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Spatial spillovers of violent conflict amplify the impacts of climate variability on malaria risk in sub-Saharan Africa

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Africa carries a disproportionately high share of the global malaria burden, accounting for 94% of malaria cases and deaths worldwide in 2019. It is also a politically unstable region and the most vulnerable continent to climate change in recent decades. Knowledge about the modifying impacts of violent conflict on climate–malaria relationships remains limited. Here, we quantify the associations between violent conflict, climate variability, and malaria risk in sub-Saharan Africa using health surveys from 128,326 individuals, historical climate data, and 17,429 recorded violent conflicts from 2006 to 2017. We observe that spatial spillovers of violent conflict (SSVCs) have spatially distant effects on malaria risk. Malaria risk induced by SSVCs within 50 to 100 km from the households gradually increases from 0.1% (not significant, P>0.05) to 6.5% (95% CI: 0 to 13.0%). SSVCs significantly promote malaria risk within the average 20.1 to 26.9 °C range. At the 12-mo mean temperature of 22.5 °C, conflict deaths have the largest impact on malaria risk, with an approximately 5.8% increase (95% CI: 1.0 to 11.0%). Additionally, a pronounced association between SSVCs and malaria risk exists in the regions with 9.2 wet days per month. The results reveal that SSVCs increase population exposure to harsh environments, amplifying the effect of warm temperature and persistent precipitation on malaria transmission. Violent conflict therefore poses a substantial barrier to mosquito control and malaria elimination efforts in sub-Saharan Africa. Our findings support effective targeting of treatment programs and vector control activities in conflict-affected regions with a high malaria risk.

violent conflict | malaria risk | climate change | sub-Saharan Africa

Significance

We show how violent conflict can worsen malaria risk in Africa. Using localized data on climate, malaria risk, and conflict events, we demonstrate that nearby conflicts can worsen malaria risk in communities up to 100-km distance. Effects are the largest in areas where the climate is most suitable for malaria transmission. Our results suggest that violent conflict poses a substantial barrier to malaria elimination efforts in Africa.

Substantial progress has been made in mitigating the vector-borne disease burden in Africa since 2000 (1, 2). In 84 malaria-endemic countries, there were an estimated 247 million malaria cases in 2021 (3). In 2019, 94% of all malaria cases and deaths took place in Africa (4), with most of them occurring in sub-Saharan Africa (5). Existing evidence indicates that climate variability, such as seasonal variations in rainfall and temperature, may enhance the expansion of falciparum malaria in Southern Africa and high-elevation regions of Eastern Africa (6, 7), and it has an important impact on infectious disease intervention and vector control efforts (5, 6, 8–10). Traditional disease surveillance (11) as well as the implementation of traditional treatment and control programs, e.g., spraying campaigns or continuous monitoring of drug efficacy, may be hampered in areas subjected to violent conflict (12). In addition to the rapidly changing climate, Africa is one of the most politically unstable continents in recent decades. Embroiled in conflicts throughout history (13), Africa has experienced an average of 28 conflicts per year since 1989 (14). As a vector-borne disease, malaria is sensitive to environmental conditions (15), which can be greatly worsened by violent conflict.

Coupled with disastrous humanitarian consequences, including injuries and deaths, violent conflict often causes forced migration, refugee flows, and destruction of physical environments and societal infrastructure (16). Such conflict can affect areas far from where it occurs, motivating the term spatial spillovers of violent conflict (SSVCs) (17). SSVCs often cause considerable damage to environments, increase human–malaria contact, and expand mosquito habitats (18). They imply not only that the effects of violent conflict may be much more severe than the literature thus far suggests but also that policy responses focusing on conflict zones may be suboptimal (17). However, few previous studies have assessed the association of SSVCs with malaria transmission in Africa, and the assessments are independent of some key climatic and environmental factors (19–21). As a result, the information obtained from the studies is typically incomplete, contested, and biased regarding the impact of violent conflict on malaria risk. Taken together,

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these factors raise uncertainty about the extent to which violent conflict can explain the patterns of malaria risk (19, 22).

Given the changing climate and sustained conflicts with no clear indication of a slowdown in Africa, we aim to quantify the synergistic effects of climate variability and SSVCs on malaria risk in politically unstable regions. Since public health infrastructures in most African countries are underprepared and geographically unequal (6), quantification is critical to comprehensively understand the human costs of violent conflict and climate variability for planning appropriate policy responses.

Formulating and implementing an effective response requires examining the effect of climatic factors such as temperature and precipitation on malaria transmission in conflict zones. Here, we investigate the synergistic effects by combining econometric methods with disparate datasets related to malaria, climate, and violent conflict (*Materials and Methods*). The malaria data used are collected from Demographic and Health Surveys (DHSs, https://www.dhsprogram.com/data/) conducted from 2006 to 2017, covering a total of 239,865 surveyed families and 1,392,429 family members in 15 sub-Saharan African countries, although DHSs might face disruptions in some conflict regions. Based on the data, we obtain the surveys from 128,326 individuals participating in malaria testing and comprehensive information about households as well as individuals. We estimate monthly air temperature at 2 m above ground level (TMP) and monthly wet days (WET) in different exposure periods using the Climatic Research Unit Time Series (CRU TS) dataset. The conflict data recorded 17,429 violent conflicts during 2005 to 2017 in sub-Saharan Africa and are captured from the Uppsala Conflict Data Program (UCDP) (*SI Appendix*, Fig. S1). The UCDP, as a standardized violent conflict dataset, allows us to identify the distance between conflict and DHS household locations and determine the range of the conflict impacts on malaria risk.

For the identification strategy, we employ a panel regression model with high-dimensional fixed effects to explore the SSVCs (with different distances to DHS households) as well as the synergistic effects of SSVCs and climate variability on malaria risk in sub-Saharan Africa. To explore the impacts of SSVCs on malaria risk varying with climatic factors, we incorporate conflict deaths, climate factors (such as temperature and rainfall), and their interactions in this model. This helps to aid in robustness against unobserved confounders (*Materials and Methods*). Our results demonstrate that SSVCs play a significant role in exacerbating malaria risk, particularly in regions with warm temperatures (20.1 to 26.9 °C at the 12-mo timescale) and frequent precipitation (at least 9.2 wet d/mo at the 12-mo timescale). We find two potential explanations for the increased malaria risk, including a decrease in household economic conditions due to excess deaths among male members and an increase in the exposure of nonimmune populations caused by refugee flows and forced population displacement.

In summary, the contributions of our study are twofold. 1) Most previous studies have focused on the direct relationship of armed conflict with malaria risk at a national scale. Our study provides household-centered evidence that armed conflict increases malaria risk more than expected by considering SSVCs on a fine-grained scale, whereas existing studies underestimate the impacts. 2) This study explores the synergistic effects of SSVCs and climate variability on malaria risk in sub-Saharan Africa. Using decadal comprehensive datasets and a panel regression model with high-dimensional fixed effects, we examine how SSVCs amplify the impacts of climate variability on malaria risk, emphasizing the importance of mitigating conflict and climate change for reducing malaria transmission. Our findings can help effectively target treatment initiatives and vector control efforts in politically unstable regions with a high malaria risk, thus bringing us closer to a malaria-free world.

