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Malaria Risk and Civil Violence*

Matteo Cervellati
University of Bologna
IZA, Bonn

Elena Esposito
HEC Lausanne

Uwe Sunde
LMU Munich
IZA, Bonn
CEPR London

Simona Valmori
University of Bologna

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Abstract

Using high-resolution data from Africa over the period 1998-2012, this paper investigates the hypothesis that a higher exposure to malaria increases the incidence of civil violence. The analysis uses panel data at the 1^o grid cell level at monthly frequency. The econometric identification exploits exogenous monthly within-grid-cell variation in weather conditions that are particularly suitable for malaria transmission. The analysis compares the effect across cells with different malaria exposure, which affects the resistance and immunity of the population to malaria outbreaks. The results document a robust effect of the occurrence of suitable conditions for malaria on civil violence. The effect is highest in areas with low levels of immunities to malaria. Malaria shocks mostly affect unorganized violence in terms of riots, protests, and confrontations between militias and civilians, rather than geo-strategic violence, and the effect spikes during short, labor-intensive harvesting periods of staple crops that are particularly important for the subsistence of the population. The paper ends with an evaluation of anti-malaria interventions.

JEL-classification: D74, J1

Keywords: Malaria Risk; Civil Violence; Weather Shocks; Immunity; Cell-level Data; Africa.

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Contact: Matteo Cervellati m.cervellati@unibo.it, Elena Esposito elena.esposito.1@unil.ch, Uwe Sunde uwe.sunde@lmu.de, Simona Valmori simona.valmori@unibo.it

1 Introduction

Civil conflicts are a major impediment for economic development. A recent stream of research has made considerable progress towards an understanding of the determinants of civil wars, which have been shown to be fuelled by geo-political motives, ethnic struggles, poor institutions, and (their interaction with) aggregate shocks. Much less is known on the determinants of small scale, widespread, localized violence that also constitutes a substantial burden to development. Narratives and reports by public agencies increasingly focus on the role of health shocks as triggers of social unrest, violence involving civilians, and predation and looting of local communities. International organizations repeatedly released warnings about the neglected secondary consequences of health shocks and call for active and timely interventions to avoid "disaster cycles".[1] In the existing literature, however, there is hardly any evidence on the role of health and health shocks for civil violence.

This paper studies the empirically unexplored role of temporary spikes in malaria risk for localized violent events. Malaria outbreaks are responsible for the largest number of human deaths in Sub Saharan Africa, accounting for ten percent of hospital admissions and causing sizable economic losses to households as consequence of incapacity for work and expenditures for treatments.[2] Surveys from several African countries record illness as the main risk perceived by individuals, followed by shortages of food and exposure to violence and raids, with malaria as the most frequently reported illness.[3]

To investigate the link between malaria risk and civil violence, we use information on geo-referenced violent events from the Armed Conflict Location Events Data (ACLED) for the entire African continent over the period 1998-2012. The units of analysis are cells of 1×1 degrees latitude and longitude. Section 2 describes the data and presents evidence for a positive effect of an increase in malaria incidence within a cell on the likelihood of civil violence at yearly frequency in Sub-Saharan Africa. A main challenge in isolating the role of malaria outbreaks for civil violence is identifying the direction of causality. The risk and severity of malaria outbreaks are affected by violence-related factors, such as conflict-related population dynamics, reduced health coverage and treatment of infections, which render the use of malaria incidence data at yearly frequency problematic in this context.

[1] For instance, the Disaster and Risk Management Guides - Epidemics of the United Nations Platform for Space-Based Information for Disaster Management and Emergency Response (UN) states that "The immediate effect of epidemics is of course that they cause illness and death. Secondary effects are social and political disruption and economic loss" (`http://www.un-spider.org/disaster-management-guides/epidemic`, accessed 21.2.2017). Likewise, as early as 2001, the WHO issued a Framework for Field Research in Africa with Malaria Early Warning Systems - Concepts, Indicators and Partners, that mentions that "A malaria epidemic may have disastrous consequences: disrupt the social, political and economic activity in a community, district/province (...) with severe political consequences" (`http://apps.who.int/iris/bitstream/10665/66848/1/WHO_CDS_RBM_2001.32.pdf`, accessed 11.7.2016).

[2] See, for instance, `http://malaria.jhsph.edu/about-malaria/` accessed 21.2.2017; see also Section 3 below.

[3] In general, the subjectively perceived risks are mainly related to shocks at the level of the community rather than at the individual level. See, for instance, the Parima-Study, Doss et al., 2008, McPeak et al., 2012.

Section 3 develops a novel approach to identifying the causal effect of malaria on civil violence that is based on specific aspects of the disease. In particular, this section provides details about the epidemiology of malaria, describes the measures of suitable conditions for malaria outbreaks and latent malaria risk, and presents the empirical strategy. Malaria is a vector-borne disease caused by the *plasmodium* parasite that cannot be transmitted directly from human to human. The vector, the female anopheles mosquito, requires suitable habitats, and short-term increases in malaria transmission are related to a specific combination of weather conditions that favor the reproduction of the parasites and the vectors. To make progress in identifying the effect of malaria, the analysis exploits geographically disaggregated weather data at high frequency and applies algorithms developed by malaria epidemiologists to construct indicators that reflect suitable conditions for malaria transmission. The occurrence of months with such conditions provides a possibility to exploit exogenous within-cell variation at yearly and at monthly frequencies.

The risk of malaria outbreaks also depends on the presence of a susceptible population. Research in epidemiology and evolutionary genetics documents that a prolonged and persistent exposure to the pathogen has favored the emergence of genetic immunities in the affected African populations. Another well-documented feature of malaria is that individuals who live in endemic areas characterized by high malaria transmission rates and who survive repeated infections at young ages develop highly protective acquired immunities. As a result, mortality among children increases with the exposure to the pathogen and peaks in endemic areas, whereas adults are actually more susceptible, and face a higher latent risk of malaria outbreaks, in epidemic areas where the stability of malaria transmission is comparatively low and the exposure to the pathogen is infrequent.[4] By leading to the geographical expansion of the pathogen and the vector, the temperature increase in the last decades has exacerbated the latent risk for adults in areas with traditionally low malaria stability.[5] The analysis identifies grid cells with high malaria risk for adults following the epidemiological literature and using non-parametric estimates of suitable weather conditions for malaria transmission.

Section 4 presents the results regarding the effect of malaria on civil violence that is obtained

[4]For instance, the *Center for Disease Control* reports that "in areas with lower transmission [...], infections are less frequent and a larger proportion of the older children and adults have no protective immunity. In such areas, malaria disease can be found in all age groups, and epidemics can occur." (`https://www.cdc.gov/malaria/about/biology/human_factors.html`, accessed 9.3.2017).

[5]The increase in the exposure to malaria for populations living in areas with historically low malaria transmission stability has been recognized by practitioners and health organizations. For instance, in an interview published on June 26, 2008, by InterPressService, Dr Willis Akhwale, head of Kenya's National Malaria Control Programme, states that "generally, the highlands were cool, there were low temperatures and there was no malaria there in the past. So, people living in the highlands have no immunity against it" (`www.ipsnews.net`). And, furthermore "This means that when it does break out in high altitude areas, the population in these areas are more vulnerable to an epidemic than the population in the lowlands where malaria has long been common. The low level of immunity adds another complication. While in the lowland areas, children are more likely to get the disease than adults who have been exposed it before, in the highlands adults and children are equally likely to be affected."

by exploiting the differential impact of exogenous short-term variation in suitable conditions for malaria outbreaks across cells with low versus high latent malaria risk for adults.[6] The baseline specification exploits exogenous within-cell variation in malaria suitable conditions at yearly and monthly frequencies. The monthly panel estimates account for seasonal effects in civil violence by including calender month fixed effects, or for temporary spikes in violence by including month fixed effects. The empirical specification controls for all time-varying characteristics that affect violence in a given cell and year by including cell-year fixed effects. The results provide evidence for a positive and sizable effect of suitable conditions for malaria for the likelihood of civil violence, but only in cells with high malaria risk for adults. The baseline results survive an extensive set of robustness checks, such as the use of non-linear estimators, the inclusion of interactions with alternative cell-specific characteristics and alternative short term weather shocks, and the use of different measures of violence (including measures of onset and termination). As a result the findings offer the first comprehensive evidence for the role of temporally and geographically confined health shocks on civil violence in Africa.

Section 5 digs deeper into the identification of the health channel by incorporating further insights from epidemiology and by performing additional robustness checks. The findings suggest that it is indeed short term variation in conditions suitable for malaria, and not generically variation in weather, that impact on violence in high malaria risk areas. The short extrinsic incubation period of malaria also implies that the spikes in the risk of outbreaks are temporary and limited in time. A richer empirical specification in terms of lags and leads confirms that the effect occurs mostly on impact (within two months), while no effect is detected for leads of the shocks. Further analysis documents that the effect is indeed related to the susceptibility of the population to malaria. A refined coding of high risk areas and semi-parametric methods document a reversed U-shaped effect that follows closely the epidemiological evidence. As additional evidence on the role of differential malaria susceptibility, we also document that higher levels of genetic immunity to malaria at the local level attenuate, although do not fully eliminate, the effect. In contrast, no effect of malaria suitable months is found in interaction with exposure to other vector-borne diseases such as Trypanosomiasis, as reflected by suitability for the Tse-Tse fly, or the prevalence of directly transmitted diseases like

[6]International organizations have emphasized the key role of this interplay between weather conditions and susceptibility of the population. For instance, the WHO states that "Malaria epidemics can occur when climate and other conditions suddenly favour transmission in areas where people have little or no immunity to malaria. [...] Unusual rainfall and/or higher temperatures might play a strong role in triggering such epidemics, especially after an extended period of drought, thereby increasing general population vulnerability.[...] Usually regions or districts at risk are not sufficiently prepared to cope with the sudden increase of malaria transmission affecting numerous people in such a short period of time. From previous experiences and unofficial records, it is estimated that among the population at risk, 30% to 50% will develop the disease with a case fatality rate ranging from 1% to 5%, depending on the rapidity and the effectiveness of the response (WHO unpublished reports)." (WHO, `http://www.who.int/malaria/publications/atoz/epidemicsmerajuly2004.pdf`, accessed 21.2.2017).

HIV. Finally, the econometric specification is extended to account for spatial contiguities and to incorporate temporal and spatial dependencies in conflict and weather conditions. The results confirm the baseline findings and document the existence of both geographical and dynamic spillovers.

Section 6 explores the mechanisms behind the health channel. Available narratives and reports by international organizations suggest that health shocks should be particularly problematic for unorganized violence. This is consistent with the perception that the risk of malaria outbreaks primarily puts the local population under stress and may temporarily reduce the opportunity cost of violence (or increase the willingness to take risks).[7] Using information on different types of violent events we find that the occurrence of unusual suitable conditions for malaria increase the likelihood of riots and protests, and of confrontations between militias and civilians, but not of struggles between the military and militias, or of geo-strategic military conflicts. In addition to being potentially fatal shocks to health, malaria infections involve important economic costs and income losses. Out-of-pocket expenditures for medical treatments are sizable, particularly when medical facilities are lacking or difficult to reach. The person-days lost for work due to malaria have been estimated as large as the days lost due to all other illnesses combined. These malaria-induced negative economic shocks presumably affect the communities especially when they take place during labor-intensive harvesting months. We explore this channel using geo-localized data for crops and harvest periods in combination with exogenous variation in malaria suitable conditions. Harvesting months tend to be associated with a lower incidence of violence. However, the occurrence of suitable conditions for malaria outbreaks during harvesting months leads to sizable increases in the likelihood of violence particularly for important subsistence crops with short harvesting seasons. We find no evidence for a comparable effect during growing seasons.

Finally, Section 7 provides a discussion of the potential role of factors that, beyond genetic immunities, could attenuate the effect of malaria risk. In particular, we provide some exploratory evidence regarding the role of anti-malarial policies at the local level, using data on the coverage of combination-drug therapies, insecticide-treated bed nets, and indoor spraying. The results suggest that anti-malarial policies have an attenuating effect on the incidence of civil violence during the occurrence of suitable conditions for malaria outbreaks in cells with high malaria risk for adults. The potential impact of malaria eradication is gauged by performing a thought experiment that provides an estimate of the predicted (reduction in) incidence of civil violence that would be observed under the counterfactual scenario in which the occurrence of malaria suitable conditions in cells with high malaria risk is completely eliminated.

[7] In fact, narratives suggest that even the mere fear of epidemics may put the population under stress and lead to violence, as illustrated by the recent examples of violence triggered by the Ebola epidemics.

Related Literature. The empirical literature on the causes of armed conflict and civil violence has grown rapidly in recent years, but the link between disease risk and violence has been little explored and remains poorly documented and understood. The empirical investigation presented in this paper contributes to the existing literature by 1) studying the role of malaria shocks for civil violence, which has so far not been documented and explored, contributing a first conceptualization and measurement of the heterogenous malaria risk and evidence of its interaction with suitable weather conditions for malaria incidence; 2) using highly disaggregated data in space and time for the whole of Africa, which allows exploiting exogenous variation within cells (yearly frequency) and exogenous variation within cells and years (at monthly frequency), thereby accounting for relevant time-invariant and time-varying cell-specific determinants of violence; 3) identifying the effect of health on conflict by exploiting the specificities of malaria epidemiology, including the role of genetic immunities and the timing of the effect; 4) exploring temporal and spatial spillovers using within cell×year variation at monthly frequencies; and 5) exploring the economic mechanisms behind the health effect using disaggregated data with a focus on the role of shocks during harvesting periods that has not been studied up to now.

Initially, research effort has been devoted to understanding the drivers of civil wars at the country level. This literature explored, in particular, the role of income and poverty, weak or non-democratic institutions, political instability and ethnic struggles, see, e.g., Fearon and Laitin (2003), Collier and Hoeffler (2004), Montalvo and Reynal-Querol (2005), as well as in Collier and Rohner (2008) Collier, Hoeffler, and Rohner (2009), among others. Specific features of the population, like ethnic polarization and genetic diversity, have also been linked to the risk of armed conflicts, see Esteban, Mayoral, and Ray (2012) and Arbatli, Ashraf, and Galor (2013). Following Miguel, Satyanath, and Sergenti (2004), several contributions have exploited exogenous year-to-year variation in weather conditions within countries over time to study the role of income shocks, see Ciccone (2011), Couttenier and Soubeyran (2014) and Berman and Couttenier (2015) for surveys of this literature. Some other studies have exploited shocks to international commodity prices to study the effect on conflict and political repression, see, e.g., Bazzi and Blattman (2014), and Caselli and Tesei (2016). Cervellati, Sunde, and Valmori (2017) contribute a first attempt to link the exposure to human pathogens across countries to the incidence of civil wars. Country level data impose serious limitations in identifying the causal effects of health shocks, however. This paper thereby contributes to the recent literature that studies the determinants of violence and conflict by examining the previously unexplored health

channel using disaggregated data for Africa.[8] Similar limitations of country level data have been pointed out for the identification of the role of features of the population (like ethnicity and genetic diversity), and of the role of economic shocks and rents from natural resources, among others.[9] Compared to cross-country panel studies (and besides the focus on violent events rather than large scale civil wars), the use of disaggregated data in the present paper allows for a substantially refined empirical identification approach and for the exploration of the underlying channels and mechanisms.

To overcome some of the limits of cross-country analysis, the literature has recently made substantial progress in identifying long-term, time-invariant determinants of conflicts using disaggregated cell-level data for Africa. Besley and Reynal-Querol (2014) document the persistence of historical conflicts across locations in Africa. Michalopoulos and Papaioannou (2016) exploit variation in country borders and provide evidence that the partitioning of historical ethnic homelands by colonial powers still breeds violence by showing that regions that host ethnic groups split by country borders are characterized by more ethnic wars and political violence against civilians. Other work has used data at the level of country-dyads, ethnic groups, or at the sub-national level for specific countries.[10]

Other recent work uses yearly variation in commodity prices for identification at the level of subnational grid cells. McGuirk and Burke (2017) study the effect of shocks to international food prices on conflict at the grid-cell level and find heterogeneous effects on conflicts over territory and conflict over economic rents. Berman, Couttenier, Rohner, and Thoenig (2017) exploit within-cell variation in commodity prices at the year level in mining areas and document a causal increase in struggles for the control of territories.

More closely related to the approach used in this paper, some recent works explore the determinants of violent events by exploiting year-to-year exogenous variation in weather conditions, see Dell, Jones, and Olken (2014) for an extensive survey. Harari and La Ferrara (2016) exploit year-to-year variation in precipitation at the grid-cell level in Sub-Saharan Africa and find that negative rainfall shocks in a year increase the likelihood of violent confrontations in the following year, but only if the shocks occur during the growing season of the main crop in the cell.[11]

[8]Cervellati et al. (2017) propose a novel composite index of the overall exposure to human pathogens in each country, which has the advantage of being informative about the overall differences in the health burden across countries. The limitation of this approach is that it does not allow exploiting the specific epidemiological features of a given pathogen to isolate the effect, the channel, and the underlying mechanism, as is possible by restricting attention to malaria in Africa as is done in this paper. Moreover, health shocks and violence typically have a sub-national dimension, which cannot be accounted for in cross-country studies.

[9]See also Blattman and Miguel (2010) and Couttenier and Soubeyran (2015) for extensive critical surveys on the advantages and limits of cross-country analysis.

[10]See, e.g., Dube and Vargas (2013) for the effect of commodity price shocks on civil conflict in Colombia, Caselli, Morelli, and Rohner (2015) for interstate resource wars, Morelli and Rohner (2015) for ethnicity-related resource ownership and conflict, Amodio and Chiovelli (2016) for changes in ethnic composition on conflict in South Africa, or König et al. (2017) for networks of alliances among different groups.

[11]In related work, Hodler and Raschky (2014) find that the occurrence of a drought in a given year reduces regional

To our knowledge, none of the existing contributions has explored the role of health shocks. By extending the scope of the investigation to health shocks, our paper thereby complements this earlier line of research and highlights that weather shocks can have different effects on the opportunity cost of violence. Specifically, an increase in precipitation can increase agricultural productivity but also the risk of a malaria outbreak. The ensuing income shock can thus be positive or negative, also depending on whether the weather shock takes place during growing or harvesting seasons. The specificity of the epidemiology of malaria also allows us to isolate the malaria channel above and beyond the direct effects of weather, e.g., on agricultural production, by conditioning on cell×year effects that implicitly absorb all shocks that affecting a cell at yearly frequency. By accounting for cell fixed effects (in yearly panel data) and cell×year fixed effects (in monthly panel data), the analysis isolates the effect of malaria shocks by implicitly accounting for both the long-term (time invariant) and short-term (yearly) cell-specific determinants of civil violence. The findings document the existence of a relevant, but previously unexplored, effect of localized health shocks for civil conflict in Africa. By using high frequency panel data for the entire African continent for over a decade, the current study represents an advancement in terms of internal and external validity. Complementary to the determinants of violence documented in the existing literature, the results also suggest that health shocks take effect on impact (within two months), are attenuated by genetic immunities, have the biggest effect on violence during harvest seasons, and in the form of unorganized social violence and confrontations between militias and civilians, rather than in terms of geo-political, ethnic or strategic struggles.

Finally, the paper relates to the growing literature on the potential effects of weather shocks and climate change on conflict. At this stage, the mechanisms linking climate change and global warming to civil violence are still hotly debated in the literature, see the extensive discussions by Hsiang et al. (2013) and Burke et al. (2015). The epidemiological specificities of the malaria-related channel documented in this paper are closely linked to the rise in global temperatures, which increased the latent malaria risk for adults in traditionally low malarial areas, and the related rise in weather variability. As discussed in more detail in Section 7, this paper provides a first step toward identifying a potentially relevant channel that has been largely overlooked in this context, and explores the possible role of health policies for the nexus between climate and conflicts.

economic activity as proxied by night light intensity, and that lower economic activity increases the risk of civil conflicts (measured in the UCDP Georeferenced Event Database in sub-national administrative regions rather than grid cells). Sarsons (2015) investigates the validity of rainfall as an instrument for income as determinant of conflict in India.

2 Data

2.1 Data on Violent Events and Covariates

Violent Events. The data for violent events is from the Armed Conflict Location and Event Data Project, the ACLED Dataset (version 4, 2014). The data cover all African countries over the period 1997-2013 at daily frequency and contain event types classified into the type of conflicts like riots and protests or violence against civilians, and the type of actors involved, including militaries, militias, civilians, among others. The analysis focuses on the period 1998-2012 to have a homogeneous sample, as the analysis controls for past realizations of conflict and uses weather data available until 2012.

Details on the construction of the gridded data are provided in Appendix A. As baseline indicator of civil violence we consider a dummy equal to one if at least one event of any type occurred in a given cell in a given year or month, respectively.[12]

Figure 1 displays the fraction of years with at least one violent event for each grid cell in Africa over the observation period 1998-2012. Approximately 60% of all cells experienced a violent event at least once during the observation period. There appears to be no clear difference in the incidence of violence depending on the location of the cell relative to the equator.[13]

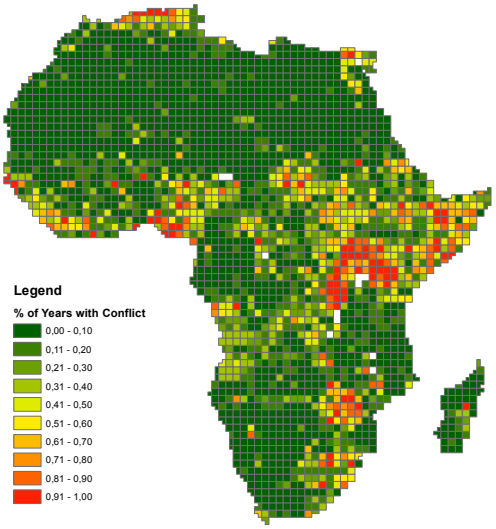


Figure 1: Spatial distribution of violent events.

