Quantifying the influence of climate variability on armed conflict in Africa, 2000–2015

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Abstract

Global climate change, expected to be one of the most severe challenges that human beings have ever encountered, has had far-reaching impacts on ecosystems and humans, among which the potentially increasing chance of violent conflict has raised attention recently. However, several years of research have produced no consensus regarding whether climate variability affects the risk of armed conflict and how it may affect conflict. In this study, we built a geographically disaggregated method to explore the relationship between climate variability from normal climate conditions and armed conflicts both on a local and regional scale. With the 10,993 conflict records acquired in 25 African countries over 16 years from 2000 to 2015, we estimated the effects of temperature and wet day variability on conflicts in agricultural and non-agricultural areas, respectively, on gridded 1° resolution. The results showed that deviations from the normal climate have a systematical impact on the risk of conflict: The risk of violence rises with increasing deviations from the temperature norms in both non-agricultural and agricultural areas. Regarding the rainfall variability, in non-agricultural areas, the risk of violence grows with increasing anomalous wet days, either more or fewer days than the annual average, while in agricultural areas, increases in violence risk only exhibit under the impact of fewer wet days than the annual average. We expect these findings would provide empirical support for policymakers and relevant organizations who need to prepare additional law enforcement and/or peacekeeping resources when climatic anomalies are detected.

Keywords Climate variability · Armed conflicts · Africa · Generalized Additive Model

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1 Introduction

Currently, the global structure is undergoing drastic changes. Since the end of the Cold War, global wealth and strategic resources have shifted, geopolitical strategic relationships between countries and groups of countries have undergone new differentiation and combination, and armed conflicts remain a serious challenge facing human society. Mortality from war and interpersonal violence results in 0.5–1 million deaths annually (Organization, 2008), with nonlethal impacts, including injuries and lost economic opportunities, affecting millions more.

Today's international relations are more complex than ever before, making it increasingly more difficult to attempt to clearly understand armed conflicts. Traditional research focuses on the impacts of armed conflict and especially on the impact of armed conflict on public health (Serneels & Verpoorten, 2012), on the population (emphasis on children) (Peltonen & Punamäki, 2010), and on economic conditions (Lopez & Wodon, 2005). However, the reality is that it is urgent to summarize new characteristics and laws from the changes in conflicts, which in turn can explain and even allow the prediction of certain phenomena of international security. Research on the impact factors of conflicts was initially focused on the fact that the occurrence of armed conflict is mainly affected by human and social factors (Quinn, 2017), such as religious conflicts (God, 2013) and racial divisions (Basedau et al., 2011). Later studies of conflict drivers and mechanisms focused on the impacts of natural and social resources on conflict (Østby et al., 2011), which were followed by studies of economic and political factors (Lingyu & Thies, 2010).

In recent years, some scholars have suggested that climate variability may be another driver of armed conflict (Schleussner et al., 2016; von Uexkull et al., 2016), because droughts are becoming more persistent and extreme weather events more frequent. One of the best-known frameworks was established by Scheffran et al., 2012 (Scheffran et al., 2012), who suggested multiple pathways and feedbacks between the climate system, natural resources, human security, and societal stability, including diverse levels of violence and conflict. It is easy to understand how climate anomalies could adversely impact natural resource, especially livelihood resources, such as water resources, pastures and farmland, leading to an increasingly fierce competition and, subsequently, to violent conflict (Brinkman & Hendrix, 2011). A study of mid-to-late Imperial China indicated that under a deteriorating climate, the state capacity of nomads and agriculturalists was both weakened. Nomads launched southerly movement and invasion toward agriculturalist polities in response to climate-induced subsistence pressure (Pei et al., 2019). Climatic conditions may also shape the economic background of a country (Bohlken & Sergenti, 2010) and the global political landscape (Cederman et al., 2013); for example, natural disasters related to extreme weather conditions, if not handled properly by the government, could cause social panic (Linke et al., 2017) and substantially increase the risk of forced displacement (Reuveny, 2007); even long-term historical climate variability tends to align with some narratives about the evolution and collapse of civilizations (Kuper & Kröpelin, 2006). These factors are all catalysts for violence and conflict.

Research over the past decade has established that climate variability and climate change may influence the risk of violent conflict. Much earlier statistical climate–conflict research focused almost exclusively on the risk of state-based conflicts such as civil war (Burke et al., 2009; Raleigh & Urdal, 2007). In recent years, climate–conflict studies are increasingly and regularly investigating implications for community violence (Döring, 2020) and social unrest occurrences (Jones et al., 2017), owing to the introduction of new

events-based datasets. Scholars are increasingly turning to national or cross-national surveys to determine how climatic conditions and events affect the acceptance and participation of individuals in collective political violence (Detges, 2017; Vestby, 2019). Recently, research published in *Nature* developed a synoptic assessment, gathering a group of 11 climate and conflict experts to get the expert elicitation and concluded that climate has affected organized armed conflict within countries (Mach et al., 2019). However, up until now, there has been relatively little scientific focus on the implications of climate variability and change for interstate armed conflict (von Uexkull & Buhaug, 2021).

