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Research article

Local sources of vulnerability to climate change and armed conflicts in East Africa

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ABSTRACT

While socioeconomic and institutional factors are crucial in explaining the onset and evolution of conflicts, recent research suggests that climate change is a further indirect driver acting as a "threat multiplier". This paper focuses on the concept of vulnerability to both climate change and conflicts to explain why some locations are more likely to engage in armed conflicts than others in the presence of a similar level of exposure to climatic changes. In particular, by means of a Spatial Autoregressive Model, we identify a set of local-specific vulnerability factors that increase conflict risk in East Africa. We employ a georeferenced database with a resolution of 25×25 km, covering the period 1997–2016. Results from our analysis provide some interesting insights: first, climate change does not increase conflict risk *per se*, but only in the presence of pre-existing vulnerabilities. Second, resource access and socioeconomic factors play a key role in driving the climate-conflict nexus especially in urban areas. In particular, vulnerability is increased whenever power is not distributed in such a way as to ensure an equitable distribution of resources. Overall, our findings suggest that, by addressing vulnerability factors that prevent adaptive capacity and an equitable distribution of resources, societies may benefit in terms of both diminished conflict risk and alleviation of climate change impacts.

1. Introduction and background

Climate change has been at the forefront of public debate as a major threat to both natural and human systems for several years. Over the last decades, an increasingly large number of studies has investigated the social impacts of climate change, including material deprivation, inequality, forced migration, adverse health effects, etc. In addition to these, a prolific strand of research focuses on the increased likelihood of conflict outbreak as a consequence of climate change impacts, the so-called climate-conflict nexus.

On the one hand, conflicts are a serious threat to livelihoods and development, so much so that Collier et al. (2003) defines them as "development in reverse", because of the costs in terms of human lives and the lingering effects they have on the whole economy for several years after the conflict has ended. Not only does conflict risk threaten societies, with detrimental consequences in terms of loss of lives, economic damage and reduced economic growth, but it can also exacerbate subsequent climate-related risks (Mason et al., 2011). On the other hand, climate change is a major security concern, affects crucial aspects of human life, especially in developing countries, and may exacerbate the social disorder and instability already in place in those countries, likely fuelling conflicts. Climate-related considerations have been made in connection with some ongoing conflicts, like the Syrian civil war (Kelley et al., 2015) and the conflict in Darfur (Brown, 2010). While socioeconomic and institutional circumstances are crucial in explaining the onset and evolution of conflicts, climate change has indirectly been associated with conflict outcomes (IPCC, 2014, 2022a) and is now recognised to act as a "threat multiplier" (Boas and Rothe, 2016). This has led scholars in this field to distinguish between direct and indirect effects of climate change on conflicts outbreak (Koubi, 2019; Sharifi et al., 2021). Among the direct effects, Koubi (2019) highlights physiological/psychological factors and resource scarcity. The latter, in particular, has been the focus of manifold studies (e.g., Maxwell and Reuveny, 2000; Berger, 2003; Audu, 2014; Vesco et al., 2020; Fatima

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et al., 2022). Some argue that resource scarcity increases conflict propensity as communities struggle to meet their most basic needs, or start competing for resource access due to their different lifestyles (e.g. farmers versus pastoralists) (Audu, 2014; Ayana et al., 2016). Moreover, spatial disaggregation in the distribution of natural resources has been linked to increased civil conflict risk through an increase in ethnic income inequality, as another relevant mechanism triggering violence (Lessmann and Steinkraus, 2019). On the other hand, among the indirect effects linking climate change to conflicts, Koubi (2019) mentions economic outcomes and migration. Since migration is a complex phenomenon, whether it leads to conflicts in the receiving regions depends largely on political, economic and social contextual factors and thus needs to be analysed on a case-to-case basis (Abel et al., 2019). Table 1 presents a synthetic view of the main relevant issues and contributions in the analysis of conflicts and environmental issues.

Diminished economic and livelihood capacities induced by climate-related stress are additional channels potentially fuelling violent activities (Sharifi et al., 2021). For example, a major pathway identified is the reduction in agricultural productivity which, in turn, can *"cause unemployment, diminish economic capacity and/or reduce availability, accessibility and affordability of essential needs such as food"* (Sharifi et al., 2021, p. 9). The effects linked to food systems are even stronger if the economic system of a country is mostly reliable on the agricultural sector, which is also the most vulnerable to climatic changes. In this case, the loss of agricultural output could produce serious consequences in terms of both economic and food security, which can eventually produce violent outcomes (e.g., Von Uexkull et al., 2016; Harari and La Ferrara, 2018; Vesco et al., 2021). Reduced crop yields may also lead to increases in food prices (Raleigh et al., 2015) and/or livestock displacement which could further increase land use competition (Maystadt and Ecker, 2014), as well as tensions between different modes of living (Kirkbride, 2008; Scheffran et al., 2019).

In its latest report, the IPCC also recognised climate change as a security issue, stating that "*at higher global warming levels, impacts of weather and climate extremes, particularly drought, by increasing vulnerability will increasingly affect violent intrastate conflict*" (IPCC, 2022b, p. 16). Hence, the IPCC suggests that the connection between climate change and armed conflicts is mediated by vulnerability, which is defined as the "propensity or predisposition to be adversely affected", arguing that about 40% of the global population is highly vulnerable to climate change impacts (IPCC, 2022a,b). In fact, areas characterized by similar exposure to the impacts of climate change do not necessarily display the same outcomes in terms of conflict outbreak, and differences in conflict outcomes may be explained by the different levels of vulnerability exhibited. Buhaug and von Uexkull (2021) are, to the best of our knowledge, the first to establish a theoretical connection among climate change, conflicts and vulnerability. They argue that many of the factors crucial to ensuring both effective adaptive capacity to climate change and long-lasting peace overlap. However, to date there is still a lack of empirical research on the connections between climate-related risks, vulnerability and conflict onset.

Vulnerable societies may be more prone to suffer detrimental effects as a consequence of climatic changes compared to less vulnerable ones (IPCC, 2022a,b). Such predisposition ultimately depends on structural economic and political relationships as well as historical cultural values and norms, assigning a strong social connotation to the concept of vulnerability (Gaillard, 2010; Wisner et al., 2014). In particular, vulnerability is due to factors that undermine an equitable distribution of income, resources and possibilities (Cappelli, 2023). Several research has provided guidance on possible indicators of vulnerability, often using composite indexes (e.g., Brooks et al., 2005; Cutter et al., 2008; Cutter et al., 2014; Kusumastuti et al., 2014; Alam, 2017; Jones et al., 2018; Fatima et al., 2022) and focusing on a specific context. This is not surprising, as socioeconomic vulnerability is often location-specific, but still some insights can be drawn. Scholars concur that resilient communities confront lower risks of violence given specific climate

Table 1
Literature review box: conflicts risk and environmental issues.