Baseline Time Invariant and Time Varying Covariates. The analysis controls for a large set of

[12]To our knowledge, there is no other comparable data set combining high temporal frequency and detailed information on aspects of conflicts such as involved actors. Alternative data, like the UCDP Georeferenced Event Dataset are only available at annual frequency and therefore not suited for the analysis at monthly resolution.

[13]See Figure A4 in the Appendix.

time varying and time invariant covariates as potentially relevant determinants of violence. The time-invariant characteristics at the grid-cell level are grouped under various headings. "Geographic Controls" include absolute latitude, mean elevation, average terrain ruggedness, total cell area, and total area of the cell occupied by water, as well as, in some specifications, average weather conditions in terms of precipitation, temperature, and the Standardized Precipitation and Evapotranspiration Index (SPEI) described below. "Location and Distances" controls include the natural logarithm of the distance to the country capital, to the coast, to the country border, to the closest river and to Addis Ababa. The "Natural Resources" controls include average land suitability for agriculture, the presence of diamond mines, and the presence of petrol fields. The "Ethnic Diversity" control measures the number of ethnic groups in the cell. In some specifications we also exploit information on population density and average night light intensity in the cell, as well as information on growing and harvesting seasons for staple crops from Harvestchoice and FAO crop calendars.

Time varying controls include information at yearly and monthly frequencies on precipitation (in mm per m^2) and temperature (in degrees centigrade). These weather data are taken from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim dataset, which offers the advantage of being not based on gauge data but on data re-analysis.[14] In addition, we make use of the Standardized Precipitation and Evapotransipration Index (SPEI).[15]

Detailed information about the construction, coding and data sources for each of the time invariant and time varying variables is provided in the Appendix in Tables D1, D2 and D3. Table D4 and Table D5 presents the descriptive statistics of the time invariant and time varying variables (at both yearly and monthly frequencies), respectively.

2.2 Patterns of Malaria Incidence and Conflicts

Malaria is a serious and potentially deadly infectious disease that is endemic in 109 countries around the world. About 3.4 billion people (almost half of the world population) live in areas with a risk of malaria contraction. According to WHO estimates, in 2013, 198 million clinical cases of malaria were recorded worldwide, causing an estimated number of 584,000 deaths (with an uncertainty range of up to 755,000). About 90% of malaria-related deaths occur south of the Sahara in Africa.[16] Malaria

[14]Re-analysis involves model simulations of past events that include the incorporation of historical observations taken form various sources, such as weather stations, satellites, and sensors. To our knowledge, these are the highest quality weather data available. They have previously been used by Kudamatsu, Persson, and Strömberg (2012) and Harari and La Ferrara (2013).

[15]The SPEI index is a combination of the Palmer Drought Severity Indix (PDSI) which is based on supply and demand of water, and of the Standardized Precipitation Index (SPI); the SPEI measures drought severity, intensity and duration, but also allows for comparisons of drought severity through space and time, including different drought types, see Vicente-Serrano et al. (2010).

[16]See `www.who.int/mediacentre/factsheets/fs094/en` and `www.cdc.gov/malaria/about/facts.html` (accessed 21.2.2017).

comes in different variants but almost all deaths worldwide occur in sub-saharan Africa due to the *tropica* variant that is caused by the *plasmodium falciparum* parasite.[17]

As discussed in more detail in Section 3, the specific features of the malaria epidemiology imply temporary spikes in malaria transmission risk that are related to weather conditions and confined in time and space. Large investments have been undertaken recently to assemble a comprehensive and reliable database on the dynamics of malaria infections in the adult population in Africa. While substantial progress has been made, serious data limitations have severely hampered the construction of database at high levels of spatial and temporal disaggregation. The best time-varying disaggregate data on malaria incidence currently available are the back-projections of clinical incidence of *plasmodium falciparum* malaria assembled by Bhatt et al. (2015). These projections are based on available survey data on malaria prevalence drawn from various sites in Sub-Saharan African countries. To project malaria incidence in locations and at times for which no survey data are available, geo-statistical models that employ a large number of environmental and socio-demographic covariates are used.[18] The resulting database provides novel estimates of malaria incidence in about 35 African countries for the years 2000 to 2015, which, to our knowledge, has not been used in the context of conflicts. Figure 2 illustrates the cross-sectional variability of (average) projected malaria incidence across the respective grid cells in Africa for the year 2000, which is the first year for which the data are available.

As preliminary step towards establishing the potential role of malaria risk for civil violence, we explore the effect of projected clinical incidence on violent events, both measured at the cell-year-level. Table 1 reports estimation results that are based on within-cell variation over time (by including cell and year fixed effects) and that control for weather conditions (and their lags) and lagged incidence of violence. The findings provide a first piece of evidence for the existence of a positive and statistically significant relationship between malaria incidence and violent events within cells over time.

The results obtained from these back-projected and spatially interpolated data for malaria incidence should be taken as purely suggestive, however. For several reasons, the back-projected malaria

[17]Other variants are *tertiana*, and *quartana* which are caused by different species of the *plasmodium* parasite (*vivax/ovale*, and *malariae*, respectively).

[18]Overall, 27,573 spatially and temporally distinct *Plasmodium falciparum* parasite rate (*Pf*PR) prevalence data, mostly for children, were used for the mapping. Available *Pf*PR were adjusted for the age of the respondent, season and type of diagnostic used. Then, time-varying continuous surfaces of *Pf*PR were obtained through a spatiotemporal Bayesian geostatistical model that exploits a host of dynamic covariates for projection. These covariates included a long list of environmental variables (including temperature, precipitation, and evapotranspiration, among others) and socio-demographic variables (including population measures, night lights and accessibility to urban centers). Out of a total of 55,000 potential covariates, 20 were condensed by selecting the subset that maximized predictive strength. Projected population-weighted clinical incidence was then constructed based on mathematical malaria transmission models as a function of *Pf*PR for children and these time-varying predicted *Pf*PR surfaces. For the prediction of clinical incidence, the model accounted for seasonality, level of treatment, and probable immune status of populations at each location. See Bhatt et al. (2015) for details.

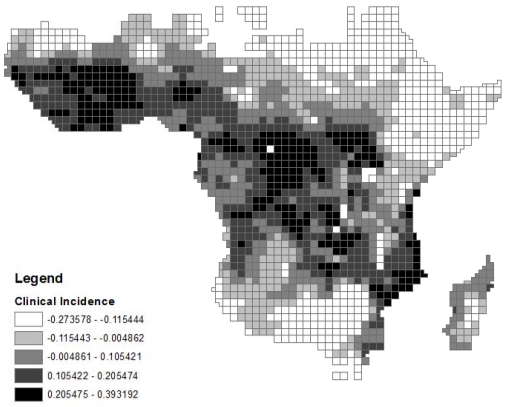


Figure 2: Clinical Incidence of Malaria for the Year 2000

Note: Projected incidence of *plasmodium falciparum* parasite prevalence from Bhatt et al. (2015), see Table D1 in the Appendix for details.

Table 1: Malaria Incidence and Violent Events

Dep. Variable	Violent Events - ACLED Yearly Data			
	(1)	(2)	(3)	(4)
Clinical Incidence of Malaria	0.189***	0.184***	0.183***	0.167***
	(0.046)	(0.046)	(0.046)	(0.043)
Weather	No	Yes	Yes	Yes
Weather Lag	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Violence Lag	No	No	No	Yes
Observations	21,853	21,853	21,853	21,853
R-squared	0.702	0.702	0.705	0.706

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year. "Clinical Incidence of Malaria" is a projection of clinical incidence of *Plasmodium falciparum* malaria (per 1000) obtained by interpolating across space and over time available malaria prevalence data retrieved from surveys using a a large number of dynamic environmental and socio-demographic covariates, see Bhatt et al. (2015) for details. The "Weather" controls include average annual temperature, average annual precipitation and average level of the Standard Precipitation and Evapotranspiration Index (SPEI); "Weather Lags" include weather controls for the previous two years. Standard errors clustered at the cell level are reported in parentheses. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

incidence data are not suited for the purpose of establishing an effect of malaria risk on civil violence. The database has been assembled with the goal of tracking the medium run evolution of malaria incidence across different regions in Africa at yearly frequencies. Although the data is available at the disaggregate level and can be mapped into 1×1 degree grid-cells, the data is based on scattered survey information about clinical cases, mostly for children and obtained from various surveys at different locations with different levels of immunity. Consequently, the information on clinical Plasmodium falciparum cases is likely subject to substantial reporting error and might be affected, among others, by the occurrence of civil conflicts and their timing. To fill the gaps between survey sites, the avail-

able malaria incidence data have been projected across space and time using Bayesian geo-statistical models that employ a large number of environmental and socio-demographic covariates. Moreover, the information has been harmonized using epidemiological models to obtain estimates of incidence for the overall population using population-weighted mathematical malaria transmission models. As mentioned above, these covariates include an extensive list of environmental variables (like precipitation, temperature, and evapotranspiration, among others) and socio-demographic variables. Given the existing literature, many of these variables are expected to be directly related to civil violence. As a result, projected incidence data are problematic when trying to isolate the role of malaria risk from other potential determinants of civil violence that have been used in the literature.

To make progress in the exploration of the role of variation in malaria risk for civil violence, the next section develops an alternative identification strategy that makes use of specific features of the malaria epidemiology to construct measures of latent malaria risk and to isolate exogenous variation in short-term weather conditions that are particularly suitable for malaria transmission across time and cells. This strategy uses data at a high spatial and temporal level of disaggregation and exploits exogenous variation in weather conditions without relying on projections.

3 Empirical Strategy

3.1 Epidemiological Background

Before discussing the measurement of malaria risk and the identification strategy, this section provides a brief summary of the relevant background regarding the epidemiology of malaria.

Plasmodium falciparum parasites are heat sensitive and require a sufficiently warm environment. The life cycle of the parasite is complex and involves a mosquito vector and a vertebrate host, such as humans. Upon infection of the host through an injection of the parasites (in sporozoite form), the parasites develop and multiply asexually, first in human liver cells, later in the red blood cells, where they cause the typical symptoms of remittent fevers, head and body aches, vomiting and diarrhea. The transmission occurs exclusively through a vector, the female *Anopheles* mosquito, which requires blood meals from vertebrate animals for ovary development. There are more than 20 species of anopheles mosquitos that differ regarding to the preferred vertebrate animals, their frequency of biting and their life span. Among these, *Anopheles gambiae*, *arabiensis* and *funestus* are the most efficient vectors of malaria for humans in Africa because they mainly target humans for their blood meals.[19] Biting an infected human and absorbing the parasite as gametocytes (i.e., in sexual forms) from the human blood, starts a cycle of growth and sexual multiplication of the parasite inside the mosquito.

[19] *Anopheles gambiae* and *funestus* are reported to take more than 90% of their blood meals from humans, see Scott and Takken (2012).

Anopheles reproduction requires lentic water reservoirs, where the eggs are laid by the female mosquito. After the eclosion, the larvae continue to develop in water, metamorphose into pupae, and eventually the adult mosquito emerges. The development from egg to adult crucially depends on the temperature and takes approximately 10-14 days, but can be as short as 5 days under very suitable conditions.[20] The ambient conditions in terms of average temperature and temperature variability also affect the parasite development within the mosquito.[21] Finally, also the transmission rate is temperature dependent, with the frequency of blood meals of *Anopheles gambiae* ranging between every 4 days at 17^{o}C and every 2 days at 25^{o}C. Adult anopheles mosquitoes live for approximately 1-2 weeks, and can act as a vector for malaria transmission only during this stage of life. The transmission involves an injection of the *plasmodium* parasite (in the form of sporozoites from the salivary glands of the mosquito) into the bitten human.[22]

Taken together, this implies that the possibility of malaria transmission is closely related to external conditions in terms of temperature and precipitation. Specifically, the transmission of malaria is limited to areas that exhibit climatic conditions that are suitable for the parasite as well as the vector. Sufficiently high levels of temperature and humidity are required for the vector to survive and develop and hence for the *plasmodium* parasite to survive. In terms of transmission, the parasites first must develop within the vector before becoming a risk for infecting humans. This extrinsic incubation period lasts from 10 to 21 days, depending on the temperature. Death of the mosquito before the end of this period prevents transmission. The intrinsic incubation time after infection through a mosquito bite varies from 7 to 30 days, with infections by *plasmodium falciparum* exhibiting the shortest incubation periods of all cases.[23] For the present analysis, this implies that malaria outbreaks can be observed within relatively short periods of particularly suitable weather conditions. This has the advantage that malaria outbreaks can be identified at a high geographical and temporal resolution.

The conditions of malaria infection range from asymptomatic or very mild cases to severe cases (including anemia, or cerebral malaria caused by *plasmodium falciparum*) and even death. First exposure to the parasite is typically associated with a febrile illness, which may become severe and even fatal. When diagnosed and treated promptly and correctly, malaria is in principle curable.[24]

[20]The first three stages of life (egg, larvae, pupae) are aquatic and during this period, the anopheles are very sensitive to outside conditions. A desiccation of the water reservoir during these phases implies death of the anopheles. At temperatures around 28^{o}C, the development during the aquatic stages is fastest, below 16^{o}C the development of larvae stops, and at temperatures below 14^{o}C the larvae die (Bayoh and Lindsay, 2003, Christiansen-Jucht et al., 2014). The emergence of adult anopheles peaks around 24^{o}C, where the development is favored by stable temperatures in contrast to temperature fluctuations (Lyons et al., 2013).

[21]Blanford et al. (2013) point at the importance of variation in temperature in addition to average temperature.

[22]See `www.cdc.gov/malaria/about/biology/Parasites.html`, `www.cdc.gov/malaria/about/biology`, and `http://malaria.jhsph.edu/about_malaria`, accessed 21.2.2017.

[23]See `http://www.cdc.gov/malaria/about/disease`, accessed 21.2.2017.

[24]After recovery, patients that have been infected sometimes experience relapses (in particular after infections with

Upon recovery, most individuals develop resistance or even protective immunity against the disease, in particular after infections with *plasmodium falciparum*. Even though the precise mechanisms are still not well understood, the existing evidence suggests that immunity to febrile infection with malaria is slow to develop and incomplete, while immunity to a lethal infection is acquired more quickly. Acquired immunity appears to reduce the growth of parasites in the blood cells and typically emerges in regions with high exposure to malaria infections (in areas of hyperendemicity and holoendemicity), where acquired immunity leads to a very high protection of surviving adults against severe symptoms and death (see, e.g., Langhorne et. al., 2008, Doolan et al., 2009).[25]

Recent evidence suggests that the acquisition of immunity is closely related to the latent exposure to infection, with protective immunity being prevalent only in regions with sufficiently high exposure (Stanisic et al., 2015). In areas with lower exposure and less frequent infections, a larger proportion of children and adults do not exhibit acquired resistance. In evolutionary genetics, malaria is also regarded as the strongest known selective pressure of the human genome, see Kwiatkowski (2005). The persistent exposure to malaria across generations for long periods of time favored the diffusion of several Mendelian genetic diseases that are protective against malaria. Among the most effective genetic factors are the prevalence of the so-called sickle cell trait, reflecting an abnormal hemoglobin gene (HbS) that provides highly effective protection against *plasmodium falciparum* (Ferreira et al., 2011), with a sizable reduction in the risk of developing cerebral malaria.[26] As consequence of an evolutionary advantage of these phenotypes, sickle cell traits are more frequent in populations in Africa or with African ancestry.[27] The role of genetic and acquired immunities in areas with high malaria stability is consistent with subjective perceptions of individuals regarding the duration and severity of fevers and cost burdens across regions with different levels of long term exposure to malaria.[28]

3.2 Malaria Risk: Data and Measurement

The identification strategy exploits specificities of the epidemiology of malaria discussed above that allow isolating temporary increases in the exposure to malaria transmission at high levels of temporal

plasmodium vivax or *ovale*).

[25]This is reflected in Figure A1 in the Appendix, which reproduces an illustration from (Langhorne et. al. 2008) and shows that the severity of infections declines with age, due to a combination of acquired immunity and selection.

[26]Other well-studied genetic factors include the absence of the Duffy blood group antigen, which acts as a receptor for *plasmodium vivax* parasites (Langhi et al.,. 2006), and G-6-PD (Glucose-6-Phosphate Dehydrogenase) Deficiency (leading to favism), a genetic deficiency of the G-6-PD enzyme that reduces the life span of red blood cells and provokes sudden destruction of red blood cells, but grants protection against malaria for males (Guindo et al., 2007).

[27]Other, less prevalent and effective genetic factors of immunity include the occurence particular combinations in the HLA complex. See also `http://www.cdc.gov/malaria/about/biology/human_factors`, accessed 21.2.2017.

[28]Chuma et al. (2010) report that fever episodes among adults and children (over five years) lasted significantly longer in districts with low transmission stability (low acute transmission districts in the highlands of Kenya) than in high transmission stability districts (Kenyan districts with high and intense perennial transmission).

and spatial disaggregation. The identification approach combines two aspects of malaria exposure. The first aspect is related to the peculiarities of the process of reproduction of the *plasmodium* parasite and the transmission vector. Given the sensitivity of the anopheles mosquito to temperature and precipitation, the risk of malaria infections in a given region at a particular point in time is closely related to the short term weather conditions in that region at that time. The second aspect is related to the susceptibility of the adult population. In areas with high transmission levels and little inter-annual variation, malaria transmission is stable (malaria is typically hyperendemic or holoendemic). In these areas, individuals of all ages are exposed to frequent infections which favor the development of acquired immunities, in particular among the adults who survived infections during younger ages. The higher evolutionary pressure also leads to the development of genetic immunities that are transmitted across generations. In contrast, in areas where malaria is less stable, and transmission levels vary substantially from year to year, the adult population exhibits lower levels of acquired and genetic immunities, and therefore faces a higher risk of serious illness once exposed to the pathogen. As consequence, areas with low to intermediate long-term exposure to malaria in terms of transmission stability are the ones that entail the highest risk of severe infections for adults.

The identification strategy combines these two aspects and exploits the differential effect of exogenous short term variation in malaria suitable conditions in areas with low and with high malaria risk for adults. In the following, we describe the construction of an indicator of months with particularly suitable conditions for malaria transmission and the classification of areas in terms of malaria exposure for adults.

3.2.1 Malaria Suitable Months

Particular combinations of temperature and precipitation result in favorable conditions for the spread of malaria. The 20th Report of the WHO Expert Committee on Malaria called for the need of reliable indicators based on highly disaggregated meteorological information to be used to prevent malaria epidemics.[29] Tanser et. al. (2003) constructed a weather-based index for Africa that represents conditions particularly suitable for malaria. The resulting binary indicator variable, labelled "Malaria Suitable Month" (or simply MSM) in the following, is constructed as follows. For grid cell i for month t, the binary indicator $MSM_{i,t}$ takes value 1 if, and only if, all of the following four conditions are satisfied:

1. Average monthly rainfall during the past 3 months ($t-2$, $t-1$, t) is at least 60mm/m^2.
2. Rainfall in at least one of the past 3 months is at least 80 mm/m^2.
3. No month in the past 12 months has an average temperature below 5^oC.

[29]The report states "An increasing number of malaria epidemics have been recently documented throughout the world, particularly in Africa. Areas become epidemic when conditions that normally limit transmission change radically as a result of abnormally heavy rains, long periods of increased humidity and temperature." (WHO, 2000, p. 6).

4. The average temperature in the past 3 months exceeds 19.5^oC+Standard Deviation of monthly temperature in the past 12 months.

Based on these conditions, the variable Malaria-Suitable Month, *MSM*, takes value 1 if the conditions are particularly suitable for malaria transmission in the given cell and month, and 0 otherwise. This index can be seen as capturing the necessary conditions for elevated malaria transmission, rather than as providing sufficient conditions.[30] For use with yearly data frequency, the variable Malaria Suitable Months is constructed as the yearly aggregate of monthly suitability conditions, and thus ranges from 0 to 12.

Weather data used for the construction of MSM, and also as covariates included in the regressions, are taken from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-Interim dataset, which offers the advantage of being not based on gauge data but on data re-analysis.[31]

3.2.2 Areas with High Malaria Risk for Adults

As discussed above, the emergence of suitable weather conditions for malaria transmission increases the risk of malaria outbreaks in the population at large, and in particular among adults, especially in areas with traditionally low to intermediate long term exposure to the pathogen.

To locate such "high risk" areas we exploit the Malaria Stability Index, an ecology-based spatial index of stability and force of malaria transmission devised by Kiszewski et al. (2004). Based on the distribution of the dominant species of *Anopheles* mosquitos and their specificities, they constructed an index of transmission force and stability as a function of several characteristics of the mosquito: i) share of blood meals taken by the mosquito, ii) the daily survival rate, and iii) location specific bio-climatological conditions that affect the extrinsic incubation period.[32] The resulting time-invariant

[30] According to Tanser et. al. (2003), the index has high predictive power for the absence of malaria outbreaks, but less predictive power for actual outbreaks. For the purpose of this paper, this implies an interpretation of the effects of MSM along the lines of an intention to treat analysis. The same index has been used by Kudamatsu, Persson, and Strömberg (2012).

[31] Re-analysis involves model simulations of past events that include the incorporation of historical observations taken form various sources, such as weather stations, satellites, and sensors. These are the best available weather data for the purpose of this study.

