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Temperature anomalies affect violent conflicts in African and Middle Eastern warm regions

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ABSTRACT

Several studies have linked high temperatures to increases in violent conflicts. The findings are controversial, however, as there has been no systematic cross-sectional analysis performed to demonstrate the generality of the proposed relationship. Moreover, the timescale of temperature/violence relationships have not been fully investigated; it is unclear how short versus long-term, or seasonal and inter-annual temperature variability contribute to the likelihood or frequency of violent events. We here perform systematic regional and grid-based longitudinal analyses in Africa and the Middle East for the period 1990–2017, using geolocated information on armed conflicts and a recently released satellite-based gridded temperature data set. We find seasonal synchrony between temperature and number of armed conflicts at the regional scale (climatic region), as well as a positive relationship in temperature and conflict anomalies on inter-annual timescales at the grid cell level (for the entire African and ME region). After controlling for 'location effects', we do not find that long-term warming has affected armed conflicts for the last three decades. However, the effects of temperature anomalies are stronger in warmer places (~5% increase per 10 °C, $P < 0.05$), suggesting that populations living in warmer places are more sensitive to temperature deviations. Taken together, these findings imply that projected warming and increasing temperature variability may enhance violence in these regions, though the mechanisms of the relationships still need to be exposed.

1. Introduction

One of the suggested adversities of global environmental and climate change is its potential negative effect on human aggression and violence (Hsiang et al., 2011; Ide, 2015; Ide et al., 2014; Raleigh et al., 2015). More specifically, it is suggested that warming may exacerbate or even trigger violence of different forms (Burke et al., 2018; Carleton and Hsiang, 2016). Aggressive behavior and inter-personal violence in response to temperature rise are well documented through field and laboratory studies (Anderson, 1989; Baron and Bell, 1976; Vrij et al., 1994). However, only in recent years has the availability of high quality data sets (see e.g. in Levin et al., 2018) and new statistical approaches (see review in Ide, 2017) allowed for quantitative tests of the link between temperature and violence at large spatial and temporal scales. The magnitude of the effect has been shown to depend on many factors, making the analysis complex and the temperature-violence relationship less straightforward (O'Loughlin et al., 2014; Schleussner et al., 2016; Von Uexkull et al., 2016).

Because climate could not be regarded as the sole, or even the primary factor affecting violent conflicts (Feitelson and Tubi, 2017; Hsiang et al., 2013), factors other than climate must be considered in the analysis. For example, different locations may exhibit different levels of conflict due to political, historical, cultural, and other potentially unobserved factors. These 'location effects' may mask any possible effect of temperature on violent conflicts. Moreover, the unobserved factors may themselves be influenced by temperature, and thus controlling for these factors in the analysis may underestimate the effect of temperature on violence (Hsiang et al., 2013).

Hence, to find whether a temperature-violence link exists across locations, causal effects should be first sought through comparing a location with itself (Gelman and Hill, 2006). In other words, one should first track how temperature and violence vary over time relative to local conditions (Wooldridge, 2010). Only then, after normalizing for 'location effects', a cross-sectional analysis may be conducted that compares the relative relationships among the different locations to disclose systematic causal effects across sites (Hsiang et al., 2013).

Although studies using this technique have shown the existence of a temperature-conflict link (e.g. Burke et al., 2009; Hsiang and Burke,

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2014), current research suffers from three main caveats. First, despite the vast literature on climate-violence research, most analyses have focused on certain limited areas that are known to struggle with violence, which has led to criticisms of sampling bias (Adams et al., 2018). Second, few quantitative assessments have addressed the seasonal effect of temperature on violence, which may be more indicative of a direct causal effect than inter-annual links, that may involve more confounding factors. Finally, there is no clear distinction in the literature between the effect of long-term temperature rise versus different short-term temperature effects, such as temperature variations (i.e. anomalies).

Seasonal analysis may expose potential direct effects of temperature on conflicts because it is not accounting for the long-term effect of temperature on conflict, which may be confounded by mediating factors other than climate. On the other hand, seasonal analysis lacks the long-term effect dimension, which may trigger, for example, human mobility, enhancing the circumstantial factors that contribute to conflicts (van Baalen and Mobjörk, 2017). However, examining temperature-conflicts links at the long-term alone may miss some important effects related to inter-annual variability such as severe drought years or extreme cooling.

Regarding the spatial scale of the analysis, it is also necessary to establish the proper theoretical foundations for the temperature-conflicts relationships. For example, a regional analysis would likely fail to assess conflict patterns due to local climate variations while, on the other hand, a fine-scale analysis will most likely miss conflicts that do not necessarily take place where the impact of climate change is most severe (Ide, 2017).

We here try to address these drawbacks and the three above-mentioned caveats by conducting a systematic longitudinal analysis spanning the entire African and the Middle Eastern (ME) regions for the period 1990–2017 using two spatial scales and three distinct time scales analyses. We conduct our analysis on both regional (climatic regions) and local (pixel-level) scales using coarse-resolution grid cells in a grid-based analysis to determine whether a temperature-conflict link exists at spatial scales. We conduct our analyses at both seasonal (monthly) and inter-annual scales, distinguishing between long-term (trends and mean) and short-term (annual deviations) temperature effects on the occurrence of violence (the likelihood of finding violence in a specific location) and violence aggravation (increases in the number of violent events), as well as a seasonal synchrony between temperature and armed conflicts.

2. Data

2.1. Violent conflicts

For information on violent conflicts, we used the most updated Georeferenced Event Dataset (GED) Global version 18.1 (2017) of the Uppsala Conflict Data Program (UCDP; Sundberg and Melander, 2013). The GED.v18.1 is UCDP's most disaggregated data set, covering individual organized lethal violent events occurring at a given time and place. We chose non-state conflicts rather than civil war conflicts because small-scale conflicts are more likely to be sensitive to environmental change (Mach et al., 2019; O'Loughlin et al., 2014). Moreover, intrastate conflicts are more likely to be caused by climate change because climatic changes may drive individuals into aggressive behavior and violence through a plethora of mechanisms (e.g. Baron and Bell, 1976; Cohen and Felson, 1979; Dewall et al., 2011). Non-state conflicts are defined by UCDP as "the use of armed force between two organized armed groups, neither of which is the government of a state, which results in at least 25 battle-related deaths in a year" (Mihai and Sundberg, 2017).

In the GED data set, each conflict is coded with a unique identifier (conflict ID), while the start date is recorded as precisely as possible with the level of precision for day, month and year indicated alongside ('Startprec' variable in GED.v18.1). For our seasonal analysis, we used conflicts indicated with a 'Startprec' level of 1–3 (level 3 means "month and year are precisely coded"), while a lower level 'Startprec' (levels 1–5; level 5 means "year is precisely coded") was used for inter-annual analysis.

A single violent event was defined here as a coded event, which is unique in terms of starting and end dates, and is not a continuation or part of a previous event. Each event was counted and assigned to a specific month and year using the reported starting date. Events were summed per month (for seasonal analysis) and per year (for inter-annual analysis), spanning the period of 1990–2017. Finally, we excluded Syria from our analysis because of the poor information on violence provided by GED.v18.1 (see also in Mihai and Sundberg, 2017), particularly in the last years of the Syrian civil war (2010-date). A grid-based spatial distribution of all violent events is provided in Fig. S1. The list of countries involved in the analysis alongside the total number of events for 1990–2017 per country are provided in Table S1.

