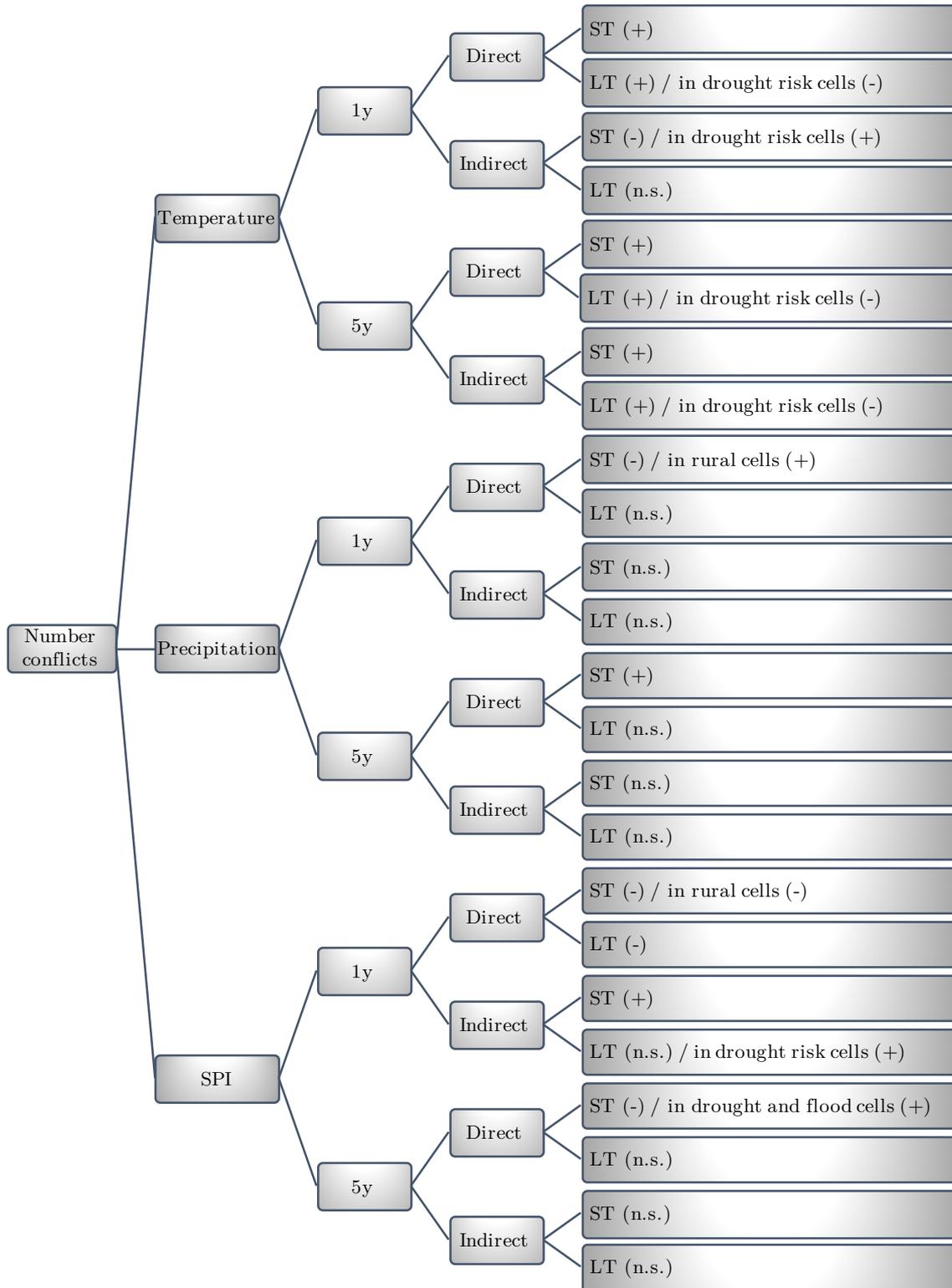
Note: (ST) Short-term and (LT) Long-term marginal effects.

When considering the SPI-12 as a precipitation-based indicator for highlighting the specific role of drought, we find additional elements revealing the crucial role of changes in climate conditions in defining the dimension and strength of violence in Africa.

At the general level, results confirm that changes in precipitations directly influence conflicts but no spatial spillovers arise. If a cell has experienced a period of drought in the previous year, the probability of having a higher number of conflicts increases by an average 0.02%. When considering a medium-term perspective, if the cell experienced a prolonged period of drought (over the past five years) the direct effect is larger than in the 1-y case with an average elasticity equal to around 0.06%. Additionally, we find that changes in precipitation levels have heterogeneous impacts according to the specific geographical features of the cell under scrutiny, revealing how crucial is the detailed characterization of the areas. If the SPI-12 index presents a positive value for the past five years it means that rainfall is continuously greater than expected. This provokes an increase in the number of conflicts if the cell is at drought risk. If the climate conditions in the cell are characterised by larger precipitation than expected, the less dry environments would entail better life condition (higher agricultural yields, water availability, pastoral activity) and more people would be attracted to live or move there, thus increasing the risk of tension. Additionally, a positive SPI over the medium-term is also associated with an increase in violence in cells at risk of floods, given the higher vulnerability of these areas to abundant rains.

6. Conclusions and policy implications

In this paper we conduct a spatially disaggregated analysis of the determinants of armed conflicts in Africa over the period 1990-2016. The empirical analysis we propose tries to jointly consider different causes of conflicts in order to better disentangle the specific role played by changes in climate variables as precipitation and temperature. By also accounting for the influence of spatial correlation and dynamic persistency, we present several novelty elements contributing to the literature on climate and conflict in Africa.

First, our results provide evidence on the key role played by contagion. Differently from other grid-based studies that focus on the likelihood of conflict to occur or not, by quantifying the number of violent events per year we find that the cut-off distance substantially reducing the propagation of violence is higher arriving at a maximum 311 km distance.

Second, we find that a conflict trap mechanism strongly influence the persistency over time of the magnitude on conflicting events.

Third, we find a strong link between an increase in temperature and conflict that is robust with respect to different specifications and to the direct and indirect pathways by which temperature affects conflict levels in a given area. The increase in temperature particularly over a medium-term horizon seems to give impulse to conflicting actions, and this nexus is strongly reinforced by what occurs in neighbouring cells. The implication we derive is mainly related to the analysis of hotspots especially

in scenario building. Projections on the role played by temperature change on occurrence and strength of conflicts should include the role of geographical spillovers, as we expect that the resulting number of projected conflicts is rather higher than in the case of neglecting the role of spatial correlation. This is also reinforced by the relatively large buffer defining the contagion effect concerning the conflict propensity itself as already discussed.

