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Forecasting the climate-conflict risk in Africa along climate-related scenarios and multiple socio-economic drivers

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ABSTRACT

This study investigates how climate change might impact economic development in the future through its effects on violence, addressing the gap in research on long-term conflict risk assessment. Using geocoded data (1° resolution) on climate and socio-economic indicators covering 1990–2050, we employ a forecasting recursive model to examine the probability and intensity of different types of conflict, under various socio-economic and climate scenarios. Our analysis reveals that climate change has both direct and indirect effects on violence, highlighting the key role of the agricultural channel, the spillover across neighbouring areas and the socio-economic context. These findings offer new insights into adaptation strategy and provide implications for the need to jointly account for the complex interactions between climate conditions, socio-economic factors, and conflict dynamics.

1. Introduction

Because climate change challenges increasingly threaten both human society and natural systems, growing attention is dedicated to understanding how these risks will affect economic well-being, development opportunities and, ultimately, social cohesion and peace in the future (O'Neill et al., 2022). The scientific debate on the potential role of changes in climatic conditions in influencing the occurrence, magnitude and persistency of violent events is growing and benefiting from multiple approaches and case studies. However, despite extensive analysis of the climate-conflict nexus from a backward perspective, a research gap remains in the analysis of long-term conflict risk projections (de Bruin et al., 2022). Several issues are still open, and uncertainty remains about the impact of different climate-related variables and the temporal horizon to be investigated (Koubi, 2019). According to Mach et al. (2019), the design of future scenarios for the climate-conflict nexus should jointly rely on the extrapolation of the mechanisms that emerged from historical relationships and the use of future climate and socioeconomic pathways. This approach aims to reduce the high level of uncertainty due to the unpredictable evolution of human behaviours and reactions to climate change effects that are fundamentally beyond previous experiences.

Contributions investigating the historical relationships indicate a link between increasing temperature and/or changing rainfall patterns and violent conflicts (Fjelde and von Uexkull, 2012), while others find no significant impacts (Buhaug et al., 2015). Different studies suggest that both higher (Salehyan and Hendrix, 2014) and lower (Almer et al., 2017) precipitations, as well as deviation from the normal rainfall level (La Ferrara and Harari, 2018) could lead to conflicts, revealing that localized effects of weather variability are gaining relevance due to the increasing availability of high-frequency climate data (Manotas-Hidalgo et al., 2021). Overall, studies based on fine-grained geographical data are increasingly suggesting that non-linearity is a key point to be addressed, as both water scarcity and its relative abundance might be a source of political instability (Raleigh and Kniveton, 2012; Salehyan and Hendrix, 2014).

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While there is not universal agreement about the magnitude or direction of climate variability's impact on violence, one point is consistently acknowledged: climate change does not necessarily increase conflict risk *per se*, but rather should be considered a threat multiplier. In this perspective, socio-economic factors and local characteristics are recognized as strong determinants of conflicts, implying the necessity of accounting for context-specific aspects which may indirectly enhance or mitigate the risk of violence.

A prominent example in this regard is given by the agricultural channel, an important (indirect) mechanism in the climate-conflicts nexus operating through shocks to agricultural production and incomes (La Ferrara and Harari, 2018; Von Uexkull et al., 2016). Agricultural activities follow a seasonal cycle, and crops are more sensitive to unfavourable conditions during the growing season. Climate anomalies recorded during those months are more likely to result in lower yields and reduced agricultural production, which would also lead to lower agricultural income, higher food prices and food insecurity. These negative effects on local socio-economic conditions could potentially fuel violence (Baronchelli, 2022; Caruso et al., 2016; Li et al., 2022).

Furthermore, previous literature agrees on the largely interconnected nature of conflict dynamics across neighbouring regions, and suggests that the consequences of local weather variability should also account for spatial interactions with surrounding territories, the main reason being that the consequences of climate-related resource scarcity and competition is likely to spread out of the primary affected areas (von Uexkull and Buhaug, 2021). This is what La Ferrara and Harari (2018) find when short-term weather stresses are directly linked to agricultural harvest. van Weezel (2020) adds evidence on the key role played by spatial spillovers in determining the influence of long-term changes in climatic conditions (mainly temperature) on local violence. Similarly, Vesco et al. (2021) identify spatial impacts of drought on crop production as a cause of civil conflict onset, especially in agriculture-dependent areas characterized by economic inequalities.

A complimentary stream of evidence is provided by Linke and Ruether (2021) suggesting that adverse climate variability increases the incentives to control scarce crops or facilitates recruitment of militants, and that violence can be used to control valuable cropland and harvests, to prevent opponent groups to access these resources. Because climate-induced resource scarcity may motivate human displacement and mobility, leading to additional pressure in areas people move to, introducing spatial lags of covariates to account for geographical spillovers is highly recommended. Especially in cases of widespread climate hazards, this may result in higher resource competition, motivation and low opportunity cost to engage in violence due to intensifying fight for water access and land use, ultimately spurring contagion across space (Benjaminsen et al., 2012).

Whether the estimated impacts are significant or not, might also result from the inclusion of local-specific controls related to socio-political features (Klomp and Bulte, 2013). More resilient communities experience lower risks of violence when facing climate stress or shocks (Burke et al., 2015), but uncertainties remain about how sources of local vulnerability and the measurement of local climate-related effects should be included in the empirical setting (Hsiang, 2016; Ide, 2017).

Despite these various aspects influencing the climate-conflict risk have been extensively analysed with a backward perspective (i.e., taking into account historical information), it has not yet been assessed (if and) how the same indirect channels and mechanisms may shape long-term conflict risk. This research gap persists even as projected down-scaled geocoded data on both climate and socio-economic features become increasingly available, providing additional opportunities to develop scenario analysis, including the occurrence and magnitude of violence as one of the negative side effects of global warming (O'Neill et al., 2020). Among the few works that have analysed the climate-related conflict risk, Hegre et al. (2016) use the Shared Socioeconomic Pathways (SSPs) to forecast conflicts over time with a recursive method at the country level. More recently, Petrova et al. (2023) analyse the incidence of the conflict trap on economic growth along SSPs and suggest that expected income through the 21st century would be about 25% lower when accounting the harm to growth caused by conflicts.[1] More fine-grained forecasting exercises are provided by Witmer et al. (2017) and Hoch et al. (2021). The former compute the conflicts projections at 1° degree resolution for Sub-Saharan Africa up to 2065 accounting for temperature anomalies under the main socio-economic dimensions from SSPs and adopting a plug-in forecasting method. Hoch et al. (2021) forecast the probability of conflicts in Africa at the level of sub-national water provinces between 2015 and 2050, adopting a machine learning approach and accounting for climate drivers indicators of water-related environmental stress.[2]

Along with these attempts, we propose a long-term forecasting analysis of armed conflicts applied to the entire African continent based on a grid of 2,653 cells at 1° resolution (each cell covers an area of around 110 × 110 km). The yearly database covers the time span 1990–2050, thus merging historical information and SSPs projections.

The first novelty of our approach is that we jointly account for both the intensive (if an area is involved by a conflict onset) and extensive (the number of conflict events recorded in a given cell in the reference year) margins, while previous climate-conflict forecasting studies performed at local scale focus either on whether a local area experienced a conflict (binary outcome) or on the number of conflicts registered. Following the intuition developed in Mack et al. (2021), working with a count dependent variable rather than a binary one allows accounting for transition from peace to war but also the relative position with respect to the average level of violence. At the same time, it is crucial to control for factors explaining why a given area may (or may not) being prone to experience conflicts onset.

Second, we enrich the modelling of the climate-conflict risk by disentangling the indirect mechanisms mediated by the agricultural channel and accounting for geographical spillovers of climate variability, while previous forecasting studies only accounted for the direct effects of climate variations *per se*. We include local indicators of long-term temperature increase, non-linear precipitation anomalies (distinguishing drying and flooding events), and focus of the agricultural channel to isolate the indirect effect of climate variability.

Third, given that not all conflictual activities may suffer from the same effect of climate, and results might be sensitive to the definition of conflict (de Bruin et al., 2022), we extract information on violent events from two alternative and widely diffused sources: the Uppsala Conflict Data Project - Georeferenced Event Dataset (UCDP), and the Armed Conflict Location & Event Data Project (ACLED). Although both sources are often interchanged (e.g., La Ferrara and Harari, 2018; Witmer et al., 2017), UCDP includes only events with at least one battle-related death, while ACLED also includes 'potential' (or 'threatened') violence which can, but not necessarily, involve human fatalities (e.g. riots, troop movements).[3]

Fourth, we develop a recursive forecasting econometric method, informed year by year by changes in the projected explanatory factors, thus producing predicted outcomes that are based on a learning process. This allows accounting for the dynamics in the forecasting method

[1] This confirms previous findings according to which conflicts negatively affect both economic growth and development outcomes (Le et al., 2022).

[2] Complimentary evidence is provided by a Special Issue (SI) of the journal *International Interactions*. The SI organized a prediction competition with the aim of collecting works based on the ViEWS system, UCDP-GED data and machine-learning methods to predict changes in the number of fatalities per month from state-based conflicts (Hegre et al., 2022; Vesco et al., 2022), i.e., (de)escalation of violence. The call (open in March 2020) requested forecasts for the near future (from October 2020 to March 2021) and test on historical data.

[3] Additional details on the two sources of conflicts data are provided in Section 2.3.

to control for the persistency of violence over time and its influence in the predicted events (Hegre et al., 2017).

Our results show that our model predicts a higher number of conflict events compared to previous studies (even higher when accounting for spatial spillovers). This suggests that when considering how climate interacts with other factors (e.g., mediated by the agricultural channel and other socio-economic drivers), its effect is stronger. Indeed, conflict events are mostly driven by indirect climate effects, here proxied by the pressure caused by unexpected changes in water availability for agriculture during the cell-specific months of the crops growing season.

We also find that the socio-economic context can play a crucial role in determining the effect of climate on conflict. Specifically, the effect is magnified in scenarios of high degree of spatial inequality and intense resource exploitation, and reduced in scenarios with a generalized lack of resource or less resource competition.