Although the claim that climate variability and extreme weather events pose a major threat to social stability and peace is being accepted by an increasing number of people (Studies, 2007), academia has not reached a consensus. For instance, theoretical work and evidence from case studies suggested that attributing violence to extreme weather and climate variability was considered clinging to a modern form of environmental determinism (Raleigh et al., 2014), environmental degradation, resource scarcity, and other impacts of adverse climatic conditions that hold much greater potential to spawn low-scale violence or breakdown of cooperation than major armed conflicts at national or international scale (Peluso et al., 2001). There were also researchers arguing that rather than climate variability, African civil wars can be explained by the generic structural and contextual conditions: prevalent ethno-political exclusion and poor national economies (Buhaug, 2010).

In this study, we collected 10,993 conflict records in 25 African countries over 16 years from 2000 to 2015, and used a geographically disaggregated approach to examine climate–conflict relationships. We used a 1° gridded analysis and included as many geographical factors as possible that have been shown to be important in understanding the distribution and causes of violence. For our main climate indicators, we calculated the climate variability as 6-month deviations in wet days and temperatures from long-term averages. We use generalized linear model (GLM) and generalized additive model (GAM) on 210,048 grid cells-years, which is the total additive number of 1° gridded cells in 25 African countries for 2000–2015, to examine climate and non-climate effects on human violence. A total of eleven covariates and conflict cases were selected for the analysis. Our estimation procedure accommodates the possible nonlinear relationship between climate variability and conflict and how does it operate in agricultural and non-agricultural area studied on a regional and national scale.

2 Materials and methods

2.1 Study region

Considering geographic zoning for Africa and its inter-regional tensions, conflicts, as well as interconnections, we selected 25 countries with a high risk of conflict in central Africa, including Sudan, Zaire, and Somalia for the analysis (Fig. S1). The region is characterized by a large number of small and weak states, constant internal strife, and external forces tearing it apart, resulting in the fragmentation of the geopolitical map. This fragmentation, in turn, has exacerbated the volatility of the regional situation and tensions between regional states, making it difficult to form a centripetal "power center". The region has thusly become a hotspot for new international geopolitical conflicts since the twenty-first century.

Specific coordinates and country attributes of the conflict cases were obtained from the Uppsala Conflict Data Program (UCDP), including all the state-based and non-state conflicts. We used the most updated Georeferenced Event Data set [GED] Global version 18.1 (2017). According to the UCDP database, the number of armed conflicts in the selected study areas of 25 countries was 10,993, accounting for 82.0% of the incidents in the African continent and 17.9% of the total occurrences worldwide during the study period (from 2000 to 2015). Here, we used a broad concept of armed conflict, which includes all types of armed conflicts, including state-based armed conflicts and non-state armed conflicts, low-intensity conflicts (such as protests and riots), and violence against civilians. Information on specific conflicts and the definition of each type of conflict is available at (www.ucdp.uu.se).

Based on the occurrence times and coordinates of every event in the UCDP database, we obtained the series of monthly raster conflict data from 2000 to 2015 with a resolution of 1×1 decimal degree by summing the total number of events per grid per month. Events were assigned to a specific year by their indicated starting dates. We did not convert it into a binary value because the numerical data can better reflect the intensity and changes of conflicts rather than only representing the presence or absence of conflicting events. The characteristics of frequency and time variation of armed conflicts can be found in Fig.S2. The raster maps of the processed conflict from 2000 to 2015 can be found in Fig. S3.

2.2 Modeling analysis

We divided the study region, which comprises 25 African countries, into 1° (~ 110×110 km) grid cells ($N = 1094$). Conflict events and covariates were reprocessed into monthly data spanning the period of 2000–2015 and geolocated within the study region. A Generalized Linear Model (GLM) was applied to examine linear effects of climatic, environmental, and social factors on violent conflicts. The Generalized Additive Model (GAM) was used to account for nonlinear effects. GAM was applied through the R package mgcv and a thin-plate spline, which allowed the factor coefficients to vary over the values within their distributions. Inspection of pairwise and multivariate associations between the predictor variables in the final model did not reveal serious identifiability problems (Fig. S4). Since there is no coefficient estimate for the splined temperature and wet days anomalies effects, we present only the p-value of such effects.

GAMs have been demonstrated to be particularly adaptable, offering a good fit for nonlinear relationships and datasets with a lot of noise in the predictor variables (Hastie & Tibshirani, 2017). This model is a generalization of multiple regressions, in which the model's additive structure is preserved while the linear regression's simple lines are replaced by nonparametric functional curves with many parameters (Lehmann, 1998). GAMs, unlike LMs, are data-driven rather than model-driven, and they allow the form of response curves to be determined from data rather than fitting an a priori parametric model, which is limited in its available shape of response. This flexibility and applicability have led to the use of GAM in a wide range of research areas, including climate change (Aalto et al., 2013; Grieve et al., 2017; Kauserud et al., 2008), ecology (Fisher et al., 2018; Pedersen et al., 2019), human health and diseases (Dominici et al., 2002; Jain et al., 2019; Ravindra et al., 2019), etc.