Fourth, the role of rainfall changes is much more nuanced. In general, the effects are smaller than for temperature and depend on the nature of activities in the cell as well as the length of time for which the change in precipitation has been observed. According with other georeferenced studies focused on selected areas (e.g. Ethiopia, Kenya, and Uganda in Raleigh and Kniveton, 2012), we find for the whole continent a local relation between changes in precipitation and conflicts only at the short-term level since an increase in yearly average rainfalls reduces conflicts except with those areas with a high agriculture specialisation where an increase in precipitations brings to higher violent events. In the case of the African continent, more than precipitation *per se* it is more appropriate to analyse drought conditions (Maystadt et al., 2015). According to marginal effects of the SPI-12 index, we confirm that a constant reduction in rainfalls with respect to a medium-term benchmark as in the 5y case reinforces the occurrence of conflicting events. Differently from what we find for temperature, this phenomenon seems to be more confined at the geographical scale since spillover effects are negligible in all model specifications.

Lastly, the results relating to other factors such as socio-economic vulnerability, institutions and resource dependence are consistent with the literature and suggest to jointly consider all these aspects when dealing with the climate-conflict nexus. For example, we find that the concentration of a high number of individuals in surrounding areas might increase conflicting situations. The policy implication directly linked to this result is the necessity to bring into the research agenda the analysis of interstate and internal migration flows at a geographically disaggregated scale together with a deeper investigation on causes of migration including changes in climate conditions, given the peculiar vulnerability of the African continent.

Summing up, our findings confirm that armed conflicts have a strong and complex local dimension that needs to be carefully considered when designing policy interventions. Action coordination is necessary both at the geographical scale and across different development and environment dimensions, since the causal linkages and feedback loops occurring in this complex framework might reduce or even nullify positive effects arising from single interventions. Rationalizations for particular linkages between climate and conflict are of course only suggestive of possible causes. Further in-depth analysis (possibly using case studies) is needed to confirm where they are in fact correct.

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APPENDIX A

Table A.1 – Main statistics

Variable	Nr Obs	Mean	ST.dev.	Min	Max
NC it	91,854	0.38	3.81	0	248.00
GDP it	91,854	601,973	3,023,916	0	120,000,000
D1y-GDP-PC it	88,452	0.04	0.04	-0.94	0.68
Pop it	91,854	256,176	716,349	0	27,000,000
Temp it	91,854	25.18	3.55	6.63	34.28
D1y-Temp it	88,452	0.00	0.03	-0.29	0.71
D5y-Temp it	71,442	0.00	0.01	-0.08	0.20
Prec it	91,854	1.93	1.74	0	13.33
D1y-Prec it	88,452	0.01	0.36	-3.00	2.95
D5y-Prec it	71,442	0.00	0.08	-0.66	0.55
SPI it	91,854	0.00	0.97	-3.72	3.72
Av5y-SPI it	71,442	0.06	0.58	-3.72	3.69
Resource-D i	91,854	0.23	0.42	0	1.00
Rural-D i	91,854	0.11	0.31	0	1.00
Drought i	91,854	2.45	1.45	0	5.00
Flood i	91,854	2.04	1.03	0	4.06
Agri VA ct	91,854	25.61	16.35	0.89	93.98
FF-Min exp ct	91,854	40.21	38.34	0.01	99.70
Agricult it	91,854	3.36	10.57	0	65.97
Resources it	91,854	9.49	25.03	0	99.70
Inst-PRS ct	91,854	2.75	0.89	0.30	5.40
Inst-Gov-Eff ct	91,854	2.80	1.24	0	6.00
Inst-Law ct	91,854	7.39	2.44	0	11.58

Table A.2 – Correlation matrix

Variable code	Variable name	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	NC																				
(2)	GDP	0.04																			
(3)	D1y-GDP-PC	-0.03	0.02																		
(4)	Pop	0.08	0.74	0.01																	
(5)	Temp	-0.01	-0.18	0.07	-0.13																
(6)	D1y-Temp	0.00	0.02	0.00	0.01	0.13															
(7)	D5y-Temp	0.00	0.03	0.02	0.01	0.20	0.56														
(8)	Prec	0.04	-0.01	-0.12	0.16	0.02	-0.04	-0.06													
(9)	D1y-Prec	0.00	0.00	0.02	-0.01	0.03	-0.03	-0.02	0.09												
(10)	D5y-Prec	0.01	-0.02	0.00	-0.02	0.11	-0.10	-0.14	0.08	0.48											
(11)	SPI	0.00	-0.01	0.07	-0.01	0.10	-0.05	-0.03	-0.03	0.02	0.39										
(12)	Av5y-SPI	-0.01	0.01	0.11	0.01	0.12	0.00	-0.02	-0.13	-0.08	0.11	0.61									
(13)	Resource-D	0.05	0.20	-0.02	0.21	-0.24	0.00	-0.01	0.07	-0.01	-0.04	-0.04	-0.04								
(14)	Rural-D	0.05	0.10	0.02	0.23	0.08	-0.01	-0.01	0.15	0.01	0.01	-0.01	-0.01	0.07							
(15)	Drought	-0.05	-0.06	0.14	-0.17	0.22	0.03	0.05	-0.73	0.03	0.11	0.18	0.23	-0.18	-0.11						
(16)	Flood	0.04	0.05	0.06	0.17	0.16	0.00	0.01	0.12	0.00	0.02	-0.05	-0.06	0.03	0.26	-0.09					
(17)	Resources	0.05	0.18	0.01	0.14	-0.15	0.00	0.01	0.01	-0.01	-0.03	-0.02	-0.01	0.71	0.02	-0.07	-0.08				
(18)	Agricult	0.04	0.04	0.03	0.20	0.12	-0.01	-0.01	0.14	0.01	0.02	0.00	0.00	0.04	0.92	-0.10	0.26	0.00			
(19)	Inst-PRS	-0.06	0.07	0.12	0.01	-0.43	0.00	-0.01	-0.12	-0.02	-0.07	-0.03	-0.04	0.12	-0.04	-0.02	-0.05	0.04	-0.07		
(20)	Inst-Gov-Eff	-0.05	0.03	0.18	0.03	-0.33	0.00	-0.01	-0.20	0.00	-0.02	0.02	0.01	0.08	-0.03	0.07	-0.05	0.03	-0.02	0.79	
(21)	Inst-Law	-0.02	0.03	0.12	0.02	-0.23	-0.05	-0.01	0.04	-0.02	-0.04	0.03	0.04	0.05	-0.01	-0.06	-0.07	0.08	-0.03	0.47	0.39

