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Climate change expected to increase conflict risks over the next decades across sub-Saharan Africa

Dong Jiang,[1,2,20] Jun Zhuo,[1,2,20] Shuai Chen,[1,20] Mengmeng Hao,[1,2,20] Xiaolan Xie,[3,*] Tobias Ide,[4] Jürgen Scheffran,[5] Ling Yao,[1,2] Wenxiang Wu,[1,2] Hou Jiang,[1,2] Jiajie Wu,[1] Jean-François Maystadt,[6,7,8] Ze Meng,[1] Jiping Dong,[1,2] Qian Wang,[9,10] Tingting Kang,[11] Kai Sun,[12] Yongqing Bai,[13] Zhenyu Wang,[14] Lei Liu,[15] Chao Yang,[16] Tian Ma,[17,18,*] Liqiang Zhang,[19,*] and Fangyu Ding[1,2,*]

*Correspondence: xiexl.20b@igsnrr.ac.cn (X.X.); tian.ma@yale.edu (T.M.); zhanglq@bnu.edu.cn (L.Z.); dingfy@igsnrr.ac.cn (F.D.)

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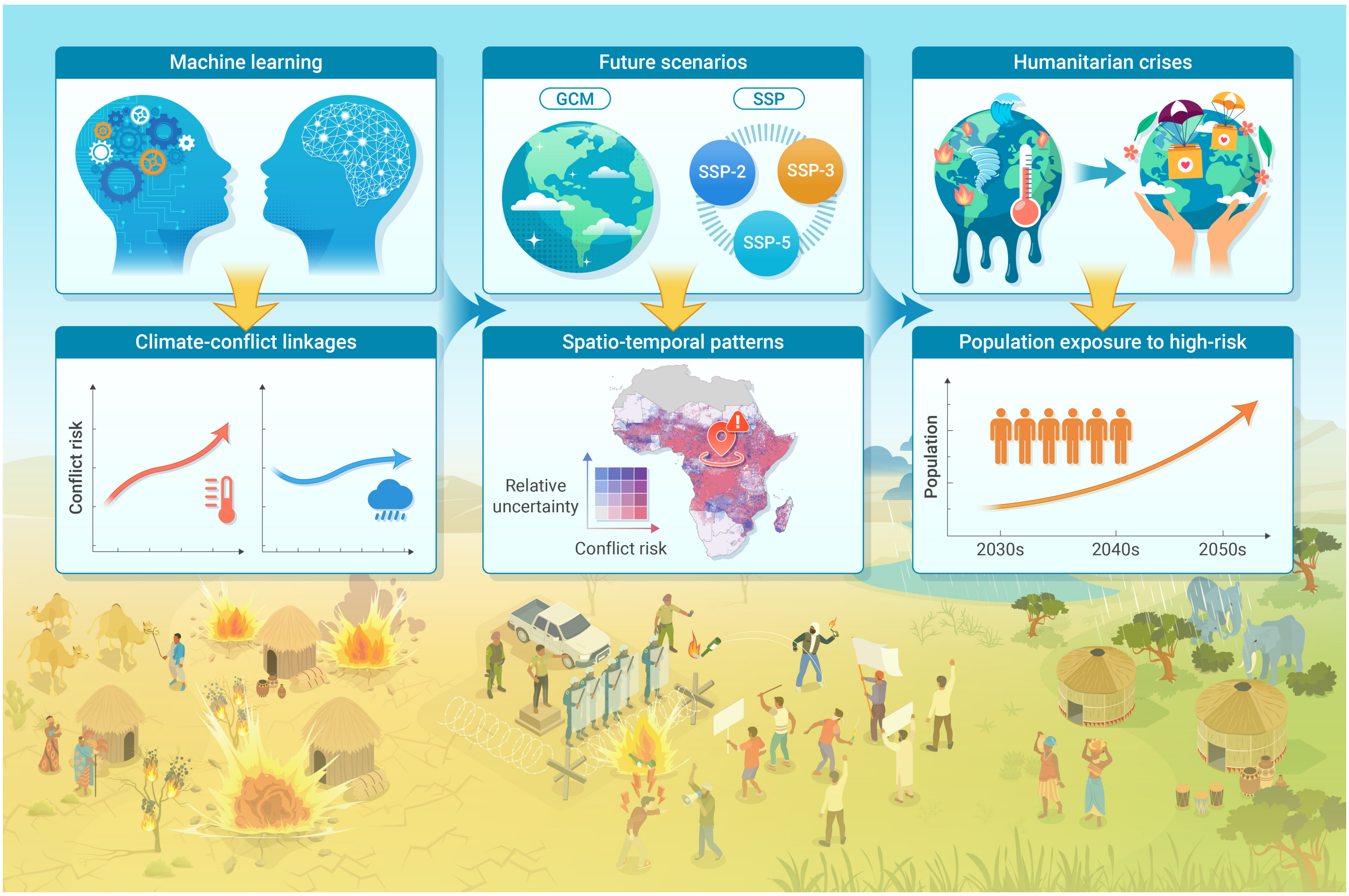
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- The climate-conflict linkages derived from machine learning models exhibit threshold effects.
- Climate change is expected to increase conflict risks over the next decades across sub-Saharan Africa.
- The change of projected spatiotemporal distribution of conflict risk will be heterogeneous.
- By the 2050s, 0.5-1.7 billion people may live at high risk zones of conflict across sub-Saharan Africa.

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[1]Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[2]College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China
[3]School of Geography & Environmental Science, Guizhou Normal University, Guiyang 550001, China
[4]Harry Butler Institute, Murdoch University, Perth 6150, Australia
[5]Institute of Geography, Center for Earth System Research and Sustainability, University of Hamburg, Hamburg 20144, Germany
[6]IRES/LIDAM, UCLouvain, Ottignies-Louvain-la-Neuve 1348, Belgium
[7]FNRS - Fonds de la Recherche Scientifique, Brussels 1000, Belgium
[8]Department of Economics, Lancaster University Management School, Lancaster LA1 4YX, UK
[9]Nuffield Department of Medicine, Centre for Tropical Medicine and Global Health, University of Oxford, Oxford OX3 7LG, UK
[10]Mahidol Oxford Tropical Medicine Research Unit, Faculty of Tropical Medicine, Mahidol University, Bangkok 10400, Thailand
[11]School of Urban Planning and Design, Peking University, Shenzhen Graduate School, Shenzhen 518055, China
[12]GeoAI Lab, Department of Geography, University at Buffalo, NY 14260, USA
[13]State Key Laboratory of Remote Sensing Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China
[14]School of Land Science and Technology, China University of Geosciences (Beijing), Beijing 100083, China
[15]School of Earth Science and Resources, Chang'an University, Shanxi 710054, China
[16]National Engineering Research Center of Geographic Information System, China University of Geosciences (Wuhan), Wuhan 430074, China
[17]Yale Institute for Biospheric Studies, Yale University, New Haven, CT 06511, United States
[18]School of the Environment, Yale University, New Haven, CT 06511, United States
[19]State Key Laboratory of Remote Sensing Science, Beijing Normal University, Beijing 100875, China
[20]These authors contributed equally
*Correspondence: xiexl.20b@igsnrr.ac.cn (X.X.); tian.ma@yale.edu (T.M.); zhanglq@bnu.edu.cn (L.Z.); dingfy@igsnrr.ac.cn (F.D.)