[32] These climate variables include a temperature threshold of 15^oC of mean monthly temperature below which anopheline vectors are assumed to remain inactive. Climate variables are measured as the average over the period 1901 to 1990. The index does not consider recovery rates from infections. The resulting index was constructed for each calender month on a grid of 0.5^o cells and then aggregated into a cross-sectional index of malaria stability. In particular, the index is computed as

$$\sum_{m=1}^{12} \frac{a_{im}^2 p_{im}^E}{-\ln p_{im}}$$

where m is calender month (1-12), i is the identity of the dominant anopheles vector, a is the proportion of this dominant vector that bites humans, p is the daily survival rate (ranging from 0 to 1), and E is the extrinsic incubation

malaria stability index is a real number ranging from 0 to approximately 38. On the level of 1×1 degree cells, the index ranges from 0 to 34.

The malaria stability index is indirectly informative about the degree of (acquired and genetic) immunity, which tends to increase with the level of stability of malaria exposure. Conversely, this implies that the index is informative about the susceptibility of the adult population in a region with respect to malaria outbreaks. The lower the stability, the less frequent are infections, and the lower the resistance (the higher the susceptibility) of the adult population. In other words, this implies that the relationship between the malaria stability and transmission index and the actual risk of malaria infections, in particular among the adult population, is low for cells with very low malaria stability, increasing with higher malaria transmission, but ultimately declining due to greater resistance and immunity.

As benchmark for the empirical analysis we construct a binary indicator for areas with high malaria risk for adults, labelled HR. To code grid-cells with $HR = 1$ in a systematic way, we regress malaria incidence estimated by Bhatt et al. (2015) (presented in Section 2.2) on malaria suitable months, MSM (constructed as described in Section 3.2.1) at yearly frequency and investigate the sensitivity of the effect of MSM for cells characterized by different levels of the malaria stability index. Concretely, for each level of the malaria stability index, we run local regressions that give large weight to cells characterized by this focal index level and symmetrically decreasing weights for cells with lower or larger malaria stability indices than the focal level.[33]

Figure 3, plots the respective coefficient estimates of the effect of MSM on malaria incidence for each of 34 local regressions against the respective level of the stability index that serves as center for the weighting function. Each of the regressions exploits within cell variation over time and includes controls for average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the respective year, year fixed effects and cell fixed effects. The estimates document that the effect of malaria suitable months on projected malaria incidence is highest for cells characterized by low to intermediate levels of the index of stability and force of malaria transmission. The effect is largest for the center of the weighting function around 7. The effect is monotonically smaller for regressions that give greater weight to

period in days ($E = 111/(T - 16)$ for *falciparum* and $E = 105/(T - 14.5)$ for *vivax* with T being the temperature in degrees centigrade). In order to obtain a finer data resolution, a minimum threshold of precipitation (10 mm) was imposed as necessary precondition for subsequent malaria transmission.

[33]In particular, we conduct 34 local regressions using a weighting function that applies weights that are monotonically decreasing to zero for values more distant from the respective center value. The weighting function used for the estimation has a symmetric logistic shape: $1 - [(m \cdot (|Center - x|)^k)/(1 + m \cdot (|Center - x|)^k)]$ with $k = 6$ and $m = 10^{-6}$. This function implies that in local regressions considerable weight is given to observations within windows of about +/- 8 index points around the respective center of the malaria stability index, $Center$. The estimation is repeated iteratively using a moving window that varies systematically the center of the weighting function for $Center = 1, 2, ..., 34$. The results are qualitatively insensitive to the particular weighting function used.

cells with higher levels of malaria stability, and becomes statistically insignificant for windows with a center of the weight function at values of malaria stability index larger than around 12.

In light of these results, we therefore construct the binary indicator HR as taking value 1 if the malaria stability index in a cell is in the interval (0,15), and value 0 for a stability index of 0 or in the interval $[15, \cdot]$ as a baseline.[34] Consistent with the results of the local regressions depicted in Figure 3, the occurrence of predicted malaria suitable months significantly increase malaria incidence in high risk HR areas.[35] This coding of high malaria risk cells, HR roughly corresponds also to the ranges of malaria transmission typically associated to epidemic, rather than endemic, areas. This preliminary analysis also confirms that malaria incidence is not increased significantly by the occurrence of suitable conditions that favor the reproduction of the anopheles mosquitos or the *plasmodium* parasite in areas characterized by high long run malaria force and stability, which are correspondingly coded $HR = 0$. Taken together, this implies that the weather-based index of Malaria Suitable Months, MSM, provides a measure of short-run infection risk, which translates into different exposure to malaria depending on the susceptibility of the population (in terms of cells with $HR = 0$ or $HR = 1$).

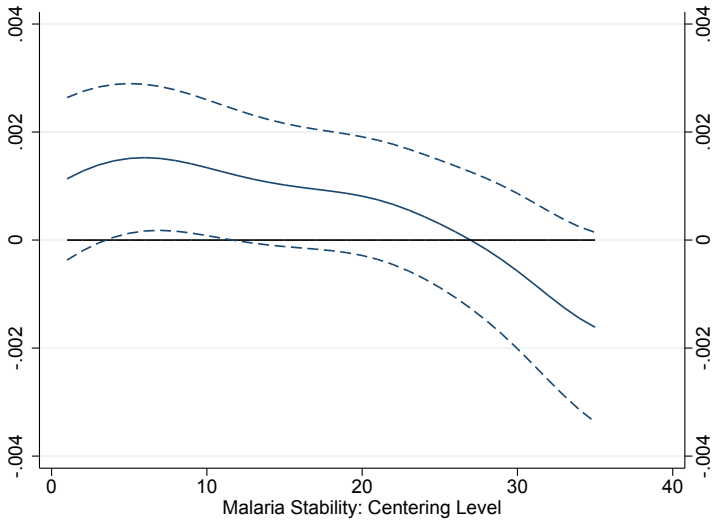


Figure 3: Effect of Malaria Suitable Months (MSM) on Clinical Incidence of Malaria

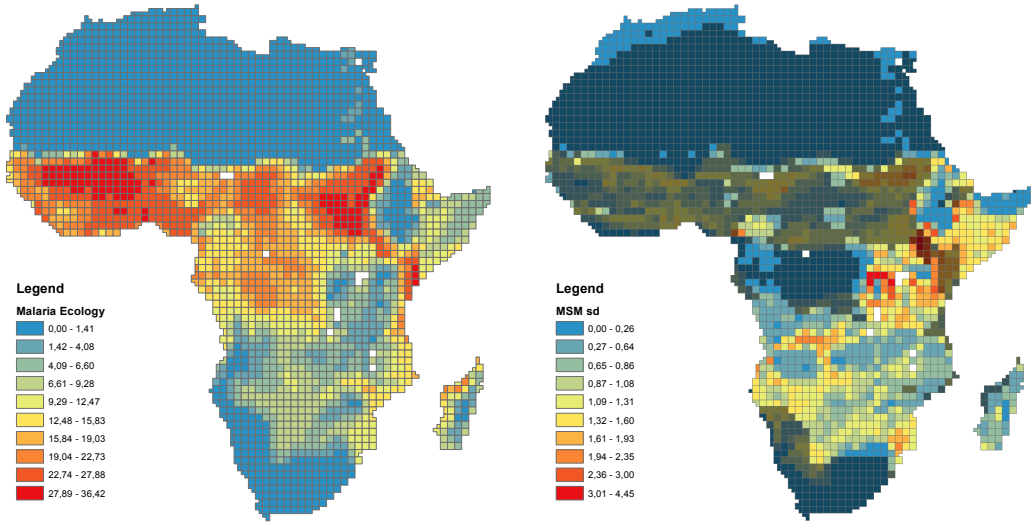
Note: Coefficients from local (weighted) regressions of the projected clinical incidence of *Plasmodium falciparum* malaria constructed by Bhatt et al. (2015), on the occurrence of Malaria Suitable Months, MSM, for increasing levels of the malaria stability index constructed by Kiszewski et al. (2004) as the center of the weighting function; see text for details.

Figure 4 (a) provides a graphical illustration of the spatial distribution of the original malaria

[34]Notice that with a maximum of the effect for a center of the weighting function at 7 and a window that gives considerable weight to cells in the perimeter of +/-8 of the index, this implies a threshold of 15 of the stability index for the construction of the binary measure HR.

[35]See the results in Table A1 in the Appendix.

stability index that is used as information to construct the baseline indicator of high malaria risk areas.[36] Figure 4(b) illustrates the variability of short term conditions suitable for malaria within cells by depicting the standard deviation of malaria suitable months in each cell. In the same Figure the high risk cells are visualized with a light shadow.



(a) Malaria Stability Index (b) MSM and High Risk Cells

Figure 4: Malaria Stability, Malaria Suitable Months (MSM) and High Malaria Risk cells, (HR)

Note: Panel (a) reports the spatial distribution of the malaria stability index (from Kiszewski et al. (2004)). Panel (b) depicts the standard deviation of Malaria Suitable Months, MSM built following Tanser et. al. (2003) (see text for details) in high risk cells ($HR = 1$, light shadow), and low risk cells, ($HR = 0$, dark shadow).

In additional analyses discussed below, we also consider alternative definitions of cells with high malaria risk regarding the malaria stability index and make use of non parametric techniques. Moreover, we also explore more explicitly the role of genetic immunities in the population measured by the diffusion of the Sickle Cell trait using disaggregate data from Piel et al. (2013).

3.3 Empirical Strategy

Following the insights from epidemiology discussed in Section 3.1, favorable short term conditions for malaria transmission imply an elevated risk of malaria infection in high risk cells, i.e., in areas with low latent malaria exposure where the population largely lacks acquired and genetic immunity

[36]See Figure A2 in the Appendix for a histogram of the distribution of the stability index across grid cells.

to infections from the pathogen. The empirical identification uses this insight and exploits the differential effect of suitable short term conditions across cells with low and high malaria risk, as discussed in Section 3.2. Reverse causality is ruled out by the fact that variation in short-run weather conditions in high and low malaria risk areas is exogenous to civil violence.

The identification strategy exploits the differential effect of exogenous variation in short term conditions suitable for malaria in high and low malaria risk areas by estimating a linear probability model of the form:

$$Violence_{i,c,t} = \alpha MSM_{i,c,t} + \beta HR_{i,c} \times MSM_{i,c,t} + \Gamma X'_{i,c,t} + \Delta Z'_{i,c,t-1} + \Phi_{i,c,t} + u_{i,c,t} \quad (1)$$

where $Violence_{i,c,t}$ is a binary indicator of civil violence in cell i in country c in period t.

The latent risk of malaria outbreaks is measured by the binary time-invariant indicator "High Malaria Risk", $HR_{i,c}$, for cell i in country c that is constructed as discussed in Section 3.2.2. The exogenous short term variation in malaria exposure is measured using the "Malaria Suitable Months" variable, $MSM_{i,c,t}$, constructed as discussed in Section 3.2.1. The coefficient of interest is β, which captures the effect of the occurrence of favorable weather conditions in a given cell i in country c in period t that exhibits high malaria risk, as compared to the occurrence in a low malaria risk cell.[37]

In the yearly data, t reflects a year, in the monthly data, t is a month. In the analysis exploiting yearly variation, MSM represents the number of malaria-suitable months in a year. In the monthly panel data the variable MSM is a dummy that takes value one if in a given month in a given cell conditions are suitable for malaria and 0 otherwise.

The vectors X and Z contain additional contemporaneous or lagged covariates. Depending on the particular specification and the data frequency, the covariates include the main effect of $HR_{i,c}$, weather conditions (and their lags) and the lagged dependent variables among others.

The vector $\Phi_{i,c,t}$ generically indicates the inclusion of different types of fixed effects at the level of cell i, country c, or period t, and possibly their interaction that can be included in isolation or jointly, depending on the specification. For instance, the baseline specification at yearly frequency exploits within cell variation over time with cell and year fixed effects (so that $\Phi_{i,c,t} = \phi_i + \phi_t$) along the lines of a difference-in-differences framework.[38] At monthly frequencies, we estimate specifications equivalent to a two-way (cell and month) fixed effects model; in addition we consider even more flexible specifications, including cell-year and calender month fixed effects, among others.

The baseline model is estimated as a linear probability model using least squares, with robust standard errors that allow for arbitrary heteroskedasticity and autocorrelation of the error term within a given cell, and spatial correlation with neighboring cells (Bester et al., 2011).

[37] Exploratory regression results presented in Table A1 in the Appendix show that the occurrence of malaria suitable months in high risk areas robustly correlates with projected malaria incidence when exploiting within-cell variation at yearly frequency.

[38] As a preliminary step we also run pooled OLS specifications that allows estimating also the effect of high risk cells, $HR_{i,c}$ including country and time fixed effects (so that $\Phi_{i,c,t} = \phi_c + \phi_t$).

4 Baseline Results

4.1 Pooled OLS – Yearly Frequency

In light of the existing literature, which mostly uses annual data frequencies, we first explore the role of malaria risk for civil violence by estimating model (1) by pooled OLS at the cell-year level. The inclusion of country fixed effects and time fixed effects also allows estimating the coefficient for the (time-invariant, cell-specific) High Malaria Risk indicator, HR. This coefficient is indicative of the effect of (time-invariant) conditions that entail high latent malaria risk on the probability of violent events.

Table 2 presents the results. To account for cell-specific differences in malaria conditions and focus on unusually suitable conditions for malaria transmission, we compute the number of malaria-suitable months for each year and cell and subtract from it the cell-specific mean across all years (Malaria Suitable Months Demeaned). The results in Table 2 Column (1) document that high malaria risk cells display a significantly higher probability of civil violence. Compared to the unconditional average of 0.18 violent events in a given year and cell, high malaria risk cells are associated with an almost 50% higher conflict risk.[39] Exogenous variation in weather conditions reflected by Malaria Suitable Months , MSM henceforth (measured by the number of demeaned malaria suitable months in a given year and cell) identify short-term variations in malaria risk, but appear to have no significant effect on violence. Based on the epidemiological aspects discussed above, the actual malaria threat constituted by suitable weather conditions for malaria transmission should depend on the latent malaria exposure and the associated level of (acquired or genetic) immunity, however. In cells in which the population is less frequently exposed to malaria shocks and thus possesses lower levels of (genetic and acquired) immunities, the health shock is expected to be stronger.

Column (2) shows that the insignificant average effect of malaria suitable weather conditions hides substantial heterogeneity: the occurrence of a month with suitable conditions for malaria transmission increases civil violence only in "High Malaria Risk" cells. There, the risk of observing a violent event increases by 1.7 percentage points (which corresponds to an increase of about 10% compared to the unconditional mean of 18%) due to the occurrence of a month with suitable conditions for malaria outbreaks, as compared to cells with low malaria risk, measured by the malaria stability index. These effects, are conditional on an extensive set of controls for geographic factors, location distances, resources, ethnic diversity, and weather conditions. Moreover, given that the intention to treat interpretation of the effects, they correspond to a lower bound of the actual effect of malaria outbreaks on conflict. The remaining columns show that the results are very similar (both in terms of statistical significance and magnitude) for extended specifications that also include controls for population density, income (measured by light night intensity), lags in weather conditions, lagged

[39] Conflict incidence is fairly similarly distributed, with 71% of all high malaria risk cells and 51% of all low malaria risk cells experiencing a violent event at least once during the observation period.

Table 2: Malaria Risk and Violence - Pooled OLS Yearly Data

Dependent Variable	Violent Events - ACLED Yearly Data						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Malaria Risk	0.088***	0.088***	0.055**	0.055**	0.035**	0.055**	0.035**
	(0.023)	(0.023)	(0.021)	(0.021)	(0.013)	(0.021)	(0.014)
	[0.008]	[0.009]	[0.008]	[0.008]	[0.007]	[0.007]	[0.007]
Mal. Suit. Months Demeaned	0.002	-0.009	-0.009	-0.008	-0.008	-0.005	-0.005
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
	[0.004]	[0.007]	[0.007]	[0.007]	[0.006]	[0.006]	[0.005]
MSM D.×High M. Risk		0.017**	0.017**	0.016**	0.014**	0.014*	0.012*
		(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
		[0.008]	[0.008]	[0.008]	[0.007]	[0.007]	[0.006]
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location-Distances	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Natural Resources	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ethnic Diversity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop./Night Lights	No	No	Yes	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags	No	No	No	Yes	Yes	Yes	Yes
Conflict Lag	No	No	No	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	No	No
Country-Year FE	No	No	No	No	No	Yes	Yes
Observations	38,340	38,340	38,340	38,340	38,340	38,340	38,340
R-squared	0.241	0.241	0.259	0.261	0.350	0.315	0.393
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "Malaria-Suitable Month" is an index that represents the number of months in the current year that were suitable for malaria to be transmitted, relative to the cell-specific mean over the observation period; "MSM D.×High M. Risk" is the corresponding interaction term; see text for details. The "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the respective year (both in levels and demeaned with respect to the yearly average). The "Weather Lags" include the first two lags of the same variables. The "Geographic Controls" include absolute latitude, mean elevation, average terrain ruggedness, total cell area, total area of the cell occupied by water, average precipitation and average temperature. The "Location and Distances" controls includes the natural logarithm of the distance to the country capital, to the coast, to the country border, to the closest river and to Adis Ababa. The "natural resources" controls include the average land suitability for agriculture, the presence of diamond mines and the presence of petrol fields. The "Ethnic-Diversity" controls for the number of ethnic groups in the cell (GREG). Country-Year fixed effects are a set of country specific year fixed effects. Panel data from 1998 to 2012 at yearly frequency. The unit of observation is a 1 x 1 degree cell. Standard errors clustered at the country level are reported in parentheses, $(\cdot)$, and Conley standard errors allowing for spatial and serial autocorrelation up to the threshold of 400 km are reported in square brackets, $[\cdot]$. ***, **, * indicate significance at 1-, 5-, and 10-% level computed using the respectively largest standard errors (country clusters or Conley) of each specification.

violence, as well as more flexible panel specifications that include country×year fixed effects.

Interactions with other weather conditions. The indicator of MSM is constructed by exploiting information about the weather conditions over the previous twelve months. According to the epidemiological literature, particularly suitable conditions for malaria transmission are a non-linear function of temperature and precipitation. This implies that variation in weather conditions *per se*, in terms of linear controls for temperature and precipitation, does not necessarily represent suitable conditions for malaria outbreaks. In fact the correlation between malaria suitable months and weather conditions, in terms of temperature, precipitation and also evapotranspiration, is quite small

(in the order of -0.10, 0.17 and 0.05, respectively). This is also illustrated in Figure 5.[40]

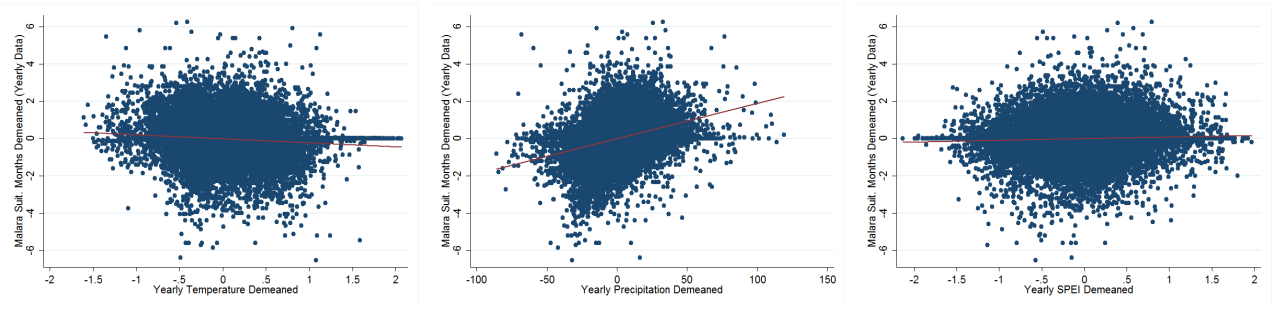


Figure 5: Unconditional correlations over time (of demeaned variables) between malaria suitable months with temperature, precipitations and SPEI at yearly frequencies.

The low correlation with other weather conditions suggests that malaria suitable months do not generically pick up weather conditions. To explore this issue more formally, Table 3 replicates the analysis by estimating extended specifications that include interactions between the time-invariant Malaria Risk indicator and precipitation, temperature, or the SPEI index alone and on top of the interaction with MSM. The results are almost identical to those shown in Table 2 and the findings reveal no significant role of interactions between high malaria risk cells and weather conditions besides the occurrence of conditions corresponding to malaria suitable months.

4.2 Within-Cell Variation – Yearly Panel

We next estimate the baseline empirical model (1) at the cell-year level, but including cell fixed effects rather than country fixed effects. This specification accounts for observable and unobservable time-invariant cell-specific characteristics that may affect conflicts. This implies in particular that time-invariant factors that have been identified as relevant determinants of civil conflict, such as geographic features favoring conflicts, the persistence of historical events and conflicts, the role of pre-colonial institutions, the ethnic composition, and the division of ethnic groups across different countries, among possible other factors, are absorbed by the cell fixed effects. Restricting attention to within-cell variation over time, including common time fixed effects and discriminating between high and low risk cells, means that the identification of the effect of short term changes in malaria risk is along the lines of a difference-in-differences framework.

Table 4 reports the respective results. Since the indicator for high malaria risk, which is based on the malaria stability index, is time-invariant, the coefficient for this indicator is not identified in specifications with cell fixed effects. The error structure again allows for spatial correlation across

[40]The correlation is also small at monthly frequencies as illustrated in Figure A3 in the Appendix.