2.2. Temperature

We used monthly maximum temperatures from the newly derived Climate Hazards Center Infrared Temperature with Stations (CHIRTS) data set (Funk et al., 2019). CHIRTS provides monthly 2-m maximum air temperatures at a high spatial resolution of 0.05° and a quasi-global coverage (60°S-70°N) from 1983 to present. Temperature estimates are derived using a combination of thermal imagery from a constellation of geostationary satellites, a high-resolution climatology from the Climate Hazards Center's Tmax climatology, and in situ monthly 2-m Tmax air temperature observations obtained from the Berkeley Earth and Global Telecommunication System (GTS). We used the temperature estimates from CHIRTS because these were shown to be suitable for monitoring temperature anomalies and extremes in data-sparse regions like Africa and the ME (Funk et al., 2019).

2.3. Population density and infant mortality rate

We test two other factors as driving factors of violence occurrence (see *Section 3.2.2.* in Methods below), population density and socio-economic status approximated by infant mortality rate (IMR). The 1 km WorldPop data set (www.worldpop.org.uk) was used to derive population density for Africa and the ME. WorldPop uses an ensemble learning method for classification, combining 30-m Landsat Enhanced Thematic Mapper (ETM) satellite imagery for high-resolution mapping of settlements and gazetteer population numbers to produce gridded population density maps at high spatial resolutions (Stevens et al., 2015). A total of five population maps (for years 2000, 2005, 2010, 2015 and 2020) available for Africa and Asia were downloaded from https://www.worldpop.org/geodata/listing?id=17, merged and cropped to get single maps for the study area extent. The five maps were then averaged to a single map layer for average population density in Africa and the ME for the period 2000–2017.

IMR was used as a proxy for socioeconomic development. Information on IMR was acquired from the Global Subnational Infant Mortality Rates, Version 1 (GSIMR.v1) of NASA's Socioeconomic Data and Application Center (CIESIN, 2005). The GSIMR.v1 data set is produced by the Columbia University Center for International Earth Science Information Network (CIESIN) and is freely available for download as raster data from https://sedac.ciesin.columbia.edu/data/collection/povmap. The GSIMR.v1 consists of IMR estimates for the year 2000 at a spatial resolution of 5 km, which were collected from vital registration data, surveys and models or estimated using reported live births and infant deaths data. Although a new version of IMR exists for the year 2015 (GSIMR.v2), we used the old version with IMR estimates for 2000, which is more representative of the period of our study. IMR is calculated as the number of infant deaths less than 1 year old divided by the number of live births and multiplied by 1000. IMR is a preferred proxy of poverty and wellbeing over other metrics like Gross Domestic Product (GDP) or population living on less than one U.S. dollar per day, because former are difficult to obtain at sub-national levels. It has also several advantages over other socioeconomic metrics. For example, it is a highly standardized measure compared to other measures. It is less likely to be influenced by skewed wealth distribution. And, information on IMR is available for ~90% or more of the population in medium and low-income countries. The IMR data set has been extensively used to study relationships between poverty and dryland vulnerability (Sietz, 2014; Sietz et al., 2011), poverty and corruption (Hauenstein et al., 2019), and land degradation and poverty (Barbier and Hochard, 2018); however, its accuracy may vary depending on the region, with some regions/countries having low-quality or even no data (Von Uexkull et al., 2016) due to lack of reliable input data, particularly in some of the rural areas.

2.4. The spatial resolution of analysis

All violent events, temperatures, IMR, and population densities were binned at a spatial resolution of 0.5° x 0.5° for African and ME regions. This was done by summing the total number of violent events and averaging temperatures, IMR, and population densities per grid for the period of overlap with the violence data (1990 – 2017). A spatial resolution of 0.5° was used instead of the original finer resolution of the data sets to overcome inaccuracies in the geolocation of the GED and IMR data sets, which have reported accuracy, in case of the GED data set, of up to the level of individual villages. Moreover, climatic, socioeconomic, and demographic factors may affect the population in an uncentred way, such that the conflict may occur far from the center of the effect (Ide, 2017; Von Uexkull et al., 2016). Using a coarser spatial resolution of 0.5° can overcome this issue. Finally, the small data set (when using the coarser spatial resolution of 0.5°) reduces computational burden while reducing the propagated error.

3. Methods

3.1. Regional analysis

3.1.1. Inter-annual trends and relationships

We used the Köppen-Geiger classification of climatic zones to distinguish between 'cool' and 'warm' areas in Africa and the ME (Fig. S2). Three zones are found in Africa: the warm equatorial zone A, the warm arid zone B, and temperate zone C. In the ME, there are also three zones: the warm arid zone B, the temperate zone C and the cold zone D in the north.

To quantify the inter-annual changes in temperature and frequency of violence at the regional level, we used two different methods: A linear trend using ordinary least squares over the timeseries period, and the mean value difference between two individual periods, where these periods were defined as the last and first 10-y periods of the timeseries (2008–2017 and 1990–1999, respectively). The Student's *t*-statistic was calculated to quantify the probability *P* of whether the trend is statistically significant and different from zero for the linear trend. We further examined whether the trends are not just artifacts of large spikes in violent events related to one or two known episodes of political violence. We did that by repeating the trend analysis after excluding these large spikes.

3.1.2. Seasonal relationships

For seasonal analysis at regional scale, we used a nonparametric Kruskal-Wallis test followed by Bonferroni correction to assess whether the median number of violent conflicts are significantly different among the months. We also used a simple linear regression between monthly mean temperature and average number of violent events to assess significant synchrony between the two along the season.

3.2. Grid-based analysis

Quantifying climatic effects on human conflict is inherently complex due to the complexity of social systems. Hence, when looking at relationships between climate and conflicts it is particularly important to acknowledge whether such statistical relationships can be interpreted causally or as links that are confounded by omitted or unobserved variables. To address this, we use in our study what is known as a "natural experiment" approach, which is closest as possible to the conventional scientific experiment approach. In such experimental design, we compare a given population to itself in time rather than to other populations. In such way, we are able to control for the many background factors (e.g. historical, sociological, economic and political) that may play important roles in enhancing violence through climatic changes in a specific population (Hsiang et al., 2013). The long-term trend in conflicts is then regarded as a gradual change related to background factors while the intersection is the population specific basic conditions. Any deviation from such a long-term trend is attributed to variations in the climatic factor (Fig. S3).

Rainfall may also play an important role in enhancing conflicts, particularly in dry regions (Feitelson and Tubi, 2017; Tubi and Feitelson, 2016). However, we here focus on temperature effects because, unlike rainfall, temperature has been hypothesized and, in some cases, demonstrated to affect violence through multiple mechanisms. At the scale of individual behavior, the leading hypotheses for increased violence under warm conditions are the General Aggression Model, which holds that higher temperatures directly trigger human aggression, and the Routine Activity Theory, which focuses on the fact that higher temperatures cause people to spend more time outdoors and engage in increased social interaction (e.g. Cohen and Felson, 1979; Dewall et al., 2011). It is possible that these hypotheses, which address individual or small group behavior, could scale to the intergroup level. Other hypotheses focus directly on the scale of organized violence. These include the Strategic Viability Mechanism, which holds that warmer temperatures have an ameliorating effect that encourages opportunistic violence: greater resource availability, easier travel routes, and lower risk of disruptive storms can all lead to increased conflict. This is frequently observed on seasonal timescales, and could hold for climate change timescales insomuch as the length of warm seasons increases under global warming (Landis, 2014).

