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Solomon M. Hsiang *et al.*

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Solomon M. Hsiang,* Marshall Burke, Edward Miguel

Introduction: Despite the existence of institutions designed to promote peace, interactions between individuals and groups sometimes lead to conflict. Understanding the causes of such conflict is a major project in the social sciences, and researchers in anthropology, economics, geography, history, political science, psychology, and sociology have long debated the extent to which climatic changes are responsible. Recent advances and interest have prompted an explosion of quantitative studies on this question.

Methods: We carried out a comprehensive synthesis of the rapidly growing literature on climate and human conflict. We examined many types of human conflict, ranging from interpersonal violence and crime to intergroup violence and political instability and further to institutional breakdown and the collapse of civilizations. We focused on quantitative studies that can reliably infer causal associations between climate variables and conflict outcomes. The studies we examined are experiments or "natural experiments"; the latter exploit variations in climate over time that are plausibly independent of other variables that also affect conflict. In many cases, we obtained original data from studies that did not meet this criterion and used a common statistical method to reanalyze these data. In total, we evaluated 60 primary studies that have examined 45 different conflict data sets. We collected findings across time periods spanning 10,000 BCE to the present and across all major world regions.

Results: Deviations from normal precipitation and mild temperatures systematically increase the risk of conflict, often substantially. This relationship is apparent across spatial scales ranging from a single building to the globe and at temporal scales ranging from an anomalous hour to an anomalous millennium. Our meta-analysis of studies that examine populations in the post-1950 era suggests that the magnitude of climate's influence on modern conflict is both substantial and highly statistically significant ($P < 0.001$). Each 1-SD change in climate toward warmer temperatures or more extreme rainfall increases the frequency of interpersonal violence by 4% and intergroup conflict by 14% (median estimates).

Discussion: We conclude that there is more agreement across studies regarding the influence of climate on human conflict than has been recognized previously. Given the large potential changes in precipitation and temperature regimes projected for the coming decades—with locations throughout the inhabited world expected to warm by 2 to 4 SDs by 2050—amplified rates of human conflict could represent a large and critical social impact of anthropogenic climate change in both low- and high-income countries.

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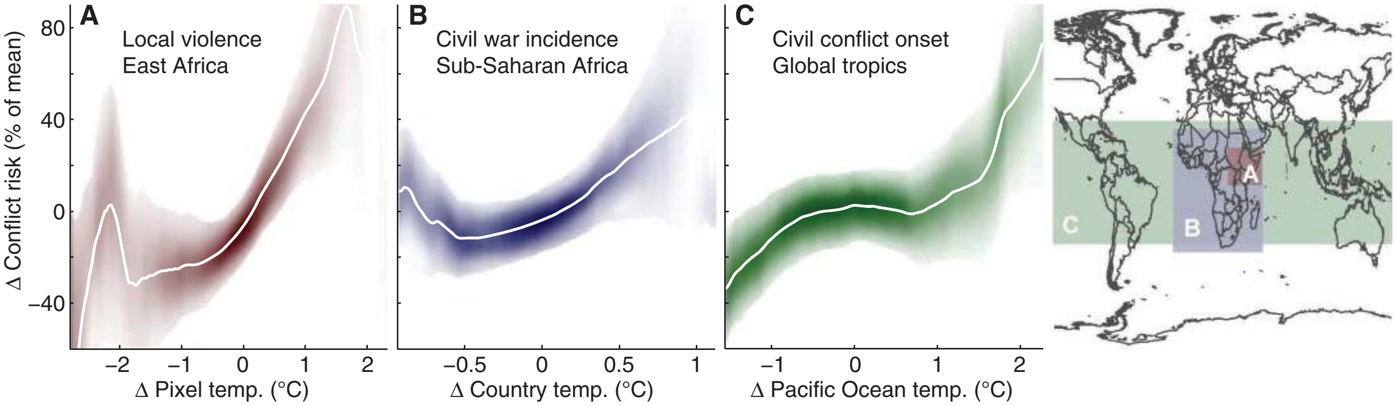
FIGURES AND TABLE IN THE FULL ARTICLE

SUPPLEMENTARY MATERIALS

Climate and conflict across spatial scales. Evidence that temperature influences the risk of modern human conflict: (**A**) local violence in 1° grid cells, (**B**) civil war in countries, and (**C**) civil conflict risk in the tropics. The map depicts regions of analysis corresponding to nonparametric watercolor regressions in (A) to (C). The color intensity in (A) to (C) indicates the level of certainty in the regression line.



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Quantifying the Influence of Climate on Human Conflict

Solomon M. Hsiang,[1,2]*†‡ Marshall Burke,[3]† Edward Miguel[2,4]

A rapidly growing body of research examines whether human conflict can be affected by climatic changes. Drawing from archaeology, criminology, economics, geography, history, political science, and psychology, we assemble and analyze the 60 most rigorous quantitative studies and document, for the first time, a striking convergence of results. We find strong causal evidence linking climatic events to human conflict across a range of spatial and temporal scales and across all major regions of the world. The magnitude of climate's influence is substantial: for each one standard deviation (1σ) change in climate toward warmer temperatures or more extreme rainfall, median estimates indicate that the frequency of interpersonal violence rises 4% and the frequency of intergroup conflict rises 14%. Because locations throughout the inhabited world are expected to warm 2σ to 4σ by 2050, amplified rates of human conflict could represent a large and critical impact of anthropogenic climate change.

Human behavior is complex, and despite the existence of institutions designed to promote peace, interactions between individuals and groups sometimes lead to conflict. When such conflict becomes violent, it can have dramatic consequences on human well-being. Mortality from war and interpersonal violence amounts to 0.5 to 1 million deaths annually (*1*, *2*), with nonlethal impacts, including injury and lost economic opportunities, affecting millions more. Because the stakes are so high, understanding the causes of human conflict has been a major project in the social sciences.

Researchers working across multiple disciplines including archaeology, criminology, economics, geography, history, political science, and psychology have long debated the extent to which climatic changes are responsible for causing conflict, violence, or political instability. Numerous pathways linking the climate to these outcomes have been proposed. For example, climatic changes may alter the supply of a resource and cause disagreement over its allocation, or climatic conditions may shape the relative appeal of using violence or cooperation to achieve some preconceived objective. Qualitative researchers have a well-developed history of studying these issues (*3*–*7*) dating back, at least, to the start of the 20th century (*8*). Yet, in recent years, growing recognition that the climate is changing, coupled with improvements in data quality and computing, has prompted an explosion of quantitative analyses seeking to test these theories and quantify the strength of these previously proposed linkages. Thus far, this work has remained scattered across multiple disciplines and has been difficult to synthesize given the disparate methodologies, data, and interests of the various research teams.

Here, we assemble the first comprehensive synthesis of this rapidly growing quantitative literature. We adopt a broad definition of "conflict," using the term to encompass a range of outcomes from individual-level violence and aggression to country-level political instability and civil war. We then collect all available candidate studies and, guided by previous criticisms that not all correlations imply causation (*9*–*11*), focus on only those quantitative studies that can reliably infer causal associations (*9*, *12*) between climate variables and conflict outcomes. The studies we examine exploit either experimental or natural-experimental variation in climate; the latter term refers to variation in climate over time that is plausibly independent of other variables that also affect conflict. To meet this standard, studies must account for unobservable confounding factors across populations, as well as for unobservable time-trending factors that could be correlated with both climate and conflict (*13*). In many cases, we obtained data from studies that did not meet this criterion and reanalyzed it with a common statistical model that did meet the criterion (see supplementary materials). The importance of this rigorous approach is highlighted by an example in which our standardized analysis generated findings consistent with other studies but at odds with the original conclusions of the study in question (*14*).

In total, we obtained 60 primary studies that either met this criterion or were reanalyzed with a method that met this criterion (Table 1). Collectively, these studies analyze 45 different conflict data sets published across 26 different journals and represent the work of more than 190 researchers from around the world. Our evaluation summarizes the recent explosion of research on this topic, with 78% of studies released since 2009 and the median study released in 2011. We collected findings across a wide range of conflict outcomes, time periods spanning 10,000 BCE to the present day, and all major regions of the world (Fig. 1).

Although various conflict outcomes differ in important ways, we find that the behavior of these outcomes relative to the climate system is markedly similar. Put most simply, we find that large deviations from normal precipitation and mild temperatures systematically increase the risk of many types of conflict, often substantially, and that this relationship appears to hold over a variety of temporal and spatial scales. Our meta-analysis of studies that examine populations in the post-1950 era suggests that these relationships continue to be highly important in the modern world, although there are notable differences in the magnitude of the relationship when different variables are considered: The standardized effect of temperature is generally larger than the standardized effect of rainfall, and the effect on intergroup violence (e.g., civil war) is larger than the effect on interpersonal violence (e.g., assault). We conclude that there is substantially more agreement and generality in the findings of this burgeoning literature than has been recognized previously. Given the large potential changes in precipitation and temperature regimes projected for the coming decades, our findings have important implications for the social impact of anthropogenic climate change in both low- and high-income countries.

Estimation of Climate-Conflict Linkages

Reliably measuring an effect of climatic conditions on human conflict is complicated by the inherent complexity of social systems. In particular, a central concern is whether statistical relationships can be interpreted causally or if they are confounded by omitted variables. To address this concern, we restrict our attention to studies with research designs that are scientific experiments or that approximate one (i.e., "natural experiments"). After describing how studies meet this criterion, we discuss how we interpret the precision of results, assess the importance of climatic factors, and address choices over functional form.

