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Temperature extremes, global warming, and armed conflict: new insights from high resolution data ☆

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ABSTRACT

This paper contributes to the debate whether climate change and global warming cause conflicts by providing novel evidence about the role of extreme temperature events for armed conflict based on high-frequency high-resolution data for the entire continent of Africa. The analysis of monthly data for 4826 grid cells of 0.75° latitude × longitude over the period 1997–2015 documents a positive effect of the occurrence of temperature extremes on conflict incidence. These effects are larger the more severe the extremes in terms of duration, and are larger in highly densely populated regions, in regions with lower agricultural productivity, and in regions with more pronounced land degradation. The results also point towards heterogeneity of the effect with respect to the type of violence and the crucial role of population dynamics. Considering the consequences of increases in the frequency of extreme events in a long-differences analysis delivers evidence for a positive effect on conflict.

Amid the diverse social and political causes, the Darfur conflict began as an ecological crisis, arising at least in part from climate change. (...) It is no accident that the violence in Darfur erupted during the drought. (...) For the first time in memory, there was no longer enough food and water for all. Fighting broke out. (...) Any peace in Darfur must be built on solutions that go to the root causes of the conflict.[1]

[*Ban Ki Moon, 2007*]

Most of today's conflicts are still essentially internal. (...) They are fuelled by competition for power and resources, inequality, marginalization and exclusion, poor governance, weak institutions, sectarian divides. They are exacerbated by climate change, population growth and the globalization of crime and terrorism.[2]

[Antonio Guterres, 2017]

1. Introduction

Climate change and civil conflict belong to the greatest challenges for developing countries, especially in Africa. Official statements, such as those by UN Secretary Generals Ban Ki Moon and Antonio Guterres, are explicit about the detrimental roles played by these phenomena, as well as their interlinkages. A look at the data confirms the increasing prevalence of both. For instance, Fig. 1 illustrates the trend in temperature, exemplified by the average temperature per month (Panel (a)) and the prevalence of extreme temperature events in a month, measured by the

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[1] *Ban Ki Moon, "A Climate Culprit In Darfur", Washington Post June 16, 2007 (http://www.washingtonpost.com/wp-dyn/content/article/2007/06/15/AR2007061501857.html).*

[2] Antonio Guterres, Secretary-General's remarks to the Security Council Open Debate on "Maintenance of International Peace and Security: Conflict Prevention and Sustaining Peace" (https://www.un.org/sg/en/content/sg/statement/2017-01-10/secretary-generals-remarks-security-council-open-debate-maintenance).

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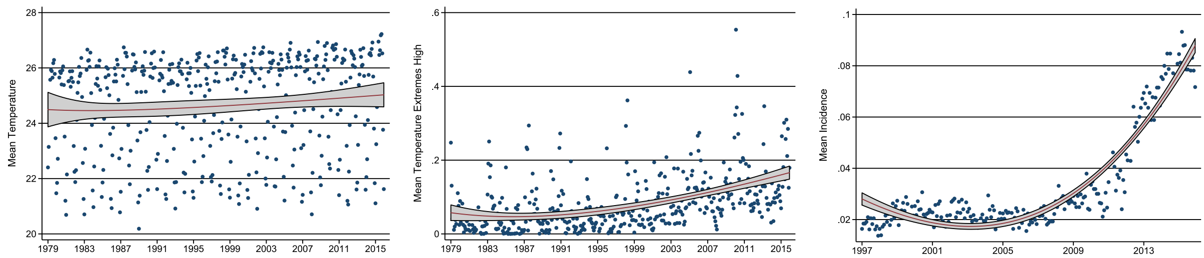


(a) Average Temperature (b) Temperature Extremes (c) Conflict Events

Fig. 1. Dynamics of Temperature, Extreme Temperature and Conflict in Africa. This figure shows the monthly evolution of temperature, extremes and conflict. Additionally, it plots fractional-polynomial predictions with 95% confidence intervals. Temperature extremes are coded as 1 if the absolute temperature deviation from month-specific means for a given cell (calculated from the training period 1979–1996) exceeds the 95 percentile threshold, and 0 otherwise. See Section 3 for a detailed data description.

incidence of deviations from calendar month specific means for a given grid cell exceeding the 95th percentile of deviations (Panel (b)). The data reveal a clear increase in both, temperature and in the frequency of extreme events over the past three decades. Over the past two decades, conflict incidence has increased starkly (Panel (c)). Fig. 2 depicts the dynamics in temperature extremes and conflict over the period 1997–2015 for a map of Africa in grid cells of 0.75° latitude/longitude. Conflict seems to have increased relatively more in regions that experienced a more pronounced increase in the prevalence of temperature extremes, which is suggestive of an interrelation.[3] This paper explores the question whether weather extremes and climate change, reflected by the frequency of events of extreme temperature which is commonly viewed as a symptom of global warming, is relevant for the outbreak of violent conflict at the disaggregate level.

The question whether climate change and global warming cause conflicts has fueled a heated debate that has been ongoing for years. One branch of the existing academic literature has pointed at evidence that supposedly shows that weather and climate variation cause conflicts, mainly as consequence of increased resource pressure due to a deterioration in the conditions for agricultural production. Another branch of the literature has disavowed this conclusion by arguing that increased conflict was mainly a problem of institutional failure, whose consequences become aggravated in the face of increased environmental pressure as well as rapid globalization. Among the reasons for the lack of consensus in the scientific literature have been methodological issues, such as sampling bias, and the heterogeneity in the narratives about the triggers of incidences of conflict and the lack of evidence regarding the channels, which is related to the fact that most of the evidence at the core of this debate is at annual frequencies and at the country or region level. In light of this, official statements, such as those by Ban Ki Moon or Antonio Guterres, both UN Secretary General officials, usually avoid being specific about causality.

This paper provides novel evidence about the role of extreme weather events related to climate change for conflict and contributes to the debate in several ways. In terms of data, the use of high-frequency high-resolution data for the entire continent of Africa allows isolating the role of weather extremes as triggers of conflict with greater precision than the previous literature and without restricting to particular areas that are more or less conflict prone, thus avoiding sampling bias. In particular, the analysis is based on monthly temperature and precipitation information for 4826 grid cells of 0.75° latitude × longitude over the period 1997–2015 and isolates the role of weather extremes for the

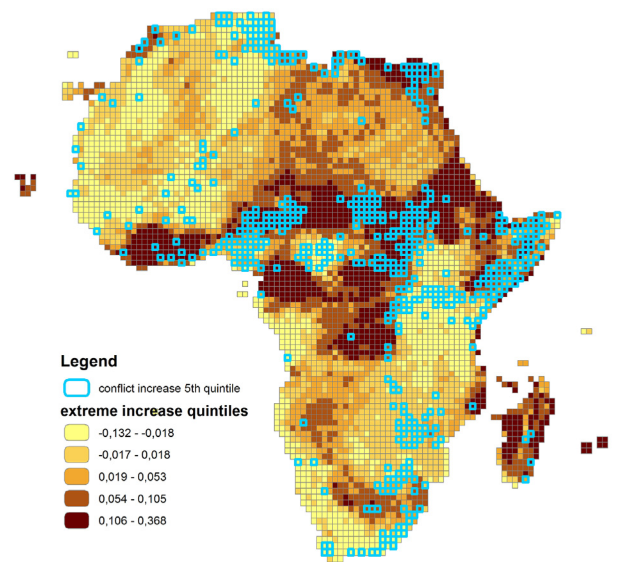


Fig. 2. Dynamics in Temperature Extremes and Conflict Incidence. The figure plots quintiles of changes in the average occurence of temperature extremes from the first half of the panel (1997–2006) to the second half of the panel (2006–2015) together with the cells belonging to the highest quintile of changes in average conflict incidence from the first half to the second half of the panel.

incidence of violent conflict events. In contrast to previous studies on extreme weather events, we consider deviation from long-run cell-specific and calender month-specific average conditions.

We find a significantly positive effect of temperature extremes on conflict incidence for both, an increase in the average number of extreme weather events and a longer duration in terms of months. The effect on conflict of extreme events that last for two months is found to be quantitatively larger than the effect of events that last for one month only. There is also some indicative evidence that this effect is non-monotonic for events that last even longer.

The quality of the data also allows for a detailed investigation of the underlying mechanisms. Among the narratives that have been mentioned in the literature, climate-related shocks to agricultural productivity and conflict for resources have been the most prominent. The analysis documents that temperature extremes have a particularly strong effect in densely populated areas and areas with low agricultural productivity.

Recent work has pointed at the role of migration in the context of climate change and conflict. When investigating the role of migration and population dynamics, our results reveal that temperature extremes have an effect on conflict mainly in areas that are loosing population or that are growing rapidly, not so much in areas with fairly stable populations. However, the types of

[3] Fig. A1 in the Appendix depicts the corresponding map for dynamics in average temperature and conflict over the period 1997–2015. See Section 3 and Appendix A for details on data, data sources and variable construction.

observed conflicts turn out to differ systematically across areas that lose population and those that gain population, providing novel insights to the mechanisms that link weather extremes and conflict. Weather extremes appear to trigger mainly violent events involving territorial changes and conflicts in rural and agricultural contexts in cells that experience out-migration and population loss. The results further show that land degradation is a critical factor for the link between temperature extremes and conflict with the effect of temperature extremes being much stronger in regions with greater degradation. These findings deliver novel evidence that is consistent with a mechanism working through the loss of agricultural productivity, in line with some of the conflict narratives that have been debated in the literature. At the same time, we find that temperature extremes are linked to riots and battles without territorial changes in areas that experience immigration and fast (presumably migration-related) population growth.