	Topics and references
Conflict risk factors	- Resource scarcity (e.g., Maxwell and Reuveny, 2000; Berger, 2003; Audu, 2014; Vesco et al., 2020; Fatima et al., 2022; Audu, 2014; Ayana et al., 2016). - Structural economic and political relationships, historical cultural values and norms (Gaillard, 2010; Wisner et al., 2014; Von Uexkull et al., 2016). - Migration (Koubi, 2019; Di Maio et al., 2023). - Physiological/psychological factors (Koubi, 2019).
Climate-conflict vulnerability	*Socio-Economic* - Diminished economic and livelihood capacities induced by climate-related stress, e.g., change in agricultural output/productivity (Sharifi et al., 2021). - Inequalities in income distribution (e.g., Hegre et al., 2003; Collier and Hoeffler, 2004; Cappelli et al., 2021) and, in general, factors that undermine an equitable distribution of resources and possibilities (Cappelli, 2023). - Ethnic status (e.g., Østby, 2008; Hillesund et al., 2018; Ide et al., 2020; Manotas-Hidalgo et al., 2021) and marginalization of individuals and social groups (Schröter et al., 2005). *Climate change and extreme events* - Link between increasing temperature and/or changing rainfall patterns and violent conflicts (Fjelde and von Uexkull, 2012; Buhaug et al., 2015). - Higher (Salehyan and Hendrix, 2014) and lower (Almer et al., 2017) precipitations, or deviation from the normal rainfall level (Harari and La Ferrara, 2018) could lead to conflicts. *Agriculture and Resource Access* - Agricultural output, crop yields, agricultural productivity and food systems (e.g., Von Uexkull et al., 2016; Harari and La Ferrara, 2018; Vesco et al., 2021; Raleigh et al., 2015; Maystadt and Ecker, 2014; Kirkbride, 2008; Scheffran et al., 2019). - Rural-urban divide (McGuirk and Burke, 2020) - Access to key resources, such as water (e.g., Gizelis and Wooden, 2010; De Stefano et al., 2017; Alam, 2017; Almer et al., 2017) and food (e.g., Simelton et al., 2012; Wheeler and Von Braun, 2013; Otto et al., 2017). - Adoption of agricultural technologies, e.g., irrigation systems (Suri and Udry, 2022).
Conflict hotspots (spatial risk factors)	- Heterogeneity in spatial distribution/access of/to natural resources (Lessmann and Steinkraus, 2019). - Regional conflict hotspots usually result from the clustering of similar internal features, e.g., geographical or social characteristics, resource endowments, climatic conditions (Silve and Verdier, 2018). - The geographical distribution of armed conflicts is largely dependent on the contagion effect induced by the spatial spillovers between neighbouring regions (e.g., Harari and La Ferrara, 2018; Cappelli et al., 2020).
Socio-economic and environmental sustainability	- Implications for development path (Alam, 2022); trade-off between with mitigation effort, economic growth and environmental sustainability (Murshed et al., 2022a; Alam et al., 2022; Singh et al., 2023); depending on the dependency on international (global) markets (Hamid et al., 2021, 2022; Murshed et al., 2022b).

conditions (Hsiang et al., 2011; Buhaug, 2015).

In order to provide guidance on the best policies to adopt to favour climate-resilient development and counteract sources of socioeconomic vulnerability, the concept of vulnerability needs to be operationalized in a holistic framework that encompasses both climate change and conflict prevention efforts. In this vein, inequalities in income distribution (e.g., Hegre et al., 2003; Collier and Hoeffler, 2004; Cappelli et al., 2021), ethnic status (e.g., Ide et al. (2020); Østby 2008; Hillesund et al., 2018; Ide et al. (2020); Manotas-Hidalgo et al., 2021) and in access to key resources, such as water (e.g., Gizelis and Wooden, 2010; De Stefano et al., 2017; Alam, 2017) and food (e.g., Simelton et al., 2012; Wheeler and Von Braun, 2013; Otto et al., 2017) are acknowledged as factors enhancing vulnerability to both climate change and conflicts in several areas. For instance, Von Uexkull et al. (2016) find that, while under most conditions droughts do not influence conflict risk, in the case of agriculturally dependent communities and politically excluded ethnic groups in poor countries, droughts constitute a risk factor for the outbreak of violent activities. Additionally, reduced access to vital resources - such as water - especially among the most vulnerable portions of the population, might be a concurring factor of vulnerability and increased conflict risk (Gizelis and Wooden, 2010). Marginalization of individuals and social groups may also prevent a universal access to resources essential for livelihood (Schröter et al., 2005), potentially giving rise to armed conflicts.

While the African continent has often been the object of analysis of most research in this field, Eastern Africa has been increasingly recognised as a particularly vulnerable region, in terms of both climatic changes and violent activities, being the region that has experienced the highest number of conflicts over the period 1997–2018 (Mack et al., 2021). One of the reasons for the scholarly interest in the Eastern Africa region is certainly the fact that this is a relatively restricted geographical area which is characterized by a "*history of violence, high dependence on natural resources for livelihoods, widespread poverty, and limited adaptive capacity*" (Van Baalen and Mobjörk, 2018, p. 3).

All of these factors make this region particularly interesting to analyse in order to gain understanding of the mechanisms driving the climate-conflict nexus and how this relates to context-specific economic, political and social dynamics that make this region particularly vulnerable. In fact, it might be that communities that display high levels of socio-economic vulnerability are also disproportionately affected by climatic impacts, and this further deteriorates adaptive capacity, thereby increasing conflict risk and creating a vicious cycle of vulnerability and harmful climate and conflict impacts (Buhaug and von Uexkull, 2021).

Building on the reviewed literature, we aim at filling the gap in the literature by providing empirical evidence regarding the identification of a specific set of socioeconomic and context-specific factors that foster vulnerability to both climate change and conflicts in East Africa at the local level.

Following recent advancements in spatial econometric techniques, which have been widely applied to study the climate-conflict nexus (e.g., Harari and La Ferrara, 2018; Breckner and Sunde, 2019; van Weezel, 2020; Cappelli et al., 2020; Vesco et al., 2021; Cappelli et al., 2022; Wang et al., 2022), we investigate how local vulnerability factors and climate change impacts may jointly make East Africa a conflict hotspot. In addition, we explicitly address the interaction between local vulnerability factors and climate change impacts to understand the mechanisms that enhance conflict risk and lead to the emergence of conflict hotspots.

The rest of the paper is structured as follows. Section 2 presents the data and the methodology used. Section 3 illustrates the main results, while Section 4 discusses relevant policy implications Section 5 concludes.

2. Material and methods

2.1. Data

For the purpose of our analysis, we build a georeferenced panel database for East Africa,[1] covering the time span from 1997 to 2016. Our grid is composed by 8217 cells with resolution of 25 × 25 km (15 arcmin).

In our analysis, we are interested in assessing if and to which extent the probability of conflicts outbreak in the Eastern African region is directly affected by changes in long-term climatic conditions and/or mediated by location-specific vulnerability factors. In order to do so, we gather data on armed conflicts from the Armed Conflict Location & Event Data Project (ACLED), which provides disaggregated and georeferenced incident information on political violence, demonstrations, and selected non-violent developments around the world. In particular, the events collected in the ACLED database can belong to six categories: i) political violence; ii) battles; iii) explosion/remote violence; iv) violence against civilians; v) riots; vi) protests. We associate these data to our grid and, for each cell i and year t, we create our dependent variable as a dummy (cd) equal to 1 if at least one conflict has been recorded, and 0 otherwise.

Explanatory variables belong to three main classes: i) climatic variables; ii) vulnerability factors related to agriculture and resource access; iii) vulnerability factors related to the socio-economic characteristics.