Figure A.1 – Total number of conflicting events by country (1990-2016)
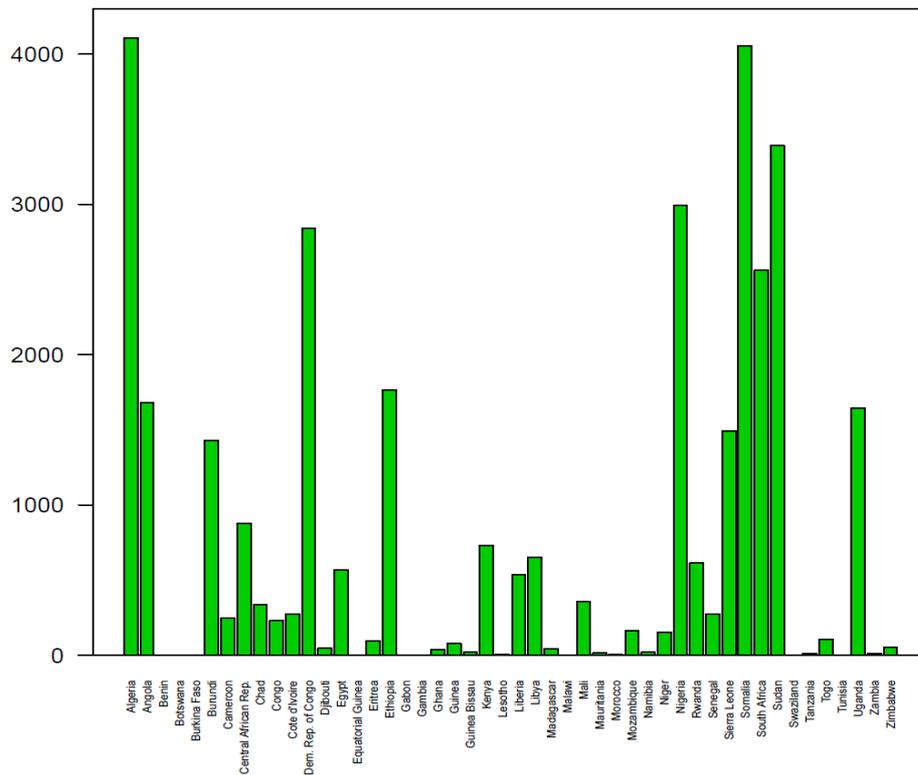
Figure A.2 – Total number of conflicting events by year (peak countries highlighted)
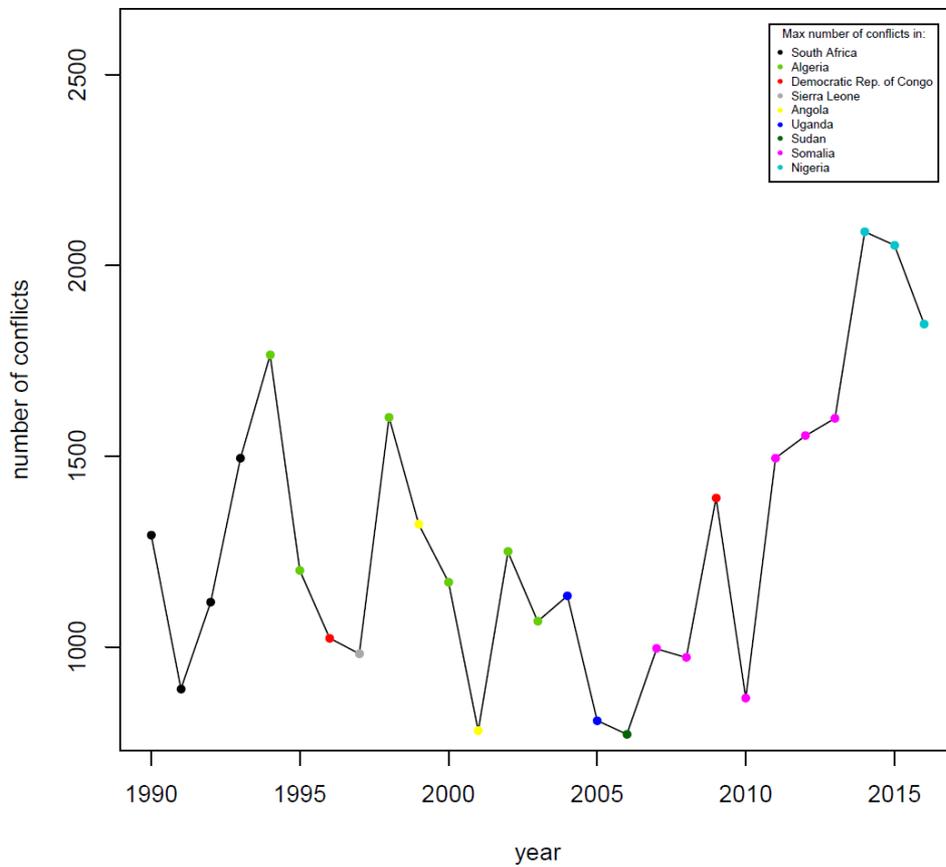
Figure A.3 – Cut-off distances with great circle formula and Queen approach

Max distance great circle formula   Max distance great circle formula+Queen
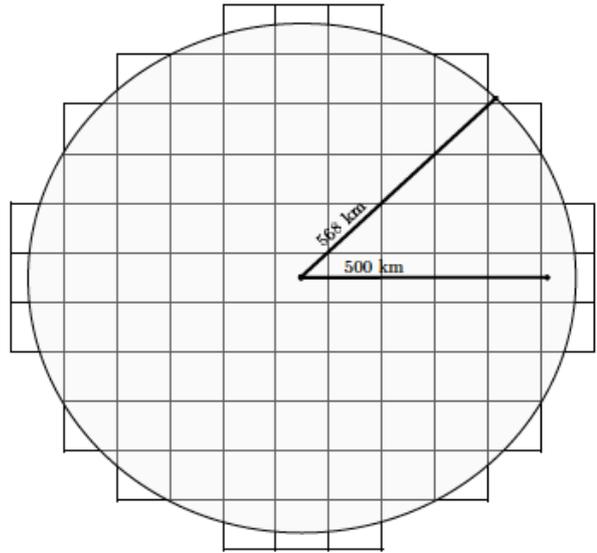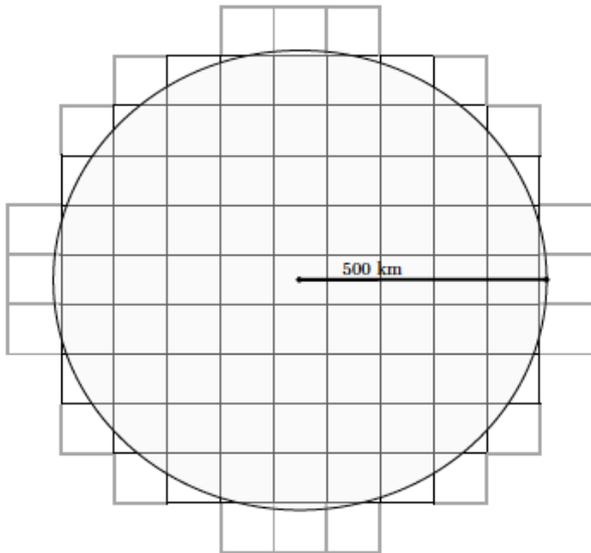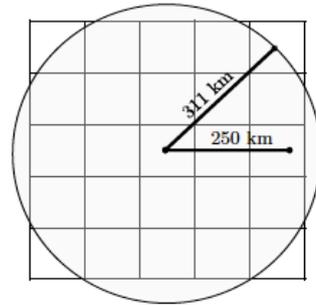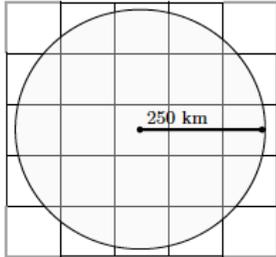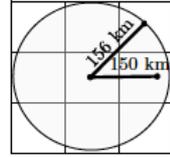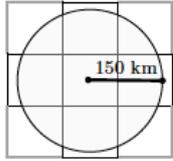
Table A.3a – Moran's I