The analysis concludes by turning to the implications of global climate change, which is typically associated with a greater frequency and longer duration of extreme weather events. Considering the role of changes in the frequency of extreme events in a long-differences analysis and applying a generalized differences-in-differences strategy delivers evidence for a positive effect of a gradual increase in the frequency of extreme events on conflict. This sheds new light on the debate about the consequences of climate change for conflict. Our findings indicate that societies do not seem to have adjusted to an increasing frequency of extremes over the observed time period. Further, the societal vulnerability to short-run climatic shocks is mirrored in the long-run results.

The remainder of the paper is structured as follows. Section 2 provides a conceptual background for the empirical analysis and discusses the contribution to the literature. Section 3 describes the data sources and the construction of the data set used in the analysis. Section 4 presents the results for the short-run effects of the occurrence of temperature extremes on conflict incidence. Section 5 turns to a long-differences analysis of the effect of a gradual increase in the frequency of extreme events on conflicts. Section 6 concludes the analysis with a brief discussion of the results.

2. Conceptual background and existing literature

2.1. Conceptual background

The nexus between climate change and civil conflict has received an increased research interest over the past years. However, the recent literature has not produced a consensus regarding the empirical relevance of this nexus, partly because of the lack of a coherent perspective and partly because of different empirical concepts and approaches that are used to investigate the existence of such a nexus. We proceed with a description of the empirical concepts and approach used in this paper in order to clarify the contribution of our paper to the existing literature.

This paper addresses the research question whether the incidence of extreme temperature events and an increase in their frequency the context of global warming are associated with increased incidence of civil conflict. The nexus between weather extremes as well their increased frequency in the context of climate change with civil conflict conceptually belongs to the category of explanations for conflict that are primarily related to economic hardship. Numerous mechanisms are conceivable through which adverse shocks to living conditions imply a reduction in the opportunity costs for conflict or an increased incentive for violence as result of fiercer competition for resources. For instance, relevant facets of economic hardship arising from extreme temperatures involve losses of income from reduced agricultural productivity or decimated livestock, lower harvest volumes or adverse commodity price variations. Most of the existing literature has been concerned with documenting a reduced form relationship using short-run weather variability and shocks to establish an empirical link between climate and conflict. Although climate change is related to changes in mean climate over long periods, the focus of weather variability has been the result of statistical considerations related to the identification of causal effects. While the present paper also exploits weather variability, the empirical analysis focuses on the role of extreme temperature events on the level of grid cells. The particular construction of extreme temperature events has several advantages in the present context. First, by looking at deviations from cell-specific calendar month-specific means, the variable of interest explicitly abstracts from seasonal climate effects. Otherwise, most of the extremes would be found in the hot season whereas there would not be much variation in the remaining year. This methodology is based on the assumption that a deviation from the long-run normal conditions can have a disruptive impact in any month. It is therefore the variation relative to the normal conditions in a given cell and month, and not an absolute weather event, that is modelled as extreme event and hypothesized as potential trigger of violence. Second, extremes are constructed relative to the distribution during a training period (1979–1996) that precedes the period for which the main analysis is conducted. The advantage of this approach is that the mean that serves as basis to construct the extremes stays constant over the estimation period. This avoids that the temperature extremes are related by construction to variation during the period of interest, allowing for a transparent benchmark and an investigation of long-run trends. Third, this measure builds on, and directly reflects, the emerging consensus in the recent literature based on historical accounts and climate projections that extreme weather events seem to become more frequent as result of global warming (Collins et al., 2013; Russo, Marchese, Sillman, & Imme, 2016). In fact, the construction of temperature events based on a training period prior to the analysis period allows for a direct test of an increasing frequency of extreme events, presumably related to global warming, as well as for an explicit analysis of long-run trends and their effects within the same sample.

In the context of the debate about the existence of a reduced form relation between climate change and conflict, one argument has been that a reduced form effect potentially merely constitutes an average association resulting from different mechanisms that have to do with the vulnerability and resilience to weather shocks of the population in different areas. Following Seter (2016), a viable empirical strategy to shed light on the research question therefore needs to operationalize the key elements of the different mechanisms that might be at play, which comprise economic hardship, favorable conditions, or migration. In order to distinguish between these mechanisms, it is useful to distinguish and clarify the appropriate temporal and spatial scale to address the research question, the population groups affected by climatic variability, the type of climatic events they react to, and the type of conflict that is the most likely outcome. In particular, the consequences of extreme weather for outbreaks of violence may depend on demographic and environmental conditions, and the related sources of economic hardship.

To address the research question, the present paper uses monthly variation at the level of grid cells of 0.75° latitude/longitude over a long time horizon over the period 1997–2015. This allows for both, a sufficiently long observation period to be able to analyze the consequences of climatic changes over long periods and a sufficiently high resolution of data to shed light on mechanisms and contributing factors. The mechanisms under considerations combine economic hardship as consequence of the occurrence of temperature extremes and migration-related factors.

The first step of the analysis is to establish the existence of a reduced form effect of the occurrence of extreme events on conflict and shed light on the role of the severity of the extreme event in terms of duration. In light of the construction of extreme events relative to cell-month-specific averages, this provides novel insights by focusing on relatively unusual conditions rather than the occurrence of an absolute extreme.

In a second step, we distinguish between different conflict types in order to disentangle the potentially various underlying mechanisms. In a third step, we address the question about the mechanism through which climate variation affects conflict focusing on economic hardship and migration. In particular, we explore heterogeneity along two dimensions that are directly related to these mechanisms and that contribute to the vulnerability to extreme events, namely population density and soil suitability in terms of caloric yield. Population density is conceptually related to both, hardship and migration. In particular, unusual weather conditions that occur in more densely populated areas with greater resource dependency and thus greater sensitivity to variations in outside conditions are expected to be associated with a greater likelihood of conflict outbreaks. Soil quality provides another, conceptually distinct, factor related to vulnerability. Temperature extremes are expected to lead to economic hardship particularly in cells with already precarious production conditions as reflected by poor soil quality.

While heterogeneity along these dimensions is suggestive of particular and potentially distinct channels, the interacting factors might themselves change over time and thereby lead to an aggravation of the vulnerability to the occurrence of extreme climatic events. To account for this dynamic aspect, a fourth step is to consider the role of migration dynamics by disentangling the effect in cells that experience predominantly out-migration from that in cells with predominantly in-migration, and from that in cells with rather stable populations. Likewise, the population in cells experiencing severe land degradation are expected to be more vulnerable to the occurrence of extreme events, and react with more violence, than the population in cells with stable conditions for agriculture. The fifth step combines the information on conflict types with the heterogeneity across cells that experience different patterns of migration or soil degradation. This sheds new light on the existence of distinct mechanisms through which the reduced form effect of the occurrence of extreme events on conflict comes about.

In a final step, the analysis turns to the consideration of changes in the average frequency of extreme events over long periods of time and their consequences for the occurrence of armed conflict. The analysis thereby contributes a coherent treatment within the same sample of the role of climate change as opposed to short-run variability in climate for conflict.

2.2. Contribution to the literature

This paper contributes to the debate about the role of weather variability and climate change for conflict, which has mainly focused on Africa. Proponents of the role of climate for conflict reported evidence pointing at a strong link between high temperatures or drought in a year and the occurrence of civil conflict (Burke, Miguel, Satyanath, Dykema, & Lobell, 2009, 2010; Burke, Dykema, Lobell, Miguel, & Satyanath, 2010), while critics pointed to methodological problems and structural factors being responsible for these results (Buhaug, Hegre, & Strand, 2010; Buhaug, 2010a, 2010b). This literature concentrated on large-scale conflicts and used annual data at the country level. More recent work used refined identification strategies and also considered small-scale conflicts, but still delivered no consensus about the role of climate, see Burke, Hsiang, and Miguel (2015) for a recent survey.[4] Our work complements this literature by considering the role of weather extremes at a much higher frequency and with grid-level data of higher resolution, as well as by documenting effect heterogeneity that provides insights regarding the underlying mechanisms.