In contrast, a number of studies have investigated the destabilizing effects of climate shocks, including temperature shocks (e.g. Hendrix and Salehyan, 2012). Under this line of thought, temperature variability and, in the context of global warming, increases in heat extremes, might trigger violence by causing destabilizing scarcities and associated resource conflicts (e.g. Tol and Wagner, 2010; Zhang et al., 2007), though it is also noted that very high temperature extremes could inhibit violence through physiological or behavioral thresholds on willingness to engage in violent activities (Landis, 2014). Our analysis is not designed to distinguish between these hypothesized mechanisms, but results could be valuable for future research addressing the mechanisms that may underlie scaling-up of aggressive behavior or group-level responses to temperature variability.

3.2.1. Inter-annual causal effects

Relationships regarded as causal effects are assessed by first distinguishing between the three kinds of effects that temperature may have on the aggravation of violence (increase in number of violent events over time) at a grid-based level:

1) Local climatologic conditions, defined on the basis of the long-term mean annual temperature ($\overline{\mathrm{T}}_i$):

$$\overline{\mathrm{T}}_i = \frac{\sum_{t=1}^{N} \mathrm{T}_{t,i}}{\mathrm{N}} \quad (1)$$

where $\mathrm{T}_{t,i}$ is the mean annual temperature in year t in grid cell i, and N is the total number of years (i.e. 28-y). $\overline{T}_i$ may affect the relative long-term change in violence (ΔViolence$_i$), defined as:

$$\Delta\text{Violence}_i = \frac{d(\text{Violence}_i)}{dt}\text{ N} \quad (2)$$

where $\frac{d(\text{Violence}_i)}{dt}$ is the slope of trend in frequency of violence (change in number of violent events per year) in grid cell i. We thus look for some systematic change in ΔViolence$_i$ with $\overline{T}_i$ (i.e. $\frac{d(\Delta\text{Violence}_i)}{d(\overline{T}_i)} \neq 0$) to state that there is a causal link between the rate of change in violence of a grid cell and its mean annual temperature. For example, if $\frac{d(\Delta\text{Violence}_i)}{d(\overline{T}_i)} > 0$ then we can say that there is a greater increase in the rate of armed conflicts in warmer locations (grids). If this is systematic and significant, then we can state that warmer places experience a greater increase in armed conflicts than cooler places.

2) The long-term change in mean annual temperature of a specific location (ΔT_i) – i.e. warming or cooling trends – may also affect ΔViolence$_i$, while ΔT_i is calculated as:

$$\Delta T_i = \frac{dT_i}{dt}\text{ N} \quad (3)$$

where $\frac{dT_i}{dt}$ is the slope of the linear trend in grid i. In this case, the relationship between ΔViolence$_i$ and ΔT_i is explored, while a significant change in both (i.e. $\frac{d(\Delta\text{Violence}_i)}{d(\Delta T_i)} \neq 0$) would mean a causal effect of warming or cooling on the rate of change in violence.

3) Finally, inter-annual variations in temperature, or more precisely temperature deviations from mean conditions ($T_{anom,i}$), may affect violence through deviations from mean frequency of violence (Violence$_{anom,i}$). In this case, the relationship between timeseries of the anomalies of temperature and violence are explored as $\frac{d(\Delta\text{Violence}_i)}{d(\Delta T_i)}$.

The anomalies of both variables are calculated simply by subtracting the original timeseries from a smoothed line fitted to the timeseries, using the local weighted scatterplot smoothing function (LOESS; Cleveland, 1979):

$$X_{anom,i} = X_{t,i} - \widehat{X_{t,i}} \quad (4)$$

where $\widehat{X_{t,i}}$ is the value of variable X (temperature or number of conflicts) at time t for grid cell i, derived from LOESS, and $X_{t,i}$ is the actual value of X at the same time t. In other words, $\widehat{X_{t,i}}$ is the expected X value for year t, considering past and future changes and is calculated similarly to the climatological mean, derived from long-term weather information. A significantly positive $\frac{d(\Delta\text{Violence}_i)}{d(\Delta T_i)}$, for example, would indicate that temperature variations (from mean conditions) affect violence in both directions – namely, positive temperature deviations increase violence, while negative deviations reduce the frequency of armed conflicts.

To account for 'location effects' and other unobserved factors, ΔViolence and Violence$_{anom}$ were both converted into relative amounts (ΔViolence' and Violence$_{anom}$') by dividing them by the mean annual number of armed conflicts of that location. This standardization of the conflict data allows for a between-site comparison, even though sites (grids) have different levels of violence. The meaning of that standardization, though, is that a grid with a greater ΔViolence', for example, does not necessarily have more violence (or even a larger increase or decrease in the total number of violent events) than a grid with a smaller ΔViolence'. The same applies to Violence$_{anom}$', which refers only to the *relative* deviation from the mean frequency of violence of the specific location. We use the non-parametric correlation of the anomalies in temperature and violence (Spearman's ρ) to assess the sensitivity of violence to temperature deviations. Not all grids were used in the analysis because LOESS cannot be applied to a relatively small number of observations spread over long timeseries periods (Cleveland, 1979). Thus, only grids with at least 20% of the total years of data with recorded events were analyzed for temperature anomaly effects. This resulted in ~40% of the total grids being analyzed. We then plotted ρ against $\overline{T}$ to assess whether the sensitivity of violence to temperature deviations is affected by local climate (i.e. temperature conditions). A systematic positive change in ρ with $\overline{T}$ (i.e. $\frac{d(\rho_i)}{d(\overline{T}_i)} > 0$ and $P < 0.05$), for example, would indicate that populations living in warmer places are more sensitive to temperature deviations in terms of violent behavior than populations living in cooler places.

Finally, we examine non-parametric relationships between ΔViolence' and ΔT or ΔViolence' and $\overline{T}$ because relationships are not necessarily linear (Anderson, 1989). Changes in these relationships across sites and temperature conditions for the three-decade period may indicate local climate (mean temperature) and/or local trends in temperature (warming or cooling) influences on violence. We report only significant relationships between ΔViolence' and ΔT, and ΔViolence' and $\overline{T}$ at $P < 0.05$.

3.2.2. Quantifying the risk of violence occurrence

To assess whether temperature may be used as a predictive factor of the risk of violence occurrence (the likelihood to find violence in a specific place) in Africa and the ME, we first look at the distribution of $\overline{T}$ in grids where violence was recorded between 1990 and 2017 (hereafter 'Sample') and compare this distribution with that in all grids of the region, including grids where violence was not recorded during 1990–2017 (hereafter 'Region'). Specifically, we look for two differences between 'Sample' and 'Region', in terms of $\overline{T}$:

(I) A systematic shift in the distribution of the 'Sample' compared to that of the 'Region', with the 'Sample' average significantly different from that of the 'Region' at $P < 0.05$
(II) A higher ratio of 'Sample' to 'Region' for binned values compared to the total ratio of 'Sample' to 'Region' (using the entire range of values in all grids).