The rest of the paper is organized as follows. In Section 2 we present the database, the count-based econometric model and the forecasting method applied to build scenarios at the grid level. Section 3 provides main results on the projections of conflicts events using both UCDP and ACLED data under different SSPs, and Section 4 concludes.

2. Data and methods

We are interested in understanding the determinants of past violence in Africa to forecast conflicts at the cell level up to 2050 under different SSPs and Representative Concentration Pathways (RCPs) scenarios. To investigate the implications that future climate and socio-economic scenarios may have on violence, we develop an empirical analysis which combines an econometric model on historical data (Section 2.1) with a forecasting analysis along different future pathways (Section 2.2).

We test our model taking as dependent variable the total number of conflict events recorded in each cell and year, as measured by ACLED and UCDP (see Section 2.3 for additional details on conflicts data). We select the variables of interest to represent the main mechanisms empirically tested by previous contributions (e.g., population size, socioeconomic development, ethnic fractionalization, geographical features) and define a parsimonious model where time-variant indicators are available for both historical and future timelines. The description of the database covering the African continent at 1° resolution from 1990 to 2050 by SSPs-RCPs, along with the definition of the indicators used in the empirical analysis, is presented in Section A.1 of the Appendix.

2.1. The econometric model

A major challenge in our analysis is represented by the fact that conflict does not arises frequently, but only in selected places and with different intensities. It follows that our outcome is a count variable characterized by overdispersion and excess of zeros (91% of all cell-year observations in UCDP and 84% in ACLED). This is an important feature of our data, which mandates to account both for the probability to observe a conflict (the extensive margin) and the intensity of the conflict (the intensive margin).

Accordingly, we model this process of selection based on the historical information using a zero-inflated negative binomial (ZINB) for count data following Cappelli et al. (2022). This model allows to properly account for the existence of structural zeros and to separate this process from the count model (Cameron and Trivedi, 2013; Hilbe, 2014). The ZINB model consists in two parts: (i) the *Count model*, here formalized as a negative binomial, is used to model the number of conflict events; (ii) the *Zero model* is binary and allows distinguish the causes behind the occurrence of structural zeros (i.e., cells not experiencing conflicts, for instance because their territory is covered by desert or water, which prevents anthropic activities, resulting in unpopulated places). The ZINB model is thus particularly useful to study the issue at hand because the event of a conflict is rare, and it is unclear whether the preponderance of peace cases typically observed in conflict datasets is due to inherent rarity of the phenomenon or to heterogeneous mix of actual and inflated peace observations (Cappelli et al., 2022; Price and Elu, 2017). Additionally, the ZINB specification is highly recommended in the case of forecasting exercises (Bagozzi, 2015).

By expressing the negative binomial component with a logistic link, the conditional mean can be written as a function of a set of covariates X_{it} explaining whether or not some cells experience violent breakouts (i.e., whether the count variable for each statistical unit is ≥ 0 across years). The *Count model* is thus given by:

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

In the *Zero model*, the probability of structural zeros π_{it} is expressed as a function of a set of covariates Z_{it} using the inverse logit function:

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

Variables included in the *Count* and *Zero* models have been selected based on prior literature and on the requirement to adopt a parsimonious specification (i.e., climate and socio-economic indicators available both for the past and future timelines). Hence, the covariates included in the *Zero model* (set Z_{it}), representative of structural zeros, are the demographic dimension (inhabitants at time $t-1$) and the geographical features of each cell (qualifying the presence of cities, desert or forest). In the baseline specification of the *Count model* we include (set X_{it}) the time-variant socio-economic indicators (lagged population, growth rate of income per capita, income distribution measured by the Gini index at the cell level) and literature-based time-invariant features (the degree of ethnic fractionalization and the proximity to the national border).[4] We then test seven alternative model specifications, including different indicators for changes in climatic conditions and the role of the agricultural channel: long-term change in temperature and precipitation, flooding and drying soil humidity conditions (measured by positive and negative values of the Standardized Precipitation Evapotranspiration Index, SPEI), and the intensity of dry and wet anomalies occurring during the main crops' growing season. We follow Von Uexkull et al. (2016) and compute our synthetic cell/year measure as the share of growing-season months in which a drought or an excess in water has been recorded.[5]

The *Count model* also incorporates a vector of fixed effects (FE). In spatial analysis the observed data usually refer to adjacent units in an uninterrupted area, and the way FE should be modelled in small-scale spatial analyses is still controversial. Recent contributions suggest adopting linear probability models with cell-specific FE (Almer et al., 2017; Breckner and Sunde, 2019): this would avoid the potential bias deriving from including a large number of FE into non-linear models applied to large samples (Fernández-Val and Weidner, 2016). However, given the nature of our count dependent variable, a mixture model specification is preferable and, to avoid the potential bias derived from an excessive number of fixed effects, we adopt country rather than cell-specific FE in the *Count model* to control for heterogeneity (Witmer et al., 2017).

We further extend the static model specification with time dynamic components to account for serial correlation and improve the model's

[4] We test the robustness of our baseline model against the following alternative specifications: we employ the change in population rather than population in level; we replace GREG data on ethnic fractionalization with information from the Geo-referencing Ethnic Power Relations (Geo-EPR) dataset; we add a proxy for institutions at the country level; we replace the forest and desert dummy variables with the continuous information on the cell's area (%) covered by desert and forest; we add in the Count model the distance from the capital city. In all these cases, our results remain unchanged. See Tables A6 and A7 in Section A.3 in Appendix.

[5] See Section A.1 in Appendix for additional details on the covariates included in the dataset.

forecasting performance. Accordingly, we adopt a parsimonious specification by introducing in the *Zero model* the lagged number of conflict events recorded in cell i in the previous year (Y_{it-1}) to control for persistency (Glaser et al., 2022).[6] Given that the impact of weather shocks is not immediate on human activities (La Ferrara and Harari, 2018), all time-variant covariates are lagged by one-year.

Finally, a key factor explaining the climate-conflict nexus is the presence of spatial dynamics associated with climate and socio-economic conditions recorded in neighbouring cells (Chica-Olmo et al., 2019). The introduction of spatial interaction effects is not trivial in count data models. Indeed, given that the ZINB *Count model* does not include a random error term, accounting for the spatial structure in the unexplained part of the dependent variable is not as straightforward as in linear regression models. The introduction of endogenous interaction effects is also controversial in count data models because there is no direct functional relationship between the regressors and the dependent variable, but only a relationship between the regressors and the conditional expectation of the response. On the contrary, the introduction of exogenous interaction effects raises no particular issues since spatially lagged regressors can be computed before the actual regression is performed and treated in the same way as the non-spatial ones (Simões and Natário, 2016). By introducing exogenous spatial spillovers, we test whether climate variability is likely to foster tensions over control for valuable cropland and harvests or water access, fuelling fights to control scarce crops also in surrounding areas.[7]

These effects (set WX_{it-1}) can be included in a spatial econometric setting by means of a non-negative weight matrix W, where the generic element w_{ij} describes whether cells i and j are neighbours, thus representing the spatial configuration of the units in the sample. The weight matrix adopted in this work only accounts for spatial spillovers across neighbouring cells: i.e., those cells located within a given distance from the considered cell. In other words, a cell is neighbour of another cell only if the centroid of the former is included within the buffer surrounding the latter. Given our gridded dataset, where all cells share the same dimension, the buffer surrounding each cell for the different cut-offs is computed on the basis of a radius that include all centroids of the cells belonging to the subsequent ring. This ensures the inclusion of all cells, allowing for consideration of cells within or tangent to a single point. Because the results can be sensitive to the choice of the cut-off, we test five distance radius to define neighbours (178, 266, 355, 444, 533 km), thus obtaining five different weight matrices, referred in the paper as to W_d, with $d \in (1, 5)$, each including the first *d-th* rings of neighbours of cell *i*.

In defining the spatial weight matrix W, geographical distances are computed by the Mercator's projection accounting for the spheroidal form of the Earth, and measured as inverse (great circle) distances via the Haversine formula between the centroids of cells. The normalization procedure is based on Ord (1975) and results in a symmetric weight matrix obtained by normalizing W by $D^{--1/2} W D^{--1/2}$, where D is a diagonal matrix containing the row sums of W, ensuring an economic interpretation of distances due to the mutual proportions between its elements (Elhorst, 2014).

The introduction in Eqs. (1)–(2) of the exogenous spatial effects, persistency, temporal dynamics and fixed effects leads to a ZINB spatial model as follows:

$$E(Y_{it}|\mathbf{X}_{it-1}, \mathbf{WX}_{it-1}, \mathbf{F}_i, \mathbf{C}_c, \mathbf{Z}_{it-1}, \mathbf{L}_i, Y_{it-1}) = (1-\pi_{it})exp(\alpha + \mathbf{X}'_{it-1}\beta + \mathbf{WX}'_{it-1}\theta + \mathbf{F}'_i\eta + \mathbf{C}'_c\varphi) \quad (3)$$

$$\pi_{it} = \frac{exp(\delta_i + \mathbf{Z}'_{it-1}\gamma + \mathbf{L}'_i\rho + Y_{it-1}\sigma)}{1 + exp(\delta_i + \mathbf{Z}'_{it-1}\gamma + \mathbf{L}'_i\rho + Y_{it-1}\sigma)} \quad (4)$$

where $\mathbf{Z}_{it-1}$ and $\mathbf{X}_{it-1}$ are lagged time-variant covariates, while $\mathbf{L}_i$ and $\mathbf{F}_i$ are time-invariant cell-based geographical features. In the *Count model* Eq. (3), θ is the coefficient of the exogenous spatial interactions associated to the covariates of neighbouring cells j (with $j \neq i$) weighted by the inverse distance matrix W ($\mathbf{WX}_{it-1}$). Country FE are given by $\mathbf{C}_c$ and serial correlation is controlled by the coefficient σ associated to Y_{it-1}.