Results

The Conflict–Malaria Relationship. To examine the impact of conflict deaths at different distances to DHS households on malaria risk, we use a series of concentric ring buffers with different sizes centered at each household and count the conflict deaths within each ring (Fig. 1). To address the biases from different areas of rings and explore the linear trends on the logarithmic scale, we apply the normalization and logarithmic transformation of conflict deaths (*Materials and Methods*). We present the reason for choosing the household location rather than the conflict location as the ring center (*SI Appendix*, Note S1). According to a prior study (23), we set the radius of the outermost ring to 250 km as the maximum distance affected by conflict.

Using the 50 km-wide rings (Fig. 1 *A* and *B*), for specific sites, we observed that the impacts of conflict deaths increased initially and then decreased with increasing distance between the household location and the conflict site. Specifically, conflict deaths in the 50- to 100-km range from the households had the largest impact on malaria risk, leading to an 11.4% increase in malaria risk with a 1% increase in conflict deaths (95% CI: 2.5 to 20.4%). To dissect the variation in the conflict impacts, we divided the 50 km-wide rings into the 10 km-wide rings (Fig. 1 *C* and *D*). The impacts of conflict deaths increased the most from the range of 50 to 60 to 90 to 100 km, with an increased risk from 0.1% (nonsignificant, $P > 0.05$) to 6.5% (95% CI: 0 to 13.0%). As a result, we observed the spatially distant effects of conflict deaths that can be described as SSVCs, especially in the distance of 50 to 100 km to households. We used the conflict deaths in the 50- to 100-km range as the independent variable of interest in the regression model for further analyses.

Robustness Checks. We conducted multiple analyses to mitigate potential biases in the estimates as follows. 1) To limit the impact of the modifiable areal unit problem (MAUP) (24), we utilized rings with two additional widths, i.e., 20 km and 30 km. The estimates of conflict deaths aligned with the observed trends as 10 km- and 50 km-wide rings were used, wherein the effect first increased and then decreased with increasing distance (*SI Appendix*, Fig. S2). 2) To mitigate the biases arising from climate sensitivity, annual climate trends, and administrative obstacles for refugees, we performed alternative specifications that incorporated 38 additional control variables in the baseline specification. That is, three types of climate variables, including TMP, monthly precipitation (PRE), and monthly diurnal temperature range (DTR) of the 1st, 2nd, ..., and 12th mo preceding the household surveys, made up the 36 control variables. The remaining two control variables were the distances from household locations to provincial and national boundaries. The results obtained from the alternative specification were consistent with those of the baseline specification (*SI Appendix*, Fig. S3). 3) To address the concern that the province fixed effects might absorb most of the variation in the independent variable (conflict deaths), we adopted alternative specifications including five other sets of fixed effects. We found that the estimates were similar to the results of the baseline regression (*SI Appendix*, Fig. S4). 4) A potential issue for our estimate was the bias caused by the nonrandom samples of conflict deaths (conflicts are more likely

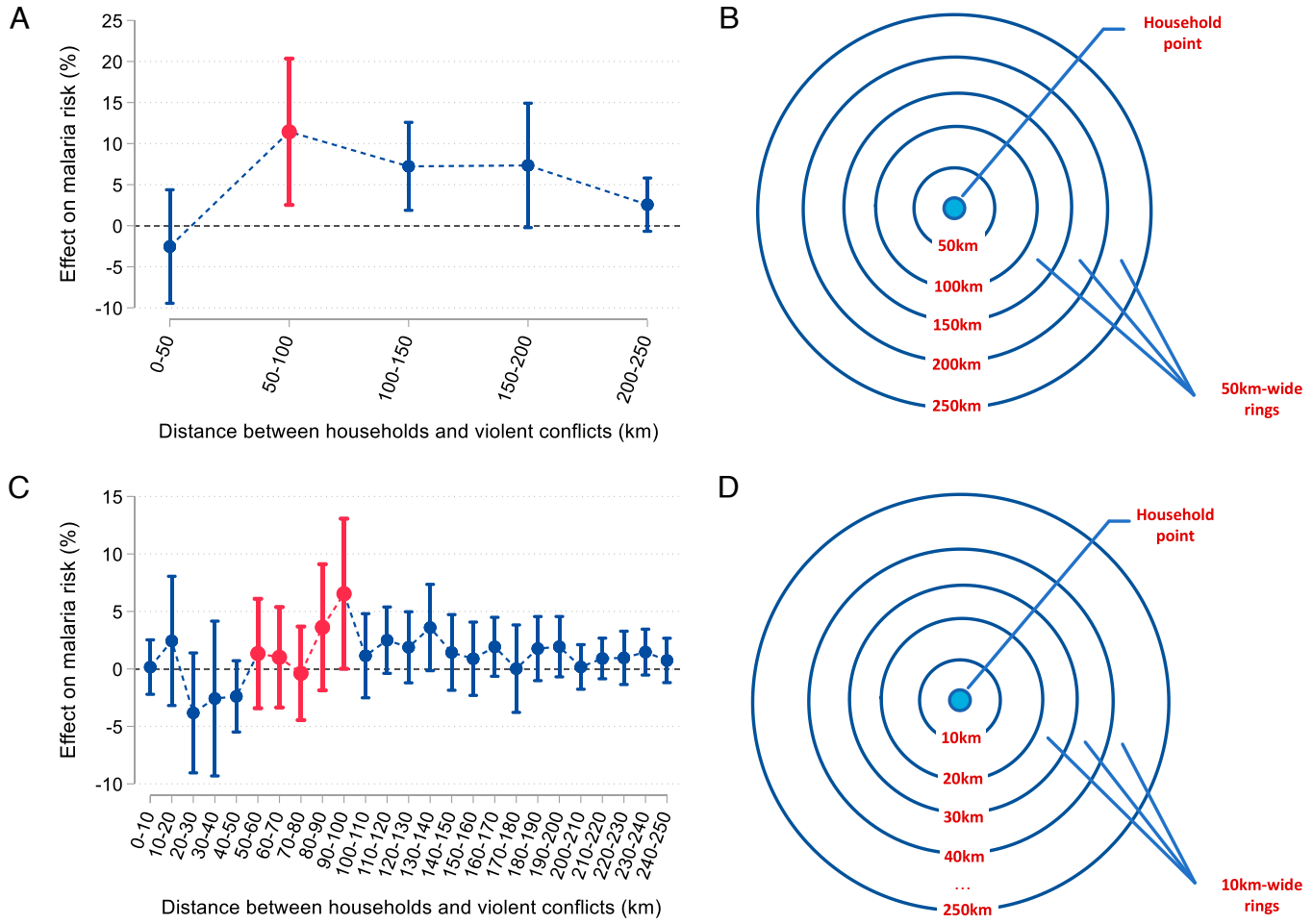

Fig. 1. Effects of conflict deaths on malaria risk. Two ring widths are used to count conflict deaths: 50 km (*A* and *B*) and 10 km (*C* and *D*). The geographic area of SSVCs for each surveyed individual is represented by a circle with a 250-km radius centered at the household location. The regression model used to support these results includes 128,326 observations. The circles and lines (*A* and *C*) indicate the estimates of conflict deaths and their 95% CIs, and full results are presented in *SI Appendix*, Tables S1 and S2.

to be observed in locations closer to where news organizations can report) or some hard-to-observe time-varying factors, such as economic conditions, grievances, and happenstance. As a step toward addressing these concerns, the number of abductions committed by armed groups (within a 50-km radius of the household) was selected as the instrumental variable (IV) to re-estimate the effect of conflict deaths on malaria risk using the two-stage least squares (2SLS) (*SI Appendix*, Method S1). Under the premise that the IV was strongly correlated with malaria risk (F statistic>10), we found that conflict deaths that occurred between 50 and 100 km to the surveyed households were significantly associated with malaria risk (*SI Appendix*, Table S3). We provided the details on how the IV was satisfied with the exclusion restriction in *Materials and Methods*. 5) We explored the impacts of conflict deaths using the inverse hyperbolic sine transformation and another normalization method (using a different Divisor, detailed in *Materials and Methods*) in alternative specifications. As presented in *SI Appendix*, Fig. S5, our findings indicated that these alternative specifications produced similar estimates in terms of statistical significance compared with the baseline specification.

