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Varying climatic-social-geographical patterns shape the conflict risk at regional and global scales

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Given that armed conflict has been seriously impeding sustainable development, reducing the frequency and intensity of armed conflicts has become an explicit goal and a common theme of the 2030 Sustainable Development Goals. Determining the factors shaping armed conflict risks in different regions could support formulating region-specific strategies to prevent armed conflicts. A machine learning approach was applied to reveal the drivers of, and especially the impact of climatic conditions on, armed conflict in Sub-Saharan Africa, the Middle East, and South Asia and characterizes their changes over time. The analyses show a rising impact of climatic conditions on armed conflict risk over the past decades, although the influences vary regionally. The overall percentage increases in the contribution of climatic conditions to conflict risks over the last 30 years in Sub-Saharan Africa, the Middle East, and South Asia are 4.25, 4.76, and 10.65 percentage points, respectively. Furthermore, it is found that the Climatic–Social–Geographical ("C–S–G") patterns that characterize armed conflict risks vary across the three studied regions, while each regional pattern remains relatively stable over time. These findings indicate that when devising defenses against conflicts, it is required to adapt to specific situations in each region to more effectively mitigate the risk of armed conflict and pursue Sustainability Development Goals.

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Introduction

On the 2030 agenda for sustainable development, one of the major goals proposed by the United Nations for sustainable development (SDG16), which is considered the prerequisite and core of all SDGs, is to promote just, peaceful and inclusive societies (Kumar and Roy, 2018). One of the main obstacles to achieving this goal of sustainable development is the constant armed conflict that has been imposing a serious threat to global peace (Le, 2021). At the aggregate level, armed conflict could lead to disastrous economic consequences, undermine the functioning of political systems and prevent countries from escaping dire poverty (Hegre et al., 2019), while at the microlevel, it has been severely disrupting individuals' life, bringing deaths and permanent injuries. Statistics show that in 2020, the number of armed conflict events reached the highest level since World War 2, accounting for over 80,000 battle-related deaths (Pettersson et al., 2021), rendering the urgency of developing measures to counter armed conflict. Identifying the armed conflict drivers in different regions could lay the foundation for devising region-specific strategies that reduce the frequency and intensity of armed conflicts, which would be a critical step toward Sustainable Development Goals.

Identifying the potential drivers and effects of armed conflict also have been a major focus of intense scientific research for quite some time (Schleussner et al., 2016). High social vulnerability is considered one of the main drivers of armed conflicts due to the uneven socio-economic situations across different regions (Minhas and Radford, 2017; Rozmarin, 2017; Bell and Keys, 2018; Elbadawi and Hegre, 2008). For example, the impacts of resources scarcity (Koubi et al., 2014), a weak economy (Elbadawi and Hegre, 2008), and ethnic discrimination (Wucherpfennig et al., 2011) on armed conflict have been agreed upon. After years of research, there has been no consensus among scholars regarding whether or how climate influences the risk of armed conflict. Although some studies support a link between climate change and armed conflict (Zhang et al., 2007, 2011; Burke et al., 2009; O'Loughlin et al., 2012; Hsiang et al., 2013; Vesco et al., 2021; Jun and Sethi, 2021; Ge et al., 2022; Schleussner et al., 2016; Ide et al., 2020), others find little evidence to back this claim (Raleigh and Urdal, 2007; Buhaug, 2010; Owain and Maslin, 2018; De Juan and Hänze, 2020; van Weezel, 2019). This is generally because the definition of armed conflict as well as the selection of area, model, and data can sway the results of the studies about climate-armed conflict links (Scheffran et al., 2012; O'Loughlin et al., 2014). In 2019, a group of scholars who have reached varied conclusions in their previous work on the relation between climate and armed conflict agreed, through an expert elicitation method, that climate change will increase the future risk of armed conflict, yet the scope of this impact remained contested (Mach et al., 2019). It can be concluded that armed conflict is affected by climatic, social, and geographical factors which have complex pathways and feedback among these factors (Scheffran et al., 2012). Determining the relative importance of driving factors to armed conflict risk is seen as the cross-cutting priority for future research on armed conflict (Mach et al., 2020). Data-science methods have been remarkably effective in flexibly accommodating conditional relationships to uncover differential effects across locations (Mach et al., 2020). With advanced machine learning methods, this study seeks to close this knowledge gap by assessing the relative impact of climatic conditions on armed conflict risks in typical areas, relative to a large range of cultural, religious, social, and economic factors.

In this study, we focus on armed conflict events within states in Sub-Saharan Africa, the Middle East, and South Asia, primarily because these are the regions that have been largely plagued by conflicts since World War 2. From 1989 to 2018, there were 170,881 armed conflicts reported in these three regions, accounting for more than 80% of the total number of armed conflicts worldwide, of which 36,778 occurred in South Asia, 60,653 in the Middle East, and 73,450 in Sub-Saharan Africa (Pettersson et al., 2021; Sundberg and Melander, 2013). Moreover, despite the similarly high incidence of armed conflict in all three regions, the driving mechanisms of their armed conflict risk are quite different because of the significant variability of geographical, climatic, and socio-economic conditions (detailed introduction in Supplementary Materials) between these three regions, thusly rendering them appropriate representatives to explore the geographically varying drivers of armed conflict.

To do so, the analysis proceeds in three steps: (1) choosing conflict-prone regions with a typically high incidence of armed conflict that is differentiated by their climatic zones (Kottek et al., 2006) (Fig. 1), (2) structuring the covariates with support of high spatial resolution data from 1989 to 2018, and (3) applying Boosted Regression Trees (BRT), a machine learning method, to quantify the linkage between Climatic-Social-Geographical factors and armed conflict risk across the regions and three different decades.

Methods

Data. This study exploits data on armed conflict events and on substantial driving factors of armed conflict risk.