For both the GLM and GAM versions of the models, we controlled for residual unmeasured regional differences by using the country-level and yearly variables. These variables were included as fixed factors rather than as random effects because some of these variables

were reported differently across countries over time; therefore, they were correlated at that spatial scale. We also included ethnic diversity as a fixed effect to account for the complex variations among the diverse ethnic groups. The negative binomial dispersion parameter, which is θ in R, was estimated using the maximum likelihood for both the GLM and GAM versions of the model. The GAM version of the model had the following functional form:

$$Y_{it} = f_1\left(tem_{it}\right) + f_2\left(wet_{it}\right) + X_{it}\beta + Country_{it} + Year_{it} + Ethnic_{it} + \varepsilon_{it} \tag{1}$$

where i = grid; t = time (months); β is a vector of coefficients associated with the matrix of independent variables X, f_1 and f_2 are thin-plate spline functions, tem_{it} is the temperature anomaly degree of grid i in t time and wet_{it} is the wet day anomaly degree of grid i in t time, country, year and ethnic are fixed effect terms; and ε is the grid month error term.

2.3 Data

After careful consideration of relevant research findings and data availability in the temporal and spatial dimensions, we have selected the most significant elements influencing the occurrence of armed conflict to add control variables beyond climate change factors to the model. We analyzed the extent to which patterns of conflict in Africa coincide with contemporaneous abnormalities under climatic conditions using the comprehensive dataset from multiple sources that include climatic, social, and geographic variables, the information of which is included in Table S1. Detailed key overviews of the data source and hypothesized links between those covariates and conflict are provided below.

2.3.1 Temperature anomaly

Warmer years were found to be associated with more violence in previous studies (Cane et al., 2013; Helman et al., 2020). Helman et al. used structural equation modeling to quantify direct and indirect effects of climate on violent conflicts in Africa and the Middle East, and they found that warming increases the risk of violence in Africa, suggesting that the response of conflict to warming depends on local temperature conditions (Helman et al., 2020). High temperature variability leads to a prolonged summer climate and that is conducive to social organization and criminal activity because mobility is easier, resources more available, and targets more plentiful (Landis, 2014). However, this argument is subject to much dispute: a research showed that these relationships change by sample size, outlying observations, and a redefinition of the dependent variable, and by the inclusion of fixed effects covariates (Sutton et al., 2010). Thus, the mechanisms of the relationships need to be further explored by applying broader testing at a finer degree of temporal disaggregation.

We obtained monthly mean gridded land surface temperature data with 0.5×0.5 decimal degree resolution from the Climatic Research Unit TS3.10 global dataset and resampled them to 1×1 decimal degree grid. The temperature anomaly was calculated as a moving average over a 6-month window compared to a long-term baseline (1916–2015). The characteristics of frequency and time variation of temperature anomaly can be found in Fig.S3 and the raster maps of the processed temperature anomaly from 2000 to 2015 can be found in Fig. S5.

2.3.2 Wet days anomaly

As one of the critical natural resource, water is a decisive factor for survival in Africa. Extreme drought may lead to violence through the reduction of livelihood resources, such as water resources, pastures and farmland (Brinkman & Hendrix, 2011), hence its negative impacts on the macroeconomy (Bohlken & Sergenti, 2010). This impact is remarkable in sub-Saharan Africa and much of Central and South Asia societies, which rely on rain-fed agriculture for income, food supply, and livelihood security. The extreme weather phenomenon flood caused by the increase in the number of rainy days will cause large-scale displacement and migration of people in addition to severe damage to the agricultural and economic structure, which intensifies the risk of conflict (Ghimire et al., 2015). All those addresses the necessity of further exploring the mechanism.

Here, we used the monthly rain days deviation gird data from the long-term baseline and excluded the seasonal differences. These data are the Climate Research Unit TS3.10 global data on $0.5° \times 0.5°$ grids for the period 2000–2015, which are resampled to $1° \times 1°$ grids. And the $1° \times 1°$ monthly wet days anomaly grid cells are processed in the same way as the temperature mentioned in the previous section. The characteristics of frequency and time variation of wet day anomaly can be found in Fig.S3 and the raster maps of the processed wet day anomaly from 2000 to 2015 can be found in Fig. S6.

2.3.3 Migrants

Immigration may put a strain on the recipient nations' economic and resource bases, drive the competition for scarce resources, and cause conflict (Reuveny, 2007). Moreover, forced displacement caused by natural disasters or extreme weather may lead to conflict through political impacts, such as migrations changing the local balance among major ethnic groups, which appears to increase the risk of violent internal political and ethnic conflicts (Williams & Krasniqi, 2018). We calculated the immigration index by using the number of immigrants minus the number of emigrants over a period. Here, we used the migrant index to indicate more inflows than outflows into the recipient country, which is to some extent a proxy for the political and social stability of this country. All data were downloaded from the United Nations Department of Economic and Social Affairs, Population Division (2019).