Table 3: Malaria Risk and Violence - Pooled OLS Yearly Data With Additional Interactions

Dependent Variable	Violent Events - ACLED Yearly Data							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Malaria Risk	0.107***	0.107***	0.107***	0.107***	0.107***	0.107***	0.106***	0.106***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Mal. Suit. Months Demeaned	0.003	-0.006	0.003	-0.006	0.002	-0.007	0.003	-0.006
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)
MSM D.×H. Mal. Risk		0.014**		0.015**		0.015**		0.013**
		(0.005)		(0.006)		(0.006)		(0.005)
Prec. D.×H. Mal. Risk	0.001	0.000					0.000	0.000
	(0.001)	(0.001)					(0.001)	(0.001)
Temp. D.×H. Mal. Risk			-0.015	-0.011			-0.011	-0.010
			(0.023)	(0.023)			(0.028)	(0.028)
SPEI. D.×H. Mal. Risk					0.002	0.001	-0.002	-0.002
					(0.015)	(0.015)	(0.017)	(0.017)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,340	38,340	38,340	38,340	38,340	38,340	38,340	38,340
R-squared	0.227	0.227	0.227	0.227	0.227	0.227	0.227	0.227
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted, relative to the cell-specific mean over the observation period;"High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. The "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the respective year. The "Weather Lags" include the first two lags of the same variables. Standard errors clustered at the country level are reported in parentheses, (·). The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

contiguous cells. The results confirm that the occurrence of malaria suitable weather conditions leads to an increase in the incidence of violent events in cells with "High Malaria Risk". These results are unaffected by controlling for lags of weather conditions and the occurrence of violence in the past year. In terms of quantitative importance the effects is very similar to the pooled OLS results; the occurrence of an additional month with suitable conditions for malaria increases the risk of violence by almost 10% in cells with high malaria risk compared to cells with low malaria risk. This also indicates that the effect of malaria risk is essentially unaffected by controlling for cell-specific characteristics.

4.3 Within-Cell Variation – Monthly Panel

Temporary shocks to malaria risk are, by their nature, closely confined in terms of time and space. The reason is that, as discussed in Section 3, short term malaria risk depends on local geographic conditions (reflecting the overall suitability for the multiplication of the vector and thus the transmission of malaria) and temporary fluctuations in weather conditions (that enable or prevent the reproduction of anopheles mosquitos and of the *plasmodium* parasite, and thus the multiplication

Table 4: Malaria Risk and Violence - Within-Cell Variation Yearly Data

Dependent Variable	Violent Events - ACLED Yearly Data						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Malaria Suitable Months	0.002	0.002	-0.008	-0.008	-0.005	-0.007	-0.005
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005))	(0.004)	(0.004)
	[0.004]	[0.003]	[0.005]	[0.005]	[0.005]	[0.008]	[0.005]
MSM×High Malaria Risk			0.015**	0.017**	0.013**	0.017**	0.013**
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
			[0.007]	[0.006]	[0.006]	[0.007]	[0.006]
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags	No	Yes	Yes	Yes	Yes	Yes	Yes
Conflict Lag	No	No	No	No	No	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	No	No	No	No
High M. Risk× Year FE	No	No	No	Yes	No	Yes	No
Country × Year FE	No	No	No	No	Yes	No	Yes
Observations	38,340	38,340	38,340	38,340	38,340	38,340	38,340
R-squared	0.465	0.467	0.467	0.468	0.521	0.473	0.523
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted, relative to the cell-specific mean over the observation period; "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the respective year. The "Weather Lags" variables include the first two lags of the "Weather Time-Varying". Panel data from 1998 to 2012 at yearly frequencies. The unit of observation is a 1 x 1 degree cell. Standard errors clustered at the cell level are reported in parentheses, $(\cdot)$, and Conley standard errors allowing for spatial and serial autocorrelation up to the threshold of 400 km are reported in square brackets, $[\cdot]$. ***, **, * indicate significance at 1-, 5-, and 10-% level computed using the largest standard errors (cell clusters or Conley) of each specification.

and transmission of malaria). The "Malaria-Suitable Month" variable has been designed by epidemiologists for the purpose of predicting the threat of malaria outbreaks at the month level. The high degree of temporal disaggregation is possible because of the short incubation period of malaria, which implies that suitable conditions should be expected to translate into elevated malaria risk within the same month or, if the health shocks peaks in the second part of the month, possibly in the following month. We continue the analysis by exploiting this specific feature and use the data at the monthly level. At monthly frequencies the variable "Malaria Suitable Month" is a binary indicator. Again, the effect of malaria suitable periods is expected to translate into increased malaria transmission mostly in "High Malaria Risk" cells.

An important advantage of using data at monthly frequencies is that it allows us not only to rely on within-cell variability over time, but it also provides the possibility to include cell×year fixed effects, which account for time-varying unobserved heterogeneity. Estimating such a rich specification thus provides an important advantage for the econometric identification as the estimation model accounts for all cell-year specific determinants of civil violence. Notice that the specification additionally accounts for all factors that increase conflict with lags at yearly frequencies. Estimating a model with cell-year fixed effects therefore accounts for factors like the effect of (lagged) income shocks,

political instability, natural disasters, or the increase in violence due to variation in the prices of commodities at yearly frequencies that have been explored in the recent literature using disaggregate data for Africa. The effects of these, and potentially other, cell-year specific factors are subsumed in the cell-year fixed effects, implying that the identification of an increased risk of civil violence due to variation in malaria exposure constitutes an additional factor above and beyond the factors identified in the literature.

Table 5 reports the main results obtained with data at the monthly level for different specifications. The specifications in Columns (1) and (2) include cell dummies and month dummies (standard two-way fixed effects), as well as controls for weather in the past 12 months (in terms of temperature, precipitation and the SPEI index).[41] Column (1) shows that (unusual) malaria suitable months in a given month do not have any significant effect on violent events on average. The results in column (2) confirm the earlier findings at yearly frequencies that unusual malaria suitable months have a positive, and sizable, effect on the likelihood of civil conflicts in "High Malaria Risk" cells. Compared to an unconditional probability of violence around 4% (0.044), the coefficient estimate of 0.008 in Column (2) implies an increase in the risk of violence of 18% when suitable weather conditions for malaria outbreaks occur in areas with a high structural risk of malaria outbreaks. Again, this corresponds to a lower bound of the actual effect of malaria outbreaks on conflict when considering that these effects are intention-to-treat.

The results in Columns (3)-(5) include cell×year fixed effects, that account for all observed and unobserved cell specific determinants of violence in a given year, and calendar month or month fixed effects, that accounts for specific months involving unusual violence across cells and temporary (e.g., seasonal) fluctuations in conflicts, respectively. Finally, Column (6) extends the specification to a dynamic panel model that accounts for past violent events. The results are essentially unaffected.

We performed several robustness checks to explore the sensitivity of the results. The robustness checks include estimates of extended models that include separate calender month fixed effects for cells above and below the equator and for cells in low and high malaria risk areas.[42] The baseline patterns also emerge with non-linear estimators.[43] Finally, as with the yearly data, the findings are robust to the inclusion of additional interactions between the high malaria risk indicator with

[41]The specification controls for weather conditions in each cell×month (again in terms of temperature, precipitation and SPEI) and the respective lags in the previous twelve months. The results are also confirmed with more parsimonious specifications that do not include weather controls. Without these controls, the occurrence of malaria suitable months may pick up unsuitable fighting conditions and/or good conditions for agriculture, see Table A2 in the Appendix.

[42]See Table A3 in the Appendix for these robustness checks.

[43]The baseline analysis has been conducted using a linear probability framework in light of the fact that the identification approach implies that the coefficient of main interest refers to an interaction term along the lines of a difference-in-difference framework. Replicating the main results using conditional Logit (fixed effects) estimators delivers similar results, suggesting that the main findings do not depend on the estimation method. The results are reported in Table A4 in the Appendix.

Table 5: Malaria Risk and Violence: Baseline - Monthly Data Panel

Dep. Variable	Violent Events - ACLED Monthly Data					
	(1)	(2)	(3)	(4)	(5)	(6)
Malaria Suitable Month	0.001	-0.003	0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
MSM×High Malaria Risk		0.008***		0.007***	0.007***	0.007***
		(0.003)		(0.003)	(0.003)	(0.003)
		[0.003]		[0.003]	[0.003]	[0.003]
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	No	No	No	No
Month×Year FE	Yes	Yes	No	No	Yes	No
Cell×Year FE	No	No	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	No	Yes
Violence Lag	No	No	No	No	No	Yes
Observations	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.242	0.242	0.413	0.413	0.414	0.413
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator that takes value 1 if the conditions in the given month in the given cell were suitable for malaria to be transmitted, and 0 otherwise; "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors clustered at the cell level are reported in parentheses, $(\cdot)$, and Conley standard errors allowing for spatial and serial autocorrelation up to the threshold of 400 km are reported in square brackets, $[\cdot]$. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

weather conditions in terms of precipitation, temperature, or precipitation and evapotranspiration (SPEI), respectively.[44] The estimation of extended specifications delivers results that are essentially unchanged.

4.4 Robustness: Coding of Violent Events

The analysis so far has focused on the occurrence of violent events of any type in a given cell in a given month. One issue that has been raised in the context of ACLED data on violence is the possibility of selective reports and differential coverage across different locations in Africa. This might be potentially problematic when exploiting variation across cells. By exploiting variation within cells and conditioning on cell-year-specific intercepts, our analysis appears to be less affected by these concerns. Nevertheless, it is difficult to completely rule out selective reporting, for instance related to the conflict types. Also, the precise geo-localization is more uncertain for some events. The high concentration of violence in specific regions leads to the question whether the results are affected by their exclusion. Moreover, instead of considering the incidence of violence, it might also be interesting to explore the role of malaria risk for the onset and termination of violent events. In

[44] See Table A5 in the Appendix.

the following, we briefly discuss the results of further robustness checks that explore these issues. The respective results are reported in the Appendix.

Events with uncertain location. The first set of robustness checks refers to the fact that for some of the conflict events in the ACLED data set the precise location is not identified. Whenever this is the case, the default in the ACLED data set is that the events are attributed to the respective capital of the country. However, there is some uncertainty regarding the reliability of this coding. To check the robustness of the results in this respect, the analysis was repeated by eliminating the conflicts that are not clearly identified in space and thus attributed to the capital city. The findings are qualitatively and quantitatively unaffected.[45]

Neuralgic Conflict Regions. In order to check to what extent the findings are driven by particular conflict events, or by events of violence that are concentrated in neuralgic regions, for instance the resurgent conflicts in Rwanda and Burundi, we replicated the analysis on a sample that excludes such regions. This delivers qualitatively and quantitatively virtually identical results.[46]

Onset and Termination. When investigating the onset of a violent event in a given cell and month, the results are qualitatively similar, but quantitatively smaller. In particular, there is a positive effect of the occurrence of favorable climatic conditions for an outbreak of violence in high risk cells compared to low risk cells. This is mirrored by a negative effect when looking at the termination of conflict as dependent variable. A similar pattern is observed also for termination of violence although the effect is less precisely estimated.[47]

Casualties. Another robustness check explores the intensive margin of violence. The results indicate that casualties caused by violent events are on average lower during months with particularly suitable conditions for malaria outbreaks in low risk areas. However, there is a positive effect of the advent of malaria suitable months in high risk cells.[48]

5 Isolating the Effect of Malaria

This section provides a more detailed exploration of further implications from the epidemiology of malaria. The purpose of the analysis is to obtain additional evidence regarding the robustness of the baseline findings reported in the previous section and to gain additional insights into the working of the health channel for civil violence.

[45]Uncertain events are coded as no conflict incidence, which implies a somewhat lower unconditional probability of conflict in the estimation sample. Table A6 in the Appendix contains the respective results.

[46]Table A7 in the Appendix documents this by presenting results for samples that do not include cells with centroids in Rwanda and Burundi, or that do not contain cells in North Africa (defined as cells with centroid in Morocco, Tunisia, Algeria, Lybia, or Egypt).

[47]See Table A8 in the Appendix.

[48]The results are based on Tobit models and reported in Table A9 in the Appendix.

5.1 Latent Malaria Risk

The dichotomous representation of latent malaria risk, and the use of a binary indicator of high latent malaria risk, is convenient since it limits possible concerns about measurement error in the malaria transmission stability. Moreover, the binary measure allows for a straightforward interpretation of the estimation results and of the magnitude of the effects in terms of a standard difference-in-differences setting. From an epidemiological perspective, however, malaria risk should not be interpreted as being dichotomous, but it should decrease with the intensity of past exposure to malaria. To explore the latent malaria risk in further detail we report the results of several robustness checks that follow from the insights of research in epidemiology.

Alternative Coding of High Malaria Risk Cells. The analysis so far has used a binary indicator for high and low risk of malaria outbreaks, based on wether for a given cell the index of malaria transmission stability by Kiszewski et al. (2004) takes on values below or above a threshold of 15, respectively (with zero stability coded as low risk). We investigated the robustness of the results with respect to this coding of malaria risk in several ways. The results turn out to be robust and qualitatively as well as quantitatively very similar for alternative thresholds.[49]

The role of cells with Malaria Stability equal to zero. The empirical analysis so far has employed a coding of cells with a malaria transmission stability index of 0 and cells with an index above a certain threshold x (e.g., 15) as low risk cells. Cells with an index in the range $(0, x)$ have been coded as high risk cells. Since malaria prevalence is effectively ruled out in cells with a malaria transmission stability index of 0, these cells might alternatively be seen as reflecting no risk instead of low risk. In view of malaria epidemiology the results should therefore not be driven by the inclusion of these areas. Specifications that exclude cells with zero malaria stability deliver very similar results.[50] Alternatively, estimating the effect of the occurrence of a malaria suitable month on conflict in cells with a malaria stability index of 0 delivers no evidence for an effect.

Interactions with Geographic Features. The latent malaria risk might be related to other geographic specific characteristics that are not fully accounted for by the dichotomous coding into high and low risk areas based on a threshold for the malaria transmission stability index. To explore this possibility, we estimated models with an extended specification that include additional interactions between malaria suitable months and land suitability, terrain ruggedness and elevation, respectively. The results of these estimates could also be informative about the features of the local geography

[49]Table A10 in the Appendix illustrates this by presenting the estimation results obtained with a high malaria risk variable that based on alternative upper thresholds of 10 and 20 for the malaria stability index, respectively. Very similar results are obtained for data with yearly frequencies. Figure A5 in the Appendix plots the corresponding coefficient estimates when varying the upper thresholds between 5 and 25 on the malaria stability index to code high risk areas.

[50]Table A11 in the Appendix.

that might have affected the historical exposure to malaria and therefore the latent malaria risk. The results reveal an unchanged positive interaction between MSM and high malaria risk. The additional interactions do not reveal a clear pattern that allows to substantially qualify the main findings, even though some are statistically significant.[51]

The Role of Population Density. The transmission cycle of malaria requires both suitable conditions for the reproduction, development and proliferation of the *anopheles* vector. A higher population density might be expected to act as a catalyst for the proposed mechanism, even though in contrast to diseases that can be transmitted directly from human to human, such as Ebola, population density is not as relevant for the transmission of the pathogen. To check that high malaria risk cells do not merely capture peculiar patterns in population density, we also considered an extended specification that adds an interaction between malaria suitable months and population density in the cell. The analysis does not reveal significant effects of population density.[52]

Interactions with Trypanosomiasis and HIV. Violent events appear to be concentrated in areas with a low malaria transmission stability but with the presence of mainly homophilic varieties of the *anopheles* mosquito such as *gambiae* or *funestus*, see, e.g., Figure 1 in Kiszewski et al. (2004). One potential confound in this context could be the presence of vectors that transmit other diseases than malaria, but that require similar habitats as *anopheles*. Alsan (2015) documents that (predicted) suitability for TseTse fly prevented the use of domesticated animals and the plow in particular areas in Africa, leading to lower political centralization, lower population density, and ultimately lower economic performance. Similar to *anopheles*, the TseTse fly takes blood meals from vertebrate and transmits diseases, in particular Trypanosomiasis, a pathogen that causes sleeping sickness in humans and nagana in domesticated animals. To explore whether the effect is confined to malaria, we extended the specification by including an additional interaction between the (predicted) suitability for the TseTse fly (*glossina*) and the occurrence of malaria suitable months. The results confirm the baseline findings and do not reveal any significant interactions between malaria suitable months and exposure to the vector of Trypanosomiasis, thereby providing an over-identification test in view of the different short term conditions for favoring temporary increases in the transmission of Trypanosomiasis and malaria.[53] We also replicated the analysis using an extended specification that accounts for the prevalence of HIV infections. The results suggest that the effect of the occurrence of suitable conditions for malaria does not interact with HIV prevalence, reflecting the fact that HIV transmission is not directly related to variation in weather conditions specific to malaria, comple-

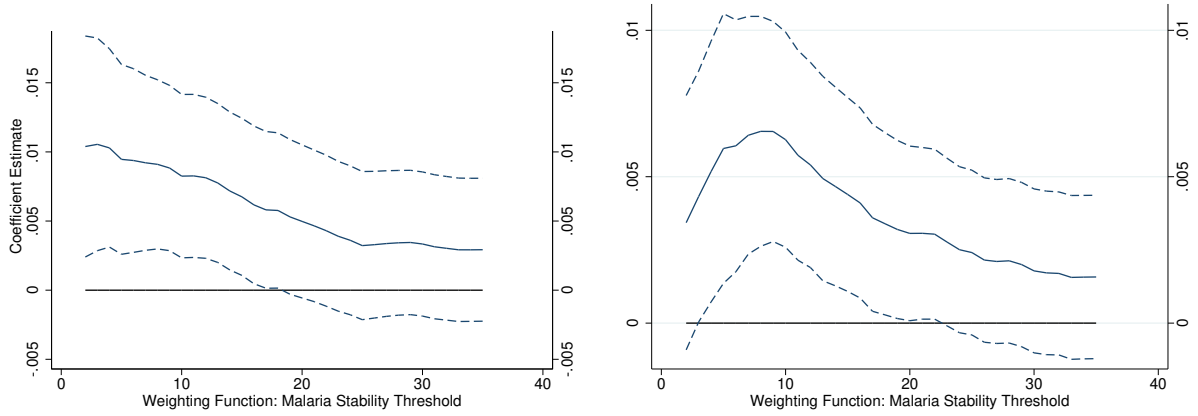
[51]See Table A12 in the Appendix for details.

[52]See Table A13 in the Appendix.

[53]See Table A14. Alternatively, this result provides an interesting placebo test in light of the fact that suitability conditions for TseTse flies and malaria transmission are slightly different, with TseTse flies exhibiting a relatively stable population pattern compared to the more complex relationship between malaria vector habitat and vector abundance in the context of variation temperature and precipitation (see, e.g., Kulkami et al., 2010).

menting recent evidence on the implications of weather-related income shocks for HIV prevalence in Africa by Burke et al. (2014).[54]

Weighted Regressions. Finally, to go beyond the dichotomous coding of high risk areas, we consider local regressions by estimating the model using a weighting scheme, where malaria risk is coded as 1 for values of the index constructed by Kiszewski et al. below a threshold, and then with lower weights that are gradually decreasing to zero as the index approaches its maximum value. Figure 6 provides a graphical illustration of the coefficient estimates obtained with such a weighting scheme applied to yearly and monthly data, respectively.[55] The findings indicate that the coefficient is largest when increasing the weight of cells in which malaria transmission is unstable, and where as a consequence the risk of malaria outbreaks in response to particularly suitable weather conditions is highest as the population can be expected to exhibit only low levels of acquired immunity. Gradually giving more weight to cells in which malaria transmission is more stable reduces the coefficient, in line with the hypothesis that the occurrence of suitable weather conditions imposes a lower immanent threat in areas where malaria is more widespread and frequent (and thus resistance and immunities are higher).



(a) Yearly Data

(b) Monthly Data

Figure 6: Coefficient Estimates for Weighted Regressions with Different Thresholds of High Risk

[54]HIV prevalence data are only available at country level. Detailed results are reported in Table A15 in the Appendix.

[55]The results are insensitive to the particular weight function used; the figure shows results for a weighting function that gives weight 0.1 to malaria stability index 0, weight 1 to malaria stability index up to the respective threshold depicted on the horizontal axis; above this threshold the weight is hyperbolically decreasing with a weight function of the form $\frac{1}{(index-threshold)+1}$. Alternatively, we experimented with a weight function $\frac{(1-0.1)}{36.41181-threshold}(index-12)$ with very similar results.

5.2 The Effect of Short Term Fluctuations in Risk

The results so far suggest that it is the combination of particularly suitable conditions for the development of the malaria parasite and vector, and not simply changes in weather conditions in terms of temperature and precipitations that trigger the effect on violence in high malaria risk cells. In this section, we explore the sensitivity of the findings to alternative codings of the malaria suitable months index and we investigate the timing of the effect more explicitly by including lags and leads as additional falsification exercise.

Sub-conditions of Malaria Suitable Month Index. To investigate in more detail whether it is one particular of the four conditions that is critically responsible for the effect, we replicated the analysis using each of the conditions in isolation, and in combination with the MSM index, as explanatory variable. The results show that it is indeed the combination of the different conditions, and not the occurrence of a single condition, that drives the findings.[56] The results provide additional evidence in support of the identification of malaria shocks imposed by the epidemiology of malaria.

Alternative Coding and Extended Sequences of Malaria Suitable Months. Given the short incubation period of malaria the effect of malaria suitable months should be detected mostly on impact. The baseline coding of MSM is conservative, however, since suitable weather conditions, which require several months to build up, could materialize in the second part of a given month, with little impact on violence. We accordingly recode the MSM index coding a month as malaria suitable if the conditions are met in a given month or in the previous one. The effect is comparable to the baseline. Having malaria suitable conditions for two subsequent months should be expected to amplify the effect on increased malaria transmission. To explore this prediction we recode MSM index in a more restrictive way by requiring suitable conditions to be in place in at least two subsequent months. The results confirm the positive effect of MSM in high risk areas. In line with the conjecture, the effect is quantitatively larger than in the baseline, even though the number of months fulfilling this more restrictive criterion is lower.[57]

Timing of the Effect. In order to check more directly the prediction that increase in malaria transmission risk should be on impact, and to get a better understanding of the dynamic pattern of effects, we also estimated extended specifications that include lags in the indicator for malaria suitable months and its interaction with the high malaria risk indicator. The results confirm that the effect is mostly on impact. The panel structure of the data thereby lends itself to a further falsification check by exploiting the leads of malaria suitable months. Figure 7 plots the coefficient estimates of a specification that includes the current occurrence as well as two lags and leads The

[56] See Table A16 in the Appendix. The third condition, the requirement that no month in the past 12 months had an average temperature below 5^oC, turns out to be redundant in the baseline estimation sample.