Armed conflict. We use the UCDP Georeferenced Event Dataset (UCDP GED) Global version 20.1 due to its high temporal resolution, which contains georeferenced episodes of armed conflict events spanning 30 years from 1989 to 2018 (Sundberg and Melander, 2013; Pettersson and Öberg, 2020). Based on UCDP GED, armed conflict events are aggregated at the grid-year level ($0.1° \times 0.1°$) and are coded as a binary dependent variable (armed conflict incidence). If there is an armed conflict event in one grid in a single year, the armed conflict incidence indicator is assigned a value of 1; otherwise, 0. In line with established conventions, armed conflict risk refers to the risk of armed conflict incidence in a given grid-year (Koubi, 2019). In the modeling, the high-risk samples refer to the grids where armed conflict has occurred; otherwise, they are low-risk samples.

Covariates. Research has pointed out that the high vulnerability could shape their risk of armed conflict (Buhaug and Von Uexkull, 2021). Thus far, the concept of vulnerability is highly contested and is often given different connotations (O'keefe et al., 1976; Alwang et al., 2001). Despite the varying definitions of vulnerability (Turner et al., 2003; Adger, 2006; IPCC, 2001; Cutter and Finch, 2008; Füssel and Klein, 2006), in this paper, it is defined in a consistent way with the United Nations Strategy for Disaster Reduction, where vulnerability refers to the conditions determined by physical, social, economic, and environmental factors or processes, which increase the susceptibility of a community to the impact of hazards (UN/ISDR, 2004). It is a reflection of the physical, social, economic, and environmental conditions of both individuals and the collective, an indicator of how people would be threatened by armed conflict. The vulnerability and the background elements together constitute the indicators of armed conflict risk. With the experience from past research, we divided the indicator system into three parts: social condition, climatic condition, and geographical condition.

Social vulnerability, in conjunction with other stressors, has led to armed conflict (Schleussner et al., 2016), which is highly correlated with the level of well-being of individuals and society. Besides, the levels of vulnerability in each region are highly

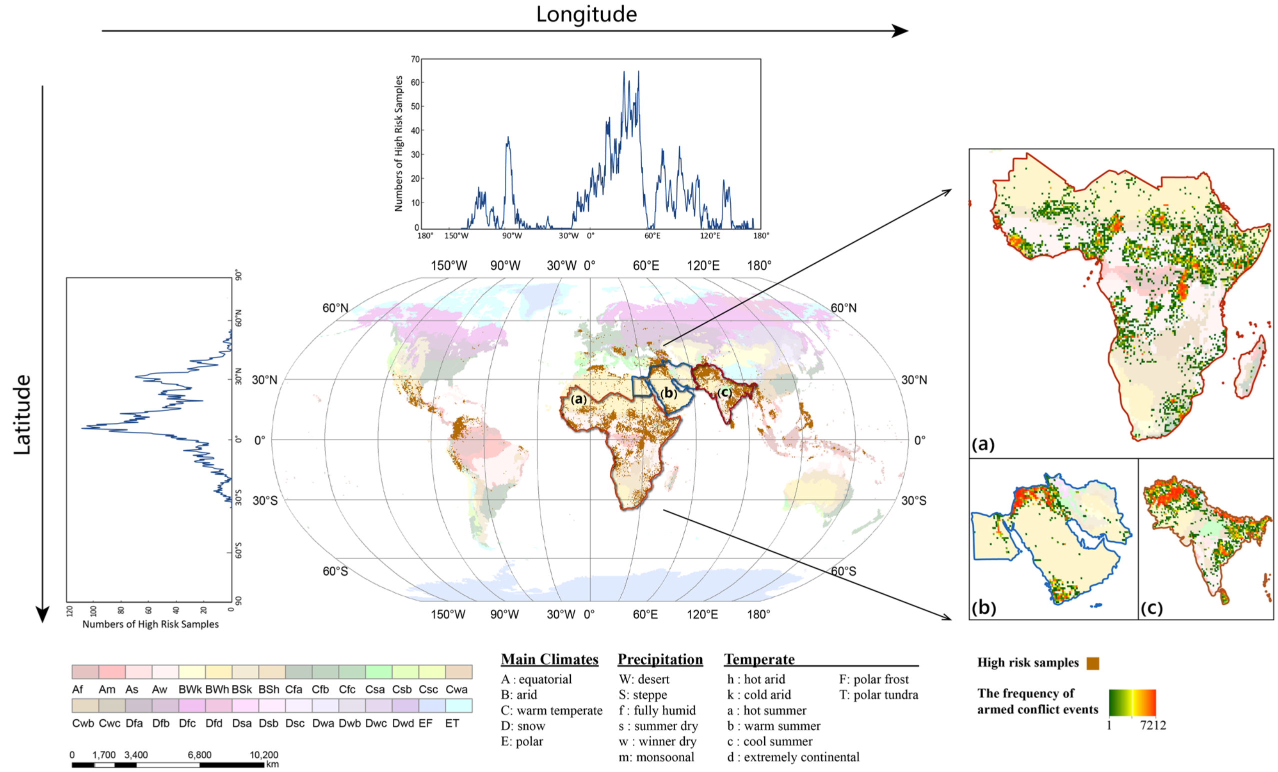

Fig. 1 The spatial distribution of armed conflict events and climatic conditions. The high-risk samples refer to the grids where armed conflict has occurred. The distribution of high-risk samples and statistical maps show the significant geographical variability in armed conflict. Sub-Saharan Africa, the Middle East, and South Asia are the areas with a high incidence of armed conflict. Focusing on analyzing these three zones, we also find significant variability in the frequency of armed conflict events and climatic conditions. The supplementary material presents detailed climatic differences between the three zones (Fig. S1).

dependent upon the economic status of individuals and nations. Thus, in theory, the social condition drivers of armed conflict risk should include those related to population density levels, remoteness of a settlement, levels of education, access to basic human rights, systems of good governance, social equity, positive traditional values, customs, and ideological beliefs and overall collective organizational systems, levels of individual and national economic reserves, levels of debt and the degree of access to credit, loans, insurance, etc. (UN/ISDR, 2004). Considering the availability of high spatial resolution data and long time span, we selected population density (Raleigh and Urdal, 2007; Hauge and Ellingsen, 1998), urban accessibility (Hegre et al., 2019), night-time lights (Owain and Maslin, 2018; Miguel et al., 2015; Nordhaus and Chen, 2015), and ethnic diversity (Wimmer et al., 2009; Esteban et al., 2012), that composed the dataset on the social conditions, which can reflect the demographic distribution, traffic convenience, general economic level, and ethnic differences. These indicators of social condition are closely related to the armed conflict risk (see Supplementary Materials for detailed description).