2.1.1. Climatic variables

We gather monthly values of temperatures and precipitations at 0.25° grid resolution from 1970 to 2016 from the African Flood and Drought Monitor (AFDM) database. Starting from these variables, to obtain an overall measure of long-term anomalous climatic variations experienced by a given cell across one year, we calculate the average level of monthly anomalous variations of temperatures and precipitations with respect to the past baseline period 1970–1989 (*Temp_ch* and *Prec_ch*, respectively).[2]

Droughts are further climatic event deserving attention and a number of indices and indicators have been developed to monitor their occurrence and severity.[3] Among these, the Standardized Precipitation Evapotranspiration Index (SPEI), developed by Vicente-Serrano et al. (2010) is widely accepted and employed, as it can be calculated for any geographical region and over any timescale, each associated with a different type of drought impact (Pandey and Ramasastri, 2001). For instance, basic droughts impacts can be monitored over a timescale up to 3 months; agricultural impacts over a timescale up to 6 months; while hydrological impacts and persistent stress conditions are usually calculated for a timescale equal to or higher than 12 months (Svoboda and Fuchs, 2016). Further, the SPEI offers a comprehensive consideration of the factors that influence soil barrenness, accounting for the impacts of both temperatures and precipitation on the humidity of terrains.

By employing the R package "SPEI" developed by Begueria and Serrano (2017), we calculate monthly values of the SPEI with a timescale of 12 months and aggregate them to obtain yearly mean values. Then, we relied on the classification formulated by McKee et al. (1993) to denote droughts and floods of different intensity. More specifically, as reported in Table 2, we divide the monthly values of SPEI into three classes of increasing precipitation intensity (from *f1* to *f3*) as representative of flood events, and other three classes of increasing drought

[1] Countries included are Burundi, Djibuti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, Sudan, Tanzania and Uganda.

[2] Being x_{imt} either temperature and precipitation recorded in cell i, month m and year t, our indicators for long-term variation is computed as follows: $x\_ch_{it} = 1/12\sum_{m=1}^{12}(x_{imt|t>1989} - 1/N\sum_{j=1}^{N}x_{imj|(1970\leq j<1990)})$.

[3] An overview of these indices and indicators can be found in the "Handbook of drought indicators and indices" by Svoboda and Fuchs (2016).

Table 2
SPEI classification.

SPEI values	Drought and flood condition	Class names
2.0 and more	Extremely wet	*f3*
1.5 to 1.99	Very wet	*f2*
1.0 to 1.49	Moderately wet	*f1*
−0.99 to 0.99	Near normal	
−1.0 to −1.49	Moderately dry	*d1*
−1.5 to −1.99	Severely dry	*d2*
−2.0 and less	Extremely dry	*d3*

Source: authors' elaboration from McKee et al. (1993).

severity (from *d1* to *d3*).

Based on this classification, we distinguish between positive values of the SPEI (SPEI_12_pos) that account for annual exposure to excess water and flood hazards, and negative values (SPEI_12_neg) that account for annual exposure to water scarcity and drought hazards.[4]

2.1.2. Vulnerability factors related to agricultural and resources access

To the extent that the agricultural channel is a major mechanism potentially fuelling climate-induced violence, we also account for a set of explanatory variables related to land use and agriculture.

First, we gathered data on different land cover typologies from the USGS, which provides global land cover data at 15 arc-min resolution, based on a 10-year collection (from 2001 to 2010). Starting from these data, we create a dummy variable assuming the value of 1 if the prevalent land cover of cells is made of water basins (*Water*), as this resource might be a particularly interesting source of vulnerability due to competing groups (e.g., fishermen, pastoralists, farmers) claiming access to water resources, especially in a situation of prolonged drought exposure.

As for agriculture-specific features, we gathered information on land use devoted to agriculture from the History Database of the Global Environment (HYDE) (Goldewijk et al., 2017). This database provides data on total cropland area per grid cell at 5 arc-min resolution (approximately 10 km) for 1990 and for the time span ranging from 2000 to 2015, hence we interpolate the original data to obtain information for the whole period of our analysis, from 1997 to 2016. In particular, from the HYDE database we collect data on total irrigated area (*Irrigation*) expressed in km.[2]

To account for the vulnerability of the agricultural sector to climatic hazards, we include a set of variables aimed at evaluating cell-specific risks due to floods and droughts during the growing season of main crops, i.e., the period in which crop yields are more sensitive to external variations (Harari and La Ferrara, 2018). We follow previous contributions and build an indicator representing the share of the growing-season months in which a drought or an excess in water has been recorded (Cappelli et al., 2022; Von Uexkull et al., 2016). More specifically, we combine climatic information provided by the SPEI index with information on the initial and last month of growing season of each cell's main crops, provided by the UCDP-PRIO (Peace Research Institute Oslo) grid database. As a first step, we build a monthly dummy variable equal to 1 if, in a given month, each cell's main crop is in the growing season. Then, we create a monthly dummy variable equal to 1 if the SPEI index is either below −2 (prolonged drought exposure) or above 2 (prolonged flood exposure). Finally, we combine information on growing season and extreme climatic conditions to obtain a measure of the relative length of the growing season affected in a given cell and year by extreme climatic conditions (*Gr_SPEI_12_d3_sh* and *Gr_SPEI_12_f3_sh*).

2.1.3. Vulnerability factors related to the socio-economic characteristics

We compile data on socio-economic characteristics from several different sources. Data on GDP come from the Gridded global dataset for Gross Domestic Product and Human Development Index, developed by Kummu et al. (2018). This dataset contains information on spatially disaggregated GDP for the years 1990–2015.[5] Hence, we interpolate data to 2016 and aggregate the cells of the original dataset to our 0.25° × 0.25 °C grid cell (approximately 25 km^2). We expect lower income to be associated with higher conflict risk.

As for information regarding population, we collect data on the total number of inhabitants per grid cell (*Population*), and the rural and urban population counts (*Rural_pop* and *Urban_pop*). The original source of data is the HYDE 3.2 Database (Goldewijk et al., 2017). Data are provided for 1990 and for the period from 2000 to 2015, with a spatial resolution of 5 arc-min (about 10 km), which correspond to 36 micro cells for each of our 25 × 25 km cell grid. To have data for the entire period 1997–2016, we interpolate and aggregate the original data by cell, summing the values of the 36 micro cells for each cell of our grid. We then use these variables to calculate the share of rural population for each cell (*Rural_pop_sh*) in order to account for the relative vulnerability of people living in rural areas with respect to those in urban places.

Following this last issue, we also account for the level of spatial inequality, since spatial variation in income, unequal access to key resources and relative deprivation may have strong influence on the risk of violence (Buhaug et al., 2011). Given the high resolution of the grid used in our analysis, we collect information on the presence and intensity of night lights to compute a proxy of the within-cell level of spatial inequality. Scholars have been increasingly employing night light data, which can be a particularly useful proxy of economic output and economic growth, especially in developing countries where statistical systems are lacking or absent (Doll et al., 2000; Chen and Nordhaus, 2011; Henderson et al., 2012). Night lights data have the advantage of being measured objectively and being available at a high spatial resolution for the entire globe since 1992 (Chen and Nordhaus, 2011).[6]

For the purpose of our analysis, we take information on night lights for the period 1992–2018 from Li et al. (2020) (30 arc-seconds resolution), associating the data to our grid cells. Our indicator is the standard

[4] Since negative values of the negative SPEI correspond to higher drought conditions, we express the variable *SPEI 12 neg* in absolute value in order to have an easier interpretation of the coefficients (i.e., larger values signal stronger climate anomalies).