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While climate change is increasingly recognized as a driver of conflict risks, most research focuses on past correlations, hence limiting our ability to project future climate-related security risks. We use machine learning techniques to predict the spatiotemporal dynamics of conflict risks and estimate the human population that would be exposed to these risks in the 2030s, 2040s, and 2050s. Our results demonstrate that climate change is associated with increasing risks of conflict over the next decades and that the change of projected spatial and temporal distribution of conflict risk will be heterogeneous, depending on conflict types and climate scenarios. We estimate that 0.5-1.7 billion people may live at high risk zones of conflict across sub-Saharan Africa by the 2050s, which is an increase of at least 391 million compared to today. Detecting such risks early provides sufficient time to plan ahead and implement mitigation strategies.

INTRODUCTION

As one of the most daunting challenges of the 21st century, climate change has potentially disruptive effects on human enterprises by, for example, possibly diminishing global food production and causing significant sea level rise.[1-4] More importantly, in places already characterized by political instability, climate change can act as a risk multiplier that causes conflict risk or exacerbates factors known to raise conflict risk.[5-7] As a result, concerns about the effect of climate change on conflict risk have been a priority for global initiatives. The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) highlighted the need for a comprehensive assessment of the climate-conflict nexus.[8] More recently, the IPCC's Sixth Assessment Report (AR6) concluded that while non-climatic factors are the dominant drivers of existing intrastate violent conflicts, in some assessed regions extreme weather and climate events have had a small, adverse impact on their length, severity, or frequency, but the statistical association is weak.[9] This evolving understanding underscores the complexity of the climate-conflict relationship and the need for further research to disentangle its mechanisms.

The scientific community has increasingly explored the potential linkages between climate change and conflict risk.[7,10,11] Initially, studies produced disparate findings, resulting in intense debates between experts. For instance, Burke et al.[12] and Hsiang et al.[13] found that climate anomalies, such as temperature extremes and precipitation variability, correlate with increased conflict risk. Conversely, Buhaug[14] and other scholars[15] challenged these findings, arguing that governance, economic resilience, and institutional strength play a far more decisive role in determining conflict outcomes. Despite these debates, a growing body of evidence suggests that climate change amplifies conflict risks, particularly in politically fragile and resource-scarce regions.[7,16] In line with this, a recent expert assessment found large agreement that climate change increases conflict risks, even though other conflict drivers are more relevant.[17]

The above studies laid the foundation for understanding climate-conflict linkages, but they remained rooted in historical data. More recently, researchers have shifted towards predictive modeling to anticipate future conflict risks. Witmer et al.[18] developed subnational conflict forecasts for Sub-Saharan Africa from 2015 to 2065, using climate-sensitive models to project conflict risks under varying environmental conditions, providing a forward-looking perspective. Similarly, Hoch et al.[19] employed machine learning methods to project armed conflict risk across Africa, incorporating three Shared Socioeconomic Pathways (SSP) and three Representative Concentration Pathway (RCP) scenarios up to 2050. These studies introduced more sophisticated methods, but they still largely relied on national and regional data, limiting their ability to capture localized conflict dynamics or assess population exposure to high-risk areas.

This study aims to address these gaps by developing a quantitative modeling framework based on machine learning to explore the impact of climate change on conflict risks, by investigating the spatiotemporal dynamics of conflict risks at finer scales, and by quantifying the population exposed to high-risk conflict zones across Sub-Saharan Africa under different climate change scenarios (Figure 1). Specifically, we focus on three types of conflict (armed conflict, violent conflict, and demonstrations). Armed conflict events are taken from the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (GED) datasets and are defined as "an incident where armed

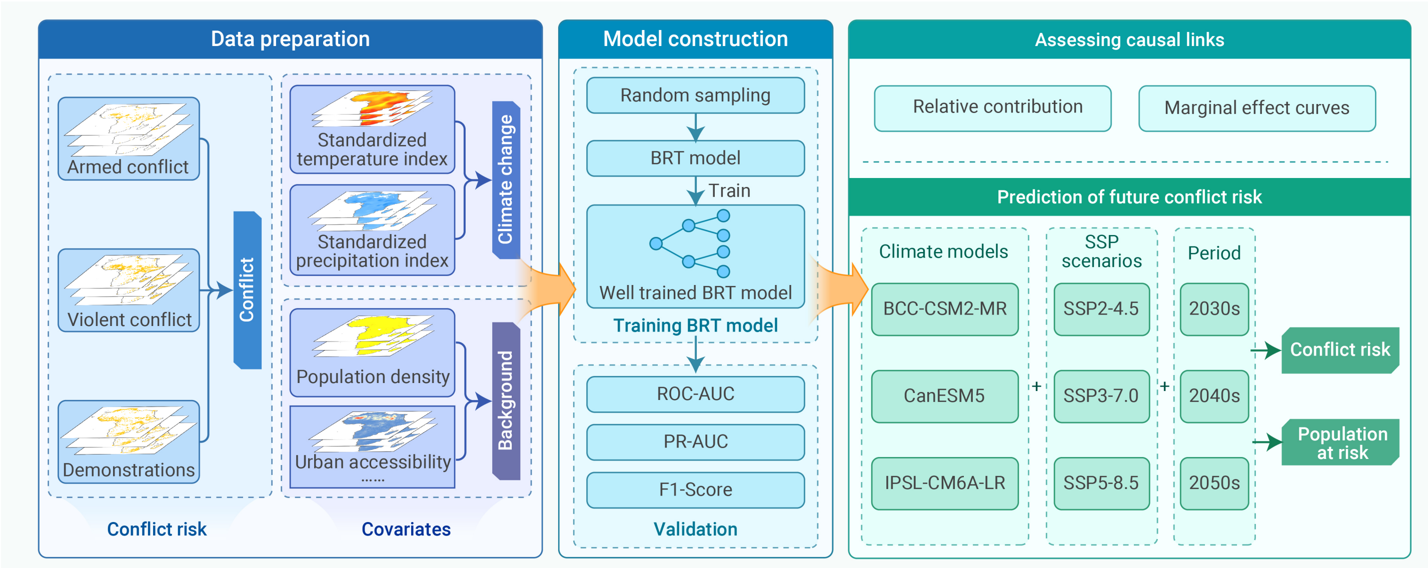

Figure 1. Analytic process overview. Successive steps starting from dataset preparation and leading to the model establishment, each processing step is described in greater detail in the Methods.

