# The impact of short and medium–term change in climate conditions on violent conflicts in Africa: a dynamic spatial panel analysis

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**Abstract**
We propose an analysis of the multiple linkages between armed conflicts and climate-related variable 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. A conflict trap mechanism is confirmed by the persistence of conflicts over time and the contagious effect across space. Climate-related variables play a significant role in determining the strength and duration of armed conflicts, with different effects depending on the temporal horizon.

**Keywords:** Climate change; armed conflicts; Africa; dynamic spatial Durbin model
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## 1. Introduction

Africa is recognized as a problematical continent, facing several challenges such as poverty, limited education and health systems, food insecurity and violence. During last decades, many African countries have experienced many conflicts and civil wars. In addition to this, the continent also suffers from the negative impacts of climate change. 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).

The African continent unfortunately represents a case study continuously put under the lens of empirical investigation since changes in temperature and rainfall patterns are expected 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, the poor institutional capacity, the unequal income distribution, the scarcity of financial resources to implement adaptation measures and the consequent low resilience to extreme events and disasters with subsequent 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). Accordingly, strong pressure on resource availability and human livelihood by exposure to changes in climatic conditions may exacerbate already vulnerable socio-economic and institutional conditions, bringing to self-reinforcing conflictual circumstances (Buhaug, 2010).

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 called 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 detecting 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. 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 is an incident related threshold of 25 deaths per year, but above that threshold the conflict variable remains unchanged independently from 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.

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 capturing some indirect effects, as for instance migration and consequent over pressure on scarce 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 in other areas might exacerbate pressures on already scarce natural resources leading to increasing violent conflicts probability (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 large scale internal migration flows. Following Buhaug (2015), we contribute in underpinning how changes in climatic conditions occurred in a reasonable time lag (past five years) in surrounding areas might generally 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 considering a set of driving forces that might explain the climate-conflict nexus by also controlling for the social vulnerability to climate change. Three channels are investigated: i) the economic resources endowment and their development path over time as a source of resilience capacity to climatic change vulnerability both at cell level and surrounding neighbours (Barnett and Adger, 2007); ii) the persistence effect over time defined as a conflict trap (Collier, 2003); iii) the potential impact of a resource curse associated to the geographical proximity of mining and fossil fuels fields (Adano et al., 2012; Bodea et al., 2016).

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 about climate change and conflicts; Section 3 describe 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 change and armed conflicts

Security is a complex issue which embraces a broad range of risk typologies. One of these risks concerns environmental transformation and climate change. It is widely recognized that climate change affects crucial aspects of human life especially in DCs, particularly through its impacts on agriculture and food security, access to water and other resources. Indeed, even though socio-economic and institutional circumstances are crucial in explaining the onset and evolution of conflicts (Buhaug, 2010), climate change and resources endowment could become aggravating factors explaining the risk of conflicts.

The linkages between climate change and conflicts have been increasingly investigated during recent years under different perspectives (Bosetti et al., 2018; 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 bringing to 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.

Several studies (Crost et al., 2018; Harari and La Ferrara, 2018; Raleigh et al., 2015; Wischnath and Buhaug, 2014) focus on the channel of agriculture, which is unquestionably the sector most exposed to climate variability, as more than 80 percent of world food production relies on rain-fed irrigation, which depends critically on the variation of the spatial and temporal distribution of precipitations (Bates et al., 2008;

FAO, 2008). In this respect, DCs are extremely vulnerable to climatic variability also from an economic point of view, since food security and employment rate are also harmed by reduction in precipitations. This explains why those regions without an irrigation system are found to be the most exposed to the risk of conflicts because of climatic variations (Daccache et al., 2015; von Uexküll, 2014). 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 debated issue and several studies have investigated the link between conflicts and climate-induced water scarcity (Brochmann and Gleditsch, 2012; Gleick, 2014). Indeed, freshwater supply turns out to be scarcer and uncertain due to climate change and pollution while the control over water resources is an instrument of war for both offensive and defensive purposes (Gleick, 1993). With respect to the agriculture and water access channels, it is worth recalling that dealing with climate-related variables is a complex issue since different aspects should 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 causal linkages between changes in climatic variables and armed conflicts are different according to the chosen climatic variable (temperature, precipitation, drought indices), time frame, and the geographical scale. As a first example, Burke et al. (2015) focus on the relevance of analysing the impact of short-term climatic variables and on the relative higher impact of 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 rainfalls in a short horizon, Fijelde and von Uexküll (2012) suggest that in a longer time horizon large negative deviations in rainfall from normal values are associated with an increased risk of violent conflicts. This uncertainty in results is reinforced by the inherent uncertainty of climate change phenomenon, bringing to the necessity to further investigate this topic by different angles.

Additionally, 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 issue is the existence of a conflict trap as emphasised in Collier (2003). According to Hegre et 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. Accordingly, whatever channel would be specifically investigated, the role of persistency over time of conflictual events needs to be carefully addressed.

The second issue strictly connected with the nature itself of conflicts is the highly probability of contagious. According to Silve and Verdier (2018), from a theoretical point of view there are at least two channels to be jointly considered. 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 they represent a key economic source and the competition for its control may increase the risk of conflicts (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 bring to an increase in conflict probability. As a perfect 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.

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 to cope with adverse socio-economic conditions and to implement adaptation policies limiting the 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 a few climate-dependent sectors, as in the case for many DCs (Castells-Quintana et al., 2017; Gizelis and Wooden, 2010). 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.

Together with the quality of institutions a fourth element that might prevent a climate-conflict vicious cycle is the reduction in social vulnerability. A sustained economic growth path 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 allows capturing 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 discovering fine-grained events as the role played by rainfall changes during crops growing season in reinforcing conflict possibility. More importantly, they suggest enclosing in such kind of analyses the role played by geographical spillovers, 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 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.

Moreover, 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, and 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 able to go to infinity 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 $p$, and in its general form can be written as:

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

$$u_{it} = \lambda M u_{jt} + \varepsilon_{it} \tag{2}$$

where $\alpha$ is the coefficient associated with persistence over time, $\rho$ is the spatial autoregressive coefficient representing the endogenous interaction effect (introduced by means of the spatial weight matrix $W$), $\beta$ is the vector of parameters associated with the explanatory variables, $\vartheta$ is the vector of parameters associated with the spatial exogenous interaction effects (introduced by means of the spatial weight matrix $D$), $\gamma_i$ are cell-specific fixed effects, $\delta_t$ are year-specific fixed effects, $\lambda$ 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 $\varepsilon_{it}$ is an $N \times 1$ 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 seem 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), that 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 1 lag for both the persistence term associated to parameter $\alpha$ and the indirect effects associated to parameter $\vartheta$.

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 110 km$^2$) relying on the most recent analysis of the climate-conflict nexus in Africa with a cell-based approach, represented by the contribution by Harari and La Ferrara (2018) where robustness checks on alternative resolution scales confirm the 1°x 1° as the most appropriate.