The Linkage of Conflict Deaths with Climate-Related Malaria Risk. The distant destruction triggered by conflict increased population exposure to harsh environments, exacerbating malaria transmission. Therefore, the malaria risk resulting from population exposure to conflict would be more pronounced if the climate was favorable for malaria-carrying mosquitoes. To validate this hypothesis, we introduced two climate variables, TMP and WET, and formed an interaction term (including the direct effects) by interacting them with conflict deaths (50 to 100 km). The climate variables were thus considered the moderators in the regression model (*Materials and Methods*). The exposure periods of each household were set to 3, 6, 9, and 12 mo before the survey date and were used to evaluate the effects of the climate on both short and long timescales.

As shown in Fig. 2, the relationship between conflict deaths (50 to 100 km) and malaria risk showed an inverted U shape across the four timescales of the TMP exposure when TMP was taken as the moderator. Specifically, conflict deaths were significant in the middle range of temperature ($P < 0.05$) and nonsignificant in the lower and higher temperature ranges ($P > 0.05$). For instance, conflict deaths had a significant impact on malaria risk within the temperature range of 20.1 to 26.9 °C in the 12-mo exposure periods (Fig. 2*D*). An average TMP of 22.5 °C over 12 mo induced the largest impact of conflict deaths on malaria risk, with an improvement of approximately 5.8% in malaria risk (95% CI: 1.0 to 11.0%) compared with individuals who did not experience conflicts (no conflict death). This suggested that 22.5 °C was a suitable temperature for malaria transmission and mosquito breeding, which was consistent with previous studies (25, 26).

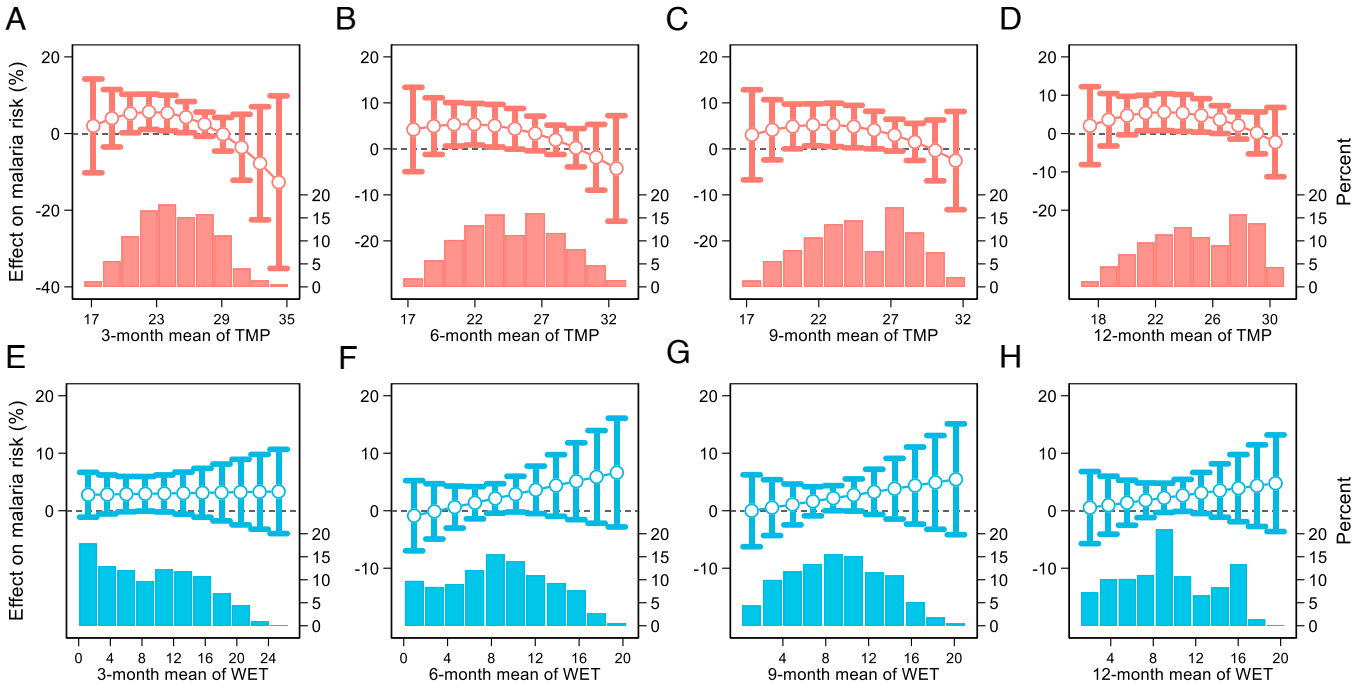

Fig. 2. Marginal effects of conflict deaths (50 to 100 km) on malaria risk moderated by climate factors. The selected moderators are TMP (*A–D*) and WET (*E–H*). The circles and lines in all subfigures denote the estimated effects of conflict deaths and their 95% CIs. The regression model (*Materials and Methods*) used to support these results includes 128,326 observations. The histograms below the plot of estimates illustrate the distribution of observed values for TMP and WET.

Considering that most of the precipitation ranges in our samples were sparse (*SI Appendix*, Fig. S6), we used WET as the moderator and included it in the interaction term. We obtained similar outcomes when we examined the impact of conflict deaths throughout four timescales, that is, conflict deaths had a greater impact on malaria risk as WET increased (Fig. 2 *E–H*). For instance, the significant impact of conflict deaths was observed as WET was over 9.2 d/mo at the 12-mo timescale (Fig. 2*H*). The findings suggested that WET was associated with malaria risk (27, 28), and a significant association existed between conflict deaths and malaria risk in areas with frequent rainfall.

To identify the sites that were vulnerable to malaria risk induced by conflict with uneven climate exposures, we selected two climate factors, i.e., the 12-mo mean of TMP and mean of WET, as the moderators to map the marginal effects of conflict deaths in sub-Saharan Africa during 2006 to 2017. When TMP was taken as the moderator, the map illustrated in Fig. 3*A* highlighted the vulnerability of malaria driven by the synergistic effect between conflict deaths and TMP in Central and Eastern Africa (*SI Appendix*, Fig. S7 provides the regional divisions of sub-Saharan Africa). In particular, the areas with pronounced impacts (5 to 6%) were geographically distributed in the highlands of Eastern and Southern Africa as well as Madagascar, where the 12-mo mean TMP was between 20.5 and 24.4 °C, a temperature range considered beneficial for mosquito survival and malaria transmission (8, 29).