force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date".[20] Violent conflict is a broad category used by the Armed Conflict Location & Event Data Project (ACLED) to refer to battles between organized armed groups, the use of explosives, and violence against civilians by organized groups. Demonstrations are also recorded by ACLED and include the gathering of a group of people to express their demands either peacefully (protests) or violently (riots) (see Methods for details).[21] For each type of conflict risk, we (i) fit an ensemble of boosted regression tree (BRT) models based on conflict event records from 2000 to 2019 and the climate deviations related covariates as well as background context factors (see Methods), and assess the impact of climate change on conflict risks, (ii) present projections of the conflict risks in the 2030s (2030-2039), 2040s (2040-2049) and 2050s (2050-2059) employing an ensemble of general circulation models (GCMs) under three SSP scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5), and (iii) estimate population living in high risk areas of conflicts under different future scenarios. By integrating machine learning techniques with climate scenario modeling, this study advances the existing literature by offering a granular, data-driven analysis of future climate-related conflict risks. The findings will contribute to improving early warning systems, guiding conflict prevention efforts, and informing climate adaptation policies in fragile regions.

MATERIALS AND METHODS

Analysis

We employed the BRT approach to perform modeling analyses of conflict risk. BRT is a powerful machine learning method that integrates decision trees with boosting techniques to improve prediction accuracy while mitigating overfitting.[22] Unlike traditional regression methods, BRT excels at capturing complex, non-linear interactions between predictors and response variables, making it well-suited for modeling socio-environmental phenomena such as conflict risk.[23,24]

Based on this method, we established a multivariate empirical relationship between the probability of conflict outbreak and covariates. Specifically, for each type of conflict risk, we fitted an ensemble of 50 BRT models based on conflict risk data and various covariates data (i.e., climate deviations related covariates and background contexts) from 2000 to 2019, ensuring model stability and reducing variance through multiple iterations. The detailed information on datasets is in Table S1 and Supplementary Information. Each of the 50 individual models was fitted using the 'gbm.step' subroutine in the package dismo (version 4.2.1) of R version 4.3.2. Based on previous experience in building the BRT model,[23] the main parameters for the model were set as follows: tree.complexity = 4, learning.rate = 0.01, bag.fraction = 0.75, step.size = 10, cv.folds = 10, max.trees = 10000, and other tuning parameters of the algorithm were held at their default values. We evaluated the performance of the ensemble BRT models using the area under the receiver operator characteristic curve (ROC-AUC), the area under the precision recall curves (PR-AUC), and F1-score. For each covariate, we calculated the value of RC and drew the marginal effect curves. In addition, we add two modeling strategies A and B to analyze the impact of climate factors on the conflict simulation. A comprehensive explanation of the BRT modeling framework, along with information on independent, and dependent variables and two strategies, is provided in the Supplementary Information.

By substituting the covariates data with estimates for 2030-2059, we can predict the future risk of conflict based on 50 ensembles of well-trained BRTs. Specifically, we used gridded estimates of temperature and precipitation from three General Circulation Models (BCC-CSM2-MR, IPSL-CM6A-LR, CanESM5) under three greenhouse gas emission scenarios (SSP2-4.5, SSP3-7.0, SSP5-8.5) from 2030 to 2059. The mean probability of conflict was computed across 50 ensemble runs and three climate models to account for inter-model variability. However, previous studies suggested evaluating projections for a single year may yield rather arbitrary results,[19] therefore we mapped the average output of conflict risk in the 2030s (2030-2039), 2040s (2040-2049), and 2050s (2050-2059). As such, we produced a total of nine final mean projections of the distribution of each type of conflict risk.

Data

Conflict risk data. To estimate the effect of current and future climate change on different conflict risk types, we chose to leverage the widely used ACLED and UCDP GED databases as sources of conflict data. These databases provide comprehensive coverage of different conflict types, enabling us to conduct a nuanced analysis of the multifaceted relationship between climate change and conflict. UCDP GED recorded three types of armed conflict events (state-based conflict, non-state conflict, and one-sided violence) with at least 1 direct death at a specific location and time.[25] ACLED is based primarily on media reports of violence geolocated to the nearest settlement.[21] These statistics provide a daily temporal resolution for conflict events such as riots, protests, violence against civilians, and clashes between rebel and government sides. We focus on violent conflict events (battles, explosions/remote violence, and violence against civilians) and demonstrations (protests and riots) to estimate the effect of climate change. To mitigate potential biases arising from differences in event reporting, we standardized data by aligning ACLED and UCDP GED events to a common geospatial grid and time frame.

Based on these two datasets, we defined two binary dependent variables for each 0.25° × 0.25° grid yearly to represent conflict risk. If at least one conflict event was reported in the given grid during the year, the value is coded 1 and 0 if not. Furthermore, to assess whether climate change might increase the risk of conflicts in regions with historically high conflict incidence, we conducted additional analyses. If a region experienced a conflict event in any year within the past two years, and there was also a conflict event in the current year, then the label of that region regarded as a historically conflict-prone area was coded as 1. If a region did not experience conflicts in the previous two years and had no conflicts in the current year, it was coded as 0. Details can be found in the Supplementary Information.

Climate dataset. Previous studies suggested conflict risk is influenced by a variety of climatic factors, such as long-term and interannual temperature as well as precipitation.[23,26] To explore the effect of current and future climate change on conflict risk, we derived the historical climate data from the Climate Research Unit (CRU) dataset from the University of East Anglia.[27] Based on these data, we generated long-term (1970-1999) mean precipitation and mean temperature distribution data. In addition, we calculated the standardized temperature index and standardized precipitation index by comparing the most recent year of data with the prior 30-year (1970-1999) climatology for those same grid locations. Standardized temperature index represents deviations from the multi-annual average temperature, values near 0 indicate normal temperature and 1 indicates that the temperature was one standard deviation hotter than usual temperatures.[28] The standardized precipitation index is calculated similarly.