In this dimension, our work is closely related to studies that use grid cells to analyze the effect of weather shocks like drought or temperature and precipitation extremes on conflict. There are several studies that use latitude-longitude grids (or other fine spatial units) as unit of observation and rely on annual variation for identification. Recent work by Harari and Ferrara (2018) studies the effects of drought during particularly critical phases of the crop cycle and finds evidence for a positive effect on annual conflict incidence at the 1° grid level. Using spatially defined ethnic homelands as unit of observation, recent work by von Uexkull, Croicu, Fjelde, and Buhaug (2016) analyzes the impact of growing season drought in Africa and Asia and documents a positive impact for agriculturally dependent and politically excluded groups on violence. This finding relates to Fjelde and Uexkull (2012) who document an effect of rainfall anomalies on communal conflict that is amplified in the presence of economic and political marginalization. Theisen et al. (2012) study the impact of drought on conflict for the African continent at the 0.5° grid level, but attribute the cause of conflict to sociopolitical factors rather than weather shocks. Further, Theisen (2012) conducts an analysis at the 0.25° grid level for Kenya and finds the cause of conflict to be political motives rather than agricultural scarcities.[5] Our work contributes to this strand of the literature by focusing on temperature extremes and long-run changes in the frequency of these extremes, as well as by shedding new light on the underlying mechanisms and revealing effect heterogeneity in various dimensions.

Methodologically, the present paper is most closely related to studies that employ grid level data and rely on high frequency data for identification. These include work by O'Loughlin et al. (2012) who analyze the impact of temperature- and precipitation anomalies on a 1° degree grid in East Africa. In a follow-up study, O'Loughlin, Linke, and Witmer (2014) expand their sample to sub-Saharan Africa. This study documents a significantly positive impact of high temperature anomalies on conflicts that differs across sub-regions and types of conflict, whereas they do not find a significant effect of precipitation anomalies. Further, they assess the quantitative importance of this effect to the impact of political, economic and geographic factors. Maystadt, Calderone, and You (2015) use quarterly data at the 0.5° grid level for the case of Sudan and Maystadt and Ecker (2014) analyze the monthly impact on Somalian administrative regions.[6] Almer, Laurent-Lucchetti, and Oechslin (2017) investigate the role of monthly variation in water scarcity, using an index of evaporation and drought, for local riots. Our paper complements these works by providing an analysis that is based on detailed weather information on the grid-cell level for the entire continent of Africa at a monthly frequency, thereby mitigating concerns about selective sampling (Adams, Ide, Barnett, & Detges, 2018). Regarding the focus on weather extremes, our paper is related to work by O'Loughlin et al. (2012, 2014) that defines extreme events as ±1 or 2 SDs of the long-term means; see also Fjelde and Uexkull (2012), Maystadt et al. (2015), Raleigh and Kniveton (2012) for similar approaches. Our approach makes use of extreme events defined as temperature events in terms of devia-

[4] This ongoing debate includes work that finds evidence for a role of climate for conflict (Hsiang, Meng, & Cane, 2011; Hsiang, Burke, & Miguel, 2013; Hsiang & Meng, 2014), and work that questions the empirical validity of such a role (Theisen, 2012; Theisen, Holtermann, & Buhaug, 2012; Gleditsch, 2012; Hegre et al., 2016).

[5] Hsiang et al. (2013) dispute the finding that temperature has no significant effect on conflict by criticizing the methodology used by Theisen (2012).

[6] Crost et al. (2015) provide related evidence for the Philippines.

tions from cell-month-specific conditions during a pre-analysis training period instead of anomalies based on deviations from long-run means. In addition, our analysis digs deeper into heterogeneity of the effects, in particular the types of conflict affected by temperature extremes, the role of population dynamics, the relevance of agricultural productivity and land degradation, and long-run patterns relating the analysis to the debate on global warming. Our work also complements recent work by Cervellati, Esposito, Sunde, and Valmori (2017) who use monthly data for a 1° grid for the entire continent of Africa to explore the role of weather fluctuations that affect the exposure of the local population to malaria as potential channel leading to increased violence. Instead of disease, our evidence focuses on mechanisms related to agricultural productivity and population dynamics.

In line with conjectures formulated in the existing literature (see, e.g., the survey by Exenberger & Pondorfer (2013)), our findings also indicate the prevalence of coexisting mechanisms taking effect in different contexts. We find conflict risk to increase in regions with declining population and high levels of land degradation, involving conflicts related to territory, agriculture and pastoralism. Therefore, in terms of mechanisms, our study complements work that argues via the loss of agricultural productivity as potential channel, including work by Harari and Ferrara (2018) and recent evidence for ethnicity-related conflict (Sarsons, 2015; von Uexkull et al., 2016). Also, our work complements evidence by Hendrix and Glaser (2007) or Raleigh and Urdal (2007) who point out environmental degradation as a critical factor for the link between climate and conflict, although this literature relies on cross-sectional analysis or time series at an annual frequency. Using cross-sectional data only, Raleigh and Urdal (2007) emphasize the importance of analyzing the relationship between demography and environmental variables in shaping the risk of civil conflict by considering an interaction between population and land degradation. The present study broadens this focus by analyzing the interplay between climate and population dynamics, and between climate and land degradation, in shaping the risk of differential types of conflict within an extensive panel analysis. Our findings indeed suggest that climatic extremes fuel conflict risk in the face of adverse environmental conditions. Further, our finding of weather extremes leading to different types of conflict in regions with different population dynamics in terms of population growth and in-migration hints to different mechanisms being responsible for this result. The results thereby reconcile some of the contradictory findings documented in the literature, e.g., by Theisen (2012). In highlighting the role of population dynamics and migration for different conflict patterns, our work also complements recent work by Bosetti, Cattaneo, and Peri (2018) and Owain and Maslin (2018) that focuses on conflict-related migration between countries. In this respect, our work contributes to the literature on climate migration and the links between environment, migration and conflict surveyed by Brzoska and Froehlich (2016). The use of data with high frequency and high resolution also sheds light on interactions between mechanisms related to economic hardship and migration that are shown to lead to outbreaks of different types of conflict, thereby complementing the existing literature that has largely studied these mechanisms in isolation (Seter, 2016).

Finally, our analysis relates to the literature on the long-run variability in the context of climate change. In this dimension, it follows the suggestion by Burke et al. (2015) pointing to the need for more comprehensive evidence for the climate-conflict link from a long-run perspective. We add to that in terms of an expansion of the sample from East Africa to the entire African continent over a more recent time period, and in terms of methodology. Specifically, we extend the focus from considering trends of average temperature to trends of temperature extremes, documenting the driving force of conflict risk to be the latter. We substantiate the long-difference results by applying a generalized differences-in-differences design which relaxes the restrictive assumption about common pre-trends. Further, our results add new insights regarding societal vulnerability towards increases in temperature (extremes) in the long-run.

3. Data

To analyze the impact of temperature shocks and long-run warming on conflict risk we construct a monthly data set for Africa for the period 1997 to 2015 for 4826 grid cells of 0.75° latitude and longitude, which corresponds to a side length of approximately 83 km at the equator.

Geo-coded data on civil conflict is obtained from the Armed Conflict Location and Event Database (ACLED). The ACLED dataset provides locations of conflicts within all African countries since 1997 (Raleigh, Linke, Hegre, & Karlsen, 2010) based on information from various sources such as newspapers, online journals and reports by humanitarian organisations. The dependent variable is a binary conflict indicator that switches on if at least one conflict has taken place in a given grid and month, where a conflict is defined as "a single altercation where often force is used by one or more groups for a political end" (Raleigh & Dowd, 2015, p. 7). Events involve a range of actors, including rebels, governments, militias, armed groups, protesters and civilians. The two main categories contained in the database are battles and riots. Riots are usually (non-violent or violent) demonstrations against the government. In some cases the target might also be private entities like businesses. Battles are defined as violent events between two groups. One of the groups might be the government but it might also be that two non governmental groups fight against each other. Battles are further split into battles that result in changes of the contested territory and battles that do not affect territorial changes. The categorization of conflicts related to agriculture or pastoralism is based on key word search in informational notes that are included in the database for each incidence.[7] Besides, we generate a category for rural conflicts based on the geographic location of their emergence. Conflicts are defined as rural regional conflicts if they take place outside of large agglomerations.[8]

Monthly time series for temperature and precipitation are obtained from the Era Interim reanalysis data set provided by the European Centre for Medium Run Weather Forecast (ECMWF).[9] Reanalysis of meteorological data ensures very high data quality by combining the strengths of all available meteorological sources. Data inputs ranging from modern radiometric measurements by satellites to local weather stations, buoys or aircrafts are comprised by using a stable assimilation scheme. This guarantees temporally and spatially consistent estimates of the weather state and alleviates the concern that the extent of measurement error resulting, for instance, from unevenly distributed weather stations is correlated with omitted factors.

Our main explanatory variable is a binary measure for temperature extremes that is constructed from the monthly time series of temperature in each available grid cell. As the climate data is available from 1979 whereas the geo-coded conflict data is only available from 1997, we use the period 1979–1996 as training

[7] Agropastoral conflicts are based on the following keywords in the contextual notes: "farm", "crop", "cattle", "herd", "grazing", "nomad", "pasture", "water".

[8] This categorization is based on cities defined by the "World Cities Database" and considers cities with at least 100 k inhabitants. The city area is approximated by a 5 km buffer around the city center.

[9] See Dee et al. (2011) for details. We use data on synoptic monthly means of precipitation and average temperature at time 0:00 and time 12:00 (step 12). To obtain total precipitation for one month we sum up the values of both times and multiply that sum by the number of days in the respective month.

period for the construction of temperature extremes. Accordingly, the period 1997–2015 serves as estimation period. For the training period we calculate, for each grid cell, calendar month-specific means and define a grid-cell and calender-month specific threshold at the 95th percentile of absolute deviations from these means. Based on this threshold, we create a binary variable for the estimation period that takes on the value 1 if a deviation exceeds this threshold.