Research Design

In an ideal experiment, we would observe two identical populations, change the climate of one, and observe whether this treatment leads to more or less conflict relative to the control conditions. Because the climate cannot be experimentally manipulated, researchers primarily rely on natural experiments in which a given population is compared to itself at different moments in time when it is exposed to different climatic conditions—conditions that are exogenously determined by

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Table 1. Primary quantitative studies testing for a relationship between climate and conflict, violence, or political instability. "Stat. test" is Y if the analysis uses formal statistical methods to quantify the influence of climate variables and uses hypothesis testing procedures (Y, yes; N, no). "Large effect" is Y if the point estimate for the effect size is considered substantial by the authors or is greater in magnitude than 10% of the mean risk level for a 1σ change in climate variables. "Reject β = 0" is Y if the study rejects an effect size of zero at the 95% confidence level. "Reject β = 10%" is Y if the study is able to reject the hypothesis that the effect size is larger than 10% of the mean risk level for a 1σ change in climate variables. –, not applicable. SSA, sub-Saharan Africa; PDSI; Palmer Drought Severity Index; ENSO, El Niño–Southern Oscillation; NAO, North Atlantic Oscillation; N. Hem., Northern Hemisphere.

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
				Interpersonal conflict (15)							
Anderson *et al.* 2000*	1950–1997	USA	Annual	Country	Temp	Violent crime	Y	Y	Y	–	(34)
Auliciems *et al.* 1995†	1992	Australia	Week	Municipality	Temp	Domestic violence	Y	Y	Y	–	(29)
Blakeslee *et al.* 2013	1971–2000	India	Annual	Municipality	Rain	Violent and property crime	Y	Y	Y	–	(42)
Card *et al.* 2011†‡	1995–2006	USA	Day	Municipality	Temp	Domestic violence	Y	Y	Y	–	(37)
Cohn *et al.* 1997§	1987–1988	USA	Hours	Municipality	Temp	Violent crime	Y	Y	Y	–	(30)
Jacob *et al.* 2007†‖	1995–2001	USA	Week	Municipality	Temp	Violent and property crime	Y	Y	Y	–	(35)
Kenrick *et al.* 1986¶	1985	USA	Day	Site	Temp	Hostility	Y	Y	Y	–	(27)
Larrick *et al.* 2011†‡‖	1952–2009	USA	Day	Site	Temp	Violent retaliation	Y	Y	Y	–	(36)
Mares 2013	1990–2009	USA	Month	Municipality	Temp	Violent crime	Y	Y	Y	–	(39)
Miguel 2005†‡	1992–2002	Tanzania	Annual	Municipality	Rain	Murder	Y	Y	N	N	(40)
Mehlum *et al.* 2006	1835–1861	Germany	Annual	Province	Rain	Violent and property crime	Y	Y	Y	–	(43)
Ranson 2012†‖	1960–2009	USA	Month	County	Temp	Personal violence	Y	Y	Y	–	(38)
Rotton *et al.* 2000§	1994–1995	USA	Hours	Municipality	Temp	Violent crime	Y	Y	Y	–	(31)
Sekhri *et al.* 2013†	2002–2007	India	Annual	Municipality	Rain	Murder and domestic violence	Y	Y	Y	–	(41)
Vrij *et al.* 1994¶	1993	Netherlands	Hours	Site	Temp	Police use of force	Y	Y	Y	–	(28)
				Intergroup conflict (30)							
Almer *et al.* 2012	1985–2008	SSA	Annual	Country	Rain/temp	Civil conflict	Y	Y	N	N	(65)
Anderson *et al.* 2013	1100–1800	Europe	Decade	Municipality	Temp	Minority expulsion	Y	Y	Y	–	(63)
Bai *et al.* 2010	220–1839	China	Decade	Country	Rain	Transboundary	Y	Y	Y	–	(50)
Bergholt *et al.* 2012‡#	1980–2007	Global	Annual	Country	Flood/storm	Civil conflict	Y	N	N	Y	(75)
Bohlken *et al.* 2011‖#	1982–1995	India	Annual	Province	Rain	Intergroup	Y	Y	N	N	(44)
Buhaug 2010#	1979–2002	SSA	Annual	Country	Temp	Civil conflict	Y	N	N	N	(22)
Burke 2012‡‖#	1963–2001	Global	Annual	Country	Rain/temp	Political instability	Y	Y	N**	N	(71)
Burke *et al.* 2009‡‖#††	1981–2002	SSA	Annual	Country	Temp	Civil conflict	Y	Y	Y	–	(64)
Cervellati *et al.* 2011	1960–2005	Global	Annual	Country	Drought	Civil conflict	Y	Y	Y	–	(54)
Chaney 2011	641–1438	Egypt	Annual	Country	Nile floods	Political Instability	Y	Y	Y	–	(70)
Couttenier *et al.* 2011#	1957–2005	SSA	Annual	Country	PDSI	Civil conflict	Y	Y	Y	–	(53)
Dell *et al.* 2012#	1950–2003	Global	Annual	Country	Temp	Political instability and civil conflict	Y	Y	Y	–	(21)
Fjelde *et al.* 2012‡#	1990–2008	SSA	Annual	Province	Rain	Intergroup	Y	Y	N**	N	(55)
Harari *et al.* 2013#	1960–2010	SSA	Annual	Pixel (1°)	Drought	Civil conflict	Y	Y	Y	–	(52)
Hendrix *et al.* 2012‡‖#	1991–2007	SSA	Annual	Country	Rain	Intergroup	Y	Y	Y	–	(46)
Hidalgo *et al.* 2010‡‖#	1988–2004	Brazil	Annual	Municipality	Rain	Intergroup	Y	Y	Y	–	(25)
Hsiang *et al.* 2011‖#	1950–2004	Global	Annual	World	ENSO	Civil conflict	Y	Y	Y	–	(51)
Jia 2012	1470–1900	China	Annual	Province	Drought/flood	Peasant rebellion	Y	Y	Y	–	(56)
Kung *et al.* 2012	1651–1910	China	Annual	County	Rain	Peasant rebellion	Y	Y	Y	–	(47)
Lee *et al.* 2013	1400–1999	Europe	Decade	Region	NAO	Violent conflict	Y	Y	Y	–	(57)
Levy *et al.* 2005‡‖#	1975–2002	Global	Annual	Pixel (2.5°)	Rain	Civil conflict	Y	Y	N**	N	(49)
Maystadt *et al.* 2013#	1997–2009	Somalia	Month	Province	Temp	Civil conflict	Y	Y	Y	–	(66)
Miguel *et al.* 2004#‡‡	1979–1999	SSA	Annual	Country	Rain	Civil war	Y	Y	Y	–	(48)
O'Laughlin *et al.* 2012‡‖#	1990–2009	E. Africa	Month	Pixel (1°)	Rain/temp	Civil/intergroup	Y	Y	Y	–	(23)
Salehyan *et al.* 2012	1979–2006	Global	Annual	Country	PDSI	Civil/intergroup	Y	Y	Y	–	(76)
Sarsons 2011	1970–1995	India	Annual	Municipality	Rain	Intergroup	Y	Y	Y	–	(45)
Theisen *et al.* 2011‡#	1960–2004	Africa	Annual	Pixel (0.5°)	Rain	Civil conflict	Y	N	N	N	(24)
Theisen 2012‡‖#	1989–2004	Kenya	Annual	Pixel (0.25°)	Rain/temp	Civil/intergroup	Y	Y	N**	N	(14)
Tol *et al.* 2009	1500–1900	Europe	Decade	Region	Rain/temp	Transboundary	Y	Y	Y	–	(60)
Zhang *et al.* 2007§§	1400–1900	N. Hem.	Century	Region	Temp	Instability	Y	Y	Y	–	(59)
				Institutional breakdown and population collapse (15)							
Brückner *et al.* 2011#	1980–2004	SSA	Annual	Country	Rain	Inst. change	Y	Y	Y	–	(78)

Continued on next page

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
Buckley *et al*. 2010‖‖	1030–2008	Cambodia	Decade	Country	Drought	Collapse	N	–	–	–	(85)
Büntgen *et al*. 2011‖‖	400 BCE–2000	Europe	Decade	Region	Rain/temp	Instability	N	–	–	–	(62)
Burke *et al*. 2010‡#	1963–2007	Global	Annual	Country	Rain/temp	Inst. change	Y	Y	Y	–	(77)
Cullen *et al*. 2000‖‖	4000 BCE–0	Syria	Century	Country	Drought	Collapse	N	–	–	–	(83)
D'Anjou *et al* 2012	550 BCE–1950	Norway	Century	Municipality	Temp	Collapse	Y	Y	Y	–	(89)
Ortloff *et al*. 1993‖‖	500–2000	Peru	Century	Country	Drought	Collapse	N	–	–	–	(80)
Haug *et al*. 2003‖‖	0–1900	Mexico	Century	Country	Drought	Collapse	N	–	–	–	(84)
Kelly *et al*. 2013	10050 BCE–1950	USA	Century	State	Temp/rain	Collapse	Y	Y	Y	–	(88)
Kennett *et al*. 2012	40 BCE–2006	Belize	Decade	Country	Rain	Collapse	N	–	–	–	(87)
Kuper *et al*. 2006	8000–2000 BCE	N. Africa	Millennia	Region	Rain	Collapse	N	–	–	–	(81)
Patterson *et al*. 2010	200 BCE–1700	Iceland	Decade	Country	Temp	Collapse	N	–	–	–	(86)
Stahle *et al*. 1998	1200–2000	USA	Multiyear	Municipality	PDSI	Collapse	N	–	–	–	(82)
Yancheva *et al*. 2007‖‖	2100 BCE–1700	China	Century	Country	Rain/temp	Collapse	N	–	–	–	(79)
Zhang *et al*. 2006	1000–1911	China	Decade	Country	Temp	Civil conflict and collapse	Y	Y	Y	–	(58)
					Number of studies (60 total):		**50**	**47**	**37**	**1**	
					Fraction of those using statistical tests:		**100%**	**94%**	**74%**	**2%**	

*Also see (33). †Shown in Fig. 4. ‡Reanalyzed using the common statistical model containing location fixed effects and trends (see supplementary materials). §Also see discussion in (32). ‖Shown in Fig. 2. ¶Actual experiment. #Shown in Fig. 5. **Effect size in the study is statistically significant at the 10% level, but not at the 5% level. ††Also see discussion in (22, 132–137). ‡‡Also see discussion in (138, 139). §§Also see (61). ‖‖Shown in Fig. 3.