The geographical conditions dataset comprises data on land use (Raleigh and Urdal, 2007; Baumann and Kuemmerle, 2016), elevation (Weidmann and Ward, 2010; Ding et al., 2017), and natural disaster hotspots (Brancati, 2016; Nel and Righarts, 2008; Nelson, 2010), which can reflect the distribution of natural resources, topographical conditions, and disaster risk. The analysis divides the climatic condition into two parts defined as climate average condition and climate variation condition. The climate average condition is the average maximum temperature, average minimum temperature, and average precipitation from 1960 to 1988. The term "climate variation condition" refers to the differences between (a) the average value of a certain climate element in each year from 1989 to 2018 and (b) the climate average condition of the corresponding element. The reasons for selecting these factors, along with the data description are detailed in the supplementary. All data are processed at the same spatial resolution ($0.1° \times 0.1°$) to match the information on armed conflict incidence.

Model. This study focuses on armed conflict risks in Sub-Saharan Africa, the Middle East, and South Asia from 1989 to 2018. To simulate the linkage of climate and armed conflict risk within these regions, we select boosted regression trees (BRT)—an ensemble method that has been widely used for data mining, particularly where large amounts of data are used—to simulate the relationship between a response variable and some set of predictor variables (Leathwick et al., 2006; Müller et al., 2013). In this study, the 'dismo' package was adopted to deploy the modeling approach in the R Version 3.3.3 statistical programming environment. To construct the BRT model, we need to build the sample dataset with high-risk samples of armed conflict incidence and equal amounts of low-risk samples, one year at a time, from 1989 to 2018. In the present study, we made 20 ensemble BRT models to reduce the randomness of every single result.

Figure S3 shows the technical flow chart of this study. To explore the linkages between climate and armed conflict risk over time, we perform simulations through our BRT model over three periods, which are 1989–1998, 1999–2008, and 2009–2018. The overall results of all the covariates put in this model are refined through spatial comparison and time series analysis. Results by covariates are provided in the online supplemental appendix 3

Table 1 The relative contributions of different conditions in time series.

Research area	Time	Relative contribution (%)				
		Climatic conditions			Geographical conditions	Social conditions
		Climate variation	Climate average	Total		
Sub-Saharan Africa	1989–1998	8.80	28.29	37.09	16.71	46.20
	1999–2008	11.27	30.51	41.77	22.17	36.06
	2009–2018	9.72	31.62	41.34	23.85	34.81
Middle East	1989–1998	0.94	23.22	24.16	12.56	63.28
	1999–2008	3.08	21.45	24.53	7.65	67.82
	2009–2018	3.37	25.55	28.92	18.79	52.29
South Asia	1989–1998	7.11	54.88	61.99	17.39	20.62
	1999–2008	8.64	48.32	56.96	26.09	16.96
	2009–2018	2.67	69.97	72.64	13.67	13.69

(Tables S1–S3). The detailed performance assessment of the BRT model is described in supplementary (Table S4 and Fig. S4).

Results

Significant geographic variability in climatic conditions to armed conflict risk. The relative contributions of the driving factors of armed conflict risk for different regions in each period are shown in Table 1 (Tables S1–S3 show the relative contribution of each covariate to armed conflict risk in three regions).

Results in Table 1 strongly suggest that climatic conditions, including climate variation conditions and climate average conditions, can be a significant driving factor of the armed conflict risk. The importance of this factor varies significantly across the three selected regions. In South Asia, the contribution of 56.96–72.64% states that armed conflict risk there can be remarkably affected by climatic conditions, followed by Sub-Saharan Africa and the Middle East with contributions of 37.09–41.77% and 24.16–28.92%, respectively. Socio-economic factors remain the main drivers of armed conflict risk in the Middle East. However, the impact of the climatic conditions on the armed conflict risk in the three regions has been gradually increasing over the past decades. The overall percentage increase in the contribution of climatic conditions is around 4.5 percentage points in Sub-Saharan Africa and the Middle East, respectively. In South Asia, the influence of armed conflict risk of climatic conditions has increased by about 11 percentage points over the last 30 years.

The impact of the climate variation conditions on armed conflict risk, however, presents rather different features, with the greatest impact on the armed conflict risk in Sub-Saharan Africa, contributing 8.80–11.27% to such risk, followed by South Asia and the Middle East with 2.67–8.64% and 0.94–3.37%, respectively. Figure 2 depicts the response curves demonstrating the linkages between the climate anomalies variables and armed conflict risk. In Sub-Saharan Africa, we find a positive relationship between minimum temperature anomaly and armed conflict risk, while the relationships between maximum temperature anomaly and precipitation to armed conflict risk are rather intricate. In the Middle East, the relationship between armed conflict risk and minimum temperature anomaly is negative, while the relationship between armed conflict risk and precipitation anomaly is positive. Figure 2 also suggests that a complex relationship exists between maximum temperature anomaly and armed conflict risk. The relationship between armed conflict risk and minimum temperature anomaly and precipitation anomaly in South Asia tends to be positive, while the link between maximum temperature and armed conflict risk is observed to be complex.

The different Climatic–Social–Geographical patterns in three typical regions. Given that armed conflict, the risk is affected by a complicated combination of various elements that fall into the categories of climatic, geographical, and social conditions, it is important to explore the Climatic–Social–Geographical patterns ("C–S–G" patterns) in different regions.

