Chapter 6

New evidence on the economics of climate and conflict

Marshall Burke[a], **Joel Ferguson**[a], **Solomon Hsiang**[a], and **Edward Miguel**[b,*]

[a]*Stanford University, Stanford, California, United States of America,* [b]*University of California, Berkeley, Berkeley, California, United States of America*

[*]*Corresponding author e-mail address:* emiguel@berkeley.edu

Chapter Outline

1 Introduction

> *"The world must come together to confront climate change. There is little scientific dispute that if we do nothing, we will face more drought, more famine, more mass displacement – all of which will fuel more conflict for decades." – US President Barack Obama, 2009 Nobel Prize acceptance speech*

Climate change and global warming are increasingly recognized by policymakers as major risk factors for armed conflict (IPCC, 2022). The incidence of armed conflict worldwide rose over the last decade as many observers believe the effects of global warming are beginning to be felt in earnest. To illustrate this point with a rough measure, while 34 countries were experiencing armed conflict on average in a given year during the decade from 2002–2011, this number increased to 50 during 2012–2021 (see brown and blue shading in Fig. 1), and total battle-related deaths also rose sharply (solid black line) and these have recently increased further due to Russia's invasion of Ukraine.

Handbook of the Economics of Conflict, Vol. 1. https://doi.org/10.1016/bs.hoec.2024.10.008

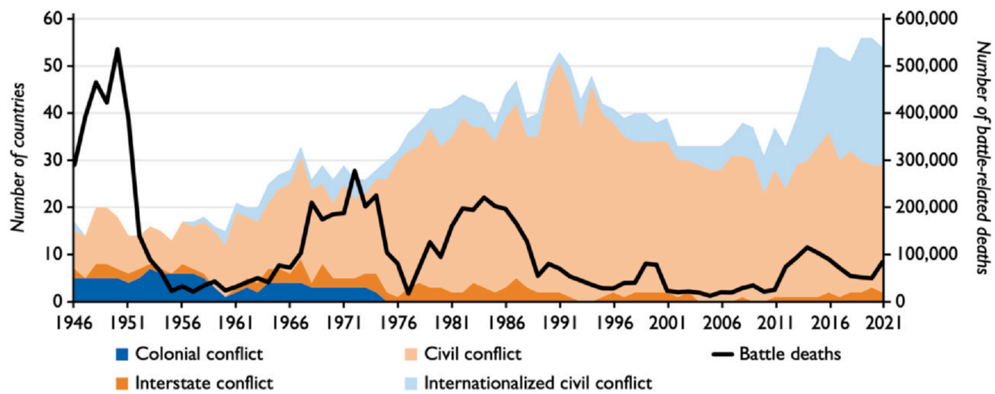

FIG. 1 Conflict events worldwide, 1946–2021 Reproduced from Palik et al. (2022).

Of course, global patterns like these could be driven by many factors, and there remains some uncertainty about the nature of the relationship between climate variation and human violence. For instance, the 2014 United Nations IPCC5 report stated that: "…[I]t remains disputed whether, and if so, how, the changing climate directly increases the risk of violent conflict in Africa" (Niang et al., 2014). The more recent IPCC6 report asserts that there is some lingering doubt about the strength of this relationship, providing "medium confidence" in the relationship: "Climate variability and extremes are associated with increased prevalence of conflict, with more consistent evidence for low-intensity organized violence than for major armed conflict (medium confidence)" (O'Neill, 2022).

Here we survey and synthesize the large – and growing – quantitative research literature that attempts to establish causal relationships between climate and human violence by utilizing panel or longitudinal data sets and quasi-random variation in local climate variation. The analysis includes recent studies found via an intensive literature search (undertaken through June 2022). This scientific literature spans multiple disciplines, including economics, political science, psychology, history, public health, and criminology, among others, and is expanding rapidly: based on a broad literature search using common keywords, over the last decade the cumulative number of studies in this broad area (across fields and methodologies) has more than doubled (Fig. 2). Given this recent explosion of studies and remaining uncertainty around the importance of the climate-conflict relationship, we hope to provide a more comprehensive assessment of the key patterns in this literature than earlier work.

This chapter makes three main contributions, laid out in each of the three subsequent sections.

First, in section 2 we carry out a meta-analysis – updating the work in Hsiang et al. (2013) and Burke et al. (2015a) with a far larger sample – and confirm that extreme climate is associated with elevated risk of both inter-group conflict and inter-personal violence. We find that a 1 sd increase in local temperature is

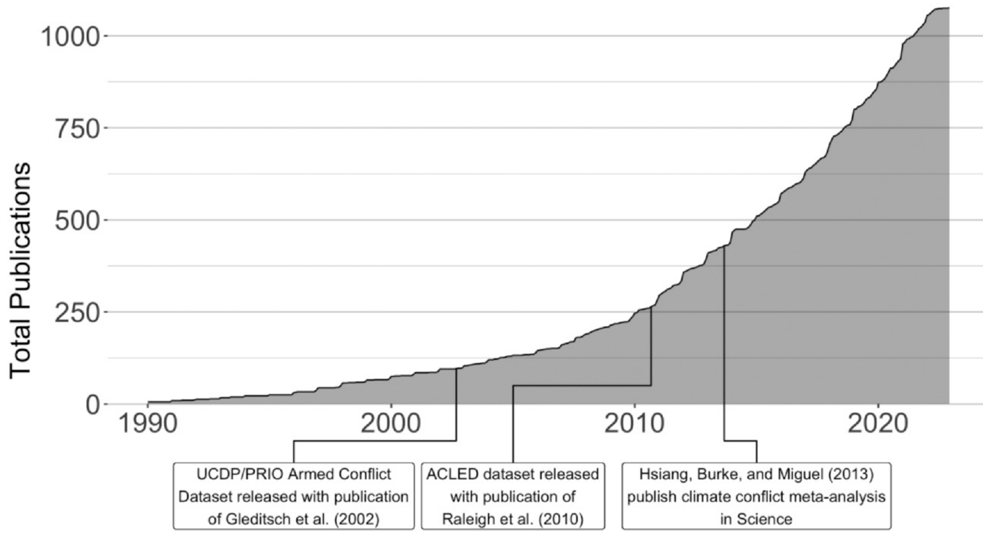

FIG. 2 Growth in publications on the climate-conflict relationship. Notes: The figure marks some milestones in this scientific literature, including the release of the UCDP/PRIO country-year level data in 2002 Gleditsch et al. (2002), the subnational level ACLED data in 2010 Raleigh et al. (2010), and the publication of the Hsiang et al. (2013) *Science* article in 2013. This count was carried out as follows. We accessed the Elsevier Search API, accessing SCOPUS, across all journals, on June 4 2022, and used the following keywords: (Conflict OR War OR Crime OR Suicide OR Self-harm) AND (Climate OR Weather OR Temperature OR Heat OR Precipitation OR Rainfall). Not all of these studies are relevant for the quantitative meta-analysis that follows but they provide an indication of the growth in research on this topic overall across various academic fields and methodologies.

associated with a 2.5 % increase in inter-group conflict and a 1.9% increase in interpersonal conflict. These estimates are highly statistically significant. Importantly, the resulting average inter-group conflict and interpersonal violence estimates are roughly three quarters smaller and one fifth smaller, respectively, than the earlier estimates, although they remain empirically meaningful. At the same time, the median estimated effect among studies included in the inter-group conflict meta-analysis remains similar at approximately 5 %. We also find evidence of significant increases in the risk of suicide and self-harm at higher temperatures, with effect magnitudes similar to inter-group violence and interpersonal violence. The bottom line is that a large and rapidly growing interdisciplinary body of research now affirms that higher than normal temperatures are associated with far greater risk of many forms of violence and conflict. In our view, this should now be seen as a robust social science empirical fact.

Second, in Section 3 we present a methodological discussion of how the use of data at different spatial and temporal scales can affect analytical results. This is highly relevant given the explosion of data at finer spatial and temporal scales over the last decade (e.g., the ACLED dataset) versus earlier data with observations only at the country-year level. We find that, holding the dataset constant, analyses that use more disaggregated data do largely reproduce the qualitative findings at more aggregated scales but the standardized magnitude of the estimated effect depends critically on the details of the specification. In particular, including fewer lagged climate shocks and failing to account for local seasonality with fixed effects can lead researchers to estimate systematically smaller effects of climate shocks on conflict. We also extend the analysis to examine effects at longer time frames, over decades or even multiple decades, and find that effect magnitudes tend to be larger in magnitude than those documented at shorter time scales. This is another piece of evidence (among others in recent work) that the process of adaptation to a warmer climate may not occur automatically even over an extended time frame, and suggests that the impacts of global warming in the coming decades could be severe for many human societies.

Third, in section 4 we describe noteworthy and important recent additions to the literature since the time of the earlier reviews (Hsiang et al., 2013; Hsiang and Burke, 2014; Burke et al., 2015a). We focus on laying out where there has also been sufficient research to speak more confidently about the mechanisms underlying the strong statistical relationships between climate and violence. In particular, as laid out in Fig. 3 there are now clusters of studies that imply that a range of factors can play a role, including: (1) economic conditions, income, and agricultural productivity; (2) socio-demographic factors; (3) migration and transportation costs; (4) policy, politics and institutions; and (5) psychological and physiological factors. We discuss the evidence for each of these mechanisms, and combinations of the channels, in particular studies and settings.

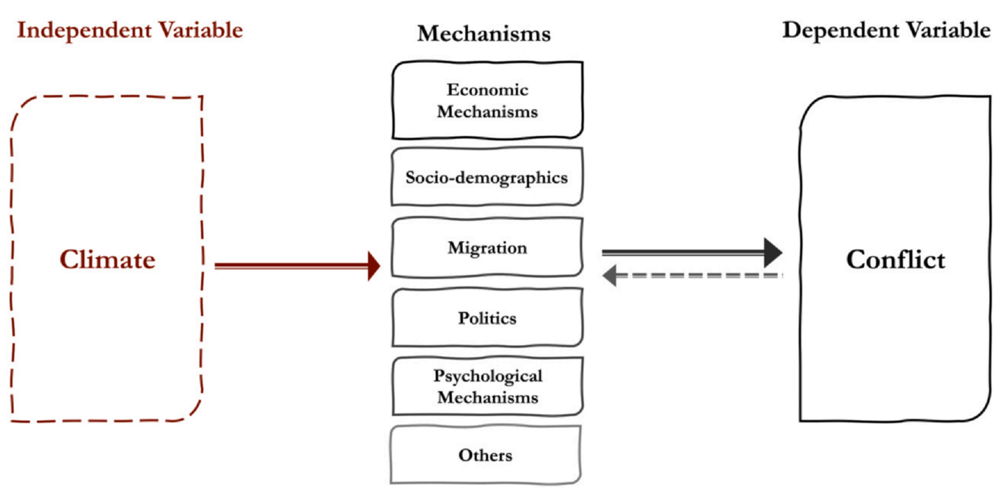

FIG. 3 Mechanisms in the climate-conflict relationship. Notes: This figure summarizes some of the main mechanisms through which climate affects conflict that we survey in this chapter. The most common types of climate shocks often considered in the existing literature include extreme temperatures, extreme precipitation, and drought. Common types of conflict outcomes include inter-group conflict (often between armed groups), inter-personal violence and crime, and suicide and other forms of self-harm. The figure also illustrates why the use of climate and weather variation as an instrumental variable for any one of these channels is potentially problematic due to the possibility of exclusion restriction violations.

There is a particularly robust body of evidence connecting adverse economic conditions to increased conflict risk across settings. In a concurrent related paper, we present new empirical evidence indicating that conflict in wealthier African countries, but not necessarily in wealthier areas within those countries, is less sensitive to climate shocks (Burke et al., 2024a). In particular, in that study we utilize a novel and highly disaggregated measure of local asset wealth across Sub-Saharan Africa, and demonstrate that the interaction between climate shocks and this wealth measure is small. In contrast, the interaction between climate shocks and national GDP per capita is large and negative, meaning that there is a substantial dampening of the effect of climate shocks in wealthier countries. Between this evidence and the other studies discussed in Section 4 of this chapter, we argue that there is now substantial evidence that economic conditions are a key mediator of the relationship between extreme climate and human violence. There is also ample evidence that the interaction of adverse economic conditions caused by climate shocks with pre-existing social and political divisions can exacerbate conflict.

The chapter concludes (Section 5) with a discussion of the policy implications of these findings, and some open research questions.

2 New meta-analysis results

The work here builds on earlier meta-analysis studies, particularly those in Hsiang et al. (2013) and Burke et al. (2015a). Those studies have been widely cited both in the scholarly and policy literatures, including in the recent IPCC6 report (IPCC, 2022). Hsiang et al. (2013) and Burke et al. (2015a) assembled all of the causal empirical evidence available at that time, reviewed it, and also carried out a meta-analysis combining data across studies. That allowed us to estimate the average impacts of climate variability on various forms of conflict in human societies, including both larger scale intergroup conflicts, like civil wars, as well as more decentralized forms like violent crime.

By design, the current chapter uses similar inclusion criteria as the Hsiang et al. (2013) and Burke et al. (2015a) articles, namely, focusing on all quantitative studies utilizing panel or longitudinal data, which allows for the inclusion of both location and time fixed effects or other time controls. These are critical for allowing the analysis to account for non-random exposure to climate, enabling us to interpret the resulting estimates as the causal impacts on conflict outcomes, exploiting the "natural experiment" induced by weather shocks.

Although there is a general distinction between the weather shocks that are examined by the studies included in this chapter and climate, it is possible to relate the estimated effects to climate change impacts. "Climate" is the joint distribution over weather that may occur in a given period, whereas "weather" refers to realizations from this distribution. The empirical approach taken here and in the literature assumes that a given response curve relates the outcome of interest (in this case various forms of conflict) to particular weather variables (e.g., annual mean temperature), potentially with additional unobserved determinants. A research design which credibly estimates the response function can then be used to simulate outcomes under climate change by drawing realizations of the relevant weather variable from the future climate distribution (Carleton and Hsiang, 2016). An important caveat is that such simulations typically assume a static response function, meaning that they describe climate change impacts in the absence of adaptation or other mechanisms through which a change in the weather distribution may alter the response function (Hsiang, 2016). To date, a handful of studies have tried to directly test this assumption and found that a static response function is generally a reasonable first-order approximation for conflict and other personal violence outcomes (Burke et al., 2015a, 2018, 2024b).

To ensure estimates are comparable across studies, we or the authors re-analyzed every study included in the meta-analysis for this chapter using a common econometric approach. We assembled and re-analyzed 50 new data-sets for this chapter. With a goal of increasing relevance for contemporary societies, in this chapter's new meta-analysis we exclude studies using historical data from periods before approximately 1960; nine of these studies had been included in the earlier Burke et al. (2015a) paper.

The statistical analysis implements regression specifications of the following general form (and then combines the results in a meta-analysis estimate):

$$Conflict_{it} = \alpha + \sum_{j=0}^{1} \boldsymbol{\beta_j} \mathbf{Climate_{i,t-j}} + \mu_i + \theta_t + \epsilon_{it}. \tag{1}$$

Here $Conflict_{it}$ is the conflict or violence outcome measure, for instance, an indicator for civil conflict or the violent crime rate in a given location i and time period t. The term $Climate_{i,t-j}$ is a vector of climate explanatory variables, typically including both the current and first lagged values (e.g., of temperature and/or precipitation in many applications), and the parameters of interest are the vector of β_j terms at each temporal lag, where the overall effect for a given variable is the linear combination of the contemporaneous and lagged terms for that variable. ϵ_{it} is the usual error term, discussed below. As different locations can exhibit differing average levels of conflict (for a wide range of geographic and historical reasons) which may be correlated with climate, the specification includes a vector of location fixed effects μ_i. Their inclusion implies that the resulting estimates are effectively comparing locations to themselves, across periods with different climate conditions. For studies that use sub-annual data, we use location $\times$ month or location $\times$ quarter fixed effects whenever possible to account for local seasonality. The vector of time-period specific constants θ_t accounts for overall time trends in conflict outcomes as well as time-trending variables (such as gradual demographic changes) that could be correlated with both climate and conflict patterns. In some cases, time period fixed effects are replaced with location-specific time trends or related approaches.

Disaggregated weather products are necessarily interpolated across space, leading to spatial autocorrelation in weather variables after residualizing against fixed effects. Broadly speaking, this autocorrelation should be dealt with by clustering at a sufficiently aggregated level, estimating heteroskedasticity autocorrelation robust standard errors with a sufficiently large spatial kernel, non-parametrically accounting for cross-sectional correlation via Driscoll and Kraay (1998) standard errors in long panel settings, or using randomization inference when there is a good model of the distribution of the weather variable(s) being studied available. Here, statistical inference is generally conducted by clustering at the unit of analysis when units are geographically large, such as states or countries, and by two-way clustering at the unit of analysis and time period when units are geographically small and there are sufficient number of time periods, as is the case in some of the more disaggregated studies.