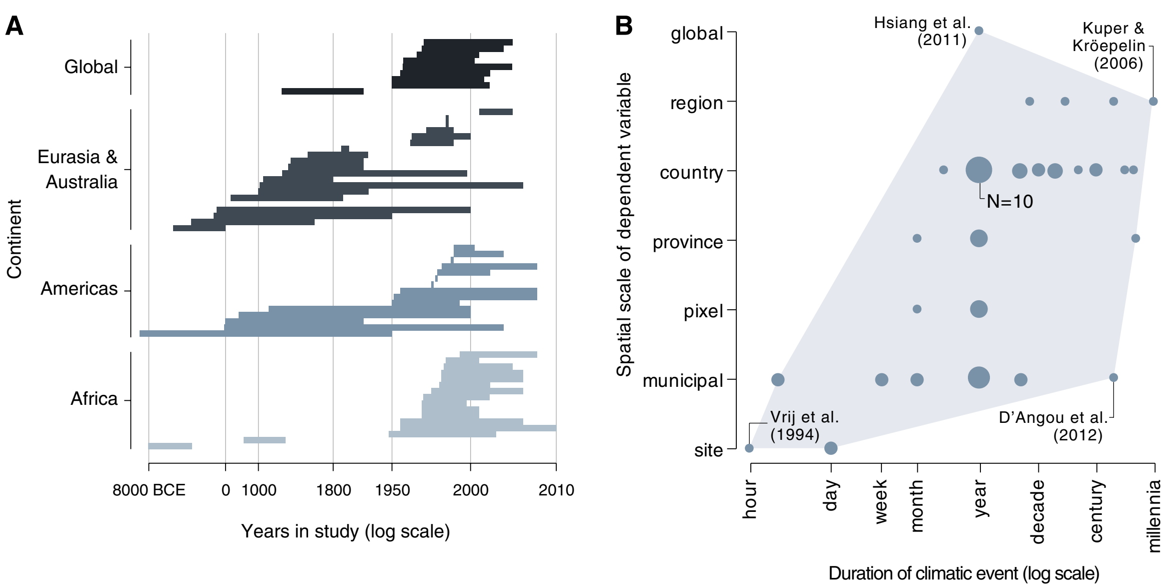

Fig. 1. Samples and spatiotemporal resolutions of 60 studies examining intertemporal associations between climatic variables and human conflict. (**A**) The location of each study region (*y* axis) plotted against the period of time included in the study (*x* axis). The *x* axis is scaled according to log years before the present but is labeled according to the year of the common era. (**B**) The level of aggregation in social outcomes (*y* axis) plotted against the time scale of climatic events (*x* axis). The envelope of spatial and temporal scales where associations are documented is shaded, with studies at extreme vertices labeled for reference. Marker size indicates the number of studies at each location, with the smallest bubbles marking individual studies and the largest bubble denoting 10 studies.

the climate system (9, 15). In this research design, a single population serves as both the control population (e.g., just before a change in climatic conditions) and the treatment population (e.g., just after a change in climatic conditions). Thus, inferences are based only on how a fixed population responds to different climatic conditions that vary over time, and time-series or longitudinal analysis is used to construct a credible estimate for the causal effect of climate on conflict (12, 15, 16).

To minimize statistical bias and improve the comparability of studies, we focus on studies that use versions of the general model

$$conflict\_variable_{it} = \beta \times climate\_variable_{it} + \mu_i + \theta_t + \epsilon_{it} \quad (1)$$

where locations are indexed by i, observational periods are indexed by t, β is the parameter of interest, and ∊ is the error. If different locations in a sample exhibit different average levels of conflict—perhaps because of cultural, historical, political, economic, geographic, or institutional differences between the locations—this will be accounted for by the vector of location-specific constants μ (commonly known as "fixed effects"). The vector of time-specific constants θ (a dummy for each time period) flexibly accounts for other time-trending variables such as economic growth or gradual demographic changes that could be correlated with both climate and conflict. In some cases, such as in time series, the θ_t parameters may be replaced by a generic trend (e.g., $\bar{\theta} \times t$) that is possibly nonlinear and is either common to all locations or may be location-specific (e.g., $\bar{\theta}_i \times t$). Our conclusions from the literature are based only on those studies that implement Eq. 1 or one of the mentioned alternatives. In select cases, when studies did not meet this criterion but the data from these analyses were publicly available or supplied by the authors, we used this common method to reanalyze the data (see supplementary materials). Many estimates of Eq. 1 in the literature and in our reanalysis account for temporal and/or spatial autocorrelation in the error term ϵ, although this adjustment was not considered a requirement for inclusion here. In the case of some paleoclimatological and archaeological studies, formal statistical analysis is not implemented because the outcome variables of interest are essentially singular cataclysmic events. However, we include these studies because they follow populations over time at a fixed location and are, thus, implicitly using the model in Eq. 1 (these cases are noted in Table 1).

We do not consider studies that are purely cross-sectional; that is, studies that only compare rates of conflict across different locations and attribute differences in average levels of conflict to average climatic conditions. Populations differ from one another in numerous ways (culture, history, etc.), many of them unobserved, and these "omitted variables" are likely to confound these analyses. In the language of the natural experiment, the treatment and control populations in these analyses are not comparable units, so we cannot infer whether a climatic treatment has a causal effect or not (*12*, *13*, *15*–*17*). For example, a cross-sectional study might compare average rates of civil conflict in Norway and Nigeria, attributing observed differences to the different climates of these countries, despite the fact that there are clearly many other relevant ways in which these countries differ. Nonetheless, some studies