Figure 3 reveals the geographically divergent "C–S–G" patterns that exist in three chosen regions by visualizing the relative contributions of climatic, social, and geographical conditions to armed conflict risk. In the Middle East, the contribution of social conditions to armed conflict risk is significantly higher than the geographical and climatic conditions. By contrast, the "C–S–G" pattern in South Asia is leaning toward the climatic conditions, while social and geographical conditions are making less relevant contributions to the risk of armed conflict. In Sub-Saharan Africa, the "C–S–G" pattern presents a relatively balanced pattern of three conditions which means that the climatic, social, and geographical conditions exert numerically similar influences on the armed conflict risk. The patterns show that while climate change has a significant impact on armed conflict risks, it only does so in combination with other social and geographic factors, indicating that climate-conflict linkages are not deterministic. Besides, the "C–S–G" pattern is relatively stable in each region, with only minor changes over time.

Discussion

In this study, driving factors with a high spatial resolution were selected as comprehensively as possible to simulate the influence mechanism of driving factors to armed conflict in Sub-Saharan Africa, the Middle East, and South Asia. Our results confirmed that the climatic conditions, including climate average conditions and climate variation conditions, are relevant drivers of armed conflict risk. More importantly, we identify different "C–S–G" patterns in these regions when analyzing all three sets of armed conflict drivers together. This suggests that the armed conflict risk is not determined by one single element but the result of a combination of complex and site-specific social, geographic, and climatic factors. And the causes of armed conflict risk vary from region to region. Therefore, it is required to devise defenses against conflicts according to local conditions to push ourselves one step further to achieve the Sustainability Development Goals.

Africa is the region with the most studies of how climate change impacts armed conflict as a result of being one of the most vulnerable continents to climate change (Adams et al., 2018). The result shows that the contribution of climatic conditions to armed conflict in Sub-Saharan Africa is 37.09–41.77%. A similar result was found in the article published in PNAS by Burke et al. (2009), indicating that the rise in temperature will increase the armed conflict risk by 54% in 2030. The results of van Weezel (2020)

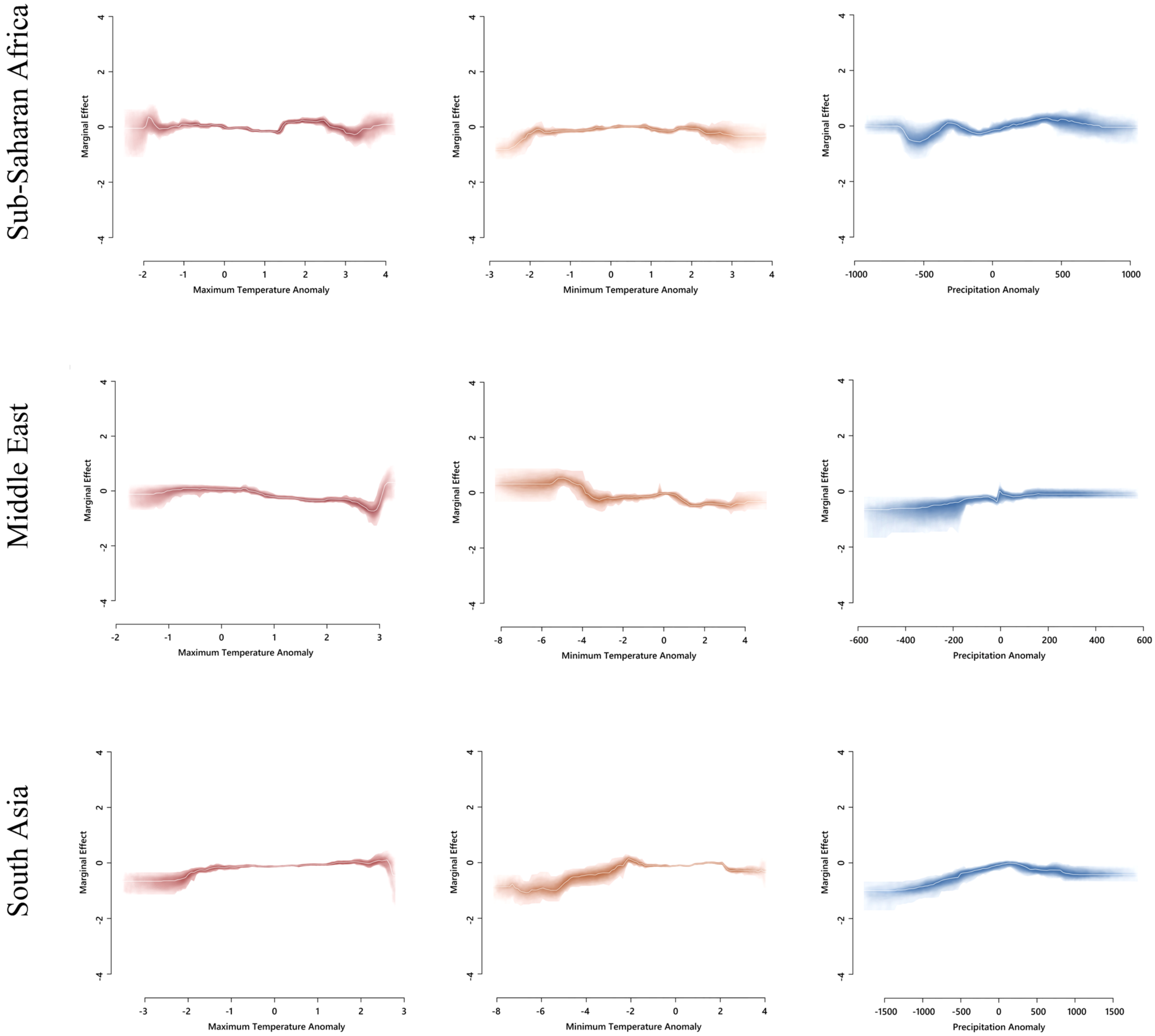

Fig. 2 The marginal effect plots of climate variation conditions in Sub-Saharan Africa, the Middle East, and South Asia. The marginal effect plots are generated by the boosted regression tree (BRT) ensemble fitted to the full incidence samples of each studied region. The white lines represent the mean effect curves calculated from the ensemble BRT models. 95% confidence intervals of climate variation variables are indicated by color: deepred, maximum temperature anomaly; light red, minimum temperature anomaly; blue, precipitation anomaly.

study showed that a two-standard deviation increase in average temperature accounts for about a 31% increase in conflict risk in Africa. O'Loughlin et al. (2012) and Fjelde and von Uexkull (2012) also demonstrated that the climatic conditions affect the armed conflict risk in Africa, consistent with the results in this study.