We use two other factors that are known to affect violence in Africa and the ME in our analysis: average population and IMR, which was used here as a proxy of socioeconomic development (Williams and Collins, 1995). Population and socioeconomic development have both been claimed to affect violence (Hegre and Sambanis, 2006; Von Uexkull et al., 2016).

We say that if (I) is true, than 'violent locations' (locations that experienced violence in the period 1990–2017) are significantly different from the entire region in terms of the analyzed factor (temperature, population or socioeconomic development approximated by IMR), which means that it is a significant factor in enhancing the risk of violence occurrence in the region. This is because the distribution of values in 'Sample' are significantly different from the normal distribution, derived from the entire population in 'Region'.

If (II) is true, then the likelihood to encounter violence under specific conditions (binned values with a greater ratio than total) is greater than normal, because the distribution of 'Sample' to 'Region' ratio for that conditions is greater than the normal distribution of the average conditions for the entire region.

To check for correlation between population density and IMR in our analysis, we regressed all grids where information on both factors exist. We found that the factors are related, with an increase in IMR for denser populations; however, the correlation was rather weak with the relationship being IMR = 7 Log(Population) + 54, and R^2 of 0.05.

Because the information on IMR from GSIMR.v1 may lack the spatial detail needed for the analysis required to assess the difference described in (II), we further calculated the 'Sample' to 'Region' ratio for groups of grids instead of for the entire range of values. Grids in both 'Sample' and 'Region' were divided into two groups based on the median IMR of the total population of grids (IMR$_{med}$ = 79 deaths per 1000 births), as follows: (1) High-IMR group, representing undeveloped locations with a low socioeconomic status and (2) low-IMR group, representing developed locations with a high socioeconomic status.

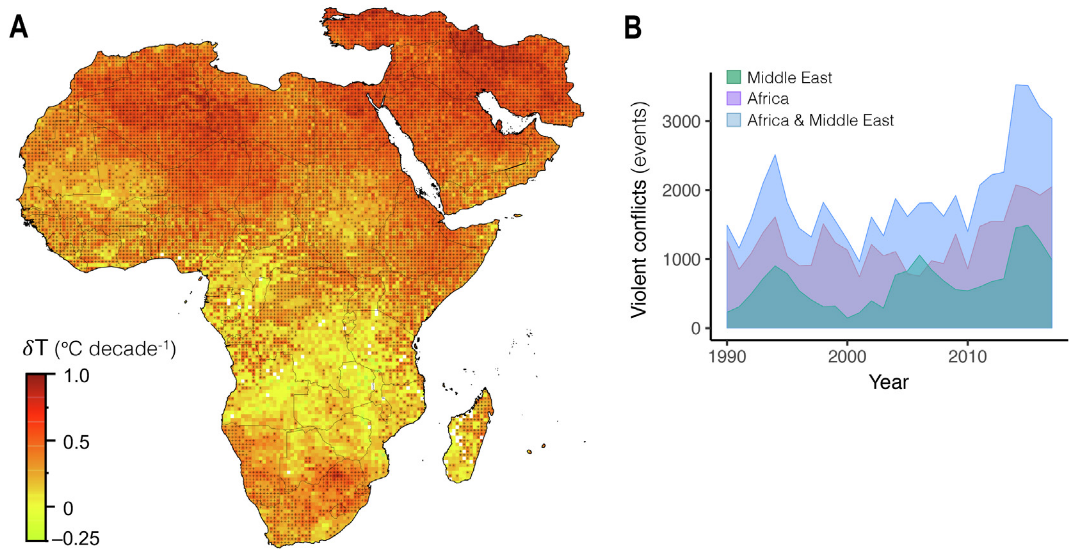

Fig. 1. Increases in temperature and violence in Africa and the Middle East in the last three decades. (**A**) Map of decadal changes in temperature by 0.5° grids (δT; 1990–2016), with plus symbols indicating grids with statistically significant linear trends (P < 0.05). (**B**) Yearly number of inter-group armed conflicts for the Middle East (green), Africa (purple) and both regions together (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4. Results

4.1. Regional trends in temperature and violence in Africa and the Middle East

The entire African and ME region faced significant warming in the last three decades (Fig. 1A). In particular, temperature increased up to 1 °C per decade in the cooler areas of the region (Fig. S4). Similarly, the frequency of armed conflicts increased by 52±68 events per year (2.7±3.5% of mean, P = 0.0003) or by 80 violent events per year when comparing the average number of events for 2008–2017 to that of 1990–1999. Increase in violence was even more severe in current decade, with a trend of 265,774± events per year (R = 0.84; P = 0.0096; 2010–2017), which is ~14% of the mean number of events per year for the entire 1990–2017 period. The increase in violence occurred in both Africa and ME regions (Fig. 1B), with a significant increase in Africa since 2005 (9.6% of mean, R = 0.93; P < 0.0001) and episodic but consistent increase in the ME since 1990 (4.0% of mean, R = 0.61; P = 0.0006; 1990–2017).

Unlike the evident regional warming, trends in violence differed among climatic zones (Fig. 2). 'Cooler' regions became in general less violent while violence increased substantially in 'warm' zones. For example, the number of violent events increased significantly in Africa's arid region (zone B in Köppen-Geiger classification) by 41 ± 40 events per year (8.2 ± 8.0% of mean, P < 0.0001) or by 71 events per year (14.2%) between 2008 and 2017 and 1990–1999 (Fig. 2A). Increase was also significant in ME's arid region with an average of 31 ± 32 events per year (9.2 ± 9.8%, P < 0.0001) or 53 events per year (15.7%) between 2008 and 2017 and 1990–1999 (Fig. 2B).

In contrast, the frequency of violence decreased significantly in Africa's temperate region (zone C) by 19 ± 20 events per year (7.0 ± 7.4%, P < 0.0001) or by 33 events per year (12.2%) between 2008 and 2017 and 1990–1999 (Fig. 2D); as well as in the ME's cold zone D by 3 ± 6 events per year (4.7 ± 9.4%, P = 0.015) or by 8 events per year (12.5%; Fig. 2F). The negative trend was marginally significant (P = 0.063; 1996–2017) in ME's cold region D even after excluding the large peak in violence at the beginning of the first decade (1990–1996; Fig. S5A), which was mostly related to a new Turkish counter-insurgency against the PKK (Jacoby, 2010). Similarly, a decrease of 9 events per year in Africa's temperate regions was still significant (P = 0.0004; 1995–2017; Fig. S5B) after excluding the large number of violent events in 1990–1994, which was related to the Natal civil war in the KwaZulu-Natal coastal province at the end of the apartheid (Kaufman, 2017). In these regions, temperature and violence were significantly correlated (Fig. 2A, B, D and F).

4.2. Seasonal synchrony between temperature and violence in climatic regions

At the seasonal scale, we find synchrony between temperature and violence in most climatic zones, where violence occurs mostly in warmer months.

Fig. 3 shows the seasonal relationships between monthly number of violent events and mean temperature, with the probability P of the linear regression alongside, indicating the significance of the relationship. Significant correlations between frequency of violence and temperature in most of these zones indicate a seasonal link between the two. Fig. 4 further shows that this relationship was generally stronger in cooler regions (Fig. 4B) which have a larger seasonal temperature cycle (Fig. 4A).