[5] Kummu et al. (2018) provide 5 arc-min resolution (approximately 10 km grid) data for two main variables: cell-based GDP per capita (PPP) and Total GDP (PPP), both expressed in constant international 2011US$. They started from country-level GDP data gathered from the World Bank's World Development Indicators (WDI) database and the CIA's World Factbook for missing countries. Then, they downscaled the national GDP data to obtain 5 arc-min resolution data on sub-national GDP per capita by first calculating population-weighted national GDP per capita from sub-national GDP per capita data from Gennaioli et al. (2013) and the HYDE population dataset. This measure was then used to calculate the ratio between population-weighted national GDP and reported sub-national GDP. Then they estimated the total GDP per capita for each cell by multiplying this ratio with the reported sub-national GDP and thus obtained georeferenced data for GDP per capita (PPP) for the time span ranging from 1990 to 2015. To obtain data on GDP, they multiplied the GDP per capita by grid-specific population data.

[6] Night light data have been used in the literature to measure human activities at several levels, including urbanization (Stathakis et al., 2015; Li et al., 2019), electrification (Doll and Pachauri, 2010; Min et al., 2013; Dugoua et al., 2018) and several dimensions of socio-economic development, such as per capita income (Pinkovskiy and Sala-i-Martin, 2016; Mveyange, 2018), poverty (Weidmann and Schutte, 2017; Andreano et al., 2021) and inequality (WB, 2018; Ivan et al., 2019), but also resilience to shocks after natural disasters (Qiang et al., 2020). The way in which night light data have been operationalized varies in the social sciences (see Dugoua et al., 2018; Gibson et al., 2021 for a summary): for example, night lights are often expressed as a logarithmic transformation of their sum to represent GDP, economic growth (Doll et al., 2006) and rural electrification (Min et al., 2013), or as average to represent a plethora of phenomena, such as local economic development (Michalopoulos and Papaioannou, 2014) and impacts of natural disasters (Cole et al., 2017).

deviation of night-time light data recorded in each grid cell, expressed in Digital Number (DN) values (*Nightlights (sd)*). Statistically, standard deviation represents a measure of dispersion, i.e., it gives a measure of how much the data are spread out around the mean. Thus, we interpret the standard deviation of night lights as a measure of vulnerability because, according to our hypothesis, it represents inequality (dispersion) in access to resources that enable development.

Finally, another significant information regarding the possible social vulnerability of a territory is ethnic fragmentation, a common measure of horizontal inequality. Ethnic division is a relevant source of vulnerability in many cases, and previous literature has found that climate-related extreme events are more likely to act as a threat multiplier of violent activities in ethnically fractionalized contexts (Schleussner et al., 2016). We collect data from the Geo-Referenced of Ethnic Groups (GREG) dataset provided by Weidmann et al. (2010) [7] and we create a time-invariant indicator which counts the number of distinct ethnic groups coexisting within a single cell (*n_ethnic*).

Table 3 reports the descriptive statistics of main variables included in our analysis.

2.2. Data visualization

Fig. 1(a) shows the total number of conflicts in East Africa across the entire period of analysis, i.e., 1997–2016. Conflicts are mainly located in the centre of the region, especially in the Horn of Africa and in the western area, while the northern and southern areas of the region are less prone to conflicts, mainly because of the presence of deserts. Fig. 1 (b), instead, shows the number of cells that have experienced multiple years of conflicts over the period 1997–2016: cells in red are those that experienced at least one conflict in more than one year, while grey cells are either not affected by conflicts, or a maximum of one-year conflict was registered over the time span considered. Fig. 1 (a) and (b) almost overlap, indicating that if a conflict occurred in the region, it is very likely that further conflicts have followed in the next few years. This might be a visual, albeit exploratory, representation of the so-called "conflict-trap" hypothesis proposed by Collier et al. (2003), which states that areas that experience a conflict are then more likely to engage in further conflicts.

Fig. 2 shows the GDP in our region of interest, for 1997 (a) and 2016 (b) respectively. As we can observe, the GDP has increased on average in large part of the cells, even though not uniformly across the region. Interestingly, some of the cells characterised by relatively higher GDP level are located in areas around water basins, e.g., the Nile river in the northern Sudan, and the lake Victoria in south-west of East Africa (at the border among Kenya, Uganda and Tanzania). The strongest GDP increase between 1997 and 2016 was recorded for Ethiopia, especially in the regions around the capital Addis Ababa.

Fig. 3 depicts our indicator for spatial inequality, proxied by the standard deviation of night lights in 1997 and 2016. Even in this case, the standard deviation of night light increased, on average, from 1997 to 2016, with some internal heterogeneities, indicating that spatial inequalities in resource access are higher in 2016 than in 1997.

Finally, Fig. 4 depicts the mean SPEI calculated over 12 months for 1997 and 2016. Fig. 4 shows how the SPEI changed considerably from the first year of analysis to the last. Indeed, in 1997, the distribution of the SPEI was rather homogeneous, with very few extreme values. On the other hand, in 2016, the difference in the distribution of the SPEI with respect to 1997 was stark: the SPEI was negative for almost the entire region, with a peak in some areas like the Sahara Desert and with values on average much more extreme. Overall, in 2016 the SPEI indicates an increase in prolonged drought conditions with respect to 1997.

2.3. The empirical model

According to Mach et al. (2020), research on the climate-conflict nexus should exploit growing access to microlevel data from diverse sources, such as satellite and drone imagery, social media and population surveys. These new types of data could be useful in understanding fine-scale variations in elements that determine neighbouring societies to experience potentially different levels of vulnerability. For instance, high spatial resolution data allow us to detect the presence of water basins and irrigation facilities, as well as the number of ethnic groups co-inhabiting a small area. In addition, the identification of factors giving rise to the emergence of conflict hotspots requires the adoption of a local perspective. This local perspective allows to account for the spatial dimension in the distribution of the data as well as to consider spatial autocorrelation in the risk of conflicts.[8]

In particular, to understand the origin of conflict hotspots, Silve and Verdier (2018) suggest considering two channels jointly. First, regional conflict hotspots usually result from the clustering of similar internal features, such as geographical or social characteristics, resource endowments, and climatic conditions that can make a region especially vulnerable to climate change and conflicts. Second, the geographical distribution of armed conflicts is largely dependent on the contagion effect induced by the spatial spillovers between neighbouring regions. To date, only a few quantitative studies at a highly disaggregated level and encompassing large datasets directly address contagion effects and spatial propagation of armed conflicts (e.g., Harari and La Ferrara, 2018; Cappelli et al., 2020). In spatial econometrics, the contagion effect among neighbouring locations can be shaped in different ways, according to the type of interaction effects used (Elhorst et al., 2014).