Future climate scenarios consist of gridded near-surface air temperature and surface precipitation fields derived from three GCMs taking part in the latest Coupled Model Intercomparison Project (CMIP6):[29] BCC-CSM2-MR,[30] IPSL-CM6A-LR,[31] and CanESM5.[32] We considered simulations conducted under SSP2-4.5, SSP3-7.0, and SSP5-8.5 greenhouse gas emission concentration pathways. To maintain internal consistency, future precipitation, and temperature data were processed using the same method we used for historical climate.

Liberal Democracy Index. Democracy plays a crucial role in conflict studies.[33] Democratic systems are typically associated with a tendency toward peaceful conflict resolution. In democratic countries, the legitimacy of political power is often established through elections and citizen participation, facilitating the resolution of disputes through negotiation and dialogue, thereby reducing the likelihood of conflict escalation.[34] To measure a nation's political system and democratic level, this study utilizes the Liberal Democracy Index obtained from the Varieties of Democracy (V-Dem) dataset to assess a country's performance in areas such as freedom, equality, and the rule of law.

Urban Accessibility. Urban accessibility refers to the convenience of transportation and transportation facilities within a city or between a city and its surrounding areas. It influences the distribution of resources in different regions of the city, including employment opportunities, education, healthcare services, and more.[35] If the accessibility in certain areas is low, it may result in uneven resource distribution, leading to the marginalization of certain social groups and potentially increasing social inequality. This, in turn, could contribute to social unrest and conflict.[36] To investigate the impact of urban accessibility on conflicts, we utilize transportation time data from the European Commission Joint Research Center website, specifically focusing on travel times from cities to urban areas with populations exceeding 50,000 inhabitants.

Ethnic Diversity. The role of ethnic diversity in conflict studies is a complex and multifaceted topic that researchers have extensively explored. Some studies suggest that in a society composed of different races and ethnicities, there may be more social fragmentation and identity differences. These differences can lead to a decrease in social cohesion, increasing the likelihood of conflict.[37] However, it is usually not ethnic diversity per se, but the exclusion of ethnic groups from political power that results in grievances and higher conflict risks.[38,39] To measure the impact of ethnic discrimination on conflict, we included a binary exclusion variable that identifies whether a particular ethnic group is excluded from the political processes of a nation from the Ethnic Power Relations (EPR) dataset.[40] The EPR dataset lists all politically relevant ethnic groups globally and provides data on the administrative power each group has obtained each year.

Gross Domestic Product. Economic factors are often one of the core driving forces behind the occurrence of conflict.[41] Issues such as uneven distribution of resources, income, poverty, and high unemployment rates typically lead to internal tension and discontent within society, serving as potential triggers for conflict.[42] The deterioration of economic conditions can spark social upheaval and deepen class divisions, thereby fostering the spread of conflict.[43] To incorporate economic elements into the modeling of conflict, this study utilizes the gross domestic product (GDP) obtained from Murakami et al.[44] as a representative indicator of economic conditions. GDP data provide information for the years 1850 to 2100 under different Shared Socioeconomic Pathways (SSPs), allowing us to integrate it with future climate data for predicting conflict. To match with climate scenarios, data under the SSP2, SSP3, and SSP5 scenarios are selected respectively.

Land Cover. There are multifaceted relationships between agricultural areas and conflict, especially in regions heavily dependent on agriculture.[38] Resources in agricultural regions, such as water and arable land, can become focal points for resource competition. Scarcity or unfair distribution of resources may lead to competition among groups, triggering conflicts.[45] Agricultural areas can be impacted by climate change, including events such as droughts and floods. Such climate variations can result in decreased agricultural output, leading to food shortages and exacerbating societal tension, potentially sparking conflicts.[46] Land-use data obtained from the LUH2 (Land-Use Harmonization) project[47] is incorporated into the model to measure the impact of agricultural areas on conflicts. The dataset includes land-use data for the years 1850-2100 under different future scenarios, to align with other datasets, we choose land-use data under scenarios SSP2, SSP3, and SSP5.

Population. To explore future population size under conflict risk, we extracted gridded population projections from the SSP spatial population scenario database (www.cgd.ucar.edu/iam/modeling/spatial-population-scenarios.html). To maintain consistency with other future datasets, we retrieved gridded population projections under scenarios SSP2, SSP3, and SSP5.

RESULTS

Performance assessment of boosted regression tree models

To validate whether climate factors improve the performance of the models, we set up two contrasting modeling strategies A and B, and constructed 50 ensemble BRT models to mitigate the randomness introduced by a single simulation (See Methods). The results show that the BRT models of strategy A performed better than that of strategy B with a significant difference ($p<0.001$), which indicates that incorporating climate factors improved the accuracy of the ensemble BRT models (Figures 2 and S1-S2). In addition, the 10-fold cross-validation of the area under the receiver operator characteristic curve (ROC-AUC) of the ensemble BRT models under strategy A performs well across the three types of conflict (armed conflict: 0.907±0.003 s.e.; violent conflict: 0.886±0.001 s.e.; demonstrations: 0.919±0.002 s.e.), suggesting that the models exhibit good simulation effectiveness.

The relative importance of each covariate

We assessed how each factor contributed to the ensemble BRT models and calculated the relative contribution (RC) of climate deviations related covariates vs. background contexts on conflict risks. Tables S2-4 show the RC of each covariate to multiple conflict risk types. In general, we find that background context factors which together contribute more than 90% of each type of conflict risk, are significant driving factors of all conflict risk types mentioned in this study. In contrast, the RC of climate change represented by the standardized precipitation index (SPI) and standardized temperature index (STI) is relatively low, accounting for less than 10% for each conflict risk.