Year	150 KM						250 KM					
	NC	GDP	POP	TEMP	PREC	SPI	NC	GDP	POP	TEMP	PREC	SPI
1990	0.13	0.19	0.29	0.75	0.98	0.72	0.09	0.17	0.25	0.76	0.94	0.64
1991	0.14	0.19	0.30	0.74	0.96	0.72	0.09	0.17	0.26	0.75	0.92	0.64
1992	0.11	0.19	0.30	0.72	0.97	0.77	0.10	0.17	0.26	0.72	0.93	0.72
1993	0.10	0.20	0.30	0.74	0.97	0.66	0.09	0.17	0.25	0.75	0.93	0.60
1994	0.15	0.20	0.30	0.74	0.98	0.70	0.10	0.17	0.26	0.74	0.94	0.61
1995	0.15	0.20	0.30	0.73	0.96	0.90	0.11	0.17	0.26	0.74	0.93	0.82
1996	0.26	0.20	0.30	0.74	0.96	0.67	0.18	0.17	0.26	0.75	0.92	0.63
1997	0.21	0.20	0.30	0.74	0.94	0.76	0.15	0.17	0.26	0.76	0.92	0.67
1998	0.20	0.20	0.31	0.75	0.97	0.90	0.14	0.17	0.26	0.76	0.93	0.80
1999	0.22	0.20	0.30	0.76	1.01	0.79	0.16	0.17	0.26	0.76	0.97	0.69
2000	0.20	0.20	0.31	0.75	0.97	0.85	0.13	0.17	0.26	0.76	0.94	0.79
2001	0.20	0.20	0.31	0.74	0.95	0.85	0.14	0.18	0.27	0.74	0.92	0.77
2002	0.23	0.20	0.31	0.73	0.95	0.83	0.15	0.18	0.26	0.75	0.92	0.77
2003	0.19	0.20	0.31	0.74	0.97	0.80	0.13	0.18	0.27	0.75	0.93	0.72
2004	0.18	0.21	0.31	0.75	0.97	0.80	0.12	0.18	0.26	0.76	0.93	0.71
2005	0.16	0.21	0.31	0.72	0.94	0.78	0.10	0.19	0.27	0.73	0.92	0.69
2006	0.18	0.21	0.32	0.76	0.96	0.90	0.13	0.19	0.27	0.77	0.93	0.82
2007	0.03	0.21	0.31	0.76	0.97	0.80	0.02	0.19	0.27	0.77	0.94	0.75
2008	0.07	0.21	0.32	0.76	1.00	0.64	0.05	0.19	0.27	0.77	0.96	0.60
2009	0.15	0.21	0.32	0.78	0.97	0.56	0.10	0.19	0.27	0.79	0.94	0.49
2010	0.02	0.21	0.32	0.78	0.94	0.56	0.02	0.19	0.27	0.79	0.90	0.48
2011	0.04	0.21	0.32	0.78	0.95	0.62	0.04	0.19	0.27	0.79	0.91	0.51
2012	0.10	0.21	0.32	0.77	0.93	0.62	0.08	0.19	0.27	0.78	0.89	0.54
2013	0.15	0.21	0.32	0.83	0.94	0.68	0.11	0.19	0.27	0.82	0.91	0.59
2014	0.19	0.21	0.32	0.77	1.01	0.64	0.14	0.19	0.27	0.78	0.95	0.56
2015	0.25	0.21	0.33	0.73	1.02	0.73	0.19	0.19	0.28	0.72	0.96	0.67
2016	0.21	0.21	0.32	0.74	1.03	0.79	0.14	0.19	0.27	0.73	0.98	0.73
Average	*0.16*	*0.20*	*0.31*	*0.75*	*0.97*	*0.74*	*0.11*	*0.18*	*0.26*	*0.76*	*0.93*	*0.67*

Table A.3b – Moran's I

Year	500 KM						1000 KM					
	NC	GDP	POP	TEMP	PREC	SPI	NC	GDP	POP	TEMP	PREC	SPI
1990	0.05	0.13	0.19	0.70	0.89	0.52	0.03	0.07	0.11	0.58	0.78	0.35
1991	0.06	0.13	0.19	0.70	0.87	0.52	0.04	0.07	0.12	0.58	0.76	0.35
1992	0.06	0.12	0.20	0.66	0.87	0.61	0.04	0.07	0.12	0.54	0.76	0.46
1993	0.06	0.13	0.19	0.69	0.87	0.48	0.03	0.07	0.12	0.57	0.74	0.31
1994	0.06	0.12	0.20	0.68	0.88	0.48	0.03	0.07	0.12	0.55	0.76	0.31
1995	0.07	0.12	0.20	0.67	0.87	0.72	0.04	0.07	0.12	0.55	0.74	0.57
1996	0.10	0.12	0.19	0.70	0.85	0.52	0.06	0.07	0.12	0.58	0.72	0.38
1997	0.10	0.12	0.20	0.70	0.87	0.54	0.05	0.07	0.12	0.58	0.77	0.36
1998	0.09	0.12	0.20	0.70	0.88	0.69	0.05	0.07	0.12	0.58	0.76	0.52
1999	0.10	0.12	0.20	0.69	0.91	0.54	0.06	0.07	0.12	0.57	0.78	0.33
2000	0.09	0.12	0.20	0.70	0.88	0.63	0.05	0.07	0.12	0.58	0.75	0.42
2001	0.10	0.13	0.20	0.68	0.87	0.63	0.05	0.07	0.12	0.56	0.76	0.41
2002	0.09	0.13	0.20	0.69	0.86	0.62	0.06	0.07	0.12	0.57	0.75	0.39
2003	0.08	0.13	0.20	0.69	0.87	0.57	0.05	0.08	0.12	0.57	0.75	0.34
2004	0.08	0.13	0.20	0.70	0.87	0.57	0.04	0.08	0.12	0.58	0.75	0.36
2005	0.06	0.13	0.20	0.67	0.87	0.55	0.04	0.08	0.12	0.55	0.77	0.35
2006	0.09	0.14	0.21	0.71	0.87	0.68	0.06	0.08	0.13	0.60	0.77	0.43
2007	0.02	0.14	0.20	0.71	0.88	0.64	0.01	0.08	0.13	0.59	0.77	0.48
2008	0.03	0.14	0.21	0.71	0.90	0.48	0.02	0.08	0.13	0.59	0.77	0.33
2009	0.06	0.14	0.21	0.73	0.89	0.36	0.04	0.08	0.13	0.62	0.78	0.23
2010	0.02	0.14	0.21	0.73	0.85	0.35	0.01	0.08	0.13	0.62	0.73	0.20
2011	0.03	0.14	0.21	0.73	0.85	0.39	0.02	0.08	0.13	0.61	0.75	0.25
2012	0.07	0.14	0.21	0.72	0.84	0.43	0.04	0.08	0.13	0.60	0.72	0.30
2013	0.08	0.14	0.21	0.76	0.85	0.49	0.04	0.08	0.13	0.64	0.74	0.39
2014	0.10	0.14	0.21	0.72	0.89	0.43	0.06	0.08	0.13	0.60	0.75	0.27
2015	0.12	0.14	0.21	0.66	0.90	0.57	0.06	0.08	0.13	0.52	0.76	0.45
2016	0.09	0.15	0.21	0.67	0.91	0.63	0.05	0.08	0.13	0.54	0.77	0.49
Average	*0.07*	*0.13*	*0.20*	*0.70*	*0.87*	*0.54*	*0.04*	*0.08*	*0.12*	*0.58*	*0.76*	*0.37*