[57] See Table A17 in the Appendix for details.

results document that future occurrence does not impact on violent events.[58] Unreported estimates deliver similar results for higher numbers of lags and leads of malaria suitable months as well as their interaction with high malaria risk.

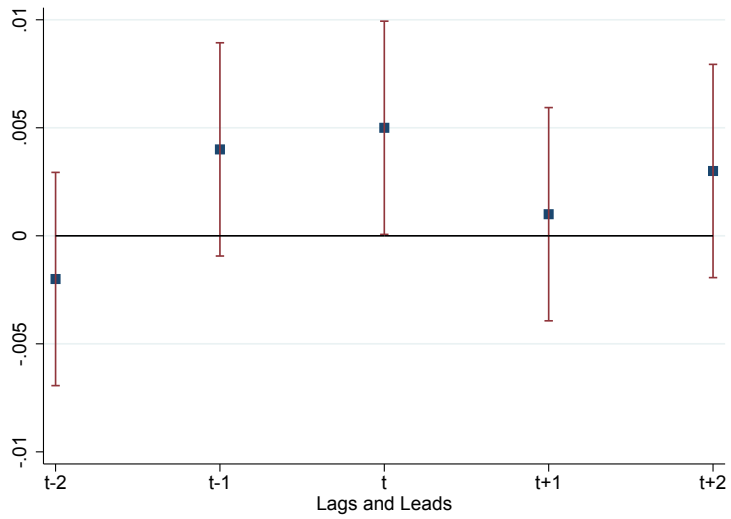


Figure 7: Coefficient Estimates of Lags and Leads. 90% confidence intervals.

5.3 Spatial Spillovers and Diffusion Effects: Spatial Models

The baseline results so far accounted for spatial clustering by allowing standard errors to be correlated across spatially contiguous cells, following the approach by Bester et al. (2011). Given the spatial disaggregation, the data provide the possibility for a more detailed analysis of spatial contiguities, both in terms of the spread of malaria risk due to suitable geo-climatological conditions and in terms of the diffusion of violent events across space. We explicitly allow for spatial contiguities in the dependent variable, estimating spatial autoregressive models (SAR).[59] To account for potential spatial autocorrelation in the explanatory variables, i.e., in the occurrence of suitable conditions for malaria outbreaks in a given month or in weather conditions in general, we also estimate spatial

[58] Table A18 in the Appendix presents the respective results with two lags and leads separately.

[59] In particular, we estimate a spatial autoregressive model of the form

$$Violence_{i,c,t} = \rho \sum_j w_{ij} Violence_{j,c,t} + \alpha MSM_{i,c,t} + \beta HR_{i,c} \times MSM_{i,c,t} + \Gamma X'_{i,c,t} + \Delta Z'_{i,c,t-1} + \Phi_{i,c,t} + u_{i,c,t}$$

where w_{ij} represents the elements of the ith row of a (row-normalized) spatial contiguity matrix W_i that contains information on the cells j with a direct common border to the cell under consideration, i. Diagonal elements equal to zero. The model is estimated using maximum likelihood. See, e.g., Elhorst (2009) for details on spatial models and their estimation.

Durbin models (SDM).[60]

Table 6 presents the results for panel specifications exploiting within-cell variation that account for spatial autocorrelation in the dependent and independent variables (SAR and SDM) at both yearly and monthly frequencies. Notice that these specifications are extremely demanding specifications both in terms of the residual variation left in the data for identification, and in terms of computational effort.[61] The table reports the direct effects as well as the total effects that take potential spatial spill-overs into account. The results are qualitatively similar and quantitatively even slightly stronger in terms of total effect compared to the baseline results. One interesting aspect of the results is that the difference in the estimates of the direct effect and the total effect is suggestive of spill-overs across cells, and of diffusion. In particular, there appear to be spill-overs in conflict from neighboring cells, as shown by the results from the spatial autocorrelation model, suggesting a diffusion of conflict across space. However, the results of the spatial Durbin models indicate that also the reduced-form effect of suitable conditions for malaria outbreaks leads to effects spilling over from contiguous cells. Given the fine geographic resolution of the data, it is not surprising to find that spatial correlations play some role, in particular when considering the explanatory variables in the context of the Spatial Durbin model. This provides a novel aspect to the discussion about spatial clustering of conflicts (see Buhaug and Gleditsch, 2008). The results are also robust to running weighted spatial models, instead of the binary indicator of high malaria risk, to account for latent malaria risk more flexibly.[62]

5.4 Genetic Immunities in the Population

The main argument for expecting heterogeneous responses to the occurrence of climatic conditions that favor the outbreak of malaria according to the malaria stability index is the lower preparedness of the population in areas with low but positive malaria stability. In these regions, the exposure is not high enough to lead to genetic immunity or social institutions to cope with malaria outbreaks

[60] In particular, a model of the form

$$\begin{aligned} Violence_{i,c,t} &= \alpha MSM_{i,c,t} + \beta HR_{i,c} \times MSM_{i,c,t} + \zeta \sum_j w_{ij} MSM_{j,c,t} + \xi \sum_j w_{ij} HR_{j,c} \times MSM_{j,c,t} \\ &\quad + \Gamma X'_{i,c,t} + \Delta Z'_{i,c,t-1} + \Phi_{i,c,t} + u_{i,c,t} \end{aligned}$$

is estimated by maximum likelihood, where where w_{ij} represents the elements of the ith row of (row-normalized) spatial contiguity matrix W_i that contains information on the cells with a direct common border to the cell under consideration, i.

[61] The models are estimated by maximum likelihood. The estimates at monthly frequencies with two ways fixed effect for the whole of Africa involve dealing with about half a million observations that involve 150 time series observations for about 2600 cells, which are connected by a unique invertible contiguity matrix. The estimate in the most extensive (and computationally intensive) specifications allows for two lags over time and in space in both violent events, malaria risk and the weather covariates. We are not aware of any previous attempt to estimate comparable spatial models at monthly frequencies for a grid map of the entire African continent.

[62] See Table A19 in the Appendix for details.

Table 6: Malaria Risk and Conflict Events: Accounting for Spatial Effects

Dependent Variable	Violent Events - ACLED - Yearly and Monthly Data			
Model	Spatial Autoregressive Model - SAR		Spatial Durbin Model - SDM	
	(1)	(2)	(3)	(4)
Direct Effects:				
Malaria Suitable Month(s)	-0.004	-0.002**	0.004	-0.002
	(0.002)	(0.001)	(0.003)	(0.001)
MSM×High Risk	0.012***	0.008**	0.006	0.006**
	(0.004)	(0.001)	(0.005)	(0.002)
Total Effects:				
Malaria Suitable Months	-0.007	-0.004*	-0.018***	-0.004
	(0.004)	(0.001)	(0.007)	(0.002)
MSM×High Malaria Risk	0.020***	0.012***	0.030***	0.014***
	(0.006)	(0.002)	(0.009)	(0.003)
Panel Frequency	Yearly	Monthly	Yearly	Monthly
Weather	Yes	Yes	Yes	Yes
Weather Lag(s)	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Month×Year FE	No	Yes	No	Yes
Observations	38,340	457,560	38,340	457,560
Number of Cells	2556	2542	2556	2542

Estimates from spatially augmented models (SAR, SDM), estimated by Maximum Likelihood. The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year (yearly data) or in the given month (monthly data). MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted (yearly data) or a binary indicator of suitable conditions in the given month (monthly data); "High Malaria Risk Area" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15. "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the respective year. The "Weather Lags" variables include the first two lags of the "Weather Time-Varying". The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequencies. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. Conley standard errors allowing for spatial and serial autocorrelation are reported in parentheses, $(\cdot)$. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency in Columns (1) and (3), at monthly frequency in Columns (2) and (4). ***, **, * indicate significance at 1-, 5-, and 10-% level.

(see also Cervellati et al., 2016). Previous results on the differential role of malaria suitable months in cells with different long term exposure to the disease are compatible with differentials in (genetic or acquired) immunization of the population.

Suitable weather conditions for malaria transmission in high risk cells should materialize in a lower malaria risk if larger fraction of the population has some form of genetic immunity. To test this prediction more explicitly we exploit information on the prevalence of the sickle cell trait and extend the specification including additional interactions between the prevalence of genetic immunities and MSM in Low and High Malaria Risk areas. The results are reported in Table 7. The baseline finding of a positive interaction between malaria suitable months and high malaria risk cells remains essentially unchanged. However, a higher prevalence of genetic immunity tends to significantly reduce the effect of malaria risk on civil violence but only within high risk areas.

Ethnic Groups and Genetic Immunities. Research in evolutionary genetics highlights that the development of specific immunities took place at the level of ethnic groups. High levels of ethnic

Table 7: The Role of Genetic Immunity (Sickle Cell Trait)

Dependent Variable	Violent Events - ACLED Monthly		
	(1)	(2)	(3)
Malaria Suitable Month	-0.007*	-0.006*	-0.008*
	(0.004)	(0.003)	(0.004)
Malaria Suitable Month×High Risk	0.016***	0.013***	0.016***
	(0.005)	(0.004)	(0.005)
(MSM)×Genetic Immunities (Sickle Cell)	0.005	0.005	0.001
	(0.004)	(0.004)	(0.001)
(MSM)×Genetic Immunities (Sickle Cell)×High Risk	-0.013**	-0.011**	-0.002**
	(0.005)	(0.005)	(0.001)
Sickle Cell Trait Prevalence	> Median	> Mean	Percentage
Weather	Yes	Yes	Yes
Weather Lags	Yes	Yes	Yes
Cell×Years Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	457,560	457,560	457,560
R-squared	0.414	0.414	0.414
N. of Cells	2556	2556	2556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; "High Malaria Risk Area" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; see text for details. "Genetic Immunities" is: i) an indicator variable taking value 1 if the average level of sickle cell disease in the cell is higher than the median in the sample and 0 otherwise, ii) an indicator variable taking value 1 if the average level of sickle cell disease in the cell is higher than the mean in the sample and 0 otherwise, iii) the average frequency of sickle cell disease in the cell. See text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current period, the "Weather Lags" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

endogamy strengthened the process of genetic selection of the human genome and favored the emergence of group specific immunities, see e.g. Modiano et al. (1996) and Dolo et al. (2005). Ethnic groups with lower genetic resistance to malaria may be relatively more exposed to an outbreak in the context of the occurrence of suitable conditions of malaria transmission. Lack of disaggregate data at the level of ethnic groups for Africa prevents explicitly checking the role of differential immunities across different ethnic groups for the effect of malaria risk in affecting violence involving them. We therefore explore this aspect in reduced form by looking for heterogenous effects in terms of the number of ethnic groups in a cell, within-cell variation (standard deviation) in the prevalence of sickle cell traits, and the interaction between these two dimensions. The results suggest a stronger effect of malaria risk in cells in which several ethnicities cohabitate, and where the variability in the immunity trait is higher.[63]

[63]See Table A20 in the Appendix for details. This evidence is consistent with differential levels of genetic immunity across ethnicities bing a potential channel for the effect of malaria on conflict. For instance, some of the reports mention conflicts involving the Fulani (Peuhl) ethnicity, which is less susceptible to malaria than other, sympatric ethnicities, see, e.g., Dolo et al. (2005), Rose-Wood et al. (2010), or Maiga et al. (2013). However, the the lack of disaggregate data at the levels of ethnic groups prevents to test this conjecture more directly.

6 Isolating Economic Mechanisms

This section explores the economic mechanisms behind the role of the increase in malaria risk. The literature has explored the determinants of confrontations between different groups in Africa with a special focus on ethnicity-based conflicts and struggles between different armed groups for the control of territories. As discussed in Section 1, an elevated malaria risk should be expected to be particularly relevant for unorganized violence leading to social unrest and violent confrontations affecting the civilian population and, possibly, episodes of predation and raids of local communities.

Social Unrest and Violence Involving Civilians. Table 8 replicates the baseline analysis for monthly data but restricts attention to the subset of violent events that involve riots or protests, violent confrontations involving militias and civilians, and fights between militaries (including the police) and rioters or protesters.

Table 8: Actors and Events: Unorganized and Social Violence

	Violent Events - ACLED								
Actors	Rioters/Protesters			Militias vs Civilians			Military vs Rioters/Prot.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Malaria Suitable Month	0.000	-0.000	0.000	-0.001	-0.001	-0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MSM×High Risk	0.002**	0.003***	0.002*	0.004**	0.004***	0.003*	0.001*	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	No	No	Yes	No	No	Yes	No	No
Month×Year FE	Yes	No	No	Yes	No	No	Yes	No	No
Cell ×Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	457,560	457,560	457,560	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.156	0.302	0.302	0.169	0.331	0.331	0.129	0.275	0.275
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month that involved the respective actors listed. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; "High Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index in the range (0,15); see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current period, the "Weather Lags" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

The results show that the occurrence of malaria suitable conditions increase the likelihood of violent events involving rioters or protesters and confrontations between militias and civilians. The effect is statistically marginally significant even when accounting for cell-year and month fixed effects.[64] There is also some evidence of increases in violence between civilians and militaries, although

[64]Notice the context of our identification strategy, this is a very demanding exercise, given the low unconditional probability of violent events of different types at the monthly level, and since the analysis accounts for cell-year fixed effects and month fixed effects.

the effect is smaller and statistically less significant. We find no evidence of a significant effect of malaria risk on geo-strategic events in terms of confrontations involving rebel groups, confrontations between militaries and rebels and events involving only militaries (including non violent events involving changes of control of territories and changes of headquarters).[65]

Health Shocks as Income Shocks: Malaria Suitable Months during Harvesting Periods. Malaria outbreaks are relevant income shocks. A single bout of malaria has been estimated to induce an income damage to a sum equivalent to 10-20 working days.[66] Among the central costs of malaria besides health impairment are reduced income or agricultural production because illness prevents individuals from working on their fields. Temporary increases in malaria transmission tend to affect local communities at large rather than single individuals. This makes malaria exposure particularly damaging during harvesting periods of important crops in each location.[67] The role of harvesting periods for violence is, per se, a priori ambiguous. On the one hand harvesting periods are critical for the production of the year in particular for staple and cash crops, which implies an elevated opportunity cost of violence with respect to production during these months. On the other hand during harvesting periods the population is more exposed to risk of looting and predation (particularly for storable crops). The occurrence of malaria shocks during harvesting unambiguously represents a negative income shock.

To identify such critical moments during the crop cycle we collected data on the harvesting seasons for the prevalent crops in each cell. The original data comes from the FAO crop calendar that reports information at the level of agro-ecological regions and that is mapped into our grid of cells. We use several alternative definitions for harvesting season at the cell level. Harvest seasons are coded as a binary indicator that takes value one during the harvesting months for each specific crop in each cell.[68] Information is then aggregated using different possible bundles of crops that are ordered in terms of energy content and in terms of the duration of the harvesting season.[69]

The results are presented in Table 9.[70] The findings indicate no evidence for an increased conflict intensity during harvest periods when looking at crops with harvesting seasons of any length or lasting (at least) four months, see Columns (1) and (2). Neither is there evidence for an interaction

[65]See Table A21 in the Appendix.

[66]See, e.g., Onwujekwe et al. (2000), Deressa et al. (2007), Sicuri et al. (2013) and `http://malaria.jhsph.edu/about-malaria/`.

[67]Estimates of the cost of malaria vary substantially depending on the marginal product of labor, see, e.g., Chima et al. (2003), or Arrow et al., (2004, Ch. 7).

[68]Different geo-climatological conditions imply that the same crop may have different harvesting seasons in different cells. The measures are constructed based on satellite images, see Table D3 for details.

[69]Harvest season information is available at the level of months, but is constant over the years. See the Appendix for a more detailed description of the construction of the data and Table D3 for a description of the different measures.

[70]Instead of using the binary indicator of latent malaria risk, identification is based on the more parsimonious weighted regression approach, which allows for a non dichotomous level of latent malaria risk and thereby avoids having to estimate additional main effects and interaction terms.

between the occurrence of malaria suitable conditions and harvest seasons. The results in Columns (3)-(5) indicate that conflicts are less likely to occur during harvesting seasons when harvest seasons are short, in particular for crops with high caloric value, possibly because of an increase in the opportunity costs of conflict. At the same time, the effect of the occurrence of malaria suitable months in high risk cells is amplified during these periods. The effect is stronger for crops with more caloric yield (and thus higher nutritional importance), and for crops with shorter harvest seasons. Additional unreported results confirm that the effect is monotonically decreasing the longer the harvest season and the lower the calory content of the respective crops harvested in a given cell and month.[71]

Table 9: Staple Crops and Malaria Risk during Harvest Seasons

Dependent Variable	Violent Events - ACLED Monthly Data				
Energy Restriction	>1000 KJ any length	>1000 KJ ≥4 months	>500 KJ ≤2 months	>1000 KJ ≤2 months	>1500KJ ≤2 months
	(1)	(2)	(3)	(4)	(5)
Malaria Suitable Month$_{HR}$	0.004*	0.005**	0.004*	0.003	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MSM$_{HR}$×Harvest Period	0.001	-0.000	0.007**	0.015***	0.016***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)
Harvest Period	-0.000	-0.001	-0.001	-0.008***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Weather	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes
Cell× Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	360,730	360,730	360,730	360,730	360,730
R-squared	0.442	0.442	0.442	0.442	0.442
Number of Cells	2,556	2,556	2,556	2,556	2,556

Weighted OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month"$_{HR}$) is an indicator that takes value 1 if the conditions in the given month in the given cell were suitable for malaria to be transmitted (monthly data), weighted by malaria risk coded as 1 for values of the index constructed by Kiszewski et al. (2004) below a threshold, and then with lower weights that are gradually decreasing to zero as the index approaches its maximum value; see text for details. Harvest period is a binary indicator for the month being a harvest month for the respective crop. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

For completeness and comparison to the literature that focuses on income shocks in terms of weather fluctuations during the growing season rather than the harvesting season, we also investigated the effect of suitable conditions for malaria transmission during the growing season.[72] These

[71]Following Henderson et al. (2012), we also checked the effect of malaria suitable months on night lights which can be informative on short term changes in income in reduced form. The results reported in Table A22 document, in particular, a negative effect of malaria suitable months in night light intensity in high risk areas which is in line with the evidence by Cervellati, Esposito and Sunde (2017). These checks also document, however, that the baseline findings are robust to including night lights as covariates suggesting the income effect of malaria risk is not fully picked up by changes in night light intensity at yearly frequencies.

[72]Growing season is constructed as a binary indicator variable taking value 1 if a cell faces temperature and moisture

estimates complement the findings by Harari and La Ferrara (2016) and Hodler and Raschky (2014), who investigated the role of weather fluctuations for income shocks in agriculture in Sub-Saharan Africa, following the insights of the seminal works by Miguel, Satyanath, and Sergenti (2004) and replicating them at the subnational level using different identification approaches. Note that changes in precipitation may have heterogeneous effects, affecting on one side rain-fed agriculture and on the other side malaria risk. In particular, high levels of precipitation reflect positive income shocks if they take place during the growing season, as studied by Harari and La Ferrara (2016). On the contrary, high levels of precipitation can induce negative income shocks, in particular if they constitute favorable conditions for malaria risk during harvesting periods, as suggested by the evidence in Table 9. The estimates provide no evidence for an increased conflict intensity due to the occurrence of suitable conditions for malaria transmission in high risk cells during growing seasons.[73] Hence, the effect of malaria exposure is robust to seasonality and other within-year factors that have been previously pointed out as major determinants of conflict.

Table 10 finally pushes the analysis one step further by studying the role of malaria suitable months for the types of conflicts studied in Table 8. The results suggest that violent event tend to spike during the harvesting periods particularly for riots and protests and for confrontations involving militias and civilians.

7 Climate, Weather Shocks, and Anti-Malarial Policies

This paper contributes novel evidence in support of the hypothesis that a higher exposure to the health-threatening risks of malaria increases the incidence of civil violence in Africa. The empirical analysis is based on high-resolution data from the whole of Africa over the period 1998-2012. The identification strategy exploits exogenous variation within grid cells over time, comparing the effect of the occurrence of weather conditions that are suitable for malaria transmission across cells with adult populations that are less or more susceptible to malaria infections. The most extensive specifications use month-by-month variation and condition on cell-year fixed effects and month fixed effects as well as spatial contiguities. The results thereby implicitly account for virtually all complementary determinants of civil violence that have been identified in the literature. The results reveal a significant and sizable effect that is robust to a large set of overidentification and falsification checks. The findings also document that the effect of malaria risk on civil violence is highest in areas with low levels of immunities, which are most vulnerable (and responsive) to random variation in malaria suitable conditions. Malaria risk appears to affect, in particular, unorganized violence in terms of riots, protests and confrontations between militias and civilians, whereas there appears to be no

conditions that are suitable for crop growth in the specific month. The measure is also constructed based on satellite images, taken from `http://harvestchoice.org/labs/measuring-growing-seasons`.

[73] The results are reported in Table A23 in the Appendix.