2.3.4 Population and agricultural land

Land resources and population density are two major social factors contributing to armed conflict. Conflict is theoretically prone to occur in countries with higher population densities where the likelihood of armed conflict increases with population growth that causes competition over natural and social resources (Østby et al., 2011). The degradation of agricultural soil and population growth can increase the probability of armed conflict over increasingly scarce resources both at the global and regional scales (Hauge & Ellingsen, 1998; Theisen, 2008). Thus, we included the population data from the Socioeconomic Data and Applications Center (SEDAC) to derive the yearly population density for the 1° cells and land use type data from the Data User Element (DUE) to produce a binary measure

of whether a grid cell contained agricultural land. The raster map of agricultural area and non-agricultural areas in the study area can be found in Fig. S7.

2.3.5 Crop production index

The uneven development of the economy is one of the key triggers for armed conflicts. Here, we used the crop production index to characterize the country's economic production in Africa. A reduction in the crop index indicates a loss of personal income, an increase in unemployment (Collier & Hoeffler, 2004), a reduction in the availability of national public goods (Marshall et al., 2015), and an increase in economic inequality (Cederman et al., 2013), all of which can exacerbate social dissatisfaction and trigger conflict. The crop production index, which was obtained from the Food and Agriculture Organization and the World Bank, presents the annual percentage change in crop production in every country, which directly influences national income.

2.3.6 Politic rights

Political rights are related to various factors such as freedom of association, freedom of expression, and the right to a trial and are associated with less repression and hence lower grievances (Fearon & Laitin, 2003). Thus, political rights are regarded as a manifestation of civil freedoms, relatively high levels of political democracy, and civil liberties that are associated with a decreased likelihood of civil conflict eruption (Basedau et al., 2011). We used the Political Rights Rating from Freedom in the World (https://freedomhouse.org/), which range from 1(free) to 7(not free) to measure the extent to which a country's government is autocratic or democratic in character. The information of its quantitative process can be found at (https://freedomhouse.org/reports/freedom-world/freedom-world-research-methodology). Because this is a parameter that reflects the annual state of each country, we have assigned this value to all the grids belonging to the country and the year. For grid cells spanning country borders, we assign the political rights value from the country with the biggest part in this grid cell.

2.3.7 Wellbeing (infant mortality rate)

The echoes of armed conflict are reflected in child mortality data (Wagner et al., 2018). As a comprehensive and sensitive health indicator, the infant mortality rate reflects the political, economic, cultural, health, and living conditions of the population as well as the quality of maternal and child health work in a country or region (García et al., 2019). Countries with different levels of development have different limits for building up conflict, and there are systematic differences in groups' vulnerabilities to environmental shocks between countries (von Uexkull et al., 2016). Therefore, we included the infant mortality rate (IWR) from the Interagency Group for Child Mortality Estimation to measure the host countries' levels of wellbeing and socioeconomic development.

2.3.8 Distance to roads

Roads are crucial for social development and stability (Moreno et al., 2020). Several studies agree that roads reduce transportation, consumption, and production costs of goods and services (Donaldson, 2018). Also, with easier access to markets and technology, better

roads offer opportunities to expand farm and non-farm production through increased availability of relevant inputs and therefore lower the input costs (Howe, 2019). However, better connectivity could also help armed groups expand their capacity because the decreased distance to roads could lower the costs of sustaining and expanding operations, which facilitates the transmission of violence to new locations and can also intensify competition for limited military resources between nearby battlefronts (Zhukov, 2012). We obtained road network data from the Socioeconomic Data and Applications Center (SEDAC) and calculated the distance between every grid cell and the nearest primary and secondary roads.

2.3.9 Distance to borders

The location of states, their proximity to one another, and especially whether or not they share "borders", emerge time and again as key variables in studies of international conflict phenomena: from major power general war to the diffusion of international conflict, to the analysis of peace between pairs of democracies (Downes, 2006; Starr & Thomas, 2005; Vasquez, 2000). International borders are considered to be related to the size of a conflict zone given the value of such borders to a rebel army (Buhaug & Gates, 2002), not only because neighboring countries can provide a safe refuge from governmental troops for rebels but also because weapons and natural resources are more easily traded and transported across these borders. Therefore, we calculated the distance between every grid cell and the nearest border.

2.3.10 Ethnic diversity

Ethnic diversity is considered one of the human and social factors that affects armed conflict. Montalvo used regression analysis to explore the relationship between the racial differentiation index and polarization index and conflict according to the number of races and the population proportions of the different races, and the results showed that there was a positive correlation between racial differentiation and armed conflict (Montalvo & Reynal-Querol, 2005). In our research, ethnic diversity is reflected by ethnic rights relations data. The source is from GeoEPR (the Ethnic Power Relations dataset, version 2018), published by Center for Comparative and International Studies, the International Conflict Research (ICR). The data are based on the opinions of more than 100 ethnic politics experts to assess the degree of ethnic political participation/exclusion (formal/informal). The use of expert intervention methods and evaluation based on expert knowledge is the advantage of this data, which cannot be achieved by many machine recognition data. Since the raw data are vector data, we transformed different group classification attributes into raster data through ArcGIS as the input data of the model. The detailed information can be found elsewhere (Ding et al., 2017).