Figure A.4 – Moran's scatterplot for main variables (calculated for year 2016)

No Conflicts (Global Moran's I = 0.140)
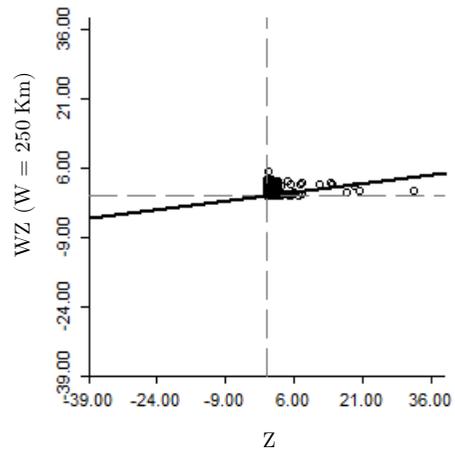
GDP (Global Moran's I = 0.145)
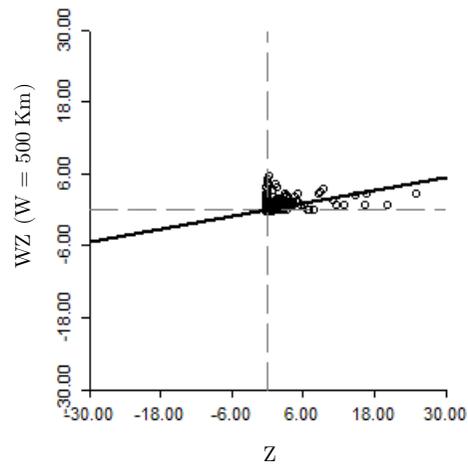
Population (Global Moran's I = 0.210)
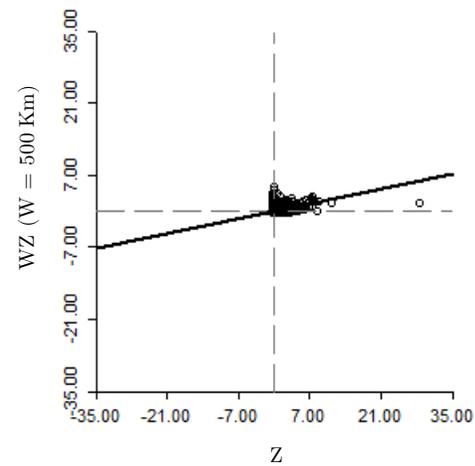
Temperature (Global Moran's I = 0.670)
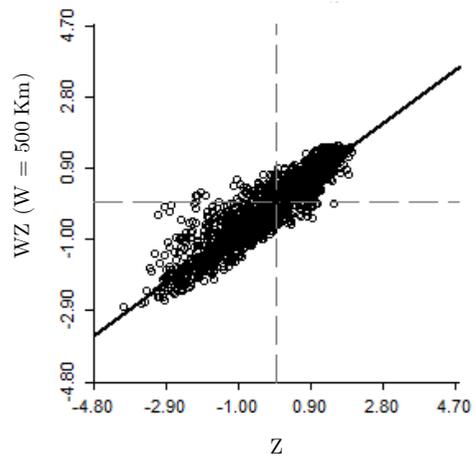
Precipitations (Global Moran's I = 0.910)
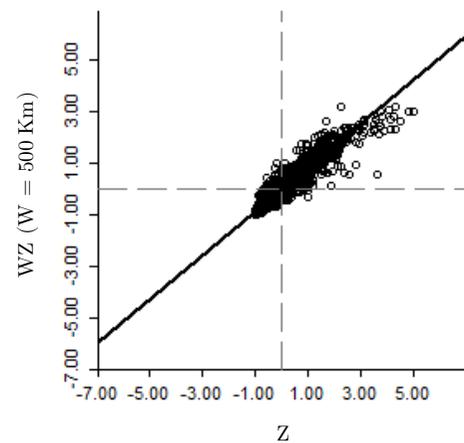
SPI (Global Moran's I = 0.629)
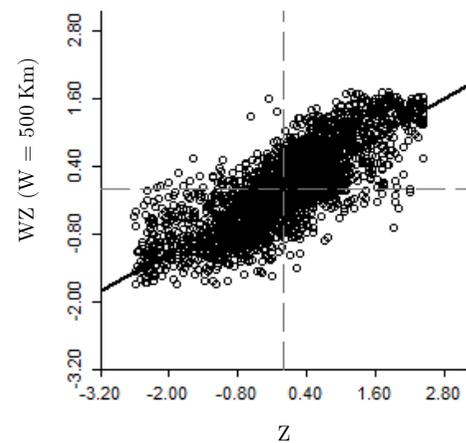
APPENDIX B

Table B.1A - Effects of cell-based climate and socio-economic features (W_{150})

	MLE SAR W_{150}-FE (t)	MLE SAR W_{150}-RE (t)	MLE SAR W_{150}-FE (t)	MLE SAR W_{150}-FE (t-1)	MLE SAR W_{150}-FE-LAG1	MLE SAR W_{150}-FE-LAG2	MLE SAR W_{150}-FE-LAG3
NC it-1 (α)					0.475***		0.463***
					(0.01)		(0.01)
W_{150}NC it (ρ)	1.133***	0.671***	0.665***	0.665***	0.628***	0.865***	0.646***
	(0.01)	(0.03)	(0.11)	(0.11)	(0.17)	(0.15)	(0.14)
W_{150}NC it-1 (lagged ρ)						0.853***	0.106***
						(0.37)	(0.23)
GDP it	-0.047***	-0.012***	-0.064***				
	(0.00)	(0.00)	(0.01)				
GDP it-1				-0.057***	-0.021***	-0.042***	-0.020***
				(0.01)	(0.01)	(0.01)	(0.01)
Pop it	0.067***	0.028***	0.047***				
	(0.01)	(0.00)	(0.02)				
Pop it-1				0.043**	0.019*	0.055***	0.021**
				(0.02)	(0.01)	(0.02)	(0.01)
Temp it	0.006	-0.034**	-0.009				
	(0.03)	(0.02)	(0.06)				
Temp it-1				0.115*	-0.053	-0.243***	-0.082**
				(0.06)	(0.04)	(0.06)	(0.04)
Prec it	-0.002	-0.005**	0.007*				
	(0.00)	(0.00)	(0.00)				
Prec it-1				0.008**	-0.001	-0.012***	-0.003
				(0.00)	(0.00)	(0.00)	(0.00)
SPI it	-0.006*	-0.001	-0.008				
	(0.00)	(0.00)	(0.01)				
SPI it-1				-0.010	-0.008	-0.008	-0.007
				(0.01)	(0.00)	(0.01)	(0.00)
Variance sigma2	0.082***	0.086***	0.082***	0.082***	0.066***	0.084***	0.069***
Theta		-0.932***					
Nr Obs.	91,854	91,854	88,452	88,452	88,452	88,452	88,452
R2_within	0.000	0.000	0.000	0.000	0.238	0.035	0.217
R2_between	0.000	0.009	0.001	0.000	0.254	0.011	0.129
R2_overall	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Haus. test FE-RE	135.14***						
Ll test	-21,307	-24,475	-16,877	-16,894	-7,348	-15,548	-7,344
AIC	42,628	48,967	33,769	33,803	14,712	31,111	14,706
BIC	42,694	49,052	33,835	33,868	14,787	31,186	14,791