In the Middle East, the contribution of climatic conditions to armed conflict risk ranges from 24.16% to 28.92% over the three periods which is considerably lower than those of social conditions. Previous studies have explored both the direct and indirect impact of climate change on armed conflict in the Middle East. Feitelson and Tubi (2017) came to the conclusion that climate change is an intermediate variable rather than a major driver of conflict in the Middle East, while David Helman et al. (2020) argued that the direct effects of climate on armed conflict risk seem to be stronger than any indirect effects. Their divergent conclusions of mechanisms for climate–conflict linkages, however, would not compromise their agreement that social variables have a comparatively greater impact on armed conflict risk than the climatic factors in the Middle East.

Deviating from the generally accepted view that socio-economic deprivation as well as diversity in religion, language, and culture are the main drivers of armed conflict (including secessionist movements) in South Asia, this study finds an unexpectedly high contribution of climatic conditions to armed conflict risk. Reasons for the high contribution could be that more than 75% of armed conflict events in South Asia occurred in Afghanistan, Pakistan, and the Kashmir region, mainly located on the edges of the Himalayan highlands and thus belonging to the high-altitude areas that are susceptible to climate change.

In this study, the contributions of the climate variation condition to armed conflict risk ranged from 0.94% to 11.27% in the three periods for each research region, which basically accords with the previous studies (Hsiang et al., 2013; Mach et al., 2019). Hsiang et al. (2013) estimate that one-standard deviation changes in climate toward warmer temperatures or more extreme rainfall

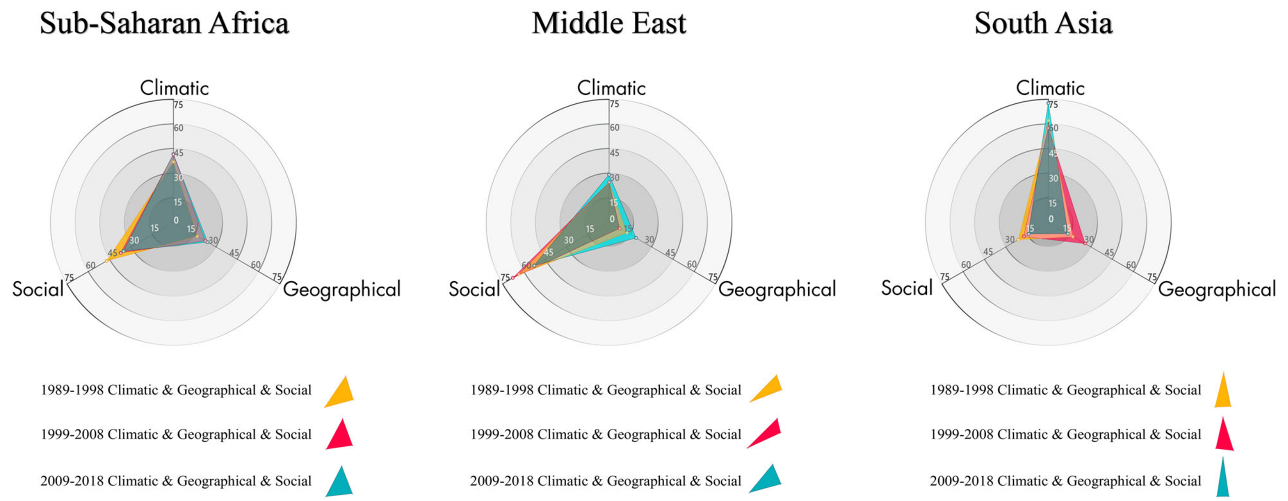

Fig. 3 The climatic–social–geographical patterns of armed conflict risk drivers in different regions. The different colors represent the "C-S-G" pattern for different periods. Yellow represents the patterns for the period 1989-1998 in three region, while red and blue represent the patterns for the periods 1999–2008 and 2009–2018, respectively.

can increase the frequency of interpersonal violence by 4% and the frequency of intergroup conflict by 14%. Aside from that, based on the structured judgments of experts from diverse disciplines, the best estimates are that 3–20% of conflict risk over the past century has been influenced by climate variability or change (Mach et al., 2019). Our results indicate that the lower range of this spectrum would be more accurate.