The Hsiang et al. (2013) and Burke et al. (2015a) studies focus on two forms of violence, namely, inter-group conflict (with $N=21$ estimates included in Hsiang et al. (2013)) and interpersonal violence and crime (with $N=11$ estimates included in Hsiang et al. (2013)), so a total of 32 quantitative estimates included in that meta-analysis in all (from somewhat fewer than 32 studies since some articles contributed multiple estimates, i.e., if they had multiple relevant outcomes). The central finding of both earlier studies is that a 1 normalized standard deviation (SD) increase (relative to the local distribution) in a climate variable (such as warmer temperature) leads to a +11% increase in inter-group conflict, and similarly to a +2.3% increase in interpersonal violence. Both of these effects are statistically significant at high levels of confidence.

The results in Hsiang et al. (2013) and Burke et al. (2015a) also received extensive attention because they implied very large effects when projecting the effects out to future climate. Over the next few decades (to 2050), depending on which part of the world one considers, there will be something like a 2 to 4 SD increase in average temperatures, so you can multiply these estimated effects above by roughly 2 to 4 times to get at the projected impacts on violence around the world due to climate change, assuming that human societies cannot come up with good adaptation mechanisms (either in terms of new technologies or public policies) before then. In other words, there could be something on the order of a 20 to 40% increase in intergroup conflict risk and 6 to 12% increase in interpersonal violence risk.

What we present in this chapter is a substantial update of that previous work, which will hopefully also be of interest for future UN IPCC assessments and policymakers. Since the 2013 and 2015 articles came out, there has been an explosion of new research (see Fig. 2), with a more than doubling of articles in this general research area. Of course, not all of these studies use data amenable to our unified approach to analysis. After an exhaustive literature review, we determined that the number of studies that can be included in the meta-analysis has risen from 30 to 80, more than doubling over this time period. In addition to examining a comprehensive set of studies on inter-group conflict (with $N=44$ studies, see Table 1, Panel A) and interpersonal violence (with $N=21$ studies, Panel B) here

TABLE 1 Summary of studies included in the meta-analyses.

Panel A: Intergroup Conflict Studies

Study (Authors and year)	Sample period	Sample region	Time unit	Spatial unit	Climate variable	Outcome variable	Sample size	Effect Estimate
Almer et al. (2017)	1990–2011	Sub-Saharan Africa	Month	Pixel (0.5°)	Temperature	Riot	1,654,724	13.93
Baysan et al. (2019)	1990–2006	Mexico	Month	Municipality	Temperature	Gang killing	115,244	2.33
Bergholt and Lujala (2012)	1980–2007	Global	Year	Country	Storm	Civil Conflict	4109	−6.34
Bohlken and Sergenti (2010)	1982–1995	India	Year	State	Rainfall	Ethnic Riot	191	−98.38
Böhmelt et al. (2014)	1997–2009	Mediterranean countries	Year	Country	Temperature	Water conflict	411	22.61
Bollfrass and Shaver (2015)	1989–2008	Global	Year	Province	Temperature	Civil war	27,544	−1.30
Bounadi (2019)	2005–2016	Afghanistan	Month	District	Temperature	Battle casualty	54,526	0.51
Breckner and Sunde (2019)	1997–2015	Africa	Month	Pixel (0.75°)	Temperature	Civil war	1,100,328	3.35
Brückner and Ciccone (2011)	1980–2004	Sub-Saharan Africa	Year	Country	Rainfall	Institutional Change	914	0.33
Buhaug (2010)	1981–2002	Sub-Saharan Africa	Year	Country	Temperature	Civil Conflict	848	−4.89
Burke (2012)	1962–2006	Global	Year	Country	Temperature	Leadership Exit	5328	0.62
Burke and Leigh (2010)	1963–2007	Global	Year	Country	Temperature	Institutional Change	3985	5.02
Burke et al. (2009)	1981–2002	Sub-Saharan Africa	Year	Country	Temperature	Civil Conflict	848	5.16
Caruso et al. (2017)	2009–2011	South Sudan	Year	County	Rainfall	Killings	234	−9.34

Caruso et al. (2016)	1993–2003	Indonesia	Year	Province	Temperature	Group violence	98	60.17
Couttenier and Soubeyran (2014)	1945–2005	Sub-Saharan Africa	Year	Country	PDSI	Civil Conflict	1426	11.83
Craig et al. (2021)	1970–2015	Global	Month	Country	Temperature	Terrorism	8910	17.81
Dell et al. (2012)	1950–2003	Global	Year	Country	Temperature	Civil War	5587	−1.13
Dell et al. (2012)	1950–2003	Global	Year	Country	Temperature	Regime Change	6550	27.13
Fetzer (2020)	2000–2014	India	Year	District	Rainfall	Conflict	8145	−9.05
Fjelde and von Uexkull (2012)	1990–2008	Sub-Saharan Africa	Year	Country	Drought	Communal Conflict	10,320	1.61
Gatti et al. (2021)	2008–2014	Indonesia	Year	District	Rainfall	Civil conflict	3216	−10.01
Gerling (2017)	1990–2007	Sub-Saharan Africa	Year	Country	Drought	Coup	643	−5.36
Gerling (2017)	1990–2007	Sub-Saharan Africa	Year	Country	Drought	Protest duration	643	9.36
Guardado and Pennings (2020)	2002–2014	West Asia	Month	District	Temperature	Conflict	7488	−1.03
Harari and Ferrara (2018)	1960–2010	Sub-Saharan Africa	Year	Pixel (1°)	SPEI	Civil conflict	35,042	7.59
Helman et al. (2020)	1992–2012	Africa & Middle East	Year	Pixel (0.5°)	Temperature	Non-state conflict	258,774	−3.60
Salehyan and Hendrix (2014)	1970–2006	Global	Year	Country	Rainfall Deviation	Social Conflict	544	11.06
Hidalgo et al. (2010)	1988–2004	Brazil	Year	Municipality	Rainfall Deviation	Land Invasion	44,340	9.72
Hodler and Raschky (2014)	1992–2010	Africa	Year	District	Rainfall	Civil conflict	84,969	−5.47
Hsiang et al. (2011)	1950–2004	Global	Year	ENSO Region	ENSO	Civil conflict	52	9.51
Kim (2016)	1960–2005	Global	Year	Country	Temperature	Coup	4959	12.43
König et al. (2017)	1998–2010	D.R. Congo	Year	Group	Rainfall	Civil conflict	960	−44.01

Continued

TABLE 1 Summary of studies included in the meta-analyses.—Cont'd

Panel A: Intergroup Conflict Studies

Study (Authors and year)	Sample period	Sample region	Time unit	Spatial unit	Climate variable	Outcome variable	Sample size	Effect Estimate
Landis (2014)	1979–2010	Global	Month	Country	Temperature	Civil war	67,367	−6.85
Landis (2014)	1979–2010	Global	Month	Country	Temperature	Non-state Conflict	51,935	3.23
Landis et al. (2017)	1997–2012	Niger River Basin	Month	Pixel (0.5°)	Temperature	Political violence	631,104	5.08
Levy et al. (2005)	1980–2002	Global	Year	Pixel (0.25°)	Rainfall	Civil War	3,709,322	−19.83
Linke and Ruether (2021)	2011–2018	Syria	Month	Sub-district	Temperature	Civil conflict	24,206	3.24
Maystadt et al. (2015)	1997–2009	N. & S. Sudan	Year	Pixel (1°)	Temperature	Civil conflict	45,543	27.05
Miguel et al. (2004)	1981–1999	Sub-Saharan Africa	Year	Country	Rainfall	Civil War	702	1.78
O'Loughlin et al. (2012)	1990–2009	East Africa	Year	Pixel (1°)	Temperature	Civil War	86,832	47.15
Shaver and Bollfrass (2022)	2003–2011	Iraq & Afghanistan	Day	City/Province	Temperature	IED Attack	1,604,634	0.99
Smith (2014)	1990–2012	Africa	Month	Country	Rainfall	Urban riot	10,403	6.07
Theisen et al. (2012)	1960–2004	Africa	Year	Pixel (0.5°)	Drought	Civil War	364,717	−0.81
von Uexkull et al. (2016)	1989–2014	Asia & Africa	Year	Ethnic group	SPEI	Ethnic civil war	7506	0.85
Wischnath and Buhaug (2014)	1950–2008	Asia	Year	Pixel (0.5°)	Temperature	Civil war	542,768	−35.16
Yeeles (2015)	1960–2006	Asia & Africa	Month	City	Temperature	Urban social unrest	28,150	11.83

Panel B: Interpersonal Violence Studies

Study (Authors and year)	Sample period	Sample region	Time unit	Spatial unit	Climate variable	Outcome variable	Sample size	Effect Estimate
Baysan et al. (2019)	2007–2010	Mexico	Month	Municipality	Temperature	Homicide	491,512	4.43
Behrer and Bolotnyy (2021)	2010–2017	Texas	Day	County	Temperature	Violent Crime	738,378	43.76
Blakeslee et al. (2021)	2011–2016	Karnataka	Day	Precinct	Temperature	Crime	912,311	2.04
Blanes i Vidal et al. (2016)	2008–2017	Manchester	Hour	City	Temperature	Domestic abuse	78,104	6.16
Card and Dahl (2011)	1995–2006	US	Day	Police Agency	Temperature	Domestic Violence	79,355	2.96
Craig et al. (2016)	2000–2011	NFL	Game	Stadium	Temperature	Aggression in sports	2788	−2.42
garg_can_2020	1998–2012	Mexico	Day	Locality	Temperature	Homicide	113 million	3.82
Horrocks and Menclova (2011)	2000–2008	New Zealand	Day	District	Temperature	Violent crime	136,813	0.85
Jacob et al. (2007)	1995–2001	US	Week	Police Agency	Temperature	Violent Crime	25,658	5.24
Jacob et al. (2007)	1995–2001	US	Week	Police Agency	Temperature	Property Crime	25,658	6.52
Larrick et al. (2011)	1952–2009	MLB	Game	Stadium	Temperature	Violent retaliation	595,500	0.80
Mares and Moffett (2016)	1995–2012	Global	Year	Country	Temperature	Homicide	844	5.97
Miguel (2005)	1992–2002	Tanzania	Year	Village	Rainfall	Murder	669	26.33
Prudkov and Rodina (2019)	2010–2015	Russia	Month	Region	Temperature	Murder & assault	4544	1.03

Continued

TABLE 1 Summary of studies included in the meta-analyses.—Cont'd

Panel B: Interpersonal Violence Studies

Ranson (2014)	1980–2009	US	Month	County	Temperature	Assault	1,344,187	1.67
Ranson (2014)	1980–2009	US	Month	County	Temperature	Murder	1,454,447	0.89
Ranson (2014)	1980–2009	US	Month	County	Temperature	Rape	1,454,447	1.06
Schinasi and Hamra (2017)	2006–2015	Philadelphia	Day	City	Temperature	Violent crime	3646	4.15
Sekhri and Storeygard (2014)	2002–2007	India	Year	District	Drought	Dowry murder	2915	−0.20
Sekhri and Storeygard (2014)	2002–2007	India	Year	District	Drought	Domestic violence	2915	1.47
Sommer et al. (2018)	2010–2017	LA & Boston	Day	City	Temperature	Violent crime	4687	1.48
Takahashi (2017)	2009–2015	Japan	Year	Prefecture	Temperature	Assault	3760	1.38
Takahashi (2017)	2009–2015	Japan	Year	Prefecture	Temperature	Murder	3760	5.46
Takahashi (2017)	2009–2015	Japan	Year	Prefecture	Temperature	Rape	3760	4.08
Tompson and Bowers (2015)	2002–2011	Glasgow	6-Hours	City	Temperature	Robbery	14,603	4.38
Trujillo and Howley (2021)	2010–2016	Barranquilla	Day	City	Temperature	Homicide	2556	−2.55
Vital and Almeida (2020)	2013–2017	Rio de Janeiro	Day	City	Temperature	Theft	391	0.20

Panel C: Self-harm Studies

Study (Authors and year)	Sample period	Sample region	Time unit	Spatial unit	Climate variable	Outcome variable	Sample size	Effect Estimate
Baylis (2020a)	2014–2016	US	Day	CBSA	Temperature	Sentiment	643,733	3.25
Baysan et al. (2019)	1990–2006	Mexico	Month	Municipality	Temperature	Suicide	608,970	2.75
Burke et al. (2018)	1968–2010	US	Month	County	Temperature	Suicide	847,790	1.21
Carleton (2017)	1967–2013	India	Year	State	Temperature	Suicide	1409	−0.08
Dixon et al. (2014)	1986–2009	Toronto	Day	City	Temperature	Suicide	8513	14.00
Fountoulakis et al. (2016)	2000–2012	Europe	Year	Country	Temperature	Female suicide	305	1.05
Fountoulakis et al. (2016)	2000–2012	Europe	Year	Country	Temperature	Male suicide	305	1.22
Mullins and White (2019)	2005–2016	US	Month	County	Temperature	Mental health issues	8294	7.23
Obradovich et al. (2018)	2002–2012	US	Day	Individual	Temperature	Mental health issues	1,961,743	0.87

Notes: This table lists all studies included in the meta-analysis. Each row corresponds to a particular outcome measured in the study. Studies included in Hsiang et al. (2013) and Burke et al. (2015a) were included in the current meta-analysis if replication data were available and there was no other study with the same combination of climate data set and outcome data set with a larger sample. Additional studies were included conditional on using panel data for intergroup violence or longitudinal data for interpersonal violence and self-harm, using a climate data set-outcome data set combination not already represented in the meta-analysis, and data being available or the authors of the study agreeing to perform additional analyses.

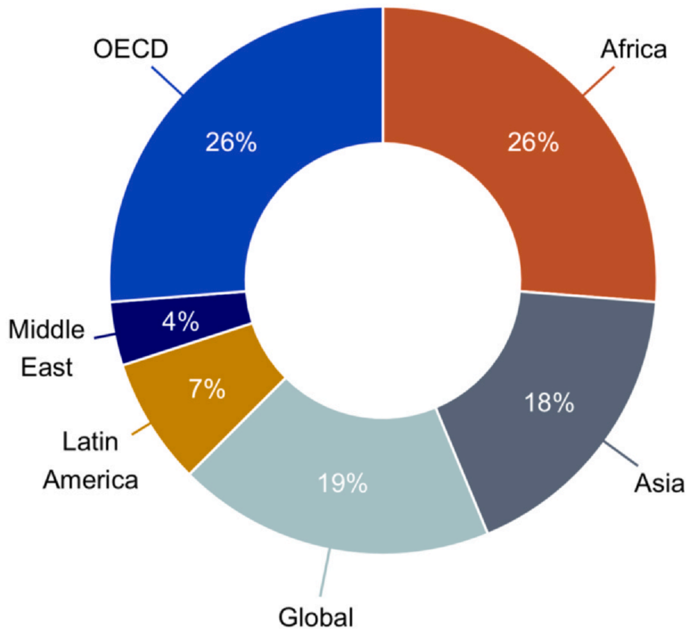

FIG. 4 Geographic distribution of studies in the meta-analyses. Notes: The figure presents the primary geographic location for the inter-group studies included in Table 1. The "Global" category includes studies covering multiple major world regions.

(as in Hsiang et al. (2013) and Burke et al. (2015a)), we now also present a meta-analysis for the emerging literature on climate effects on self-harm and suicide (with N = 8 studies or estimates, Panel C).

We searched for studies to be included in the meta-analyses as follows. We began by screening the set of papers that cite either Hsiang et al. (2013) or Burke et al. (2015a) by reading the abstract to determine whether suitable data were used for an empirical analysis. Those that passed screening were read fully to finally determine whether or not they were eligible for inclusion. The references of papers that were fully read were also checked to identify additional studies that potentially fulfilled the inclusion criteria. Once a study was determined to be eligible for inclusion, we downloaded the replication data if available. If not, we contacted the author(s), asking if they could share the relevant data or were willing to run additional analyses that we would include in the meta-analysis. In the case of the latter, we would send the authors the relevant specification and check the returned code (when possible) to ensure the specification had been implemented correctly. This was a time-consuming endeavor, carried out by the authors of this chapter as well as multiple research assistants (gratefully mentioned in the acknowledgments). All 50 studies added since the Burke et al. (2015a) paper were re-analyzed, either by us or the authors of the studies, in order to generate comparable estimates that can be included in the meta-analysis.