Another aspect to carefully consider is the spatial spillover effects. First, we must recall that if an explanatory variable $X_k$ changes in a particular unit, not only the response variable in that unit will change (which is the direct effect), but also the response variable in other units (which is the indirect or spillover effect). Because of these feedback effects, that arise due to the impacts passing through neighbouring units and back to the units themselves, conclusions about spatial spillovers 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 effects of $X_k$, while the off-diagonal elements of the same matrix represent the indirect effects. Such effects represent marginal effects and can thus be considered as elasticities. More in details, 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 punctual coefficient estimates $\beta_k, \vartheta_k$ are reported in Appendix B.[1] 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:

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

where $\tau$ and $\eta$ 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,

[1] Direct, indirect and total effects 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 effects 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.

corresponding to an inverse distance between centroids by around 180 km. Accordingly, we apply the Mercator's projection map accounting for spheroidal form of the earth and we 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.[2]

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.[3]

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 best performing 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 as income and population the cut-off obtained with the global

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[2] 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. 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).

[3] 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.

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 until the 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.[4]

### *3.2. Data*

The empirical analysis is conducted on an original georeferenced database that combines conflict data 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.[5]

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 punctual geographical coordinates. We define our dependent variable (hereafter called as number of conflicts) as the sum of any conflicting event — 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 occurred in a specific year.[6] This choice presents several positive aspects. First, ACLED has a limited time span starting from 1997 while UCDP starts from 1989. Second, ACLED doesn't allow distinguishing conflicts on the basis of the number of deaths. Third the quality of UCDP geocoding and precision information is far superior to ACLED. This is particularly important when examining geographic dimensions of conflicts.

The explanatory variables related to climatic conditions try to represent both weather conditions related to the geo-localisation of each cell and changes occurring in the short and medium-term and are elaborated from the African Flood and Drought Monitor developed by Princeton University in collaboration with ICIWaRM and UNESCO-IHP that 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 on Global

[4] 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.

[5] 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.

[6] 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.

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 one year lag in order to account for short-term variations (anomalies) and average precipitation changes over the past five years as a 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.[7] 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 including climatic conditions 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 detecting vulnerability to climate change we have also included some time invariant variables: i) the percentage of land covered by rural areas in each cell elaborated from the Global Land Cover dataset (MODIS-based Global Land Cover Climatology); 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 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

[7] 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.

to this geographical feature allows us accounting 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 probability, short and medium-term changes in precipitations with the time variant land coverage by rural activities, and with drought-risk and flood-risk probability. The same is applied by interacting the SPI-12 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 whatever exhaustible resource (coal, oil, natural gas, minerals) 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 final 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 export 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 by also controlling for the quality of institutions, according to most recent advancement in resource curse hypothesis contributions (Sarmidi et al., 2014).[8]

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 is somehow overlapped 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

[8] A complete list of variables with main statistics and correlation matrix are provided in Appendix A.

water bodies.[9] As for climate dynamics, during last years temperature has increased 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

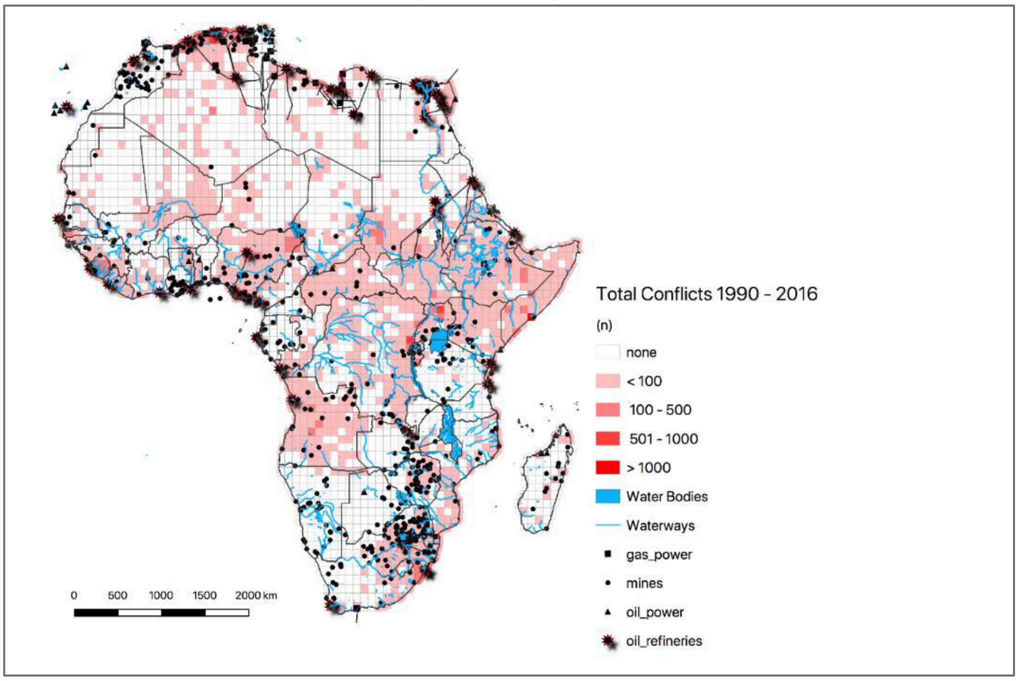
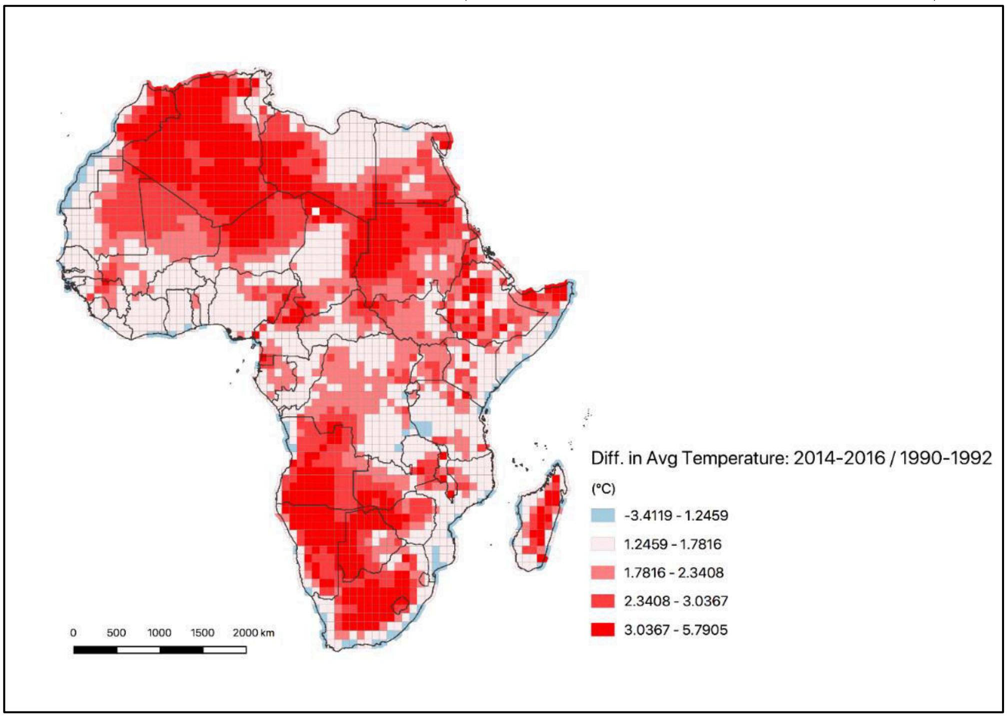