Note: Robust (clustered id) standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.1B - Effects of cell-based climate and socio-economic features (W_{250})

	MLE SAR W_{250}-FE (t-1)	MLE SAR W_{250}-FE-LAG1	MLE SAR W_{250}-FE-LAG2	MLE SAR W_{250}-FE-LAG3
NC it-1 (α)		1.721***		0.493***
		(0.01)		(0.01)
W_{250}NC it (ρ)	0.457***	0.866***	0.479***	1.122***
	(0.03)	(0.11)	(0.09)	(0.00)
W_{250}NC it-1 (lag ρ)			0.362***	0.059
			(0.24)	(0.16)
GDP it-1	-0.057***	-0.060***	-0.047***	-0.013**
	(0.01)	(0.01)	(0.01)	(0.01)
Pop it-1	0.040**	0.245***	0.036**	0.034***
	(0.02)	(0.01)	(0.02)	(0.01)
Temp it-1	0.061	-6.206***	-0.269***	-0.571***
	(0.06)	(0.04)	(0.06)	(0.04)
Prec it-1	0.006*	-0.301***	-0.008**	-0.024***
	(0.00)	(0.00)	(0.00)	(0.00)
SPI it-1	-0.010	0.035***	-0.009	-0.005
	(0.01)	(0.00)	(0.01)	(0.00)
Variance sigma2	0.083***	0.069***	0.082***	0.067***
Nr Obs.	88,452	88,452	88,452	88,452
R2_within	0.000	0.000	0.058	0.000
R2_between	0.000	0.001	0.001	0.001
R2_overall	0.000	0.000	0.000	0.000
Ll test	-16,611	-7,249	-15,455	-8,083
AIC	33,236	14,513	30,925	16,184
BIC	33,302	14,588	31,000	16,268

Note: Robust (clustered id) standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

Table B.1C - Effects of cell-based climate and socio-economic features (W500)

	MLE SAR W$_{500}$-FE	MLE SAR W$_{500}$-FE-LAG1	MLE SAR W$_{500}$-FE-LAG2	MLE SAR W$_{500}$-FE-LAG3
NC it-1 (α)		0.396***		0.455***
		(0.01)		(0.01)
W$_{500}$NC it (ρ)	0.291***	0.409***	0.431***	0.672***
	(0.01)	(0.06)	(0.04)	(0.04)
W$_{500}$NC it-1 (lag ρ)			2.245***	0.140***
			(0.16)	(0.09)
GDP it-1	-0.060***	-0.029***	0.027***	-0.020***
	(0.01)	(0.01)	(0.01)	(0.01)
Pop it-1	0.033*	0.004	0.086***	0.010
	(0.02)	(0.01)	(0.02)	(0.01)
Temp it-1	0.033	-0.397***	-5.699***	-0.451***
	(0.07)	(0.04)	(0.06)	(0.04)
Prec it-1	0.004	-0.008***	-0.317***	-0.021***
	(0.00)	(0.00)	(0.00)	(0.00)
SPI it-1	-0.008	-0.008	0.055***	-0.004
	(0.01)	(0.00)	(0.01)	(0.00)
Variance sigma2	0.086***	0.071***	0.042***	0.070***
Nr Obs.	88,452	88,452	88,452	88,452
R2_within	0.000	0.001	0.000	0.001
R2_between	0.003	0.037	0.000	0.000
R2_overall	0.000	0.000	0.000	0.000
Ll test	-17,637	-8,564	-16,745	-7,857
AIC	35,288	17,145	33,506	15,731
BIC	35,354	17,220	33,581	15,816

Note: Robust (clustered id) standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01

Table B.2 - Effects of different spatial lag model specifications

	MLE SAR W_{250}-FE-AR M_{150}	MLE SAR W_{250}-FE-AR M_{250}	MLE SAR W_{250}-FE-AR M_{500}	MLE SAR W_{250}-FE-LAG1-D_{150}	MLE SAR W_{250}-FE-LAG1-D_{250}	MLE SAR W_{250}-FE-LAG1-D_{500}	MLE SAR W_{250}-FE-LAG3-D_{500}
NC it-1 (α)	0.419***	0.420***	0.420***	0.480***	0.614***	0.477***	0.487***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
W_{250}NC it (ρ)	0.317***	0.311***	0.322***	0.552***	1.601***	0.527***	1.006***
	(0.14)	(0.18)	(0.16)	(0.11)	(0.11)	(0.11)	(0.00)
W_{250}NC it-1 (lag ρ)							-0.032**
							(0.16)
GDP it-1	-0.031***	-0.032***	-0.034***	-0.058***	0.021**	-0.037***	-0.011
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pop it-1	0.024**	0.025**	0.027**	0.056***	0.002	0.045***	0.040***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Temp it-1	0.011	0.006	-0.017	2.735***	2.659***	1.001***	1.163***
	(0.05)	(0.05)	(0.05)	(0.08)	(0.09)	(0.08)	(0.08)
Prec it-1	0.002	0.002	0.002	0.053***	0.081***	0.021***	0.039***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
SPI it-1	-0.010*	-0.011*	-0.012*	-0.007	-0.026**	-0.017*	-0.024***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Spatial spillovers with $D_{150,250,500}$ inverse distance weight matrix							
GDP it-1				0.106***	-0.022**	0.018***	-0.021
				(0.15)	(0.09)	(0.06)	(0.06)
Pop it-1				-0.060**	0.103***	-0.018*	0.052
				(0.30)	(0.18)	(0.11)	(0.11)
Temp it-1				-5.217***	-3.403***	-0.721***	-0.979***
				(1.14)	(0.73)	(0.40)	(0.40)
Prec it-1				-0.116***	-0.134***	-0.021***	-0.042***
				(0.10)	(0.06)	(0.03)	(0.03)
SPI it-1				-0.012	0.021**	0.060	0.012***
				(0.14)	(0.08)	(0.05)	(0.05)
Variance sigma2	0.070***	0.070***	0.070***	0.069***	0.060***	0.069***	0.068***
$M_{150,250,500}$ (λ)	0.266***	0.191***	0.150***				
Nr Obs.	88,452	88,452	88,452	88,452	88,452	88,452	88,452
R2_within	0.255	0.256	0.255	0.001	0.000	0.036	0.002
R2_between	0.755	0.760	0.697	0.028	0.000	0.007	0.003
R2_overall	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ll test	-6,948	-7,060	-7,028	-7,236	-7,231	-7,229	-8,068
AIC	13,914	14,139	14,075	14,498	14,488	14,484	16,163
BIC	13,999	14,223	14,159	14,620	14,610	14,606	16,295