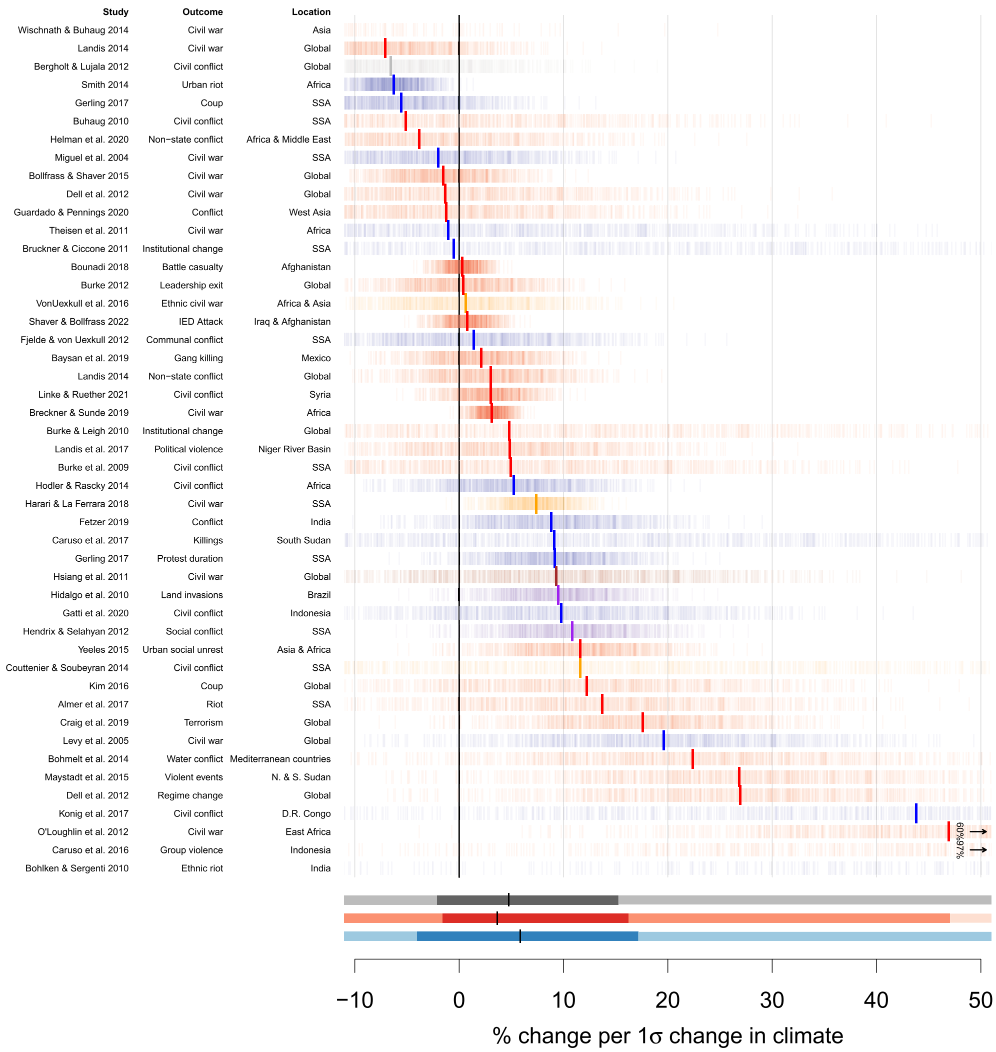

FIG. 5 Meta-analysis of intergroup conflict studies. Notes: This figure shows estimated effects of climate shocks on intergroup conflict and confidence distributions. All estimates are standardized to be the percent change in the outcome due to a one standard deviation change in the climate variable. Each row has a dark mark representing the estimate for an individual study-outcome and 1000 light marks drawn from the corresponding asymptotic distribution: a normal distribution with mean given by the estimate and variance given by the square of its standard error. The color of each row corresponds to the climate variable studied: temperature (red), rainfall (blue), rainfall deviation (purple), ENSO (brown), storms (gray), or drought (orange). The three horizontal bars along the x-axis display quantiles of the estimated effect distribution. For a given bar, the black vertical line represents the median, the darkest bar the 25th-75th percentile interval, the second darkest bar the 5th-95th percentile, and the lightest bar the 2.5th-97.5th percentile. Each quantile is calculated from the combined set of 1000 draws from the asymptotic distribution for all studies where the climate variable is temperature (red), rainfall (blue), or anything (gray).

In addition to the studies included in these meta-analyses, we also identified other articles that contain credible evidence on the importance of particular mechanisms linking climate variation to human conflict, many of which are discussed in the next section (and are listed in Table A.1).

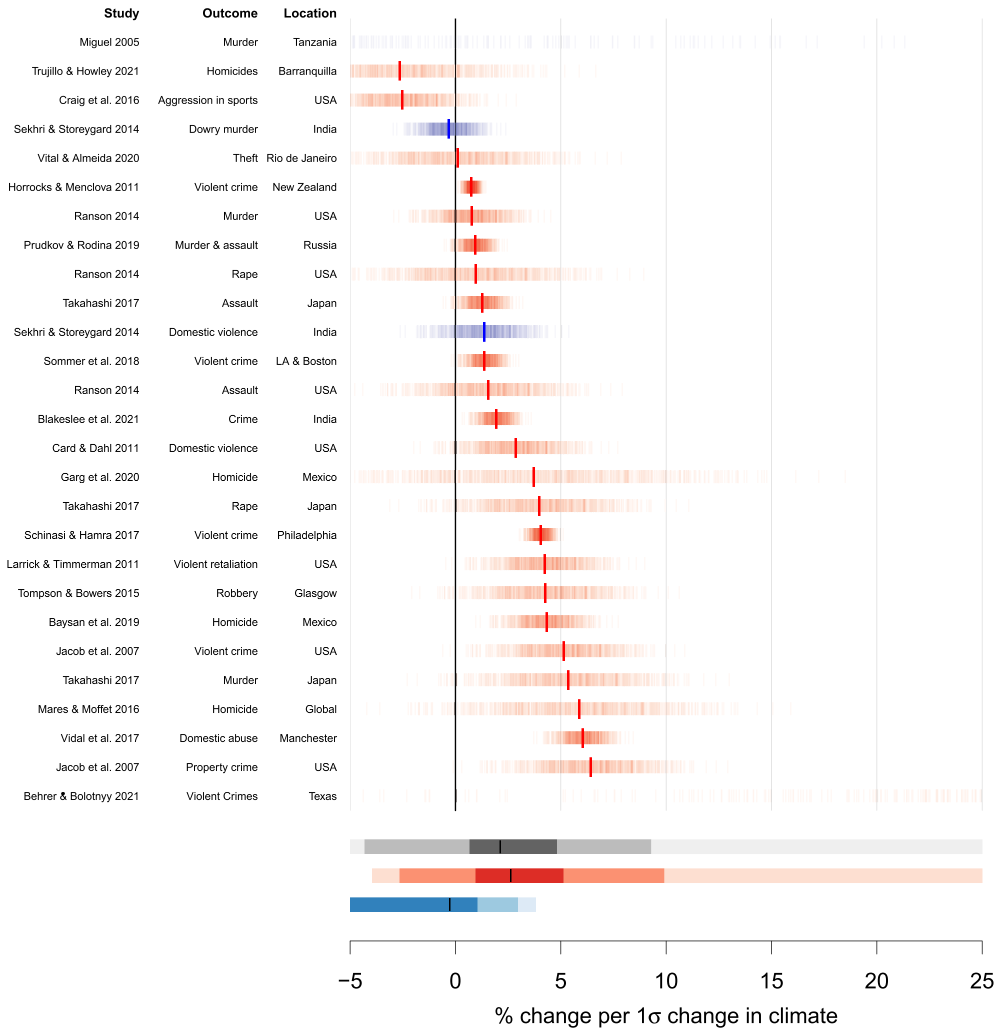

FIG. 6 Meta-analysis of interpersonal violence studies. Notes: See notes to Fig. 5.

An attractive feature of the collection of studies included in the meta-analyses is that the 80 studies we include come from many different regions of the world spanning a wide range of income levels, as well as many global scale studies. Fig. 4 shows the regional composition of the intergroup study sample. The pool of studies analyzed in the current meta-analysis has broader geographic coverage than those of the Hsiang et al. (2013) and Burke et al. (2015a) articles, and thus could provide more general conclusions.

So what does the expanded body of evidence on the climate-conflict relationship show now? And how does it differ from the conclusions of the earlier articles?

We begin with the results on inter-group conflict (based on N = 44 studies and 47 distinct estimates). The meta-analysis results are presented graphically in Fig. 5 (and Figs. 6 and 7 for inter-personal violence and self-harm, respectively, have the same figure structure). In the left column of the the

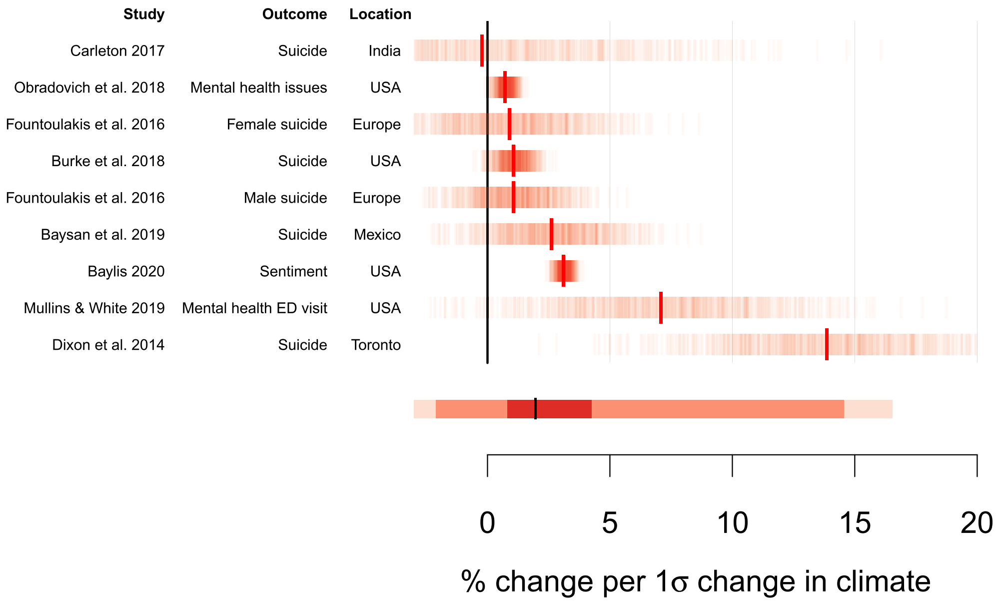

FIG. 7 Meta-analysis of self-harm studies. Notes: See notes to Fig. 5.

figure, you can see the names of the authors of the studies and their geographic location (reproducing information in Table 1 above). They come from all over the world, as noted, including many studies on civil conflict in low-income regions but also riots, coups, communal violence, and other forms of organized violence in other regions and globally. The main estimated effect of climate variation on inter-group conflict from each individual study is shown in the figure, where red colors indicate studies that focus on temperature impacts, blue denote precipitation studies, and yellow denotes drought. The vertical black line denotes a zero effect.

It is visually apparent that most studies have estimated effects to the right of the zero line, meaning there is increased violence in response to climate shocks. Some have estimated effects of 10 %, 20 % or even larger impacts for each anomalous 1 SD increase in local climate. There is another cluster of studies with estimates closer to and typically not statistically distinguishable from zero. The shading around each estimate captures the uncertainty around each estimate with 1000 draws from its asymptotic distribution.

In the bottom panel we combine these individual study estimates' asymptotic distributions into overall distributions of estimated effects in the literature. The darker shading on the horizontal lines at the bottom denotes the inter-quartile range of study estimates, and the full horizontal distance, which is generally not visible, captures the 2.5th-97.5th quantile range. The upper dark gray line combines all studies, and shows that the inter-quartile range of the combined effect distribution of all studies runs from close to zero up to around 15 % per 1 SD increase in a climate shock.

TABLE 2 Subsample meta-analysis estimates.

Sample	Inverse variance-weighted estimate	Standard error	Median estimate	N
		Panel A: Intergroup		
All	2.53	(0.59)	5.08	47
Earlier Studies	6.34	(1.39)	6.37	22
Recent Studies	1.70	(0.65)	3.35	25
Country+	3.83	(1.65)	3.23	19
Sub-Country	2.34	(0.63)	5.31	28
Year	5.10	(1.19)	5.47	33
Sub-Year	1.70	(0.68)	3.23	14
Temperature	2.45	(0.68)	3.30	26
Temperature+	2.49	(0.68)	4.19	28
Rain	−0.35	(1.55)	7.26	14
Africa	2.97	(0.86)	5.31	20
Africa Temperature	3.93	(1.14)	5.16	7
Non-Africa	2.15	(0.81)	3.24	27
		Panel B: Interpersonal		
All	1.90	(0.12)	2.04	27
		Panel C: Self-Harm		
All	2.15	(0.16)	1.22	9

Notes: This table presents inverse variance-weighted meta-analysis estimates for different samples. "All" includes all studies for the type of conflict described in the panel title. "Earlier Studies" includes studies that were included in Hsiang et al. (2013) or Burke et al. (2015a). "Recent Studies" is the complement of "Earlier Studies". "Country+" includes all studies where the spatial unit of analysis is countries or larger geographic units. "Sub-Country" is the complement of "Country+". "Year" includes studies for which the temporal unit of analysis is years. "Sub-Year" is the complement of "Year," and all studies in this group have temporal unit of analysis shorter than a year. "Temperature" includes studies where temperature is the climate variable of interest. "Temperature+" includes temperature, drought, and ENSO studies. "Rain" includes studies where a continuous measure of rainfall is the climate variable of interest. "Africa" includes studies where the entire geographic coverage of the study is within Africa. "Africa Temperature" is the intersection of "Africa" and "Temperature". "Non-Africa" is the complement of "Africa". "Sub-Country" includes studies where the spatial unit of analysis is smaller than countries. Standard errors are calculated under the assumption that errors across studies are uncorrelated.

We also present a number of meta-analysis estimates in Panel A of Table 2. Specifically, we calculate inverse variance-weighted average estimated effects. The overall inter-group estimate suggests that a 1 SD adverse change in climate is associated with a 2.53 % (SE 0.59) increase in conflict, and the median estimate is 5.08 %. Appendix Fig. A.1 shows that the meta-analysis estimate

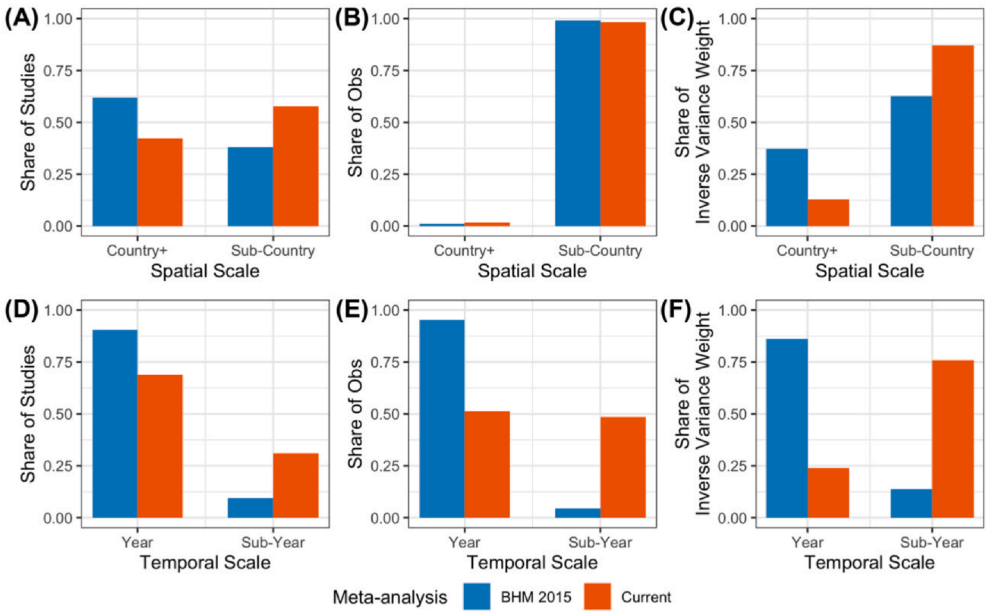

FIG. 8 Notes: This figure compares the sample of inter-group conflict studies included in the current meta-analysis to the sub-sample included in Burke et al. (2015a). Panels a, b, and c separate studies by spatial unit of analysis, with "Country+ " referring to studies where the spatial unit of analysis is country or larger and "Sub-Country" refers to studies where the spatial unit of analysis is smaller than countries. Panels d, e, and f separate studies by temporal unit of analysis. In these panels, "Year" refers to studies where the temporal unit of analysis is years and "Sub-year" refers to studies where the temporal unit of analysis is shorter than years. Panels a and d report the share of studies in each category by meta-analysis. Panels b an e show the number of observations comprising the studies in each category by meta-analysis. Finally, Panels c and f show the share of total inverse variance weights given in each category conditional by meta-analysis using the estimated coefficients and standard errors of the current meta-analysis.

remains very stable when dropping one study at a time, suggesting that the effect is not driven by any particular estimate. The average overall effect of 2.53 % is far smaller than the 11 % average effect estimate on inter-group conflict in Hsiang et al. (2013) and Burke et al. (2015a), but the effects remain highly statistically significant ($p < 0.01$) and meaningful in magnitude using the expanded sample of studies we consider. The median estimate of 5.08 % in the new meta-analysis is smaller than the median estimate of 13.8 % in Burke et al. (2015a). Recall that most regions of the world are projected to warm by between 2 to 4 SD's in the coming three decades, so multiplying the updated mean (median) effect 2 to 4 fold implies projected increases in inter-group violence on the order of 5–10 % (10–20 %) unless human societies can come up with new ways to adapt to climate change.