2.3.11 Capital city

Conflict has been proved to be more likely to emerge (and dislodge incumbents) closer to the capital (Campante et al., 2019). Capitals are considered an influencing factor in conflict not only because they are the centers of national politics and the seat of a country's government but also because they often have the most resources (Buhaug & Gates, 2002), which plays an important role in financing the purchase of arms for conflict. We obtained the longitude and latitude of the capitals through Google and transferred them onto a binary grid.

3 Results

The temporal characteristics of conflicts and climatic variability in the study area are shown in Fig. S2. The number of conflicts increased with fluctuations from 2000 to 2015, hitting a high point of 1179 in 2009 that is followed by a fall in the next year and rising continuously until 2014 when the figure had risen to 1818 conflicts. In terms of climatic variability, it appears that the overall number of days of rainfall during the study period was lower than the average of previous years, while the temperature was higher than the multi-year average. The years 2001, 2002, 2004, 2009, 2011, and 2015 exhibit considerable climate fluctuations, with hotter and drier periods, while 2007 and 2010 were years wetter than the multi-year average. Regarding the temperature, the years 2000 to 2015 were all warmer than the multi-year average. The summary of all covariates is provided in Table S2.

3.1 The overall effect of climatic variability on conflict

The result of GLM showed a statistically highly significant relationship between temperature anomalies and conflict with a 0.908 estimate value ($p < 0.01$) and a statistically significant effect of wet days anomalies on conflict with a -0.066 estimate value ($p < 0.05$) (Table 1, column a). After applying the spline function in climate variability and taking country, year, and ethnic diversity as fixed effects factors in the GAM model, the effect of temperature and rainfall day anomalies on conflict was even more significant ($p < 0.01$) (Table 1, column b). Apart from climate covariates, there are also a few factors, including population density, politic right, migrants, IMR, distance to borders, agricultural land, and capital city that have significant effects (population density, politic right, migrants $p < 0.05$, and other covariates have a $p < 0.01$) on conflict in both results of GLM (Table 1, column a) and GAM (Table 1, column b). The effect of economic factor (crop production index) on conflict was further explored in an additional model, which can be found in Supplementary Materials.

Figure 1 shows the simulated relationship between temperature anomaly and wet day anomaly with conflict for the given weather conditions of the 1094 grid cells of 25 countries and the density distributions of the temperature and wet day anomalies. Both climate anomaly variables significantly affected the risk of conflict, as shown in Table 1 column b, but to varying degrees depending on the severity of the anomalies. The study period, 2000–2015, was much hotter than the historical comparison period (1916–2015), and the risk of conflict increased as the temperature rose (Fig. 1a). When the temperature was higher than usual by more than 1 °C, the coefficient estimate predicted more violent conflict by more than 0 logged events, which corresponded to a relative risk ratio of more than 1 (value > 1 indicates increase, and value < 1 indicates decrease). Figure 1b shows that the study period had almost the same number of wet days as the historical comparison period, and the risk of conflict increased when there were unusually few wet days.

3.2 The different effects of climatic variability on conflict in agricultural and non-agricultural regions

The results of modeling the agricultural and non-agricultural regions are provided separately in Table1, columns c, d, e, f. In Table 1, columns a and b demonstrate a similar positive relationship between agricultural area and conflicts (estimate value 0.372 and $p < 0.01$, Table 1 column b). Temperature anomaly and wet day anomaly have significant effects on

Table 1 Negative binomial regression models for the total number of violent events per grid cell from 2000 to 2015

	a) GLM		b) GAM		c) GLM(Agricultural area)		d) GAM(Agricultural area)		e) GLM(non-agricultural areas)		f) GAM(non-agricultural areas)	
	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value	Estimate	z-value
Intercept	-8.013	-12.065*	-7.303	-10.923*	-4.006	-4.622*	-3.442	-3.910*	-10.156	-9.014*	-9.224	-8.156*
Temperature	0.908	20.784*	p-value	0.00*	1.014	12.738*	p-value	0.00*	0.871	16.622*	p-value	0.000*
Wet day	-0.066	-2.410†	p-value	0.00*	-0.198	-4.976*	p-value	0.00*	-0.020	-0.553	p-value	0.003*
Population	0.000	2.470†	0.000	2.712*	0.000	-2.246†	0.000	-1.864	0.000	2.300†	0.000	2.496†
Politic Right	0.060	2.247†	0.055	2.035*	0.017	0.347	0.023	0.471	0.068	2.116†	0.061	1.882
Crop Production Index	-0.166	-1.094	-0.212	-1.381	-0.859	-3.415*	-0.883	-3.472*	-0.173	-0.878	-0.254	-1.277
Migrants	-1.270	-6.033*	-1.127	-5.308*	-2.490	-7.137*	-2.451	-6.961*	-0.993	-3.778*	-0.806	-3.033*
IMR (wellbeing)	5.280	6.754*	4.934	6.281*	3.236	3.036*	3.125	2.906*	5.705	5.144*	5.016	4.508*
Distance to Borders	-0.266	-14.390*	-0.261	-14.019*	-0.238	-7.140*	-0.231	-6.883*	-0.255	-11.445*	-0.242	-10.747*
Distance to Roads	-0.178	-1.435	-0.134	-1.086	1.090	1.734	1.012	1.599	-0.249	-1.896	-0.204	-1.557
Agricultural Land	0.373	9.092*	0.372	9.022*								
Capital City	1.494	13.382*	1.470	13.117*	1.633	8.436*	1.692	8.726*	1.609	10.124*	1.541	9.682*
Log-likelihood	-28,881.8		-28,809.8		-9961.9		-9930.7		-18,499.1		-18,434.6	
AIC	57,877.6		57,758.6		20,029.8		19,985.4		37,108.2		37,006.7	
AUC	0.790		0.794		0.798		0.801		0.789		0.794	
N	210,048		210,048		48,960		48,960		161,088		161,088	