Note: Robust (clustered id) standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3 – Impact of climate and socio-economic conditions (MLE SAR W_{250}-FE-LAG1-D_{500})

	(1)	(2)	(3)	(4)	(5)
NC it-1 (α)	0.752***	0.535***	0.486***	0.753***	0.520***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
W_{250}NC it (ρ)	0.529***	0.521***	0.518***	0.527***	0.858***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.11)
GDP it-1	-0.006	-0.037***	-0.041***	-0.007	-0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Pop it-1	0.033**	0.053***	0.057***	0.033**	0.035**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Temp it-1	2.435***	2.340***	2.320***	2.438***	1.109***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Prec it-1	0.045***	0.038***	0.036***	0.045***	0.035***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
SPI it-1	-0.010	-0.010	-0.010	-0.010	-0.021**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Resources it	-0.000	-0.000*	-0.000**	0.000	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Int-Resources it				-0.000**	-0.000*
				(0.00)	(0.00)
Agricult it	-0.002*	-0.003***	-0.003***	-0.002*	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nr year from indep ct	0.040***	0.012	0.005	0.042***	0.093***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inst-Law & Order ct	-0.001				
	(0.00)				
Inst-Gov Eff ct		-0.003***		-0.002**	
		(0.00)		(0.00)	
Inst-PRS ct			-0.013***		-0.003
			(0.00)		(0.00)
Spatial spillovers with D_{500} inverse distance weight matrix					
GDP it-1	0.122*	0.241***	0.277***	0.113*	-0.022
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Pop it-1	-0.124	-0.239**	-0.295***	-0.098	0.007
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
Temp it-1	-1.694***	-1.605***	-1.582***	-1.696***	-0.908***
	(0.42)	(0.42)	(0.42)	(0.42)	(0.40)
Prec it-1	-0.043***	-0.035***	-0.032***	-0.042***	-0.036***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
SPI it-1	-0.019	-0.024	-0.030	-0.017	0.010**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Variance sigma2	0.070***	0.070***	0.070***	0.070***	0.066***
Nr Obs.	88,452	88,452	88,452	88,452	88,452
R2_within	0.022	0.003	0.000	0.021	0.003
R2_between	0.006	0.008	0.005	0.008	0.000
R2_overall	0.000	0.000	0.000	0.000	0.000
Ll test	-8,115	-8,120	-8,106	-8,115	-7,105
AIC	16,263	16,274	16,247	16,267	14,246
BIC	16,423	16,434	16,406	16,436	14,415
Condition number	6.43	6.64	9.59	10.89	10.89

Note: Robust (clustered id) standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.4 – Impacts of 1y changes in climate and socio-economic conditions (MLE SAR W_{250}-FE-LAG1-D_{500})

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NC it-1 (α)	0.475***	0.479***	0.475***	0.476***	0.483***	0.483***	0.483***	0.483***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
W_{250}NC it (ρ)	0.496***	0.530***	0.497***	0.509***	0.557***	0.557***	0.555***	0.558***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
GDP it-1	-0.038***	-0.038***	-0.039***	-0.038***	-0.036***	-0.036***	-0.036***	-0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D1y-GDP_PC it-1	0.202***	0.213***	0.202***	0.205***	0.217***	0.216***	0.216***	0.217***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Pop it-1	0.046***	0.048***	0.046***	0.047***	0.048***	0.047***	0.047***	0.048***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Temp it-1	0.347***	0.353***	0.344***	0.355***	0.390***	0.389***	0.387***	0.392***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
D1y-Temp it-1	1.857***	1.844***	1.860***	1.855***	1.825***	1.824***	1.826***	1.823***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
D1y-Temp it-1 dr	-0.496***	-0.496***	-0.497***	-0.499***	-0.495***	-0.498***	-0.494***	-0.495***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Prec it-1	0.028***	0.028***	0.027***	0.028***	0.045***	0.045***	0.045***	0.045***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D1y-Prec it-1					-0.015***	-0.022***	-0.016	-0.014*
					(0.01)	(0.01)	(0.01)	(0.01)
D1y-Prec it-1 rur						0.074***		
						(0.02)		
D1y-Prec it-1 dr							0.000	
							(0.00)	
D1y-Prec it-1 fl								0.000
								(0.00)
SPI it-1	-0.021**	-0.021**	-0.027	-0.027	-0.027***	-0.025***	-0.027***	-0.027***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
SPI it-1 rur		-0.012						
		(0.02)						
SPI it-1 dr cells			0.003					
			(0.01)					
SPI it-1 fl				0.004				
				(0.01)				
Resources it	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Int-Resources it	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Agricult it	-0.002***	-0.003***	-0.002***	-0.002***	-0.002**	-0.002***	-0.002**	-0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nr year from indep ct	0.025*	0.027**	0.024*	0.025*	0.035***	0.037***	0.035***	0.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inst-PRS ct	-0.006*	-0.006	-0.006*	-0.006	-0.005	-0.005	-0.005	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Spatial spillovers with D_{500} inverse distance weight matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP it-1	0.016***	0.016***	0.015***	0.015***	0.014***	0.015***	0.014***	0.014***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
D1y-GDP_PC it-1	-0.351***	-0.349***	-0.347***	-0.347***	-0.341***	-0.340***	-0.341***	-0.342***
	(0.36)	(0.36)	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)
Temp it-1	-0.445***	-0.465***	-0.447***	-0.461***	-0.506***	-0.503***	-0.501***	-0.509***
	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)	(0.61)
D1y-Temp it-1	-1.031***	-1.020***	-1.033***	-1.026***	-1.004***	-1.002***	-1.006***	-1.001***
	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)
D1y-Temp it-1 dr	0.315***	0.317***	0.316***	0.318***	0.317***	0.318***	0.317***	0.319***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Prec it-1	-0.026***	-0.029***	-0.027***	-0.027***	-0.041***	-0.040***	-0.041***	-0.041***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
D1y-Prec it-1					0.012***	0.020***	0.009	0.002
					(0.03)	(0.03)	(0.07)	(0.05)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D1y-Prec it-1 rur						-0.105***		
						(0.13)		
D1y-Prec it-1 dr							0.001	
							(0.02)	
D1y-Prec it-1 fl								0.004*
								(0.02)
SPI it-1	0.010**	0.021***	0.005	-0.003	0.015***	0.012**	0.015***	0.015***
	(0.05)	(0.05)	(0.10)	(0.15)	(0.05)	(0.05)	(0.05)	(0.05)
SPI it-1 rur		-0.107***						
		(0.19)						
SPI it-1 dr cells			0.003					
			(0.03)					
SPI it-1 fl				0.005				
				(0.06)				
Variance sigma2	0.069***	0.069***	0.069***	0.069***	0.069***	0.069***	0.069***	0.069***
Nr Obs.	85,050	85,050	85,050	85,050	85,050	85,050	85,050	85,050
R2_within	0.087	0.026	0.084	0.027	0.016	0.018	0.010	0.020
R2_between	0.000	0.004	0.000	0.002	0.007	0.005	0.011	0.004
R2_overall	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ll test	-6,902	-6,896	-6,899	-6,900	-6,901	-6,895	-6,900	-6,900
AIC	13,849	13,843	13,849	13,850	13,852	13,844	13,854	13,855
BIC	14,065	14,077	14,082	14,083	14,086	14,097	14,106	14,107
Condition number	10.80	11.07	11.41	10.89	10.80	10.80	10.80	10.80