By construction, the frequency of extremes in the training period is 5 percent. In the estimation period this frequency is higher (11 percent), which indicates that the average increase in temperature observable over the sample period comes along with a corresponding shift in the entire distribution. Further, it is notable that an increase of the intra-annual variance elevates the tails of the distribution and thereby the evolution of extremes (see Fig. A3 in the Appendix). Precipitation declines on average over the sample period and therefore low precipitation extremes and drought increase in frequency, while the intra-annual standard deviation within a cell declines.

To proxy agricultural productivity we employ the "Caloric Suitability Index" developed by Galor and Özak (2016). In contrast to previously used, weight-based measures of agricultural suitability, this index takes the caloric return of agricultural yields into account. This permits a straightforward comparison of output across regions. The Caloric Suitability Index is based on data for potential crop yields from the Global Agro-Ecological Zones project (GAEZ) by the Food and Agricultural Organization (FAO) which are transformed into caloric output using information on the caloric content of the respective crops. Estimates of potential yields are based on agro-climatic factors which ensures exogeneity with respect to human intervention. Further, the caloric suitability measure constitutes a long-term, time invariant estimate and therefore remains unaffected by the evolution of climate.[10]

Information on the exposure to land degradation comes from the World Atlas of Desertification (UNEP, 1992). The data on soil degradation contained in the Atlas is adopted from the Global Assessment of Human-induced Soil Degradation (GLASOD) project, funded by the United Nations Environment Program (UNEP) and coordinated at the International Soil Reference and Information Centre (ISRIC). Soil degradation is assessed and averaged over the recent past (5 to 10 years) at the time of its compilation in 1990. The measure of soil degradation is based on ratings by a large number of soil scientists that are specialists for their respective geographical regions. This expert rating classifies the extent of soil degradation into 5 categories (0–4). For instance, category 0 implies that there is no sign of present degradation whereas category 4 implies extreme degradation with the terrain being irreclaimable.

Demographic data on population density, population growth and net migration are obtained from the Gridded Population of the World Database (CIESIN, 2016). This data is provided in 5-year intervals (1995, 2000, 2005, 2010 and 2015).[11] To be able to use these data in a time-varying specification, we linearly interpolate the population density data between these points in time on an annual basis. Population growth rates are calculated as log difference between population density levels in 1995, 2000, 2005, 2010 and 2015 and accordingly reflect 5-year growth rates. These growth rates are also interpolated at an annual level. Information on net migration takes birth rates and death rates into account by substracting the natural increase in population from the change in population density, and therefore reflects the number of people migrating into a grid. The baseline analysis uses migration information for the period 1990–2000, robustness checks consider migration patterns since 1970.[12] Details about data sources and variable construction are contained in Appendix A. Table A1 in the Appendix presents summary statistics for the main variables of the analysis.

4. Weather extremes and conflict

4.1. Empirical framework

This section presents results for the short-run effects of the occurrence of weather extremes on conflict incidence. The empirical framework models the incidence of a conflict event in grid cell i in month t, $c_{i,t}$, as

$$c_{i,t} = \alpha + \beta TE_{i,t} + \delta \mathbf{X}_{i,t} + \mathscr{I}_{i,t,m,M,E} + \epsilon_{i,t}, \quad (1)$$

where $TE_{i,t}$ is the prevalence of a temperature extreme in grid cell i in month t as described in the previous section, and $\mathbf{X}_{i,t}$ is a vector of weather controls, which include, in particular, the average temperature and precipitation in a cell during a given month. The error term $\epsilon_{i,t}$ allows for clustering within cells, as well as for spatial clustering among neighboring cells (Conley robust standard errors) in some of the robustness checks.[13] In addition, the empirical model accounts for various specifications of time-invariant and time-varying factors that might influence conflict incidence and that are subsumed in the vector of binary indicator variables $\mathscr{I}_{i,t,m,E,T}$. In particular, this vector accounts for time invariant heterogeneity across grid cells by ways of grid cell fixed effects ν_i, and for time-specific waves in conflict incidence by including fixed effects for each year of the observation period, ν_t, as well as for month-of-year (calender month) fixed effects ν_m, or (running) month effects that are allowed to vary by the location relative (in terms of North or South) to the equator, $\nu_{M\cdot E}$. In addition, more extensive specifications account for country-specific time-varying factors by the inclusion of country-specific year fixed effects $\nu_{i\cdot t}$, country-year-calender month fixed effects $\nu_{i\cdot t\cdot m}$, or common month effects, ν_M, as well as various permutations.

The identification of the coefficient of interest β relies on the assumption that the occurrence of a weather extreme, TE_{it}, in a cell and month is exogenous to the occurrence of a conflict event in this cell during this month. The data on weather events is from reanalysis data based on raw data from different sources, including in particular satellite data as described above. Variation in this variable relative to a threshold for extreme events that is based on the 95% interval in the pre-analysis period 1979–1997 is therefore not systematically influenced by the occurrence of (small-scale) conflict. Hence, the identifying assumption is that Variation in TE_{it}, conditional on the set of controls, is exogenous to conflict incidence is plausibly satisfied.[14]

[10] A map of caloric suitability is shown in Fig. A4 in the Appendix.

[11] Appendix Fig. A5 shows a map that illustrates the averaged distribution of population density across cells over the entire estimation period, as well as the location of cities.

[12] Out of the available 4864 cells, the estimation sample discards 38 cells that exhibit implausible demographic information in terms of extreme outliers, resulting in 4826 cells that are used for the analysis. Unreported results indicate that none of the main findings is affected by this omission. Details are available upon request.

[13] When adjusting the standard errors for spatial dependency along the lines of Conley (1999, 2008). The distance cut-off for spatial contiguity is 200 km (and thus includes two neighbouring grid cells in each direction) and a lag cutoff of 20. The results are robust to alternative specifications.

[14] One potential caveat that has been discussed in the context of empirical analyses using ACLED data is reporting bias. However, the ACLED documentation suggests that this mainly referred to analyses conducted for earlier periods and to the accuracy of casualty data, and less to incidence data as used in our analysis. For our results to be affected by reporting bias, one would have to assume that the omitted variable governing the reporting coverage is correlated with weather extremes above and beyond all controls that have been included. We view this as very unlikely.

4.2. Main results

4.2.1. Baseline results

Table 1 displays the results for different specifications of the empirical model, with grid cell fixed effects in Column (1), grid and year fixed effects in Column (2), and additional calender month effects by hemisphere in Column (3). Across all specifications, the occurrence of an extreme temperature event implies a significantly higher likelihood of the incidence of a violent event. Quantitatively, the effect in Columns (2) and (3) corresponds to an increase in the likelihood of conflict incidence in a given month and cell of 0.002, or approximately 7% compared to the unconditional mean of 0.03. Reassuringly, qualitatively and quantitatively very similar results are obtained with more extensive specifications that account for country-specific year effects, country-year-month effects or country-specific calendar month effects.[15] In light of the very stable coefficient estimates across a variety of specifications with different extensive sets of fixed effects, the results suggest that extreme temperature events affect conflict through mechanisms that work above and beyond other factors that vary at levels accounted for by the various specifications. Likewise, the results are unaffected when considering extreme temperature events lagged by one month.[16] In line with earlier results on the role of rainfall on conflict in mainly agricultural regions (Harari & Ferrara, 2018; Miguel, Satyanath, & Sergenti, 2004), the results also indicate that a shortage of rain increases conflict incidence, presumably due to resource constraints. It is worth noting, however, that these earlier studies effectively used variation at the yearly level, or variation in rainfall during particular seasons of the year (in particular growing seasons), whereas the present application accounts for recurrent heterogeneity in conflict activity during neuralgic months by the inclusion of year and calender month fixed effects. In this sense, the results complement these earlier findings, while pointing at an independent significant effect of weather extremes. The finding that temperature extremes are associated with higher conflict risk confirms previous findings, particularly by O'Loughlin et al. (2014), using a refined measure of temperature extremes and considering a sample that includes the entire African continent.