Table 10: Type of Events, Malaria Risk and Harvest Seasons

Dependent Variable	Violent Events - ACLED Monthly Data					
Actors	Rioters/Protesters		Militias vs Civilians		Military vs Riot/Prot.	
	(1)	(2)	(3)	(4)	(5)	(6)
Malaria Suitable Month$_{HR}$	0.003***	0.002**	0.003**	0.003*	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
MSM$_{HR}$×Harvest Period	0.004**	0.004*	0.005*	0.005*	0.003*	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
Harvest Period	-0.002	-0.002	-0,003	-0.002	-0.001	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes
Cell× Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	Yes	No	Yes
Observations	358,740	358,740	358,740	358,740	358,740	358,740
R-squared	0.305	0.305	0.358	0.359	0.299	0.299
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556

Weighted OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month"$_{HR}$) is an indicator that takes value 1 if the conditions in the given month in the given cell were suitable for malaria to be transmitted (monthly data), weighted by malaria risk coded as 1 for values of the index constructed by Kiszewski et al. (2004) below a threshold, and with weights that are gradually decreasing to zero as the index approaches its maximum value; see text for details. Harvest period is a binary indicator for the month being a harvest month for crops with energy content of more than 1000 KJ and harvest periods ≤2 months. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequencies. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

effect on geo-strategic violent events involving only the military, or struggles for the control over territories. The results also indicate that the effect of malaria risk on violence involving civilians spikes in conjunction with short harvesting periods of staple crops that are particularly important for the subsistence of the population.

The analysis suggests a potentially important role of a largely overlooked link between geography and climate (reflected in the long-term conditions for malaria endemicity and transmission stability) and weather shocks (that cause a temporarily elevated risk of malaria outbreaks) for civil violence. This interaction is closely related to the process of global warming, which leads to both changes in climate, particularly in terms of increasing average temperature, and weather, in terms of changes in the variability of temperature and precipitation. In this respect, the results of this paper provide a novel facet to the ongoing debate about the mechanisms linking climate change to civil violence, see Burke and Hsiang (2015) for an extensive survey of the existing findings.[74] Evidence on the malaria-related channel in this paper is based on an identification strategy that follows from the epidemiological specificities of malaria transmission, which are closely related to temperature and precipitation.[75] Increasing temperatures have been linked to the expansion of the spatial distribution

[74]The role of temperature and climate change for civil violence is a fascinating topic that has been brought to the forefront by several recent contributions including Burke et al. (2009, 2010), Buhaug (2010a, 2010b) and Sutton et al. (2010), Hsiang et al. (2011, 2013), and Buhaug et al. (2015), among others.

[75]In a broader perspective, the findings also complement the evidence for the role of weather fluctuations on economic

of malaria to areas where it had not been present, or was not stable, in the past (see, e.g. Siraj et al., 2014). At the same time, climate change is likely to contribute to an increasing weather variability (see, e.g., IPCC, 2012). This, together with a weakening of malaria control in some countries, has been suggested as the main reason for malaria resurgence in many countries (see, e.g., Zhou et al., 2004; Cohen et al., 2012).

In view of the predicted changes in global climate, the saliency of weather-induced health shocks and their potential effects on violence is unlikely to decrease in the future in the absence of specific interventions. Genetic immunities reduce the effect of malaria risk. These traits emerged, however, over a long period of persistent exposure to malaria in pre-modern societies. An effective malaria vaccine that is suitable for application to large populations might be on its way, but is not yet available. Anti-malarial policies have been implemented in the last years in Africa, although with varying intensity across different locations and periods. The main interventions included, for instance, artemisinin-based therapy often used in combination with other policies like the distribution of insecticide treated bed nets, and indoor spraying and coating of walls and other surfaces with residual insecticides. Recent research collected information on these policies at disaggregate level of a subset of cells in Africa.[76] An open question is therefore whether malaria prevention and treatment have effects beyond improving health also in terms of civil violence.

Table 11 presents estimation results that account for genetic immunity and for the time-varying level of anti-malarial policies within cells. The analysis is conducted and the yearly level for the subset of cells with high malaria risk in which anti-malarial policy data are available. The results confirm the moderating effect of genetic immunities also for this sub-sample. A greater coverage in terms of anti-malarial policies is negatively correlated to violent events. More interestingly, the results reveal a negative interaction between malaria suitable months and anti-malarial policy coverage, suggesting that health policies mitigate the effect of malaria on conflict.[77] Given the nature of the data on policies (which record actual coverage that could itself be affected by violence), these findings should be interpreted with caution. Nevertheless, they are suggestive of a potentially substantial but so far largely neglected indirect effect of health intervention in reducing civil violence.[78]

The identification of an effect on civil violence in areas with high latent malaria risk in combination with the occurrence of a short-term trigger based on exogenous variation at highly spatial and temporal resolution also provides potentially relevant insights for the priority of containment policies

performance by Dell, Jones, and Olken (2012) by documenting a further channel through which weather fluctuations can operate.

[76]The policy data are only available at the yearly level for endemic areas. For details see, e.g., Bhatt et al. (2015).

[77]Table A24 in the Appendix provides additional results for the moderating effect of health policies.

[78]The effect is sizable. The effect of the occurrence of a malaria suitable month for cells below the 25th percentile of the distribution of anti-malarial policies (where coverage is 0.0015) is essentially not mitigated by policies. In contrast, the occurrence of a malaria suitable month in cells at the 75th percentile of the distribution (where coverage is 0.14) has essentially no effect on civil violence.

Table 11: Moderating Effects of Health Policies

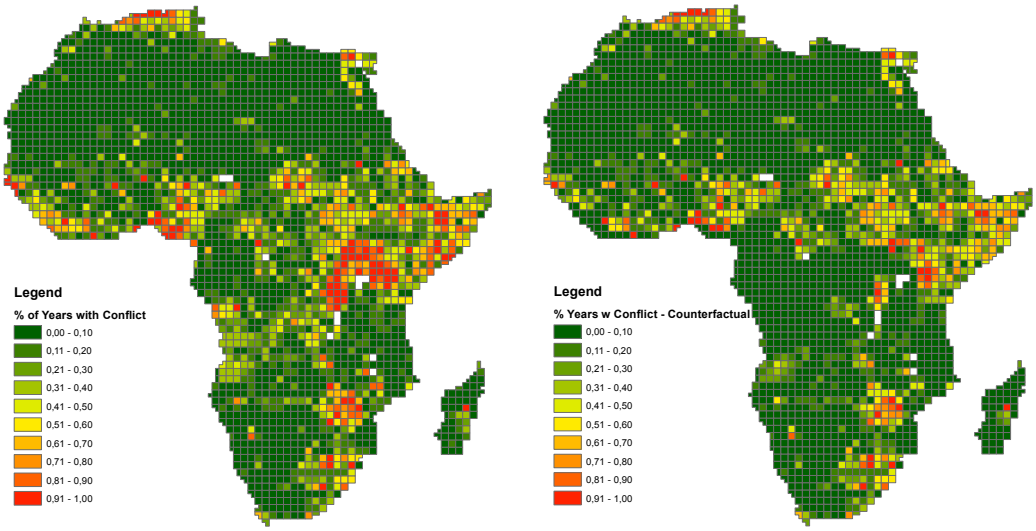
	Violent Events - ACLED Monthly Panel			
Moderating Factor:	Genetic Immunities		Anti-Malarial Policies	
	(1)	(2)	(3)	(4)
Malaria Suitable Month	0.009***	0.009***	0.016***	0.015***
	(0.003)	(0.003)	(0.004)	(0.004)
$MSM\times$(Sickle Cell - %)	-0.072**			
	(0.035)			
$MSM\times$(Sickle Cell - Dummy)		-0.006*		
		(0.003)		
Anti-Malarial Policies (av. coverage)			-0.178***	
			(0.014)	
$MSM\times$A-M Policies(av. coverage)			-0.096***	
			(0.032)	
Anti-Malarial Policies (max. coverage)				-0.054***
				(0.016)
$MSM\times$A-M Policies (max coverage)				-0.045***
				(0.017)
Weather	Yes	Yes	Yes	Yes
Weather Lags	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	172,260	172,260	172,260	172,260
R-squared	0.279	0.279	0.308	0.307

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; sample restricted to "High Malaria Risk Areas" as indicated by a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; see text for details. "Genetic Immunity" is the average level of sickle cell disease in the cell in % of the population, or measured by a binary indicator relative to the sample mean; Policies are the coverage of artemisinin-based combination therapy, insecticide treated bednet, and indoor residual spraying; policies are measured by the average of the three coverage rates, or by the maximum coverage of any one policy; see text for details. For reasons of data availability, the analysis is restricted to cells in which anti-malarial policy data are available. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current period, the "Weather Lags" include the lags in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

in certain regions. The main goal of the econometric analysis performed in the paper was to explore the role of malaria risk for civil violence. The development of a tool for directing measures of prevention of outbreaks of malaria and malaria-related violence is clearly beyond the scope of the current paper. The empirical specification can, however, potentially be helpful for predicting latent spikes in violence, or for performing evaluations of the potential benefits of an eradication of malaria. As an illustrative example of the potential impact of malaria eradication, one can use the estimates of the baseline model at the cell-year level to quantify the reduction in violent events that would be obtained by switching off the additional effect of malaria suitable months in high risk areas. The results of such an exercise deliver a predicted reduction of 14% of the incidence of violent events (compared to a standard deviation of 27%).

Figure 8 depicts the results of this "Malaria-Vaccine" thought experiment. Figure 8(a), which replicates Figure 1, reports the actual incidence of violent event in terms of share of periods with at least one conflict event. Figure 8(b) reports the (predicted) incidence that would have been observed under the counterfactual scenario in which the occurrence of malaria suitable months have

no impact on malaria risk.[79] The counterfactual exercise suggests that an elimination of all malaria-related conflict would reduce conflict in central Africa, particularly in the Great Lakes region and Eastern DRC, but also in some Western parts of DRC or the deltas of the rivers Congo and Niger. While this counterfactual exercise is purely illustrative, the results suggest that further research on risk factors related to malaria may be useful for a better understanding of the determinants of weather-driven civil violence and of the possibilities for its containment.



(a) Violent Events - Observed (b) Violent Events - Counterfactual

Figure 8: Comparing Actual and Predicted (Counterfactual) Conflict Incidence

Figure 8(a) depicts the actual incidence of violent events (fraction of years with at least one conflict over the period 1997-2012). Figure 8(b) depicts the predicted incidence of violent events obtained under a counterfactual "Malaria-Vaccine" scenario that switches off the estimated effect of malaria suitable months.

[79]Formally, we predict the incidence of violence in each cell year using the baseline specification (corresponding to Column (3) of Table 4) and the same model with the estimated effect of malaria suitable months in high risk cells set to zero. We use the difference between the two predicted models to get the average predicted reduction in incidence of violence (in terms of a share lying in the [0-1] interval, in each cell. Finally we use information on the actual frequency of conflicts to compute the counterfactual predicted incidence for each cell over the full period.

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A Data Sources and Summary Statistics

A.1 Data Sources

Table D1: Data Sources and Description of Main Variables of Interest

Variable Description and Data Sources
Incidence of *Plasmodium falciparum* Malaria Incidence: *Clinical Incidence of Malaria (Projected).* Modeled clinical incidence of Plasmodium falciparum malaria (2000-2015), detrended for country-specific non-linear time trends. Measured as number of cases per 1000 people per year. Source: Bhatt et al. (2015), retrieved from http://www.map.ox.ac.uk/.
Malaria Stability: *Malaria Stability Index.* Index measuring the force and stability of malaria transmission based on biological characteristics of diverse vector mosquitoes and their interaction with climate. Data source: Kiszewski, Mellinger, Spielman, Malaney, Sachs, and Sachs (2004).
Cells with High Malaria Risk. Based on the malaria stability index, we constructed a dummy variable - High Malaria Risk (HR) - which takes value one in cells with a low to intermediate value of the malaria force and stability of transmission index. This variables takes value 0 in cells where malaria cannot be transmitted, either because *Anopheles* vectors are not present or because climatic conditions for transmission are absent, and in cells with with very high Malaria Ecology (larger than 15). Data source: Kiszewski, Mellinger, Spielman, Malaney, Sachs, and Sachs (2004).
Malaria Risk predicted from Weather Variables: *Malaria Suitable Month.* Index predicting whether the month is suitable for malaria transmission, based on an algorithm requiring determined threshold of temperature and precipitation in up to 12 months before. The algorithm was computed with temperature and precipitation data from ECMWF ERA-Interim dataset ECMWF ERA-Interim dataset Dee, Uppala, Simmons, Berrisford, Poli, Kobayashi, Andrae, Balmaseda, Balsamo, Bauer, et al. (2011).
Malaria Suitable Months. Index predicting the number of malaria-suitable months for the year, based on the Malaria Suitable Month described above.
Malaria Suitable Months Demeaned. Index predicting the difference between the malaria-suitable months for the year and the sample average, based on the Malaria Suitable Month described above.
Measures of Civil Violence: *Baseline: Any Conflict.* Dummy variable taking value one if in the cell there was at least once conflict event within the year (within the month, for the monthly panel analysis). Conflict Events include the categories: Battle-Government regains territory, Battle-No change of territory, Battle-Rebels overtake territory, Headquarters or base established, Non-violent activity by a conflict actor, Non-violent transfer of territory, Riots/Protests and Violence against civilians. Source: ACLED Version 4 (1997-2013), ACLED - Armed Conflict Location and Event Data Project.
Rioters/Protesters Dummy variable taking value one if in the cell there was at least once conflict event involving both rioters or protesters among the actors. Coded based on interaction codes. Source: ACLED Version 4 (1997-2013) - Armed Conflict Location and Event Data Project.
Military vs. Rioters/Protesters Dummy variable taking value one if in the cell there was at least once conflict event involving both rioters or protesters and military among the actors. Coded based on interaction codes. Source: ACLED Version 4 (1997-2013) - Armed Conflict Location and Event Data Project.
Military vs. Civilians Dummy variable taking value one if in the cell there was at least once conflict event involving both civilians and military among the actors. Coded based on interaction codes. Source: ACLED Version 4 (1997-2013) - Armed Conflict Location and Event Data Project.
Rebels Dummy variable taking value one if in the cell there was at least once conflict event involving rebels among the actors. Coded based on interaction codes. Source: ACLED Version 4 (1997-2013) - Armed Conflict Location and Event Data Project.
Military vs. Rebels Dummy variable taking value one if in the cell there was at least once conflict event involving both rebels and military among the actors. Coded based on interaction codes. Source: ACLED Version 4 (1997-2013) - Armed Conflict Location and Event Data Project.
Non-Violent Events and Only Military Dummy variable taking value one if in the cell there was at least once conflict non-violent events or events involving only military. Coded based on interaction codes. Source: ACLED Version 4 (1997-2013) - Armed Conflict Location and Event Data Project.

Table D2: Data Sources and Description of Main Variables of Interest (ctd.)

Variable Description and Data Sources
Cell Specific Controls:
Average Temperature. Average annual cell temperature (baseline period 1961-1990). Source: FAO/IIASA, 2011-2012. Global Agro-ecological Zones (GAEZ v3.0). FAO Rome, Italy and IIASA, Laxenburg, Austria.
Average Precipitation. Average cell monthly precipitation mm/month (baseline period 1961-1990). Source: CRU CL 2.0 data from New, Lister, Hulme, and Makin (2002).
Land Suitability. Average land suitability in the cell. Source: Ramankutty, Foley, Norman, and McSweeney (2002).
Diamond Mines. Indicator variable taking value 1 if at least one petrol field is located in the cell, 0 otherwise. Source: Gilmore et al. (2005)
Petrol Fields. Indicator variable taking value 1 if at least a diamond mine is located in the cell, 0 otherwise. Source: Lujala et al. (2007).
Mean Elevation. Average cell elevation. Source: National Oceanic and Atmospheric Administration (NOAA) and U.S. National Geophysical Data Center, TerrainBase, release 1.0 (CD-ROM), Boulder, Colo.
Tse Tse Suitability Average predicted suitability for tsetse flies in the ethnic homeland of the respondent's ethnic group. Source: predicted suitability for tsetse flies is constructed as the sum of predicted suitability (0 to 1) for the presence of Tsetse groups (Fusca, Morsitans and Palpalis). Data produced for FAO - Animal Health and Production Division and DFID - Animal Health Programme by Environmental Research Group Oxford (ERGO Ltd) in collaboration with the Trypanosomosis and Land Use in Africa (TALA) research group at the Department of Zoology, University of Oxford.
Total Water Area. Total area occupied by water in the cell (seas, oceans, lakes and rivers). Source: constructed with Digital Chart of the World inwater shapefile and the Digital Chart of the World oceans and sea shapefile. *Cell Area.* Natural logarithm of the cell area.
Ln Distance Coast. Natural logarithm of the average cell distance to closest coast. Source: constructed with coastline shapefile from Global Self-consistent Hierarchical High-resolution Geography Version 4.2.2 January 1, 2013.
Ln Distance Capital. Natural logarithm of the average cell distance to the country capital. Source: constructed with the World Capital shapefile.
Ln Distance Border. Natural logarithm of the cell distance to closest border. Source: constructed with coastline shapefile from Global Self-consistent Hierarchical High-resolution Geography Version 4.2.2 January 1, 2013.
Ln Distance River. Natural logarithm of the average cell distance to the closest river. Source: constructed using Major Rivers World Selected (p3w) shapefile (from www.naturalearth.com).
Ln Distance Adis Ababa. Natural logarithm of the geodesic distance to Adis Ababa.
Absolute Latitude. Absolute latitudinal distance of the centroid of the cell.
Population. Average population in the cell in year 1995. Source: constructed as the mean population across 2.5 arc-minutes grid. Data from he Center for International Earth Science Information Network - CIESIN - Columbia University, United Nations Food and Agriculture Programme - FAO, and Centro Internacional de Agricultura Tropical - CIAT. 2005. Gridded Population of the World, Version 4 (GPWv3): Population Count Grid. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). http://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-count.
Night Lights. Average night light intensity in the cell. Source: constructed with data from NOOA National Geophysical Data Centre for the year 2000.
Sickle Cell Trait Prevalence Percentage. Average predicted frequency of sickle haemoglobin alleles in the general population in the cell. Source: Piel et al. (2013) .
Sickle Cell Trait Prevalence Median. Indicator variable taking value 1 if the average predicted frequency of sickle haemoglobin alleles in the general population in the cell is higher than the sample median, 0 otherwise. Source: Piel et al. (2013).
Sickle Cell Trait Prevalence Mean. Indicator variable taking value 1 if the average predicted frequency of sickle haemoglobin alleles in the general population in the cell is higher than the sample mean, 0 otherwise. Source: Piel et al. (2013).

Table D3: Data Sources and Description of Main Variables of Interest (ctd.)

Variable Description and Data Sources
Weather Time-Varying Controls: *Average Temperature.* Average monthly/yearly temperature in the cell. Source: data from ECMWF ERA-Interim dataset ECMWF ERA-Interim dataset Dee, Uppala, Simmons, Berrisford, Poli, Kobayashi, Andrae, Balmaseda, Balsamo, Bauer, et al. (2011). *Average Precipitation.* Total monthly/average yearly precipitation in the cell. Source: data from ECMWF ERA-Interim dataset ECMWF ERA-Interim dataset Dee, Uppala, Simmons, Berrisford, Poli, Kobayashi, Andrae, Balmaseda, Balsamo, Bauer, et al. (2011). *SPEI.* Average standardised precipitation-evapotranspiration index in the cell, normalized at 4 months. Source: SPEIbase v2.2 from http://digital.csic.es/handle/10261/48169. *Average Temperature.* Average monthly/yearly temperature in the cell. Source: data from ECMWF ERA-Interim dataset ECMWF ERA-Interim dataset Dee, Uppala, Simmons, Berrisford, Poli, Kobayashi, Andrae, Balmaseda, Balsamo, Bauer, et al. (2011). **Data on Harvest Seasons and Growing Seasons:** *Staple 1000 Any Lenght Harvest.* Dummy variable taking value 1 if in the cell, the month is a harvesting month for at least one of the staples that have a energy content above 1000 KJ (maize, corn, rice, wheat, sorghum). Source: FAO crop calendar. *Staple 1000 Long Harvest.* Dummy variable taking value 1 if in the cell, the month is a harvesting month for at least one of the staples that have an energy content above 1000 KJ (maize, corn, rice, wheat, sorghum) and an average harvesting season for this set of crops which is longer than 3 months. Source: FAO crop calendar. *Staple 500/1000/1500 Short Harvest.* Dummy variable taking value 1 if in the cell, the month is a harvesting month for at least one of the staples that have an energy content above respectively 500/1000/1500 KJ (maize, corn, rice, wheat, sorghum for 1000, maize, corn, rice, wheat, sorghum, cassava, soybeans, plantain for 500 and maize, corn, rice for 1500) and an average harvesting season for this set of crops which is strictly shorter than 3 months. Source: FAO crop calendar. *Growing Season.* Dummy variable taking value 1 if a cell faces temperature and moisture conditions that are suitable for crop growth in the specific month. The measures are constructed based on satellite images, taken from `http://harvestchoice.org/labs/measuring-growing-seasons`. **Policy Data:** *Anti-Malarial Policies.* Anti-Malarial Policies (av. coverage) is the average coverage in the cell in the year for three major anti-malaria policies: Insecticide treated bednet coverage (ITN), Indoor residual spraying coverage (IRS) and Artemisinin-based combination therapy coverage (ACT). Anti-Malarial Policies (max coverage) is the cell year average coverage of the policy with the higher coverage. Source: Bhatt et al. (2015), retrieved from http://www.map.ox.ac.uk/.

A.2 Data Construction

Grid. The empirical analysis exploits panel data across cell of 1 x 1 degree of size. In order to construct the cells, we superimposed a grid of equally-sized cells on the territory of interest. Our 1 x 1 cells' grid is constructed aggregating 0.5 x 0.5 cells. Of the 0.5 x 0.5 cells, we only keep cells whose centroid falls within the African coastline. At the equator a 1 x 1 degree cells correspond broadly to a square whose sides measure around 110 km. Moreover, in the baseline sample we only keep 1 x 1 cells for which information on variables listed in the table D1 is available.