Note: Robust (clustered id) standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.5 - Impacts of 5y changes in climate conditions (MLE SAR W$_{250}$-FE-LAG1-D$_{500}$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
NC it-1 (α)	0.467***	0.484***	0.488***	0.559***	0.458***	0.456***	0.456***	0.466***	0.477***	0.624***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
W$_{250}$NC it (ρ)	0.518***	0.519***	0.738***	1.207***	0.565***	0.545***	0.524***	0.591***	0.719***	1.993***
	(0.00)	(0.00)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
GDP it-1	-0.042***	-0.042***	-0.019*	0.007	-0.029***	-0.031***	-0.030***	-0.028***	-0.021**	0.038***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
D1y-GDP_PC it-1	0.756***	0.758***	0.264***	0.317***	0.243***	0.241***	0.241***	0.256***	0.258***	0.381***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Pop it-1	0.042***	0.047***	0.050***	0.071***	0.045***	0.044***	0.041***	0.041***	0.050***	0.119***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Temp it-1	0.651***	0.654***	0.508**	1.059***	0.286	0.266	0.246	0.336*	0.459**	1.986***
	(0.21)	(0.21)	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)	(0.20)
D5y-Temp it-1	1.502***	3.209***	1.021***	0.560**	1.210***	1.239***	1.236***	1.144***	1.058***	-0.231
	(0.20)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
D5y-Temp it-1 dr		-0.918***	-0.345***	-0.354***	-0.342***	-0.344***	-0.339***	-0.349***	-0.343***	-0.376***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Prec it-1	0.037***	0.039***	0.016***	0.028***	0.011*	0.011**	0.015	0.016	0.019	0.048***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
D5y-Prec it-1							0.004	-0.004	0.020	0.021
							(0.01)	(0.02)	(0.01)
D5y-Prec it-rur								0.086***		
								(0.02)		
D5y-Prec it-1 dr									-0.005	
									(0.00)	
D5y-Prec it-1 fl										-0.004
										(0.00)
SPI it-1	-0.017	-0.015					-0.018*	-0.018*	-0.020**	-0.028***
	(0.01)	(0.01)					(0.01)	(0.01)	(0.01)	(0.01)
Av5y-SPI it-1			-0.009	-0.015	-0.057	-0.073				
			(0.03)	(0.03)	(0.06)	(0.07)				
Av5y-SPI it-1 rur				0.031						
				(0.05)						
Av5y-SPI it-1 dr					0.021					
					(0.02)					
Av5y-SPI it-1 fl						0.038				
						(0.03)				
Resources it	0.001**	0.001**	0.001**	0.001	0.002**	0.002**	0.002**	0.001**	0.001**	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Int-Resources it	-0.001***	-0.001***	-0.001***	-0.000	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Agricult it	-0.003***	-0.003**	-0.002*	-0.001	-0.002**	-0.002**	-0.002**	-0.003**	-0.002*	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nr year indep ct	0.019	0.014	0.093***	0.227***	0.042**	0.031*	0.030*	0.060***	0.086***	0.448***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
PRS ct	-0.008*	-0.004	0.000	0.020***	-0.007	-0.007	-0.008*	-0.007	-0.001	0.048***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Spatial spillovers with D$_{500}$ inverse distance weight matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GDP it-1	0.022***	0.019***	-0.043	-0.028***	0.050	0.053	0.065	0.058	-0.035	-0.065***
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
D1y-GDP_PC it-1	-0.881***	-0.867***	-0.201***	-0.442	-0.256***	-0.259***	-0.273***	-0.261***	-0.199***	0.257***
	(0.36)	(0.36)	(0.36)	(0.36)	(0.37)	(0.36)	(0.37)	(0.37)	(0.37)	(0.37)
Temp it-1	-0.768***	-0.774***	-0.709***	-1.327***	-0.476***	-0.453***	-0.417***	-0.504***	-0.661***	-2.416***
	(0.98)	(0.98)	(0.93)	(0.94)	(0.93)	(0.94)	(0.93)	(0.93)	(0.93)	(0.93)
D5y-Temp it-1	-0.654***	-1.820***	-0.367***	0.788	-0.537***	-0.558***	-0.576***	-0.505***	-0.408***	0.852***
	(0.93)	(1.04)	(1.01)	(1.01)	(1.01)	(1.02)	(1.01)	(1.01)	(1.01)	(1.01)
D5y-Temp it-1 dr		0.588***	0.221***	0.231***	0.217***	0.217***	0.214***	0.215***	0.218***	0.267***
		(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Prec it-1	-0.035***	-0.037***	-0.021***	-0.036***	-0.015***	-0.014***	-0.019**	-0.017*	-0.011	0.035***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.09)	(0.09)	(0.09)	(0.09)
D5y-Prec it-1						0.012	-0.016	-0.029***	-0.029***	-0.029***

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
						(0.09)	(0.11)	(0.09)	(0.09)	(0.09)
D5y-Prec it-1 rur						-0.017***				
						(0.18)				
D5y-Prec it-1 dr							0.045**			
							(0.02)			
D5y-Prec it-1 fl								0.051*	0.051*	0.051*
								(0.03)	(0.03)	(0.03)
SPI it-1	0.080	0.054				0.062	0.067	0.083	0.013**	
	(0.05)	(0.05)				(0.05)	(0.05)	(0.05)	(0.05)	
Av5y-SPI it-1			0.016	0.066***	0.012	-0.011				
			(0.14)	(0.15)	(0.30)	(0.38)				
Av5y-SPI it-1 rur				-0.081*						
				(0.44)						
Av5y-SPI it-1 dr					-0.063					
					(0.08)					
Av5y-SPI it-1 fl						-0.032				
						(0.15)				
Variance sigma2	0.069***	0.069***	0.067***	0.063***	0.068***	0.068***	0.068***	0.068***	0.067***	0.056***
Nr Obs.	74,844	74,844	74,844	74,844	74,844	74,844	74,844	74,844	74,844	74,844
R2_within	0.000	0.001	0.001	0.001	0.040	0.009	0.032	0.000	0.002	0.000
R2_between	0.004	0.006	0.002	0.000	0.000	0.049	0.008	0.000	0.000	0.004
R2_overall	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ll test	-6,266	-6,266	-5,493	-5,488	-5,484	-5,478	-5,492	-5,485	-5,491	-5,491
AIC	12,575	12,578	11,031	11,026	11,018	11,007	11,033	11,023	11,036	11,036
BIC	12,768	12,790	11,243	11,257	11,248	11,237	11,264	11,272	11,286	11,285
Condition number	10.81	10.84	10.85	11.13	11.53	10.96	10.85	10.85	10.88	10.87

Note: Robust (clustered id) standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$