The RC of SPI (Figure 3) and STI (Figure 4), however, presents a clear pattern among different types of conflict risk. The RC is highest for armed conflict risk, followed by violent conflict and demonstrations (Table S5). To assess the relationship between each climate deviation related covariate and conflict risk, we plotted the marginal effect curves, which show how conflict risk varies with specific factors while all other variables are kept constant at their mean. Figure 3 suggests that a moderate reduction in temperature reduced the risk of conflict, while positive temperature deviations increased conflict risk across sub-Saharan Africa from 2000-2019. For SPI, Figure 4

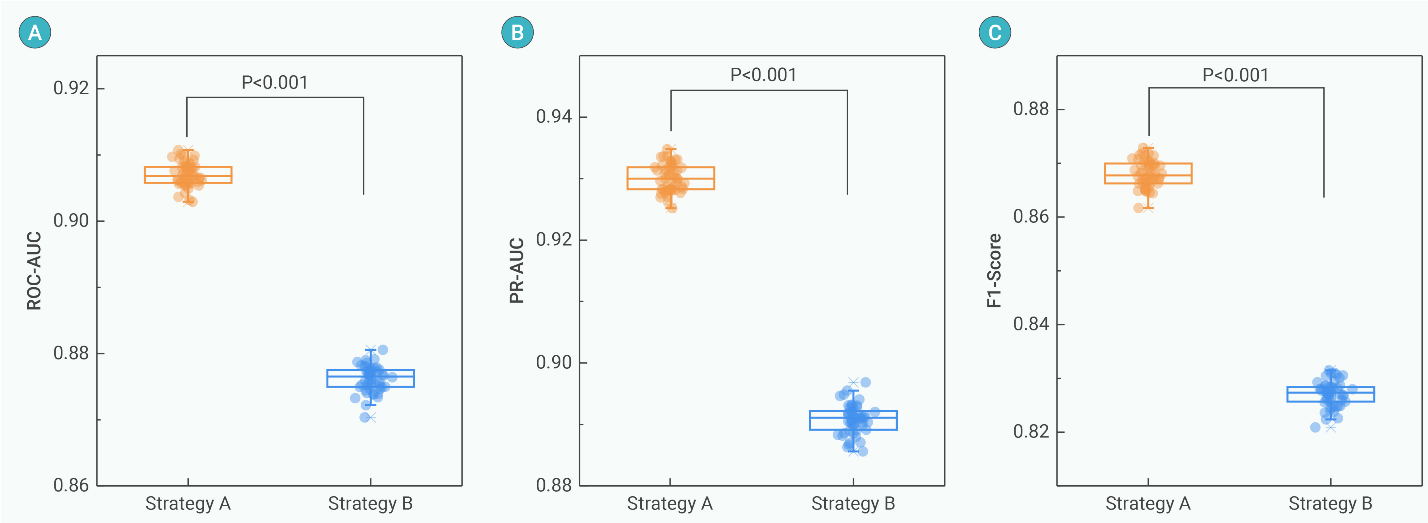

Figure 2. Precision comparison of modeling strategies A (the pairing of background contexts with climate deviations related covariates) and B (background contexts without climate factors) for the risk of armed conflict during the validation process (A) ROC-AUC, (B) PR-AUC, and (C) F1-score. The p value was determined by the two-tailed Mann–Whitney test (n = 50). Plots show the median, first and third quantiles, upper and lower bounds.

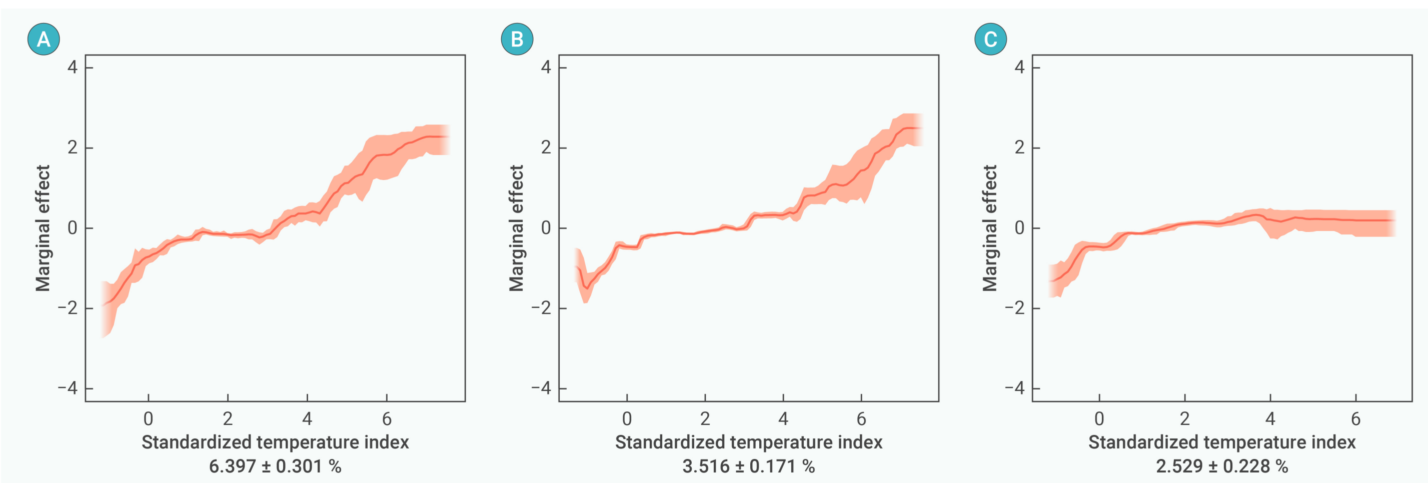

Figure 3. Marginal effect curves of the standardized temperature index on conflict risks: (A) armed conflict, (B) violent conflict, and (C) demonstrations White central lines represent mean effect estimates derived from ensemble boosted regression tree (BRT) analyses, bounded by red-shaded 95% confidence intervals. Subplots are arranged in descending order of SPI's relative influence (mean ± SD percentage contribution values shown in each panel).