Violent Events Data. The analysis is based on the data provided by the Armed Conflict Location and Event Data Project, ACLED Version 4 (1997-2013). The data provide information on events of political violence including geo-referenced information on the specific dates and locations of these events, as well as a categorization of the types of event, the groups involved, fatalities and changes in territorial control. The information includes events such as battles, killings, riots, and recruitment activities of rebels, governments, militias, armed groups, protesters and civilians. We associate each geo-referenced conflict event to a 1 x 1 degree cell. For the subset of conflict events that take place on the border within two cells, we associate the event to both cells. We drop conflict events that fall outside of our grid of 1 X 1 degree cells. Each cell is associated to the country where its centroid falls.

Weather Data. Precipitation and Temperature data are taken from the European Centre for Medium-Range Weather Forecast (ECMWF) ERA-Interim dataset Dee et al. (2011). Following the instructions, precipitation data are retrieved as synoptic monthly means (at time 00, step 12 and time 12, step 12) and then multiplied by the number of days in that particular month. For precipitation, we selected the variable 'Total Precipitation', while for temperature we downloaded the variable '2 metre temperature'. For both temperature and precipitation, the original data were retrieved resampled at a 0.125 x 0.125 degree resolution (where the actual data resolution is 0.75 x 0.75) at a monthly level frequency. Then, 1 x 1 degree averages were computed both at monthly and yearly level.

Harvesting Season Data for the harvesting are from FAO crop calendars[80]. FAO provides crop-specific information for a vast set of crops for a large set of African countries. The unit of observation of FAO data are agro-ecological regions, which correspond to administrative regions at the first or second level of aggregation (with the level of aggregation changing across countries). We constructed a map of FAO agro-ecological regions exploiting GADM database of Global Administrative Areas.[81] Since multiple FAO regions may fall into a unique 1 degree x 1 degree cells, we had to aggregate harvesting season information. As baseline, we attributed to the cell the harvesting season of the agro-ecological region with the shortest harvesting season. We retrieved information for a long list of crops cultivated in Africa available in the FAO database. These crops include: banana, bean (broad), bean (common), cashewnut, cassava, coconut, corn, groundnut, hyacinth beans, maize, manioc, millet, onion, pea (dry), plantain, potato, rice, sorghum, soybean, sweet potato, tomato, wheat and yam, among others. Our main interest is on harvesting periods. To build indexes of harvesting season, we used information on nutrient content of major staple vegetable foods. The baseline aggregation include staple crops that have an average energy content (per 100g portion) higher than 1000 kJ.[82] As a robustness, we defined two other crop bundles: 1) staple crops with energy content higher than 1500 kJ;[83] 2) staple crops with energy content higher than 500 kJ.[84] We differentiated between long and short harvesting seasons. Since the length of harvesting season changes, even for the same crop, according to the regions, we computed a short harvesting season indicator for each bundle of staple crops. In other words, take for instance the crop bundles 1000 (energy higher than 1000 kJ per portion). In the dataset, the cell-month takes value one if that month in that cell is a harvesting month for at least one of the staple crops in the bundle (maize, corn, rice, wheat, sorghum). Indicator in each cell-month takes value one only if in that cell the crop has an average harvesting season of strictly less than 3 months. We explore alternative estimations where we decrease and increase this constraint.

[80] http://www.fao.org/agriculture/seed/cropcalendar/searchbycountry.do

[81] The matching between FAO agro-ecological regions and GADM regions is not always straightforward. In some instances, an administrative region can contain more than one agro-ecological zones. In these circumstances, we proceeded as follows: i) we assigned to the administrative region the agro-ecological zones with the largest area, ii) if the regions had a similar extension, we assigned to the administrative region the agro-ecological zones with the largest population (whenever mentioned in FAO description).

[82] These crops are maize, corn, rice, wheat, sorghum.

[83] These crops are maize, corn, rice.

[84] These crops are maize, corn, rice, wheat, sorghum, cassava, soybeans, plantain.

A.3 Summary Statistics

Table D4: Summary Statistics: Time-Invariant Cell-Specific Characteristics

Variable	Mean	Std. Dev.	Min.	Max.	N
High Malaria Risk Area	0.374	0.484	0	1	2,556
Average Precipitation	54.715	50.977	0.025	267.597	2,556
Average Temperature	23.941	3.547	10.14	30.386	2,556
Mean Elevation	620.060	418.416	-160.056	2511.889	2,556
Ruggedness	62484.521	83068.974	442.507	690458.25	2,556
Total Water Area	0.287	0.655	0	8.101	2,556
Diamond Mines	0.067	0.251	0	1	2,556
Petrol Fields	0.1	0.3	0	1	2,556
Land Suitability	0.246	0.267	0.001	0.996	2,556
Absolute Latitude	16.519	9.333	0	37	2,556
Ln Distance to Capital	1.689	0.656	0	2.882	2,556
Ln Distance to Coast	13.049	1.104	4.823	14.405	2,556
Ln Distance to Border	11.429	1.206	4.467	13.485	2,556
Ln Distance to River	12.763	1.238	3.875	14.498	2,556
Migratory Distance	3041.172	1409.347	78.073	5976.241	2,556
Ln Area Polygon	23.16	0.162	21.626	23.24	2,556
Ethnic Groups	1.993	1.166	1	7	2,556
Night Lights	2.593	1.133	2	30.012	2,556
Population Density	22.899	76.53	0.01	2190.551	2,556
Sickle Cell Immunity	0.044	0.036	0	0.167	2,556

Table D5: Summary Statistics: Conflict and Weather Data

Variable	Mean	Std. Dev.	Min.	Max.	N
Yearly Panel					
Any Violent Event ACLED	0.186	0.389	0	1	38,340
Mal. Suitable Months Dem.	-0.018	0.794	-6.176	6.412	38,340
Precipitation	62.234	68.734	0	392.144	38,340
Temperature	24.162	3.446	10.85	31.994	38,340
SPEI	-0.384	0.628	-2.763	1.731	38,340
Anti-Malarial Policies (av. coverage)	0.081	0.093	0	0.546	21,684
Anti-Malarial Policies (max. coverage)	0.173	0.187	0	1	21,684
Monthly Panel					
Any Violent Event ACLED	0.045	0.206	0	1	457,560
Malaria Suitable Month	0.269	0.444	0	1	457,560
Precipitation	62.311	95.863	0	1143.606	457,560
Temperature	24.145	5.661	2.038	40.68	457,560
SPEI	-0.383	0.956	-5.136	4.294	457,560
Rioters/Protesters ACLED	0.01	0.101	0	1	457,560
Militia vs. Civilians ACLED	0.014	0.117	0	1	457,560
Military vs. Rioters/Protesters	0.005	0.072	0	1	457,560
Rebels ACLED	0.016	0.126	0	1	457,560
Military vs. Rebels ACLED	0.01	0.102	0	1	457,560
Only Military & Non-Violent Events ACLED	0.003	0.051	0	1	457,560
Harvest 1000 KJ/any length	0.351	0.477	0	1	358,740
Harvest 1000 KJ/$\leq$ 4	0.18	0.384	0	1	358,740
Harvest 500 KJ/$\leq$ 2	0.107	0.309	0	1	358,740
Harvest 1000 KJ/$\leq$ 2	0.081	0.273	0	1	358,740
Harvest 1500 KJ/$\leq$ 2	0.045	0.208	0	1	358,740

B Additional Figures

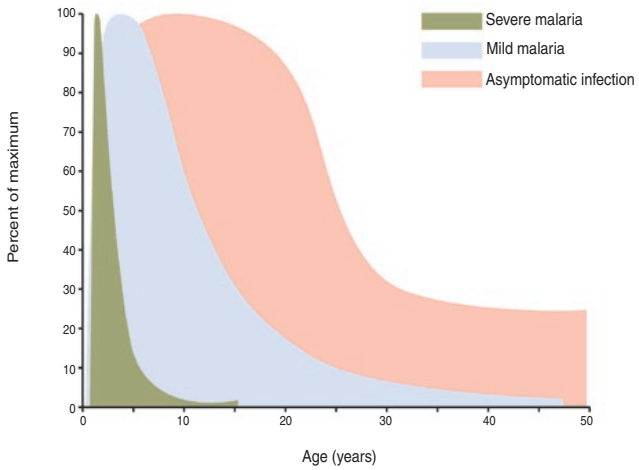
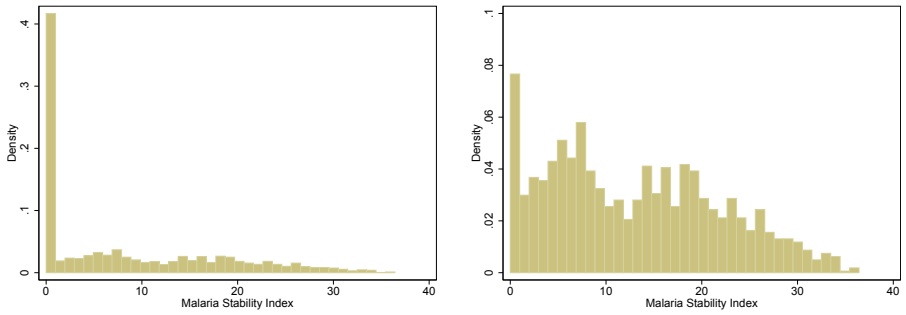


Figure A1: Severity of Malaria Infections by Age in Areas with High Stability of Transmission. Figure extracted from Langhorne et al. (2008, Figure 1b).



(a) All Cells ($N = 2556$)

(b) Only Cells With Index >0 ($N = 1630$)

Figure A2: Distribution of Malaria Stability across Cells

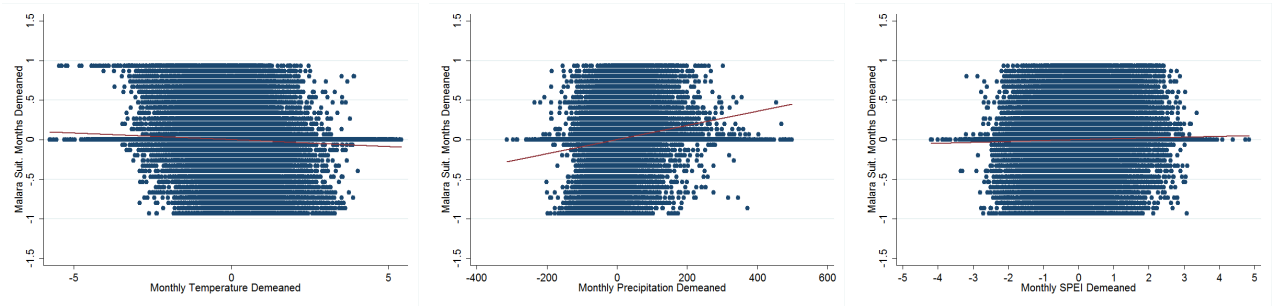


Figure A3: Unconditional correlations over time (of demeaned variables) between malaria suitable months with temperature, precipitations and SPEI at monthly frequencies.

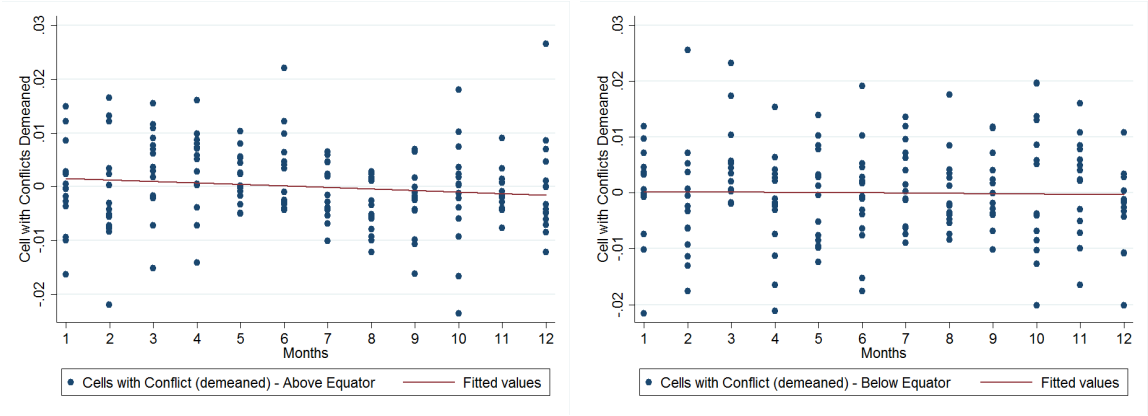
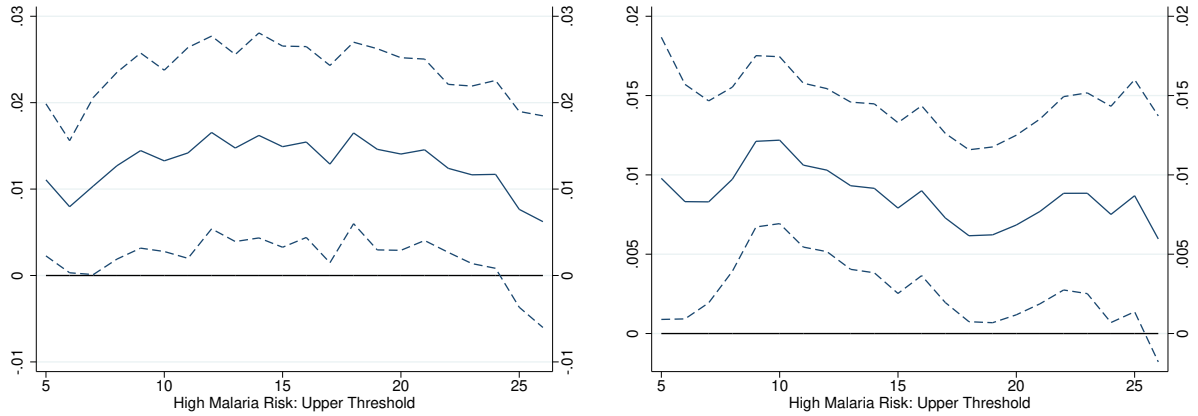


Figure A4: Fractions of cells with at least one Conflict Event (ACLED Database 1998-2012) demeaned above and below the equator. Panel at monthly frequencies.



(a) Yearly Data

(b) Monthly Data

Figure A5: Coefficient Estimates for Different Thresholds of High Risk

C Additional Tables

This Appendix reports the Tables with detailed estimation results of the various robustness checks and additional analyses discussed in the text.

Baseline: Further Results

- Table A1: Malaria Suitable Months, High Malaria Risk and Malaria Incidence;
- Table A2: Specifications without Climatic Controls;
- Table A3: Dynamic Panel Specifications - Monthly Data;
- Table A4: Logit Specification - Monthly Panel;
- Table A5: Interactions with Weather Variables - Monthly Panel;
- Table A6: Eliminating Violent Events With Uncertain Location;
- Table A7: Eliminating Neuralgic Conflict Regions;
- Table A8: Alternative Coding of Violent Events: Onset and Termination;
- Table A9: Alternative Coding of Violent Events: Number of Casualties;

Exploration of the Health Channel: Further Results and Robustness

- Table A10: Alternative Coding of High Malaria Risk Cells - Monthly Panel;
- Table A11: Excluding Cells with Malaria Stability = 0 - Monthly Panel;
- Table A12: Alternative Interactions With Geographic Characteristics;
- Table A13: Exploring the Role of Population Density;
- Table A14: Interactions with other diseases - Tse-Tse Fly Prevalence;
- Table A15: Interactions with other diseases - HIV;
- Table A16: Sub-conditions of Malaria Suitable Months Index - Monthly Panel;
- Table A17: Extended Sequences of Malaria Suitable Months - Monthly Panel;
- Table A19: SAR and SDM Spatial Models with Weights;
- Table A20: Malaria Risk and Interactions with Ethnic and Genetic Diversity;

Economic Mechanism Behind the Health Channel: Further Results

- Table A21 Actors and Events: Organized and Political Violence;
- Table A22: Malaria Risk and Income - Night Light Intensity;
- Table A23: Accounting for Malaria Risk during the Growing Seasons;

Discussion: Extended Specifications

- Table A24: Moderating Effects of Health Policies - Extended;

Table A1: Malaria Suitable Months, High Malaria Risk and Malaria Incidence

Dep. Variable	Clinical Incidence of Pf Malaria - Yearly Data					
	(1)	(2)	(3)	(4)	(5)	(6)
Malaria Suitable Months (MSM)	-0.000	0.001	0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MSM×High Malaria Risk				0.002**	0.002**	0.002**
				(0.001)	(0.001)	(0.001)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather	No	Yes	Yes	No	Yes	Yes
Weather Lag	No	No	Yes	No	No	Yes
Observations	21,853	21,853	21,853	21,853	21,853	21,853
R-squared	0.702	0.705	0.706	0.705	0.706	0.706

OLS estimates (linear probability model). The dependent variable is projected clinical incidence of Plasmodium falciparum malaria (per 1000) as constructed by Bhatt et. al (2015). MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted in the analysis using yearly data; MSM is a binary indicator of whether a given month is suitable for malaria to be transmitted in the analysis using monthly data; "High Malaria Risk" represents a binary indicator for intermediate malaria exposure in terms of ecology; see text for details. In the yearly data, "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the year; "Weather Lags" include weather controls for the previous two years. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A2: Specifications without Climatic Controls

Dep. Variable	Violent Events - ACLED			
	Yearly Data		Monthly Data	
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.003	-0.015**	-0.002**	-0.007***
	(0.003)	(0.004)	(0.001)	(0.002)
MSM×High Malaria Risk		0.020***		0.009***
		(0.005)		(0.002)
Cell FE	Yes	Yes	No	No
Year FE	Yes	Yes	No	No
Cell×Year FE	No	No	Yes	Yes
Month×Year FE	No	No	Yes	Yes
Observations	38,340	38,340	457,560	457,560
R-squared	0.464	0.465	0.414	0.414
Number of Cells	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable in (1) and (2) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year; the dependent variable in (3) and (4) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted (yearly data), or a binary indicator whether the current month was suitable for malaria to be transmitted (monthly data), respectively. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. Panel data from 1998 to 2012 at monthly frequencies. The unit of observation is a 1 x 1 degree cell. Panel data at yearly frequency in Columns (1) and (2), at monthly frequency in Columns (3) and (4). "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A3: Extended Specifications and Dynamic Panel - Monthly Panel

	Violent Events - ACLED Monthly Data						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Malaria Suitable Month	0.001	-0.003	0.002	-0.004	-0.002	-0.003	-0.003
	(0.001	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)
MSM×High Malaria Risk		0.006***		0.010**	0.007***	0.007***	0.007**
		(0.002)		(0.005)	(0.003)	(0.003)	(0.003)
Any Violence Lag	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	No	No	No	No	No
Month×Year FE	Yes	Yes	No	No	No	No	Yes
Cell×Year FE	No	No	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes	No
Month FE× Above Equator	No	No	No	No	Yes	No	No
Month FE× High M. Risk	No	No	No	No	No	Yes	No
Observations	457,560	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.278	0.278	0.41	0.41	0.41	0.41	0.41
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A4: Logit Specification - Monthly Panel

	Violent Events - ACLED Monthly Data			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.094***	-0.237***	0.016	-0.101**
	(0.023)	(0.036)	(0.028)	(0.041)
MSM×High Malaria Risk		0.248***		0.191***
		(0.047)		(0.048)
Any Violence Lag	No	No	Yes	Yes
Weather	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Month×Year FE	Yes	Yes	Yes	Yes
Observations	266,580	266,580	266,580	266,580
Number of Cells	1,481	1,481	1,481	1,481

Logit Fixed Effects estimates. The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator that takes value 1 if the conditions in the given month in the given cell were suitable for malaria to be transmitted, and 0 otherwise; "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A5: Interactions with Weather Variables - Monthly Panel

	Violent Events - ACLED Monthly Data							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Malaria Suitable Month	-0.003*	-0.003*	-0.003*	-0.003*	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MSM×High Malaria Risk (10)	0.011***	0.010***	0.010***	0.011***				
	(0.003)	(0.002)	(0.002)	(0.003)				
MSM×High Malaria Risk (15)					0.008***	0.007***	0.007***	0.008***
					(0.003)	(0.003)	(0.003)	(0.003)
Prec. D.×H. Mal. Risk	-0.000			-0.000	-0.000			-0.000
	(0.000)			(0.000)	(0.000)			(0.000)
Temp. D.×H. Mal. Risk		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
SPEI. D.×H. Mal. Risk			0.001	0.001			-0.000	-0.000
			(0.001)	(0.001)			(0.001)	(0.001)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	457,560	457,560	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.414	0.414	0.414	0.414	0.414	0.414	0.414	0.414
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 10, or 15, respectively; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A6: Eliminating Violent Events With Uncertain Location

	Violent Events - ACLED			
	Yearly Data		Monthly Data	
	(1)	(2)	(3)	(4)
Malaria Suitable Month	0.002	-0.006	0.002	-0.002
	(0.003)	(0.004)	(0.001)	(0.002)
MSM×High Malaria Risk		0.014***		0.007**
		(0.005)		(0.003)
Weather	Yes	Yes	Yes	Yes
Weather Lags 1-12	No	Yes	Yes	Yes
Cell FE	Yes	Yes	No	No
Year FE	Yes	Yes	No	No
Cell×Year FE	No	No	Yes	Yes
Month×Year FE	No	No	Yes	Yes
Observations	38,340	38,340	457,560	457,560
R-squared	0.46	0.468	0.407	0.407
Number of Cells	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable in (1) and (2) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year; the dependent variable in (1) and (2) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted (yearly data), or a binary indicator whether the current month was suitable for malaria to be transmitted (monthly data), respectively. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. Panel data from 1998 to 2012 at yearly frequency in Columns (1) and (2), at monthly frequency in Columns (3) and (4). The unit of observation is a 1 x 1 degree cell. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A7: Eliminating Neuralgic Conflict Regions