* $p<0.01$ using grid-clustered SEs

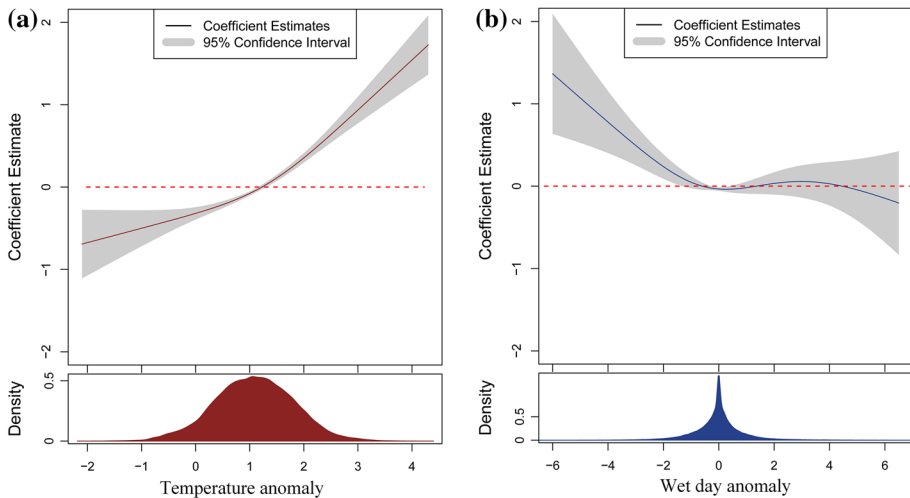† $p<0.05$ using grid-clustered SEs

Fig. 1 The coefficient estimates and 95% confidence interval over the range of temperature anomaly (**a**) and wet day anomaly (**b**) for the model in Table 1, column d and f

conflict in both agricultural and non-agricultural regions with $p < 0.01$ in Table 1, columns d and f.

Figure 2 shows the different patterns of climatic variability impact in the agricultural and non-agricultural areas, respectively. The shape of the temperature anomalies on conflict in Fig. 2 was roughly consistent with what is shown in Fig. 1, featuring a positive relationship between temperature anomaly and conflict, whereas the impact of wet days on conflict varied with land use type: the conflict decreased with increasing wet days in agricultural region, but this effect begin to wane when wet days exceed the baseline in the agricultural regions (Fig. 2b), which can be seen from the overlap between the confidence interval and the dashed zero line in Fig. 2b; in the non-agricultural areas, Fig. 2d shows a U-shaped association between wet-day anomaly and conflict.

In terms of other control covariates, the effect of political rights on conflicts was not significant in agricultural-dependent areas ($p > 0.05$ in Table 1, column c, d, e, f), while the crop production index was significantly related to conflicts (estimate value -0.883 and $p < 0.01$) in agricultural areas (Table 1, column d) rather than in the non-agricultural areas (Table 1, column f). The log likelihood, Akaike Information Criterion (AIC), and Area Under the Curve (AUC) were used to measure the validity of these model simulations. In simulations of the same cohort of data, the GAM model has a much smaller AIC and a much larger AUC compared to the GLM, indicating a better fit. It is evident from Table 1 that the GAM for the agricultural area has the largest AUC (Table 1, column d) at 0.801 and the smallest AIC at 19,985.4.