The change in effect magnitudes appears to be driven by both a different composition of studies in the new analysis as well as our updated statistical approach, which carries out a more uniform re-analysis across all studies. For instance, the meta-analysis intergroup violence estimate is smaller using the updated re-analysis method even when using the sub-sample of studies included Burke et al. (2015a) due to our more unified approach to specification choice and statistical inference. Using only those earlier studies, we estimate a meta-analysis effect of 6.34 %, as opposed to an effect of 1.70 % among only the new intergroup violence studies added for this chapter.

Such a large reduction in the estimated effect warrants exploration. Fig. 8 shows that the composition of studies has changed substantially over time in terms of the geographic and temporal size of the units of analysis, which may have contributed to the large reduction in estimated effects. Studies of inter-group conflict in the previous meta-analyses were much more likely to use countries as the geographic unit of analysis and year as the temporal unit of analysis. With the proliferation of spatially and temporally disaggregated conflict data (most importantly, the ACLED dataset), recent studies have shifted towards sub-country and sub-year units of analysis, which also tend to produce smaller meta-analysis estimates. Inter-group studies with country or larger units of analysis have a meta-analysis estimate of 3.83 % as opposed to 2.34 % for sub-country studies and year-level studies have a meta-analysis estimate of 5.1 % compared to 1.7 % for sub-year studies (Table 2). We show in section 3 that the use of shorter time periods in particular may have contributed to the reduction in the meta-analysis estimate.

A number of climate variables have been explored in relation to inter-group conflict but temperature and rainfall are especially prevalent. The inverse variance weighed average effect for temperature is very close to the overall estimate, with a 1 SD increase in temperature corresponding to a 2.45 % increase in intergroup conflict. Rainfall does not have a statistically significant relationship with inter-group conflict according to our inverse variance-weighted meta-analysis estimate, although the median of the meta-analysis distribution is large at 7.26 % (Table 2).

The most common setting for inter-group conflict studies in the meta-analysis is Africa, with over 40 % of the sample. The inverse variance-weighted estimate for studies in Africa is a 2.97 % increase in inter-group conflict per 1 SD increase in climate ($p < 0.01$). This is slightly larger than the 2.15 % estimated for studies outside of Africa ($p < 0.01$). The inverse variance-weighted estimate for temperature in the African sample of studies is notably larger than in the full collection of temperature studies at 3.93 % ($p < 0.01$).

While we do not conduct analysis of non-linear temperature effects, there is some evidence in the literature that extreme cold also increases the likelihood of conflict Iyigun et al. (2017). Similar non-linearity and non-monotonicity has been found in the case of economic growth Burke et al. (2015b). If growth partially mediates the relationship between climate and conflict, it is feasible that low temperature shocks would also increase conflict incidence.

The results suggest that at the very least, temperature and related phenomena such as drought significantly increase the likelihood of inter-group conflict in a variety of global settings. Even if the magnitude of the implied average and median effects are somewhat smaller than earlier estimates in Hsiang et al. (2013) and Burke et al. (2015a), they remain large and of substantive importance.

Fig. 6 presents analogous results for interpersonal violence studies (N = 21 studies and 27 separate estimates), including outcomes such as homicide, armed robbery, and assault, among others. Again, the present meta-analysis includes roughly twice as many studies as found in Hsiang et al. (2013) or Burke et al. (2015a). Notably, newly included studies use data from many from low- and middle-income settings (including Brazil, Colombia, India and Mexico) whereas the 2013 meta-analysis predominantly featured studies of interpersonal conflict in wealthy countries such as the US. There is much less variety in the climate variable of interest in the interpersonal sample compared to inter-group: all but three studies focus on local temperature variation.

There is once again a range of estimated effects, with most indicating positive effects and a fairly tight cluster around 2 %. The inverse variance-weighted meta-analysis indicates that local climate variation (including higher temperatures) tends to increase homicides, armed robbery, and assaults. The mean estimated effect in the meta-analysis is 1.90 % (SE 0.12) per 1 SD increase in local climate, and the median effect is similarly 2.04 % (Table 2, Panel B). This is roughly 20 % smaller than the comparable estimates in Hsiang et al. (2013) and Burke et al. (2015a) but is statistically significant (p-value < 0.01) and still meaningful in magnitude. Projecting forward a few decades, by 2050 global warming could lead to increases on the order of 4 to 8 % in interpersonal violence in the absence of successful adaptation or other changes.

Finally, there is a smaller but growing literature on how higher temperatures affect various forms of self-harm, including suicide or mental health distress, with studies from India, the US, Mexico, Canada, and Europe (N = 8 studies based on 9 estimates, see Fig. 7). There are multiple potential channels linking elevated temperatures to self-harm (as we discuss in the next section) including a psychological or physiological response, or effects operating through deteriorating economic conditions.

Overall, the mean increase in self-harm in response to 1 SD anomalously higher local temperature is 2.15 % (SE 0.16), which is significant at $p < 0.01$ and broadly similar in magnitude to the mean inter-group and inter-personal violence effect estimates (Table 2, Panel C).

Taken together, there is strong evidence that climate shocks like elevated temperatures lead to more intergroup conflict, inter-personal violence, and self-harm, with effects that are statistically significant and meaningful in magnitude across all three dimensions. One takeaway from the updated analysis is that estimated magnitudes are smaller than they were in earlier meta-analyses, albeit still substantial, due to a combination of different studies included in the meta-analyses (due to the recent explosion of research in this field) as well as our different statistical approach in this chapter which attempted to apply a common econometric model across studies (rather than taking the authors' preferred estimate, as we generally did in the earlier 2013 and 2015 articles).

The next section examines how variable the estimated effects are with the use of data aggregated at different spatial and temporal scales, and across econometric specifications that differ in the inclusion of time lags of the key climatic explanatory variables.

3 Lessons for analysis across spatial and temporal scales

Compared to the earlier meta-analysis work in the Hsiang et al. (2013) and Burke et al. (2015a) articles, there are far more inter-group conflict studies that utilize finer geographic and time scales, below the level of the country-year which was the modal level of analysis in the earlier meta-analyses. The rise in disaggregated analyses has been enabled in part by the increasing use of data, like the well-known ACLED dataset, that has information at the subnational level and time scales of less than a year.

Fig. 8 illustrates the rise in spatially disaggregated studies in Panel a along with its implications on the share of observations (Panel b) and inverse-variance weight (Panel c) in the intergroup meta-analysis estimate at the sub-country level. The share of studies using a unit of analysis smaller than country rose from about 38.1 % to 57.7 % while the share of inverse variance weight for those studies increased by about 25 % points to a total of over 85 %. A similar pattern is apparent for the growing importance of studies that have time scales of less than a year: for studies included in the meta-analyses of 2013 and 2015 nearly all observations (Panel e) and weight in the analysis (Panel f) is derived from year level studies, while studies with more fine-grained time scales dominate the current meta-analysis presented in this chapter.

A related point (not shown directly in the figure) is that the share of weight in the average meta-analysis effect estimate accounted for by the most statistically precise estimates has slightly increased. Of the studies included in the earlier meta-analysis, the three with the most weight in the analysis — namely, Harari and Ferrara (2018), Baysan et al. (2019), and Hidalgo et al. (2010) — accounted for slightly more than half (53.2 %) of the weight. In the current meta-analysis, the three most weighted studies — Breckner and Sunde (2019), Bounadi (2019), and Shaver and Bollfrass (2022) — received 55.5 % of the weight. These patterns raise the question of how analysis at different levels of spatial and temporal aggregation affects results and conclusions regarding the climate-conflict relationship.

In principle, there are a wide range of temporal and spatial scales that could be of interest, and this could vary for different outcome variables. It might be advantageous to focus on highly localized effects (in time and space) if local effects might become diluted at higher levels of aggregation. At the same time, focusing on short-run effects in a small geographic area could lead the analysis to understate true effects that emerge more gradually over months or years with lags, or that spread out to nearby areas due to the natural dynamics of armed conflict. The appropriate scale certainly lies somewhere between studying the climate-conflict link at the kilometer-minute scale and the global-century scale – but where exactly should scholars focus? And how much do results change when using data at different scales?

We examine this issue by combining the Uppsala Conflict Data Program's Global Event Data (GED) together with the Climate Hazards Center Infrared Temperature with Stations (CHIRTS) data set to form a panel data set covering Africa from 1989–2016, which allows us to estimate comparable regressions at different temporal and spatial scales, importantly with the exact same data and in the same settings; focusing on African societies is natural given that the region has been a major focus of recent research on this topic. In other words, this approach enables us to assess the effect of aggregation alone along these two dimensions on estimates (while holding other factors constant). We also examine how effect estimates differ across distinct econometric specifications that account for different numbers of time lags, which turns out to be an important determinant of estimated effect magnitudes.

The results in Fig. 9 present estimated temperature effects on intergroup conflict incidence at a range of spatial scales from 0.5 to 2 degrees and up to the country level, and from a time scale of one month, a year, a decade, and to long differences between the 1989–1998 and 2007–2016 averages, so nearly three decades.[1] This captures the range of scales commonly found in most intergroup conflict studies in the existing literature (see section 4 on Mechanisms for more details on the data used in specific studies); some interpersonal violence studies have even finer geographic or temporal time frames (e.g., crime rates in a given week at the municipality level). The figure presents both the relative effect magnitude (the length of the bars) and the level of statistical significance (the stars), and shows how they vary across specifications that do and do not account for seasonality and temporal lags.

This exercise yields several robust patterns. First, the climate-conflict relationship has the same sign (higher temperature leads to more conflict) across all temporal and spatial scales examined here, as indicated by the direction of the bars (none are negative). Second, across all of the scales at the subnational level, the relationship remains highly statistically significant, usually at $p < 0.01$ (indicated by the three stars), while at the country level the effect is only significant when using the long difference time frame. The documented causal relationship between elevated temperatures and more human violence is not just found at particular spatial or temporal scale, but rather appears quite general across scales.

Third, estimated effect sizes are significantly larger when considering effects over the long difference. Subnational effects also generally increase in magnitude as the time scale lengthens, with decade scale effects larger than year effects, and

[1] In separate work not shown here, we also carried out related analysis using spatial first difference regressions. These do not generally yield results similar to the more standard specifications presented here, likely because a small number of mountainous locations exhibit the majority of the variation in spatial differences in temperature.

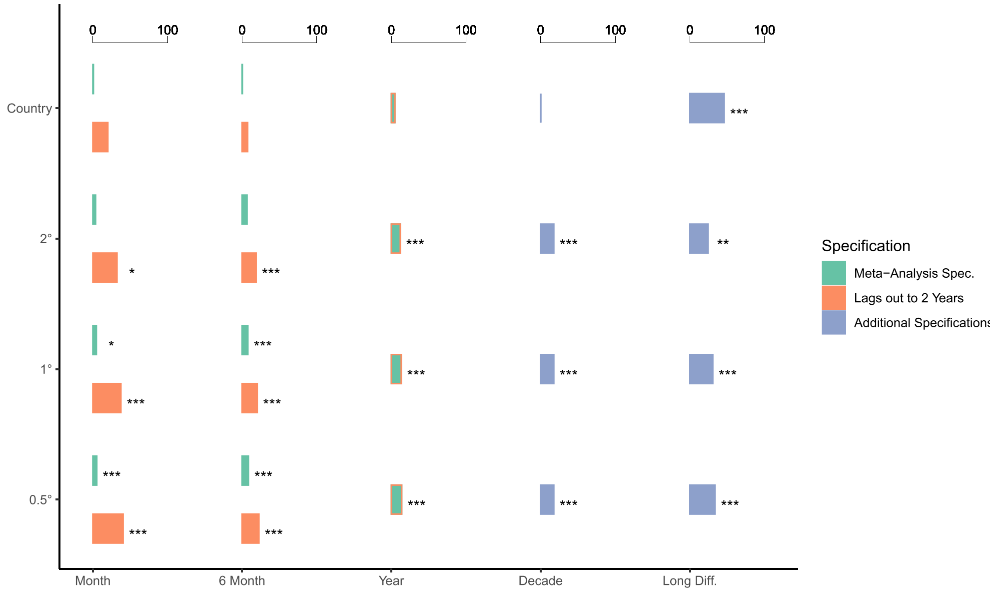

FIG. 9 Estimated Temperature Impacts on Intergroup Conflict at Different Spatial and Temporal Scales and across Regression Specifications. Notes: This figure shows the results of a set of specifications estimating the effect of temperature on conflict incidence using a single data set (in Africa, as described in the main text). The data set is constructed on a 0.5° × month scale. Aggregation in time and space is done by averaging for temperature and taking the maximum for conflict incidence. The "Meta-Analysis Spec." specification includes contemporaneous temperature along with its first lag. For the month and 6 month level, location × timescale and year fixed effects are included, e.g. location × month and year, and at the year level includes location and year fixed effects. The "Lags out to 2 Years" specifications have the same fixed effects as the "Meta-Analysis Spec." specifications, but include lags out to two years prior. For example, at the month level there would be contemporaneous temperature and 23 lags. The orange border around the green "Meta-Analysis Spec." estimates at Year scale indicate that this specification includes lags out to 2 years. The Decade specifications do not include any lags. The long difference specification uses the difference between mean conflict incidence in 2007–2016 and 1989–1998 as the outcome and the difference between average temperature in the same time periods as the explanatory variable. The plotted estimates are the sum of the estimated effects on all lags of temperature and p-values are calculated from an F-test of the null hypothesis that the sum of the coefficients is 0 using the location-clustered variance-covariance matrix.

long difference effects larger than decade effects. (Note that for consistency the year scale estimates account for both temperature in the current year and the previous year, so across two years in all.) In other words, extended higher temperature shocks have much larger effect sizes than shocks that last for a shorter duration. This is an important result in its own right and provides little reason to believe that there has been widespread successful adaptation to higher temperatures in existing data (since adaptation would lead to lower sensitivity and dampened effects following extended adverse climatic shocks).

Fourth, estimated effects are sensitive to the econometric specification, as shown by the results at the 1 month and 6 month scales. In these cases, the top row (the green block) is the effect estimate using a sparse specification that only includes 2 time lags at that scale (in other words, for the monthly results, it includes temperature in the current month and past month as explanatory variables). Most estimated effects in this case are relatively small in magnitude, albeit highly statistically significant in some cases. The second row (the orange block) includes two years of time lags as explanatory variables. When two years of time lags are accounted for, estimated effects are far larger in magnitude (across all spatial scales shown here) than the other specification and are statistically significant for the 0.5, 1 and 2 degree scales. They are also similar in magnitude to (if not somewhat larger than) the estimates generated using data at the scale of 1 year. The divergence in estimates derived from specifications with and without time lags suggests that the common regression specification used in the current meta-analysis may lead to conservative estimates of the effect of temperature on intergroup conflict.

A key implication is that it is critical to account for sufficient numbers of time lags when estimating the climate-conflict relationship, and focusing only on immediate responses in the same month or two (or even a six month period) would lead one to drastically underestimate the actual total effect of temperature shocks on conflict outcomes. There are many reasons for this pattern, including the delayed effect of rainfall on later crop yields (due to growing season timing), as well as the time needed to organize insurgencies and fighting units, and other potential conflict dynamics. Moreover, the effect of extended warming is larger in magnitude than temporary shocks at all spatial scales, an indication that adaptation to changing climatic conditions has generally been limited to date.

To better understand what underlies these patterns, the next section discusses new research evidence on the channels linking climate to violence.

4 Recent contributions with a focus on mechanisms linking climate and conflict

4.1 Overview of literature on mechanisms

There has been a clear increase in the research that investigates not just the overall impact of climate shocks on conflict outcomes (which was surveyed in section 2) but also in the mechanisms that account for this relationship. Understanding the nature of these mechanisms, and how they might help in the design of effective public policy responses, has long been highlighted as a major gap in the literature (since at least Hsiang et al. (2013)). A main point of our discussion in this section is that there has been considerable progress in understanding mechanisms over the last decade, and we survey some of the lessons that have emerged from these studies in this section. Table A.1 contains a list of studies we have identified that contribute to understanding the underlying mechanisms.