Moreover, the variation in temperature extremes contains relevant information for conflict incidence in terms of predictive power.[17]

The estimates for the baseline specification correspond to the effect of an extreme weather event in a given month on conflict incidence. One might suspect that the duration of this extreme is not irrelevant for the implications for conflict. In order to explore the sensitivity of the results with respect to the length of extreme events, we estimated an extended model, where the prevalence of extreme events was decomposed into events that lasted for exactly one month, for exactly two months, or three or more months. Table 2 presents the corresponding results. The findings indeed suggest that the effect of extreme weather events on conflict is non-linear in the length of the extreme weather events. The effect is larger for extreme events that last for two months than for events that last only one month, presumably due to the greater impact on distress and hardship associated with extended extreme events. On the other hand, events that last for three months or longer do not seem to have an independent effect, probably because of possibilities to cope with prolonged extreme events or other reactions of adjustment, relief, or adaptation. Generally, the length of extreme events may trigger two opposing effects that are reflected in these results. On the one hand, the severity of distress increases with the endurance of the shock which in turn aggravates it's impact on conflict risk. On the other hand, societies may start to react to the shock and implement coping strategies. Further, it is conceivable that weather shocks do not turn into civil conflict instantaneously. Of course the time span of reaction depends on the mechanism in place; relevant factors might for instance be the speed of bio-geographic transformation processes, or, depending on the conflict type, the formation process of conflict. All variables are measured as monthly means, hence it is conceivable that the (main) reaction to the weather shock is captured if including a second month in the analysis. Fig. A7 shows the effect of temperature extremes that have been going on since t = 1 to t = 7 months with estimation results shown in Table A4. The temperature extremes unfold their impact on conflict most strongly in the second month. These results also document, however, that the baseline specification delivers a conservative estimate of the effect of extreme weather events on conflict.

Table 1
Baseline Results: Extreme Temperature Events and Conflict.

Dep. var.: incidence civil conflict	(1)	(2)	(3)
Extreme Event	0.525***	0.197***	0.191***
	(0.0626)	(0.0588)	(0.0596)
Temp (mean)	0.00650***	0.00250	0.00381
	(0.00240)	(0.00238)	(0.00323)
Prec (mean)	−0.00196***	−0.00119***	−0.00112***
	(0.000287)	(0.000280)	(0.000289)
Adjusted R^2	0.000	0.016	0.016
N	1100328	1100328	1100328
Grid	4826	4826	4826
Grid FE	✓	✓	✓
Time FE		✓	✓
Month FE			✓
Month*Equator FE			✓

OLS (linear probability model) fixed effects estimation results. The dependent variable is the incidence of a conflict event in a given cell and month. All coefficients are multiplied by 100. Clustered standard errors at grid level in parentheses. ***/**/* indicate significance at 1%/5%/10%, respectively.

Instead of estimating the effect on any conflict event, one might wonder about the potential heterogeneity in the effect of weather extremes on conflicts of different types. To investigate this conjecture, we replicate the analysis while restricting attention to particular conflict types. In particular, using the categorizations and narratives supplied with the ACLED data, we consider battles resulting in a change of contested territory, battles without changes of territory, conflicts involving farmers and/or pastoralist (agropastoral conflicts), conflicts occurring in rural areas, and riots. To gain some overview, we replicate the analysis for the entire sample. The corresponding results are shown in Table 3. Weather extremes mainly show a positive effect on territorial conflicts and conflicts in agricultural/rural areas.

4.2.2. Interacting factors: population density and caloric suitability

One problem pervading the existing literature on the effects of climate for conflict is the lack of a common and coherent narrative underlying the evidence. One reason for this lack might be the fact that climate or weather extremes affect individuals in different ways depending on the respective living environment. In the following, we explore the role of some of the interacting factors that have been mentioned in the discussion.

The existing literature suggests that extreme weather events have particularly devastating effects on health and resources in

[15] The results are reported in Table A2 in the Appendix.

[16] See Table A3 in the Appendix.

[17] To explore the predictive power, we conducted a forecasting exercise. In particular, we conducted repeated random sub-sampling and estimated the model for each round using the respective training samples. Using these estimates, we then predicted conflict incidence for the validation samples and compared it to the actual incidence. The results demonstrate that the model predictions are highly correlated with observed conflict incidence out of sample, see Fig. A6 in the Appendix. Alternatively, Fig. A7 in the Appendix plots a ROC-curve, which illustrates the overall performance of the baseline model.

Table 2
Baseline Results: Extreme Temperature Events of Different Lengths.

Dep. var.: incidence civil conflict	(1)	(2)	(3)	(4)
One Month Extreme	0.137*			0.148**
	(0.0703)			(0.0705)
Two Months extreme		0.486***		0.498***
		(0.147)		(0.147)
Three or more Months Extreme			−0.0200	0.0103
			(0.117)	(0.117)
Adjusted R^2	0.016	0.016	0.016	0.016
N	1100328	1100328	1100328	1100328
Grid	4826	4826	4826	4826
Grid FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Month*Equator FE	✓	✓	✓	✓

OLS (linear probability model) fixed effects estimation results. The dependent variable is the incidence of a conflict event in a given cell and month. All regressions include average temperature and precipitation levels as controls. All coefficients are multiplied by 100. Clustered standard errors at grid level in parentheses. ***/**/* indicate significance at 1%/5%/10%, respectively.

Table 3
Baseline Results: Extreme Temperature Events and Conflict Types.

	(1) Battle (terr)	(2) Battle (non-terr)	(3) Agropastoral	(4) Rural Region	(5) Riot
Extreme Event	0.147***	0.000455	0.0508***	0.179***	0.0184
	(0.0405)	(0.0115)	(0.0167)	(0.0560)	(0.0195)
Adjusted R^2	0.003	0.000	0.003	0.013	0.002
N	1100328	1100328	1100328	1100328	1100328
Grid	4826	4826	4826	4826	4826
Grid FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Month*Equator FE	✓	✓	✓	✓	✓

OLS (linear probability model) fixed effects estimation results. The dependent variable is the incidence of a conflict event in a given cell and month. All regressions include average temperature and precipitation levels as controls. All coefficients are multiplied by 100. Clustered standard errors at grid level in parentheses. ***/**/* indicate significance at 1%/5%/10%, respectively.

areas in which the population exhibits a high degree of vulnerability due to low resilience. Such areas are typically associated with high population density and low agricultural productivity. In order to test this conjecture, we consider an extended specification in which the effect of weather extremes on conflict is allowed to vary with population density or the suitability of the soil for food production, as measured by the potential caloric yield per unit of land. The corresponding results are contained in Table 4. In fact, weather extremes exhibit a greater effect in areas with high population density. Likewise, the effect is amplified in areas where the caloric suitability of the soil is comparably low. Both effects are present in isolation as well as when added jointly in the same specification.[18]

The fact that permanent agricultural scarcity or high population pressure significantly weakens the resilience to climatic shocks points towards a channel that works through rising agricultural scarcity in the face of extreme climatic conditions. This hypothesis is supported by the finding that conflicts in a rural and agricultural context or conflicts involving territorial changes are particularly sensitive to the occurrence of weather extremes. One facet of this mechanism might be climatic stress in the growing season of grid specific crops which translates into increasing annual conflict risk

Table 4
Extreme Temperature Events and Conflict: The Role of Population and Productivity.

Dep. var.: incidence civil conflict	(1)	(2)	(3)
Extreme Event	1.161***	0.400***	2.653***
	(0.222)	(0.0829)	(0.402)
Log Population Density (interpolated)	−1.109***		−1.121***
	(0.246)		(0.245)
Extreme Event × Log Population Density (interpolated)	0.191***		0.352***
	(0.0353)		(0.0535)
Extreme Event × Caloric Suitability		−0.000245***	−0.000795***
		(0.0000755)	(0.000131)
Adjusted R^2	0.016	0.016	0.016
N	1085604	1099188	1085292
Grid	4814	4821	4811
Grid FE	✓	✓	✓
Time FE	✓	✓	✓
Month FE	✓	✓	✓
Month*Equator FE	✓	✓	✓

OLS (linear probability model) fixed effects estimation results. The dependent variable is the incidence of a conflict event in a given cell and month. All regressions include average temperature and precipitation levels as controls. All coefficients are multiplied by 100. Clustered standard errors at grid level in parentheses. ***/**/* indicate significance at 1%/5%/10%, respectively.

(Harari & Ferrara, 2018). However, also alternative mechanisms are conceivable such as battles over fruitful land or over water resources that may occur in any months of the year. To take a

[18] Notice that the main effect of soil suitability, which is a time-invariant variable, is absorbed by the cell fixed effects. The algorithm on which the population density data are based has changed in 2005 (from v3 to v4, see CIESIN, 2016). To account for this change in the variable construction, we replicated the estimation with a more flexible specification that additionally includes an interaction term of extremes with an indicator variable that reflects the timing of this change. The results are shown in Table A5 in the Appendix and suggest that the main results remain unaffected.

closer look at this nexus we estimated empirical models with more extensive specifications including cell-year-specific fixed effects into the regressions. The results reveal that indeed part of the effect of monthly temperature extremes on conflict risk is accounted for by grid-specific annual factors.[19] This finding is consistent with a mechanism as outlined above or might indicate a grid-specific trend of climate and conflict pointing towards potential long-run consequences of global warming. This will be subject of analysis in Section 5. Notably, even in this highly restrictive specification that accounts for grid-year-specific fixed effects, temperature extremes retain an effect on conflict that remains statistically significant and quantitatively relevant, in particular when accounting for regional vulnerability in terms of high population pressure.