The Democratic Republic of Congo (DRC) was chosen as it is not only the second-largest country in Africa but also conflict-ridden that could represent the country with the highest number of conflicts. From 2000 to 2015, there were a total of 1580 conflicts reported in DRC, according to UCDP. The year with the most conflict of DRC was 2009 with 475 records, and it has been suffering from grinding fighting and continued conflicts, such as First Congo War (1996–1997), Second Congo War (1998–2003), and Kivu conflict (2004-present).
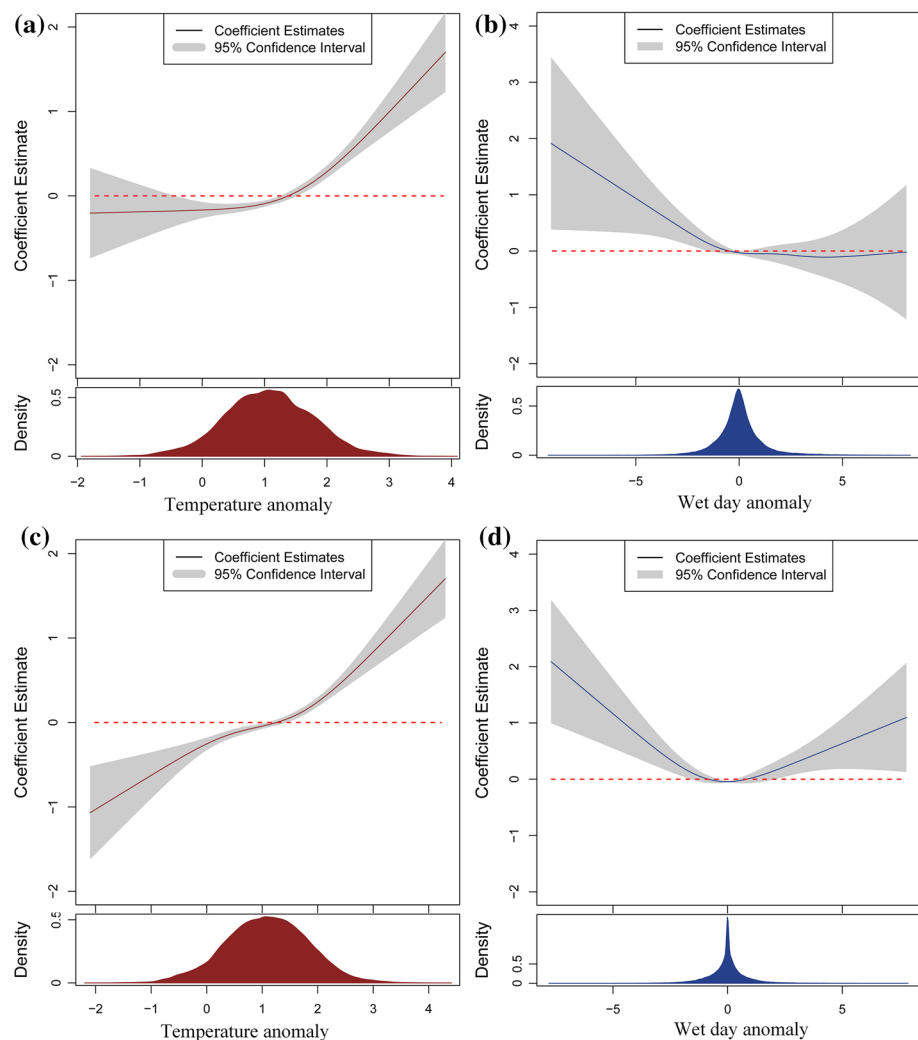
Fig. 2 The coefficient estimates and 95% confidence interval for a range of temperature anomalies (**a**) and wet day anomalies (**b**) for the agricultural area model in column b of Table 1 and the temperature anomalies for the non-agricultural areas (**c**) and wet day anomalies for the non-agricultural area (**d**) for the model in column f of Table 1

Table S3 summarizes conflict and variables as well as the model results in DRC, which shares the same formula as model (1) except the country fixed factor. The results show that temperature and wet day anomaly have significant effects on conflict ($p < 0.01$) in DRC as well. The simulated relationship between climate and conflict in DRC is shown in Fig. S8: the increased temperature anomaly resulted in the growing risk of conflict (Fig.S8a), and the relationship between wet day anomaly and conflict was depicted a U-shape curve (Fig. S8b), which is consistent with the effect we observed in non-agricultural region as shown in Fig. 2d.

In terms of control factors in the model for DRC, immigration rate and capital city show significant positive effects on conflict with estimates of 0.0238 and 3.4593 while distance to roads and borders have significant negative impacts on conflict with estimates of -3.0858 and -1.0076. The Akaike Information Criterion (AIC) and Area Under the Curve (AUC) produced by this model were estimated to be 7933.9678 and 0.8379, indicating the good performance of this model.

4 Conclusion

We estimated the impact of climate change-related factors on armed conflict using GLM and GAM approaches, as well as socioeconomic and underlying geographical control variables, at both the national and regional levels scales, with the following primary conclusions:

Temperature anomalies and rainfall day anomalies have a significant impact on armed conflict in Africa: temperature anomalies were positively correlated with violent conflicts (i.e., more violence in warmer years), while anomalies in the number of wet days were negatively related to conflicts (i.e., more violence in years with less wet days).

These systematic impacts vary by land-use patterns: increases in deviations from the temperature norms could enhance the probability of violence in both non-agricultural and agricultural areas. On the other hand, wet days exceeding the normal number of days could lead to rising conflicts in non-agricultural areas while having no effect in agricultural areas. The influence of climatic variability on conflict in the Democratic Republic of Congo (DRC) follows the same pattern as its impact we found in non-agricultural regions: higher temperatures, fewer wet days, and more wet days than the long-term standard line could increase the chance of conflict.