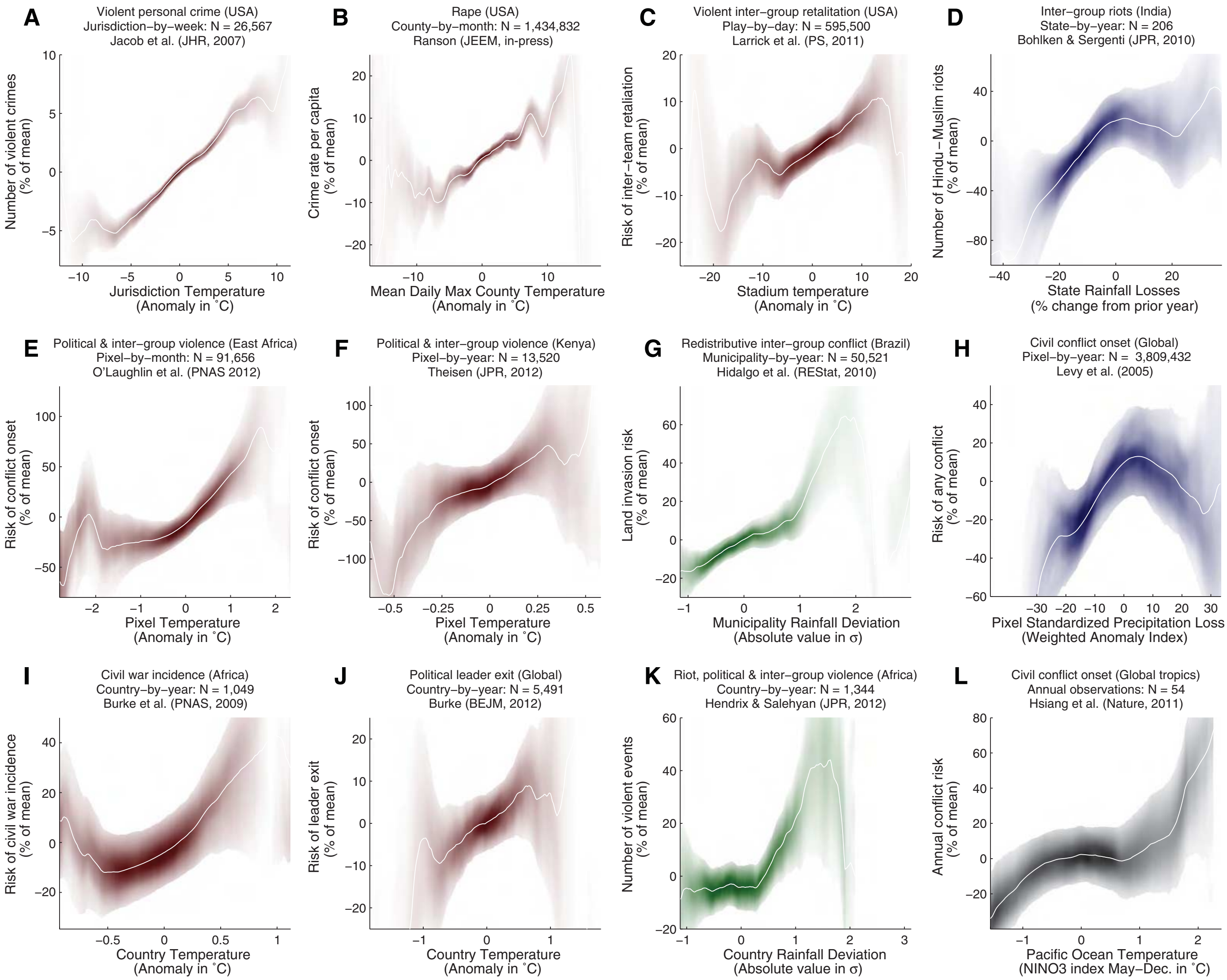

Fig. 2. Empirical studies indicate that climatological variables have a large effect on the risk of violence or instability in the modern world. (**A** to **L**) Examples from studies of modern data that identify the causal effect of climate variables on human conflict. Both dependent and independent variables have had location effects and trends removed, so all samples have a mean of zero. Relationships between climate and conflict outcomes are shown with nonparametric watercolor regressions, where the color intensity of 95% CIs depicts the likelihood that the true regression line passes through a given value (darker is more likely) (*128*). The white line in each panel denotes the conditional mean (*129*, *130*). Climate variables are indicated by color: red, temperature; green, rainfall deviations from normal; blue, precipitation loss; black, ENSO. Panel titles describe the outcome variable, location, unit of analysis, sample size, and study. Because the samples examined in each study differ, the units and scales change across each panel (see Figs. 4 and 5 for standardized effect sizes). "Rainfall deviation" represents the absolute value of location-specific rainfall anomalies, with both abnormally high and abnormally low rainfall events described as having a large rainfall deviation. "Precipitation loss" is an index describing how much lower precipitation is relative to the prior year's amount or the long-term mean.

use cross-sectional analyses and attempt to control for confounding variables in regression analyses, typically using a handful of covariates such as average income or political indices. However, because the full suite of determinants of conflict is unknown and unmeasured, it is probably impossible that any cross-sectional study can explicitly account for all important differences between populations. Rather than presuming that all confounders are accounted for, the studies we evaluate compare Norway or Nigeria only to themselves at different moments in time, thereby ensuring that the structure, history, and geography of comparison populations are nearly identical.

Some studies implement versions of Eq. 1 that are expanded to explicitly control for potential confounding factors, such as average income. In many cases, this approach is more harmful than helpful because it introduces bias in the coefficients describing the effect of climate on conflict. This problem occurs when researchers control for variables that are themselves affected by climate variation, causing either (i) the signal in the climate variable of interest to be inappropriately

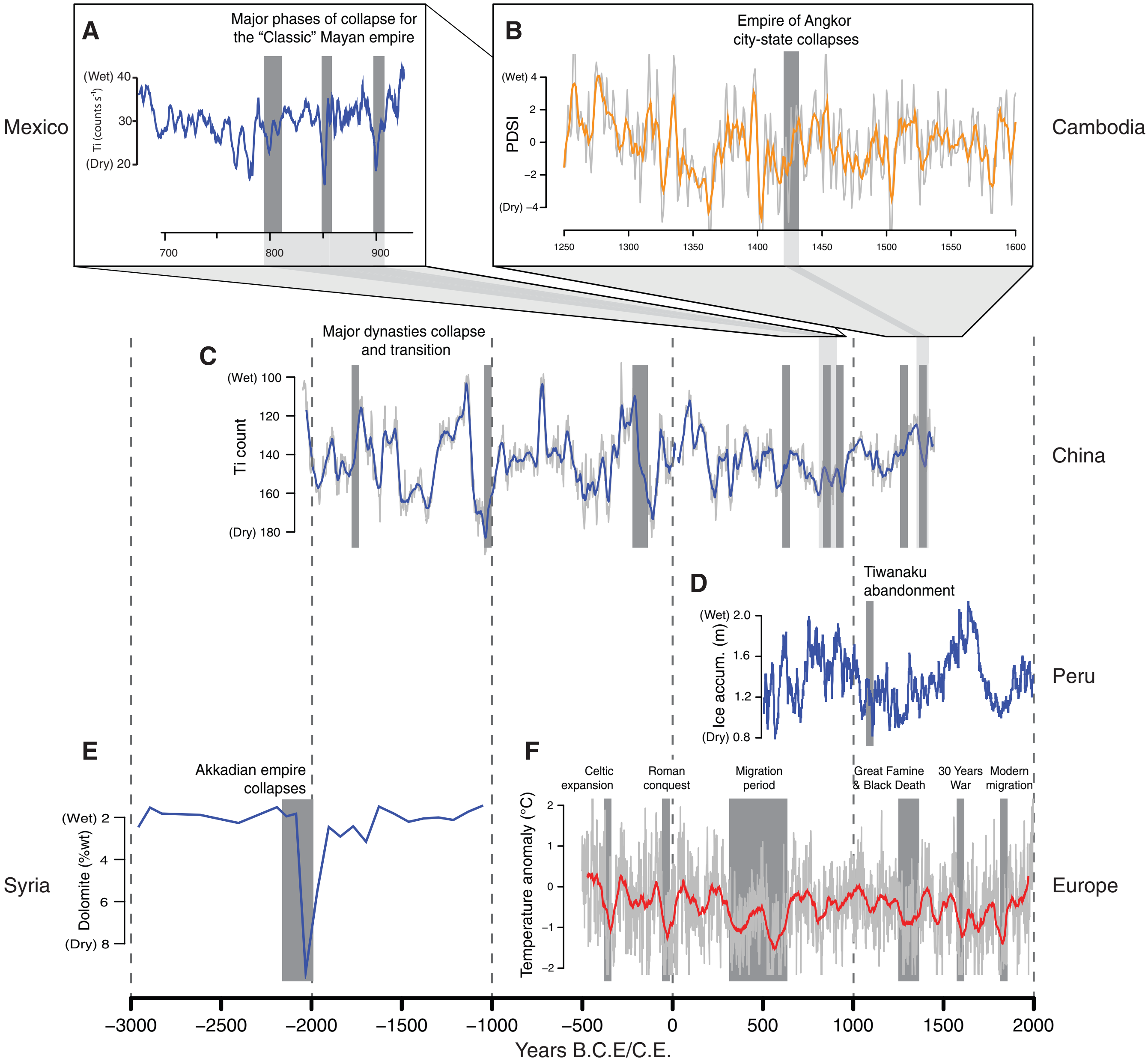

Fig. 3. Examples of paleoclimate reconstructions that find associations between climatic changes and human conflict. Lines are climate reconstructions (red, temperature; blue, precipitation; orange, drought; smoothed moving averages when light gray lines are shown), and dark gray bars indicate periods of substantial social instability, violent conflict, or the breakdown of political institutions. (**A**) Alluvial sediments from the Cariaco Basin indicate substantial multiyear droughts coinciding with the collapse of the Maya civilization (*84*). (**B**) Reconstruction of a drought index from tree rings in Vietnam, the Palmer drought severity index (PDSI), shows sustained megadroughts prior to the collapse of the Angkor kingdom (*85*). (**C**) Sediments from Lake Huguang Maar in China indicate abrupt and sustained periods of reduced summertime precipitation that coincided with most major dynastic transitions (*79*). The collapse of the Tang Dynasty (907) coincided with the terminal collapse of the Maya (A), both of which occurred when the Pacific Ocean altered rainfall patterns in both hemispheres (*79*). Similarly, the collapse of the Yuan Dynasty (1368) coincided with collapse of Angkor (B), which shares the same regional climate. (**D**) Tiwanaku cultivation of the Lake Titicaca region ended abruptly after a drying of the region, as measured by ice accumulation in the Quelccaya Ice Cap, Peru (*80*). (**E**) Continental dust blown from Mesopotamia into the Gulf of Oman indicates terrestrial drying that is coincident with the collapse of the Akkadian empire (*83*). (**F**) European tree rings indicate that anomalously cold periods were associated with major periods of instability on the European continent (*62*).

absorbed by the control variable or (ii) the estimate to be biased because populations differ in unobserved ways that become artificially correlated with climate when the control variable is included. This methodological error is commonly termed "bad control" (*12*), and we exclude results obtained using this approach. The difficulty in this setting is that climatic variables affect many of the socioeconomic factors commonly included as control variables: things like crop production, infant mortality, population (via migration or mortality), and even political regime type. To the extent that these outcome variables are used as controls in Eq. 1, studies might draw mistaken conclusions about the relationship between climate and conflict. Because this error is so salient in the literature, we provide examples below. A full treatment can be found in (*12*, *18*).

For an example of (i), consider whether variation in temperature increases conflict. In many studies of conflict, researchers often employ a standard set of controls that are correlates of conflict, such as per capita income. However, evidence suggests that income is itself affected by temperature (*19*–*21*), so if part of the effect of temperature on conflict is through income, then controlling for income in Eq. 1 will lead the researcher to underestimate the role of temperature in conflict. This occurs because much of the effect of temperature will be absorbed by the income variable, biasing the temperature coefficient toward zero. At the extreme, if temperature influences conflict only through income, then controlling for income would lead the researcher in this example to draw exactly the wrong conclusion about the relationship between temperature and conflict: that there is no effect of temperature on conflict.