4.2.3. Alternative measures and estimation methods

The analysis so far has focused on extreme weather events in terms of temperature. Much of the existing literature has instead focused on rainfall and droughts. Additional results for alternative specifications of extreme events that focus on either low precipitation or droughts or indexes that combine temperature and rainfall as well as evapotranspiration deliver qualitatively similar results.[20] We do however find that the effect of low precipitation extremes and drought is more sensitive to the inclusion of time fixed effects, an issue that has been discussed previously by Couttenier and Soubeyran (2014). The importance of accounting for extreme events relative to the cell-calender month average instead of considering absolute extremes is illustrated by the results for extreme events coded as monthly temperature exceeding the 95 percentile threshold of the grid-specific temperature distribution.[21] In light of the research question underlying this paper we concentrate attention on the effects of extreme temperature events in the remainder of the analysis.[22]

We analyzed whether the relationship between temperature extremes and civil conflict is robust to different specifications. First, we investigate the effects of temperature extremes on conflict along the intensive margin. In particular, we consider the effect on the number of conflict incidences as well as the number of conflict-related fatalities. Temperature extremes have a significantly positive effect on both measures, indicating that beyond being a trigger for conflict at the extensive margin, temperature extremes also affect the severity of conflicts. This implies that ongoing conflicts can be aggravated by the appearance of climatic shocks. To investigate this issue in more detail, we analyze the impact on conflict onsets separately from that on incidence by setting the conflict measure to 1 in the month of the onset of a new conflict, and 0 otherwise. While the results point to an overall significant impact, the effect is quantitatively smaller and statistically insignificant for some specifications, which suggest that part of the effect is related to the prolongation of ongoing conflict.[23] The estimation of average marginal effects using a logit model also confirms the baseline results. Finally, to correct for spatial auto-correlation of the residuals we employ Conley-robust standard errors.[24]

4.3. Additional results

4.3.1. The role of population dynamics

The previous findings suggest that temperature extremes affect individuals differently in different environments. This implies that extreme events might exhibit interactions with local conditions, reflecting different living conditions and resilience, which might be related to population dynamics and migration patterns. In particular, the occurrence of weather extremes in environments in which people are forced to move away from their homes might create different tensions than in regions that attract population inflows. Obviously, weather extremes might affect conflict in different ways and through different mechanisms, leading to potentially complicated and multi-faceted patterns of effects and narratives. To investigate this issue, we consider population dynamics in terms of population growth and migration as factors that might interact with weather extremes, thereby providing further insights regarding the vulnerability of regions towards climatic shocks.

In an attempt to address this issue, we replicate the previous analysis but group the grid cells by their population dynamics in terms of population density, population growth, or net migration. The split by quartiles of population density effectively constitutes a different way of replicating the analysis of Table 4. To avoid the potential concern that population dynamics are simultaneously influenced by temperature extremes in the estimation month we base the sample splits on pre-annual values of population density and population growth, while migration data comes mostly from the pre-analysis period (1990–2000). This avoids having to consider the potential feedbacks of conflicts on other causes of population growth and migration and allows focusing attention to the exploration of the effect of climatic distress caused by temperature extremes in the face of differential population dynamics.

The findings, shown in Panel A of Table 5, reveal a non-linear effect for cells characterized by different population density. In particular, we find a positive effect of weather extremes on conflict in the most densely populated quartile of cells. In contrast, the findings indicate that weather extremes have no effect on conflict in cells belonging to the three other quartiles.

Panels B and C adopt a more dynamic perspective by focusing on the heterogeneity in the effect by population dynamics. In Panel B of Table 5, the cells are split into quartiles by population growth. While this can include any reasons for population growth, i.e., fertility, mortality and migration, this setting delivers additional insights into the vulnerability and crowding that might be the key factor that leads to an effect of weather extremes on conflict. The results reveal a different picture than those obtained when considering heterogeneity in the level of population density. In particular, when considering population growth, the effect of weather extremes turns out to be u-shaped. The effect is essentially zero (and even negative but insignificant) in the two intermediate quartiles, whereas weather extremes appear to have a significantly positive effect on conflict in the quartiles with the lowest and the highest rates of population growth. In order to identify the role of migration, Panel C of Table 5 presents results for a sample split by net migration rates. The results document a similarly u-shaped pattern, although the effect is significantly positive

[19] Table A6 in the Appendix shows the corresponding results for an extended specification of Table 4 and a substantial increase in the variation explained by the empirical model.

[20] See Fig. A2 for the evolution of precipitation (extremes) and conflict over time. Tables A7 and A8 present the main effects and for the results regarding population density and caloric suitability for precipitation and droughts, respectively. A drought is defined as a month in which a low precipitation and high temperature extreme occur simultaneously. Table A9 contains results when including all weather variables in one specification. Tables A10 and A11 report corresponding results for extreme events based on the standardized precipitation and evapotranspiration index (SPEI); these events are based on the (1-month) SPEI index and extreme events are calculated analogous to extreme temperature events, where the threshold for particularly low (negative) deviations from calendar month specific means are obtained from the training period 1979–1996.

[21] See Table A12 in the Appendix.

[22] In addition, compared to temperature, the variability in precipitation over time and across space is higher and increasing, such that an analysis of the consequences of global warming on conflict through precipitation is less straightforward (see, e.g., Coumou & Rahmstorf (2012), Huntingford, Jones, Livina, Lenton, & Cox (2013), and Pendergrass, Knutti, Lehner, Deser, & Sanderson (2017) as well as Fig. A2).

[23] See Table A13.

[24] See Table A14.

Table 5
Extreme Temperature Events and Conflict: The Role of Population Dynamics.

	Dependent Variable: Conflict Incidence			
Quartile	Q1	Q2	Q3	Q4
	Panel A: Population Density			
Extreme Event	0.00537	−0.134	0.198	0.332**
	(0.0396)	(0.0820)	(0.130)	(0.168)
Adjusted R^2	0.003	0.010	0.018	0.030
N	257616	257424	257508	257100
Grid	1326	1506	1566	1402
	Panel B: Population Growth			
Extreme Event	0.424***	0.159	−0.136	0.224**
	(0.133)	(0.124)	(0.0985)	(0.114)
Adjusted R^2	0.015	0.023	0.012	0.004
N	257088	256812	256896	257004
Grid	2415	2949	2999	2621
	Panel C: Net Migration			
Extreme Event	0.546***	−0.0879	−0.00494	0.161
	(0.157)	(0.0969)	(0.0607)	(0.131)
Adjusted R^2	0.027	0.014	0.004	0.019
N	273828	274056	273828	274056
Grid	1201	1202	1201	1202
Grid FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Month*Equator FE	✓	✓	✓	✓

OLS (linear probability model) fixed effects estimation results. The dependent variable is the incidence of a conflict event in a given cell and month. All regressions include average temperature and precipitation levels as controls. The assignment to quartiles related to population density and population growth is based on values from the respective previous year. All coefficients are multiplied by 100. Clustered standard errors at grid level in parentheses. ***/**/* indicate significance at 1%/5%/10%, respectively.

only for the lowest quartile, and positive but insignificant for the highest quartile. The results are not affected by ongoing conflict events, as documented by results for an extended specification that includes lagged conflict incidence as control variable.[25]

These findings are consistent with completely different narratives and mechanisms for cells characterized by different population dynamics. Areas with the highest rates of population growth or net migration are likely to be destination areas for refugees, which are presumably also areas of higher density. In these areas, weather shocks might also constitute a major threat to the provision with resources, thereby triggering conflicts. Also, it is conceivable that the areas with the lowest population growth or lowest (most negative) net migration are areas where conflicts are most sensitive to temperature extremes. Likewise, these are the areas that individuals might see themselves forced to leave in the face of environmental shocks and emerging subsistence constraints. This interpretation of the results implicitly assumes that migration and population dynamics during the pre-analysis period and during the analysis are comparable. In order to explore the sensitivity of the results with respect to changes in population dynamics, we replicated the analysis for net migration rates measured over alternative pre-analysis periods.[26] The estimation results for these alternative settings deliver qualitatively and quantitatively very similar results.[27] The results are also similar when considering migration patterns weighted by population density.[28]

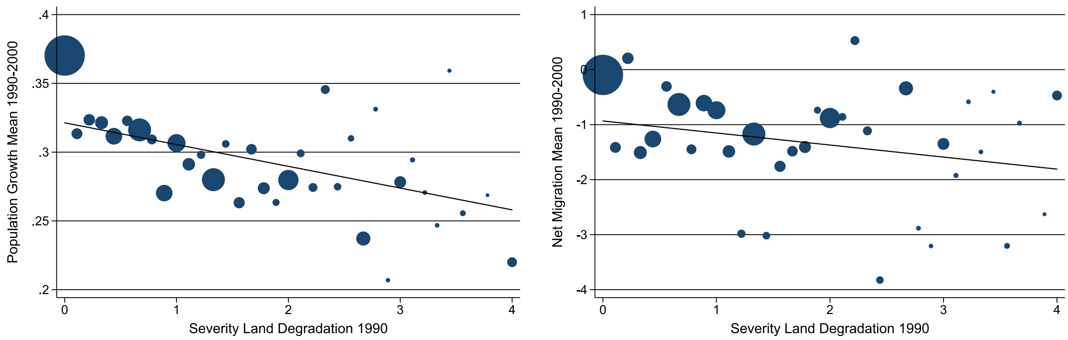
The previous findings indicate that the effect of weather extremes on conflict incidence might exhibit a different intensity depending on the concrete environment, as reflected by the respective population dynamics. In order to further disentangle the different mechanisms at work, we combined the analysis for different conflict types with the heterogeneity of the effect of temperature extremes in different environments and investigated whether there is also heterogeneity regarding the type of conflicts that are triggered by weather extremes in different environments. Replicating the analysis for different conflict types while distinguishing cells by population dynamics reveals that conflicts are mostly related to territorial battles and concentrated in rural regions when considering the quartiles of cells that grow least in terms of population or experience the greatest level of out-migration.[29] In contrast, in cells that grow in terms of population or experience in-migration, weather extremes have weaker effects on battles involving territorial changes or rural conflicts, but instead are associated with the outbreak of non-territorial battles, agro-pastoral conflicts, and riots.[30] This heterogeneity in conflict types substantiates the conjecture that differential mechanisms are in place that link temperature shocks to the outbreak of conflict, depending on the local circumstances in terms of population dynamics.