Figure 2 - Change in temperature (av. 2014—2016 w.r.t. av. 1990-1992)

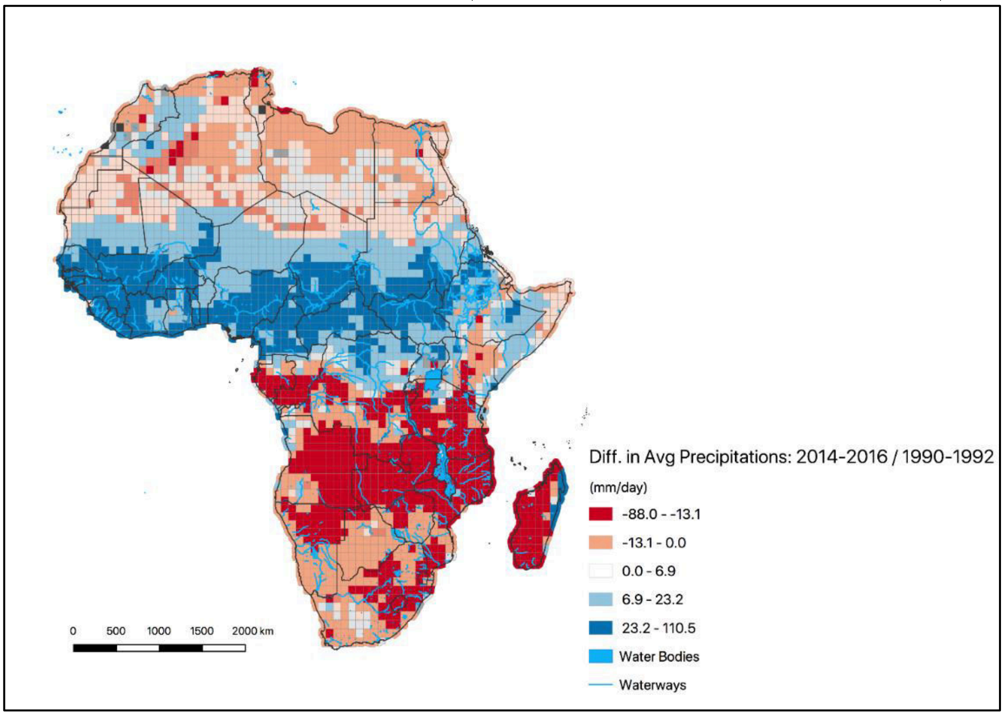



As for precipitation, the average year values for rainfall levels have also changed dramatically and with substantial heterogeneity across the continent, increasing in the Tropical Bell and substantially decreasing in Sub-Saharan Africa (Figure 3).

[9] Selected statistics and Figures representing the quantification and distribution over space and time of the number of conflicts are provided in Appendix A.

By comparing these Figures, it is quite evident that some of the most violent zones of Africa (e.g., Northern and South-West Africa) have experienced both an increase in temperature and a reduction in precipitation, thus becoming drier and at risk of drought. At the same time, the most populated places characterised by relative abundance of precipitation as in the case of the Horn of Africa, rainfall levels substantially increased over time within the three decades here analysed in terms of both intensity (mm per day) and variation across each year. The combination of increased level and variability of rainfalls is recognised as a source of increasing risk of floods and/or destruction of crop yields, negatively influencing resource availability and livelihood in already vulnerable areas.

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 performing 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 ($\gamma_i$) and year ($\delta_t$) fixed effects in order to capture potential omitted variables effect.[10] All

[10] 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

variables with sub-script $i$ 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 characteristics of each cell in the form:

$$\begin{aligned} NC_{it} = \alpha NC_{it-1} + \rho W_{250km} NC_{it} + \beta^{x} X_{it} + \vartheta^{x} D_{500km} \mathrm{X}_{it} + \beta^{z} Z_{it-1} \\ + \vartheta^{z} D_{500km} Z_{it-1} + \beta^{k} K_{ct} + \vartheta^{k} D_{500km} K_{ct} + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned} \quad (6)$$

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:

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

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:

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

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 and Table 5 summarizing the effects of the main variables reporting the sign of the corresponding effect and visualizing the specific climate change condition under scrutiny.

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.

Table 1 – Variable description and original source

| Variable | Description | Source |
|---|---|---|
| Cell-based/time variant | | |
| NC it | Number of conflicting events | UPPSALA-UCDP |
| GDP it-1 | Gross Domestic Product (Th. US$ PPP constant 2005) | SEDAC |
| D1y-GDP-PC it-1 | One-year var of GDP per capita w.r.t. t-1 (%) | Authors' elaboration |
| Pop it-1 | Population (number) | HYDE |
| Temp it-1 | Temperature (yearly average value, °C) | AFDM |
| D1y-Temp it-1 | One-year var of temperature w.r.t. t-1 (%) | Authors' elaboration |
| D5y-Temp it-1 | Average 5y var of temperature in t-1 (%) | Authors' elaboration |
| Prec it-1 | Precipitation (yearly average value, mm/day) | AFDM |
| D1y-Prec it-1 | One-year var of precipitation w.r.t. t-1 (%) | Authors' elaboration |
| D5y-Prec it-1 | Average 5y var of precipitation in t-1 (%) | Authors' elaboration |
| SPI it-1 | SPI-12 (yearly average value, index) | AFDM |
| 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. Tot Export (%) | WDI-World Bank |
| Inst-PRS ct | General PRS 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 |

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 provide evidence on the key role played by contagion as the estimated spatial $\rho$ (associated to the number of conflicts in neighbouring cells) is always positive and statistically significant.[11] Secondly, we show that persistency over time (represented by coefficient $\alpha$) 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 has always a negative sign meaning that areas with higher income are less likely to assist to conflicting episodes, according to findings described in Busby et al. (2014). On the contrary, a relatively higher population count has a positive direct effect on number of conflicts. This is straightforward, since *ceteris paribus* conflicts are more likely to occur in highly populated places. The only exceptions where the effect is negative are associated to 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 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). 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) when considering 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 to GDP in level could be interpreted as a sign of the negative impact associated to 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

[11] 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.

neighbouring cells are experiencing a relatively higher increase in income per capita growth w.r.t. to cell *i*, this could bring to 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.