Significant differences in violence among months were noted in the cold region of the ME (zone D), and, interestingly, in equatorial Africa (zone A), where more violence occurred in the warmer months (blue and red bands at the bottom of the boxplots in Fig. 3). Moreover, increase in the frequency of violence was four times larger in summer (June-August) compared to winter months (Nov-Feb; +22 *vs.* + 5 events per month per year, P < 0.05 in a full factorial ANCOVA test for the interaction year × season) during 2008–2015 in the ME (overlapping years of the 'Arab Spring' period; Levin et al., 2018), suggesting a positive seasonal effect of warm temperatures on violence at the regional scale.

4.3. Temperature anomalies have greater effect on violence in warmer places

Results from the grid-based inter-annual analysis indicate that the range in ΔViolence' was between –20% and 22% across Africa and the ME (Fig. 5A). Also, most of the ρ's from the non-parametric correlations between $\text{Violence}_{\text{anom}}'$ and T_{anom} were positive (Fig. S6), of which 47% were also statistically significant at P < 0.05 and 52% at P < 0.1.

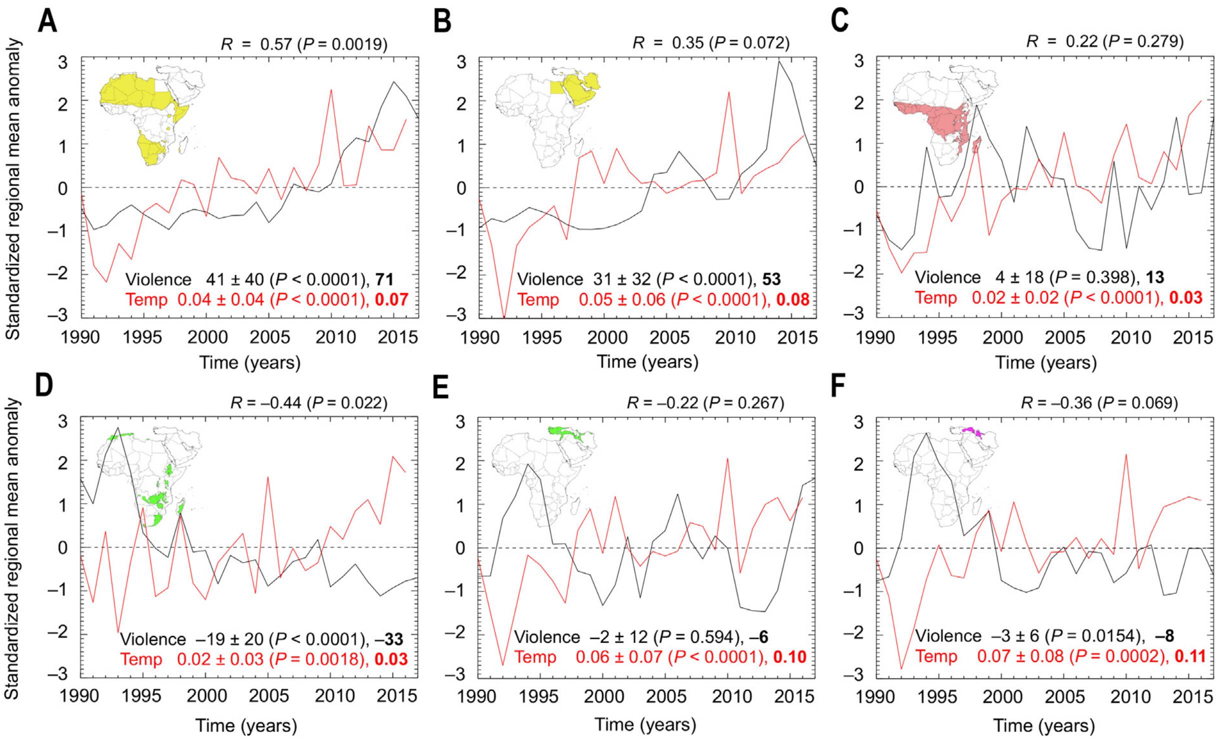

Fig. 2. Regional inter-annual variations in mean temperature and violence. Standardized regional mean temperature anomaly (red) and armed conflicts (black) for Köppen-Geiger climatic zones in Africa and the Middle East. 'Warm' regions are in the top row and 'cooler' regions are at the bottom. The region is indicated by the map in each graph (**A** and **B** for arid B-zones; **C** for equatorial Africa's A-zone; **D** and **E** for temperate zones, and **F** for ME's boreal zone D). The linear trend (±one standard deviation) per year and its significance level P for temperature (°C change per year) and violence (change per year in number of events) are indicated, followed by the mean value difference between the last and first 10-year periods (in bold). The correlation coefficient R and its P value between violence and temperature are indicated at the top of the graphs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Positive ρ's imply that violence generally increased in warm years and decreased in cool years with a relative magnitude of change proportional to the ranked temperature anomaly. The magnitude of ρ was independent of the trend in violence, with an average ρ of $+0.40$ and $+0.42$ for negative and positive ΔViolence' (trends in violence), respectively ($P = 0.36$ in a paired t-test; comparable blue and red symbol sizes in Fig. 5A).

ΔViolence' was indifferent to the long-term change in temperature (slope ~ 0; Fig. 5B), meaning that changes in violence were not affected by warming or cooling trends in the analysis period. However, ΔViolence' increased with $\overline{T}$ by an average of ~ 1% per 1 °C ($P < 0.0001$; Fig. 5C), indicating a greater increase in violence for warmer locations.

The correlation between temperature and violence anomalies (ρ) increase with $\overline{T}$ ($P = 0.0062$; Fig. 5D), indicating higher violence sensitivity to temperature anomaly in warmer places. ρ increased by 0.49% per 1 °C, suggesting that the T_{anom}–$Violence_{anom}'$ link becomes stronger for warmer locations.

4.4. Population and socioeconomic development affect violence occurrence, but no apparent effect of temperature

Results of the violence occurrence analysis (factors affecting the likelihood to find violence in a specific place) show that the mean population density and the average IMR (proxy of socioeconomic status) of the 'Sample' (grids with violence) are both higher than those of 'Region' (total grids in the two regions), with a mean population density of 72,000 persons per grid and an average IMR of 98 deaths per 1000 births for 'Sample' compared to 17,500 persons per grid and 82 deaths per 1000 births for 'Region' ($P < 0.0001$ in a paired t-test, for both; Fig. 6, A and B). Nearly 61% of the grids in 'Sample' were classified as high-IMR, meaning that 'Sample' was statistically different than 'Region' and high-IMR was more common in 'Sample' than low-IMR. The average $\overline{T}$ for 'Sample', on the other hand, was quite similar to that of 'Region', with a slightly lower 30.0 °C compared to $\overline{T} = 30.3$ °C of the 'Region' (Fig. 6C), suggesting no direct influence of temperature on whether or not a grid cell experienced violence during the period of analysis.

'Sample' to 'Region' ratios increased linearly with the log population density (Sample/Region[%] = 14.4 Log(Pop) – 39.6; $R^2 = 0.95$) and logarithmically with IMR (Sample/Region[%] = 9.7 Ln(IMR); $R^2 = 0.44$; ratios shown as red histograms in Fig. 6, A and B), reflecting the positive skew of the 'Sample'. For both factors the ratio was larger than the total ratio (horizontal dashed line in Fig. 6A,B) for larger values. When classified by groups, the 'Sample' to 'Region' ratio was 29.2 ± 18.6% for high-IMR compared to 18.7 ± 11.2% of the low-IMR group ($P < 0.05$ from a paired t-test). In contrast to population density and IMR, the 'Sample' to 'Region' $\overline{T}$ ratio was within or lower than the total ratio, with little change across the entire range of values (Sample/Region[%] = –0.14 $\overline{T}$ + 27.2; $R^2 = 0.05$; Fig. 6C).