In particular, we identify five leading mechanisms behind the climate-conflict relationship: (1) economic mechanisms, such as income, dependence on agriculture; (2) socio-demographic factors such as religion, ethnicity, marriage customs, etc; (3) migration and transportation costs; (4) policy, politics and institutions; and (5) psychological and physiological mechanisms, such as anger, stress, etc. One punchline of the review is that different mechanisms tend to be more important or active in particular settings. So there is not necessarily a one-size-fits-all public policy response to climate shocks, but the growing body of research provides greater insight into which types of factors could matter more in certain settings. This appears to be a useful first step in crafting effective policy responses to counter climate change.

Given the scores of studies in this area (see Table A.1), it is impossible for us to describe the methodology, data and results of each of these articles in any detail. Instead we opt to focus on a smaller number of studies that are particularly distinctive or influential in their approach, spread across these categories, that shed light on more general patterns in the literature. It is also the case that many studies provide evidence on the importance of more than one channel, for instance, some findings noted below indicate that income shocks matter but differentially so, depending on local socio-demographic characteristics or political institutions. In such cases (of which there are several), we note these interactions and overlaps. Readers interested in a more complete listing of studies with summaries of key findings can find it in Table A.1. In this section, we mainly focus on key patterns in the literature (rather than repeating the content in the table), synthesizing findings across multiple studies.

4.2 Empirical approaches to understanding mechanisms

Before discussing key lessons, it is worth taking a short econometric detour. The studies on mechanisms that we focus on in this section typically employ one of two statistical approaches.

First, many of the studies utilize a research design similar to the one we have focused on so far, namely, estimating the effect of climate shocks on outcomes using panel (longitudinal) data, as in Eq. (1). The difference here is many of these studies examine impacts of climate variation on variables that they interpret as mechanisms (or *mediators*) for the effect of climate on conflict, rather than on the ultimate conflict outcome per se. For instance, they might ask how higher temperatures affect local economic conditions (where deteriorating living standards could be a mechanism connecting climate shocks to conflict). Taken together, the effects of climate shocks on multiple mechanisms combine to yield the overall reduced form effect of climate on conflict and violence that is the focus of the meta-analysis estimates (refer back to Fig. 3 for an illustration).

Second, and in an alternative approach, some studies instead examine how particular factors affect the strength of the estimated relationship between climate and conflict (in other words, serving as *moderators*) in regression specifications similar to Eq. (1) but including interactions. To illustrate, the analysis might estimate how much less sensitive local crime rates are to higher temperatures in wealthier versus poorer municipalities, where lower sensitivity in richer areas would shed light on the role of economic conditions in enabling or dampening climate impacts. In the table, we distinguish between whether the analysis in an individual study focuses on mediators (the first approach) or moderators (the second), or both. In our view, both approaches provide useful evidence on the nature and strength of the channels linking climate to conflict.

4.3 Key lessons on channels

We organize the discussion in this section around four broad patterns in the emerging literature on mechanisms, recognizing that there are many other important findings that we simply do not have space to discuss in detail here (and that may not fit neatly into these general patterns); for those, we again refer the reader to appendix Table A.1 with summaries of findings.

Lesson 1: Reliance on agriculture, and shocks to agricultural production and prices, are associated with more violent conflict.

This is one of the largest sub-literatures we identified, cutting across many historical periods and geographies. Using data across countries in the recent period, Goyette and Smaoui (2019) and Salehyan and Hendrix (2014) find that the climate-conflict relationship is significantly stronger in more agriculturally dependent countries. In contemporary African societies, Harari and Ferrara (2018) show that climate shocks (specifically, temperature and precipitation) significantly affect conflict risk. Importantly, this only holds for climate shocks that occur during agricultural growing seasons, direct evidence for the importance of an agricultural income channel.

Historically, Jia (2014) documents that the adoption of drought-resilient crops (here, sweet potatoes) in China during the period 1470–1900 significantly lowers the effect of droughts on conflict outbreaks (specifically, peasant revolts), suggesting the importance of income smoothing mechanisms in limiting the risk of violence. There is a related finding from contemporary Indonesia: Gatti et al. (2021) show that poor rainfall triggers local conflict (across multiple dimensions of violence) in Indonesia but the relationship is dampened where there is good local irrigation infrastructure for the staple crop (rice). This is presumably because local crop yields and economic conditions are no longer as closely tied to the weather when there is improved irrigation.

There is also increasing evidence that shocks to agricultural prices and real wages are important drivers of conflict. McGuirk and Burke (2020) show that a 1 SD increase in an agricultural production price index in an African sample reduces local conflict by about 17 %, while a 1 SD increase in consumer price index increases conflict by 9 % (although this latter effect is not significant). This pattern suggests that distributional considerations are important, and that it is important to think through how particular price shocks affect local living standards, for instance, since an increase in staple prices could end up leading to improved local economic conditions for rural producers (even while it reduces real wages for city dwellers). In a study of major urban areas in Africa, Smith (2014) finds that 1 SD increase in food prices as a result of rainfall shocks increases the probability of unrest by 14.3 % to 17.8 %. Guardado and

Pennings (2020) exploit sub-national variation in the onset and intensity of the harvest (i.e., harvest shocks) in three countries (Afghanistan, Iraq, and Pakistan), and show that harvest shocks significantly reduce the probability of insurgent attacks. Since harvest shocks are associated with a positive labor demand shock in their setting, the finding is consistent with the importance of the opportunity cost channel in mediating the climate-conflict relationship.

Agricultural shocks are not just associated with greater risk of intergroup violence, but also affect the likelihood of self-harm. Using decades of suicide data for India, Carleton (2017) shows that elevated temperatures during the agricultural growing season (which can be damaging to crops) are associated with significantly higher suicide rates. Higher temperatures in other times of the year do not have the same effect in her sample (although as already noted in the meta-analysis, higher temperatures are associated with higher suicide rates in a range of societies and time periods).

Lesson 2: The effects of agricultural and other income shocks are shaped by local social divisions, migration options, and political institutions.

Communities and households facing climate shocks may adopt many different coping strategies, one of which could be moving to a different area in some cases. When they do so, a body of research indicates that the nature of social and political institutions is important for determining whether this could lead to violent conflict.

Historically, Pei and Zhang (2014) show that climate induced migration by herder communities into regions inhabited by agricultural communities in ancient China significantly increases the probability of conflict. There are parallel findings in contemporary societies. Eberle et al. (2020) find that a 1°C increase in temperature leads to a 54 % increase in the likelihood of conflict in areas populated by both farmers and herders in Africa, compared to a 17 % increase in areas populated only by farmers or only by herders. This suggests that competition for resources between these two distinct social groups acts as a mediator of the climate-conflict relationship. This is a major issue in multiple African countries, including in Nigeria, the most populous African country. In related work, Guariso and Rogall (2021) find that a 1 SD increase in rainfall *inequality* across neighboring areas increases the likelihood of ethnic conflict by 50 %, and these results only hold for groups that are politically excluded, again highlighting the role of political divisions and institutions in mediating conflict. (See also von Uexkull et al. (2016) for a related finding on the importance of ethnic political exclusion in mediating the climate-conflict relationship.).

An important recent contribution in this area is McGuirk and Nunn (2021), who find that lower rainfall (including drought events) induce transhumant groups, which engage in seasonal migration tied to pastoralism, to migrate to areas inhabited by agriculturalists, leading to elevated rates of conflict. One way to understand this result is that migrating herders need to constantly look for food and water for their livestock, and when climatic conditions are not favorable for them, it leads them to encroach on cultivated land, leading to conflict. Since herders and farmers typically belong to different ethnic and religious groups, this could generate social conflict, although it is important to note that this conflict would at its base have an economic cause (namely, resource scarcity). It may also have a political solution: the authors also find that herder-cultivator clashes in West Africa are dampened when herders have more political power, presumably because in those cases it is easier to reach political deals to resolve or avoid conflicts. This points to the key role of political institutions, and democratic representation in particular, in possibly helping to address climate related stress in the coming decades.

These studies indicate that in some cases, in-migration of herder communities can spark conflict with other groups. However, this pattern does not appear to generalize across all contemporary societies. In a global sample, Bosetti et al. (2021) show that migrant inflows are not associated with increased conflict in receiving locations, and Petrova (2021) documents a similar pattern for migrants in Bangladesh. Importantly, Bosetti et al. (2021) also find that countries with traditions of emigration (higher past flows) are significantly less sensitive to higher temperatures, in terms of generating conflict, than countries with smaller previous diasporas, suggesting that improved mobility can serve as an important safety valve in situations of potential social instability driven by climate shocks.

Yet improved geographic mobility can also increase conflict risk. Rogall (2021) studies the role of rainfall in mobilizing the population for genocide in Rwanda in 1994, and finds that heavier than usual rainfall, interacted with the length of dirt roads (which become impassable with heavy rainfall), reduced militant groups' ability to mobilize civilians to take part in that conflict. This finding suggests that weather may affect logistical decision-making in conflict, at least in the short run. However, the limited causal evidence on this channel makes it difficult to conclude much more. Exploring this mobilization mechanism further may be a fruitful area of future research.

Lesson 3: Public policies that reduce income and employment volatility can dampen the risk of violence.

The findings in Jia (2014) and Gatti et al. (2021) described above already indicated that the ability to smooth agricultural incomes (through the adoption of sweet potatoes in China and improved irrigation in Indonesia) played a role in reducing conflict risk. Several recent studies have detailed how expansion of government income assistance and social protection programs targeted to poor households and communities can play a similar role in dampening conflict along all three dimensions that we consider, intergroup conflict, interpersonal conflict, and self-harm, and we present evidence for all three in turn here.

In the context of rural India, Fetzer (2020) first shows that extreme monsoon rainfall shocks are associated with higher levels of intergroup conflict, in terms of local Naxalite rebel violence. He then examines the impact of the gradual roll-out of the National Rural Employment Guarantee program (NREGA), the world's largest public jobs program in terms of beneficiaries, which number in the tens of millions each month, and which provides paid manual labor jobs (often on public works projects) for low-income adults. He finds that the expansion of NREGA almost completely offsets the effects of these adverse climate (monsoon rainfall) shocks on conflict in India: note the before versus after contrast in the right hand panels in Fig. 10, where the largely flat relationship in the bottom right panel indicates little sensitivity to climate shocks.

Garg et al. (2024) first document that higher temperatures are associated with significantly more homicides (interpersonal violence) in Mexico, consistent with patterns shown earlier in related work by Baysan et al. (2019). Garg et al. (2024) then examine how the expansion of the pioneering Mexican Progresa conditional cash transfer program affects this relationship; the program targeted poor households for large cash grants provided that they enrolled their children school and made regular health clinic visits. They show that the effect of temperature on homicide crime rates falls to be statistically indistinguishable from 0 in areas receiving the assistance program before rising to previous levels after initially receiving the program.

The decline is presented graphically in Fig. 11 reproduced from their paper. Here the horizontal axis captures a time dimension, where the roll out of the Progresa program in a particular area occurs at Year = 0. This is when the cash transfers start in a given area, and this roll out was staggered over time across Mexico. Before the expansion of this social protection program, there was high sensitivity of local homicide rates to current temperature shocks, with effects of around 0.4%, but immediately after the program starts, these effects fall to slightly below zero where before rising to previous levels over the next five

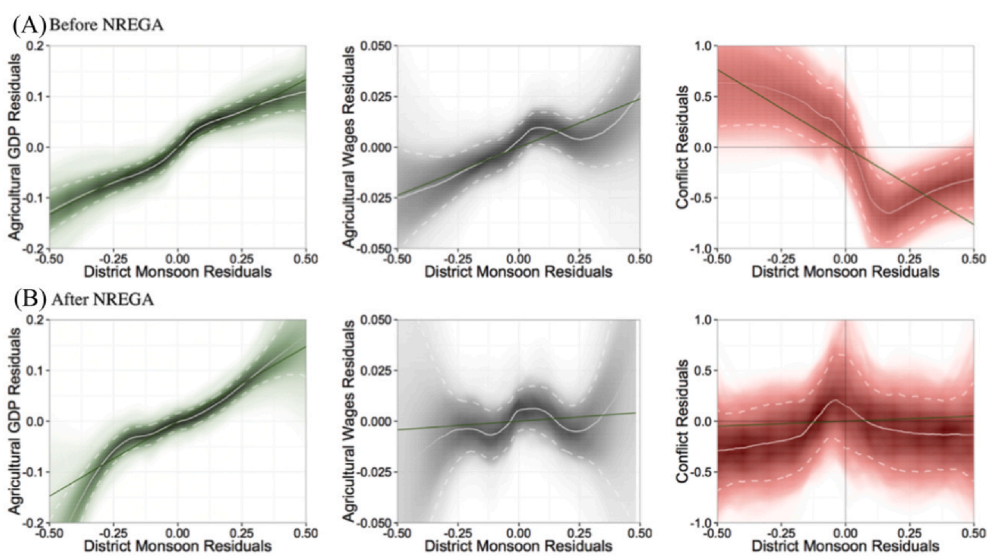

FIG. 10 Non-parametric local linear regressions of residualized outcomes on residualized monsoon shocks (i.e., after removing both district fixed effects as well as region by NREGA phase by time effects). Reproduced from Fetzer (2020), Figure 5.

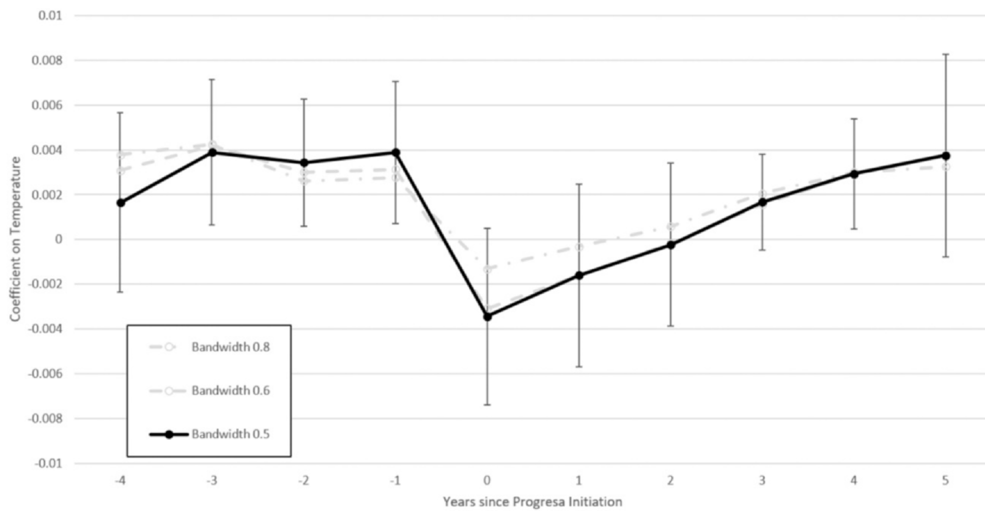

FIG. 11 Event study of progresa program on effect of temperature on homicides in Mexico. Reproduced from Garg et al. (2024), Figure 3.

years. As in the case of intergroup violence in India, with homicides in Mexico once economic conditions for the poor improve (in terms of levels and lower volatility), there is a much weaker link between climate shocks and local violence, at least in the first few years of the program.

Self-harm outcomes are also sensitive to climate shocks in agricultural communities (as already discussed above in Carleton (2017) in India), and may be affected by government programs. An illustration of the importance of government programs is found in Christian et al. (2019), which examines suicide rates in Indonesia. Several pieces of evidence highlight the central role of income levels and volatility. First, areas experiencing worse (lower) rainfall levels have significantly more suicides, as indicated by the downward sloping relationship in Fig. 12. Second, the authors show that receipt of a large-scale government conditional cash transfer program (Program Keluarga Harapan, PKH) is associated with a sizeable drop in suicide rates, by approximately 18 %. This finding holds both in a randomized control trial (RCT) sample as well as when exploiting program roll-out in a difference-in-differences framework. In a main finding, the authors then go on to show that the relationship between poor rainfall and local suicide rates is significantly weaker (less steeply negative) in areas receiving the cash assistance program, falling by approximately two thirds. This provides further evidence that government income support for poor households can play an important role in reducing the risk that climate shocks translate into violence, in this case, into self-harm.

Lesson 4: Independent of income-related mechanisms, there are psychological and physiological channels that link extreme temperature to conflict.