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: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Another element composing 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 to 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. In fact, 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 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 levels 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. When temperature increases in already drought areas, we find on the contrary a reduction in number of events by around 0.5%. This specific result might capture different mechanisms. First, very drought 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 sheperds do not fight during a time of scarcity but during periods of plenty. We will turn on this point when commenting on the role of precipitations.

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 at the local level. The only significant effect is defined in the case of 1y change where an increase by 1% in rainfalls 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 it. First, if 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.

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 the 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 1y case with an average elasticity equal to around 0.06%. Additionally, we also confirm that changes in precipitation levels have heterogeneous impacts according to the specific geographical features of the cell under scrutiny. If the SPI-12 index presents a positive value for the past five years it means that rainfalls are continuously larger 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.

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 |

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)

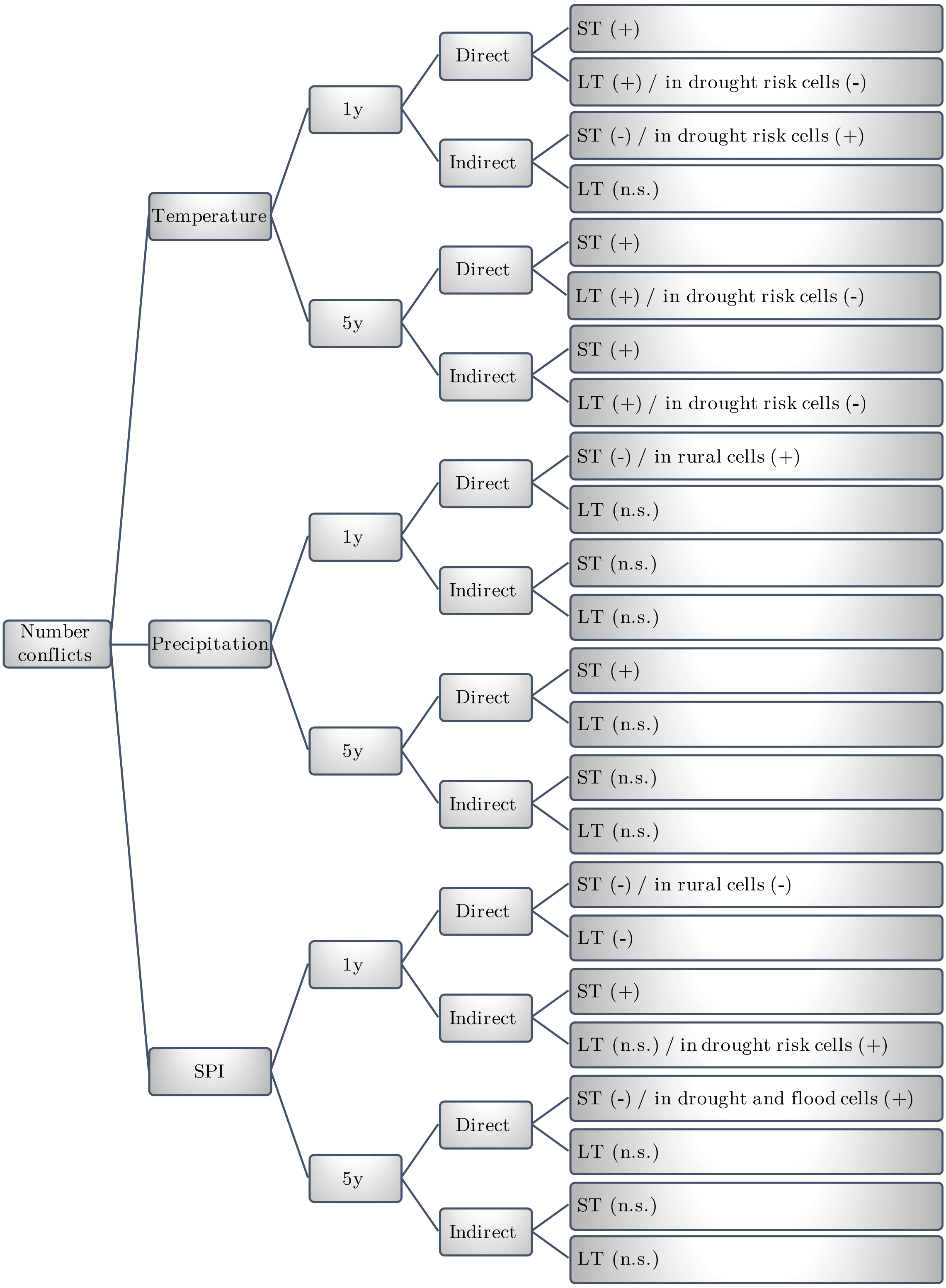
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Long-term Direct | | | | | | | | | | |
| GDP $_{it-1}$ | -0.079*** | -0.083*** | -0.032 | 0.021 | -0.041 | -0.822 | -0.055 | 0.045 | -0.024 | 0.090 |
| D1y-GDP-PC $_{it-1}$ | 1.538*** | 1.597*** | 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.

## 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 with respect to previous contributions.

First, by addressing the role of spatial spillovers we find that non-homogenous economic growth patterns at the local scale might exacerbate already vulnerable areas bringing to increased conflict propensity. The consequent policy implication is that in vulnerable areas development goals deserve to be achieved with equitable distribution as the first criterion to be respected.

Second, a high population density is a clear source of emerging frictions according to previous results (O'Loughlin et al., 2012; Theisen, 2012). In addition, we find that the concentration of a high number of individuals in surrounding areas might even 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.

Another aspect of socio-economic vulnerability we stress is related to the agriculture sector. Given the high number of cooperation projects applied to this sector, we suggest concentrating aid flows and also research activities for technology transfer in reducing vulnerability of agriculture to changes in climate conditions, particularly in those areas that are expected to be more exposed to strong anomalies.

Our results also provide evidence on the key role played by contagion and persistency over time thanks to the adoption of a dynamic spatially lagged model. In particular, 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.

With respect to specific climate conditions, our findings are in line with literature focusing on Africa as the number of conflicts arises when temperature increases. The novelty of our approach consists in considering the whole continent instead of selected areas, and more importantly disentangling short and medium-term changes in climate conditions and accounting for the role of geographical spillovers.

We emphasise two original results. 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.

Results related to changes in rainfalls are mixed. According with other georeferenced studies mainly focused on selected areas (e.g. Ethiopia, Kenya, and Uganda in Raleigh and Kniveton, 2012), we find 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.

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.

**References**


Adano, W. R., Dietz, T., Witsenburg, K., Zaal, F. (2012). Climate change, violent conflict and local institutions in Kenya's drylands. Journal of Peace Research, 49: 65–80.

Anselin, L. (1988). Spatial econometrics: methods and models. Kluwer, Dordrecht.

Anselin, L., Bera, A. K., Florax, R., Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics, 26: 77–104.

Auffhammer, M., Hsiang, S. M., Schlenker, W., Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy, 7: 181–198.