2.2. The forecasting approach

Long-term forecasting exercises involve predicting multiple steps ahead, typically facing growing uncertainty especially in the case of recursive phenomena. Indeed, forecasting handled recursively means that each step ahead is computed using prior forecasts as input. Three main groups of multi-step forecasting methods are available for recursive estimation.

First, the plug-in method use historical data to estimate the model coefficients, which are then applied multiple times across the entire future time span. Predicted values are obtained by repeatedly using the fitted model, with unknown future values replaced by their own forecasts (Ing, 2003).

Second, the direct method involves estimating coefficients of the h-step prediction model separately at each step model using a rolling window approach. This method uses specific windows of data to re-estimate the parameters over the out-of-sample period. Thus, a distinct model for each forecasting horizon is estimated solely using the observed data, with forecasts computed as the first out-of-sample prediction (Chevillon, 2007; Ing, 2003). Given that the direct strategy does not use approximated values to compute the forecast, it is immune to the accumulation of errors. However, each h-th model is obtained independently from the others, resulting in conditional independence of the forecasts that can affect predictive accuracy due to the inability to account for complex dependencies over time (Ben Taieb et al., 2012).

Third, the recursive method also employs a multi-step strategy, adopting either a rolling or recursive-window approach. The former uses fixed-length temporal windows that roll over time to track forecasts, while the latter employs increasing temporal windows incorporating all available historical data plus previous forecasts to re-estimate the models. The recursive approach combines aspects of both plug-in and direct methods by using a different model at each step (like the direct method) and incorporating previous forecasts as input (like the plug-in method) (Petropoulos et al., 2022).[8]

Both plug-in and the recursive approaches require previous forecasts for computing new forecasts, allowing prediction errors to accumulate (i.e., errors associated to intermediate forecasts will propagate forward). In contrast, direct forecasting is immune to the accumulation of errors, as it does not require to iterate the forecast, but the different models that it considers are learned independently, and this induces a conditional independence of the different forecasts that can affect the forecasting accuracy. Moreover, the direct approach involves a

[6] In a robustness check we include the lagged number of conflict events in the count model rather than in the zero model, and the results remain qualitatively unchanged. See Tables A6 and A7 in Section A.3 in Appendix.

[7] Spatial interactions have been modelled in different ways by the literature. Research interested in understanding the intensive margin of conflict outbreak (thus neglecting its extensive margin) modelled spatial interactions with (either or both) spatially-lagged dependent and independent variables (see among others (Cappelli et al., 2020, 2024)). On the contrary, Cappelli et al. (2022), who choose to account for both the intensive and the extensive margin of conflict outbreak, had to consider exogenous spatial spillovers (as this was the only possibility offered by the current econometric literature in this setting), i.e., whether changing climate and socio-economic conditions recorded in neighbouring areas have an impact on conflict. We choose to follow this latter approach, as it allows for a more comprehensive understanding of conflict dynamics, and we extend it by also considering forecasted data.

[8] While the plug-in approach requires estimation of only one model (whose coefficients are used multiple times to iterate on the forecasting horizon), direct and recursive forecasting methods require the estimation of multiple models, thus imposing a heavier computational burden.

Table 1
Scenario setting.

	RCP	GHG emissions	Estimated average warming (2041–2060)	SSP framework
SSP1	2.6	Low GHG emissions: CO2 emissions cut to net zero around 2075	1.7 °C	Green growth paradigm (van Vuuren et al., 2017)
SSP2	4.5	Intermediate GHG emissions: CO2 emissions around current levels until 2050	2.0 °C	Middle of the road (Fricko et al., 2017)
SSP3	8.5	Very high GHG emissions: CO2 emissions triple by 2075	2.4 °C	Regional rivalry (Fujimori et al., 2017)
SSP4	4.5	Intermediate GHG emissions: CO2 emissions around current levels until 2050	2.0 °C	A world of deepening inequality (Calvin et al., 2017)
SSP5	8.5	Very high GHG emissions: CO2 emissions triple by 2075	2.4 °C	Fossil-fuelled development (Kriegler et al., 2017)

diminishing sample size as the forecasting horizon increases, leading to increased variance in the parameter estimates and Mean Square Forecast Errors (MSFE).

Lastly, a bias–variance trade-off exists in choosing between rolling and recursive forecasting schemes. Using earliest available data that do not conform to present data-generating process may yield biased parameter estimates and forecasts, may yield biased parameter estimates and forecasts. However, reducing the sample to minimize heterogeneity increases variance in parameter estimates and MSFE. Thus, a balance is needed between using too much or too little data to estimate model parameters. Notably, a recursive approach based on a rolling window would imply at some point the use of only past forecasts (without historical data) for model estimation in case of a long forward temporal horizon and limited backward information (Marcellino et al., 2006).

The recursive strategy with recursive windows seems to be the best choice in the case of long-term forecasts with a relatively short-term backward period using historical observations (Ben Taieb and Hyndman, 2014). Thus, we apply a recursive approach where, in each h-step, the forecasted value is obtained by running a distinct one-step model that incorporates the previous forecasted value as input. Formally, this is expressed as:

$$\hat{y}_{N+h} = \begin{cases} \hat{f}_h(y_N, y_{N-1}, \dots, y_{N-g}) \text{ if } h = 1 \\ \hat{f}_h(\hat{y}_{N+1}, y_N, y_{N-1}, \dots, y_{N-g}) \text{ if } h = 2 \\ \hat{f}_h(\hat{y}_{N+T}, \dots, \hat{y}_{N+1}, y_N, y_{N-1}, \dots, y_{N-g}) \text{ if } h = T \end{cases} \tag{5}$$

where $g \in (0, N)$ represents the historical data (1990–2020), and $h \in (1, T)$ denotes the forecasting horizon (2021–2050).[9]

Similar to Hoch et al. (2021), we consider a forecasting timeline up to 2050 under different scenarios. Projected climate data are defined by three RCPs about future Greenhouse Gas (GHG) emissions paths: RCP 2.6 (mitigation scenario), RCP 4.5 (stabilization scenario) and RCP 8.5 (very high GHG emissions scenario). Projections for socio-economic indicators (GDP, population, and Gini index) follow SSPs narratives coherent with the 6th IPCC Assessment Report (Arias et al., 2021), using the same SSP-RCP combination adopted by Witmer et al. (2017) to ensure comparability across studies.[10] The scenario setting used in the forecasting exercise is summarized in Table 1.

2.3. Conflict data

Our dependent variable is the total number of conflict events per cell/year. Given that results might be sensitive to the definition of conflict (de Bruin et al., 2022), we extract information on violent events from two sources. The first is the Uppsala Conflict Data Project - Georeferenced Event Dataset (UCDP), which records violent events from 1990.[11] The second source is the Armed Conflict Location & Event Data Project (ACLED), which similarly provides dyadic conflict data with a high level of spatial accuracy from 1 January 1997.

The UCDP and ACLED datasets are similar in nature, but differ in their reporting criteria. First, one inclusion rule in UCDP is to record all events (of all UCDP conflict dyads that crossed the 25-deaths threshold in a single year) resulting in at least one battle-related death.[12] In contrast, ACLED cover political violence (i.e., the use of force by a group with a political purpose or motivation) and includes events without imposing any fatalities threshold (Eck, 2012). Moreover, the conflicts sides and the types of violence are also partly different in the two datasets. In UCDP the actors can be governments or organized groups resulting in three types of conflicts: state-based if one side is the government of an independent state, non-state based (recording violence between formally or informally organized groups) and violence against civilians. ACLED adopts a different classification and includes also non-violent conflict-related events like troop movements, demonstrations, riots and disorders among civilians.[13] Finally, the two datasets also source information differently. UCDP relies primarily on global newswires (about 60%) and English-language reports,[14] while ACLED incorporates also traditional media (in over 20 languages, not privileged English), new media (e.g., Twitter, Telegram, WhatsApp), public and private reporting (e.g., Amnesty International, official state-reported events), and partnerships with local conflict observatories (Raleigh and Kishi, 2019).

As a result, the datasets cover partly different events: UCDP is more conservative, focusing on armed force events, while ACLED includes potentially violent events such as protests, riots and demonstrations, which may (but not necessarily do) involve violence.[15] Given UCDP's

[9] Notation in Eq. (5) is simplified by dropping the i subscript representing different statistical units.

[10] In this exercise, the RCP coupled with SSP4 represents the intermediate emissions profile, as one the three RCPs suggested by the AR6 to be coupled with the socio-economic trends.

[11] Global version 22.1. UCDP is built according to the methodology developed by Sundberg and Melander (2013) with data January 1989 and December 2020 updated by Pettersson et al. (2021).

[12] The UCDP GED Codebook (version 22.1) defines an event as "An incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date" (Hogbladh, 2022). More specifically, the event dataset traces the events of all UCDP conflict dyads (i.e., two conflicting primary parties or party killing unarmed civilians) for both active (i.e., at least 25 battle related deaths recorded) and non-active years.

[13] ACLED adopts the following conflict classification: violent events (e.g., battles and violence against civilians); demonstration (protests and riots); non-violent actions (activities of violent groups that may contribute to political instability and future events).

[14] UCDP sources include: global newswire reporting (about 60%); global monitoring and translation of local news performed by the BBC; secondary sources such as local media, NGO and IGO reports, field reports, books etc. From the UCDP GED Codebook v22.1: "The process is done in a "two-pass" system, first by consulting newswire sources for the entire globe then by consulting local/specialized sources based on information obtained from the first pass".

[15] According to Raleigh and Kishi (2019), UCDP captures only events where larger and organized groups are involved and whole countries with persistent but low-level conflict are missing in certain years of coverage.

stricter event counting compared to ACLED, choosing one dataset over the other risks underestimating or overestimating forecasted conflict events.[16] Therefore, we use both UCDP and ACLED sources to compute two alternative dependent variables as the sum of all violent events (excluding conflicts between two or more states) recorded within each cell's boundaries in all the years the conflicts last.