In our case, we are interested in understanding the emergence of conflict hotspots resulting from local vulnerability factors as well as from the direct contagion effect of conflicts themselves. Accordingly, we employ a Spatial Autoregressive Model (SAR) for panel data, which accounts for the spatial autocorrelation in the dependent variable. We introduce the endogenous interaction effect by means of an inverse distance row-normalized *NxN* matrix *W*, *N* being the number of cells included in the sample. The generic element $w_{i,j}$ thus captures whether or not cells i and j are neighbours, based on a threshold of 1065 km.[9]

The econometric model we estimate is the following:

$$Conflict_{it} = \alpha + \rho \sum_{j \neq i, j=1}^{n-1} W_{ij} Conflict_{jt} + X_{it}^{CC}\beta_{CC} + X_{it}^{SE-V}\beta_{SE-V} + X_{it}^{AR-V}\beta_{AR-V} + X_{it}^{OC}\beta_{OC} + \gamma_t + \mu_i + \varepsilon_{it}$$

where $Conflict_{it}$ is the probability of conflict onset in cell i and time t; ρ is the endogenous spatial interaction effect (introduced by means of the spatial weight matrix W) capturing the contagion effect due to the presence of conflicts in neighbouring cells; X^{CC} is the set of variables related to climatic variations experienced by cell i in time t; $X^{SE\text{-}V}$ is the set of covariates representing socio-economic characteristics and vulnerability factors; $X^{AR\text{-}V}$ is the set of covariates accounting for vulnerability related to agriculture and resource access; μ_i are cell-specific fixed effects; γ_t are year-specific fixed effects; ϵ_{it} is the error term.

3. Results

Table 4 reports results for the baseline SAR model on a panel of 8217 grid-cells for the years 1997–2016, while Table 5 extends results to the inclusion of local vulnerability factors.

[7] In the GREG dataset, data are divided into zones (represented by polygons), within which there can be a maximum of three ethnic groups. However, our cells do not perfectly match the polygons, hence our cells may include more than three distinct ethnic groups.

[8] As a preliminary step, we calculate global and local spatial autocorrelation indices for our data, whose results are available in the Supplementary Material.

[9] The inverse distance matrix has been created using a great circle formula and Queen approach.

Table 3
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Cd	164,340	.0227942	.1492473	0	1
Nc	164,340	.0716624	1.421807	0	240
Temp_ch	164,340	.9161746	1.076306	−4.781434	12.17524
Prec_ch	164,340	3.318654	15.14216	−81.42947	190.5371
SPEI_12_pos	164,340	.1956271	.2448528	0	2.817094
SPEI_12_neg	164,340	−.4680026	.3172101	−2.852388	0
Water	164,340	.0181331	.1334333	0	1
Irrigation	164,340	.2496431	2.381488	0	81.48996
Gr_SPEI_12d1_sh	164,340	.2637166	.368272	0	1
Gr_SPEI_12d2_sh	164,340	.1145373	.2778505	0	1
Gr_SPEI_12d3_sh	164,340	.0567402	.2055339	0	1
Gr_SPEI_12f1_sh	164,340	.0870068	.2312239	0	1
Gr_SPEI_12f2_sh	164,340	.040877	.1622214	0	1
Gr_SPEI_12f3_sh	164,340	.0176734	.1099326	0	1
GDP_pc	164,340	16.28259	10.15217	0	93.0036
Population	164,340	3438.448	9839.137	0	350,673.7
Rural_pop_sh	164,340	.8795083	.2720016	0	1
Nightlights (sd)	164,340	.4679066	1.401314	0	24.22019
N_ethnic	164,340	1.36461	.7023711	0	6

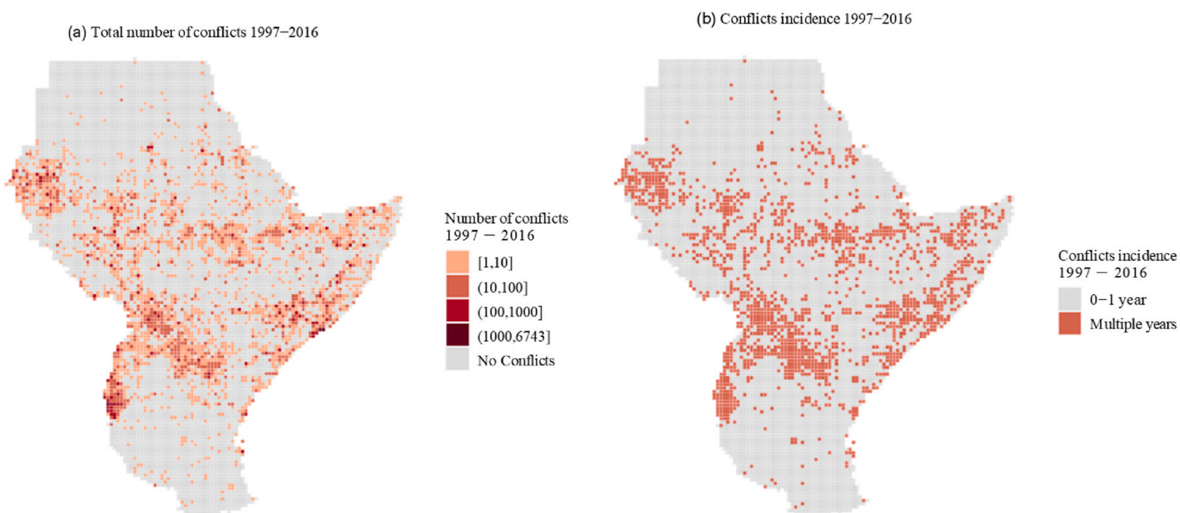

Fig. 1. (a) Total number of conflicts, 1997–2016; (b) Cells with multiple years of conflicts, 1997–2016.

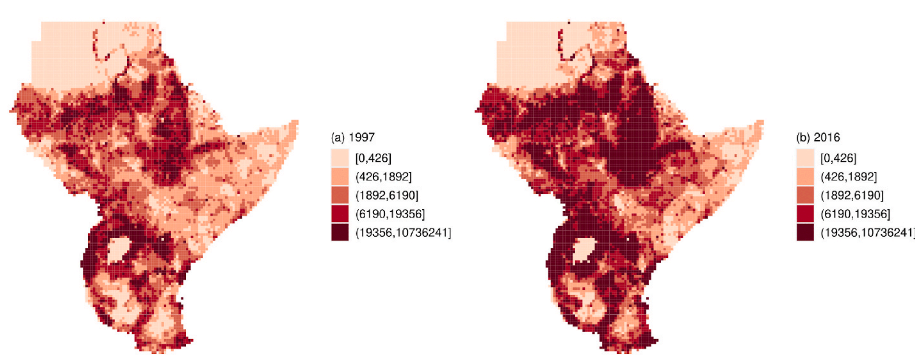

Fig. 2. (a) GDP in 1997 (in thousands USD); (b) GDP in 2016 (in thousands USD).

The baseline model includes the spatially lagged dependent variable, the socio-economic drivers in terms of GDP and population, the climatic characteristics and the first vulnerability factor, i.e., our proxy of spatial inequalities in resource access as represented by the standard deviation of night lights.