Based on the maps shown in Fig. 3*B* and *SI Appendix*, Fig. S8, we observed the spatial associations between the malaria risk induced by conflict and the different climate zones in sub-Saharan Africa. The areas with the most significant impacts of conflict deaths on malaria risk were predominantly located in the tropical rainforest climate zones and the basin of Lake Victoria, which is the largest lake on the African continent, as well as Madagascar. These regions provided vital breeding grounds for mosquitoes in the form of standing water derived from rainfall (27) (at least 10.6 d/mo of WET over 12 mo), serving as essential larval and pupal habitats.

Conflict deaths were mainly concentrated in Central and Eastern Africa, especially in Mali, Nigeria, Sudan, South Sudan, Ethiopia, Somalia, and DR Congo during 2006 to 2017 (Fig. 3*C*). To reflect the diverse severity of conflict and the moderating effects of climate on the conflict–malaria response across different regions, we overlaid any two maps from Fig. 3 *A–C* to obtain the visual representations in Fig. 3 *D–F*. As shown in Fig. 3 *D–F*, the dark regions were primarily found in the Eastern African highlands, including Ethiopia, eastern DR Congo, and South Sudan. The findings underscored that in the three countries, more attention should be paid to the amplified vulnerability of malaria risk caused by conflict when the following two catalysts were combined: suitable temperature (20.5 to 24.4 °C of TMP over 12 mo) and frequent precipitation (at least 10.6 d/mo of WET over 12 mo).

The Mechanism of the SSVCs Impacts. As shown in Fig. 4 *A–D*, we noted that SSVCs altered the demographic composition of households by reducing the proportion of adult men in households. The proportion of adult men aged 15 to 49 in households decreased by 1.1% (95% CI: 0.2 to 2.0%) for every 1% increase in conflict deaths (50 to 100 km) during 2006 to 2017. However, children aged 0 to 14, adult women aged 15 to 49, and elderly people above 50 did not exhibit substantial changes. During conflict, adult men were often conscripted or murdered, which indirectly exacerbated household vulnerability (30, 31). As shown in Fig. 4*E*, malaria risk declined by 2.2% (95% CI: 0.7 to 3.7%) as the proportion of adult men in households increased by 1%. In agrarian societies, adult men were typically the primary income earners for their families (32). As depicted in Fig. 4*F*, a higher proportion of adult men was

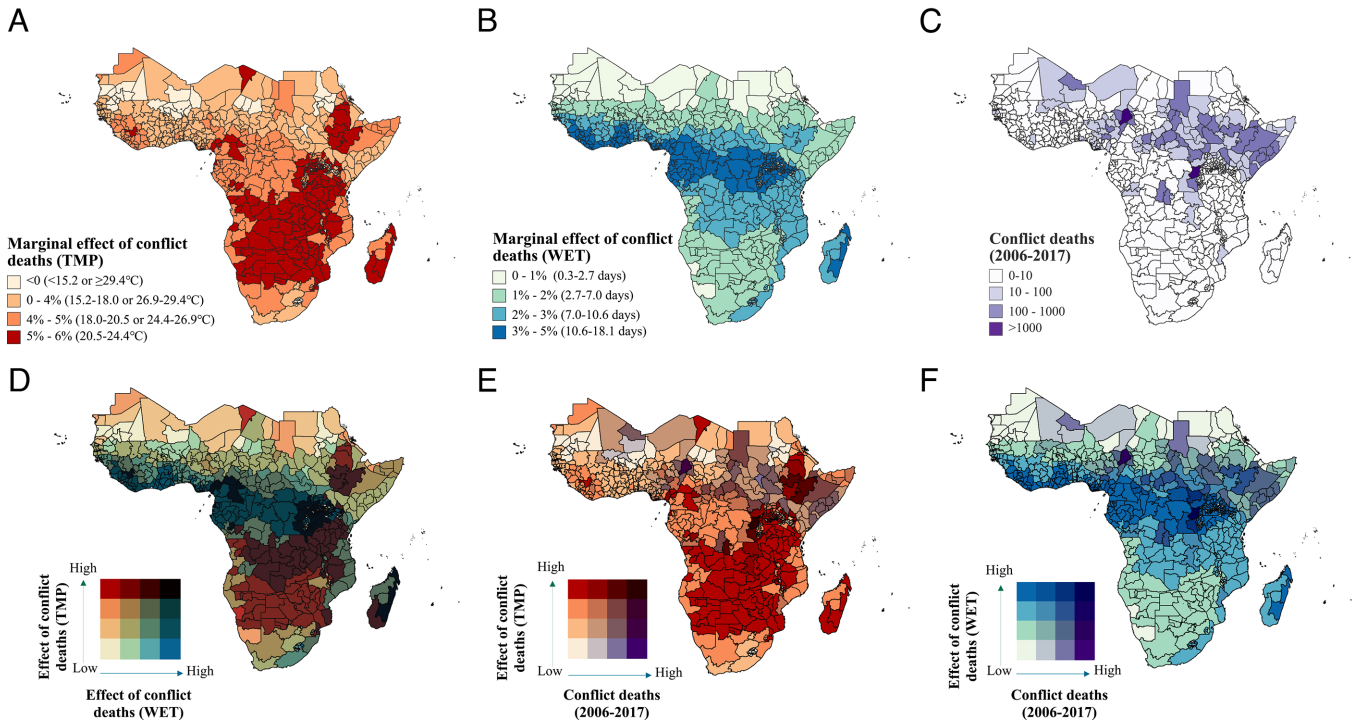

Fig. 3. Mapping of the marginal effects of conflict deaths (50 to 100 km) during 2006 to 2017. (*A*–*C*) The marginal effect of conflict deaths on malaria risk, moderated by TMP in (*A*) and WET in (*B*). Regional conflict deaths that measure the severity of conflicts in (*C*). The darker red areas indicate a greater malaria risk resulting from the synergistic impact between conflict deaths and TMP (the moderator), and the darker blue areas indicate a greater risk resulting from the synergistic effect between conflict deaths and WET (the moderator). Areas in shades of purple reflect the intensity of conflict deaths. (*D*–*F*) Bivariate choropleth maps combining any two of three variables presented in (*A*–*C*).

associated with less time to get water and greater odds that the households had access to drinking water, electricity, refrigerators, higher income (defined in *SI Appendix*, Note S2), and mosquito nets. Thus, in sub-Saharan African countries, the high mortality rates of working-aged males resulting from SSVCs were disastrous for household income, as well as access to infrastructure and healthcare resources (33). We defined households with a high and medium malaria risk based on TMP and WET (as illustrated in *SI Appendix*, Fig. S9). Specifically, the households with a TMP of 20.5 to 24.4 °C or WET > 10.6 d/mo were defined as households with a climate-related high malaria risk, and those with a TMP of 18.0 to 20.5 °C or 24.5 to 26.9 °C or the WET of 7.0 to 10.6 d/mo were defined as households with a climate-related medium malaria risk. The results in *SI Appendix*, Table S9 confirmed that the SSVC-related decrease in the proportion of adult men was still significant among the households with climate-related high and medium malaria risks.