	Violent Events - ACLED			
	Yearly Data		Monthly Data	
Sample Without	Rwanda/Burundi	North Africa	Rwanda/Burundi	North Africa
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.008*	-0.008*	-0.003*	-0.003
	(0.004)	-0.004	(0.002)	-0.002
MSM×High Malaria Risk	0.017***	0.016***	0.009***	0.007***
	(0.005)	-0.005	(0.002)	-0.003
Weather	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	No	No
Year FE	Yes	Yes	No	No
Cell×Year FE	No	No	Yes	Yes
Month×Year FE	No	No	Yes	Yes
Observations	38,265	30,150	456,660	359,460
R-squared	0.464	0.458	0.403	0.412

OLS estimates (linear probability model). The dependent variable in (1) and (2) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year; the dependent variable in (3) and (4) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. North Africa is defined as cells with centroid in Morocco, Tunisia, Algeria, Lybia, or Egypt. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted, or a binary indicator whether the current month was suitable for malaria to be transmitted, respectively. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency in Columns (1) and (2), at monthly frequency in Columns (3) and (4). "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A8: Alternative Coding of Violent Events: Onset and Termination

Dep. Variable	Onset of Violence		Termination of Violence	
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.006	-0.002	0.009	0.025
	(0.004)	(0.002)	(0.008)	(0.02)
Malaria Suitable Month×High Malaria Risk	0.013**	0.005***	-0.015*	-0.038
	(0.005)	(0.002)	(0.009)	(0.023)
Panel Data	Yearly	Monthly	Yearly	Monthly
Weather	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes
Cell FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Cell×Year FE	No	Yes	No	Yes
Month×Year FE	No	Yes	No	Yes
Observations	34,202	478,246	9,697	33,161
R-squared	0.02	0.197	0.026	0.151
Number of Cells	2,510	2,510	1,504	1,495

OLS estimates (linear probability model). The dependent variable in (1)-(2) is a binary indicator variable taking value 1 if a conflict event occurred in the given year (month), but there was no conflict in the previous year (month); the indicator is set to missing if a given year (month) records a conflict event in an ongoing conflict, i.e., when there was a conflict event in the previous year (month). The dependent variable in (3)-(4) is a binary indicator variable taking value 1 if in the given year (month) there is no conflict event, but there was a conflict in the previous year (month); the indicator is set to missing if the previous year (month) records no conflict event. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted (yearly data), or a binary indicator whether the current month was suitable for malaria to be transmitted (monthly data), respectively. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. In the yearly data, "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the year; "Weather Lags" include weather controls for the previous two years. In the monthly data, "Weather" controls are at monthly level and "Weather Lags" include weather controls for the previous 12 months. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency in Columns (1) and (3), at monthly frequency in Columns (2) and (4). "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A9: Alternative Coding of Violent Events: Number of Casualties

Dep. Variable	# Casualties	
	(1)	(2)
Malaria Suitable Month	-56.814**	-60.398***
	(23.886)	(3.832)
Malaria Suitable Month×High Malaria Risk	128.877***	131.915***
	(33.364)	(3.109)
Panel Data	Tobit	Tobit
Weather	Yes	Yes
Weather Lag	Yes	Yes
Cell×Year FE	Yes	Yes
Month FE	Yes	No
Month×Year FE	No	Yes
Observations	457,560	457,560
Log pseudolikelihood	-85968	-85128

Tobit estimates. The dependent variable in (1)-(2) is a count of the reported casualties during a conflict event in the given year (month); the variable takes value zero in case there was no reported conflict event, or if there was an event with zero reported casualties. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" represents controls for average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) for the respective month, and "Weather Lags" include weather controls for the previous 12 months. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A10: Alternative Coding of High Malaria Risk Cells - Monthly Panel

	Violent Events - ACLED Monthly Data					
	(1)	(2)	(3)	(4)	(5)	(6)
Malaria Suitable Month	-0.003**	-0.003	-0.003*	-0.004	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MSM×High Malaria Risk (10)	0.011***	0.010***	0.010***			
	(0.002)	(0.002)	(0.002)			
MSM×High Malaria Risk (20)				0.007***	0.006**	0.006**
				(0.003)	(0.003)	(0.003)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE ×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	No	Yes	No
Month×Year FE	No	No	Yes	No	No	Yes
Observations	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.413	0.413	0.414	0.413	0.413	0.414
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A11: Excluding Cells with Malaria Stability = 0 - Monthly Panel

	Violent Events - ACLED Monthly Data			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.003	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
MSM×High Malaria Risk (10)	0.010***	0.010***		
	(0.002)	(0.003)		
MSM×High Malaria Risk (15)			0.006**	0.006**
			(0.003)	(0.003)
Weather	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes
Cell FE×Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No
Month×Year FE	No	Yes	No	Yes
Observations	291,780	291,780	291,780	291,780
R-squared	0.410	0.411	0.41	0.411
Number of Cells	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A12: Alternative Interactions With Geographic Characteristics

	Violent Events - ACLED					
	Yearly Data			Monthly Data		
	(1)	(2)	(3)	(4)	(5)	(6)
Malaria Suitable Month	-0.018***	-0.009**	-0.011**	0.001	-0.001	-0.001
	(0.005)	(0.004)	(0.005)	(0.003)	(0.002)	(0.003)
MSM×High Malaria Risk	0.013**	0.014**	0.012*	0.007**	0.009***	0.008**
	(0.005)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)
MSM×Land Suitability	0.034***			-0.009*		
	(0.01)			(0.005)		
MSM×Ruggedness		0.001*			-0.001*	
		(0.006)			(0.007)	
MSM×Elevation			0.001**			0.001
			(0.005)			(0.001)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	No	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	No	No	No
Cell×Year FE	No	No	No	Yes	Yes	Yes
Month FE	No	No	No	Yes	Yes	Yes
Observations	38,340	38,340	38,340	457,560	457,560	457,560
R-squared	0.468	0.467	0.467	0.413	0.413	0.413
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable in (1) - (3) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year; the dependent variable in (4) - (6) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted (yearly data), or a binary indicator whether the current month was suitable for malaria to be transmitted (monthly data), respectively. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency in Columns (1)-(3), at monthly frequency in Columns (4)-(6). "Month FE" correspond to separate intercepts for each calender month. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A13: Exploring the Role of Population Density

	Violent Events - ACLED Monthly Data			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	0.002	-0.003	0.002	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)
MSM×High Malaria Risk		0.008***		0.007***
		(0.002)		(0.003)
MSM× Population Dens.	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Weather	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes
Cell×Year FE	Yes	Yes	Yes	Yes
Month×Year FE	No	No	Yes	Yes
Observations	457,560	457,560	457,560	457,560
R-squared	0.413	0.413	0.413	0.413

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A14: Interactions with other diseases - TseTse Fly Prevalence

	Violent Events - ACLED Monthly Data			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	0.003*	-0.002	0.003*	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)
Malaria Suitable Month×High Malaria Risk		0.008***		0.007**
		(0.003)		(0.003)
Malaria Suitable Month×TseTse Prevalence	-0.006	-0.004	-0.006	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Weather	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes
Cell×Year FE	Yes	Yes	Yes	Yes
Month×Year FE	No	No	Yes	Yes
Observations	360,540	360,540	360,540	360,540
R-squared	0.412	0.412	0.412	0.412

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "TseTse Prevalence" is a binary indicator for the prevalence of the TseTse fly (glossina spp.) based on a coding of the TseTse suitability index being lower or higher than the mean across cells. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 2 years or 12 months proceeding the current year or month, respectively. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A15: Interactions with other diseases - HIV

	Violent Events - ACLED			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.001	-0.005	0.000	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Malaria Suitable Month×High Malaria Risk		0.009***		0.008***
		(0.003)		(0.003)
Malaria Suitable Month×HIV Prevalence	0.003	0.000	0.001	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Weather	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes
Cell×Year FE	Yes	Yes	Yes	Yes
Month×Year FE	No	No	Yes	Yes
Observations	391,860	391,860	391,860	391,860
R-squared	0.410	0.410	0.410	0.410

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. "HIV Prevalence (high)" refers to cells in countries with HIV infections higher than the mean. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 2 years or 12 months proceeding the current year or month, respectively. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A16: Sub-conditions of Malaria Suitable Month Index - Monthly Panel

	Violent Events - ACLED Monthly Data					
	(1)	(2)	(3)	(4)	(5)	(6)
Malaria Suitable Month		-0.003		-0.002		-0.003
		(0.002)		(0.002)		(0.002)
MSM×High Malaria Risk		0.008***		0.007**		0.006**
		(0.003)		(0.003)		(0.003)
Average monthly rainfall	0.000	-0.001				
during $(t-2, t-1, t)$ is at least 60mm/m^2	(0.003)	(0.003)				
Average monthly rainfall c.×High Malaria Risk	0.000	0.003				
	(0.004)	(0.004)				
Minimum monthly rainfall			0.013	0.012		
(at least one of the past 3 months >80mm/m^2			(0.014)	(0.014)		
Minimum monthly rainfall×High Malaria Risk			-0.006	-0.003		
			(0.025)	(0.025)		
Average temperature (last 3 months >19.5^oC+					-0.009**	-0.008*
Standard Deviation av. temp. last 12 months)					(0.004)	(0.004)
Average temperature×High Malaria Risk					0.004	0.004
					(0.005)	(0.005)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.413	0.413	0.413	0.413	0.413	0.413
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator whether the current month was suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. The average temperature requirement states that the average temperature in the past 3 months exceeds 19.5^oC+Standard Deviation of monthly temperature in the past 12 months. The third MSM requirement mentioned in the text that no month in the past 12 months had an average temperature below 5^oC, turns out to be redundant in the baseline estimation sample and is therefore omitted. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A17: Extended Sequences of Malaria Suitable Months - Monthly Panel

	Violent Events - ACLED Monthly Data			
MSM Definition	t or $t-1$		only if t and $t-1$	
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.001	-0.003*	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
MSM×High Malaria Risk	0.006**	0.007***	0.007**	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Any Violence Lag	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes
Cell×Year FE	Yes	No	Yes	No
Month FE	Yes	No	Yes	No
Cell FE	No	Yes	No	Yes
Month×Year FE	No	Yes	No	Yes
Observations	457,560	457,560	457,560	457,560
R-squared	0.413	0.242	0.287	0.1680
Number of Cells	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator that takes value 1 if all criteria for the month to be suitable for malaria to be transmitted were met in the current or preceding month in columns (1) and (2), or were met in both the current and the previous month in columns (3) and (4); "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A18: Malaria Risk and Violence: Timing of the Effect

Dependent Variable	Violent Events - ACLED Monthly Panel			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.003	-0.004*	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Malaria Suitable Month ×High Risk	0.006**	0.008***	0.006**	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
LAGS:				
Malaria Suitable Month(t-1)	-0.001		-0.001	
	(0.002)		(0.002)	
Malaria Suitable Month(t-1)×High Risk	0.005		0.005	
	(0.003)		(0.003)	
Malaria Suitable Month(t-2)	-0.001		0.001	
	(0.002)		(0.002)	
Malaria Suitable Month(t-2)×High Risk	-0.003		-0.003	
	(0.003)		(0.003)	
LEADS:				
Malaria Suitable Month(t+1)		-0.000		-0.000
		(0.002)		(0.002)
Malaria Suitable Month(t+1)×High Risk		0.001		0.001
		(0.003)		(0.003)
Malaria Suitable Month(t+2)		-0.002		-0.001
		(0.002)		(0.002)
Malaria Suitable Month(t+2)×High Risk		-0.002		0.002
		(0.003)		(0.003)
Weather	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
Month×Year FE	No	No	Yes	Yes
Observations	457,560	452,476	457,560	452,476
R-squared	0.236	0.237	0.242	0.241
Number of Cells	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; "High Risk" is the binary indicator for high risk areas for adults; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors clustered at the country level are reported in parentheses, (·). The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A19: SAR and SDM Spatial Models with Weights

Dependent Variable	Any Violent Event - ACLED Yearly and Monthly Data			
Model	Spatial Autoregressive Model - SAR		Spatial Durbin Model - SDM	
	(1)	(2)	(3)	(4)
Data	Yearly	Monthly	Yearly	Monthly
Direct Effects:				
Malaria Suitable Month$_{HR}$	0.006***	0.003***	0.009***	0.002*
	(0.001)	(0.001)	(0.002)	(0.001)
Total Effects:				
Malaria Suitable Months$_{HR}$	0.010***	0.003***	0.006	0.007***
	(0.002)	(0.001)	(0.004)	(0.002)
Panel	Yearly	Monthly	Yearly	Monthly
Weather	Yes	Yes	Yes	Yes
Weather Lag (2)	Yes	No	Yes	No
Weather Lag (12)	No	Yes	No	Yes
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Month×Year FE	No	Yes	No	Yes
Observations	38,340	457,560	38,340	457,560
Log Likelihood	-8058	70548	-8035	70591
Number of Cells	2556	2542	2556	2542

Estimates from spatially augmented models (SAR, SDM), estimated by Maximum Likelihood. The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year or given month, respectively. MSM ("Malaria-Suitable Month"$_{HR}$) is an indicator that takes value 1 if the conditions in the given month in the given cell were suitable for malaria to be transmitted (monthly data), weighted by malaria risk coded as 1 for values of the index constructed by Kiszewski et al. (2004) below a threshold, and then with lower weights that are gradually decreasing to zero as the index approaches its maximum value; see text for details. "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the respective year. The "Weather Lags" variables include the first two lags of the "Weather Time-Varying". We report standard errors in parentheses. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequencies. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level computed using the largest standard errors (country clusters or Conley) of each specification.

Table A20: Malaria Risk and Interactions with Ethnic and Genetic Diversity

	Panel A: Yearly Data					
Dependent Variable	Any Conflict Event - ACLED					
Sample:	Ethnic Groups		Sickle Cell		Ethnic Groups / Sickle Cell	
	=1	>1	sd ≤ median	sd > median	1 / sd ≤ median	>1 / sd > median
	(1)	(2)	(3)	(4)	(5)	(6)
MSM	0.008	-0.008*	-0.020***	-0.002	-0.005	-0.004
	(0.009)	(0.005)	(0.008)	(0.005)	(0.014)	(0.005)
MSM × High M. Risk	-0.005	0.015***	0.016*	0.016***	0.007	0.019***
	(0.01)	(0.006)	(0.009)	(0.006)	(0.016)	(0.007)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,304	22,592	20,528	20,368	12,080	14,144
R-squared	0.028	0.031	0.038	0.032	0.034	0.033
Number of Cells	1,144	1,412	1,283	1,273	755	884
	Panel B: Monthly Data					
Dependent Variable	Any Conflict Event - ACLED					
Sample:	Ethnic Groups		Sickle Cell		Ethnic Groups / Sickle Cell	
	=1	>1	sd ≤ median	sd > median	1 / sd ≤ median	>1 / sd > median
	(1)	(2)	(3)	(4)	(5)	(6)
MSM	0.006	-0.006***	-0.009*	-0.002	0.001	-0.004
	(0.004)	(0.002)	(0.005)	(0.002)	(0.009	(0.002)
MSM × High M. Risk	-0.004	0.011***	0.011**	0.007**	0.003	0.010***
	(0.004)	(0.003)	(0.006)	(0.003)	(0.01)	(0.004)
Weather	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lag	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218,880	268,416	244,992	242,304	144,192	167,616
R-squared	0.009	0.009	0.015	0.007	0.015	0.008
Number of Cells	1,140	1,398	1,276	1,262	751	873

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year/month. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted in the analysis using yearly data in Panel A; MSM is a binary indicator of whether a given month is suitable for malaria to be transmitted in the analysis using monthly data in Panel B; "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High Malaria Risk" is the corresponding interaction term; see text for details. The "Weather" controls include the average temperature, the average precipitation and the effective rainfall (the Standard Precipitation and Evapotranspiration Index -SPEI) registered in the year in the analysis using yearly data in Panel A; "Weather Lags" include weather controls for the previous two years. "Weather" controls are at monthly level Panel B; "Weather Lags" include weather controls for the previous 12 months. Ethnic groups is a count of ethnic groups in the cell. Sickle Cell indicates whether the standard deviation of the prevalence of the sickle cell trait in a cell satisfies the respective threshold. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A21: Actors and Events: Organized and Political Violence

	Violent Events - ACLED								
Actors	Rebels			Military vs Rebels			Non-Violent Ev. & Only Military		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Malaria Suitable Month	0.001	0.002	0.001	-0.001	0.001	-0.000	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MSM×High Malaria Risk	0.000	0.000	0.001	0.002	0.000	0.002	0.000	-0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	No	No	Yes	No	No	Yes	No	No
Month×Year FE	Yes	No	No	Yes	No	No	Yes	No	No
Cell ×Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes	No	No	Yes
Observations	457,560	457,560	457,560	457,560	457,560	457,560	457,560	457,560	457,560
R-squared	0.182	0.398	0.399	0.157	0.355	0.356	0.051	0.215	0.216
Number of Cells	2,556	2,556	2,556	2,556	2,556	2,556	2,556	2,556	2,556

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month that involved the respective actors or satisfies the respective criterion. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; "High Malaria Risk Area" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current period, the "Weather Lags" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A22: Malaria Risk and Income – Night Light Intensity

Dependent Variable	Light Intensity		Violent Events (ACLED Yearly Data)	
	(1)	(2)	(3)	(4)
Malaria Suitable Month	0.003***	0.006***	0.003	-0.003
	(0.001)	(0.002)	(0.003)	(0.005)
MSM×High Malaria Risk		-0.004**		0.010*
		(0.002)		(0.006)
Weather	No	Yes	No	Yes
Weather Lags 1-12	No	Yes	No	Yes
Light Intensity	No	No	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	30,672	30,672	30,672	30,672
R-squared	0.971	0.971	0.333	0.333

OLS estimates (linear probability model). The dependent variable in (1) and (2) light intensity, the dependent variable in (3) and (4) is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given year. MSM ("Malaria-Suitable Month") is an index that represents the number of months in the current year that were suitable for malaria to be transmitted. "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at yearly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A23: Accounting for Malaria Risk during the Growing Seasons

Dependent Variable	Violent Events - ACLED Monthly Data			
	(1)	(2)	(3)	(4)
Malaria Suitable Month	-0.001	-0.002	0.001	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)
MSM×High Malaria Risk	0.007**	0.008***	0.007**	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Growing Season	-0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
MSM×Growing Season			-0.002	-0.001
			(0.003)	(0.003)
Weather	Yes	Yes	Yes	Yes
Weather Lags 1-12	Yes	Yes	Yes	Yes
Cell× Year FE	Yes	No	Yes	No
Month FE	Yes	No	Yes	No
Cell FE	No	Yes	No	Yes
Month×Year FE	No	Yes	No	Yes
Observations	306,720	306,720	306,720	306,720
R-squared	0.414	0.243	0.414	0.243

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") a binary indicator that takes value 1 if the conditions in the given month in the given cell were suitable for malaria to be transmitted (monthly data); "High Malaria Risk" is a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; "MSM×High M. Risk" is the corresponding interaction term; see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current month, the "Weather Lags 1-12" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. "Month FE" correspond to separate intercepts for each calender month, "Month×Year FE" correspond to separate intercepts for each month in the sample. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.

Table A24: Moderating Effects of Health Policies - Extended

	Violent Events - ACLED								
	≥ Median			≥ Mean			Share of covered		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Malaria Suitable Month	0.009**	0.012***	0.014***	0.007**	0.006*	0.007**	0.007**	0.007**	0.011***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MSM×ACT coverage	-0.008			-0.005			-0.032		
	(0.006)			(0.006)			(0.036)		
ACT coverage	0.013***			0.006			-0.021*		
	(0.004)			(0.004)			(0.013)		
MSM×ITN coverage		-0.013**			-0.002			-0.017	
		(0.006)			(0.006)			(0.015)	
ITN coverage		0.023***			0.012***			0.045***	
		(0.004)			(0.003)			(0.010)	
MSM×IRS coverage			-0.014**			-0.006			-0.070***
			(0.006)			(0.006)			(0.013)
IRS coverage			0.019***			0.004			0.051***
			(0.004)			(0.003)			(0.010)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Lags	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month×Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,976	131,976	131,976	131,976	131,976	131,976	131,976	131,976	131,976
R-squared	0.301	0.301	0.301	0.300	0.301	0.300	0.300	0.301	0.301

OLS estimates (linear probability model). The dependent variable is a binary indicator variable taking value 1 if at least one conflict event (ACLED dataset) was registered in the given cell in the given month. MSM ("Malaria-Suitable Month") is a binary indicator of whether a given month is suitable for malaria to be transmitted; sample restricted to "High Malaria Risk Areas" as indicated by a binary indicator for intermediate malaria exposure taking value 1 for cells with an average malaria transmission stability index larger than 0 and lower than 15; see text for details. Policies are the cell-mean coverage of artemisinin-based combination therapy (ACT), insecticide treated bednet (ITN), and indoor residual spraying (IRS); see text for details. "Weather" controls include average temperature, precipitation and effective rainfall (SPEI index) registered in the current period, the "Weather Lags" include average temperature, precipitation and effective rainfall (SPEI index) in each of the 12 months proceeding the current month. Standard errors are clustered at the cell level. The unit of observation is a 1 x 1 degree cell. Panel data from 1998 to 2012 at monthly frequency. ***, **, * indicate significance at 1-, 5-, and 10-% level, respectively.