The formation of regionally diversified "C–S–G" patterns is determined in accordance with their different conditions and different ways of feedback. Located in the poorest region in the world, countries in Sub-Saharan Africa are highly dependent on rainfed agriculture for economic production, which is most vulnerable to climate change. The temperature has also been found to exacerbate competition over resources and violence between herders and farmers in Africa (Maystadt et al., 2015; Eberle et al., 2020; Maystadt and Ecker, 2014). It is here where the social and climatic conditions are the major drivers of armed conflict risks, accounting for (a) a generally high risk of various forms of conflict due to socio-economic conditions and (b) the high vulnerability to climate change and limited adaptive capacity. The "C–S–G" pattern in the Middle East is rather shaped by regional peculiarities such as oil abundance, scarce water resources, regional rivalries, and ethnic or religious nationalism. Consequently, the social condition has the greatest impact on the armed conflict risk in the Middle East. Though social condition-related indicators are active drivers of armed conflict in both Sub-Saharan Africa and the Middle East, the different vulnerabilities of these two regions distinguish their resilience to the risk of armed conflict from each other. Naturally, a high economic level and sufficient social management (e.g., low socio-economic vulnerability) can dampen the occurrence of armed conflicts, while the low levels of economy and uneven distribution of resources would rather induce armed conflicts (Pinstrup-Andersen and Shimokawa, 2008). Hence, though both regions are majorly affected by their social conditions, while most states in Sub-Saharan Africa become too economically fragile, under the impact of climate change or other fluctuating factors, to respond to the armed conflict risk (Bell and Keys, 2018), the economic conditions of Middle East render it more resilient to the risk than Sub-Saharan Africa. The "C–S–G" pattern in South Asia results from areas with a high frequency of armed conflict events being highly susceptible to climate change. Research suggests that climate change increases flood risks in Bangladesh, which could result in great migration to India and communal tensions in the receiving (Reuveny, 2007). Water scarcities (particularly in the Himalayas region) and an increasing number of storm and flood disasters (particularly in coastal and riverine areas) increase local grievances and facilitate recruitment efforts from extremist groups (Barnett and Adger, 2007; Ide et al., 2021). In sum, resource competition, socio-economic deprivation, and migration caused by climate change (in combination with other social and geographic factors) can potentially increase the risk of armed conflict in South Asia, rendering the region most prone to climate-conflict risks.

Compared with previous studies that provide inconclusive evidence about the climate-armed conflict nexus that cannot quantify the magnitude of such an impact, this study offers three main contributions. Firstly, the scale of this study is a high-resolution geographic grid with $0.1° \times 0.1°$, which enables us to tap geospatial variations in climate and armed conflict risk. Secondly, we use a wide range of spatially quantifiable geographical and social controls that have an enormous impact on the transmission of climate change to conflict risk. Lastly, on the basis of the previous research, this study determines the relative contribution of the climatic condition to armed conflict risk and finds the Climatic–Social–Geographical ("C–S–G") patterns in their respective regions.

Identifying the relative importance of climate as a driving factor of armed conflict risk is a critical step forward to resolve one of the uncertainties in research on armed conflict and dealing with the future challenges in predicting the risk of armed conflict in a changing climate. An important limitation is the inability to incorporate factors with coarser spatial and time resolutions. For instance, other social and economic variables like the detrimental legacy of the slave trade or colonization in terms of the interpersonal trust or institutional capacity (Nunn, 2020; Nunn and Wantchekon, 2011; Acemoglu et al., 2001), cannot be integrated into the "C–S–G" framework. Further research could also better distinguish the channels—e.g. through prices and productivity—through which climatic conditions affect the risk of armed conflict. Meanwhile, an in-depth analysis of the vulnerability and resilience of different regions is also required to better explain the spatial heterogeneity of conflict occurrence. Future research would also benefit from identifying sub-regional patterns as the three regions studied in our analysis and "C–S–G" differences between neighboring countries (or even the different regions in the same country) can be quite substantial. In general, despite the uncertainties in the study of quantifying implications of driving factors for armed conflict, it is quite necessary to consider these results when designing future policies for sustainable development.

Data availability

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

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References

Acemoglu D, Johnson S, Robinson J (2001) The colonial origins of comparative development: an empirical investigation. J Econ Hist 61:517–517. https://doi.org/10.1017/S0022050701228113

Adams C, Ide T, Barnett J, Detges A (2018) Sampling bias in climate–conflict research. Nat Clim Chang 8:200–203. https://doi.org/10.1038/s41558-018-0068-2

Adger WN (2006) Vulnerability. Glob Environ Change-Human Policy Dimens 16:268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006

Alwang J, Siegel PB, Jørgensen SL (2001) Vulnerability: a view from different disciplines. The World Bank

Barnett J, Adger WN (2007) Climate change, human security and violent conflict. Political Geogr 26:639–655. https://doi.org/10.1016/j.polgeo.2007.03.003

Baumann M, Kuemmerle T (2016) The impacts of warfare and armed conflict on land systems. J Land Use Sci 11:672–688. https://doi.org/10.1080/1747423X.2016.1241317

Bell C, Keys PW (2018) Conditional relationships between drought and civil conflict in sub-Saharan Africa. Foreign Policy Anal 14:1–23. https://doi.org/10.1093/fpa/orw002

Brancati D (2016) Political aftershocks: the impact of earthquakes on intrastate conflict. J Confl Resolut 51:715–743. https://doi.org/10.1177/0022002707305234

Buhaug H (2010) Climate not to blame for African civil wars. Proc Natl Acad Sci USA 107:16477–16482. https://doi.org/10.1073/pnas.1005739107

Buhaug H, Von Uexkull N (2021) Vicious circles: violence, vulnerability, and climate change. Annu Rev Environ Resour 46:545–568. https://doi.org/10.1146/annurev-environ-012220-014708

Burke MB, Miguel E, Satyanath S, Dykema JA, Lobell DB (2009) Warming increases the risk of civil war in Africa. Proc Natl Acad Sci USA 106:20670–20674. https://doi.org/10.1073/pnas.0907998106

Cutter SL, Finch C (2008) Temporal and spatial changes in social vulnerability to natural hazards. Proc Natl Acad Sci USA 105:2301–2306. https://doi.org/10.1073/pnas.0710375105

De Juan A, Hänze N (2020) Climate and cohesion: the effects of droughts on intra-ethnic and inter-ethnic trust. J Peace Res 58:151–167. https://doi.org/10.1177/0022343320974096

Ding F, Ge Q, Jiang D, Fu J, Hao M (2017) Understanding the dynamics of terrorism events with multiple-discipline datasets and machine learning approach. PLoS ONE 12:e0179057. https://doi.org/10.1371/journal.pone.0179057

Eberle UJ, Rohner D, Thoenig M (2020) Heat and Hate: Climate Security and Farmer-Herder Conflicts in Africa. CEPR Discussion Paper No. DP15542. Available at SSRN: https://ssrn.com/abstract=3753942

Elbadawi I, Hegre H (2008) Globalization, economic shocks, and internal armed conflict. Def Peace Econ 19:37–60. https://doi.org/10.1080/10242690701365160