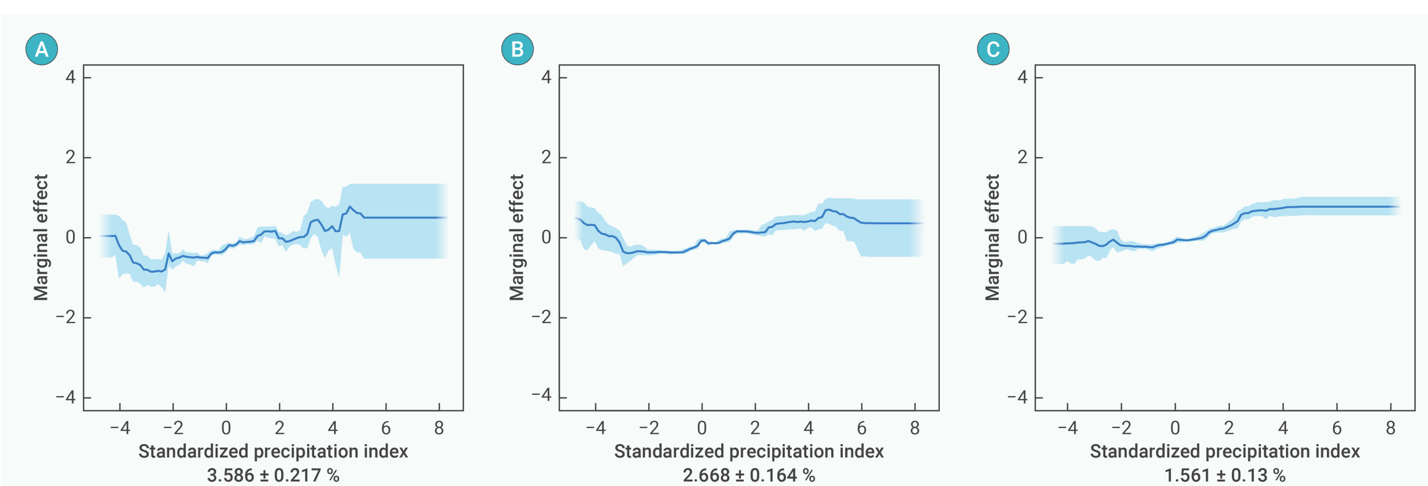

Figure 4. Marginal effect curves of the standardized precipitation index on conflict risks: (A) armed conflict, (B) violent conflict, and (C) demonstrations White central lines represent mean effect estimates derived from ensemble boosted regression tree (BRT) analyses, bounded by blue-shaded 95% confidence intervals. Subplots are arranged in descending order of SPI's relative influence (mean ± SD percentage contribution values shown in each panel).

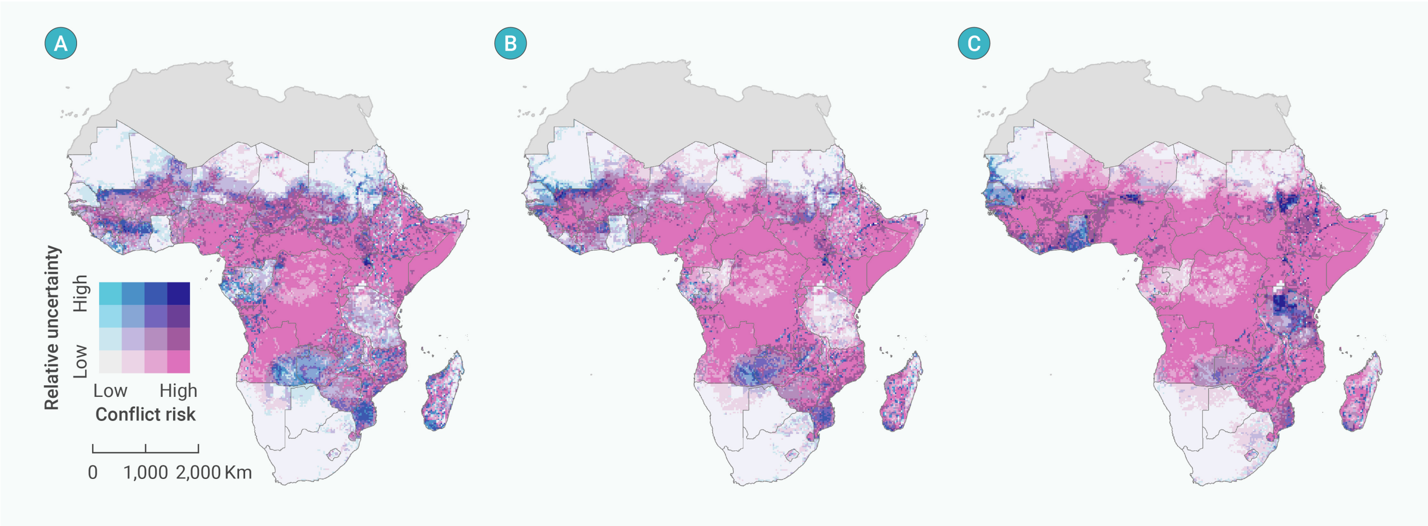

Figure 5. Spatio-temporal pattern of the predicted armed conflict risk over time under the SSP5-8.5 scenario It depicts the spatial and temporal patterns of the predicted conflict risk and their relative uncertainty for (A) the 2030s, (B) the 2040s, and (C) the 2050s.

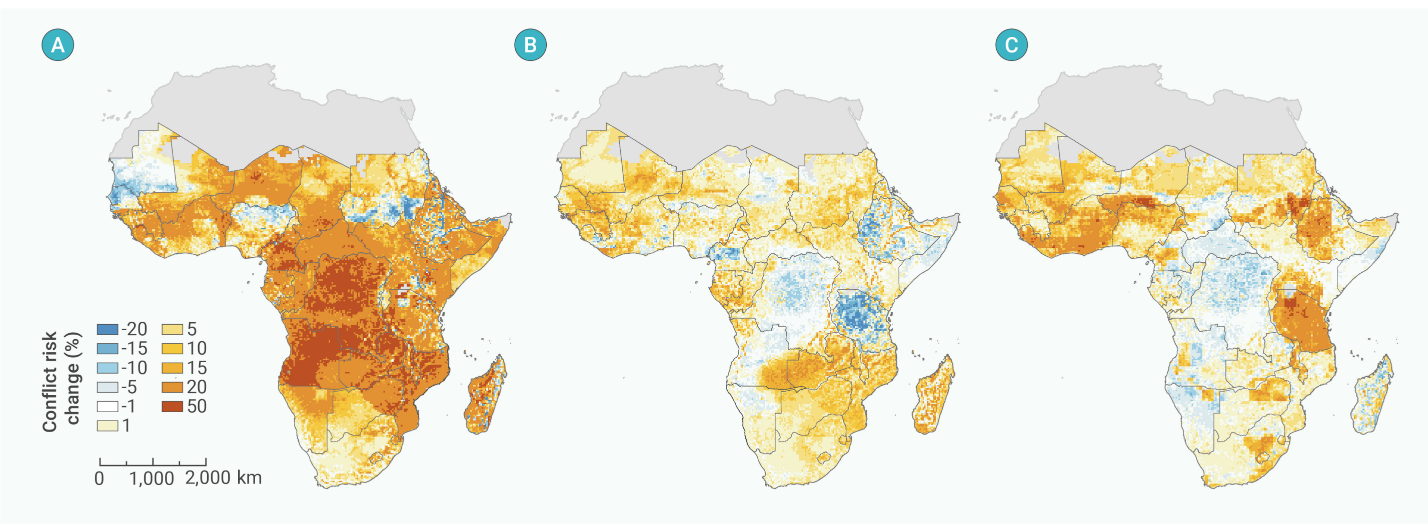

Figure 6. The changes in projected armed conflict risk under the SSP5-8.5 scenario (A) from the 2010s to 2030s, (B) from the 2030s to 2040s, and (C) from the 2040s to 2050s.