5. Discussion and conclusions

Our work complements and adds to previous studies by: (1) providing a first grid-based quantitative analysis of the temperature-conflicts link in the ME; (2) providing a first regional-based analysis that considers climatic regions; (3) describing seasonal relationship patterns of temperature and violence; and (4) distinguishing between short and long-term effects of temperature on violent conflicts. These aspects were previously not, or only partly, considered by others. Findings from this study were aimed to shed light upon temperature–conflicts links at different spatial and temporal scales.

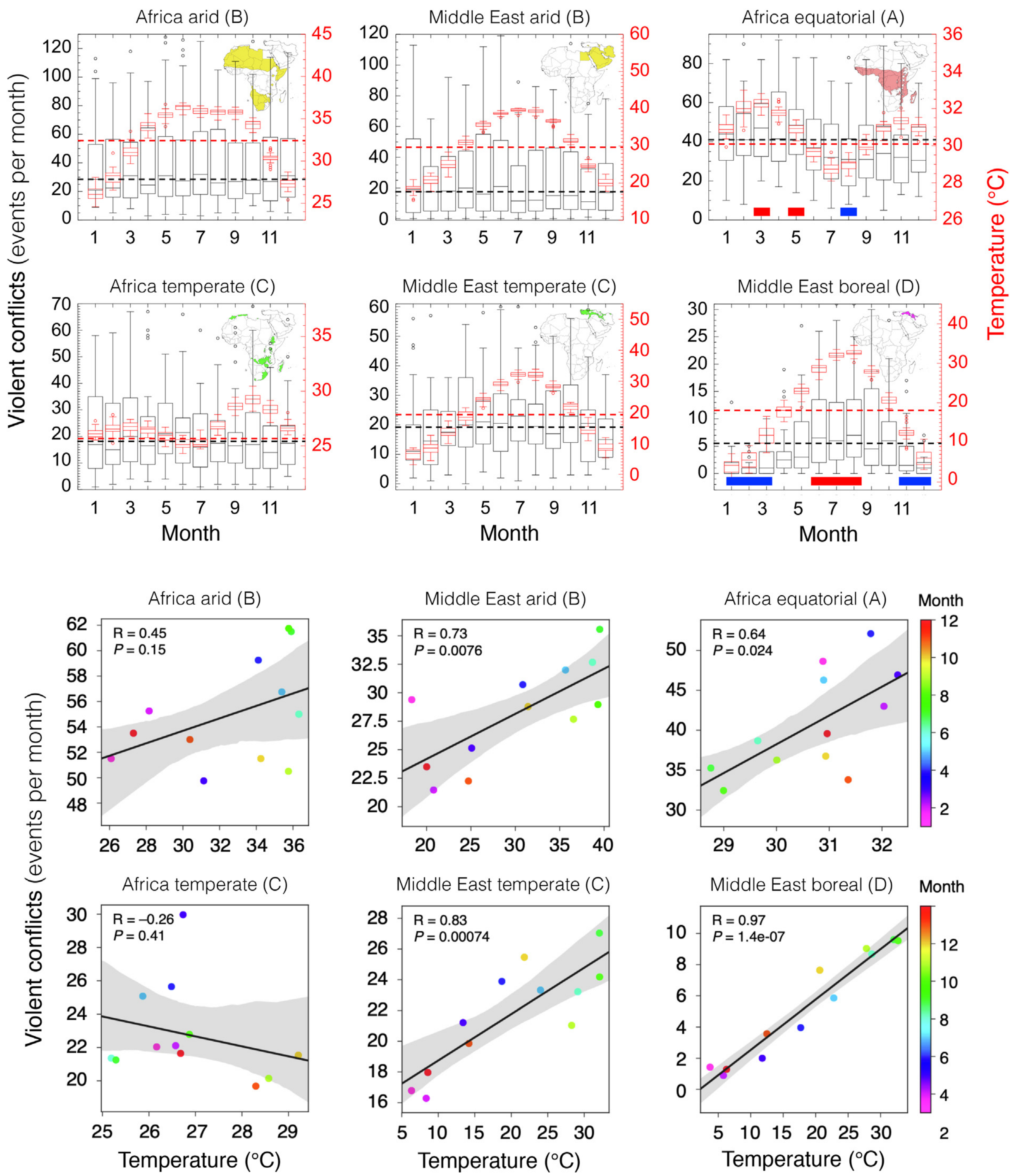

Fig. 3. Seasonal synchrony between temperature and violent conflicts. (Upper) Boxplots showing median, 1st and 3rd quartiles of monthly number of events and temperature for Köppen-Geiger climatic zones in Africa and the Middle East. Zones indicated by the map in each graph are the same as in Fig. 2. (Bottom) Scatterplots of the correlations between mean monthly number of violent events and temperature for the same zones as above. The correlation, R, and its *P*-value are indicated. Horizontal dashed lines in boxplots indicate the mean number of violent events per month (black) and mean temperature (red). Blue and red bands at the bottom of the boxplots indicate months with statistically significant low and high number of events, respectively, from a nonparametric Kruskal-Wallis test followed by Bonferroni correction. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Our results indicate that when taking all factors into account (i.e. not considering 'location effects') violent places do not differ from other parts of Africa and the ME in terms of local temperature. A rather weak influence of mean temperature on violence occurrence compared to other factors, such as population density and socioeconomic status, may be the reason for that (O'Loughlin et al., 2014; Von Uexkull et al., 2016). Yet, when analyzing only violent places (i.e. considering 'location effects') the influence of temperature variations on the frequency of inter-group violence was evident, particularly in warm locations. Interestingly, though, we did not find a direct evidence that warming affects the frequency of conflicts during the period of analysis (1990–2017), in contrast to previous reports. Burke et al. (2009) showed that an increase of 1 °C increases the frequency of conflicts by 4.5% at a country-level in Africa in the same year. By comparing quantitative results across numerous studies, Hsiang et al. (2013) reached a conclusion that warmer conditions generate more conflicts