2.4. Climate variability and the agricultural channel

Our primary target variables are derived from monthly data on temperature and precipitation. Historical climate data have been retrieved from the African Flood and Drought Monitor (AFDM) while climate projection data have been collected from the World Climate Research Programme's Coupled Model Intercomparison Project phase 5 (CMIP5) and across the three aforementioned RCPs.[17]

We incorporate two set of indicators to measure climate variability *per se*. First, we calculate the long-term changes in climatic conditions (temperature and precipitation) relative to the benchmark period 1970–1989. Second, we use the Standardized Precipitation Evapotranspiration Index (SPEI), a composite measure of soil moisture, to account for relative excess or deficiency of water availability that can affect the ability to meet the demands of human activities and the environment (Hayes et al., 2011; Parsons et al., 2019; Pandey and Ramasastri, 2001).

We further identify the agricultural activities as a critical (indirect) mechanism linking changes in climatic conditions to political stability and armed conflicts, primarily through implications for food security and worsening socio-economic conditions. Consistent with prior research, we recognize the seasonal nature of agricultural activities and their varying exposure to climate variability within the growing season (Jones et al., 2017; La Ferrara and Harari, 2018). Crop losses due to adverse climate conditions during critical growing periods can indeed lead to reduced agricultural production, lower income, and higher food prices, all of which contribute to local socio-economic strains. These factors can foster grievances, resource competition, and low opportunity costs for engaging in violence, thereby contributing to political instability.[18] Consequently, we compute our indicators by jointly considering monthly SPEI value, and the growing seasons of main crops within each grid cell. We adopt the approach of Von Uexkull et al. (2016), measuring the proportion of growing-season months affected by drought or excess water. Accordingly, the study provides insights into the potential pathways through which climate change may influence conflict dynamics in Africa, highlighting the importance of considering agricultural vulnerabilities and adaptive capacities in conflict forecasting models.

In our analysis, we assume that the crops' growing season remains unchanged up to 2050, and we do not account for future adaption in our models. We acknowledge that this is a strong assumption, implying that economic agents do not adjust their behaviour in response to changing environmental or socio-economic conditions. The main motivation behind this choice is given by data constrained, i.e. it is due to the lack of cell-specific information on anticipated adaptation efforts.

For instance, adaptations in response to changes in the agricultural growing season, shifts in cultivated crops due to adverse climate conditions, the adoption of more advanced agricultural practices (e.g., irrigation, other farmers-supporting measures) could boost agricultural productivity (Montaud et al., 2017) and mitigate the impact of climate change on food security and livelihoods, potentially reducing the risk of conflict. Furthermore, adaptation strategies promoting environmental peacebuilding, such as natural resource management initiatives or conflict resolution mechanisms, may play a pivotal role in mitigating the climate change's indirect effects on conflict dynamics. In the absence of such data, it is challenging to incorporate cell-specific adaptation strategies into our forecasting model.

3. Results

3.1. Identification strategy

We test a baseline specification, which does not includes climate variables,[19] along with seven additional models with alternative climate covariates. These variables either capture direct effects of climate variability on violence (Models 1–4) or the indirect effects through the agricultural channel mediated by the crops growing season (Models 5–7).[20]

To identify the empirical design that minimizes model residuals based on the historical data (1990–2020 for UCDP;1997–2020 for ACLED), given the non-linearity of the ZINB count model, we use the Pearson residuals that correct for the unequal variance by dividing by the standard deviation of $\hat{y}$. In analytical terms:

$$p_{it} = \frac{y_{it} - \hat{\mu}_{it}\left(1 - \hat{\pi}_{it}\right)}{\sqrt{\hat{\mu}_{it}\left(1 - \hat{\pi}_{it}\right)\left[1 + \hat{\mu}_{it}\left(1 + \hat{\alpha}\right)\right]}} \tag{6}$$

where y_{it} is the observed conflict event in cell i at time t and $\hat{\mu}_{it}\left(1 - \hat{\pi}_{it}\right)$ is the expected value estimated by the model. In Eq. (6)$\hat{\mu}_{it}$ represents the negative binomial component, $\hat{\pi}_{it}$ is the logistic link function and $\hat{\alpha}$ is the negative binomial overdispersion parameter.

We run the different models considering both UCDP and ACLED data, finding that the mean squared Pearson residuals per year indicate similar error terms across tested models (Figures A9a–A9b). Notably, the baseline model (without climate variables) underestimates the number of conflicts and generates the highest residuals over the long run.[21]

Following the methodology proposed by Colaresi and Mahmood (2017), we conduct a validation experiment to compare the forecasting capabilities of the recursive method (Eq. (5)) against the direct method with rolling windows. In doing so, we select Model 7 for its comprehensive representation of vulnerability to climate impacts on human activities. Three reasons are behind this choice: (i) it includes the long-term changes in climatic conditions, represented by the average temperature change over the past five years relative to the 1970–1989 benchmark period (see Eq. (8) in section A.1 in Appendix); (ii) it accounts for the indirect effects, quantified by the proportion of the growing-season months experiencing severe droughts ($SPEI36 < -0.99$) or significant excess of water ($SPEI36 > 0.99$) occurred; (iii) for both UCDP and ACLED data it is associated to the lowest AIC and BIC values.[22]

[16] Figure A1 in appendix compares the total number of ACLED and UCDP conflicts events over the period 1997–2020, highlighting a growing gap in recent years. Observe that in order to have more reliable estimates across time and space, and more comparable results across data sources, we restrict ACLED data to deadly events.

[17] More details on the climate and agricultural indicators are presented in Section A.1 of the Appendix.

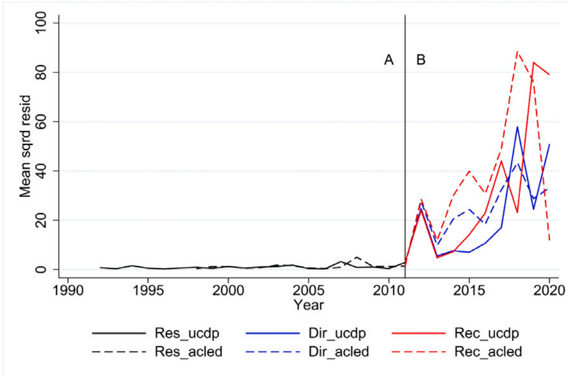
[18] This is consistent with previous studies suggesting that increases in local food prices are associated with increases in violence (Gutiérrez-Romero, 2022).

[19] Alternative specifications and robustness checks on the baseline model are reported in Tables A6 and A7 in Section A.3 .

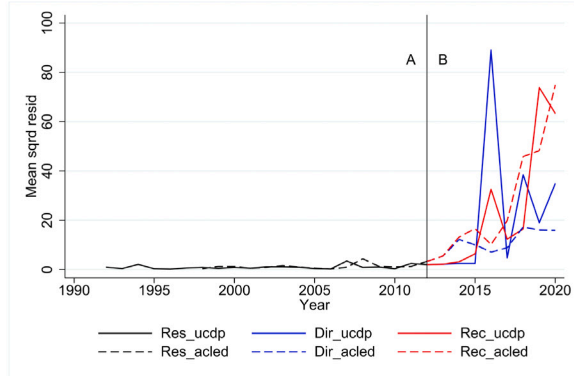
[20] Results are reported in Tables A1–A2 for UCDP and ACLED, respectively.

[21] When very large or outlier errors are squared, the score gives worse performance to those models that make large wrong predictions. In what follows we adopt the mean squared Pearson errors for both the identification strategy and the evaluation of forecasting capacity in the form of MSFE. Pearson residuals are available from 1992 for UCDP and from 1998 for ACLED due to the lagged structure of the base model as in Eqs. (3)–(4).

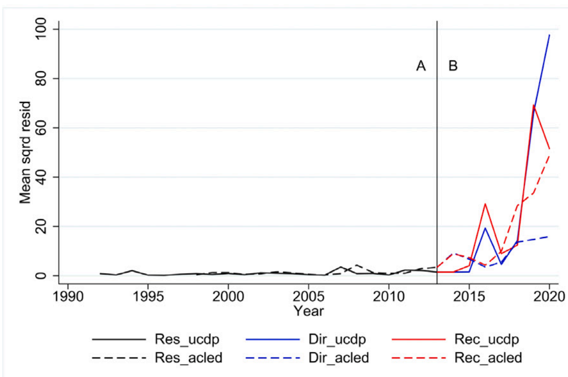
[22] We perform a battery of robustness exercises to test for: (i) potential divergences associated to the choice of the baseline scenario used for the period 2017–2020; (ii) robustness of statistical significance of coefficients in recursive windows for the validation period 2017–2020; (iii) robustness to alternative fixed effects (see Section A.3 in Appendix).



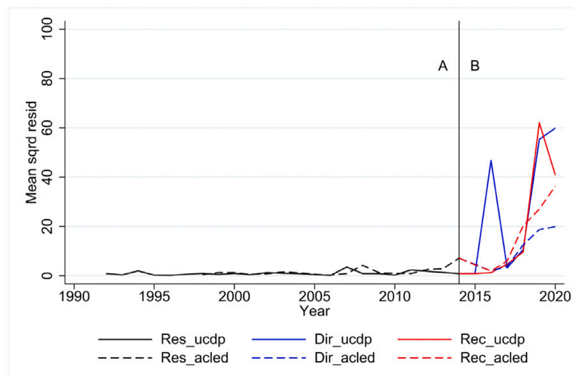
(a) $A \in (1991, 2011)$ and $B \in (2012, 2020)$



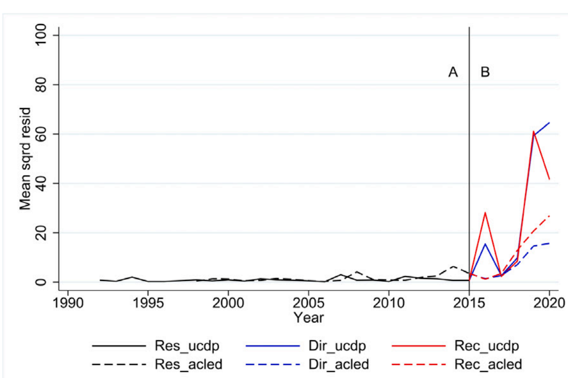
(b) $A \in (1991, 2012)$ and $B \in (2013, 2020)$