The key role of economic conditions comes through in all of the literature "lessons" noted above, even in the studies of self-harm in low- and middle-income countries (LMICs) that were just discussed (e.g., Carleton (2017),

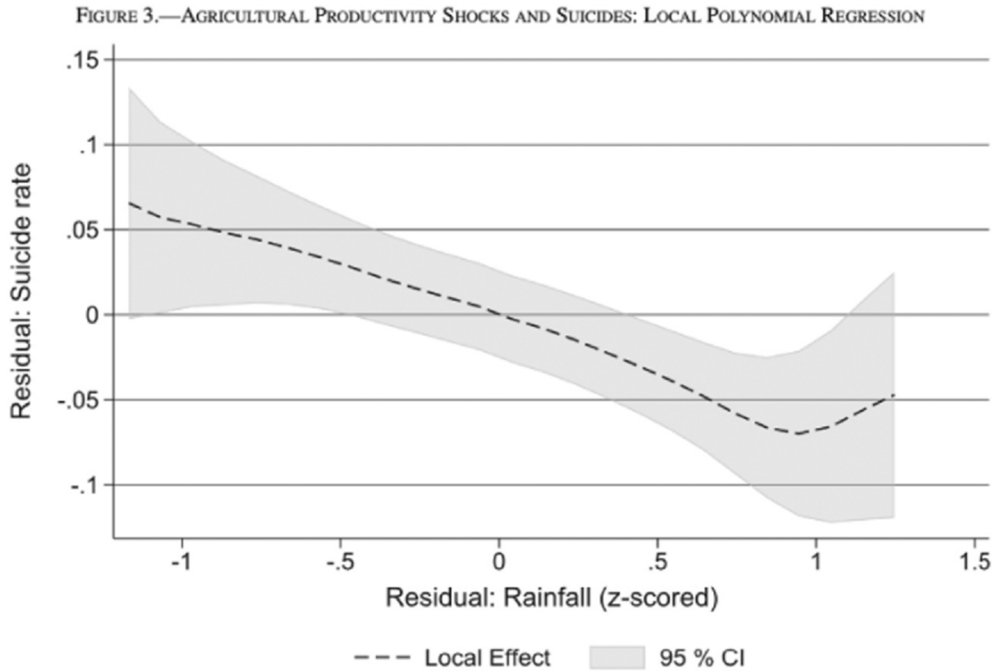

FIG. 12 Christian et al. (2019) Ag productivity shocks and suicides. Reproduced from Christian et al. (2019), Figure 3.

Christian et al. (2019)). However, there are patterns in the literature that economic conditions cannot explain, most notably the rapid response of both interpersonal violence and self-harm to higher temperatures in richer societies (like the US and other OECD countries) where short-run variation in household incomes are not closely tied to climate drivers. These studies are presented in the meta-analysis discussion above (in Section 2).

There is now also evidence on how people's behavior and psychology change at higher temperatures from both social media use and from controlled lab environments. Baylis (2020a) utilized data from billions of tweets, and analyzed them using natural language processing algorithms, to show that the use of profanity and aggressive language is significantly higher at extremely low and especially at extremely high temperatures. This sheds light on how elevated temperatures in particular may affect social cooperation, cohesion, and trust, all of which would presumably be adversely affected by more aggressive communication styles.

There is a literature (mainly in psychology) that tries to explore how intrinsic psychological or physiological mechanisms are affected by higher temperatures but most rely on correlations or small numbers of subjects rather than research designs similar to those that we focus on in this piece. A notable exception is Almås et al. (2019), which carries out economics lab experiments in both Berkeley, California and Nairobi, Kenya in which participants were randomly allocated to either normal temperature rooms (at roughly 20°C/68°F) or high temperature rooms (at 30°C/86°F) and their economic choices and behaviors were measured over one hour. Many core economic behaviors and preferences (e.g., time and risk preferences) did not change significantly in the hot room relative to the cool room in either site. But the authors do document that participants in the hot room in the Nairobi sample often reacted more aggressively in the Joy of Destruction game (in which they can costlessly and anonymously destroy the endowment of another player), and this finding survives a multiple testing adjustment. This is experimental evidence for a direct psychological or physiological mechanism that emerges at higher temperatures and may contribute to violent conduct, although of course in the lab, there is no actual physical aggression. Echoing the results of several other studies discussed above (including McGuirk and Nunn (2021)), the temperature effects are more pronounced among individuals who come from politically marginalized ethnic groups in Kenya, suggesting that — whether the underlying channel is mainly economic deprivation or a psychological response — social divisions and political inclusion appear to be important moderators.

5 Discussion

This chapter surveys the burgeoning research literature examining the empirical links between climate and conflict, and updates previous meta-analysis estimates, assesses important methodological issues around the scale of statistical analysis, and discusses recent evidence on underlying mechanisms.

The meta-analysis results reinforce the previous conclusion that rising temperatures and extreme rainfall will contribute to conflict risk across many settings and types of violence. In particular, we survey and carry out a meta-analysis of the exploding literature on links between climate and conflict, a body of scientific evidence that has more than doubled in the last decade since the Hsiang et al. (2013) *Science* study.

The bottom line conclusion remains qualitatively the same: for inter-group and inter-personal violence, as well as for a new body of work on self-harm, higher than normal temperatures and adverse rainfall shocks are statistically associated with elevated local violence outcomes. This relationship holds across many different geographic settings and types of conflict, and the statistical significance of these relationships (in terms of being able to reject a null effect) has grown since the earlier meta-analyses given the larger sample sizes and broader coverage of recent work. At the same time, the magnitudes of the estimated effect on intergroup conflict is substantially smaller, though they remain substantial and of practical importance given that the world is projected to warm by at least 2 degrees Celsius in the coming decades (IPCC, 2022).

A key scientific advance of the recent research in this area is the expansion of evidence on the multiple mechanisms, and associated public policies, that appear to reduce climate risks. One robust pattern is that higher living standards reduce the sensitivity to climate, a finding that we demonstrate across

Sub-Saharan Africa in a concurrent paper (Burke et al., 2024a). Related to this, several economic policies that provide greater employment opportunities or boost incomes for households – such as cash transfers – have been shown to greatly reduce the effect of adverse climate shocks in low- and middle-income country settings (especially of note are the results in Fetzer (2020), Garg et al. (2024), and Christian et al. (2019)). This encouraging evidence points toward concrete public policy approaches and ways forward in this space.

Beyond economic conditions, the new body of research contains more evidence on other specific mechanisms and policies that matter, including socio-demographic factors, migration and transportation, politics and institutions, and psychological and physiological factors, where the precise channels that drive violence appear to strongly depend on the specific context. That said, the study of mechanisms linking extreme climate to conflict outcomes, as well as research on concrete policies that can be shown to reduce conflict risk, remains a frontier research topic with potentially large social value. The design of specific social protection programs — and potentially policies in other sectors — that can reduce the sensitivity of local violence to warming temperatures is a major global priority.

Other directions of interest in this area include: more research on how the effects of climate shocks are moderated by local income levels as well as political institutions (including democratic representation); how climate affects the logistics and organization of conflict; and more detailed projections for what the associated results mean for conflict risk in the coming decades, taking into account more realistic assumptions about the pace and nature of adaptation and other socio-economic and technological changes.

At the same time that there has been some intellectual progress in understanding the issues surveyed in this chapter, the world's failure to slow global warming remains a major concern and threatens to increase conflict risk globally. Moreover, economic growth has stagnated (or become negative) in many low- and middle-income countries since the COVID-19 pandemic started in early 2020, and more recently with the disruptions to global agricultural trade and rising food prices due to the brutal Russian invasion of Ukraine. This deterioration of global environmental and economic conditions raises major concerns regarding political stability and the risk of conflict, violence and crime around the world, given what we now know. We fear that the coming decade could be a perilous moment for global peace, and that it could shine a spotlight on how critical continued economic development will be in allowing poor countries to deal with climate change. More evidence on how best to prevent climate and economic shocks from increasing violence in our societies cannot come soon enough.

Acknowledgments

Authors are listed in alphabetical order. We are grateful to Shreya Chandra, Jerry Min, Gwyneth Miner, Jonathan Old, Shreya Sarkar, and Nachi Shah for excellent research assistance. All errors are our own.

Appendix

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Salehyan and Hendrix (2014)	165 countries	Civil conflict and terrorism	PDSI, precipitation, and temperature	Income	Agricultural dependence	Moderator	–	Less agriculturally dependent societies have weaker link between rainfall and political violence: 1 SD increase in rainfall (measured as average absolute precipitation) leads to 0.39 more battle deaths across all countries. This effect is 10x higher for African countries (vs. Africa), 1.7x higher for countries dependent on Agriculture, and 9.5x higher for countries below < Median GDPpc.
von Uexkull et al. (2016)	Africa & Asia	Civil conflict	PDSI	Income	Agricultural dependence	Moderator	–	Drought seems particularly harmful in places with high agricultural dependence and for politically excluded ethnic groups. Successive years of drought have large cumulative effects.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Crost et al. (2018)	Philippines	Number of casualities, number of violent incidents	Rainfall	Income	Agricultural production	Mediator	–	An increase in dry-season rainfall leads to an increase in agricultural production and dampens conflict intensity: a 10 cm increase in dry season rainfall is associated with 0.59 fewer casualties in the following year. By contrast, an increase in wet-season rainfall is harmful to crops and increases the likelihood of conflict (by 0.28 more incidents).
Axbard (2016)	Indonesia	Piracy	Fishing conditions	Income	Income	Moderator	–	Improvements in fishing conditions - a function of temperature in combination with other oceanographic conditions - induce an income effect that make fishermen select away from piracy. Above median fishing conditions reduce the incidence of piracy attacks by 21%. These effects are driven by areas with slow economic growth in non-fishing occupations, suggesting that the income effect operates through changes in income opportunities.

Rothler et al. (2020)	India	Suicide	Drought, temperature	Income	Irrigation, access to credit	Moderator	–	The incidence of droughts increases the suicide rate in India by 19.1% - this effect is only driven by (male) farmers, is concentrated during agricultural seasons, decreases with irrigation cover, and increases with farmer indebtedness.
Buhaug et al. (2015)	Sub-Saharan Africa	Conflict	Rainfall	Income	Food production	Mediator	Null	Rainfall linked to food production as measured by FAO, but not conflict - 1 unit increase in food production per capita lowers #civil conflict events by 0.695; but effect not significant
Jia (2014)	China	Peasant revolt	Drought, flood	Income	Resilient crop	Moderator	–	The adoption of sweet potato, a weather-resilient crop, halved the impact of extreme droughts on peasant revolts in 15th–20th century China, relative to provinces that did not adopt the weather-resilient crop.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Almer et al. (2017)	Africa	Violent events	SPEI	Income	Water scarcity	Mediator	–	The effects of drought on violent outbreaks is more pronounced in grid cells with water scarcity, measured as less blue water per capita (relative to a long term average). Overall, a 1 SD decreae in SPEI increases conflict by 8.3%, but the effect increases by 1.69x in areas with water scarcity.
Shaver et al. (2019)	Africa	Civil conflict	Precipitation	Income	Non-irrigated land	Mediator	–	Replicates Miguel et al 2004: economic growth reduces conflict by 2.25% points; 2.66% points when instrumenting with rainfall x non-irrigated cropland. The study also finds that ruggedness increases the likelihood of conflict by 0.39% points (through smaller shares of irrigated cropland).

Gatti et al. (2021)	Indonesia	Civil conflict	Rainfall	Income	Irrigation infrastructure	Moderator	–	Lower rainfall leads to an increase in the number of conflict incidents and the effect is mitigated by irrigation infrastructure: a 1 SD decrease in rainfall increases conflict by 0.29 incidents per district year, and a one standard deviation increase in irrigation capacity reduces this effect by approximately 36%.
Goyette and Smaoui (2019)	Global	Civil conflict	Temperature	Income	Agricultural potential (land suitability)	Moderator	–	A better [worse] endowment in agricultural potential mitigates [exacerbates] the effect of temperature on conflict incidence: in countries with low [high] agriculture suitability (low [high] endowment), a 1°C increase in temperatures increases [decreases] conflict incidence by 3pp [5pp].
Koren et al. (2021)	Kenya	Protest	Climate shocks	Income	Food and water security	Moderator	–	Food insecurity and water insecurity together are associated with more conflict.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Eberle et al. (2020)	Africa	Farmer-Herder Conflicts in Africa	Temperature	Income	Resource competition	Mediator	–	A 1°C increase in temperature leads to a 54% increase in the likelihood of conflict in areas populated by both farmers and herders, compared to 17% increase in farmer/herder only populated areas, suggesting competition for resources between the two social groups as a mediator of the climate-conflict relationship.
garg_can_2020	Mexico	Homicide	Temperature	Income	Cash transfers	Moderator	–	Cash transfers (through Progresa) reduce the effect of temperature on crime in Mexico by 75%; without the cash transfers, a 1°C increase in temperature has a 2.1% effect on crime (homicide rates).
Christiana and Elbourneb (2018)	Europe (ancient roman empire)	Mutinities, emperor assasinations	Rainfall	Income	Food scarcity	Mediator	–	Lower rainfall adversely affects food availability, increasing likelihood of mutinty among roman troops and hence assasinations of roman emperors: 1 SD lower rainfall increase the occurrence of mutinies by 13.3%.

Guardado and Pennings (2020)	Afghanistan, Iraq, Pakistan	Insurgent / militant attacks in month m relative to total attacks in a year	Harvest shock (interaction of intensity and onset of harvest)	Income	Agriculture, employment opportunities	Mediator	–	In all three countries, the intensity of conflict is lower at harvest than at other times of the year, with greater falls in areas with larger areas under cultivation: onset of harvest reduces the average number of monthly attacks by around 6–22% in Iraq, 20% in Pakistan, and 8–18% in Afghanistan
Raleigh et al. (2015)	24 African countries	ACLED conflict	Precipitation	Income	Food prices	Mediator	–	Use simultaneous equations to estimate effects of rainfall deviations on food prices and conflict. Negative rainfall shocks increase food prices and increase prevalence of violence; and doubling a food prices is associated with a 13% increase in conflict.
Cohen and Gonzalez (2019)	Mexico	Criminal charges	Temperature	Income	Alcohol prices	Moderator	–	Higher alcohol prices attenuate the effects of temperature on criminal charges. 18% of all weather-related crimes are triggered by excessive use of alcohol, and 1% higher alcohol prices are associated with 0.5% fewer offences from drunk people.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Harari and Ferrara (2018)	Africa	Conflict	SPEI	Income; SES	Agriculture	Mediator	–	1 SD lower SPEI during last year's growing season increases conflict by 8%, but SPEI has no effect on conflict outside of growing season. Ethnic cleavages and low state capacity exacerbate effect of conflict.
Petrova (2021)	Bangladesh	Protest	Drought	Migration	Internal migration	Mediator	Null	A drought shock resulting in lost harvest increases migration likelihood, but migrant receiving areas are not statistically more likely to experience protests.
Koubi et al. (2021)	Kenya	Protest	Environmental events	Migration (in)	Migrants' protest propensity	Mediator	+	Individuals who had experienced both gradual or sudden environmental shocks at their initial location are more likely to join and participate in social movements about migrant rights.
Cattaneo and Foreman (2022)	World	Militarized International Disputes	Rainfall	Migration	In-migration	Mediator	+	1% increase in climate-induced migration increases the probability of (inter-state) conflict in receiving destination by 0.001 pp over a mean incidence 0.13 pp per year.

McGuirk and Nunn (2021)	Africa	Violent conflict	Precipitation	Migration (in), SES	Suitability to both agriculure and pastoralism	Mediator	+	Areas bordering transhument areas are 39% more likely to experience conflict with a 1 SD decrease in precipitation. Greater political power for transhument groups alleviates the effects on conflict, although aid, agriculture, forestry and land conversation projects do not (if anything, the latter actually slightly worsen the effect on conflict).
Bosetti et al. (2021)	World	Civil conflict	Temperature and precipitation	Migration	Migration (out and in)	Moderator	Out: −; in: null	Out migration serves as a "pressure release valve" and attenuates the effects of climate on conflict. A 1 SD increase in temperatures increases the probability of conflict in low-diaspora countries by 30%. The effect is also higher for low income countries.
Rogall (2021)	Rwanda	Genocide prosecutions	Rainfall	Migration	Transportation costs	Mediator	+	Rainfall along dirt roads before start of Rwandan genocide led to less military, and subsequently less civilian, participation by making remote villages inaccesible, thus reducing conflict. Conversely, lower rainfall induced 13 additional deaths from 1 additional external militiaman.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Chambru (2019)	Pre-modern France	Social conflicts, subsistence related conflicts	Temperature	Policy	The local experience of political leaders	Moderator	–	One standard deviation increase in temperature increased the probability of social conflicts by about 5.3%; leaders with higher level of local experience were better able to cope with adverse weather conditions (and completely offset the effect on conflict)
Fetzer (2020)	India	Conflict	Rainfall	Policy, income	NREGA	Moderator	–	NREGA reduces impact of negative rainfall shocks on income and subsequently conflict by −1.4% (before NREGA 1% reduction in rainfall increases conflict by 1.4%)

Cervellati et al. (2017)	World	Civil conflict	Drought, temperature	Psych	Disease	Mediator	+	Drought and heat waves promote the prevalence of disease vectors, which increase the likelihood of civil conflict by reducing opportunity cost through reduced potential lifetime earnings. 60% increase in conflict with a 1 SD increase in disease environment; effect is 3.6 −5 pp higher in the event of a weather shock
Mehra et al. (2019)	Uganda		Recent exposure to drought	Psych	Psychological traits relevant to conflict	Mediator	+	Droughts lead to 0.23 SD lower Agreeableness, 0.26 SD lower Conscientiousness and 0.11 SD lower Emotional Stability (obverse of neuroticism) - traits that dictate impulse restraint, conscience and aggression. This suggests one possible mechanism through which climatic shocks increase conflict.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
Tiihonen et al. (2017)	Finland	Violent crime	Temperature	Psych	Peripheral seratonin transmitter density	Mediator	+	Low seratonin levels and high ambient temperatures are associated with higher rates of violent crimes in Finland.
Blakeslee et al. (2021)	India	Violent vs property crimes	Daily and seasonal variations in temperature and precipipation	Psych	Psychological responses to daily variations and income responses to seasonal variations	Mediator	+	1°C rise in daily maximum temperature is associated with 0.5% increase in the expected crime count on a given day. Violent crimes respond to both daily and seasonal variation in temperatures and rainfall, whereas property crimes only respond to seasonal variation. This is consistent with the existence of both (same-day) psychologically driven and (seasonal) agricultural-income driven impacts of weather on crime.