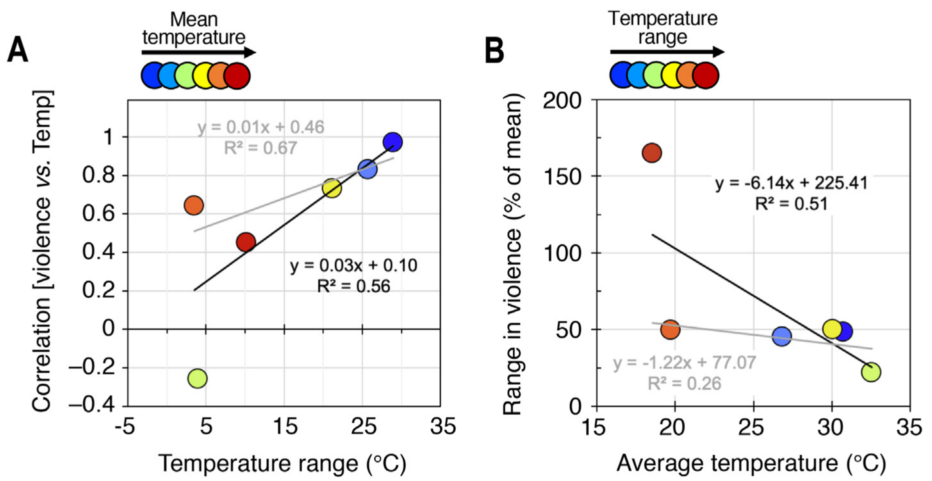

Fig. 4. Cooler regions with a wider range in temperature from winter to summer have the stronger violence – temperature seasonal synchrony. Relationships between (**A**) the monthly violence – temperature correlation (indicated on plots in Fig. 2) and the seasonal temperature range (mean temperature of hottest month minus that of coldest month); and between (**B**) the range in violence (number of events in month with maximum violence minus that in month with the minimum violence) and mean annual temperature, for the 6 regions in Fig. 2. Correlations shown are with all regions (black) and excluding the negative correlation in Africa's zone C (gray) in (**A**), and ME's zone B in (**B**). Symbol colors from blue to red indicate increasing (**A**) regional mean annual temperature and (**B**) seasonal temperature range. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with an increase of ~13% in inter-group violence per 1σ rise in temperature. Here, we could not directly confirm the effect of long-term warming, but rather showed its effect indirectly. This does not necessarily mean that the long-term temperature trend has no effect on violence, but rather emphasizes the difficulty of controlling for factors other than temperature when looking for long-term relationships at inter-annual timescales.

While we are aware of the fact that the GED battle-related deaths data set miss small-scale violent events, which are believed to be the most affected by climate, this is currently the most accurate global data set available on violent conflicts. Moreover, the exact and consistent definition of a violent conflict event in the GED data enables us to analyze this phenomenon across time and space, providing a global picture of organized lethal violence. Thus, we believe that in spite of the fact that temperature might affect small-scale violence (violent events without deaths), as previously shown by others (Tubi and Feitelson, 2016), in our study it does not clearly show a direct impact on long-term trends in these moderately sized armed conflicts.

The potential for a long-term effect, though, is evident indirectly when considering 'location effects' in the analysis. The effect of temperature variations on conflicts was found to be stronger in warmer locations, being 10% stronger in places with a mean annual maximum temperature of 40 °C compared to places with a mean annual maximum temperature of 20 °C (i.e. an equivalent effect of 5% increase in the strength of the temperature-conflicts link per each 10 °C of warming).

Increase in population density and decrease in socioeconomic status (higher IMR) are both associated with enhanced likelihood of violence occurrence. In regions where the vast majority of the population is rural and more dependent on natural resources (such as much of sub-Saharan Africa) the likelihood of conflict can be hypothesized to be greater, particularly if water scarcity is taken into account. This means that we should expect more violence in rural, rather than in urban areas, at least in sub-Saharan Africa. However, as many previous studies have shown, larger populations may increase conflict risk through a larger pool of

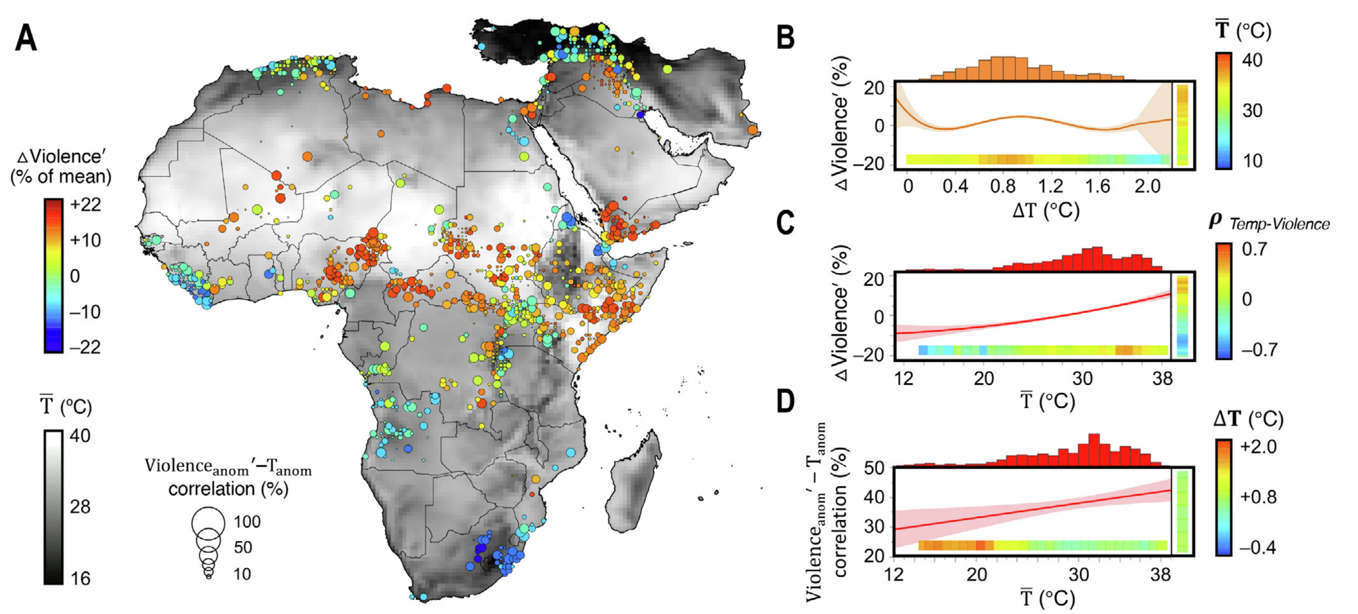

Fig. 5. Stronger effect of temperature anomaly on violence in warmer areas. (**A**) Map of the relative change in violence (ΔViolence'; 1990–2017), mean annual temperature ($\overline{T}$) and the correlation between the anomalies of temperature (T_{anom}) and violence ($Violence_{anom}'$), indicated by the size of the symbol. Nonparametric regressions of (**B**) ΔViolence' against long-term temperature change (△T), with summed binned values of $\overline{T}$ at the bottom; (**C**) ΔViolence' and $\overline{T}$, with summed binned values of the Spearman's rank of the correlation (ρ) between timeseries of temperature and violence; and (**D**) $Violence_{anom}'$–T_{anom} non-parametric correlations (%) against $\overline{T}$, with summed binned values of △T. Histograms show the distribution of the independent variables. Confidence curves are 95% for the fitted line. Note that coolest places (blue hue in horizontal band in **B**) experienced the largest △T (~2°C). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