SSVCs led to substantial increases in the number of refugees or internally displaced people and increased the pressures on host countries and regions due to limited resources and inadequate infrastructures. This promoted the competition between immigrants and local impoverished populations for resources including the share of limited public facilities (e.g., toilets and water sources) and medical services (e.g., available mosquito nets), which increased human–malaria contact and reduced access to healthcare systems (20, 34). Additionally, refugees residing in settings other than designated camps (35) might use irregular modes of travel. There was a significant association between subnational violent conflicts, especially for those occurring within a 50 to 100 km radius, and a reduced likelihood of individuals being able to obtain bed nets (*SI Appendix*, Fig. S10). The forced migration caused by conflict and logistical disruptions resulted in a shortage of resources and an enhanced likelihood of interaction between nonimmune and immune populations (36). This, in turn, might enhance malaria risk. As shown in Fig. 5*A*, households with poor socioeconomic conditions had a higher malaria risk resulting from SSVCs compared to those with good living conditions. In comparison to all samples, households with climate-related medium and high malaria risks (TMP of 18.0 to 26.9 °C or WET ≥ 7.0 d/mo) were more likely to contain a higher percentage of malaria-vulnerable households, particularly those without electricity, improved sources of drinking water, or improved sanitation services (Fig. 5*B*).

Discussion

Climate change has been identified as a key driver for malaria resurgence in Africa (37, 38). However, the risk and mortality of vector-borne diseases in a specific geographic area are jointly determined by climate factors and the factors such as household socio-demographics, public health systems, and SSVCs. These factors interact with each other, and the effect of one factor may be moderated by the processes related to other factors (39). The recent and ongoing emergence of malaria in sub-Saharan Africa underscores the considerable impacts of climate variability and violent conflict on the risk and prevalence of the disease.

Violent conflict has caused an increased spread of malaria by degrading environments as well as impeding access to preventive measures (40), health services and treatment (41) and by increasing the population exposure to Anopheles mosquitoes during irregular travel, which may reduce access to the healthcare systems (20, 34). Our study reveals a discernible pattern of the relationship between conflict deaths and malaria risk, characterized by the effects varying with distance changes. Specifically, the

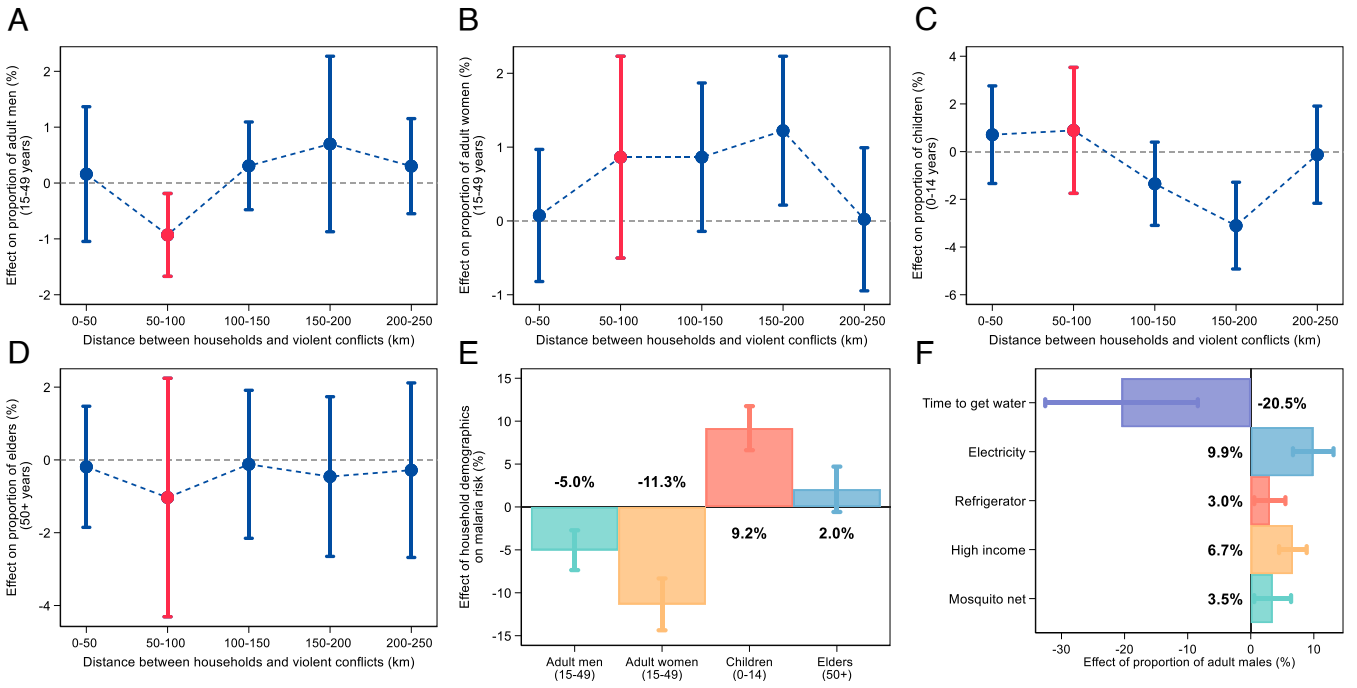

Fig. 4. SSVCs increase adverse climatic exposure by reducing the proportion of adult men. (*A*–*D*) The impact of a 1% increase in conflict deaths on household demographics at various distances from the household locations (0 to 50, 50 to 100, 100 to 150, 150 to 200, and 200 to 250 km), including the percentages of adult men aged 15 to 49 in (*A*), adult women aged 15 to 49 in (*B*), children aged 0 to 14 in (*C*), and elderly people over 50 y in (*D*). The circles and lines represent the estimated effects of conflict deaths and their 95% CIs. (*E*) The effect of household demographics on malaria risk. (*F*) The impact of the proportion of adult men in households on how long it takes to get water as well as the likelihood that the households have access to electricity, a refrigerator, high income, and mosquito nets. The bar plots and lines show the estimated effects of the proportion of adult men and their 95% CIs in (*E*–*F*). The sample sizes of adult men, adult women, children, and elderly people are 99,953, 268,876, 823,489, and 200,111, respectively.

impact of conflict deaths is nonsignificant in locations proximate to the participating households, grows as distance increases, and subsequently diminishes. This pattern can be attributed to two distinct factors. First, the magnitude of the effect of conflict deaths on households or individuals may be underestimated due to the lack of DHS coverage in conflict-adjacent areas. Second,