For an example of (ii), imagine that a measure of politics (i.e., democracy) and temperature both have a causal effect on conflict and both politics and temperature have an effect on income, but that income has no effect on conflict. If politics and temperature are uncorrelated, estimates of Eq. 1 that do not control for politics will still recover the unbiased effect of temperature. However, if income is introduced to Eq. 1 as a control but politics is left out of the model, perhaps because it is more difficult to measure, then there will appear to be an association between income and conflict because income will be serving as a proxy measure for politics. In addition, this adjustment to Eq. 1 also biases the estimated effect of temperature. This bias occurs because the types of countries that have high income when temperature is high are different, in terms of their average politics, from those countries that have high income when temperature is low. Thus, if income is held fixed as a control variable in a regression model, the comparison of conflict across temperatures is not an "apples-to-apples" comparison because politics will be systematically different across countries at different temperatures, generating a bias that can have either sign. In this example, the inclusion of income in the model leads to two incorrect conclusions: It biases the estimated relationship between climate and conflict and implicates income as playing a role in conflict when it does not.

Statistical Precision

We consider each study's estimated relationship between climate and conflict, as well as the estimate's precision. Because sampling variability and sample sizes differ across studies, some analyses present results that are more precise than other studies. Recognizing this fact is important when synthesizing a diverse literature, as some apparent differences between studies can be reconciled by evaluating the uncertainty in their findings. For example, some studies report associations that

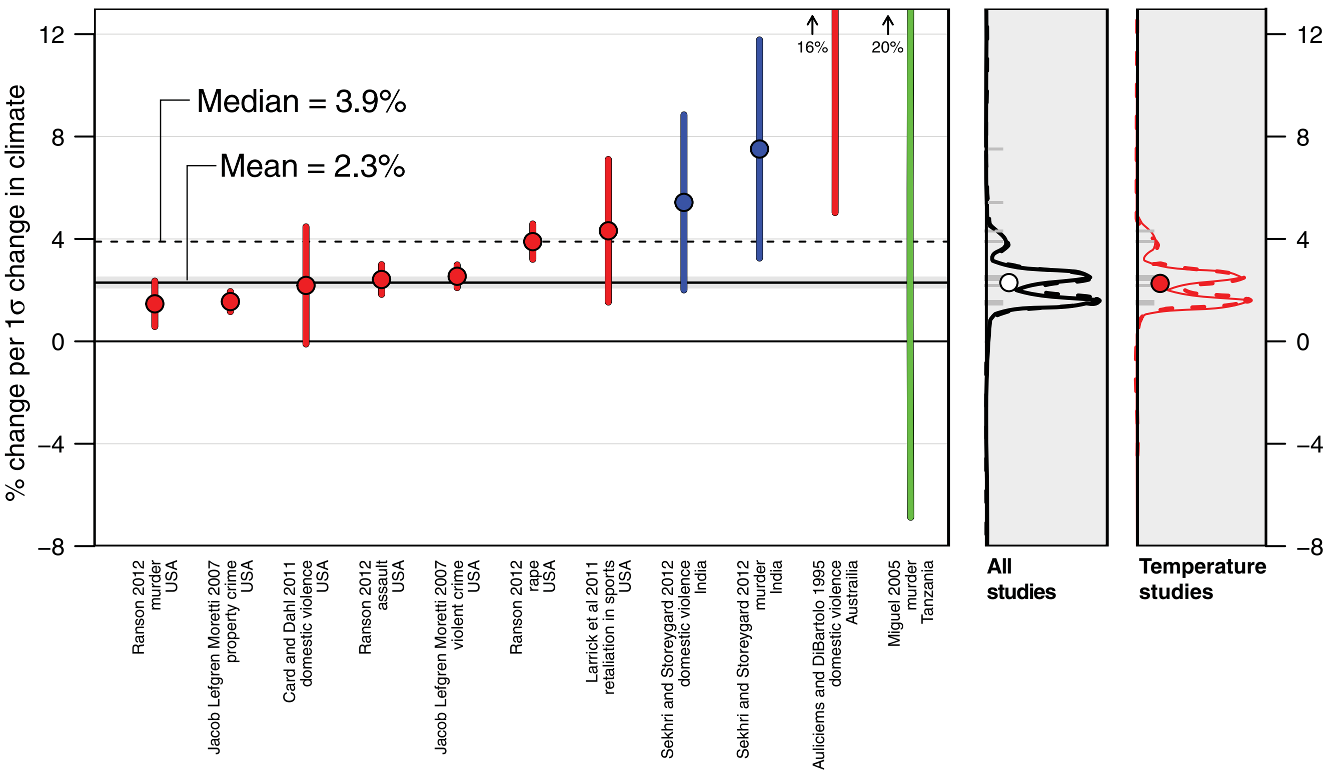

Fig. 4. Modern empirical estimates for the effect of climatic events on the risk of interpersonal violence. Each marker represents the estimated effect of a 1σ increase in a climate variable, expressed as a percentage change in the outcome variable relative to its mean. Whiskers represent the 95% CI on this point estimate. Colors indicate the forcing climate variable: A coefficient is positive if conflict increases with higher temperature (red), greater rainfall loss (blue), or greater rainfall deviation from normal (green). The dashed line indicates the median estimate; the top solid black line denotes the precision-weighted mean, with its 95% CI shown in gray. The panels on the right show the precision-weighted mean effect (circles) and the distribution of study results for all 11 results looking at individual conflict or for the subset of 8 results focusing on temperature effects. Distributions of effect sizes are either precision-weighted (solid lines) or derived from a Bayesian hierarchical model (dashed lines). See the supplementary materials for details on the individual studies and the calculation of mean effects and their distribution.

are very large or very small but with uncertainties that are also very large, leading us to place less confidence in these extreme findings. This intuition is formalized in our meta-analysis, which aggregates results across studies by down-weighting results that are less precisely estimated.

The strength of a finding is sometimes summarized in a statement regarding its statistical significance, which describes the signal-to-noise ratio in an individual study. However, in principle, the signal is a relationship that exists in the real world and cannot be affected by the researcher, whereas the level of noise in a given study's finding (i.e., its uncertainty) is a feature specific to that study—a feature that can be affected by a researcher's decisions, such as the size of the sample they choose to analyze. Thus, although it is useful to evaluate whether individual findings are statistically significant and it is important to down-weight highly imprecise findings, individual studies provide useful information even when their findings are not statistically significant.

To summarize the evidence that each statistical study provides while also taking into account its precision, we separately consider three questions for each study in Table 1: (i) Is the estimated average effect of climate on conflict quantitatively "large" in magnitude (discussed below), regardless of its uncertainty? (ii) Is the reported effect large enough and estimated with sufficient precision that the study can reject the null hypothesis of "no relationship" at the 5% level? (iii) If the study cannot reject the hypothesis of "no relationship," can it reject the hypothesis that the relationship is quantitatively large? In the literature, often only the second question is evaluated in any single analysis. Yet, it is important to consider the magnitude of climate influence (first question) separately from its statistical precision,

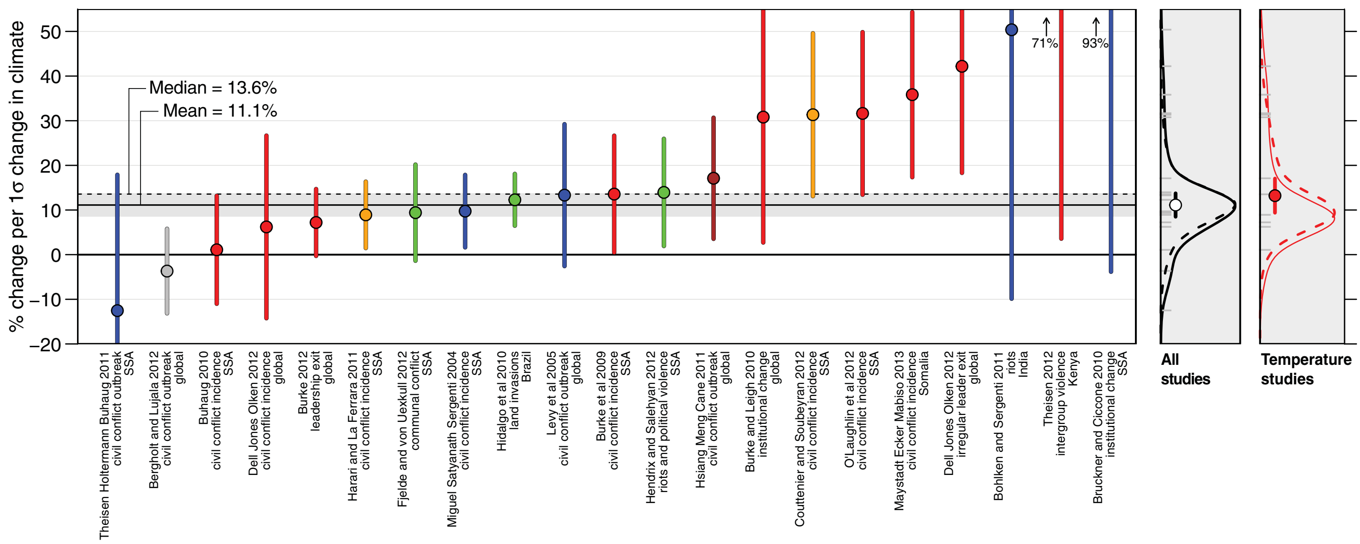

Fig. 5. Modern empirical estimates for the effect of climatic events on the risk of intergroup conflict. Each marker represents the estimated effect of a 1σ increase in a climate variable, expressed as a percentage change in the outcome variable relative to its mean. Whiskers represent the 95% CI on this point estimate. Colors indicate the forcing climate variable: A coefficient is positive if conflict increases with higher temperature (red), greater rainfall loss (blue), greater rainfall deviation from normal (green), more floods and storms (gray), more El Niño–like conditions (brown), or more drought (orange), as captured by different drought indices. The dashed line indicates the median estimate; the top solid black line denotes the precision-weighted mean, with its 95% CI shown in gray. The panels at right show the precision-weighted mean effect (circles) and the distribution of study results for all 21 results looking at intergroup conflict or for the subset of 12 results focusing on temperature effects (which includes the ENSO and drought studies). Distributions of effect sizes are either precision-weighted (solid lines) or derived from a Bayesian hierarchical model (dashed lines). See the supplementary materials for details on the individual studies and on the calculation of mean effects and their distribution.