Younan et al. (2018)	California	Aggressive behaviors	Long-term daily ambient temperature	Psych	Socioeconomic status and gender	Moderator	+	A 1°C increase in 2 –3 year average temperature increases aggressive behavior by 36% points. These associations were slightly stronger among girls and families of lower socioeconomic status but greatly diminished in neighborhoods with more green space
Baryshnikova et al. (2021)	LA, NYC, Chicago, Indianapolis	Crime	Temperature	Psych	Sleep (deprivation)	Mediator	+	Suggests that sleep deprivation might be a mechanism based on results on the lags of hourly weather data
Baylis (2020b)	US, Australia, India, South Africa, Philippines, Kenya, Uganda	Average sentiment	Temperature	Psych	Sentiment (twitter)	Mediator	+	Below 12°C and above 30°C, a 1°C increase in temperature is associated with decline of 0.09 and 0.23 standard deviations in sentiment
Almås et al. (2019)	Berkeley and Nairobi	Destructive behavior	Temperature	Psych	Thermal stress	Mediator	+	Participants in the treatment group exhibit a 50% increase in likelihood of destruction relative to control group. These effects are more pronounced among ethnically marginalized participants.

Continued

TABLE A.1 Summary of studies identifying mechanisms driving the climate-conflict relationship.—Cont'd

Study	Study region	Dep. Var	Indep. Var	Mechanism	Mech: Type	Mediator / moderator	Sign	Summary
De Juan and Wegenast (2020)	East Africa	Violent conflict	Droughts	Psych	(1) Individual level intra-ethnic and inter-ethnic trust, (2) heterogenous drought impacts across ethnic groups	Mediator	−	Droughts are associated with an increase in both intra and inter group trust (1 SD increase in drought index increases trust by 0.1 SD). However, this effect only holds for low levels of horizontal inequality.
Wilkowski et al. (2009)			Temperature	Psych	Anger	Mediator	+	Show two-way causal relationship between anger related words and hot temperatures in a set of lab experiments.
Christian et al. (2019)	Indonesia	Suicide	Rainfall	Psych, income	Mediator: depression induced by agricultural income loss; moderator: case transfers	Mediator and moderator	−, −	1 SD increase in subdistrict rainfall (from long-run average) lowers the suicide rate by 0.08 (6% of national baseline) and depression by 0.12 of a standard deviation. cash transfers lower suicides by 0.3 suicides per 100 K inhabitants in a year with subdistrict rainfall 1 SD below its long-run mean, but only lower suicides by 0.1 suicides per 100 K inhabitants in a year with subdistrict rainfall 1 SD above its long-run mean.

Moreno-Medina (2021)	US	Crime	Precipitation	SES	Religiosity	Mediator	Null	Religiosity might not affect violent crime: rainfall on sunday morning has no effect on violent crime.
Guariso and Rogall (2021)	Africa	Ethnic conflict	Precipitation	SES	Rainfaill inequality	Mediator	+	1 SD increase in rainfall inequality causes 4 pp increase in ethnic conflict likelihood, about 50
Rexer (2022)	Nigeria	Insurgency (extremist violence)	Rainfall	SES	(1) Female pre-marriage income and expected bride-price (2) male marriage prospects	Mediator	+	In the 2SLS models, a one-point increase in the Gini coefficient of brides increases Boko Haram fatalities by an 0.7–1.5 annual deaths (9 −20%). This effect is entirely driven by polygamous communities; there is no effect for monogamous communities.

Notes:This table provides a list of papers exploring mechanisms in the climate-conflict relationship found during the course of the search for studies to include in the meta-analysis. Mechanisms explored in this table fall into two broad categories: moderators and mediators. Moderators studies explore a mechanism that alters the climate-conflict relationship. Mediator studies explore a mechanism that acts as a channel through which climate affects conflict. Mechanisms are then categorized into five types (Mech: Type): income, migration, policy, psychology, and social. The conlict dependent variable (Dep. Var) and climate independent variable of interest (Indep. Var) are listed along with the study's citation, the geographic region covered in the study, the sign of the estimated coefficient on the moderator, and a short summary of the paper. Some studies listed only explore potential mechanisms, without exploring conflict related outcomes. For those studies the dependent variable is left unlisted.

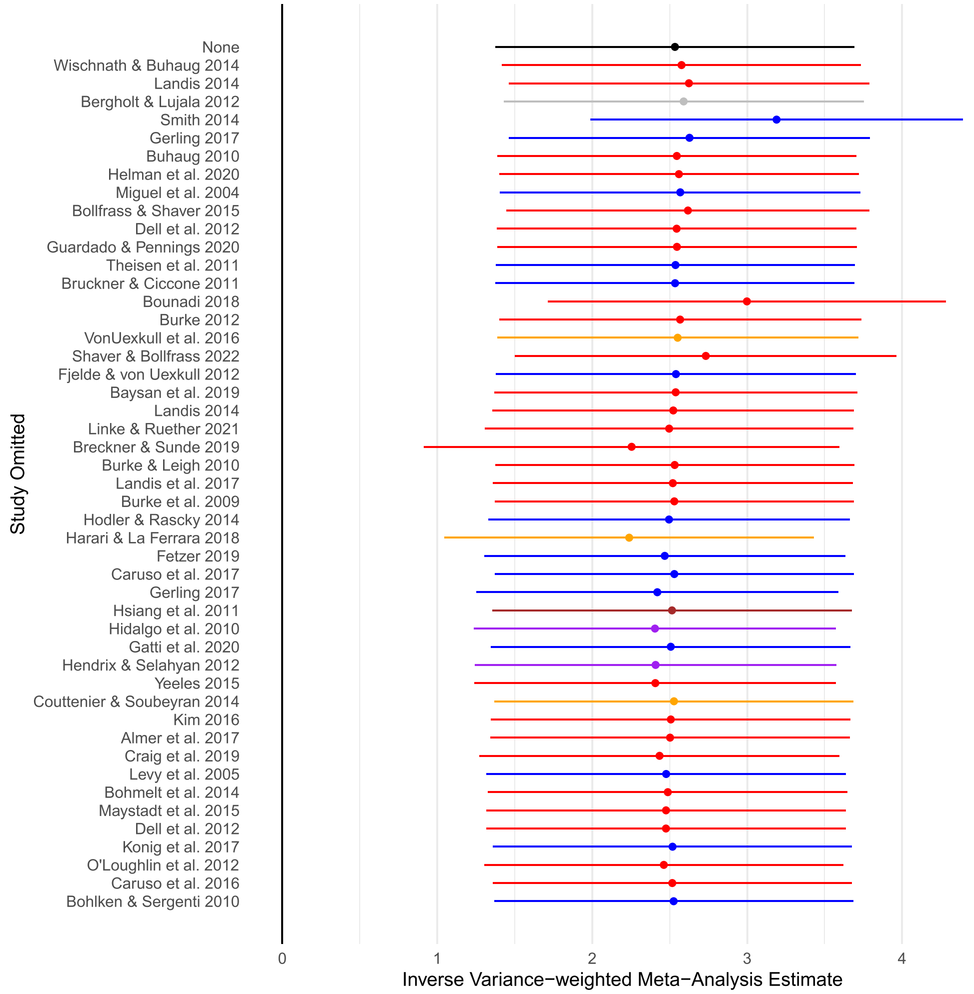

FIG. A.1 Leave-one-out Group Conflict Meta-analysis Estimates. Notes: This figure shows inverse variance-weighted meta-analysis estimates and 95% confidence intervals for the entire sample of group conflict studies as well as each subset constructed by leaving out a single study. The x-axis gives the meta-analysis estimates in terms of percent increase in conflict outcome per standard deviation in the climate variable. Studies which estimate the effect of temperature are shown in red, rainfall in blue, rainfall deviations in purple, storms in grey, ENSO in brown, and PDSI or SPEI in orange.

References

Almås, I., Auffhammer, M., Bold, T., Bolliger, I., Dembo, A., Hsiang, S., Kitamura, S., Miguel, E., Pickmans, R., 2019. Destructive Behavior, Judgment, and Economic Decision-making under Thermal Stress. Tech. rep. w25785. National Bureau of Economic Research, Cambridge, MA doi: 10.3386/w25785.

Almer, C., Laurent-Lucchetti, J., Oechslin, M., 2017. Water scarcity and rioting: disaggregated evidence from Sub-Saharan Africa. Journal of Environmental Economics and Management 86, 193–209. https://doi.org/10.1016/j.jeem.2017.06.002

Axbard, S., 2016. Income opportunities and sea piracy in Indonesia: evidence from satellite data. American Economic Journal: Applied Economics 8 (2), 154–194. https://doi.org/10.1257/app.20140404

Baryshnikova, N., Davidson, S., Wesselbaum, D., 2021. Do you feel the heat around the corner? The effect of weather on crime. Empirical Economics. https://doi.org/10.1007/s00181-021-02130-3

Baylis, P., 2020a. Temperature and temperament: evidence from Twitter. Journal of Public Economics 184, 104161. https://doi.org/10.1016/j.jpubeco.2020.104161

Baylis, P., 2020b. Temperature and temperament: evidence from Twitter. Journal of Public Economics 184, 104161. https://doi.org/10.1016/j.jpubeco.2020.104161

Baysan, C., Burke, M., González, C., Hsiang, S., Miguel, E., 2019. Non-economic factors in violence: evidence from organized crime, suicides and climate in Mexico. Journal of Economic Behavior & Organization 168, 434–452. https://doi.org/10.1016/j.jebo.2019.10.021

Behrer, A.P., Bolotnyy, V., 2021. Heat, crime, and punishment. Hoover Institution Economics Workin Papers 21114.

Bergholt, D., Lujala, P., 2012. Climate-related natural disasters, economic growth, and armed civil conflict. Journal of Peace Research 49 (1), 147–162. https://doi.org/10.1177/0022343311426167

Blakeslee, D., Chaurey, R., Fishman, R., Malghan, D., Malik, S., 2021. In the heat of the moment: economic and non-economic drivers of the weather-crime relationship. Journal of Economic Behavior & Organization 192, 832–856. https://doi.org/10.1016/j.jebo.2021.11.003

Blanes i Vidal, J., Bolte, L., Kirchmaier, T., 2016. Domestic abuse: what do we know about it? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2867580

Bohlken, A.T., Sergenti, E.J., 2010. Economic growth and ethnic violence: an empirical investigation of Hindu—Muslim riots in India. Journal of Peace Research 47 (5), 589–600. https://doi.org/10.1177/0022343310373032

Böhmelt, T., Bernauer, T., Buhaug, H., Gleditsch, N.P., Tribaldos, T., Wischnath, G., 2014. Demand, supply, and restraint: determinants of domestic water conflict and cooperation. Global Environmental Change 29, 337–348. https://doi.org/10.1016/j.gloenvcha.2013.11.018

Bollfrass, A., Shaver, A., 2015. The effects of temperature on political violence: global evidence at the subnational level. In: Ebi, K.L. (Ed.), PLoS One 10https://doi.org/10.1371/journal.pone.0123505

Bosetti, V., Cattaneo, C., Peri, G., 2021. Should they stay or should they go? Climate migrants and local conflicts. Journal of Economic Geography 21 (4), 619–651. https://doi.org/10.1093/jeg/lbaa002

Bounadi, M., 2019. Weather and Conflicts in Afghanistan.

Breckner, M., Sunde, U., 2019. Temperature extremes, global warming, and armed conflict: new insights from high resolution data. World Development 123, 104624. https://doi.org/10.1016/j.worlddev.2019.104624

Brückner, M., Ciccone, A., 2011. Rain and the democratic window of opportunity. Econometrica 79 (3), 923–947. ⟨http://www.jstor.org/stable/41237773⟩.

Buhaug, H., 2010. Climate not to blame for African civil wars. Proceedings of the National Academy of Sciences 107 (38), 16477–16482. https://doi.org/10.1073/pnas.1005739107

Buhaug, H., Benjaminsen, T.A., Sjaastad, E., Magnus Theisen, O., 2015. Climate variability, food production shocks, and violent conflict in Sub-Saharan Africa. Environmental Research Letters 10 (12), 125015. https://doi.org/10.1088/1748-9326/10/12/125015

Burke, M., Ferguson, J., Hsiang, S., Miguel, E., 2024a. Will wealth weaken weather wars? AEA Papers and Proceedings 114, 65–69. https://doi.org/10.1257/pandp.20241055

Burke, M., González, F., Baylis, P., Heft-Neal, S., Baysan, C., Basu, S., Hsiang, S., 2018. Higher temperatures increase suicide rates in the United States and Mexico. Nature Climate Change 8 (8), 723–729. https://doi.org/10.1038/s41558-018-0222-x

Burke, M., Hsiang, S.M., Miguel, E., 2015a. Climate and conflict. Annual Review of Economics 7 (1), 577–617. https://doi.org/10.1146/annurev-economics-080614-115430

Burke, M., Hsiang, S.M., Miguel, E., 2015b. Global non-linear effect of temperature on economic production. Nature 527 (7577), 235–239. https://doi.org/10.1038/nature15725

Burke, M., Zahid, M., Martins, M.C., Callahan, C., Lee, R., Avirmed, T., Heft-Neal, S., Kiang, M., Hsiang, S., Lobell, D., 2024b. w32985. Are We Adapting to Climate Change? Technical Report. National Bureau of Economic Research,, Cambridge, MA, pp. w32985. https://doi.org/10.3386/w32985. w32985.

Burke, M.B., Miguel, E., Satyanath, S., Dykema, J.A., Lobell, D.B., 2009. Warming increases the risk of civil war in Africa. Proceedings of the National Academy of Sciences 106 (49), 20670–20674. https://doi.org/10.1073/pnas.0907998106

Burke, P.J., Leigh, A., 2010. Do output contractions trigger democratic change? American Economic Journal: Macroeconomics 2 (4), 124–157. https://doi.org/10.1257/mac.2.4.124

Burke, P.J., 2012. Economic growth and political survival. The B. E. Journal of Macroeconomics 12, 1. https://doi.org/10.1515/1935-1690.2398

Card, D., Dahl, G.B., 2011. Family violence and football: the effect of unexpected emotional cues on violent behavior. The Quarterly Journal of Economics 126 (1), 103–143. https://doi.org/10.1093/qje/qjr001

Carleton, T.A., 2017. Crop-damaging temperatures increase suicide rates in India. Proceedings of the National Academy of Sciences 114 (33), 8746–8751. https://doi.org/10.1073/pnas.1701354114

Carleton, T.A., Hsiang, S.M., 2016. Social and economic impacts of climate. Science 353 (6304), aad9837. https://doi.org/10.1126/science.aad9837

Caruso, R., Khadka, P., Petrarca, I., Ricciuti, R., 2017. The economic impact of peacekeeping. Evidence from South Sudan. Defence and Peace Economics 28 (2), 250–270. https://doi.org/10.1080/10242694.2015.1122282

Caruso, R., Petrarca, I., Ricciuti, R., 2016. Climate change, rice crops, and violence: evidence from Indonesia. Journal of Peace Research 53 (1), 66–83. https://doi.org/10.1177/0022343315616061

Cervellati, M., Sunde, U., Valmori, S., 2017. Pathogens, weather shocks and civil conflicts. The Economic Journal 127 (607), 2581–2616. https://doi.org/10.1111/ecoj.12430

Chambru, C., 2019. Do the Right Thing! Leaders, Weather Shocks and Social Conflicts in Pre-Industrial France.Tech. rep. No. 161.⟨https://www.zora.uzh.ch/id/eprint/186150/⟩.

Christian, C., Hensel, L., Roth, C., 2019. Income shocks and suicides: causal evidence from Indonesia. The Review of Economics and Statistics 101 (5), 905–920. https://doi.org/10.1162/rest_a_00777

Cohen, F., Gonzalez, F., 2019. Understanding Crime in Mexico with Temperature and Price Data. ⟨https://www.inet.ox.ac.uk/files/Criminality_paper_WP_version_2018.pdf⟩.