First, coherently with our expectations, the coefficient ρ associated to the endogenous spatial interaction effect (i.e., whether at least a conflict has been recorded in neighbouring cells) is positive and statistically significant in all model specifications. This result provides strong support for the so-called contagion effect according to which a conflict occurring in one territory increases the likelihood of conflicts outbreak

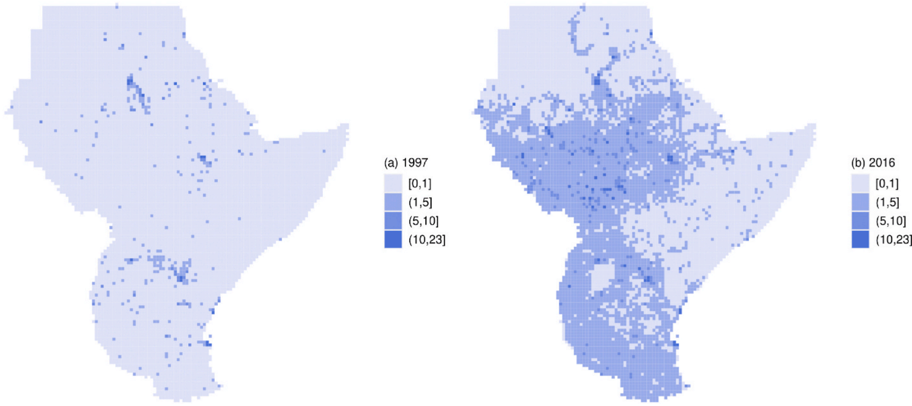

Fig. 3. Night lights expressed in standard deviation in (a) 1997 and (b) 2016.

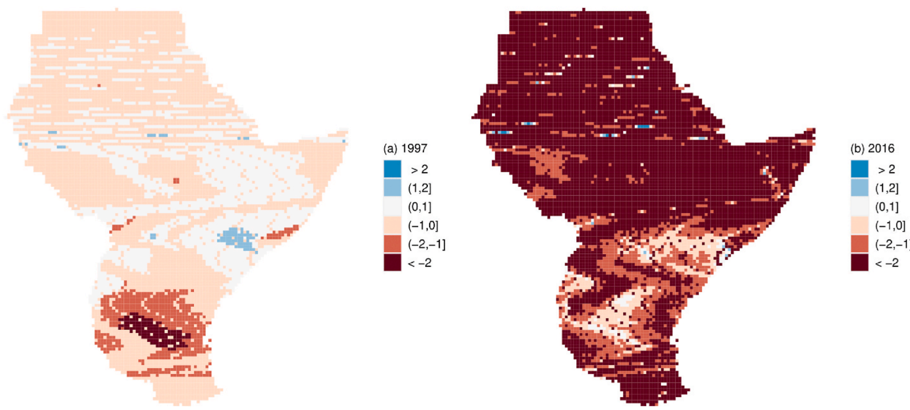

Fig. 4. Spei 12 in (a) 1997 and (b) 2016.

Table 4
SAR baseline model.

	(1)	(2)	(3)	(4)
GDP pc (ln)	−0.0851***	−0.0855***	−0.0856***	−0.0859***
	(0.0071)	(0.0071)	(0.0072)	(0.0071)
Population (ln)	0.1399***	0.1409***	0.1406***	0.1413***
	(0.0146)	(0.0147)	(0.0147)	(0.0147)
Nightlights (sd)	0.0033***	0.0034***	0.0034***	0.0034***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Temp ch		0.0011	0.0025**	0.0023*
		(0.0011)	(0.0012)	(0.0012)
Prec ch		−0.0000	0.0000	0.0000
		(0.0000)	(0.0000)	(0.0000)
Temp ch2			−0.0004*	−0.0004*
			(0.0003)	(0.0003)
Prec ch2			0.0000	
			(0.0000)	
SPEI 12 neg				0.0034
				(0.0033)
SPEI 12 pos				0.0037
				(0.0039)
Spatial ρ	0.8269***	0.8270***	0.8256***	0.8248***
	(0.0137)	(0.0137)	(0.0137)	(0.0137)
Variance σ^2	0.0331***	0.0331***	0.0331***	0.0331***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
N	1.6e+05	1.6e+05	1.6e+05	1.6e+05
R^2	0.0386	0.0392	0.0391	0.0394

This table shows coefficients for a SAR model with a rw11 matrix across the years 1997–2016. Additional controls include year dummies and a structural break dummy in 2013. Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

also in surrounding areas.

As for the role of socio-economic conditions, we find a negative and statistically significant effect of GDP per capita on the probability of conflicts.[10] The effect is robust across all specifications and it is in line with previous literature linking higher levels of development to a lower conflict risk (e.g. Collier and Rohner, 2008; Ray and Esteban, 2017). On the other hand, as expected, higher population count has a positive effect on conflict risk, as in more populated places tensions are more likely to arise.

The coefficient of the variable *Nightlights (sd)*, our proxy of spatial inequality, is positive and statistically significant, suggesting that, regardless of climatic conditions, a higher level of (within-cell) unequal access to key resources (e.g., energy and infrastructures) increases the likelihood of conflict outbreak. Turning to climatic factors, the coefficient associated with long term changes in precipitation is not statistically different from 0. On the other hand, temperature anomalies have a positive effect on conflict risk but, as we can see in Models 3–4, their effect is quadratic: after a certain threshold (which corresponds to 3.125 °C), the effect of temperature anomalies turns negative. However, cells characterized by these extreme anomalous variations in temperatures correspond to less than 5% of our sample. Therefore, results for about 95% of our cells are in line with the literature linking higher variations in temperature to conflict outcomes (Burke et al., 2015; O'Loughlin et al., 2012). Finally, long-term conditions of drought and/or flood do not seem to have an impact on conflict risk *per se*.

[10] In a robustness check, we control for GDP per capita growth in place of the logarithm of GDP per capita, and the results maintain the same sign and level of significance.

Table 5
SAR vulnerability model.