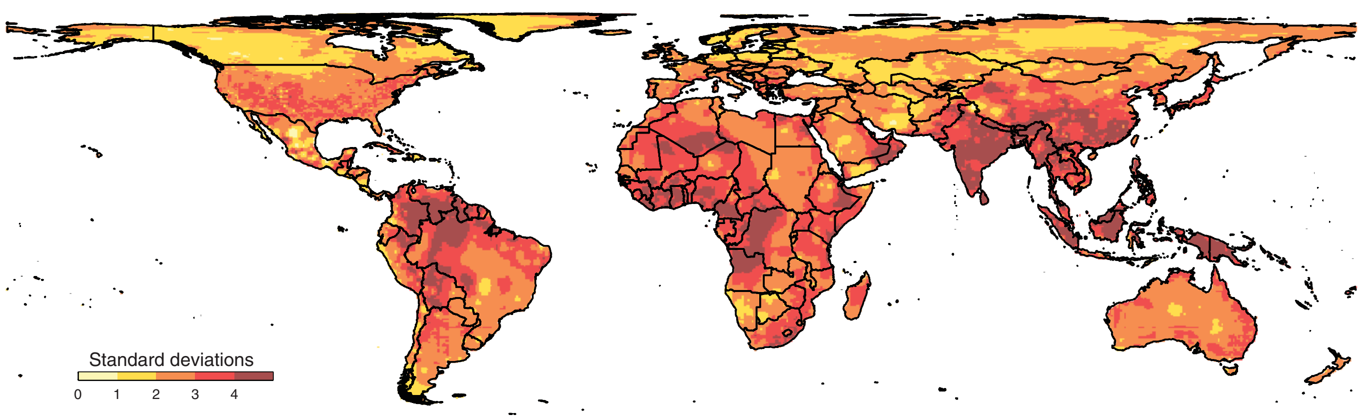

Fig. 6. Projected temperature change by 2050 as a multiple of the local historical SD (σ) of temperature. Temperature projections are for the A1B scenario and are averaged across 21 global climate models reporting in the Coupled Model Intercomparison Project (CMIP3) (*96*). Changes are the difference between projected annual average temperatures in 2050 and average temperatures in 2000. The historical SD of temperature is calculated from annual average temperatures at each grid cell over the period 1950–2008, using data from the University of Delaware (*131*). The map is an equal-area projection.

because the magnitude of these effects tells us something about the potential importance of climate as a factor that may influence conflict, so long as we are mindful that evidence is weaker if a study's results are less certain. In cases in which the estimated effect is smaller in magnitude and not statistically different from zero, it is important to consider whether a study provides strong evidence of zero association—that is, whether the study rejects the hypothesis that an effect is large in magnitude (third question)—or relatively weak evidence because the estimated confidence interval (CI) spans large effects as well as zero effect.

Evaluating Whether an Effect Is Important

Evaluating whether an observed causal relationship is "important" is a subjective judgment that is not essential to our scientific understanding of whether there is a causal relationship. Nonetheless, because importance in this literature has sometimes been incorrectly conflated with statistical precision or inferred from incorrect interpretations of Eq. 1 and its variants, we explain our approach to evaluating importance.

Our preferred measure of importance is to ask a straightforward question: Do changes in climate cause changes in conflict risk that an expert, policy-maker, or citizen would consider large? To aid comparisons, we operationalize this question by considering an effect important if authors of a particular study state that the size of the effect is substantive, or if the effect is greater than a 10% change in conflict risk for each one SD (1σ) change in climate variables. This second criterion uses an admittedly arbitrary threshold, and other threshold selections would be justifiable. However, we contend that this threshold is relatively conservative, as most policy-makers or citizens would be concerned by effects well below 10% per 1σ. For instance, because random variation in a normally distributed climate variable lies in a 4σ range for 95% of its realizations, even a 3% per 1σ effect size would generate variation in conflict of 12% of its mean, which is probably important to those individuals experiencing these shifts.

In some prior studies, authors have argued that a particular estimated effect is unimportant based on whether a climatic variable substantially changes goodness-of-fit measures (e.g., R^2) for a particular statistical model, sometimes in comparison to other predictor variables (*14*, *22*–*24*). We do not use this criterion here for two reasons. First, goodness-of-fit measures are sensitive to the quantity of noise in a conflict variable: More noise reduces goodness of fit; thus, under this metric, irrelevant measurement errors that introduce noise into conflict data will reduce the apparent importance of climate as a cause of conflict, even if the effect of climate on conflict is quantitatively large. Second, comparing the goodness of fit across multiple predictor variables often makes little sense in many contexts, because (i) longitudinal models typically compare variables that predict both where a conflict will occur and when a conflict will occur, and (ii) these models typically compare the causal effect of climatic variables with the noncausal effects of confounding variables, such as endogenous covariates. These are "apples-to-oranges" comparisons, and the faulty logic of both types of comparison is made clear with examples.

For an example of (i), consider an analyst comparing violent crime over time in New York City and North Dakota who finds that the number of police on the street each day is important for predicting how much crime occurs on that day, but that a population variable describes more of the variation in crime because crime and population in North Dakota are both low. Clearly this comparison is not informative, because the reason that there is little crime in North Dakota has nothing to do with the reason why crime is lower in New York City on days when there are many police on the street. The argument that variations in climate are not important to predicting when conflict occurs because other variables are good predictors of where conflict occurs is analogous to the strange statement that the number of police in New York City is not important for predicting crime rates because North Dakota has lower crime that is attributable to its lower population.

For an example of (ii), suppose that both higher rainfall and higher household income lower the likelihood of civil conflict, but household income is not observed, and instead, a variable describing the average observable number of cars each household owns is included in the regression. Because wealthier households are better able to afford cars, the analyst finds that populations with more cars have a lower risk of conflict. This relationship clearly does not have a causal interpretation, and comparing the effect of car ownership on conflict with the effect of rainfall on conflict does not help us better understand the importance of the rainfall variable. Published studies that make similar comparisons do so with variables that the authors suggest are more relevant than cars, but the uninformative nature of comparisons between causal effects and noncausal correlations is the same.

Functional Form and Evidence of Nonlinearity

Some studies assume a linear relationship between climatic factors and conflict risk, whereas others assume a nonlinear relationship. Taken as a whole, the evidence suggests that, over a sufficiently large range of temperatures and rainfall levels, both temperature and precipitation appear to have a nonlinear relationship with conflict, at least in some contexts. However, this curvature is not apparent in every study, probably because the range of temperatures or rainfall levels contained within a sample may be relatively limited. Thus, most studies report only linear relationships that should be interpreted as local linearizations of a more complex, and possibly curved, response function.

As we will show, all modern analyses that address temperature impacts find that higher temperatures lead to more conflict. However, a few historical studies that examine temperate locations during cold epochs do find that abrupt cooling from an already cold baseline temperature may lead to conflict. Taken together, this collection of locally linear relationships indicates a global relationship with temperature that is nonlinear.

In studies of rainfall impacts, the distinction between linearity and curvature is made fuzzy by the multiple ways that rainfall changes have been parameterized in existing studies. Not all studies use the same independent variable, and because a simple transformation of an independent variable can change the response function from curved to linear and visa versa, it is difficult to determine whether results agree. In an attempt to make findings comparable, when replicating the studies that originally examine a nonlinear relationship between rainfall and conflict, we follow the approach of Hidalgo *et al*. (*25*) and use the absolute value of rainfall deviations from the mean as the independent variable. In studies that originally examined linear relationships, we leave the independent variable unaltered. Because these two approaches in the literature (and our reanalysis) differ, we make the distinction clear in our figures through the use of two different colors.

Results from the Quantitative Literature

We divide this section topically, examining, in turn, the evidence on how climatic changes shape personal violence, group-level violence, and the breakdown of social order and political institutions. Results from 12 example studies of recent data (post-1950) are displayed in Fig. 2. These findings were chosen to represent a broad cross section of outcomes, geographies, and time periods, and we used the common statistical framework described above to replicate these results (see supplementary materials). Findings from several studies of historical data are collected in Fig. 3, where the different time scales of climatic events can be easily compared. Table 1 lists and describes all primary studies. For a detailed description and evaluation of each individual study, see (*26*).

Personal Violence and Crime

Studies in psychology and economics have repeatedly found that individuals are more likely to exhibit aggressive or violent behavior toward others if ambient temperatures at the time of observation are higher (Fig. 2, A to C), a result that has been obtained in both experimental (*27*, *28*) and natural-experimental (*29*–*39*) settings. Documented aggressive behaviors that respond to temperature range from somewhat less consequential [e.g., horn-honking while driving (*27*) and interplayer violence during sporting events (*36*)] to much more serious [e.g., the use of force during police training (*28*), domestic violence within households (*29*, *37*), and violent crimes such as assault or rape (*30*–*35*, *38*)]. Although the physiological mechanism linking temperature to aggression remains unknown, the causal association appears robust across a variety of contexts. Importantly, because aggression at high temperature increases the likelihood that intergroup conflicts escalate in some contexts (36) and the likelihood that police officers use force (28), it is possible that this mechanism could affect the prevalence of group-level conflicts on a larger scale.