Barnett, J. Adger, W. N. (2007). Climate change, human security and violent conflict. Political Geography, 26: 639–655.

Bates, B., Kundzewicz, Z. W., Wu, S., Palutikof, J. P. (Eds.). (2008). Climate change and water. IPCC Secretariat, Geneva.

Benjaminsen, T. A., Alinon, K., Buhaug, H., Buseth, J. T. (2012). Does climate change drive land-use conflicts in the Sahel? Journal of Peace Research, 49: 97–111.

Billor, N., A. S. Hadi, and P. F. Velleman. 2000. BACON: Blocked adaptive computationally efficient outlier nominators. Computational Statistics and Data Analysis, 34: 279–298.

Bodea, C., Higashijima, M., Singh, R. J. (2016). Oil and Civil Conflict: Can Public Spending Have a Mitigation Effect? World Development, 78: 1–12.

Bosetti, V., Cattaneo, C., Peri, G. (2018). Should they stay or should they go? Climate Migrants and Local Conflicts (No. w24447). Cambridge, MA: National Bureau of Economic Research.

Braithwaite, A. (2010). Resisting infection: How state capacity conditions conflict contagion. Journal of Peace Research, 47: 311319.

Brochmann, M., Gleditsch, N. P. (2012). Shared rivers and conflict – A reconsideration. Political Geography, 31: 519–527.

Brzoska, M., Fröhlich, C. (2016). Climate change, migration and violent conflict: vulnerabilities, pathways and adaptation strategies. Migration and Development, 5: 190210.

Buhaug, H. (2010). Climate not to blame for African civil wars. Proceedings of the National Academy of Sciences, 107: 16477–16482.

Buhaug, H. (2015). Climate–conflict research: some reflections on the way forward. Wiley Interdisciplinary Reviews: Climate Change, 6: 269–275.

Burke, M. B., Miguel, E., Satyanath, S., Dykema, J. A., Lobell, D. B. (2009). Warming Increases the Risk of Civil War in Africa. Proceedings of the National Academy of Sciences, 106: 20670–20674.

Burke, M., Hsiang, S. M., Miguel, E. (2015). Climate and conflict. Annual Review of Economics, 7: 577–617.

Burrows, K., Kinney, P. (2016). Exploring the climate change, migration and conflict nexus. International Journal of Environmental Research and Public Health, 13: 443.

Busby, J. W., Smith, T. G., Krishnan, N. (2014). Climate security vulnerability in Africa mapping 3.01. Political Geography, 43: 51–67.

Butler, C. K., Gates, S. (2012). African range wars: Climate, conflict, and property rights. Journal of Peace Research, 49: 23–34.

Cai, R., Feng, S., Oppenheimer, M., Pytlikova, M. (2016). Climate variability and international migration: The importance of the agricultural linkage. Journal of Environmental Economics and Management, 79: 135–151.

Castells-Quintana, D., Lopez-Uribe, M. del P., McDermott, T. K. J. (2017). Geography, institutions and development: a review of the long-run impacts of climate change. Climate and Development, 9: 452–470.

Cattaneo, C., Bosetti, V. (2017). Climate-induced International Migration and Conflicts. CESifo Economic Studies, 63: 500–528.

Cilliers, J. (2009). Climate change, population pressure and conflict in Africa. Institute for Security Studies Papers No. 178: 1–20.

Collier, P. (2003). Breaking the Conflict Trap: Civil War and Development Policy. World Bank Publications.

Croicu, M., Sundberg, R. (2017). UCDP GED Codebook version 17.1. Department of Peace and Conflict Research, Uppsala University, available online at: http://ucdp.uu.se/downloads/ged/ged181.pdf (last download 08/01/2019).

Crost, B., Duquennois, C., Felter, J. H., Rees, D. I. (2018). Climate change, agricultural production and civil conflict: Evidence from the Philippines. Journal of Environmental Economics and Management, 88: 379–395.

Daccache, A., Sataya, W., Knox, J. W. (2015). Climate change impacts on rain-fed and irrigated rice yield in Malawi. International Journal of Agricultural Sustainability, 13: 87–103.

Dell, M., Jones, B. F., Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. Journal of Economic Literature, 52(3), 740-798.

Devlin, C., Hendrix, C. S. (2014). Trends and triggers redux: Climate change, rainfall, and interstate conflict. Political Geography, 43: 27–39.

Eckstein, D., Künzel, V., Schäfer, L. (2017). Global Climate Risk Index 2018: Who Suffers Most From Extreme Weather Events? Weather-Related Loss Events in 2016 and 1997 to 2016. Germanwatch Nord-Süd Initiative eV.

Elhorst, J. P. (2001). Dynamic models in space and time. Geographical Analysis 33: 119–140.

Elhorst, J. P. (2014). Spatial econometrics: from cross-sectional data to spatial panels. Springer, Heidelberg, New York, Dordrecht, London.

Ember, C. R., Abate Adem, T., Skoggard, I., Jones, E. C. (2012). Livestock Raiding and Rainfall Variability in Northwestern Kenya. Civil Wars, 14: 159–181.

FAO (2008). Climate change and food security: a framework document. Interdepartmental Working Group On Climate Change Document, FAO, Rome.

Fjelde, H., von Uexkull, N. (2012). Climate triggers: Rainfall anomalies, vulnerability and communal conflict in Sub-Saharan Africa. Political Geography, 31: 444–453.

Gizelis, T.-I., Wooden, A. E. (2010). Water resources, institutions, intrastate conflict. Political Geography, 29: 444–453.

Gleick, P. H. (2014). Water, Drought, Climate Change, and Conflict in Syria. International Security, 18: 79–112.

Gleick, P. H. (1993). Water and Conflict: Fresh Water Resources and International Security. International Security, 18: 79–112.

Harari, M., La Ferrara, E. (2018). Conflict, Climate, and Cells: A Disaggregated Analysis. The Review of Economics and Statistics, forthcoming.

Hegre, H., Buhaug, H., Calvin, K. V., Nordkvelle, J., Waldhoff, S. T., Gilmore, E. (2016). Forecasting civil conflict along the shared socioeconomic pathways. Environmental Research Letters, 11: 054002.

Hendrix, C. S., Glaser, S. M. (2007). Trends and triggers: Climate, climate change and civil conflict in Sub-Saharan Africa. Political Geography, 26: 695–715.

Holmberg, J. (2008). Natural resources in sub-Saharan Africa: assets and vulnerabilities. Current Africa Issue 39/2008. Uppsala: Nordiska Afrikainstitutet.

Hsiang, S. M., Meng, K. C., Cane, M. A. (2011). Civil conflicts are associated with the global climate. Nature, 476: 438–441.

Hsiang, S. M., Burke, M., Miguel, E. (2013). Quantifying the influence of climate on human conflict. Science, 341: 1235367.

Hsiang, S. M., Burke, M. (2014). Climate, conflict, and social stability: what does the evidence say? Climatic Change, 123: 39–55.