	(1)	(2)	(3)	(4)	(5)	(6)
GDP_pc	−0.0783***	−0.0860***	−0.0860***	−0.0862***	−0.0860***	−0.0866***
	(0.0072)	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0072)
Population (ln)	0.1250***	0.1416***	0.1409***	0.1407***	0.1377***	0.1397***
	(0.0140)	(0.0148)	(0.0147)	(0.0148)	(0.0147)	(0.0148)
Nightlights (sd)	0.0032***	0.0034***	0.0034***	0.0034***	−0.0030	0.0031***
	(0.0010)	(0.0010)	(0.0021)	(0.0010)	(0.0010)	(0.0010)
Temp_ch	0.0020	0.0023*	0.0023*	0.0022*	0.0023*	0.0023*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
$Temp\_ch^2$	−0.0005*	−0.0005*	−0.0004*	−0.0004*	−0.0004*	−0.0004*
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Prec_ch	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SPEI_12_neg	0.0782***	0.0030	0.0030	0.0022	−0.0007	0.0038
	(0.0113)	(0.0033)	(0.0033)	(0.0046)	(0.0032)	(0.0033)
SPEI_12_pos	0.0892***	0.0032	0.0037	0.0035	−0.0004	−0.0189***
	(0.0175)	(0.0040)	(0.0039)	(0.0039)	(0.0038)	(0.0056)
Rural Population (%)	−0.0710**					
	(0.0337)					
Rural population*SPEI_12_neg	−0.0850***					
	(0.0114)					
Rural population*SPEI_12_pos	−0.0970***					
	(0.0180)					
Gr_SPEI_12d3_sh		0.0024				
		(0.0057)				
Gr_SPEI_12f3_sh		0.0023				
		(0.0050)				
Water#SPEI_12_neg			0.0223*			
			(0.0118)			
Irrigation				0.0024*		
				(0.0014)		
Irrigation#SPEI_12_neg				−0.0015**		
				(0.0007)		
Nighlights (sd)*SPEI_12_pos					0.0072**	
					(0.0028)	
Nighlights (sd)*SPEI_12_neg					0.0082**	
					(0.0023)	
1.n_ethnic#SPEI_12_neg						−0.0048
						(0.0050)
2.n_ethnic#SPEI_12_neg						0.0153**
						(0.0078)
3.n_ethnic#SPEI_12_neg						0.0214*
						(0.0125)
4.n_ethnic#SPEI_12_neg						−0.0596
						(0.0415)
5.n_ethnic#SPEI_12_neg						−0.1297*
						(0.0696)
6.n_ethnic#SPEI_12_neg						−0.0655***
						(0.0049)
1.n_ethnic#SPEI_12_pos						0.0198***
						(0.0071)
2.n_ethnic#SPEI_12_pos						0.0303***
						(0.0096)
3.n_ethnic#SPEI_12_pos						0.0303*
						(0.0168)
4.n_ethnic#SPEI_12_pos						−0.0144
						(0.0592)
5.n_ethnic#SPEI_12_pos						0.2305
						(0.1781)
6.n_ethnic#SPEI_12_pos						0.0797***
						(0.0076)
Spatial ρ	0.8260***	0.8248***	0.8251***	0.8245***	0.8235***	0.8255***
	(0.0136)	(0.0138)	(0.0137)	(0.0137)	(0.0138)	(0.0137)
Variance σ^2	0.0331***	0.0331***	0.0331***	0.0331***	0.0331***	0.0331***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
N	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05	1.6e+05
R^2	0.0427	0.0395	0.0391	0.0391	0.0393	0.0390

This table shows coefficients for a SAR model with a rw11 matrix across the years 1997–2016. Additional controls include year dummies and a structural break dummy in 2013. Standard errors are in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5 adds on to Table 4, concentrating on possible sources of vulnerability that drive the climate-conflict nexus. In particular, we introduce several interaction terms to jointly assess the role of local sources of vulnerability and climatic factors, and test whether climate change impacts bring about different conflict outcomes in the presence of a similar level of exposure but a different level of vulnerability. Results in this case are especially interesting. We find that long-term climatic stress such as prolonged droughts and excessive terrain humidity, for instance in the aftermath of floods or water bombs, are possible channels of increased conflict risk not *per se*, but in combination with some specific sources of vulnerability.

This is the case if we look at Model 3 where we test the differentiated effect of extremely dry climatic conditions depending on the geographical distribution of water basins. Accordingly, in Column 3, the variables *SPEI_12_negs* and *Water#SPEI_12_negs* record the intensity of drought in cells characterised, respectively, by absence and presence of water basins. The results indicate that extremely dry climatic conditions foster competition for water resources, constituting a source of increased conflict risk in cells featured by the presence of natural water basins. On the other hand, prolonged drought conditions coupled with access to irrigation systems decrease conflict risk (Model 4), while the presence of artificial irrigation systems *per se* is associated with higher likelihood of conflicts. These findings seem to suggest that cells characterized by parcels of agricultural land artificially irrigated and parcels relying on rainfall precipitation are especially subject to instability and violence. However, as the intensity of drought stress increases, the presence of technical innovation in agriculture becomes a source of resilience for the region.

Taken together, these results provide mixed evidence on the role of vulnerability factors related to agriculture and resource access in mediating the climate-conflict nexus. To further explore this link, we try to disentangle the potential effects associated to the supply vs. demand side of the agricultural channel: i.e., whether the conflict risk is more sensitive to the reduction of livelihoods and income of farmers and people employed in the agriculture sector, or to changes in food and crop prices (and food security threat) ultimately affecting final consumers. In order to do so, we investigate the role of demographic distribution between rural and urban areas, under the assumption that the former are more exposed to supply-side effects while the latter may be more at risk due to demand-side mechanisms. Hence, in Model 1 we control for the share of urban population in each cell i and year t, and interact this variable with the positive and negative SPEI indicators. Our results suggest that: i) the likelihood of conflicts is higher in more urbanized areas; ii) when controlling for the rural-urban divide, the occurrence of extreme climatic conditions (both dry and wet) increases the conflict risk; iii) the effect of these climate variations is relatively lower as the share of rural population increases.

In a similar vein, the non-significant effect of the share of crops' growing season affected by either prolonged drought or flood conditions in Model 2 contributes to excluding the production side of the agricultural channel as a source of increased vulnerability to climate change and conflicts in East Africa. This, especially if read in conjunction with the increased risk of conflict posed by spatial inequality in access to infrastructures, might indicate that urban areas in East Africa are more exposed to conflict risk compared to rural areas.

A final source of social vulnerability is related to the co-presence of different ethnic groups in a given area (Model 6). Our results highlight different behaviours in response to different climatic conditions. In extremely dry conditions, we find an increased risk of conflicts if an area is co-inhabited by two or three different ethnic groups, and a diminished risk of conflicts in the presence of five or six different ethnic groups. This differentiated effect might be related to the inability of ensuring a fair distribution of power in the presence of a limited number of competing ethnic groups. On the other hand, when a given area is affected by extremely wet conditions that, by their nature, occur over a much shorter time span, the likelihood of conflict outbreak is greater, irrespective of the number of coexisting ethnic groups.

4. Discussion

Our empirical work sheds new light on the climate-conflict nexus by investigating the vulnerability factors that explain why some locations are more likely to engage in armed conflicts than others in the presence of a similar level of exposure to climatic changes. In particular, we focus our analysis on the concept of vulnerability to both climate change and armed conflicts and, accordingly, on the identification of a specific set of factors that enhance vulnerability in Eastern African countries at a high-resolution geographical level (about 25 km^2). Grounding on the literature studying vulnerability to climate change, we consider vulnerability as a combination of socioeconomic and context-specific factors. Further, instead of relying on a composite indicator of vulnerability, we account for different aspects of vulnerability separately, in order to identify key factors where policymakers can intervene to improve local resilience.

From a methodological perspective, we employ a Spatial Autoregressive Model to capture the spatial and context-specific dimension of vulnerability factors in driving the climate-conflict nexus in East Africa. Results from our analysis provide some interesting insights: first, we find that climate change does not increase conflict risk *per se*, but only in presence of pre-existing vulnerability. This result is especially relevant, as it can help explain the disagreement in the literature about the impact of climate change on conflict propensity. In particular, our results seem to suggest that there is no generalisable direct link between climate change and conflicts, but rather that climate change acts as a threat multiplier in the presence of specific source of vulnerability.

Second, in line with the literature on climate change vulnerability, we find that socio-economic factors such as spatial inequality, as represented by the standard deviation of night lights, play a key role in the climate-conflict nexus. This result adds new verve to the acknowledgement of vulnerability as a social construction, being inequality in access to key resources for adaptation a pillar of this strand of literature (Thomas et al., 2019). In particular, we find that vulnerability is enhanced whenever power is not distributed in such a way as to ensure an equitable distribution of resources. This result emerges in connection with several aspects in our empirical analysis: it is true, for instance, in relation to infrastructures, which are key to ensure a decent quality of life in urban contexts.