In low-income settings, extreme rainfall events that adversely affect agricultural income are also associated with higher rates of personal violence (40–42) and property crime (43). High temperatures are also associated with increased property crime (34, 35, 38), but violent crimes appear to rise with temperature more quickly than property crimes (38).

Group-Level Violence and Political Instability

Some forms of intergroup violence, such as Hindu-Muslim riots (Fig. 2D), tend to be more likely after extreme rainfall conditions (44–47). This relationship between intergroup violence and rainfall is primarily documented in low-income settings, suggesting that reduced agricultural production may be an important mediating mechanism, although alternative explanations cannot be excluded.

Low water availability (23, 46, 48–57), very low temperatures (58–63), and very high temperatures (14, 21, 23, 51, 64–66) have been associated with organized political conflicts in a variety of low-income contexts (Fig. 2, E, F, H, I, K, and L). The structure of this relationship again seems to implicate a pathway through climate-induced changes in income, either agricultural (48, 67–69) or nonagricultural (20, 21), although this hypothesis remains speculative. Large deviations from normal precipitation have also been shown to lead to the forceful reallocation of wealth (25) (Fig. 2G) or the nonviolent replacement of incumbent leaders (70, 71) (Fig. 2J).

Some authors recently suggested that contradictory evidence is widespread among quantitative studies of climate and human conflict (72–74), but the level of disagreement appears overstated. Two studies (22, 24) estimate that temperature and rainfall events have a limited impact on civil war in Africa, but the CIs around these estimates are sufficiently wide that they do not reject a relatively large effect of climate on conflict that is consistent with 35 other studies of modern data and 28 other studies of intergroup conflict. Within the broader literature of primary statistical studies, these results represent 4% of all reported findings (Table 1). Isolated studies also suggest that windstorms and floods have limited observable effect on civil conflicts (75) and that anomalously high rainfall is associated with higher incidence of terrorist attacks (76).

Institutional Breakdown

Under sufficiently high levels of climatological stress, preexisting social institutions may strain beyond recovery and lead to major changes in governing institutions (77–79) (Fig. 3C), a process that often involves the forcible removal of rulers. High levels of climatological stress have also led to major changes in settlement patterns and social organization (80, 81) (Fig. 3D). Finally, in extreme cases, entire communities, civilizations, and empires collapse entirely after large changes in climatic conditions (62, 79, 80, 82–89) (Fig. 3, A to C, E, and F). These documented catastrophic failures all precede the 20th century, yet the level of economic development in these communities at the time of their collapse was similar to the level of development in many poor countries of the modern world [see (26) for a comparison], an indicator that these historical cases may continue to have modern relevance.

Synthesis of Findings

Once attention is restricted to those studies able to make rigorous causal claims about the relationship between climate and conflict, some general patterns become clear. Here, we identify, for the first time, commonalities across results that span diverse social systems, climatological stimuli, and research disciplines.

Generality: Samples, Spatial Scales, and Rates of Climate Change

Social conflicts at all scales and levels of organization appear susceptible to climatic influence, and multiple dimensions of the climate system are capable of influencing these various outcomes. Studies documenting this relationship can be found in data samples covering 10,000 BCE to the present, and this relationship has been identified multiple times in each major region, as well as in multiple samples with global coverage (Fig. 1A).

Climatic influence on human conflict appears in both high- and low-income societies, although some types of conflict, such as civil war, are rare in high-income populations and do not exhibit a strong dependence on climate in those regions (51). Nonetheless, many other forms of conflict in high-income countries, such as violent crime (35, 38), police violence (28), or leadership changes (71), do respond to climatic changes. These forms of conflict are individually less extreme, but their total social cost may be large because they are widespread. For example, during 1979–2009 there were more than 2 million violent crimes (assault, murder, and rape) per year on average in the United States alone (38), so small percentage changes can lead to substantial increases in the absolute number of these types of events.

Climatic perturbations at spatial scales ranging from a building (27, 28, 36) to the globe (51) have been found to influence human conflict or social stability (Fig. 1B). The finding that climate influences conflict across multiple scales suggests that coping or adaptation mechanisms are often limited. Interestingly, as shown in Fig. 1B, there is a positive association between the temporal and spatial scales of observational units in studies documenting a climate-conflict link. This might indicate that larger social systems are less vulnerable to high-frequency climate events, or it may be that higher-frequency climate events are more difficult to detect in studies examining outcomes over wide spatial scales.

Finally, it is sometimes argued that societies are particularly resilient to climate perturbations of a specific temporal scale: Perhaps these societies are capable of buffering themselves against short-lived climate events, or alternatively, they are able to adapt to conditions that are persistent. With respect to human conflict, the available evidence does not support either of these claims. Climatic anomalies of all temporal durations, from the anomalous hour (28) to the anomalous millennium (81), have been implicated in some form of human conflict (Fig. 1B).

The association between climatic events and human conflict is general in the sense that it has been observed almost everywhere: across types of conflict, human history, regions of the world, income groups, the various durations of climatic changes, and all spatial scales. However, it is not true that all types of climatic events influence all forms of human conflict or that climatic conditions are the sole determinant of human conflict. The influence of climate is detectable across contexts, but we strongly emphasize that it is only one of many factors that contribute to conflict [see (90) for a review of these other factors].

The Direction and Magnitude of Climatic Influence on Human Conflict

We must consider the magnitude of the climate's influence to evaluate whether climatic events play an important role in the occurrence of conflict and whether anthropogenic climate change has the potential to substantially alter future conflict outcomes. Quantifying the magnitude of climatic impact in archaeological and paleoclimatological studies is difficult because outcomes of interest are often one-off cataclysmic events (e.g., societal collapse), and we typically do not observe how the universe of societies would have responded to similar-sized shocks. Modern data samples, however, generally contain a large number of comparable social units (e.g., countries) that are repeatedly exposed to climatic variation, and this setting is more amenable to statistical analyses that quantify how changes in climate affect the risk of conflict within an individual social unit.

To compare quantitative results across studies of modern data, we computed standardized effect sizes for those studies where it was possible to do so, evaluating the effect of a 1σ change in the explanatory climate variable and expressing the result as a percentage change in the outcome variable. Because we restrict our attention to studies that examine changes in climate variables over time, the relevant SD is based only on intertemporal changes at each specific location instead of comparing variation in climate across different geographic locations.

Our results are displayed in Figs. 4 and 5 (colors match those in Figs. 2 and 3). Nearly all studies suggest that warmer temperatures, lower or more extreme rainfall, or warmer El Niño–Southern Oscillation (ENSO) conditions lead to a 2 to 40% increase in the conflict outcome per

1σ in the observed climate variable. The consistent direction of temperature's influence is particularly notable because all 27 modern estimates (including ENSO and temperature-based drought indices, 20 estimates are shown in Figs. 4 and 5) indicate that warmer conditions generate more conflict, a result that would be extremely unlikely to occur by chance alone if temperature had no effect on conflict. It is more difficult to interpret whether the signs of rainfall-related variables agree because these variables are parameterized several different ways, so Figs. 4 and 5 present likelihoods for different parameterizations separately. However, if all modern rainfall estimates are pooled (including ENSO and rainfall-based drought indices, 13 estimates are shown in Figs. 4 and 5) using signs shown in Figs. 4 and 5, then the signs of the effects in 16 out of 18 estimates agree.

Under the assumption that there is some underlying similarity across studies, we compute the average effect of climate variables across studies by weighting each estimate according to its precision (the inverse of the estimated variance), a common approach that penalizes uncertain estimates (*91*). We also calculate the CI on this mean by assuming independence across studies, although this assumption is not critical to our central findings (in the supplementary materials, we present results where we relax this assumption and show that it is not essential). The precision-weighted average effect on interpersonal conflict is a 2.3% increase for each 1σ change in climatic variables (SE = 0.12%, $P < 0.001$; Fig. 4 and table S1) and the analogous estimate for intergroup conflict is 11.1% (SE = 1.3%, $P < 0.001$; Fig. 5 and table S1). These precision-weighted averages are relatively uninfluenced by outliers because outlier estimates in our sample tend to have low precision and, thus, low weight in the meta-analysis. The corresponding medians, which are also insensitive to outliers, are comparable: 3.9% for personal conflict and 13.6% for group conflict. If we restrict our attention to only the effects of temperature, the precision-weighted average effect is similar for interpersonal conflict (2.3%); however, for intergroup conflict, the effect rises to 13.2% per 1σ in temperature (SE = 2.0, $P < 0.001$; Fig. 5). Regarding the interpretation of these effect sizes, we note that whereas the average effect for interpersonal violence is smaller than the average effect for intergroup conflict in percentage terms, the baseline number of incidents of interpersonal violence is dramatically higher, meaning a small percentage increase can represent a substantial increase in total incidents.

We estimate the precision-weighted probability distribution of study-level effect sizes in Figs. 4 and 5 and in table S1. These distributions are centered at the precision-weighted averages described above and can be interpreted as the distribution of results from which studies' findings are drawn. The distribution for interpersonal conflict is narrow around its mean, probably because most interpersonal conflict studies focus on one country (the United States) and use very large samples and derive very precise estimates. The distribution for intergroup conflict is broader and covers values that are larger in magnitude, with an interquartile range of 6 to 14% per 1σ and the 5th to 95th percentiles spanning –5 to 32% per 1σ (table S1). We estimate that for the intergroup and interpersonal conflict studies, respectively, 10 and 0% of the probability mass of the distributions of effect sizes lies below zero.