Other factors significantly affecting conflicts were population (positive—more violence in higher populated areas), political rights (positive—more violence in regions with less freedom), the number of migrants (negative—more violence with fewer migrants), infant mortality rate (positive—more violence where IMR is higher), as well as the distance to borders (negative—more violence closer to borders) and capital cities (positive—more violence far from the capital city).

5 Discussion

Despite a substantial and expanding amount of research on the relationship between climate and conflict in Sub-Saharan Africa, their findings remain unclear and contentious. Here, we simulated the effect of climate variability on armed conflict at a high spatial resolution of 1° and high temporal resolution of 1 month on both regional and country scales. We also made a comparison between the results in agricultural and non-agricultural areas using the same model. Our analysis would make important contribution to the climate-conflict literature with our results indicating that climate anomaly variables (temperature and wet day anomalies) would significantly affect the risk of conflict in both agricultural and non-agricultural areas and on both regional and national level.

We find that temperature above average is associated with a higher likelihood of conflict both on regional and national level, which was consistent with some previous research conclusions (Cane et al., 2013; Helman et al., 2020; Hsiang et al., 2011). For example,

Hsiang et al. used meta-analysis of 60 prior studies and found that temperature substantially increases the likelihood of interpersonal and intergroup conflict (Hsiang et al., 2013). The effect of temperature on conflict works through local economic conditions: in the agricultural field, excessive temperatures can stymie normal crop development and increase evapotranspiration of crops (Helman & Zaitchik, 2020), hence the reduced agricultural productivity that worsens resource competitiveness, income inequality, and exacerbates class tensions. In the industrial and political field, economic output and growth diminish with increased temperature (Dell et al., 2012); in a more microeconomic setting, large variation of temperature may influence individual health and diminish personal physical and cognitive labor productivity that overall causes the rise in the likelihood of conflict (Mares & Moffett, 2016). Here, we verified that temperature is not only positively related to conflict in agriculturally nourished areas but also in non-agricultural areas through separate simulations in the two types of areas with evidence to support those industrial and personal hypothetical links.

Regarding the effect of rainfall variability, we demonstrate its negative relationship with conflict: the chance of conflict increases with decreasing wet days, which has been agreed in many studies (Fjelde & von Uexkull, 2012; Koubi, 2019; Vanden Eynde, 2018). Communal or rebel conflict events in those African countries are influenced by a combination of resource scarcity and resource abundance, which are particularly sensitive to extreme rainfall variations. We modeled agricultural and non-agricultural areas separately. This enabled us to find the varying impact of climate anomalies depending on the land type. Africa is especially sensitive to rainfall shocks, given the dependence of many African economies on agriculture (Koubi, 2012). Droughts caused by unusually few wet days, which alter land use, crops and devastate livestock, drastically reduce household home consumption, increase competition for resources such as drinking water and arable land and increases the risk of conflict. This pattern is particularly significant in agricultural areas, whereas in non-agricultural areas, any form of variation in days of rainfall compared to the year-round average could increase the risk of conflict. This finding adds evidence to an 'abundance' narrative, where resources spur rent-seeking/wealth-seeking and recruitment of people to participate in violence. It is also found that wet periods increase communal violence in Ethiopia, Kenya, and Uganda (Raleigh & Kniveton, 2012; Theisen, 2012). A myriad of causes is expected to lead to conflict in the case of nonrenewable resources such as oil and diamonds (Koubi, 2019).

Our findings suggest that climate anomalies affect conflict in Africa. Given the geographic focus of the study, the conclusions of this work are applicable mainly in the 25 conflict-prone African countries. However, they are arguably generalizable to the other countries in Africa and even in other continents. Though climate anomalies may not be the determining factor of conflict, they do affect the risk of conflict directly or indirectly in Africa as a threat multiplier. In the context of the controversial role of climate factors in history and ongoing violent conflicts, this study has provided deeper insight and more accurate modeling, adding another solid piece of statistical evidence that aligns with this perspective. It is hoped that this study can attract the attention of government agencies and related organizations. When climatic anomalies are detected, some protective measures and safeguards should be prepared to prevent the occurrence or intensification of conflicts.

However, there are some limitations: not all variables met the standards of 1° spatial resolution and 1-month temporal resolution, such as migrants, wellbeing and political rights, which means they can only provide differences at the country level and year level, which might have affected the accuracy of this simulation because they lack the required detailed temporal and spatial information. An additional uncontrolled factor is complex

human behavior, which makes it impossible to measure the human adaptive capacity to climate variability and to determine to what extent climate anomalies can lead to conflict. As human sociology is such a large category, this article can only provide some evidence for the cause of conflict from a statistical perspective. Given the marked inconsistency in the available quantitative evidence linking climate and conflict, in our view, the top research priority in this field should be to conclusively establish the causal mechanisms of climate-related conflict and build a sustainability assessment system. For the collection of more comprehensive and finer-scale elements, modeling and analyzing different types of conflicts, including protests, riots, and livestock theft, at different temporal and spatial resolutions can be a further step in future research.

Declarations

Conflict of interest There are no competing interests in this research.

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