This is confirmed by our results on the rural-urban demographic divide, which highlight a higher conflict propensity in urban areas. These findings are consistent with previous studies according to which in food-producing areas an increase in prices has mixed effects on conflicts (i.e., lower intensity of conflicts related to control of territory, but higher conflict over the appropriation of surplus), while in more urbanized areas both forms of conflict are likely to escalate due to price increases (McGuirk and Burke, 2020). Indeed, climate-induced resource scarcity may result in higher food and crop prices and, to the extent that food and agricultural products constitute a relative high share of households' budget, this mechanism is likely to fuel stronger conflict risk also in urban areas, especially in those contexts in which many people live in disadvantage conditions and are subject to high level of inequality (McGuirk and Burke, 2020; Paglialunga et al., 2022). These results suggest that conflict dynamics in the East Africa region are mainly located in urban areas, as opposed to rural areas. Indeed, prolonged drought and flood conditions also increase conflict risk when coupled with spatial inequality in access to resources, as proxied by the standard deviation of night lights, and dispersion in access to resources is higher in cells with a relatively lower share of rural population.

In rural contexts, our results suggest that a great source of vulnerability is related to the access to key resources such as water basins, which are essential for the livelihood of some agricultural and farmer communities, and whose unequal distribution ultimately magnifies conflict risk. This evidence is in line with previous literature (e.g., Gizelis and Wooden, 2010; Almer et al., 2017) highlighting that, when climatic conditions are extreme, competition over an essential resource such as water arises. An additional source of contention in rural contexts is represented by irrigation systems. African countries are still strongly dependent on the agricultural sector, and the contribution of agriculture to the national economic system is quite heterogeneous across regions and it is highest in East Africa: agricultural activities account for about 30% of the regional GDP, and the share of people employed in the agricultural sector has been over 60% during the last five decades. At the same time, in Eastern African countries the adoption of agricultural technologies (e.g., irrigation systems) is still lagging behind and almost all farmers rely on rainfed agriculture (Suri and Udry, 2022). Because of the limited availability of irrigation systems, our findings suggest that these become a source of contention as they make it possible only for small share of the territories to cope with the difficulties encountered in cultivating in dry land. However, during times of excessive drought that lasts for very long periods, the availability of irrigation systems activates cooperative mechanisms by alleviating the risk of conflict. In these situations, it is plausible that agricultural harvests are greatly reduced, and livelihoods of local people are prioritized over trade.

Additionally, the importance of power distribution emerges in relation to the number of ethnic groups co-inhabiting in a given area: in the presence of prolonged droughts, conflicts and vulnerability arise only when ethnic groups are present in a number which is not sufficiently small or sufficient large to ensure a share of power to each one. To illustrate, when a limited number of ethnic groups (e.g., two or three) is present in a same territory, competition for prevailing over the others increases. This might be related to the co-existence of (likely one) dominant ethnic group and other politically marginalized ethnic groups. In this case, it is likely that increases in drought could increase conflict risk (Von Uexkull et al., 2016), especially when exclusionary mechanisms are coupled with political processes (Seter et al., 2018). Inter-group inequality is likely to affect the relationship between prolonged drought conditions and conflict risk, especially in the case of politically marginalized ethnic groups. If environmental hazards unequally affect different ethnic groups, this might lead to waning trust across them, increasing the probability of conflict (De Juan and Hänze, 2021). On the other hand, in the presence of a multitude of ethnic groups it is more likely for everyone to get a share of power, hence tensions quieten.

A different picture emerges when a given area is affected by extremely wet conditions: in this case, irrespective of the number of ethnic groups, the likelihood of conflict outbreak is greater. Arguably, in the case of extremely wet conditions, the environmental hazard manifests itself in a very short time span and is very destructive. This will require immediate actions to counteract the adverse impacts. Accordingly, if the society exposed to such hazards is not adequately prepared to adapt to this kind of extreme events, the eventuality of a conflict becomes a much more plausible outcome (Buhaug et al., 2008). In fact, trust in local institutions is a key factor in mitigating the relationship between floods and communal violence (Petrova, 2022). Furthermore, in the case of flood-related events, the onset of political unrest is more likely if a number of conditions are satisfied, namely the exclusion of ethnic groups from political power (Ide et al., 2021). This is because small and politically excluded ethnic groups usually experience most conflicts related to environmental factors (Raleigh, 2010).

5. Conclusions

This paper advances research in the literature on vulnerability to climate change and armed conflicts at the local level. Our results highlight the need to carefully evaluate local sources of vulnerability when designing measures to both improve adaptation to climate change and enhance peace and stability. The risk of violent activities as a result of disruptions of economic livelihoods, unequal possibilities and access to vital resources is, in the end, an extreme manifestation of a vulnerability that, if corrected, would greatly diminish conflict risk. Becoming a climate-resilient society implies targeting the same sectors that are plausible channels in the climate - conflict nexus.

In this respect, both bottom-up and top-down policies can be useful to improve adaptation and resilience of local communities. Bottom-up policies can include, for instance, the engagement of all relevant stakeholders at the community level to facilitate conflict resolution, as well as to foster community-based resource management and the establishment of a locally shared climate adaptation strategy. Top-down strategies should prioritize the incorporation of climate resilience into resource management strategies to ensure a sustainable use and an equitable allocation. Conflicts over control of water basins can be mediated, for example, by expanding access to water resources during extremely dry periods (e.g., through extended provision of irrigation facilities, as suggested by our results and in line with Ward (2022)), complemented by property rights protection (Butler and Gates, 2012) and heightened state capacity (Gizelis and Wooden, 2010; Döring, 2020). Further, as our results suggest, conflict prevention necessarily goes through the reduction of inequalities in income and in access to resources, which constitute a great source of vulnerability and the ultimate cause of conflict outbreak (Lessmann and Steinkraus, 2019).

If societies exposed to adverse climatic impacts are unprepared or lack adaptive capacity, struggles over resources, as well as migrations and armed conflicts outbreak turn out to be increasingly likely. However, this set of relationships is extremely complex, in that climate change can certainly exacerbate pre-existing vulnerabilities (Buhaug and von Uexkull, 2021). Our study focuses on the effects of climate-related impacts on conflict outbreak as mediated by local vulnerability factors, providing a helpful yet partial understanding of the complexity of the climate-vulnerability-conflict nexus. Hence, future research should further investigate the relationship among climate change, conflict risk and vulnerabilities in a systemic way, by also accounting for mutual influences and the possibility of vicious cycles.

Further, the identification of location-specific vulnerability factors could provide a useful starting point for further insights for the development of climate-resilient strategies that also account for conflict risk. Hence, such analysis could then serve as an insightful foundation for future research on other vulnerable regions worldwide, providing tailored suggestions for policymakers to enhance climate-resilient and peaceful societies.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: We acknowledge funding from the PRIN 2022 project 202252P92X 'Assessing Public Policy effectiveness in minimising Local Impacts with Climate-related AdapTation Expenditures (APPLICATE)'.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.120403.

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