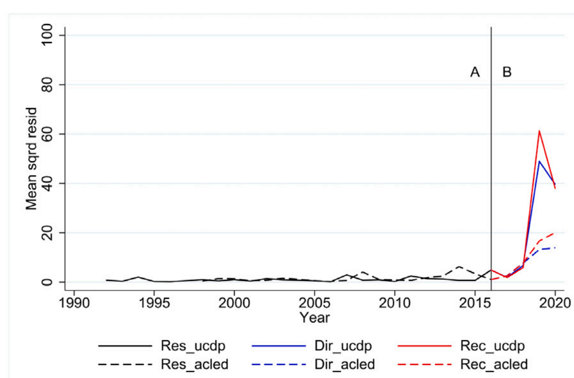
(c) $A \in (1991, 2013)$ and $B \in (2014, 2020)$



(d) $A \in (1991, 2014)$ and $B \in (2015, 2020)$



(e) $A \in (1991, 2015)$ and $B \in (2016, 2020)$



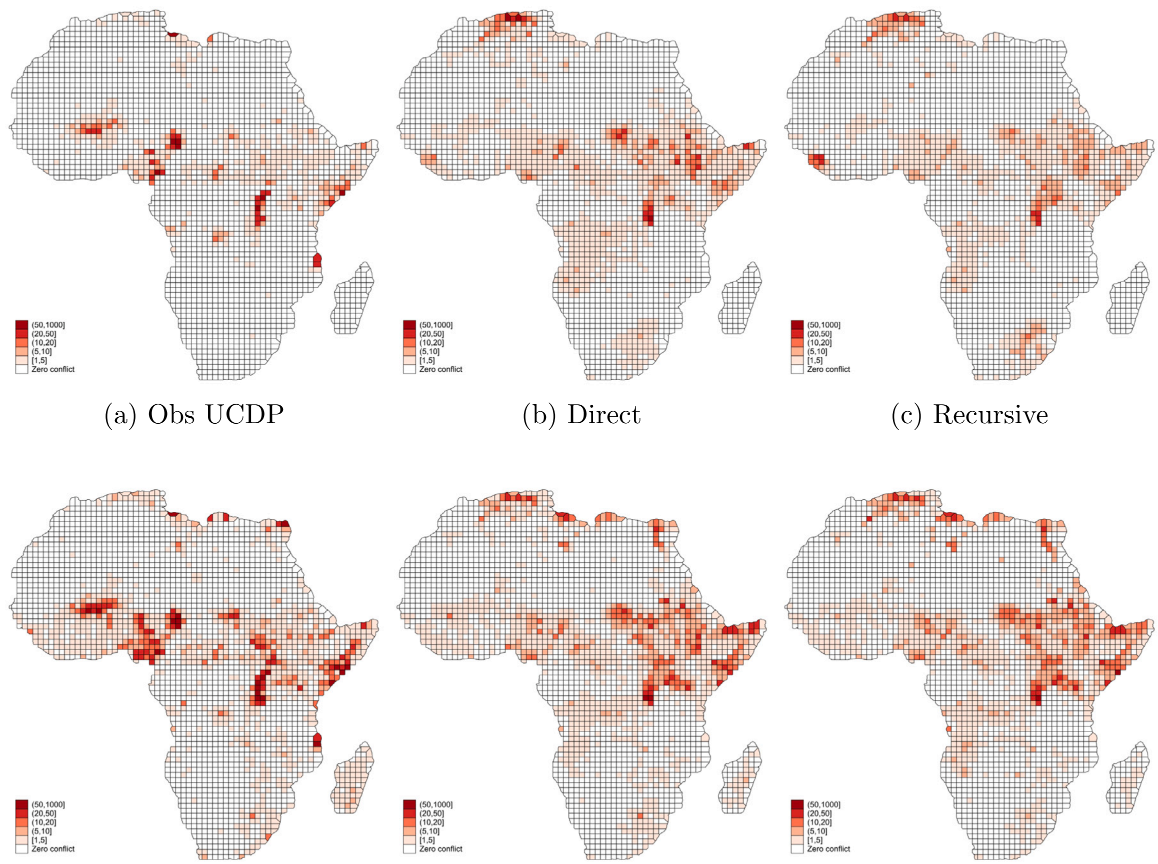
(f) $A \in (1991, 2016)$ and $B \in (2017, 2020)$

Fig. 1. MSFE with Pearson residuals (model 7 with SSP2 baseline).
Note: *A* refers to the training period for which the black lines represent mean squared of Pearson residuals. *B* refers to the validation period with coloured lines reporting the MSFE computed as Pearson residual.

In Fig. 1 we present the MSFE computed on Pearson residuals per year from the recursive and direct methods, considering different training (*A*) and validation (*B*) periods for both UCDP and ACLED.[23] Short-term forecasting (i.e., short validation periods B as in Figs. 1(e)–1(f)) show overlapping MSFE paths for direct and recursive methods in both UCDP (solid lines) and ACLED (dashed lines). However, longer validation periods (Figs. 1(a)–1(b)) exhibit more heterogeneous MSFE values, indicating increased forecasting uncertainty. Given such mixed results on prediction capacity and the limitations of the direct method (short-term availability of historical information for the backward rolling windows), in what follows we apply the ZINB estimator and a recursive model with recursive windows approach for forecasting up to 2050, as given by Eq. (5) applied to Eqs. (3)–(4) with $W = 0$ (spatial interactions excluded).

To compare the predictive capacity of the direct and recursive approaches, we group the forecasted number of conflicts events into

[23] The training period uses historical observation for all covariates, while the validation period includes observed values for the response variable and projected covariates.



(a) Obs UCDP (b) Direct (c) Recursive

(d) Obs ACLED (e) Direct (f) Recursive

Fig. 2. Alternative forecasting methods (year 2020). Note: Number of conflicts events are expressed as three-year average (2017–2020).

classes. Given that the socio-economic and climate variables for the period 2017–2020 are derived from future scenarios, we account for this dimension of uncertainty and test potential divergences associated to the choice of the SSP-RCP baseline scenario used. Accordingly, we evaluate Model 7 across five SSP-RCP scenarios for both UCDP and ACLED, presenting the results in terms of average number of conflict events per cell across scenarios. The visual representation of the difference between the direct and recursive methods in terms of class-based distribution of observed and predicted conflicts events is provided by Fig. 2. Considering the experiment with the longest validation period ($B \in (2012, 2020)$) as in Fig. 1(a), cells are classified based on the average predicted number of conflict events into the following classes: [0,1), [1,5], (5,10], (10,20], (20,50], (50, ∞).

In UCDP data, the percentage of cells falling into a different class compared to observed data ranges from 12% in 2012 to 25% in 2020 when using the recursive method, and from 11% to 33% with the direct method. Similar results are observed in ACLED, where the percentages are slightly higher for both methods. Overall, the recursive method achieves an average accuracy of around 80% for UCDP and 75% for ACLED. This suggests that forecasts based on the more conservative and homogeneous UCDP dependent variable are generally more accurate.

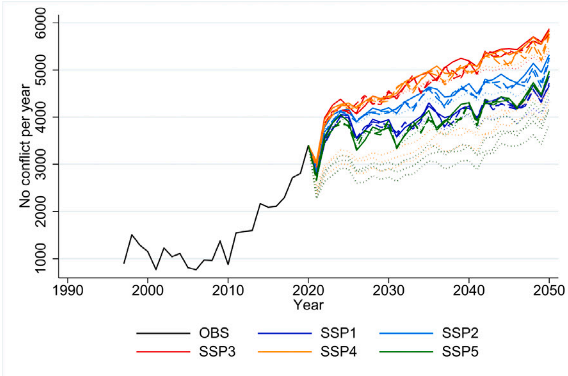
3.2. Conflicts projections under SSPs by 2050

Models in Tables A1–A2 are used to forecast conflicts events by 2050. Figs. 3(a)–3(b) compare the sum of cell-based conflict events per year across all seven models, applied to both UCDP and ACLED data under the five SSPs. Solid lines depict results from Model 7 (long-term indirect impact of climate change via agricultural activities), dashed lines show forecast from Models 5–6 (shorter-term indirect impact), and dot lines represent models accounting only for the direct effect of changes in climatic conditions (Models 1–4). Different colours denote the five SSP-RCP scenarios.

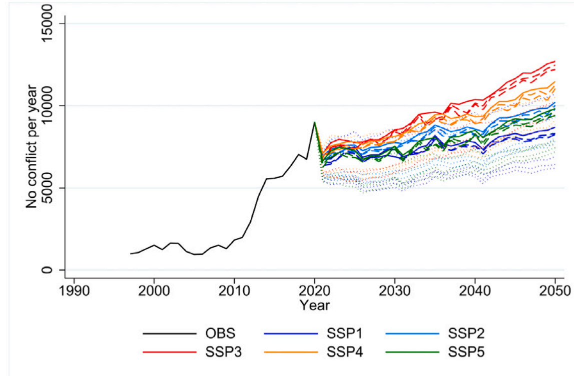
Three results are worth noting. First, the forecasted number of events using UCDP is substantially lower than ACLED, primarily due to the difference in historical values, especially after 2010 where the gap between the two data sources becomes larger (see Figure A1).

Second, worse socio-economic scenarios (SSP3 and SSP4) corresponds to higher violence intensity, with varying trends in conflict events across scenarios, dependent on the conflict data source. Overall, our results suggest that within similar socio-economic context, the number of forecasted UCDP conflicts remains similar regardless of the climatic scenario, while ACLED conflicts are amplified under worse climatic conditions. In the case of UCDP (Fig. 3(a)) SSP3 and SSP4 present the highest and overlapping trend, and an overlap also occurs between SSP1 and SSP5, characterized by relative higher economic growth and lower population growth, but associated to very different climate scenario (the most optimistic RCP 2.6 for SSP1 and the most pessimistic RCP 8.5 for SSP5). Conflicts events predicted by SSP2 are in the middle of the road as expected. This coupling evidence seems driven more by socio-economic variables rather than climate-related patterns. Conversely, ACLED forecasts (Fig. 3(b)) are more responsive to worsening climatic conditions, and no overlapping between different scenarios emerges in this case. These results suggest that ACLED data, which adopt a less conservative approach in the definition of conflict events, seem to better represent the relative vulnerability of disadvantaged social groups to external climatic shocks. Accordingly, worsening climatic conditions may bring to a larger number of lower-intensity conflictual episodes over years.