Ide, T., Scheffran, J. (2014). On climate, conflict and cumulation: suggestions for integrative cumulation of knowledge in the research on climate change and violent conflict. Global Change, Peace Security, 26: 263–279.

Kelejian, H. H. Prucha, I. R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. Journal of Econometrics, 157: 53–67.

Koubi, V., Bernauer, T., Kalbhenn, A., & Spilker, G. (2012). Climate variability, economic growth, and civil conflict. Journal of Peace Research, 49(1), 113–127.

Le Sage, J. P. Pace, R. K. (2009). Introduction to spatial econometrics. CRC Press, Taylor Francis Group, Boca Raton.

LeSage, J. P., Pace, R. K. (2014). The biggest myth in spatial econometrics. Econometrics, 2: 217–249.

Marchiori, L., Maystadt, J. F., Schumacher, I. (2012). The impact of weather anomalies on migration in subSaharan Africa. Journal of Environmental Economics and Management, 63: 355–374.

Maystadt, J. F., Ecker, O. (2014). Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks?. American Journal of Agricultural Economics, 96: 1157–1182.

Maystadt, J. F., Calderone, M., You, L. (2015). Local warming and violent conflict in North and South Sudan. Journal of Economic Geography, 15: 649–671.

McBride, M., Milante, G., Skaperdas, S. (2011). Peace and war with endogenous state capacity. Journal of Conflict Resolution, 55: 446–468.

Mehlum, H., Moene, K., Torvik, R. (2006). Cursed by resources or institutions? World Economy, 29: 1117–1131.

Meier, P., Bond, D., Bond, J. (2007). Environmental Influences on Pastoral Conflict in the Horn of Africa. Political Geography, 26: 716–735.

Miguel, E., Satyanath, S., Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. Journal of Political Economy, 112: 725–753.

Moore, F., Diaz, D.B., (2015). Temperature impacts on economic growth warrant stringent mitigation policy. Nature Climate Change, 5: 127–131.

Nordås, R., Gleditsch, N. P. (2007). Climate change and conflict. Political Geography, 26: 627–638.

O'Loughlin, J., Witmer, F. D. W., Linke, A. M., Laing, A., Gettelman, A., & Dudhia, J. (2012). Climate variability and conflict risk in East Africa, 1990–2009.

Proceedings of the National Academy of Sciences of the United States of America, 109(45), 18344–18349.
Onuoha, F. (2010). Climate change, population surge and resource overuse in the Lake Chad area. In D. A. Mwiturubani and J. A. van Wyk (Eds.), Climate Change and Natural Resources Conflicts in Africa, Institute for Security Studies Monographs, 170: 2345.
Ord, K. (1975). Estimation methods for models of spatial interaction. Journal of the American Statistical Association, 70: 120–126.
Otto, I. M., Reckien, D., Reyer, C. P., Marcus, R., Le Masson, V., Jones, L., ... & Serdeczny, O. (2017). Social vulnerability to climate change: a review of concepts and evidence. Regional Environmental Change, 17: 1651–1662.
Raleigh, C., Choi, H. J., Kniveton, D. (2015). The devil is in the details: An investigation of the relationships between conflict, food price and climate across Africa. Global Environmental Change, 32: 187–199.
Raleigh, C., Kniveton, D. (2012). Come rain or shine: An analysis of conflict and climate variability in East Africa. Journal of Peace Research, 49: 51–64.
Raleigh, C., Urdal, H. (2007). Climate change, environmental degradation and armed conflict. Political Geography, 26: 674–694.
Reuveny, R. (2007). Climate change-induced migration and violent conflict. Political Geography, 26: 656–673.
Ross, M. L. (2004). What do we know about natural resources and civil war? Journal of Peace Research, 41: 337–356.
Sarmidi, T., Hook Law, S. and Jafari, Y. (2014). Resource Curse: New Evidence on the Role of Institutions, International Economic Journal 28: 191–206.
Silve, A., Verdier, T. (2018). A theory of regional conflict complexes. Journal of Development Economics, 133: 434–447.
Sundberg, R., Melander, E. (2013). Introducing the UCDP Georeferenced Event Dataset. Journal of Peace Research, 50: 523–532.
Theisen, O. M. (2012). Climate clashes? Weather variability, land pressure, and organized violence in Kenya, 1989–2004. Journal of Peace Research, 49: 81–96.
von Uexküll, N. (2014). Sustained drought, vulnerability and civil conflict in Sub-Saharan Africa. Political Geography, 43: 16–26.
Weintrit, A., Kopacz, P. (2011). A Novel Approach to Loxodrome (Rhumb-Line), Orthodrome (Great Circle) and Geodesic Line in ECDIS and Navigation in General." Methods and Algorithms in Navigation, Marine Navigation and Safety of Sea Transportation. Leiden: A Balkema Book, CRC Press, Taylor and Francis: 123–132.
Weir, T., Virani, Z. (2011). Three linked risks for development in the Pacific Islands: Climate change, disasters and conflict. Climate and Development, 3(3), 193–208.
Wischnath, G., Buhaug, H. (2014). Rice or riots: On food production and conflict severity across India. Political Geography, 43: 6–15.
WMO (2018). WMO Statement on the state of the global climate in 2017. Working Document No 1212, Geneva, Switzerland.
Yu, J., de Jong, R. Lee, L. F. (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both N and T are large. Journal of Econometrics, 146: 118–134.

# 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)

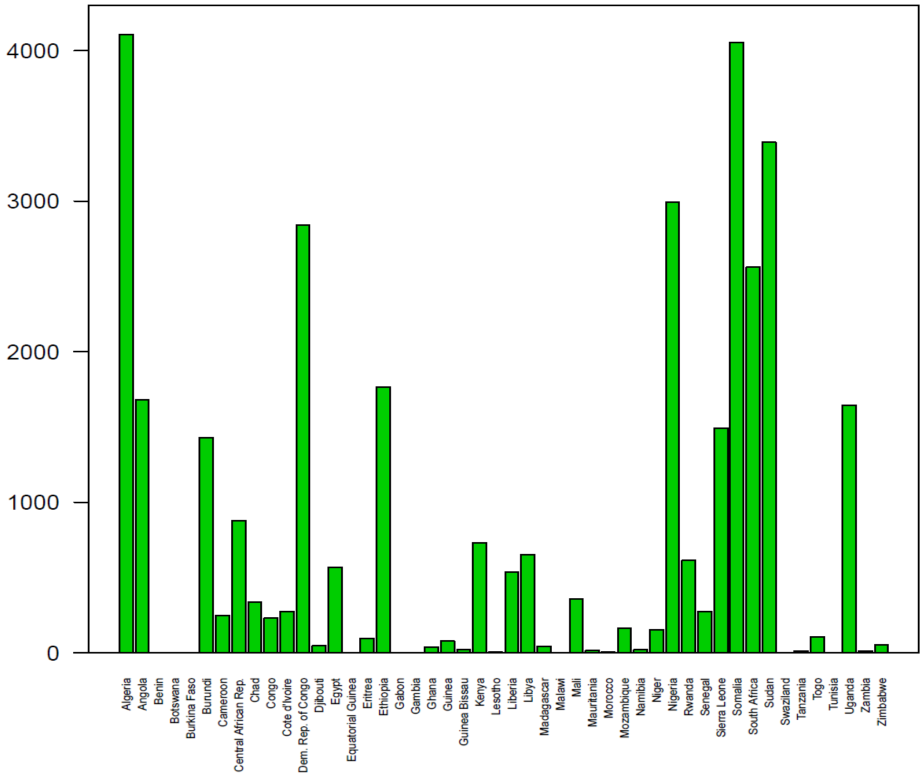



Figure A.2 – Total number of conflicting events by year (peak countries highlighted)