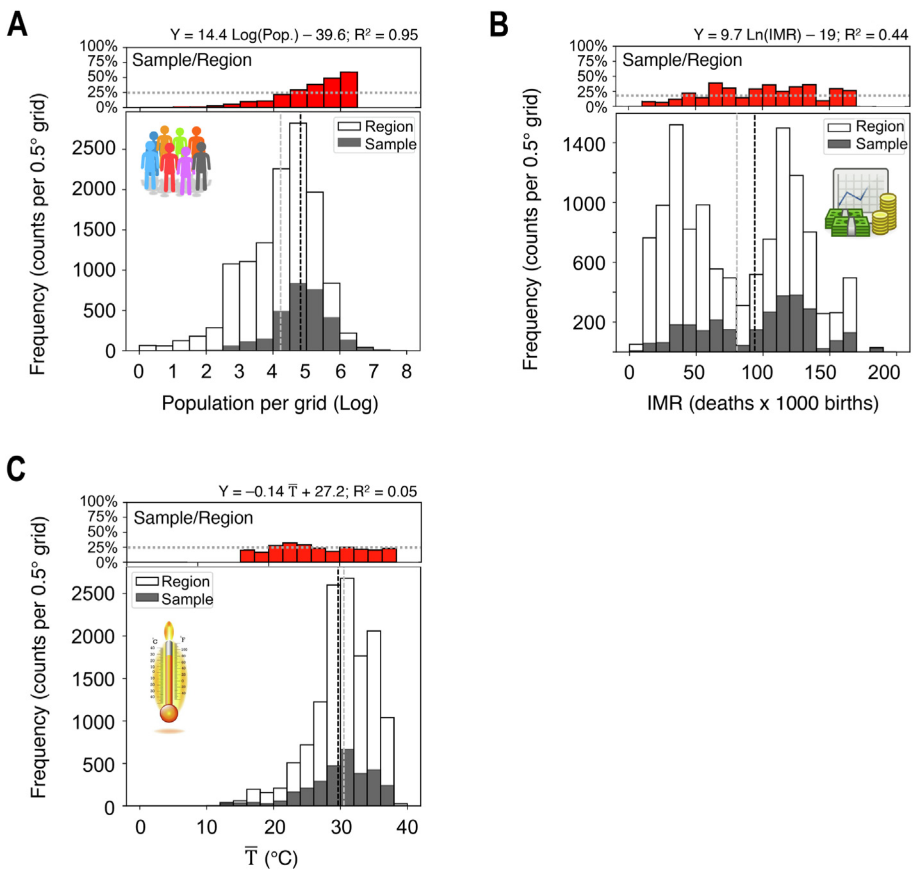

Fig. 6. High population density and low socioeconomic status increase the risk of conflicts in Africa and the Middle East, but no apparent effect of local temperature. Distributions of grids where armed conflicts occurred during 1990–2017 ('Sample') and of all grids in the region ('Region') for (**A**) log population density per grid, (**B**) infant mortality rate (IMR; number of deaths per 1000 births), used a as proxy for socioeconomic status, and (**C**) long-term mean temperature ($\overline{T}$; °C). A skew in 'Sample' relative to 'Region' means statistically different conditions in violent grids than in the total grids of the region. Vertical dashed lines indicate the averages of 'Region' (gray) and 'Sample' (black). Red histograms show significant 'Sample' to 'Region' ratios ($P < 0.05$) for binned values. A ratio above the horizontal line (Sample/Region including all grids) means deviation from normal distribution and a greater probability of violence occurrence. Trend in ratios (Y, quantified as the percentage of Sample/Region) is indicated above with respective R^2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

people willing to engage in violence under unfavorable conditions (Goldstone, 2002; Raleigh and Hegre, 2009). Or, violence may be more easily triggered by climate change in areas where a high population density places an extra pressure on the already scarce available resources (Urdal, 2005). This is particularly true following climate-related disasters (Ide et al., 2020).

Likewise, populations of low socioeconomic status are often more likely to be involved in violence (Hegre and Sambanis, 2006; Hsiang et al., 2011), particularly when stress on resources is high (Von Uexkull et al., 2016). Population density and IMR may be related. We find in our study a significant but rather weak correlation between the two, meaning that population density and IMR are likely to have, at least to some extent, independent influences on armed conflicts.

Our seasonal analysis reveals that changes in the frequency of violence are coupled with seasonal variations in temperature across climatic zones in Africa and the ME. This is an important result, because unlike the inter-annual relationship that may involve unobserved indirect effects (e.g. warming on resources and resources on violence; Carleton, 2017; von Uexkull et al., 2016), seasonal relationships imply a more direct effect. Viewed from the perspective of individual behavioral tendencies, this relationship could be caused by stressful conditions during warm summers due to temperature rise, which may enhance aggressive behavior (General Aggression Model - GAM; Dewall et al., 2011). Indeed, aggressive behavior was found to be augmented following temperature rise in both laboratory and field experiments (Anderson, 1989; Baron and Bell, 1976; Vrij et al., 1994). Exposure to warming and even to words related to hot temperatures has shown to increase aggressive thoughts and hostile perceptions (DeWall and Bushman, 2009), while these may be translated to physical violence. On the other hand, increase in violent conflicts during warm periods may also result from the simple fact that more people are outdoor interacting with each other when the weather is warm (Routine Activity Theory - RAT; Cohen and Felson, 1979). The hot season also coincides with the dry season, which may further support the RAT in this case because people are less busy in agriculture during the dry season, or are more able to travel. Viewed at the level of organized groups, our results are also consistent with the Strategic Viability Mechanism (Landis, 2014), in that the warm season is often associated with greater access to resources and lower inhibition on travel, both of which may increase opportunities for violent groups to act. Insomuch as violence emerges spontaneously out of individual conflicts, theories like GAM or RAT might apply. But insomuch as violence at the scale considered in this study requires some form of organization or planning, theories like the Strategic Viability Mechanism might be more relevant. Thus, the exact mechanisms by which temperature rise affect violent conflicts at the seasonal scale still need to be determined. Future research could address the behavioral mechanisms that underlie this scaling-up of aggressive behavior, from interpersonal aggression to violence between groups.

Overall, our findings highlight the relative influence that temperature anomalies may have on violent conflicts, particularly in warm locations. Although we did not find a direct effect of the 27-year trends in temperatures on violence, the higher sensitivity of violence to temperature anomalies in warmer places suggest potential adverse effects of long-term warming on violence. These findings support previous studies that have identified a positive temperature-violent conflicts relationship (Burke et al., 2009; Hsiang et al., 2013) and expand those to the ME region where few quantitative studies exist (Adams et al., 2018). Moreover, our analysis was not confined to specific areas, but spanned the entire African and ME regions, thus emphasizing the generality of the findings. This is important, as previous studies have been criticized as being products of a "streetlight effect," or sampling on the dependent variable, because they have focused on specific violence-prone regions (Adams et al., 2018). Finally, the link found here at the seasonal timescale points out a direct effect of temperature on conflicts, in accordance to inter-personal GAM and RAT theories.

Nevertheless, the influence of climate on violence is inherently complex, and our study is limited by certain simplifying assumptions. These include the fact that we have not considered a location's history of violence in a time-varying sense; it is possible that a conflict in one year alters the potential for another conflict for some period of time into the future. Additionally, we have attempted to control for location effects by adopting a longitudinal analysis approach. However, it is possible that conditions related to governance, ethnic interactions, and other conflict-relevant factors might change through time, or that these conditions might act as effect modifiers.

Considering our findings and increasing warming projected for these regions (Lelieveld et al., 2016), future increases in the frequency of violence may be expected. Yet, there is a need to understand the mechanisms by which temperature actually affect the occurrence and frequency of violence. This is key to improve our readability for future violent conflicts outbreaks and response to violence aggravation in violence-prone locations.

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CRediT authorship contribution statement

David Helman: Conceptualization, Data curation, Project administration, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Benjamin F. Zaitchik:** Conceptualization, Data curation, Project administration, Investigation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloenvcha.2020.102118.

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