Couttenier, M., Soubeyran, R., 2014. Drought and civil war in Sub-Saharan Africa. The Economic Journal 124 (575), 201–244. https://doi.org/10.1111/ecoj.12042

Craig, C., Overbeek, R.W., Condon, M.V., Rinaldo, S.B., 2016. A relationship between temperature and aggression in NFL football penalties. Journal of Sport and Health Science 5 (2), 205–210. https://doi.org/10.1016/j.jshs.2015.01.001

Craig, C.M., Overbeek, R.W., Niedbala, E.M., 2021. A global analysis of temperature, terrorist attacks, and fatalities. Studies in Conflict & Terrorism 44 (11), 958–970. https://doi.org/10.1080/1057610X.2019.1606992

Crost, B., Duquennois, C., Felter, J.H., Rees, D.I., 2018. Climate change, agricultural production and civil conflict: evidence from the Philippines. Journal of Environmental Economics and Management 88, 379–395. https://doi.org/10.1016/j.jeem.2018.01.005

De Juan, A., Wegenast, T., 2020. Temperatures, food riots, and adaptation: a long-term historical analysis of England. Journal of Peace Research 57 (2), 265–280. https://doi.org/10.1177/0022343319863474

Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature shocks and economic growth: evidence from the last half century. American Economic Journal: Macroeconomics 4 (3), 66–95. https://doi.org/10.1257/mac.4.3.66

Dixon, P., Sinyor, M., Schaffer, A., Levitt, A., Haney, C., Ellis, K., Sheridan, S., 2014. Association of weekly suicide rates with temperature anomalies in two different climate types. International Journal of Environmental Research and Public Health 11 (11), 11627–11644. https://doi.org/10.3390/ijerph111111627

Driscoll, J.C., Kraay, A.C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics 80 (4), 549–560. https://doi.org/10.1162/003465398557825

Eberle, U.J., Rohner, D., Thoenig, M., 2020. Heat and Hate: Climate Security and Farmer-Herder Conflicts in Africa.Technical Report 15542, C.E.P.R. Discussion Papers.⟨https://ideas.repec.org/p/cpr/ceprdp/15542.html⟩.

Fetzer, T., 2020. Can workfare programs moderate conflict? Evidence from India. Journal of the European Economic Association 18 (6), 3337–3375. https://doi.org/10.1093/jeea/jvz062

Fjelde, H., vonUexkull, N., 2012. Climate triggers: rainfall anomalies, vulnerability and communal conflict in Sub-Saharan Africa. Political Geography 31 (7), 444–453. https://doi.org/10.1016/j.polgeo.2012.08.004

Fountoulakis, K.N., et al., 2016. Climate change but not unemployment explains the changing suicidality in Thessaloniki Greece (2000–2012). Journal of Affective Disorders 193, 331–338. https://doi.org/10.1016/j.jad.2016.01.008

Garg, T., McCord, G.C., Montfort, A., 2024. Can Social Protection Reduce Environmental Damages?

Gatti, N., Baylis, K., Crost, B., 2021. Can irrigation infrastructure mitigate the effect of rainfall shocks on conflict? Evidence from Indonesia. American Journal of Agricultural Economics 103 (1), 211–231. https://doi.org/10.1002/ajae.12092

Gerling, L., 2017. Center for Interdisciplinary Economics Discussion Paper Series, 46.

Gleditsch, N.P., Wallensteen, P., Eriksson, M., Sollenberg, M., Strand, H., 2002. Armed conflict 1946–2001: a new dataset. Journal of Peace Research 39 (5), 615–637. https://doi.org/10.1177/0022343302039005007

Goyette, J., Smaoui, M., 2019. Civil armed conflicts: the impact of the interaction between climate change and agricultural potential (Work in progress).

Guardado, J., Pennings, S., 2020. The Seasonality of Conflict. World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-9373

Guariso, A., Rogall, T., 2021. Rainfall Inequality, Political Power, and Ethnic Conflict in Africa. Working Paper.

Harari, M., Ferrara, E.L., 2018. Conflict, climate, and cells: a disaggregated analysis. The Review of Economics and Statistics 100 (4), 594–608. https://doi.org/10.1162/rest_a_00730

Helman, D., Zaitchik, B.F., Funk, C., 2020. Climate has contrasting direct and indirect effects on armed conflicts. Environmental Research Letters 15 (10), 104017. https://doi.org/10.1088/1748-9326/aba97d

Hidalgo, F.D., Naidu, S., Nichter, S., Richardson, N., 2010. Economic determinants of land invasions. Review of Economics and Statistics 92 (3), 505–523. https://doi.org/10.1162/REST_a_00007

Hodler, R., Raschky, P.A., 2014. Economic shocks and civil conflict at the regional level. Economics Letters 124 (3), 530–533. https://doi.org/10.1016/j.econlet.2014.07.027

Horrocks, J., Menclova, A.K., 2011. The Effects of Weather on Crime. ⟨https://www.nzae.org.nz/wp-content/uploads/2011/08/Horrocks_and_Menclova__The_Effects_of_Weather_on_Crime.pdf⟩.

Hsiang, S., 2016. Climate econometrics. Annual Review of Resource Economics 8 (1), 43–75. https://doi.org/10.1146/annurev-resource-100815-095343

Hsiang, S.M., Burke, M., 2014. Climate, conflict, and social stability: what does the evidence say? Climatic Change 123 (1), 39–55. https://doi.org/10.1007/s10584-013-0868-3

Hsiang, S.M., Burke, M., Miguel, E., 2013. Quantifying the influence of climate on human conflict. Science 341 (6151), 1235367. https://doi.org/10.1126/science.1235367

Hsiang, S.M., Meng, K.C., Cane, M.A., 2011. Civil conflicts are associated with the global climate. Nature 476 (7361), 438–441. https://doi.org/10.1038/nature10311

IPCC, 2022. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Climate Change 2022: Impacts, Adaptation and Vulnerability. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Iyigun, M., Nunn, N., Qian, N., 2017. Winter Is Coming: The Long-Run Effects of Climate Change on Conflict, 1400–1900.Working Paper 23033, National Bureau of Economic Research.

Jacob, B., Lefgren, L., Moretti, E., 2007. The dynamics of criminal behavior: evidence from weather shocks. Journal of Human Resources XLII (3), 489–527. https://doi.org/10.3368/jhr.XLII.3.489

Jia, R., 2014. Weather shocks, sweet potatoes and peasant revolts in historical China. The Economic Journal 124 (575), 92–118. https://doi.org/10.1111/ecoj.12037

Kim, N.K., 2016. Revisiting economic shocks and coups. Journal of Conflict Resolution 60 (1), 3–31. https://doi.org/10.1177/0022002713520531

Koren, O., Bagozzi, B.E., Benson, T.S., 2021. Food and water insecurity as causes of social unrest: evidence from geolocated Twitter data. Journal of Peace Research 58 (1), 67–82. https://doi.org/10.1177/0022343320975091

Koubi, V., Nguyen, Q., Spilker, G., Böhmelt, T., 2021. Environmental migrants and social-movement participation. Journal of Peace Research 58 (1), 18–32. https://doi.org/10.1177/0022343320972153

König, M.D., Rohner, D., Thoenig, M., Zilibotti, F., 2017. Networks in conflict: theory and evidence from the great war of Africa. Econometrica 85 (4), 1093–1132. https://doi.org/10.3982/ECTA13117

Landis, S.T., 2014. Temperature seasonality and violent conflict: the inconsistencies of a warming planet. Journal of Peace Research 51 (5), 603–618. https://doi.org/10.1177/0022343314538275

Landis, S.T., Rezaeedaryakenari, B., Zhang, Y., Thies, C.G., Maciejewski, R., 2017. Fording differences? Conditions mitigating water insecurity in the Niger River Basin. Political Geography 56, 77–90. https://doi.org/10.1016/j.polgeo.2016.10.002

Larrick, R.P., Timmerman, T.A., Carton, A.M., Abrevaya, J., 2011. Temper, temperature, and temptation: heat-related retaliation in baseball. Psychological Science 22 (4), 423–428. https://doi.org/10.1177/0956797611399292

Levy, M.A., Thorkelson, C., Vörösmarty, C., Douglas, E., Humphreys, M., 2005. Freshwater Availability Anomalies and Outbreak of Internal War: Results from a Global Spatial Time Series Analysis.

Linke, A.M., Ruether, B., 2021. Weather, wheat, and war: security implications of climate variability for conflict in Syria. Journal of Peace Research 58 (1), 114–131. https://doi.org/10.1177/0022343320973070

Mares, D.M., Moffett, K.W., 2016. Climate change and interpersonal violence: a "global" estimate and regional inequities. Climatic Change 135 (2), 297–310. https://doi.org/10.1007/s10584-015-1566-0

Maystadt, J.-F., Calderone, M., You, L., 2015. Local warming and violent conflict in North and South Sudan. Journal of Economic Geography 15 (3), 649–671. https://doi.org/10.1093/jeg/lbu033

McGuirk, E., Burke, M., 2020. The economic origins of conflict in Africa. Journal of Political Economy 128 (10), 3940–3997. https://doi.org/10.1086/709993

McGuirk, E.F., Nunn, N., 2021. Transhumant Pastoralism, Climate Change and Conflict in Africa, 39. ⟨https://www.ibread.org/wp-content/uploads/2021/05/pastoralism_conflict_27_04.pdf⟩.

Mehra, S., Stopnitzky, Y., Alloush, M., 2019. Economic Shocks and Personality Traits of the Ultra-Poor. 10.13140/RG.2.2.29462.80960.

Miguel, E., 2005. Poverty and witch killing. The Review of Economic Studies 72 (4), 1153–1172. https://doi.org/10.1111/0034-6527.00365

Miguel, E., Satyanath, S., Sergenti, E., 2004. Economic shocks and civil conflict: an instrumental variables approach. Journal of Political Economy 112 (4), 725–753. https://doi.org/10.1086/421174

Moreno-Medina, J., 2021. Sinning in the rain: weather shocks, church attendance and crime. The Review of Economics and Statistics 1–46. https://doi.org/10.1162/rest_a_01024

Mullins, J.T., White, C., 2019. Temperature and mental health: evidence from the spectrum of mental health outcomes. Journal of Health Economics 68, 102240. https://doi.org/10.1016/j.jhealeco.2019.102240

Niang, I., Ruppel, O.C., Abdrabo, M.A., Essel, A., Lennard, C., Padgham, J., Urquhart, P., 2014. Africa. In: Barros, V.R. (Ed.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1199–1265.

O'Neill, B.C., et al., 2022. Key risks across sectors and regions. In: Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Intergovernmental Panel on Climate Change.

O'Loughlin, J., Witmer, F.D.W., Linke, A.M., Laing, A., Gettelman, A., Dudhia, J., 2012. Climate variability and conflict risk in East Africa, 1990–2009. Proceedings of the National Academy of Sciences 109 (45), 18344–18349. https://doi.org/10.1073/pnas.1205130109

Obradovich, N., Migliorini, R., Paulus, M.P., Rahwan, I., 2018. Empirical evidence of mental health risks posed by climate change. Proceedings of the National Academy of Sciences 115 (43), 10953–10958. https://doi.org/10.1073/pnas.1801528115

Palik, J., Obermeier, A.M., Rustad, S.A., 2022. Conflict Trends: A Global Overview, 1946–2021. Tech. rep. Oslo. ⟨https://www.prio.org/publications/13178⟩.

Pei, Q., Zhang, D.D., 2014. Long-term relationship between climate change and nomadic migration in historical China. Ecology and Society 19 (2), art68. https://doi.org/10.5751/ES-06528-190268

Petrova, K., 2021. Natural hazards, internal migration and protests in Bangladesh. Journal of Peace Research 58 (1), 33–49. https://doi.org/10.1177/0022343320973741

Prudkov, P.N., Rodina, O.N., 2019. Cold temperatures, stress, and violence. Heliyon 5 (5), e01619. https://doi.org/10.1016/j.heliyon.2019.e01619

Raleigh, C., Choi, H.J., Kniveton, D., 2015. The devil is in the details: an investigation of the relationships between conflict, food price and climate across Africa. Global Environmental Change 32, 187–199. https://doi.org/10.1016/j.gloenvcha.2015.03.005

Raleigh, C., Linke, A., Hegre, H., Karlsen, J., 2010. Introducing ACLED: an armed conflict location and event dataset: special data feature. Journal of Peace Research 47 (5), 651–660. https://doi.org/10.1177/0022343310378914

Ranson, M., 2014. CCrime, weather, and climate change. Journal of Environmental Economics and Management 67 (3), 274–302. https://doi.org/10.1016/j.jeem.2013.11.008

Rexer, J.M., 2022. The Brides of Boko Haram: economic shocks, marriage practices, and insurgency in Nigeria. The Economic Journal ueac003. https://doi.org/10.1093/ej/ueac003

Rogall, T., 2021. Mobilizing the masses for genocide. American Economic Review 111 (1), 41–72. https://doi.org/10.1257/aer.20160999

Rothler, Y., Blakeslee, D., Fishman, R., 2020. Economic Factors Mediate the Impact of Drought on Farmer Suicides in India.

Salehyan, I., Hendrix, C.S., 2014. Climate shocks and political violence. Global Environmental Change 28, 239–250. https://doi.org/10.1016/j.gloenvcha.2014.07.007

Schinasi, L.H., Hamra, G.B., 2017. A time series analysis of associations between daily temperature and crime events in Philadelphia, Pennsylvania. Journal of Urban Health 94 (6), 892–900. https://doi.org/10.1007/s11524-017-0181-y

Sekhri, S., Storeygard, A., 2014. Dowry deaths: response to weather variability in India. Journal of Development Economics 111, 212–223. https://doi.org/10.1016/j.jdeveco.2014.09.001

Shaver, A., Bollfrass, A.K.2022. Disorganized Political Violence: A Demonstration Case of Temperature and Insurgency. Working Paper.

Shaver, A., Carter, D.B., Shawa, T.W., 2019. Terrain ruggedness and land cover: improved data for most research designs. Conflict Management and Peace Science 36 (2), 191–218. https://doi.org/10.1177/0738894216659843

Smith, T.G., 2014. Feeding unrest: disentangling the causal relationship between food price shocks and sociopolitical conflict in urban Africa. Journal of Peace Research 51 (6), 679–695. https://doi.org/10.1177/0022343314543722

Sommer, A.J., Lee, M., Bind, M.-A.C., 2018. Comparing apples to apples: an environmental criminology analysis of the effects of heat and rain on violent crimes in Boston. Palgrave Communications 4 (1), 138. https://doi.org/10.1057/s41599-018-0188-3

Takahashi, R., 2017. Climate, crime, and suicide: empirical evidence from Japan. Climate Change Economics 08 (01), 1750003. https://doi.org/10.1142/S2010007817500038

Theisen, O.M., Holtermann, H., Buhaug, H., 2012. Climate wars? Assessing the claim that drought breeds conflict. International Security 36 (3), 79–106. https://doi.org/10.1162/ISEC_a_00065

Tiihonen, J., Halonen, P., Tiihonen, L., Kautiainen, H., Storvik, M., Callaway, J., 2017. The association of ambient temperature and violent crime. Scientific Reports 7 (1), 6543. https://doi.org/10.1038/s41598-017-06720-z

Tompson, L.A., Bowers, K.J., 2015. Testing time-sensitive influences of weather on street robbery. Crime Science 4 (1), 8. https://doi.org/10.1186/s40163-015-0022-9

Trujillo, J.C., Howley, P., 2021. The effect of weather on crime in a torrid urban zone. Environment and Behavior 53 (1), 69–90. https://doi.org/10.1177/0013916519878213

Vital, T., Almeida, E., 2020. Crime and rain: is there a correlation?

von Uexkull, N., Croicu, M., Fjelde, H., Buhaug, H., 2016. Civil conflict sensitivity to growing-season drought. Proceedings of the National Academy of Sciences 113 (44), 12391–12396. https://doi.org/10.1073/pnas.1607542113

Wilkowski, B.M., Meier, B.P., Robinson, M.D., Carter, M.S., Feltman, R., 2009. Hot-headed" is more than an expression: the embodied representation of anger in terms of heat. Emotion 9 (4), 464–477. https://doi.org/10.1037/a0015764

Wischnath, G., Buhaug, H., 2014. On climate variability and civil war in Asia. Climatic Change 122 (4), 709–721. https://doi.org/10.1007/s10584-013-1004-0

Yeeles, A., 2015. Weathering unrest: the ecology of urban social disturbances in Africa and Asia. Journal of Peace Research 52 (2), 158–170. https://doi.org/10.1177/0022343314557508

Younan, D., Li, L., Tuvblad, C., Wu, J., Lurmann, F., Franklin, M., Berhane, K., McConnell, R., Wu, A.H., Baker, L.A., Chen, J.-C., 2018. Long-term ambient temperature and externalizing behaviors in adolescents. American Journal of Epidemiology 187 (9), 1931–1941. https://doi.org/10.1093/aje/kwy104