4.3.2. Land degradation

One factor that is often discussed as potential driver of migration and that has received revived interest in the context of climate change is environmental degradation. To investigate whether environmental stress relates to the vulnerability found for cells with the lowest population growth or migration we first look at the relationship between land degradation and population growth or net migration, respectively. Fig. 3 illustrates this relationship. The plot suggests that indeed areas with greater land degradation in the sense of sensitivity of soil productivity experience lower population growth and more out-migration in the following decade.

To explore this aspect in more detail, we repeat the analysis by allowing for differential effects of weather extremes in cells with

[25] See Table A15 in the Appendix.
[26] In particular, we consider net migration rates over the periods 1970–1980, 1980–1990, and 1970–2000. Net migration patterns over these periods are comparable, with correlation coefficients around 0.5 or higher.
[27] See Table A16 in the Appendix.
[28] See Table A17.
[29] The corresponding results are shown in Panels A and C of Table A18 in the Appendix.
[30] The corresponding results are shown in Panels B and D of Table A18 in the Appendix.



(a) Population Growth (b) Net Migration

Fig. 3. Land Degradation and Population Dynamics. This figure plots population density and net migration relative to the degree of land degradation. Severity of land degradation is rounded to the closest decimal level (0.1). Population growth (over the period 1990–2000) and net migration (over the period 1990–2000) are then averaged for each bin. The marker size corresponds to the number of grid-month observations in each bin. The figure is based on a sample that excludes cells that are outliers in terms of population growth or net migration (measured by the 95th percentile).

different degrees of land degradation in our analysis. Table 6 presents the corresponding estimates. The results document that weather extremes mainly affect conflict in cells with higher degrees of land degradation, supporting the vulnerability hypothesis and pointing towards a connection between the effects found in the first quartile of population growth or migration and environmental degradation. In additional results for specifications that also distinguish between different conflict types and account for regions with low and high levels of land degradation, respectively, the pattern of the pooled analysis is largely confirmed.[31] The results also show that this is particularly the case for grid cells that experienced strong land degradation. Here the effect corresponds closely to the findings for grid cells with low population growth or net migration where battles involving changes of territory, conflicts in the context of agriculture and pastoralism and in rural regions are significantly affected by temperature shocks. Overall, the results suggest that the effect found in the lower tail of the distribution of population dynamics might be related to scarcities arising from declines in agricultural production. In contrast, the effect found in the upper tail of the distribution of population dynamics seems to unfold in a different context, potentially involving greater vulnerability arising from increased population pressure.

Taken together, the results reveal new insights into the interplay of extreme temperature events with different mechanisms leading to conflict outbreaks. Complementing and extending the classification suggested by Seter (2016), the evidence presented so far suggests that mechanisms related to economic hardship and migration might crucially interact and lead to outbreaks of different types of conflict.

Table 6
Extreme Temperature Events and Conflict: The Role of Land Degradation.

	(1) All	(2) High Degradation	(3) Low Degradation
Dep. var.: incidence civil conflict			
Extreme Event	−0.0529	0.306***	0.0458
	(0.0773)	(0.0943)	(0.0717)
Extreme Event × Land Degradation	0.249***		
	(0.0647)		
Adjusted R^2	0.016	0.020	0.011
N	1066356	558600	541728
Grid	4677	2450	2376
Grid FE	✓	✓	✓
Time FE	✓	✓	✓
Month FE	✓	✓	✓
Month*Equator FE	✓	✓	✓

OLS (linear probability model) fixed effects estimation results. The dependent variable is the incidence of a conflict event in a given cell and month. All regressions include average temperature and precipitation levels as controls. The sample split into grids with high- and low land degradation is based on the median value of land degradation in 1990. All coefficients are multiplied by 100. Clustered standard errors at grid level in parentheses. ***/**/* indicate significance at 1%/5%/10%, respectively.

5. Long-run trends: climate change and conflict

The results so far document that the occurrence of weather extremes is associated with the incidence of violent conflict events in high resolution data of monthly frequency and a narrowly defined spatial environment of grid cells of 0.75° latitude and longitude. As discussed in the Introduction, the frequency and severity of extreme weather events seems to have increased over the past three decades. Fig. 4 provides additional evidence for this by plotting the average number of extreme temperature events per month at the grid cell level, weighted by the duration of the respective extreme events. The figure shows that the frequency of events as well as the duration of these events have increased. In light of the results presented in the last section, this suggests that climate change might have considerable consequences for the incidence of conflict. In contrast to being exposed to short-run fluctuations, societies may adapt to gradually moving levels of temperature or extremes. But it might also be the case that the effect exacerbates, for instance when the underlying vulnerability due to ongoing environmental degradation rises. In order to investigate this issue in more detail, this section presents the results of a long-run analysis of trends in temperature extremes and conflict incidence. This analysis complements an analysis for long-run effects that directly builds on the results of the previous section. At the same time, this analysis complements the earlier results by shedding light on the role of climate change, in the sense of changes in the frequency of extreme events over longer periods of time, as opposed to the effects of climate variability in terms of the occurrence of an extreme event in a given month.[32]

[31] The results are shown in Table A19 in the Appendix.

[32] See Seter (2016) for a discussion of the confusion about climate variability and climate change in the existing literature.

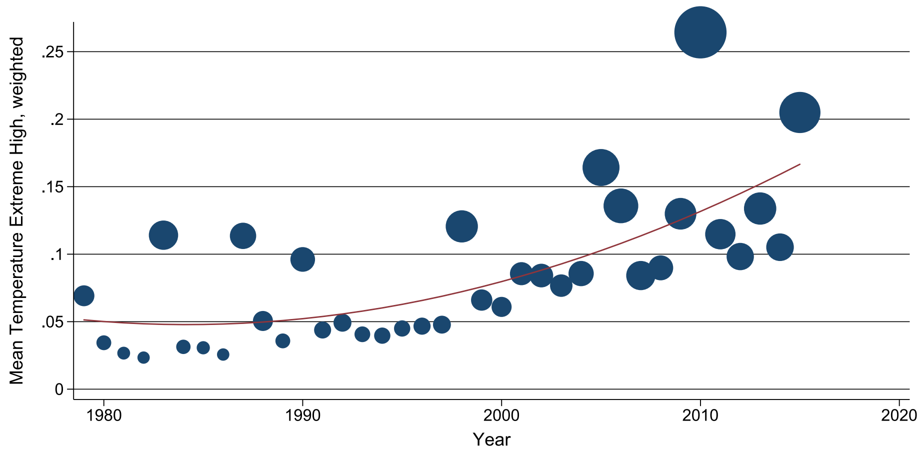


Fig. 4. Dynamics of Extreme Temperature Events in Africa. This figure plots the average annual number of extreme temperature events across all cells by year, weighted by the average length of extreme events in terms of consecutive months. See Section 3 for a detailed data description.

5.1. Empirical framework

The analysis is based on variation in the long-run trends of extreme temperature events and conflict incidence over the observation period 1997–2015. We conduct two sets of analyses that are based on the logic of a differences-in-differences (DiD) approach in long differences and a generalization thereof. The baseline empirical framework underlying the long-differences analysis splits the data into two equally long observation periods, 1997(1)-2006(6) and 2006(7)-2015(12) and computes the difference in the average incidence of conflict in a cell and relates it to the difference in the average incidence of extreme temperature events. In particular, with $\overline{C}_{i1}$ denoting the average conflict incidence in grid cell i during the first half of the observation period (1997–2006), and $\overline{C}_{i2}$ denoting the average conflict incidence in the same grid cell during the second half of the observation period (2006–2015), the (long) difference in conflict incidence in cell i is given by $\overline{DC}_i = \overline{C}_{i2} - \overline{C}_{i1}$.[33] This difference in conflict incidence is then related to the long difference in weather extremes, which is computed analogously as the difference in the average frequency of extreme temperature events in grid cell i during the second half of the observation period, $\overline{TE}_{i,2}$, relative to the corresponding average during the first half of the observation period, $\overline{TE}_{i,1}$, as $\overline{DTE}_i = \overline{TE}_{i,2} - \overline{TE}_{i,1}$. The long difference estimation is then based on the empirical model

$$\overline{DC}_i = \alpha + \gamma \overline{DTE}_i + \phi_r + \phi_c + \epsilon_i \,, \tag{2}$$

where the empirical specification includes controls for climate zone fixed effects ϕ_r and country fixed effects ϕ_c. This setting corresponds to a differences-in-differences (DiD) estimator using long differences.[34] In essence, this specification corresponds to the graphical illustration in Fig. 2. The identification of the coefficient of interest, γ, relies on the assumption of a common trend in conflict, α, across all cells within a given climate zone and country.[35]