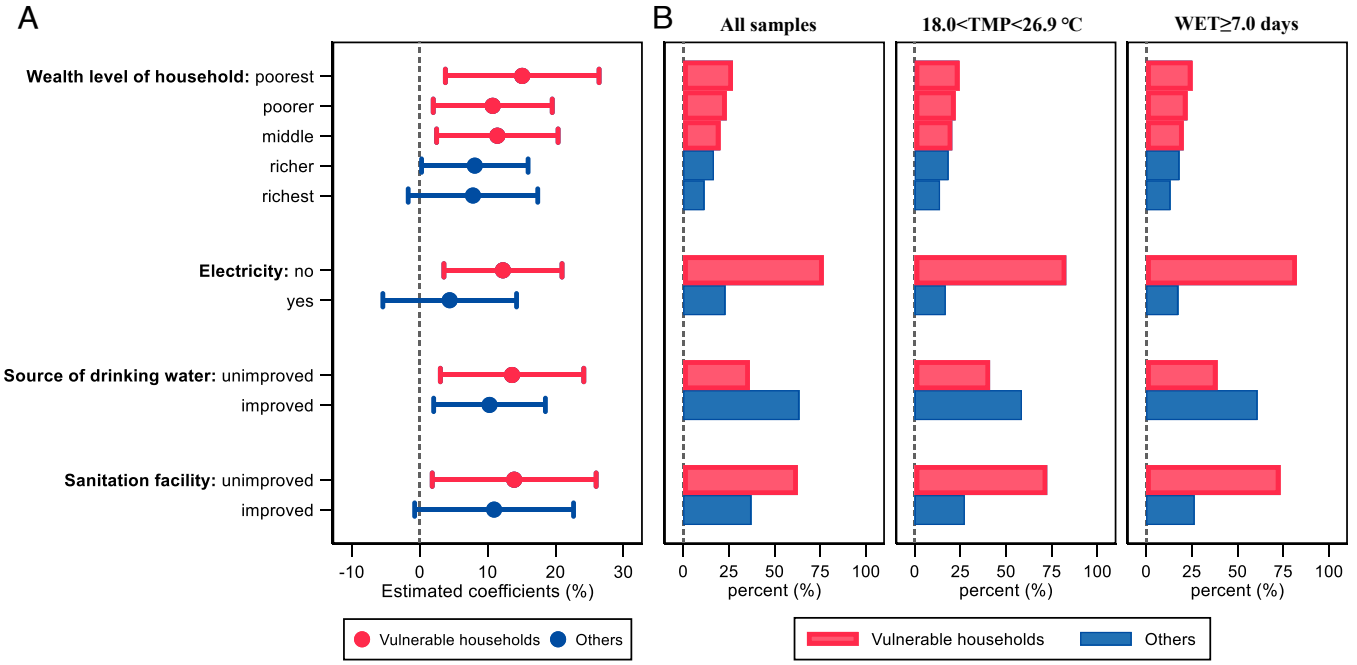

Fig. 5. SSVCs increase adverse climatic exposures by affecting disadvantaged populations. (*A*) Heterogeneous effects of a 1% increase in conflict deaths (50 to 100 km) on malaria risk among populations across different socioeconomic households. The circles and lines denote the estimated effects of conflict deaths and their 95% CIs. (*B*) The proportion of individuals across different socioeconomic groups in all samples (128,326 people), the sample with a TMP of 18.0 to 26.9 °C (81,802 people, 63.7%), and the samples with WET≥ 7.0 days/month (86,725 people, 67.6%). The proportions of the samples are shown in bar plots.

the impact of violent conflict on households far from the conflict may have intensified, partly owing to population displacement (23, 36, 41, 42). Our findings highlight a marked SSVC that is possibly caused by displacement, showcasing a surge in malaria risk (or disease transmission) within a certain range (50 to 100 km). In contrast to individual violent conflicts, which are more frequently observed at shorter distances (<200 km), SSVCs resulting from multiple violent conflicts at greater distances (>200 km) may lead to less noticeable or more random impacts on malaria. We provide quantitative evidence of SSVCs, revealing the distance at which conflict exerts its impact and the magnitude of its influence on malaria risk. Our results imply that SSVCs may be on par with, or even surpass, the direct impact caused by the conflict itself (<50 km) on malaria transmission (43).

Our study indicates that the climate suitable for malaria-carrying mosquitoes is a crucial factor that exacerbates the distant impact of conflicts on malaria risk. Malaria risk in sub-Saharan Africa has been amplified by the effect of warm temperature or persistent rainfall in the regions with high conflict deaths. By examining the marginal effects of both the TMP and WET on the conflicts' distant effect on malaria risk, we find that the Eastern African highlands in Ethiopia, DR Congo, and South Sudan are particularly vulnerable regions that witness a greater proliferation in malaria risk under the combined influence of SSVCs and climate. This finding is consistent with those of previous studies showing that these highlands are emerging hotspots for malaria risk due to climate change over the past few decades (8, 10, 44–46). The highlands in Eastern Africa experienced incessant violent conflicts from 2006 to 2017. If civil unrest continues, the delivery of health interventions is hard to achieve, and the malaria burden in these regions is subjected to rising temperatures. Additionally, climate change may enhance the malariogenic potential, leading to the re-emergence of malaria epidemics in Africa (8, 47). Predictions regarding the shifting suitability of malaria indicate that new endemic regions may emerge in Southern and Central Africa, where people have little or no immunity to the disease (48). The emergence of malaria owing to violent conflict and climate change presents a considerable challenge for delivering health interventions and protecting vulnerable populations. This reveals the urgent need for robust malaria control measures in these regions.

Finally, we present two types of empirical evidence that SSVCs increase population exposure to malaria-carrying mosquitoes. First, SSVCs result in a decline in the proportion of adult men (aged 14 to 49 y) in households, leaving behind a large number of women and children as widows and orphans (30, 31). Reports from Rwanda (49–51) indicate that female- and widow-headed households are particularly vulnerable to poverty and health issues, further promoting malaria risk. Evidence from our study indicates that these households may be prevalent in the regions highly vulnerable to climate-related malaria risk. Second, SSVC-related forced migration is associated with an increase in malaria risk. Our findings reveal that large populations in sub-Saharan African countries are vulnerable to malaria because they lack access to electricity, high-quality sanitation, and improved sources of drinking water. Vulnerability is particularly acute in the areas with a climate-sensitive malaria risk, which enhances permanent vector breeding habitats and increases vector–human contact rates. Malaria can be imported by refugees carrying parasites, including resistant strains, and can result in a repeat occurrence of endemic transmission (52–54). Additionally, a large number of nonimmune refugees may flee to areas with a high malaria prevalence, where they will be highly exposed to mosquitoes, especially in areas with favorable vector environments (36, 42). Displaced populations are often far from health facilities (16, 55), and their health needs may differ from those of local residents. This strains the capacity of local health systems and increases the risk of infectious disease. Importantly, the limited availability of insect repellent or mosquito nets in villages located in conflict zones further promotes the exposure of civilians or refugees to mosquito vectors (56).

This study is helpful for accurately detecting the areas subjected to climate variability and armed conflict where populations are apt to be exposed to the Anopheles mosquito vector and Plasmodium malaria parasite. Our findings highlight the need to consider how SSVCs exacerbate climate effects on malaria risk for policy planning and the implementation of infectious disease control interventions. They allude to the potential for mitigating malaria risk in sub-Saharan African countries by reducing conflict alongside other important factors, such as environmental degradation and climate change, and thus have implications for mitigating the impacts of infectious diseases.