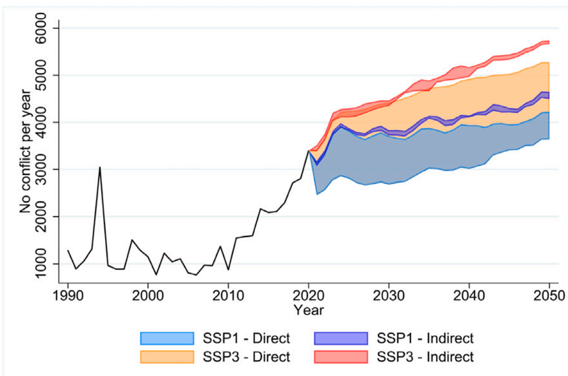
Third, across all SSPs scenarios, Model 7 (solid lines), which includes long-term indirect climate impacts mediated by the agricultural



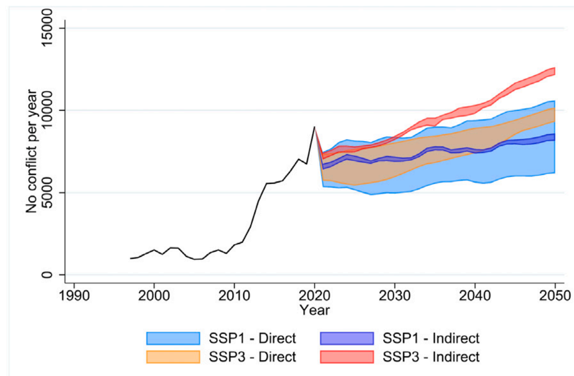
(a) SSPs with different models (UCDP)



(b) SSPs with different models (ACLED)



(c) SSP1 and SSP3 (UCDP)



(d) SSP1 and SSP3 (ACLED)

Fig. 3. Conflicts projections by 2050 under SSPs (UCDP and ACLED).

channel, consistently predicts the highest number of conflict events. In contrast, in models accounting for direct climate effects (Models 1–4, dot lines) the number of predicted conflict events is sensibly lower. To further stress this point,we examine SSP3 (highest conflict risk) and SSP1 (lowest conflict risk), highlighting the range of variation in the number of conflict events predicted from models accounting for direct (Models 1–4) and indirect (Models 5–7) climate indicators. Figs. 3(c)–3(d) show the results for UCDP and ACLED. Models capturing direct climate effects generally imply lower conflict risk and a larger range of variation compared to those incorporating indirect effects via the agricultural channel. Consistent with previous literature, our findings confirm that accounting for climate variability alone can either amplify or mitigate conflict risk relative to current observations. However, when indirect mechanisms are considered and climatic changes are not accompanied by adaptation measures, the risk of violence escalates.

Overall, these results confirm that forecasting exercises can be strongly affected by the methodology used to collect data on conflicts, independently from the robustness of the estimation approach, and by the modelling of variables capturing climate variability.

3.3. *The role of spatial dynamics*

The recursive forecasting model is then applied to the ZINB specification that includes spatial interactions. We compute the Global Moran's I index on Pearson residuals from Eqs. (3)–(4), in the time span 1990–2020 with $W = 0$, as follows:

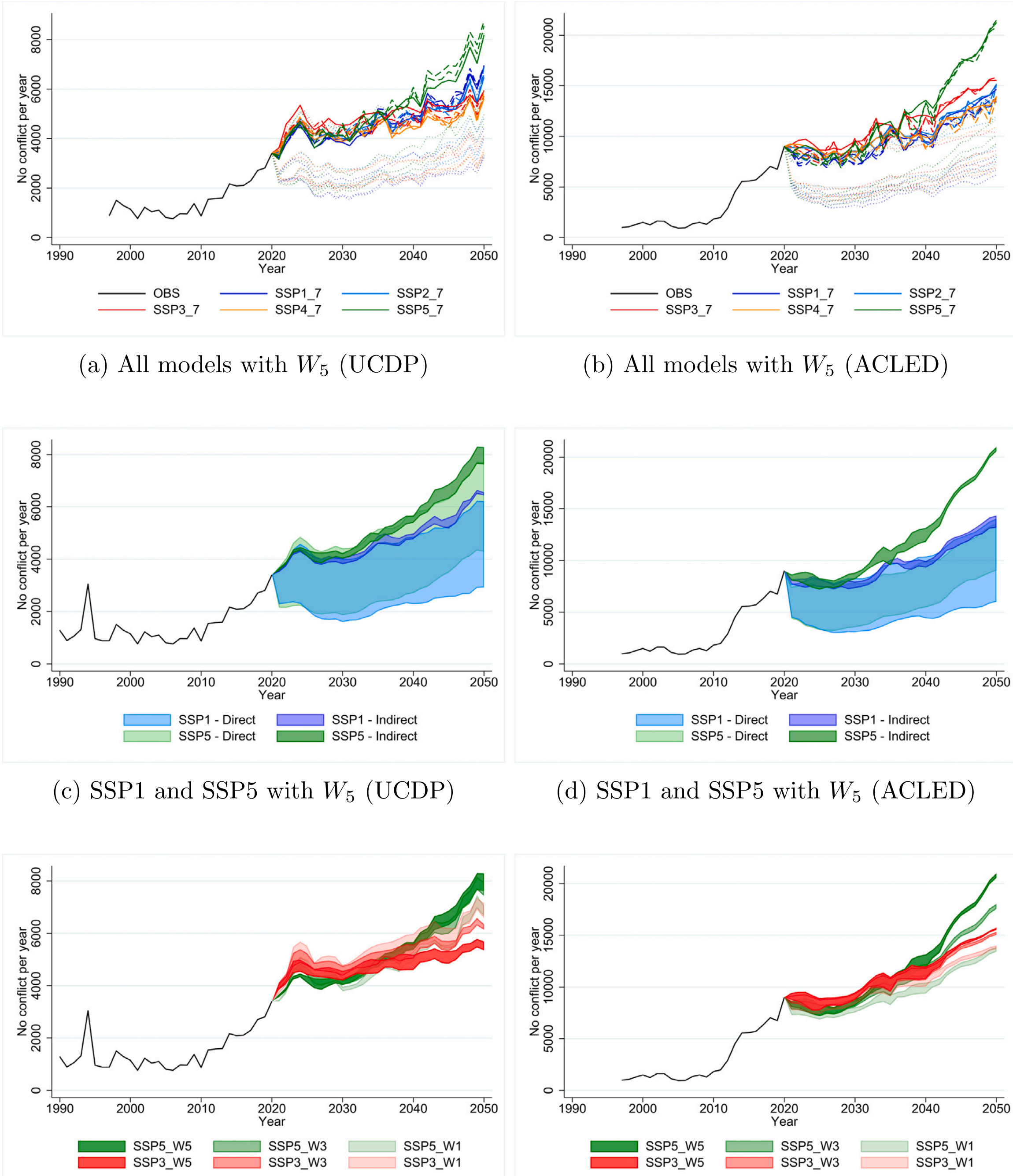
$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\left(p_i - \bar{p}\right)\left(p_j - \bar{p}\right)}{\sum_{i=1}^{N}\left(p_i - \bar{p}\right)^2} \tag{7}$$

where N is the number of spatial units (i.e. 2,653 cells), p_i and p_j are the Pearson residuals for spatial unit i and j, $\bar{p}$ is the mean value of residuals per year and w_{ij} is the bilateral inverse distance between i and j based on the five W_d symmetrically normalized weight matrices. We compute the Global Moran's I on Pearson residuals for most recent years for both data sources accounting for different spatial weights. Our results confirm that the spatial correlation of the residual term is always statistically significant, and a matrix $W_d \neq 0$ should be considered (see Table A3).

Since no *a priori* information guides the selection of the best weight matrix, we adopt the same model selection strategy described in Section 3.1 and compare Pearson residuals (Eq. (6)) obtained from Model 7. Since the results reveal that there is no unique indication on a spatial weight to be preferred across all years (Figure A12), we apply the widest range (W_5 = 533 km) to map the distribution of conflicting events across cells by 2050, while testing alternative weights for robustness. Notably, the projected number of conflict events is larger when accounting for spatial interactions and a change in pattern across SSPs also emerges with respect to our previous results (see Figs. 4(a)–4(b)).[24] Five specific results are worth mentioning when comparing forecasts with and without spatial correlation.

First, results confirm our previous findings: violent conflict events are mostly driven by the indirect impact of changes in long-term climatic conditions on human activities, as proxied by the pressure played by unexpected changes in water availability on agricultural harvest and food security, even in the case of local spillovers. This pattern is evident in Figs. 4(c)–4(d) where we select the scenario associated to the highest

[24] We use the same graphical representation as in Figs. 3(a)–3(b): solid lines represent results from model 7; dashed lines result from models 5–6 (shorter-term indirect impact of climate change); dot lines result from models 1–4 (direct impact of climate change).



(a) All models with W_5 (UCDP) (b) All models with W_5 (ACLED)

(c) SSP1 and SSP5 with W_5 (UCDP) (d) SSP1 and SSP5 with W_5 (ACLED)

(e) SSP3 and SSP5 with $W_d \in (1,5)$ (UCDP) (f) SSP3 and SSP5 with $W_d \in (1,5)$ (ACLED)

Fig. 4. Conflicts projections by 2050 with spatial interaction (UCDP and ACLED).
Note: The matrices W_1, W_3 and W_5 are calculated based on the great circle formula, Queen approach, and a threshold equal to, respectively, 178, 355, and 533 km.