Esteban J, Mayoral L, Ray D (2012) Ethnicity and conflict: theory and facts. Science 336:858–865. https://doi.org/10.1126/science.1222240

Feitelson E, Tubi A (2017) A main driver or an intermediate variable? Climate change, water and security in the Middle East. Glob Environ Change-Hum Policy Dimens 44:39–48. https://doi.org/10.1016/j.gloenvcha.2017.03.001

Fjelde H, Von Uexkull N (2012) Climate triggers: rainfall anomalies, vulnerability and communal conflict in Sub-Saharan Africa. Political Geogr 31:444–453. https://doi.org/10.1016/j.polgeo.2012.08.004

Füssel H-M, Klein RJT (2006) Climate change vulnerability assessments: an evolution of conceptual thinking. Clim Change 75:301–329. https://doi.org/10.1007/s10584-006-0329-3

Ge Q, Hao M, Ding F, Jiang D, Scheffran J, Helman D, Ide T (2022) Modelling armed conflict risk under climate change with machine learning and time-series data. Nat Commun 13. https://doi.org/10.1038/s41467-022-30356-x

Hauge W, Ellingsen T (1998) Beyond environmental scarcity: causal pathways to conflict. J Peace Res 35:17. https://doi.org/10.1177/0022343398035003003

Hegre H, Allansson M, Basedau M, Colaresi M, Croicu M, Fjelde H, Hoyles F, Hultman L, Högbladh S, Jansen R, Mouhleb N, Muhammad SA, Nilsson D, Nygård HM, Olafsdottir G, Petrova K, Randahl D, Rød EG, Schneider G, Von Uexkull N, Vestby J (2019) ViEWS: a political violence early-warning system. J Peace Res 56:155–174. https://doi.org/10.1177/0022343319823860

Helman D, Zaitchik BF, Funk C (2020) Climate has contrasting direct and indirect effects on armed conflicts. Environ Res Lett 15 https://doi.org/10.1088/1748-9326/aba97d

Hsiang SM, Burke M, Miguel E (2013) Quantifying the influence of climate on human conflict. Science 341:1235367. https://doi.org/10.1126/science.1235367

Ide T, Brzoska M, Donges JF, Schleussner C-F (2020) Multi-method evidence for when and how climate-related disasters contribute to armed conflict risk. Glob Environ Change-Human Policy Dimens 62 https://doi.org/10.1016/j.gloenvcha.2020.102063

Ide T, Kristensen A, Bartusevičius H (2021) First comes the river, then comes the conflict? A qualitative comparative analysis of flood-related political unrest. J Peace Res 58:83–97. https://doi.org/10.1177/0022343320966783

IPCC (2001) Climate change: impacts, adaptation and vulnerability. IPCC

Jun T, Sethi R (2021) Extreme weather events and military conflict over seven centuries in ancient Korea. Proc Natl Acad Sci USA 118 https://doi.org/10.1073/pnas.2021976118

Kottek M, Grieser J, Beck C, Rudolf B, Rubel F (2006) World map of the Koppen–Geiger climate classification updated. Meteorol Z 15:259–263. https://doi.org/10.1127/0941-2948/2006/0130

Koubi V (2019) Climate change and conflict. Annu Rev Political Sci 22:343–360. https://doi.org/10.1146/annurev-polisci-050317-070830

Koubi V, Spilker G, Boehmelt T, Bernauer T (2014) Do natural resources matter for interstate and intrastate armed conflict? J Peace Res 51:227–243. https://doi.org/10.1177/0022343313493455

Kumar R, Roy P (2018) War and peace: is our world serious about achieving Sustainable Development Goals by 2030? J Fam Med Prim Care 7:1153–1156. https://doi.org/10.4103/jfmpc.jfmpc_231_18

Le K (2021) Armed conflict and child weight in DR Congo. Adv Public Health 2021:1–11. https://doi.org/10.1155/2021/6931096

Leathwick JR, Elith J, Francis MP, Hastie T, Taylor P (2006) Variation in demersal fish species richness in the oceans surrounding New Zealand: an analysis using boosted regression trees. Mar Ecol-Prog Ser 321:15. https://doi.org/10.3354/meps321267

Mach KJ, Adger WN, Buhaug H, Burke M, Fearon JD, Field CB, Hendrix CS, Kraan CM, Maystadt JF, O'loughlin J, Roessler P, Scheffran J, Schultz KA, Von Uexkull N (2020) Directions for research on climate and conflict. Earth Future 8:e2020EF001532. https://doi.org/10.1029/2020EF001532

Mach KJ, Kraan CM, Adger WN, Buhaug H, Burke M, Fearon JD, Field CB, Hendrix CS, Maystadt JF, O'loughlin J, Roessler P, Scheffran J, Schultz KA, Von Uexkull N (2019) Climate as a risk factor for armed conflict. Nature 571:193–197. https://doi.org/10.1038/s41586-019-1300-6

Maystadt J-F, Ecker O(2014) Extreme weather and civil war: does drought fuel conflict in Somalia through livestock price shocks Am J Agr Econ 96:1157–1182

Maystadt JF, Calderone M, You LZ (2015) Local warming and violent conflict in North and South Sudan. J Econ Geogr 15:649–671. https://doi.org/10.1093/jeg/lbu033

Miguel E, Satyanath S, Sergenti E (2015) Economic shocks and civil conflict: an instrumental variables approach. J Political Econ 112:29. https://doi.org/10.1086/421174

Minhas S, Radford B (2017) Enemy at the gates: variation in economic growth from civil conflict. J Confl Resolution 61:2105–2129. https://doi.org/10.1177/0022002716639100

Müller D, Leitão PJ, Sikor T (2013) Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees. Agric Syst 117:66–77. https://doi.org/10.1016/j.agsy.2012.12.010

Nel P, Righarts M (2008) Natural disasters and the risk of violent civil conflict. Int Stud Q 52:27. https://doi.org/10.1111/j.1468-2478.2007.00495.x