There are limitations in this study. First, ongoing violent conflicts may hinder the DHSs in some conflict areas, which makes the data locally incomplete and potentially biased. It is possible to underestimate the impacts of SSVCs in proximity to conflict areas since the surveys are more likely to cover households that are less impacted by conflicts. Moreover, missing households in conflict areas may encounter humanitarian crises (57) and have limited access to health care (58), which further exacerbates local vulnerability to malaria. Second, conflicts may not be documented in the areas far from news organizations according to the UCDP reports (59). This potentially causes the overestimated impacts of conflict deaths. Third, unavailable data such as population dissatisfaction with governments and community-level socioeconomic inequality still hinder us from checking the exogeneity of the IV to some unobserved variables related to malaria transmission and interventions. Finally, the observed increase in malaria risk can be triggered by severe antimalarial drug shortages, self-treatment, high rates of relapse, and reinfection, which limit our ability to fully explain the changes and resistance. If information about refugee flows at a subnational level is obtained, the impacts of conflict deaths will be estimated more precisely. High-frequency mobile phone data may enable us to accurately identify the impact of forced immigration or internal displacement on public health (60).

Materials and Methods

Data. The malaria data are derived from the DHSs which are a set of nationally representative household surveys conducted periodically in low-income and middle-income countries worldwide. We capture the data from 55 DHSs between 2006 and 2017, covering 15 sub-Saharan African countries (https://www.dhsprogram.com/data/). The data come from 239,865 surveyed households and 1,392,429 family members, distributed across 8,428 DHS cluster points (*SI Appendix*, Fig. S1). Malaria risk is measured as a binary variable. Notably, 128,326 people with complete personal information are tested for malaria risk. They comprise two groups: children aged 0 to 5 and adult women aged 15 to 49. In our samples, the average malaria risk is 18%, and the human malaria species is Plasmodium falciparum.

Violent conflict data are captured from the UCDP Georeferenced Event Dataset (GED) Global version 22.1, which is UCDP's most disaggregated dataset, covering individual events of organized violence (phenomena of lethal violence occurring at a given time and place) (61). These events are sufficiently fine-grained to be geo-coded down to the village level, with temporal durations disaggregated to a single day. As the explanatory variable of the primary concerns, we calculate the conflict deaths recorded by the UCDP in the 12 mo before the date of the DHS.

We obtain historical climate data from the 0.5°latitude by 0.5°longitude monthly gridded climate dataset of CRU TS version 4.06 (62). Using ArcGIS Pro 3.0 software, we extract the raster values of the climate variables (i.e., TMP, PRE, WET, and DTR) according to the location of each surveyed household.

Previous studies provide evidence of a correlation between the normalized difference vegetation index (NDVI) and malaria risk (63, 64). We include the NDVI in the baseline model specification as a control variable. The NDVI data are obtained from the MODIS VI products with a 250 m spatial resolution (MOD13, http://modis.gsfc.nasa.gov/, date accessed: 2022/10/31). We calculate the mean of the NDVI within a 5-km buffer centered at each DHS household point.

The dataset of the abductions committed by armed groups is captured from the Armed Conflict Location and Event Data Project (ACLED) (65). This dataset includes 2,360 abductions from 2005 to 2017 (covering the period of the DHSs) in sub-Saharan Africa.

Normalization and Transformation for the Independent Variable of Interest. The rings used to count the conflict deaths have different areas, which influence the magnitudes of the estimates and introduce biases. To address this issue, we normalize the variable of the conflict deaths based on the ring area (Eq. **1**).

$$\overline{Death} = \frac{Death}{Divisor}, \quad [1]$$

where *Death* is the conflict deaths within each ring for a 12-mo period (prior to the DHS survey), and $\overline{Death}$ is the normalized *Death*. *Divisor* is determined by the ring area and used for the normalization.

As listed in Table 1, we provide two types of Divisor (i.e., Divisor1 and Divisor2). Divisor1 is used in the main regression model and its value is 1% of the ring area (unit: km^2). Divisor2 is the ring area and is employed in the alternative specification for robustness tests. Since Divisor2 is 100 times larger than Divisor1, replacing Divisor1 with Divisor2 in the specification may lead to an increase of two orders of magnitude in the estimates. Whether the magnitude change of the estimates brings the change in the statistical significance of the estimates remains to be examined in the baseline specification and alternative specification.

In addition, we use the natural logarithm *Log_death* of $\overline{Death}$ (Eq. **2**) to explore the linear trend of the conflict deaths on the logarithmic scale. *Log_death* is taken as the independent variable of interest in the main regression. We also conduct a robustness check by replacing the logarithmic transformation with the inverse hyperbolic sine transformation (i.e., $arcsinh(\overline{Death}+1)$) in the main regression.

$$Log\_death = log(\overline{Death} + 1), \quad [2]$$

where $\overline{Death} + 1$ is used to avoid the logarithm of zero when $\overline{Death} = 0$.

The Main Regression Model. We use a panel regression with high-dimensional fixed effects to estimate the impact of conflict deaths at different distances to DHS households on malaria risk. The baseline specification of the estimated strategy is shown in Eq. **3**.

Table 1. The values of Divisor based on the ring areas

Variables of conflict deaths	Ring area	Divisor1	Divisor2
Conflict deaths in 0 to 50 km	$2{,}500\pi$ km^2	25π	$2{,}500\pi$
Conflict deaths in 50 to 100 km	$7{,}500\pi$ km^2	75π	$7{,}500\pi$
Conflict deaths in 100 to 150 km	$12{,}500\pi$ km^2	125π	$12{,}500\pi$
Conflict deaths in 150 to 200 km	$17{,}500\pi$ km^2	175π	$17{,}500\pi$
Conflict deaths in 200 to 250 km	$22{,}500\pi$ km^2	225π	$22{,}500\pi$

$$Ma_{i,h,p,y,m} = \sum_{k=1}^{n} \beta_k Log\_death_{k,h,y,m} + \mu_{p,y} + \sigma_{p,m} + \delta X_{i,h,p,y,m} + \epsilon_{i,h,p,y,m}, \quad [3]$$

where $Ma_{i,h,p,y,m}$ is a binary variable, indicating that the result of the malaria test of individual *i* in household *h* in a province *p* in month *mo* year *y* is positive ($Ma_{i,h,p,y,m} = 1$) or negative ($Ma_{i,h,p,y,m} = 0$). *n* in $\sum_{k=1}^{n} \beta_k Log\_death_{k,h,y,m}$ is related to the width of the selected ring buffer. For the 50 km-wide ring, $n = 5$. We then obtain the 12-mo sum of the conflict deaths with distances of 0 to 50 km, 50 to 100 km, 100 to 150 km, 150 to 200 km, and 200 to 250 km, respectively, from the location of household *h*. $Log\_death_{k,h,y,m}$ (k = 1,2,3,4,5) denotes the value of the logarithmic transformation and normalization of the sum. $\mu_{p,y}$ and $\sigma_{p,m}$ indicate province-by-year fixed effects and province-by-month fixed effects. Province-by-year fixed effects control for year-specific shocks in each province, such as macroeconomic trends, and industrial or population structural changes. Province-by-month fixed effects control for month-specific shocks in each province, such as seasonality in malaria risk or monthly local events. $\epsilon_{i,h,p,y,m}$ is the error term.