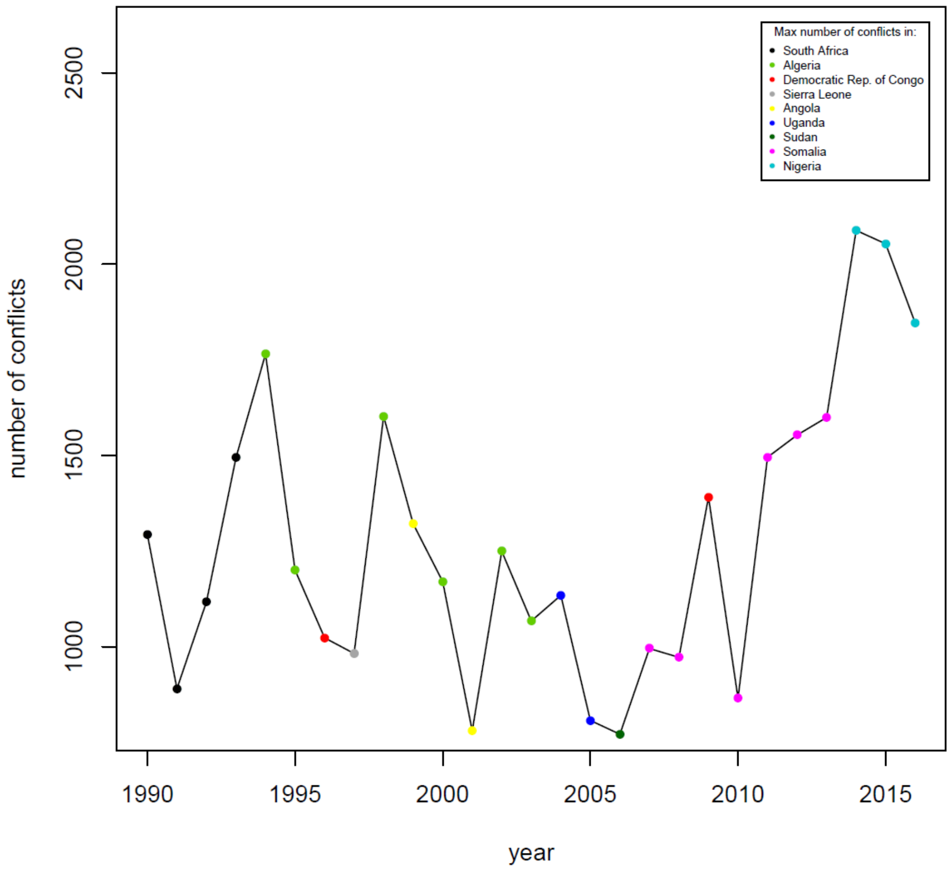


Figure A.3 – Cut-off distances with great circle formula and Queen approach

Max distance great circle formula | Max distance great circle formula+Queen

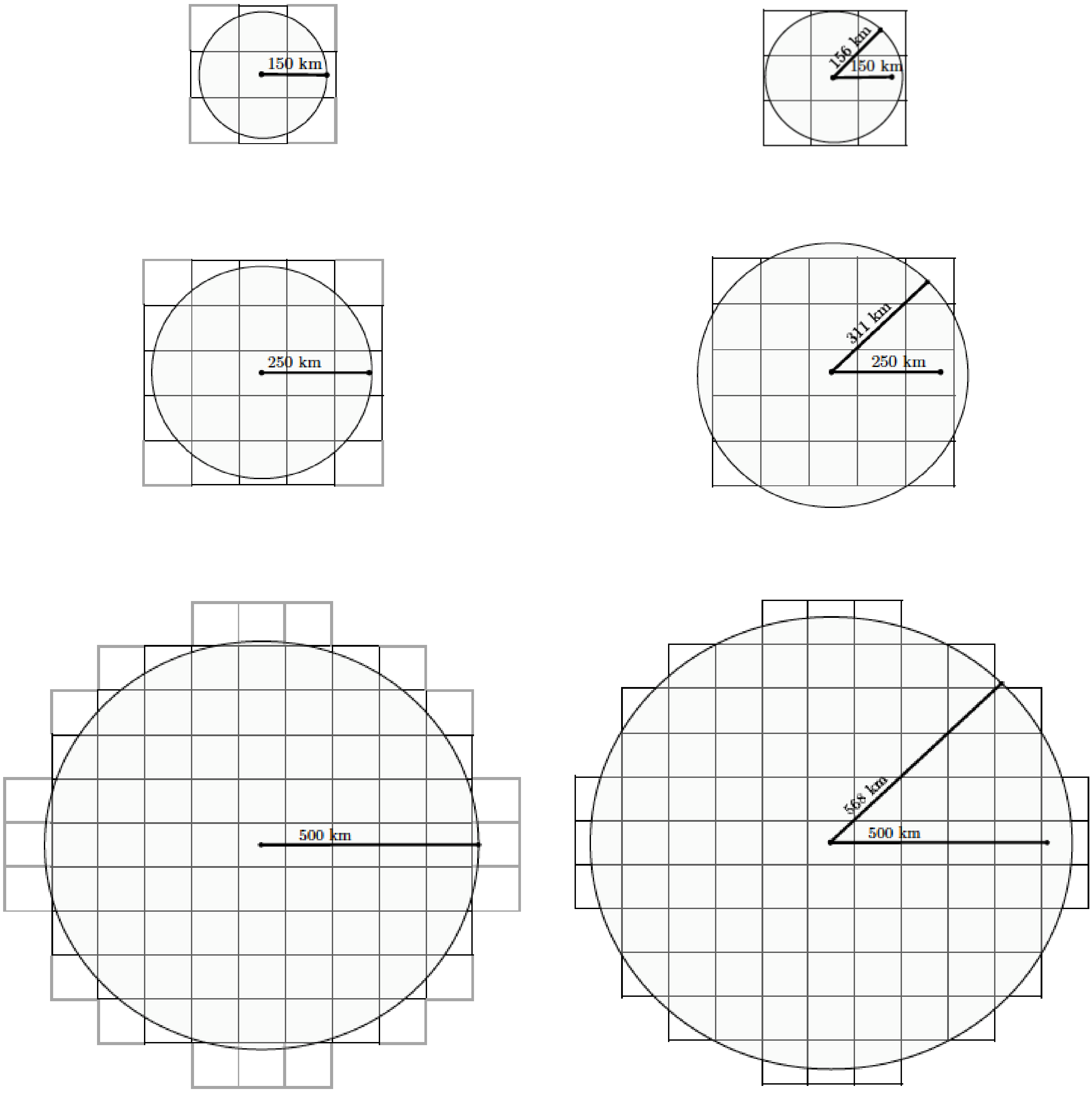


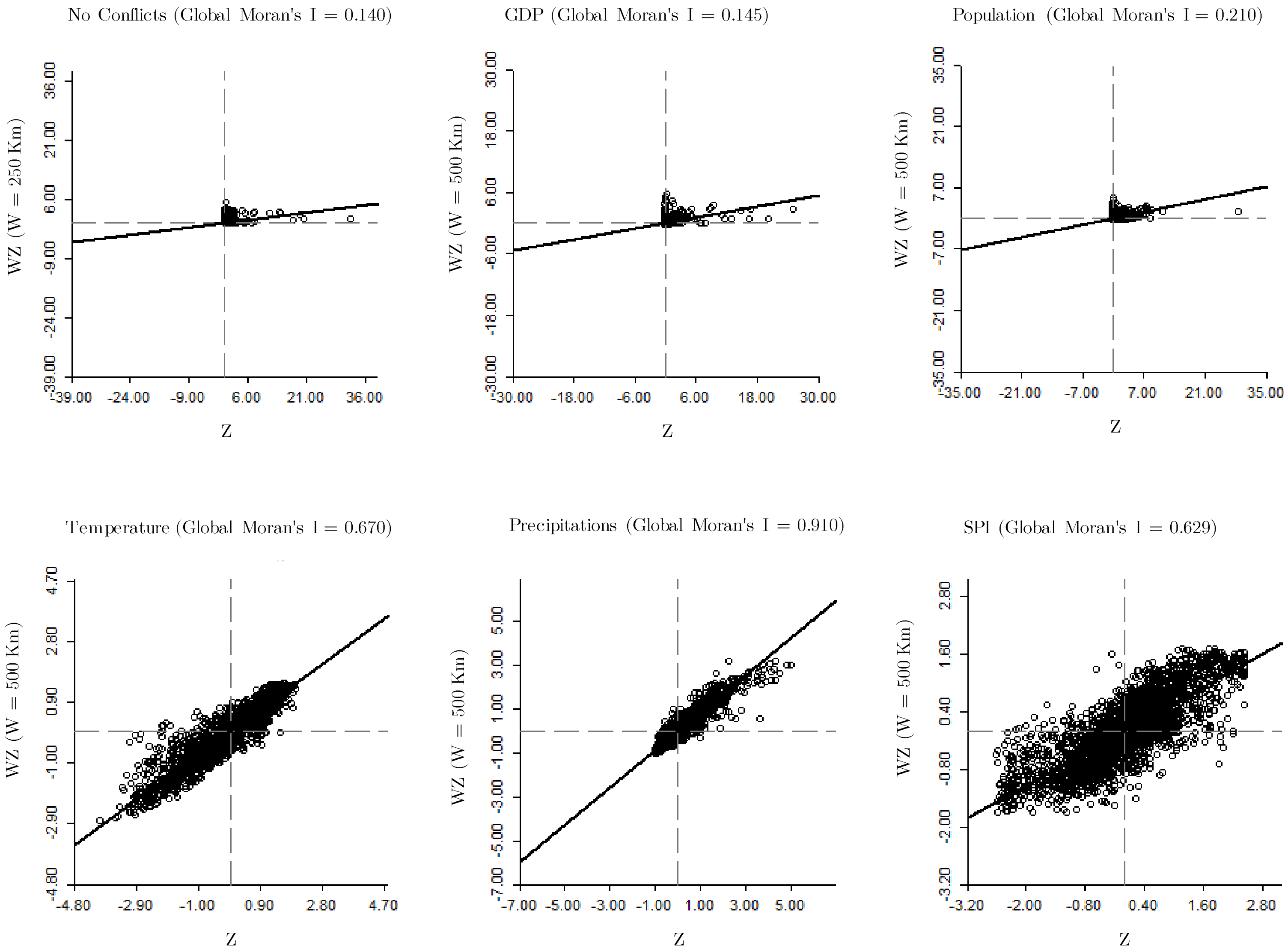
Table A.3a – Moran's I

| | 150 KM | | | | | | 250 KM | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | 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

| | 500 KM | | | | | | 1000 KM | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | 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)



## 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 ($\alpha$) | | | | | 0.475$^{***}$ | | 0.463$^{***}$ |
| | | | | | (0.01) | | (0.01) |
| $W_{150}$NC it ($\rho$) | 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 $\rho$) | | | | | | 0.853$^{***}$ | 0.106$^{***}$ |
| | | | | | | (0.37) | (0.23) |
| GDP it | -0.047$^{***}$ | -0.012$^{***}$ | -0.064$^{***}$ | | | | |
| | (0.00) | (0.00) | (0.01) | -0.057$^{***}$ | -0.021$^{***}$ | -0.042$^{***}$ | -0.020$^{***}$ |
| GDP it-1 | | | | (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 ($\alpha$) | | 1.721*** | | 0.493*** |
| | | (0.01) | | (0.01) |
| $W_{250}$NC it ($\rho$) | 0.457*** | 0.866*** | 0.479*** | 1.122*** |
| | (0.03) | (0.11) | (0.09) | (0.00) |
| $W_{250}$NC it-1 (lag $\rho$) | | | 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 ($\alpha$) | | $0.396^{***}$ | | $0.455^{***}$ |
| | | (0.01) | | (0.01) |
| $W_{500}$NC it ($\rho$) | $0.291^{***}$ | $0.409^{***}$ | $0.431^{***}$ | $0.672^{***}$ |
| | (0.01) | (0.06) | (0.04) | (0.04) |
| $W_{500}$NC it-1 (lag $\rho$) | | | $2.245^{***}$ | $0.140^{***}$ |
| | | | (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 ($\alpha$) | 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 ($\rho$) | 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 $\rho$) | | | | | | | -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*** |
| $M_{150,250,500}$ ($\lambda$) | 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 ($\alpha$) | 0.752*** | 0.535*** | 0.486*** | 0.753*** | 0.520*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| $W_{250}$NC it ($\rho$) | 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 ($\alpha$) | 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 ($\rho$) | 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* | | | | | | | | |
| 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) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 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 ($\alpha$) | 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 ($\rho$) | 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) | (0.01) | (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* | | | | | | | | | | |
| 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$^{***}$ |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | (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; $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$