shows that extreme positive or negative precipitation deviations are associated with an increased risk of conflict. Overall, the marginal effect curves indicate that there was a similar pattern across climate deviations related to covariates and different types of conflict risk. In other words, even though they are not the most important risk factor, temperature, and precipitation deviations increase the risk for the occurrence of all three types of conflicts. Figure S3 illustrates the marginal effect curves of each climate deviation related covariate on various types of conflict risk in regions with historically high conflict occurrence rates. The results indicate that in areas with higher baseline conflict levels, climate change can also increase the incidence of conflict, hence providing support for a threat multiplier effect.[17]

Conflict risks over the next decades

Having demonstrated the impact of climate change on conflict risk, we predicted the spatio-temporal pattern of different types of conflict risk under three SSPs in the 2030s, 2040s, and 2050s based on the projected climatic data derived from three GCMs (see Methods for detailed information, Figures 5-6 & S4-12). The maps reporting the differences in armed conflict risk between current (the 2010s) and future (2030s-2050s) environmental conditions indicate that the high-risk area of conflict will likely expand in the next decades, yet with significant disparities in the distribution of high-risk areas between different types of conflict.

Armed conflict (Figures 5-6 & S5-6) shows similar patterns compared to violent conflict (Figures S7-9). Irrespective of which SSP scenario is considered, the high-risk areas of both armed conflict and violent conflict are anticipated to expand beyond their current distributions when most parts of Nigeria, Sudan, the Horn of Africa, and the southern DRC are at high risk by the 2050s. Additionally, across all scenario SSPs, we discover that conflict will mostly spread throughout Sub-Saharan Africa over time. Compared with a present-day baseline (the 2010s, Figure S4), the probability of conflict outbreaks in places such as Cameroon, Angola, and the Democratic Republic of the Congo (DRC) will increase significantly already in the 2030s. Although the prediction results are mainly consistent across all SSP scenarios, projections reflect the scenario storylines and show greater conflict probability in SSP5-8.5 compared to SSP2-4.5 and SSP3-7.0, and this difference between scenarios is consistent over time. In other words, the more severe the impacts of climate change, the more violent conflict risks will spread geographically.

For demonstrations (Figures S10-12), our prediction suggests that the high-risk area of demonstrations will be concentrated in Nigeria, South Africa, and Ethiopia by 2050s under all SSP scenarios. Moreover, the risk of demonstrations in each region is found to significantly change between the 2010s and 2030s, whereas just a minor shift was seen between the 2030s and 2050s. Specifically, from the 2010s to the 2030s, the probability of demonstrations risk is expected to increase in almost all regions in Africa, with large changes observed in Angola, Chana, and Ethiopia, while a decrease occurs in most

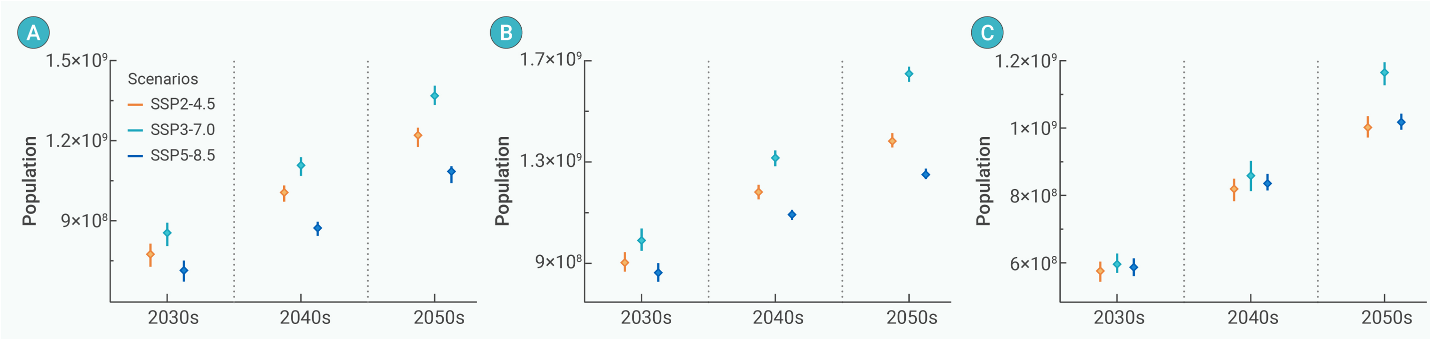

Figure 7. Projected number of people exposed to the high risk zones of three types of conflict (A. Armed conflict B. Violent conflict, and C. Demonstrations) in sub-Saharan Africa in the 2030s, 2040s, and 2050s under different SSP scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5) The error bars are defined as ranges.

areas in Somalia. The distributions of demonstrations risk show no obvious difference under the three scenarios, suggesting a relatively small effect of climate change on demonstrations.

Population living in areas with high conflict risks

We evaluated the existing and future human population in high-risk areas of conflict based on predicted human population values from SSP2, SSP3, and SSP5 to determine how many people would be impacted by the extension of the high-risk area of conflict (Figure 7 & Table S6). In this section, we focus on armed conflict risk and consider population projections in areas with an estimated high risk (an instance is classified as high risk if its conflict risk exceeds 0.5) under SSP5-8.5. We find that the human population living in high-risk areas of conflict may increase from 228 million today to 714 million by 2030s, to 873 million by 2040s, and to 1085 million by 2050s (not factoring in population movement). This result suggests that the population living in high-risk areas of conflict is expected to grow under future climate change. Moreover, we counted the top 10 countries with the highest number of people living in areas at high risk of conflict in the 2010s, 2030s, 2040s, and 2050s under different scenarios (Tables S7-9). Countries like Nigeria, Ethiopia, Somalia, and South Sudan will remain major conflict hotspots in terms of the number of people vulnerable to the risk of conflicts, while the Democratic Republic of Congo will become a major focus by the 2030s.