Nelson T (2010) When disaster strikes: on the relationship between natural disaster and interstate conflict. Glob Chang Peace Secur 22:155–174. https://doi.org/10.1080/14781151003770788

Nordhaus W, Chen X (2015) A sharper image? Estimates of the precision of nighttime lights as a proxy for economic statistics. J Econ Geogr 15:217–246. https://doi.org/10.1093/jeg/lbu010

Nunn N (2020) The historical roots of economic development. Science 367:eaaz9986. https://doi.org/10.1126/science.aaz9986

Nunn N, Wantchekon L (2011) The slave trade and the origins of mistrust in Africa. Am Econ Rev 101:3221–3252. https://doi.org/10.1257/aer.101.7.3221

O'keefe P, Westgate K, Wisner B (1976) Taking the naturalness out of natural disasters. Nature 260:566–567

O'loughlin J, Linke AM, Witmer FD (2014) Modeling and data choices sway conclusions about climate-conflict links. Proc Natl Acad Sci USA 111:2054–2055. https://doi.org/10.1073/pnas.1323417111

O'loughlin J, Witmer FD, Linke AM, Laing A, Gettelman A, Dudhia J (2012) Climate variability and conflict risk in East Africa, 1990–2009. Proc Natl Acad Sci USA 109:18344–18349. https://doi.org/10.1073/pnas.1205130109

Owain EL, Maslin MA (2018) Assessing the relative contribution of economic, political and environmental factors on past conflict and the displacement of people in East Africa. Palgrave Commun 4 https://doi.org/10.1057/s41599-018-0096-6

Pettersson T, Davies S, Deniz A, Engström G, Hawach N, Högbladh S, Öberg MSM (2021) Organized violence 1989–2020, with a special emphasis on Syria. J Peace Res 58:809–825. https://doi.org/10.1177/00223433211026126

Pettersson T, Öberg M (2020) Organized violence, 1989–2019. J Peace Res 57:597–613. https://doi.org/10.1177/0022343320934986

Pinstrup-Andersen, Shimokawa S (2008) Do poverty and poor health and nutrition increase the risk of armed conflict onset? Food Policy 33:513–520. https://doi.org/10.1016/j.foodpol.2008.05.003

Raleigh C, Urdal H (2007) Climate change, environmental degradation and armed conflict. Political Geogr 26:674–694. https://doi.org/10.1016/j.polgeo.2007.06.005

Reuveny R (2007) Climate change-induced migration and violent conflict. Political Geogr 26:656–673. https://doi.org/10.1016/j.polgeo.2007.05.001

Rozmarin M (2017) Vulnerability and reconciliation: managing vulnerability as part of peacemaking. Isr Aff 23:545–560. https://doi.org/10.1080/13537121.2017.1306926

Scheffran J, Brzoska M, Kominek J, Link PM, Schilling J (2012) Climate change and violet conflict. Science 336:3. https://doi.org/10.1126/science.1221339

Schleussner C, Donges J, Donner R, Schellnhuber H (2016) Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries. Proc Natl Acad Sci USA 113:9216–9221. https://doi.org/10.1073/pnas.1601611113

Sundberg R, Melander E (2013) Introducing the UCDP georeferenced event dataset. J Peace Res 50:523–532. https://doi.org/10.1177/0022343313484347

Turner BL I, Kasperson RE, Matson PA, Mccarthy JJ, Corell RW, Christensen L, Eckley N, Kasperson JX, Luers A, Martello ML, Polsky C, Pulsipher A, Schiller A(2003) A framework for vulnerability analysis in sustainability science Proc Natl Acad Sci USA 100:8074–8079. https://doi.org/10.1073/pnas.1231335100

Un/Isdr (2004) Living with risk: a global review of disaster reduction initiatives. UN Publications

Van Weezel S (2019) On climate and conflict: precipitation decline and communal conflict in Ethiopia and Kenya. J Peace Res 56:514–528. https://doi.org/10.1177/0022343319826409

Van Weezel S (2020) Local warming and violent armed conflict in Africa. World Dev 126. https://doi.org/10.1016/j.worlddev.2019.104708

Vesco P, Kovacic M, Mistry M, Croicu M (2021) Climate variability, crop and conflict: exploring the impacts of spatial concentration in agricultural production. J Peace Res 58:98–113. https://doi.org/10.1177/0022343320971020

Weidmann NB, Ward MD (2010) Predicting conflict in space and time. J Confl Resolution 54:883–901. https://doi.org/10.1177/0022002710371669

Wimmer A, Cederman L-E, Min B (2009) Ethnic politics and armed conflict: a configurational analysis of a new global data set. Am Sociol Rev 74:316–337. https://doi.org/10.1177/000312240907400208

Wucherpfennig J, Weidmann NB, Girardin L, Cederman L-E, Wimmer A (2011) Politically relevant ethnic groups across space and time: introducing the GeoEPR dataset. Confl Manage Peace Sci 28:423–437. https://doi.org/10.1177/0738894210393217

Zhang DD, Brecke P, Lee HF, He Y-Q, Zhang J (2007) Global climate change, war, and population decline in recent human history. Proc Natl Acad Sci USA 104:5. https://doi.org/10.1073/pnas.0703073104

Zhang DD, Lee HF, Wang C, Li B, Pei Q, Zhang J, An Y (2011) The causality analysis of climate change and large-scale human crisis. Proc Natl Acad Sci USA 108:17296–17301. https://doi.org/10.1073/pnas.1104268108

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DJ, QSG, MMH, and FYD designed research; DJ, MMH, FYD performed the research; MMH, FYD, XXL, and JYF analyzed data; MMH and YSQ wrote the first draft of the paper; TI, J-FM, and SC gave useful edits, comments, and suggestions to this work; All authors reviewed and approved the final version of the manuscript.

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The authors declare no competing interests.

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Ethical approval was not applicable.

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This article does not contain any studies with human participants performed by any of the authors.

Additional information

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