(SSP5) and lowest (SSP1) conflict risk. Similarly to Figs. 3(c)–3(d), Models 1–4 (direct climate effects) consistently predict fewer conflict events compared to Models 5–7 (indirect effects via the agricultural channel), while exhibiting a wider range of variation.

Second, when considering the role of spatial dynamics, SSP5 emerges as the worst case scenario in the long-term. It thus emerges a clear change in the patterns of total conflict events estimated from UCDP (Fig. 4(e)) and ACLED (Fig. 4(f)) with respect to results that do not incorporate spatial relations. As previously discussed, in this latter case there is a large divergence across the five SSPs over time, with the SSP3, related to the hardest impact of climate change and vulnerability, being the worst case. In contrast, when spatial correlation is accounted for, the highest frequency of violence is associated with SSP5, the socio-economic pattern based on large exploitation of natural resources fuelling economic growth at the expense of an increasing inequality in welfare distribution. This is particularly pronounced in ACLED data (Fig. 4(f)) from 2040 onward. Since both SSP3 and SSP5 share the same climate trend (RCP 8.5), differences in conflict patterns are mainly driven by cell-based economic growth and income distribution. Despite SSP5 showing higher aggregate GDP across Africa if compared to the other scenarios, it is also coupled with the largest (and increasing in time) concentration of income. Indeed, while in the short-term in the SSP5 the spatial concentration of wealth across neighbouring cells is decreasing, from 2035–2040 this trend is reversed, signalling that the large increase in income is concentrated in fewer cells.[25] This seems to suggest that while in the short-term higher GDP growth (SSP5) can compensate for climate damages and mitigate potential violence outbreak, in a longer horizon increasing income concentration and the unequal access to welfare resources across spatial neighbours could activate vicious cycles of resource competition and conflicts.

The third result emerges from the comparison of selected SSPs across different spatial distances. We focus on the number of conflict events predicted from the three most pessimistic models (i.e., Models 5, 6, 7) and test different spatial weights matrices. In Figs. 4(e)–4(f) we select SSP3 and SSP5 and, for each scenario, the darker the colour of the graph area, the wider the radius of spatial relations (i.e., 178, 355, 533 km). For both UCDP and ACLED data, the upper and lower bounds of forecasted event frequencies are given by the two extreme distances, albeit with opposite trends. In ALCED, the less conservative data including also riots and disorders, the highest distance corresponds to the upper bound and the shortest distance to the lower bound of forecasted events. The opposite result is obtained by considering as a response variable violent events according to a more conservative approach, as in UCDP (with some exception for SSP5). This further confirm the different sensitivity of forecasts to changes in climatic and socio-economic conditions occurring at the local scale, strongly influenced by the nature of the response variable adopted.

The changes in ranking across SSPs is also impacting the geography of violence, as emerged from mapping the number of predicted conflict events by 2050 when spatial correlation with W_5 is accounted for (Figs. 5–6), using the same classes as for testing the prediction capacity of the model (as in Fig. 2). Spatial spillovers drive violence and disorders to be geographically widespread and more intense in frequency, especially in densely populated areas with potentially higher economic growth prospects. Intensive resources exploitation combined with high income inequality could intensify the competition for rent, thereby fuelling the conflicts.

Conversely, scenarios characterized by intensified climate change pressure along with worsening well-being conditions (i.e., SSP3-SSP4) correspond to a relative decrease in the frequency of forecasted conflicts events compared to models without spatial spillovers (see Figures A10–A11). This last result could be interpreted as indicative of reduced resource competition when challenging livelihood conditions lead to a generalized lack of basic needs, with long-distance migration being among the primary adaptation strategies.

4. Conclusions

In this paper we present a forecasting analysis on violent conflict events in Africa up to 2050 along different climate-related future scenario, and accounting for multiple socio-economic drivers and vulnerability. We apply a forecasting dynamic recursive approach to a non-linear model designed for count response variables with many zeros. We further develop a model that accounts for spatial correlation in order to investigate the role of geographical spillovers in the diffusion of violence. Climate-induced changes in agricultural productivity, for instance, can trigger resource competition and exacerbate existing socio-economic disparities, leading to stronger tensions and conflict escalation. By incorporating spatial dependencies into our analysis, we better capture the diffusion of conflict spillovers and the propagation of climate-related impacts across contiguous areas. This approach enables us to explore how climate conditions recorded in one geographic cell may influence conflict outcomes in neighbouring cells, thereby providing a more comprehensive understanding of the spatial dynamics of violent conflicts. Importantly, our results confirm that these effects are not confined to isolated areas but can spill over into adjacent regions, amplifying the overall impact of climate change on conflict dynamics across the African continent up to 2050.

We compare the results obtained by applying the same forecasting method to two widely-used conflict data sources, i.e., UCDP (which tends to be more conservative, focusing on events involving armed force and resulting in at least one battle-related death) and ACLED (which captures a wider spectrum of potential or threatened violence). Three main results are worth mentioning.

First, exposure to environmental risk caused by pessimistic scenarios on climate change impacts is strictly connected with an increase in the frequency of violent events. Nonetheless, not all conflictual activities respond equally to climate shocks, and the quantification (and distribution) of the predicted events diverge between the two data sources. Model forecasts based on UCDP conflicts differ across SSPs according to the projected dynamics mainly based on socio-economic vulnerability. On the opposite, forecasts based on ACLED data seem to better capture the direct impact of long-term change in climatic conditions. Accordingly, we find that predictions on the climate-conflict nexus are significantly affected by the type of data used for measuring the breakout of disorders (e.g., actual or threatened violence), and one way to reduce uncertainty is to account for such divergence in modelling exercises with multiple models and datasets. These insights into the nuances of the climate-conflict nexus emphasize the importance of accounting for such discrepancies in modelling exercises to reduce uncertainty and improve the robustness of forecasts.

Second, violence is mostly driven by the indirect effects of climate variability through the so-called agricultural channel. The forecasted number of conflicts events is magnified when we jointly account for the pressure played by long-term climatic conditions and for the local agricultural system. In our exercise we proxy this dimension with the pressure played by unexpected changes in water availability recorded during the growing season of local agricultural crops. Whatever SSP scenario is tested, and independently from the conflict data source used, when assessing this agriculture-related indirect impact of climate change the number of forecasted events is higher, confirming that the agricultural sector may play a crucial role in the future. Overall, this result underscores the need for comprehensive approaches that integrate climate adaptation strategies with efforts to promote sustainable agricultural practices and enhance resilience among vulnerable communities.

Third, the introduction of geographical spillovers allows detecting a different sensitivity of forecasts to changes in climatic and socio-economic conditions occurring at the local scale. In the case of UCDP data (e.g., actual violence), the impact of spatial interactions is higher for short distances. This suggests that these conflicts react more strongly to more localized threats, with near-neighbouring areas being more susceptible to the spread of violence. This could be due to factors such as proximity to or shared resources (e.g., water sources or arable land), which facilitate the transmission of conflict-related dynamics. On the opposite, when accounting for all types of disorders irrespective of any selection criteria on the magnitude of violence, as in the case of ACLED data (e.g., threatened violence), the impact of climatic and socio-economic conditions of neighbouring areas increases with the geographical distance. This indicates that the effects of these conditions extend beyond immediate neighbours and have a broader spatial reach. We also find that, when accounting for the geographical spillovers, the socio-economic context plays a crucial role in determining the climate-related conflict risk: the effect is magnified in scenarios characterized by high degree of spatial inequality and intense resource exploitation (SSP5), and downsized in cases of generalized lack of resource (SSP3).

[25] We calculate the Herfindahl index of concentration based on GCP per capita across neighbouring cells for different distance matrix. In all cases, the index for SSP5 follows a U-shape pattern: it decreases up to 2035–2040 (on average by 0.25% per year) and then it starts increasing (on average by 0.10% per year). A similar U-shape pattern is associated also to SSP1, and this evidence explains the increased number of conflict events predicted during the last decade 2040–2050 in SSP1 if compared to the results without spatial relations. See Figure A13.