We underscore two additional crucial considerations for the incorporation of province-level fixed effects. First, variables such as TMP and PRE that are highly correlated with malaria risk would be absorbed by household-level fixed effects. Consequently, we adopt province-level fixed effects in the main regression. Second, to enhance the model's precision in capturing variations and heterogeneity within these provinces but also to avoid the absorption of critical factors, we incorporate the interaction between the province and residence type (urban or rural people), rather than solely relying on the province, as the province fixed effects we used.

To minimize the influence of the observed confounders, we control for three sets of confounders in the vector $X_{i,h,p,y,m}$. The first set consists of the factors related to the climate and environment, including the 12-mo means of TMP, PRE, and NDVI before each survey. The second set is the household-related variables such as the sex of the household head, the number of mosquito nets, transportation availability such as motorcycles and cars, main floor materials, and the number of rooms for sleeping. The final set of variables are the variables about individuals including age, sex, the relationship with the household head, and whether he/she is a usual resident (or visitor) (please refer to *SI Appendix*, Table S10 for a detailed description of the control variables and their descriptive statistics).

Robustness Checks. We perform several robustness tests to validate the sensitivity of our estimates. First, to limit the issue of the MAUP problem, particularly the scale effect (66), we compare the magnitudes of the estimates, as rings with different sizes are selected.

Second, a concern of the baseline specification of our model is that climate variability may influence malaria risk in a certain month or season in specific locations. To address the concern of this issue, we replace the 12-mo mean of each climate factor (including TMP, DTR, and PRE) with its respective values of the 1st, 2nd, ..., and 12th mo before the DHSs. In addition, conflicts can be affected by provincial and national boundaries, and refugees and displaced people encounter obstacles in crossing provincial and national borders (67). Thus, we include two variables that represent the distance between each survey point and the provincial as well as national boundaries in the baseline specification.

Another potential issue for the identification is that province-level fixed effects may absorb most of the variation in the independent variable. To address the concern of this issue, we compare the results of the specifications with the inclusion of six different sets of fixed effects, that is, province-by-year + province-by-month (baseline specification), country-by-year + province-by-month, province-by-year + country-by-month, country-by-year + country-by-month, province + year-by-month, and country + year-by-month fixed effects.

Additionally, to address the concerns about the potential impacts of the selection biases and the omitted time-varying variables in the main regression, we select the number of abductions committed by armed groups (within a 50-km radius from the households) as the IV to re-estimate the effect of conflict deaths on malaria risk. For the IV to be valid, it should have a strong correlation with malaria risk and meet the exclusion restriction. As listed in *SI Appendix*, Table S3, the necessary strong correlation is verified in the first-stage regressions

(Kleibergen–Paap F-statistics > 10). The exclusion restriction can be justified if the IV is independent of the confounders related to malaria risk and only affects the risk through the conflicts. The requirement is satisfied by the following two conditions. First, abduction may be uniformly distributed over space and time at the city or subprovincial level (68), especially when we control for province-by-year and province-by-month fixed effects. To demonstrate the exogeneity of abduction for malaria risk, we conduct a series of exogeneity checks, and all results are listed in *SI Appendix*, Tables S4–S6. We find that the IV is uncorrelated with socioeconomic conditions at the household level (several studies used the DHS household samples to represent regional poverty (69–71)), climate and environment, population density, the number of medical facilities, the price of staple food, and the potential government influence in the region (measured by the distance to the capital, and the distances to the boundaries of provinces and countries). Second, abductions committed by armed groups aim to acquire funds for armed activities (72). Out of the 2,360 abductions in the ACLED dataset (65), we find that none of them resulted in fatalities. Of the abductions, only nine were connected to the destruction of buildings, and one was connected to a hospital. Furthermore, militants were unlikely to remain in the same locations after the abductions, and they probably fled to other areas for ransom demands (73). These findings suggest that abductions may have little impact on local malaria transmission and interventions. We give the details of the 2SLS estimation in *SI Appendix*, Method S1.

For testing model robustness when adopting the inverse hyperbolic sine transformation and another normalization method (replacing Divisor1 with Divisor2 in the regression), we undertake three alternative specifications, including the specifications adopting $arcsinh(Death/Divisor\ 1 + 1)$ (inverse hyperbolic sine transformation), $log(Death/Divisor\ 2 + 1)$, and $arcsinh(Death/Divisor\ 2 + 1)$ (using both of inverse hyperbolic sine transformation and Divisor 2). We compare their estimates with those of the baseline specification ($log(Death/Divisor\ 1 + 1)$).

Synergistic Effects of Conflict Deaths and Climate on Malaria Risk. We construct an interaction term of conflict deaths and climate factors (TMP, PRE, and WET) in Eq. **3**, to explore the synergistic effects between conflict deaths and climate on malaria risk. The specific estimation strategy is presented in Eq. **4**.

$$Ma_{i,h,p,y,m} = \beta(Conflict_{h,y,m} \times Climate_{h,y,m}) + \alpha Conflict_{h,y,m} + \mu_{p,y} + \sigma_{p,m} + \delta X_{i,h,p,y,m} + \epsilon_{i,h,p,y,m}, \quad [4]$$

where $Conflict_{h,y,m}$ is a binary variable. $Conflict_{h,y,m} = 1$ if a conflict (50 to 100 km) occurs and causes more than one death; otherwise, $Conflict_{h,y,m} = 0$. $Climate_{h,y,m}$ represents the climate variable, which is taken as the moderator including TMP, PRE, or WET. To identify the effects of both short- and long-term climate-related exposures within a year, the 3-, 6-, 9-, and 12-mo means of each climate variable before household h is investigated are all considered in the regression model. $Conflict_{h,y,m} \times Climate_{h,y,m}$ is the interaction term, and its coefficient β represents the significant difference in malaria risk due to climate variability between the individuals experiencing and not experiencing the conflict which causes more than one death.

Mechanism of the SSVCs. We use the following three models to explain the mechanism of SSVCs: a) SSVCs reducing the proportion of adult men in households; b) the relationship between the decreased proportion of adult men and malaria risk; and c) the vulnerability of disadvantaged populations to malaria risk due to SSVCs. The model used for (a) and (b) is similar to Eq. **3**, while the one for (c) is similar to Eq. **4** except that we replace the moderator. Please refer to *SI Appendix*, Methods S2–S4 for detailed descriptions of these three models.

Data, Materials, and Software Availability. The household and individual datasets are available from https://www.dhsprogram.com/ (74). The conflict dataset is available from http://www.pcr.uu.se/data/ (75). The product that provides NDVI is available from https://modis.gsfc.nasa.gov/ (76). The climate dataset is available from https://crudata.uea.ac.uk/cru/data/hrg/ (77). The abduction dataset is available from http://www.acleddata.com/ (78). The population dataset from WorldPop is available from https://www.worldpop.org (79). The food price dataset is available from https://dataviz.vam.wfp.org/ (80). The dataset about the location of health facilities in sub-Saharan Africa is available from https://data.humdata.org/dataset/health-facilities-in-sub-saharan-africa (81). The maps of Africa used in this study is available from https://www.gadm.org/ (82). The codes for the regression analysis and figures are available from https://github.com/qiweiyu1223/SSVC_climate_malaria (83).

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