To relax the common trend assumption, we also apply a generalized version of this long-differences estimator that is based on differences over three time periods. In particular, we repeat the analysis by dividing the observation period into three sub-periods (1997–2002, 2003–2008, 2009–2015), and computing the respective differences $\overline{DC}_{it}$ and $\overline{DTE}_{it}$. Since there are three sub-periods, this allows computing two differences per cell i and, consequently, estimating an extended model in differences that includes cell fixed effects μ_i and a trend component $I23$ that reflects the differences between the second and third sub-period. The generalized long difference model is then estimated as

$$\overline{DC}_{i,t} = \mu_i + \gamma \overline{DTE}_{i,t} + \psi I23_{i,t} + \epsilon_{i,t} \,. \tag{3}$$

5.2. Results

Panel A of Table 7 presents the results for the long-differences specification (2). The results show separate estimates for the effect of variation in the frequency of extreme temperature events over the two subperiods, and of the long difference in temperature, as well as both.[36] The results show that cells that experienced a stronger increase in temperature extremes, or in temperature, also experienced a more pronounced increase in conflict incidence. This finding indicates that societies do not fully adapt to slowly changing levels of mean temperature or extreme events. The results for the joint specification in Column (3) further indicate that the increase in weather extremes exhibits the stronger and more robust effect.

In order to explore the robustness of these results with respect to potentially different trends in climate and conflict at the grid-level, we also estimated the model for long differences across three sub-periods (1997–2002, 2003–2008, 2009–2015) applying the Generalized DiD model (3). The respective results are presented in Panel B of Table 7. By considering three periods, the model effectively accounts for grid-specific trends in conflict incidence and thus identifies how this trend is affected by trend changes in weather extremes (and temperature), thereby relaxing the common trend assumption underlying the DiD estimator with only two time periods in Panel A. The results indicate that there is an increase in the frequency of conflict incidence over time, as reflected by the trend coefficient ψ for $I23 = 1$. More importantly, even beyond grid-specific trends and this overall trend increase, a rise in the incidence of temperature extremes is related to rising conflict incidence in the long-run. The results in Table 7 Column (3) indicate that an increase in the

[33] Averages are calculated over the entire first half of the estimation period (9.5 years) instead of restricting to observations at arbitrary short time windows at the beginning and end of the panel. This reduces the concern of averages being driven by outlying years in terms of conflict incidence or climate. However, the results are robust to alternative specifications. See for instance Tables A20 and A21 for an alternative specification using a 7-year window, or Tables A22 and A23 using a 8-year window at the beginning and end of the sample period to construct averages for the long difference estimation.

[34] A similar approach is applied by Dell, Jones, and Olken (2012) who analyze the impact of differences in temperature on differences in economic growth in the long-run.

[35] Note that without controls for climate zone and country fixed effects, the estimation of (2) is equivalent to a regression in levels of $\overline{C}_{it}$ on $\overline{TE}_{it}, t = 1, 2$, with the inclusion of cell fixed effects.

[36] Long differences in temperature have been computed analogously to long differences in conflicts and extreme events.

Table 7
Extreme Weather Events and Conflict: Long-Differences.

	Dependent Variable: Diff Conflict Incidence		
	Panel A: DiD (Two Periods)		
Diff Extreme Event	0.0951***		0.0838***
	(0.0220)		(0.0272)
Diff Temp		0.0188***	0.00537
		(0.00584)	(0.00719)
r2	0.219	0.217	0.219
N	4826	4826	4826
Climate Zone Trend	✓	✓	✓
Country Trend	✓	✓	✓
	Panel B: GDD (Three Periods)		
Diff Extreme Event	0.0206		0.0416**
	(0.0147)		(0.0182)
Diff Temp		−0.00189	−0.0106
		(0.00638)	(0.00811)
I23 = 1	0.0312***	0.0315***	0.0306***
	(0.00157)	(0.00158)	(0.00168)
r2	0.527	0.527	0.527
N	9652	9652	9652
Grid Trend	✓	✓	✓

Panel A: OLS estimation results. The dependent variable is the difference in the average incidence of conflict events in a given cell and month between 1997–2006 and 2006–2015, ($\overline{DC}_i$), with one observation per grid cell. Panel B: OLS fixed effects estimation results. The dependent variable is the difference in the average incidence of conflict events in a given cell and month between 1997–2002 and 2003–2008, and between 2003–2008 and 2009–2015, ($\overline{DC}_{it}$), with two observations per grid cell. See text for details. ***/**/* indicate significance at 1%/5%/10%, respectively.

frequency of temperature extremes (reflected by an increase in differences of long-run averages by 1) leads to an increase in the frequency of conflicts by 0.084 or 0.042, respectively. For the latter, this corresponds to twice the unconditional mean of the increase in conflict incidence in terms of differences of long-run averages, which is 0.018. This implies that the coefficients of the long-run analysis are considerably larger in magnitude than the coefficients found in the short-run analysis.

Additional results obtained for a Generalized DiD model that allows for time-varying trends within countries and climate zones confirm these findings.[37] In further analyses, we also investigated whether the effect of climate change in terms of an increasing frequency of weather extremes and mean temperatures becomes more pronounced over time, i.e. whether the effect of climate change on conflict becomes stronger in the later sub-periods. Although the estimates indicate a positive coefficient of the impact of extremes on conflict in later sub-periods, the effects turn out to be statistically insignificant when including region-specific time varying trends.[38] Hence, while we find evidence for an increase in the frequency of weather extremes leading to an increase in the frequency of conflict incidence, we find no evidence that this effect becomes stronger over time.

We also replicated the analysis while allowing for heterogeneity in the effect by agricultural productivity, population density, land degradation, population growth, net migration and absolute changes in population density. By and large, the results mirror those obtained with month-by-month variation.[39] In particular, the increase in weather extremes entails particularly strong increases in conflict incidence in areas with low agricultural productivity, high population density, population density changes, and high vulnerability of agricultural production as reflected by greater land degradation. The main effect of the increase in weather extremes remains large and significant across all specifications.

[37] See Panel A of Table A24 in the Appendix for the corresponding results.
[38] See Panel B of Table A24 in the Appendix for the respective results.
[39] See Table A25 in the Appendix.

6. Discussion

This paper provides novel evidence for the role of weather extremes and climate change reflected by the frequency of temperature extremes for violent conflict in Africa. Estimations based on a fine spatial resolution of 0.75° latitude and longitude and month-by-month variation document a positive effect of the occurrence of temperature extremes on conflict incidence. These effects increase with the severity of the extreme in terms of its duration, and are larger in highly densely populated regions, in regions with lower agricultural productivity, as measured by potential caloric yield, and in regions with more pronounced land degradation. The results also point towards heterogeneity in the effect regarding the type of violence and a crucial role of population dynamics. Regions experiencing an outflow of population exhibit different types of conflict in response to weather extremes than regions experiencing population inflows. This indicates the co-existence of different mechanisms that are relevant in different contexts. More research is needed to disentangle these mechanisms, for instance via using finer spatial resolution targeted to isolating particular mechanisms. More advanced spatial econometric models could also help to identify indirect effects that are transmitted across space, for instance in the context of weather shocks that cause agricultural losses in rural areas and lead to price shocks or food shortages, and ultimately an increase in violence, in neighboring urban areas.

The findings of this paper also contribute to the debate about the role of climate change for conflict by documenting a link between the increase in the frequency and severity of extreme temperature events and conflict, using a (generalized) difference-in-differences approach spanning almost two decades, from 1997–2015. The results resemble those obtained for short-run variability in the sense that regions with a higher increase in extreme temperature events are shown to have experienced a larger increase in the incidence of violence. Also the differential effects with respect to population density, population dynamics, agricultural suitability and land degradation are confirmed, as well as the robustness to differential trends in regions that experience different severity of climate change.

The results provide evidence in line with the introductory quotes of UN secretary generals Ban Ki Moon and Antonio Guterres and help reconciling some of the open issues in the literature. In particular, the heterogeneity of the effects is consistent with different narratives for outbreaks of violence in the context of weather shocks or climate change that have been argued to be inconsistent with mono-causal views of climate change affecting conflict. Moreover, the results illustrate the central role of interacting mechanisms, in particular population dynamics, migration, and environmental degradation, in linking weather shocks or climate change to violent conflict and different types of violent events. However, by the design of the empirical analysis using high-frequency and high-resolution data, the analysis does not provide direct evidence for the role of institutions or institutional failures for the nexus between climate and conflict. Future work is needed to isolate institutional aspects that operate at the cell level at high frequency and options for policy in containing and avoiding climate-driven conflict.

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 associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.worlddev.2019.104624.

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