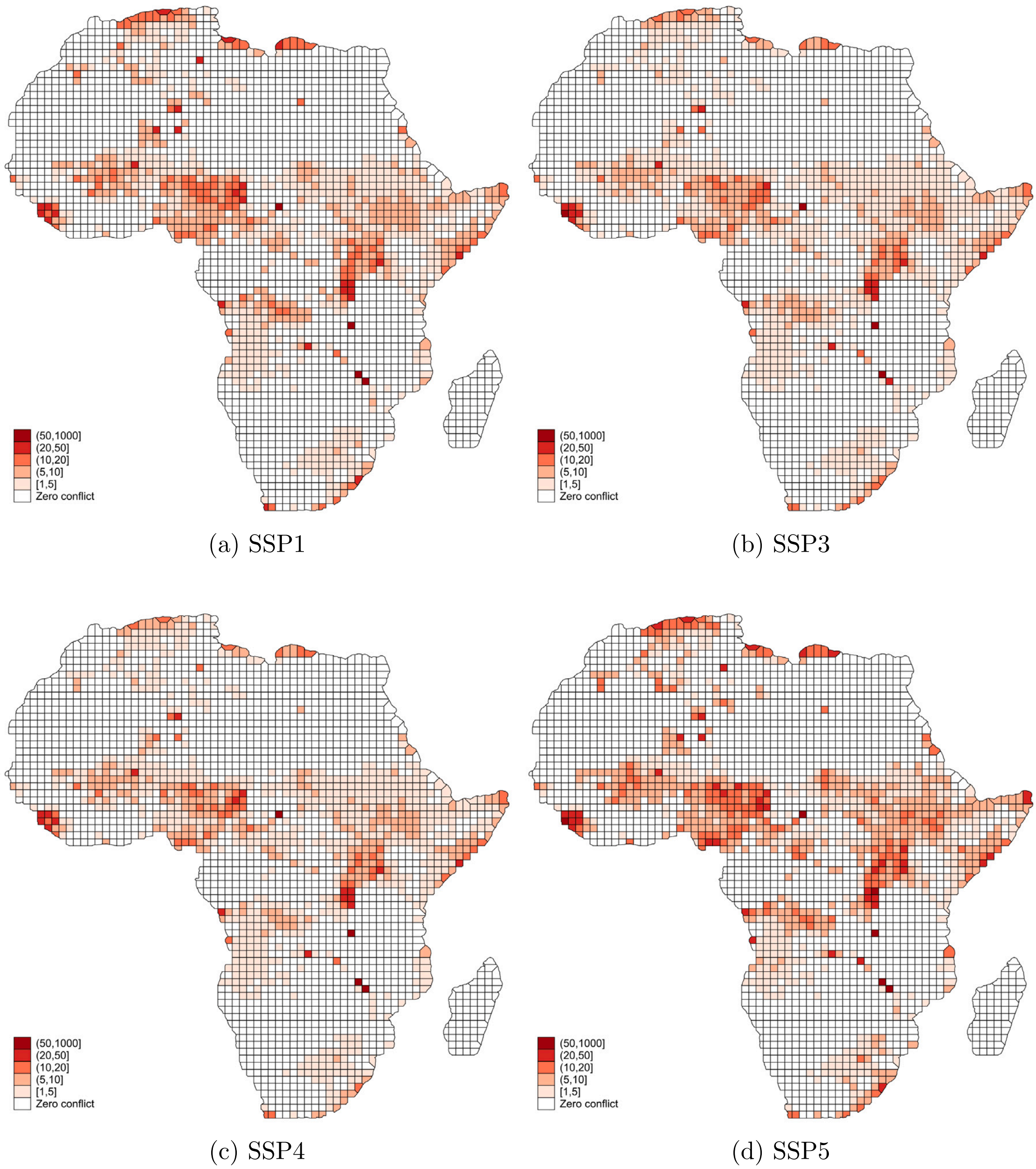


Fig. 5. Conflicts by cell in 2050 with spatial interaction (UCDP).

Taken together, these findings highlight the importance of considering geographical spillovers in understanding the sensitivity of conflict forecasts to changes in environmental and socio-economic conditions.

Overall, these results suggest that changes in the socio-economic context will play a determinant role in defining how strongly climate variability is likely to affect violence, and stronger effects may emerge when accounting for the geographical spillovers. These findings have important policy implications for the design and implementation of conflict prevention and resolution strategies, emphasizing the need for context-specific interventions that should also address the underlying drivers of climate vulnerability and promote resilient practices. At the same time, this evidence underlines the importance of coordinating policies and support efforts across broader geographical areas, which implies that addressing the climate-conflicts risk and its underlying causes requires more than just localized interventions. Due to the existence of spatial spillovers, the effects on conflicts extend beyond immediate locations, impacting neighbouring regions. This interconnectedness emphasizes the need for collaborative efforts across regions to effectively address and mitigate the impacts of conflicts. In other words, climate shocks can have far-reaching consequences, and addressing them comprehensively requires coordinated action and cooperation across different geographical scales.

We also observe that our forecasts are higher with respect to previous literature (Hoch et al., 2021), and even higher when accounting for spatial spillovers. This may suggest that the effect of climate on conflicts reported in other works represent a lower bound with respect to the present study (i.e., when considering how climate indirectly interacts with other factors and in absence of adaptation actions, its effect increases). It has to be noted that our modelling approach, taking climate indicators as exogenous and without imposing any expectation about future adaptation, is mostly reflecting historical dynamics and the status quo. This further highlights the importance of implementing

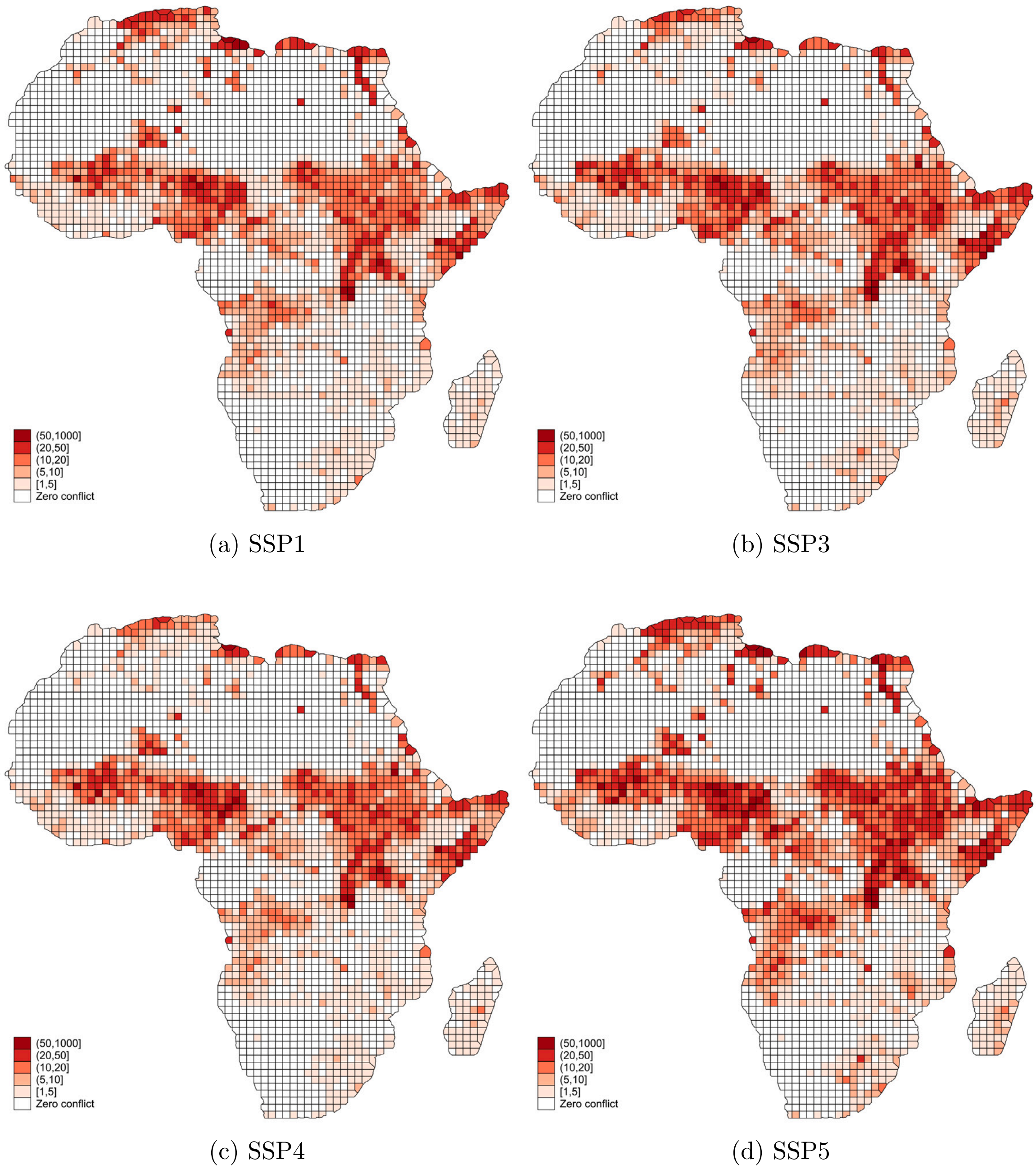


Fig. 6. Conflicts by cell in 2050 with spatial interaction (ACLED).

adaptive measures to mitigate the adverse effects of climate change, especially on agricultural systems and livelihoods.

The (data-constrained) parsimonious specification adopted in this paper could be further enriched in future research by accounting for local forms of adaptation in terms of, for instance, changes in institutional and technological aspects or in human behaviour in response to climate events (e.g., migration/mobility, adoption of livelihood coping strategies). For example, adaptations in response to changes in the agricultural growing season or shifts in cultivated crops due to adverse climate conditions could significantly influence conflict dynamics. The adoption of more advanced agricultural practices, such as irrigation or other farmers-supporting measures, may also mitigate the impact of climate change on food security and livelihoods, potentially reducing conflict risk. Furthermore, adaptation strategies aimed at promoting environmental peacebuilding, such as natural resource management initiatives or conflict resolution mechanisms, could play a crucial role in mitigating the indirect effects of climate change on conflict dynamics. Future research should explicitly tackle this limitation, and explore the potential influence of adaptation strategies on the relationship between climate change and armed conflict. Indeed, by incorporating such considerations, future studies can provide a more comprehensive understanding of the complex interactions between climate conditions, socio-economic factors, and conflict dynamics.

Finally, two additional limitations should be noted. First, as for the choice of the considered time frequency of the data (yearly, instead of, e.g., monthly), we acknowledge that this approach may raise concerns about the accuracy of the conclusions when predicting a large number of observations. However, the lack of higher-frequency data about historical and future socio-economic conditions constitutes a strong constraints in this regard. Hence, instead of adopting discretionary assumptions (e.g., to transform yearly data in monthly data), our preferred approach is to maintain the original time frequency of raw data (which is annual for most of the data sources), while exploiting the monthly variations when available (i.e., as in the case of climate and agricultural indicators). Second, while our empirical framework aligns with previous studies and relies on established econometric methods, future research should further investigate the applicability of (and comparison across) different methodologies. Among other things, future research should: explore the potential benefits of employing higher-frequency observations; model (endogenous) spillover effects using count data models (provided that these will be made available from the literature in the future); adopt combinations of (geographic and non-geographic) weight matrices (when more granular data to model spatial interactions will become available);[26] exploit alternative forecasting techniques (such as machine learning algorithms) and provide explicit comparisons across these different methodologies.

CRediT authorship contribution statement

Caterina Conigliani: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Valeria Costantini:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Elena Paglialunga:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Andrea Tancredi:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors declare that no generative artificial intelligence (AI) nor AI-assisted technologies were used in the writing process.

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[26] See for example (Debarsy and LeSage, 2018; Debarsy and Ertur, 2019; Debarsy and Lesage, 2021; Lesage and Cashell, 2015; LeSage, 2015).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econmod.2024.106911.

Data availability

I have shared the link to the dataset and script at

Dataset for Forecasting the climate-conflict risk in Africa (Original data) (Mendeley Data)

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