DISCUSSION

Past research highlighted that conflict risk is strongly shaped by political and economic factors.[17,48] Our findings support this pattern further and show that political-economic conditions are primarily responsible for the distribution of conflict risk. The RC values of climate change range from 4.1% to 9.98% across different types of conflict models, which is consistent with an expert group's estimation that 3-20% of conflict risk has been influenced by climate change.[6,17] We note that the impact of climate change on conflict risk estimated in this study is comparable to the estimates in another study at the global scale, yet our estimated value is larger.[23] This discrepancy provides further evidence that, due to the unique vulnerability and pronounced reliance on agriculture in the sub-Saharan Africa region, conflicts in this area are particularly vulnerable to the impacts of climate change than other parts of the world.[24,49] Climate change hence increases the probability of conflict risk to some extent, particularly when extreme precipitation, drought, and heat occur.[50] Our findings underscore that the relationship between climate variables and conflict risk is not linear but rather exhibits threshold effects. For instance, while moderate deviations in SPI may have a limited impact on conflict risk, extreme deviations can significantly escalate the likelihood of violent conflicts (Figure 3B). This non-linear pattern aligns with prior research, which has similarly identified threshold effects in the climate-conflict nexus.[12,13] Such findings suggest that climatic conditions become critical drivers of conflict only when they surpass specific thresholds, underscoring the importance of extreme climatic events in exacerbating conflict risks and debates around tipping points in the climate security literature.[17,51] All categories of conflict risk are strongly connected with extreme variations in temperature and precipitation, but the relationship is weakest when demonstrations occur, indicating that violent conflict is more vulnerable to climatic deviation than non-violent conflict.[52] This raises doubts about common claims that low-intensity conflicts are more susceptible to climate change risks than large-scale conflicts.[53,54]

This study also indicates that increased risks of conflict over the next decades are associated with global warming, and the change of projected spatial and temporal distribution of conflict risk will be heterogeneous. The results are broadly in line with earlier studies and show that the distribution of future high-risk areas varies across different types of conflict.[18,19,55] In addition, our study estimated at a more detailed level (i.e., 0.25° × 0.25°) of future conflict patterns in sub-Saharan Africa. High-risk areas for all types of conflict usually exist in regions that already suffer from the high prevalence of conflict.[19] Also in line with findings from earlier studies, we find that the future levels of conflict risk in sub-Saharan Africa will be higher than current ones if emissions continue to rise throughout the next decades.[18] In addition, an increase in conflict-prone areas can be expected for the pathway of high future CO_2 emissions (SSP5-8.5) in comparison to the medium-high emission scenario (SSP3-7.0) and the stabilizing forced scenario (SSP2-4.5). Overall, our results highlight that climate change is expected to substantially aggravate conflict risk across sub-Saharan Africa.

Our projections of the future conflict risk also suggest that beyond the next decades, particularly in the 2050s, the high-risk areas of all conflict types will continue to spread outside of their current distribution areas, which may result in a sharp rise in the number of people living in high-risk areas. With a focus on SSP5-8.5, our analysis shows that an additional 857 million people will be at high risk of armed conflict in the 2050s compared to the 2010s. Besides the expansion of high-risk areas, we also find that population growth in currently high-risk areas will increase the number of people exposed to the predicted future risk. Hence, conflicts would affect more people in increasingly populated areas even if high-risk areas do not expand immediately.

Our findings indicate that with ongoing and future changes in climate, more regions in Africa will face an elevated risk of conflicts. To effectively mitigate the harms posed by conflict risks in the context of climate change, ambitious policies for climate change mitigation need to be implemented. Simultaneously, there is a need for additional adaptation strategies to reduce the likelihood of conflicts in the medium term.[56] These strategies encompass enhancing water resource management to ensure sustainability, adopting crops resilient to drought or adapted to higher temperatures, improving irrigation systems, and formulating more flexible agricultural management plans, among others.[57,58] Crucially, these strategies must be conflict-sensitive, as their formulation and implementation can directly influence the resilience of societies and ecosystems in the face of climate change and research has shown that maladaptation can result in conflict.[59] By fostering synergies between climate adaptation and conflict prevention measures, our findings contribute to enhancing social stability and security. This approach not only helps to maintain the sustainability of the economy, society, and environment but also supports the achievement of both global and regional SDGs (Sustainable Development Goals), particularly in areas related to peace, justice, and strong institutions (SDG 16) and climate action (SDG 13). This dual focus on adaptation and conflict mitigation offers a comprehensive framework for building resilience and advancing sustainable development in fragile regions.

There are some limitations to our study. First, our analysis adopted two known comprehensive conflict datasets, UCDP GED and ACLED, to increase the robustness of the results, but well-known data bias in reported conflict events may add uncertainty to our results.[60] Second, while the machine learning models utilized in our study enable us to provide the contribution rates of each independent variable to the dependent variable and the visualization of the marginal effect curves of each climate covariate on various types of conflict risk, thereby enhancing interpretability, we acknowledge that, despite these advantages, the model has limitations in fully exploring causal mechanisms. This restricts our ability to comprehensively understand the causal mechanisms through which climate change affects conflicts. Third, due to the difficulty in obtaining other indicators representing income and development, this study only incorporates GDP to represent the level of income. This may affect the accuracy of the forecast to some extent. In conclusion, our study goes beyond the existing model-based quantitative studies in the climate-conflict field. Our results provide reliable and convincing evidence of the past and future climate-conflict linkages that can help to identify vulnerable regions and develop risk mitigation strategies as early as possible.

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AUTHOR CONTRIBUTIONS

F. D. and X.X. conceived and designed the study. F. D., X. X., S. C., M. H. and D. J. collected the data and carried out the computations. D. J., X. X., F. D., L. Z., S. C., T. M., M. H. and J. Z. analyzed the data. D. J., X. X. and F. D. wrote the paper. S. C., T. I., J. S., W. W., L. Y., H. J., J. W., J. M., J. Z., Z. M., J. D., Q. W., T. K., K. S., Y. B., Z. W., L. L.and C. Y. gave some useful suggestions to this work. F. D., X. X., D. J., L. Z. and T. M. revised the manuscript. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

All data that support the findings in this study are publicly available.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.59717/j.xinn-geo.2025.100139

LEAD CONTACT WEBSITE

Fangyu Ding: https://www.researchgate.net/profile/Fangyu-Ding