Figures 4 and 5 make it clear that even though there is substantial agreement across results, some heterogeneity across estimates remains. It is possible that some of this variation is meaningful, perhaps because different types of climate variables have different impacts or because the social, economic, political, or geographic conditions of a society mediate its response to climatic events. For instance, poorer populations appear to have larger responses, consistent with prior findings that such populations are more vulnerable to climatic shifts (*51*). However, it is also possible that some of this variation is due to differences in how conflict outcomes are defined, measurement error in climate variables, or remaining differences in model specifications that we could not correct in our reanalysis.

To formally characterize the variation in estimated responses across studies, we use a Bayesian hierarchical model that does not require knowledge of the source of between-study variation (*92*) (see supplementary materials). Under this approach, estimates of the precision-weighted mean are essentially unchanged, and we recover estimates for the between-study SD (a measure of the underlying dispersion of true effect sizes across studies) that are half of the precision-weighted mean for interpersonal conflict and two-thirds of the precision-weighted mean for intergroup conflict (median estimates; see supplementary materials, fig. S3, and tables S2 and S3). By comparison, if variation in effect sizes across studies was driven by sampling variation alone, then this SD in the underlying distribution of effect sizes would be zero. This finding suggests that true effects probably differ across settings, and understanding this heterogeneity should be a primary goal of future research.

Publication Bias

Publication bias is a long-standing concern across the sciences, with a common form of bias arising from the research community's perceived preference for positive rather than null results. Although it is always possible that publication bias played a role in the publication of a specific analysis, there are multiple reasons why publication bias is unlikely to be driving our findings about the literature on climate and conflict. First, we include working papers in our analysis (as is common practice in the social sciences), thereby eliminating editorial selection. Second, the central results presented here are replicated in multiple disciplines and across diverse samples. Third, the large number of positive findings present in the literature since 2009 could provide limited professional incentive for researchers to publish yet another positive finding, and benefits might be higher to those who publish results with alternative findings. Fourth, many analyses are not explicitly focused on the direct effect of climate on conflict but instead use climatic variations instrumentally (*25*, *35*, *48*, *71*, *77*) or account for it as an ancillary covariate in their analysis [e.g., (*37*)] while trying to study a different research question, indicating that these authors have little professional stake in the sign, magnitude, or statistical significance of the climatic effects they are presenting. Fifth, we reanalyze the raw data from many studies using a common statistical framework, possibly undoing adjustments that authors might be making to their analysis (consciously or unconsciously) that make their findings appear stronger. Partial support for this idea is provided by individual studies that present significant results, but whose results are only marginally significant or no longer significant after our reanalysis (see supplementary materials for details). Finally, we look for evidence of publication bias by examining whether the statistical strength of individual studies reflects their sample size (*93*) and do not find systematic evidence of strong bias in absolute terms or in comparison to other social science literature (see fig. S4, table S4, and supplementary materials).

Implications for Future Climatic Changes

The above evidence, taken at face value, makes the case that future anthropogenic climate change could worsen conflict outcomes across the globe in comparison to a future with no climatic changes, given the large expected increase in global surface temperatures and the likely increase in variability of precipitation across many regions over coming decades (*94*, *95*). Recalling our finding that a 1σ change in a location's temperature is associated with an average 2.3% increase in the rate of interpersonal conflict and a 13.2% increase in the rate of intergroup conflict, and assuming that future populations will respond to climatic shifts similarly to how current populations respond, one can consider the potential effect of anthropogenic warming by rescaling expected temperature changes according to each location's historical variability. Although not all conflict outcomes have been shown to be responsive to changes in temperature, many have, and the results uniformly indicate that increasing temperatures are harmful in regions that are temperate or warm initially. In Fig. 6, we plot expected warming by 2050, computed as the ensemble mean for 21 climate models running the A1B emissions scenario, in terms of location-specific SDs (*96*). Almost all inhabited locations warm by >2σ, with the largest increases exceeding 4σ in tropical regions that are already warm and currently experience relatively low interannual temperature variability. These large climatological changes, combined with the quantitatively large effect of climate on conflict—particularly intergroup conflict—suggest that amplified rates of human conflict could represent a large and critical impact of anthropogenic climate change

Two reasons are often given as to why climate change might not have a substantive impact on human conflict: Future climate change will occur gradually and will, thus, allow societies to adapt, and the modern world today is less susceptible to climate variation than it has been in the past. However, if slower-moving climate shocks have smaller effects, or if the world has become less climate-sensitive, it is unfortunately not obvious in the data. Gradual climatic changes appear to adversely affect conflict outcomes, and the majority of the studies we review use a sample period that extends into the 21st century (recall Fig. 1). Furthermore, some studies explicitly examine whether populations inhabiting hotter climates exhibit less conflict when hot events occur but find little evidence that these areas are more adapted (*31*, *38*). We also note that many of the modern linkages between high-temperature anomalies and intergroup conflict have been characterized in Africa (*14*, *23*, *52*, *64*, *66*) or the global tropics and subtropics (*21*, *51*), regions with hot climates where we would expect populations to be best adapted to high temperatures. Nevertheless, it is always possible that future populations will adapt in previously unobserved ways, but it is impossible to know if and to what extent these adaptations will make conflict more or less likely.

Studies of nonconflict outcomes do indicate that, in some situations, historical adaptation to climate is observable, albeit costly (*97*–*100*), whereas in other cases there is limited evidence that any adaptation is occurring (*19*, *101*). To our knowledge, no study has characterized the scale or scope for adaptation to climate in terms of conflict outcomes, and we believe this is an important area for future research. Given the quantitatively large effect of climate on conflict, future adaptations will need to be dramatic if they are to offset the potentially large amplification of conflict.

Future Research

Given the marked consistency of available quantitative evidence linking climate and conflict, in our view, the top research priority in this field should be to narrow the number of competing explanatory hypotheses. Beyond efforts to mitigate future warming, limiting climate's future influence on conflict requires that we understand the causal pathways that generate the observed association. This task is made difficult by the likely situation that multiple mechanisms contribute to the observed relationships and that different mechanisms dominate in different contexts. The rich qualitative literature (*3*–*7*) suggests that a multiplicity of mechanisms may be at work.

To date, no study has been able to conclusively pin down the full set of causal mechanisms, although some studies find suggestive evidence that a particular pathway contributes to the observed association in a particular context. In most cases, this is accomplished by "fingerprinting" the effect of climate on an intermediary variable, such as income, and showing that the same statistical fingerprint is visible in the climate's effect on conflict. This approach, typically called "instrumental variables" (*12*) in the social sciences, identifies a mechanism linking climate and conflict under the assumption that climate's only influence on conflict is through the particular intermediate variable in question. Because this assumption is often difficult or impossible to test, evidence from this approach is more suggestive than conclusive in uncovering mechanisms (*51*).

An alternate and promising research design that can help rule out certain hypotheses is to study situations in which plausibly exogenous events block a proposed pathway in a treated subpopulation and then to compare whether the climate-conflict association persists or disappears in both the treatment and control subpopulations. In an example of this approach, Sarsons examines whether rainfall shortages in India lead to riots because they depress local agricultural income (*45*). By showing that rainfall shortages and riots continue to occur together in districts with dams that supply irrigation, investments that partially decouple local agricultural income from temporary rain shortfalls, Sarsons argues that the rainfall effect on riots is unlikely to be operating solely through changes in local agricultural income.

Plausible Mechanisms

The following hypotheses have, in our judgment, received the strongest empirical support in existing analyses, although the evidence is still often inconclusive. A common hypothesis focuses on local economic conditions and labor markets and argues that when climatic events cause economic productivity to decline (*19*–*21*, *68*, *69*, *102*–*104*), the value of engaging in conflict is likely to rise relative to the value of participating in normal economic activities (*48*, *52*, *105*–*110*). A competing hypothesis on state capacity argues that these declines in economic productivity reduce the strength of governmental institutions (e.g., if tax revenues fall), curtailing their ability to suppress crime and rebellion or encouraging competitors to initiate conflict during these periods of relative state weakness (*61*, *70*, *71*, *77*–*79*, *84*, *85*).

A second set of hypotheses focuses on what have, more generally, been termed "grievances." Hypotheses about inequality contend that when climatic events increase actual (or perceived) social and economic inequalities in a society (*111*, *112*), this could increase conflict by motivating attempts to redistribute assets (*25*, *34*, *35*, *43*). Evidence linking changes in food prices to conflict (*61*, *113*–*115*) can be interpreted similarly—for example, food riots due to a government's perceived inability to keep food affordable—particularly when some members of society can influence food markets (*111*, *116*).

Climate-induced migration and urbanization might also be implicated in conflict. If climatic events cause large population displacements or rapid urbanization (*97*, *117*, *118*,), this might lead to conflicts over geographically stationary resources that are unrelated to the climate (*119*) but become relatively scarce where populations concentrate. Changes in climate might also affect the logistics of human conflict (*76*, *120*), for example, by altering the physical environment (e.g., road quality) in which disputes or violence might occur (*52*, *120*, *121*). Finally, climate anomalies might result in conflict because they can make cognition and attribution more difficult or error-prone, or they may affect aggression through some physiological mechanism. For instance, climatic events may alter individuals' ability to reason and correctly interpret events (*27*, *28*, *30*, *31*, *34*–*36*), possibly leading to conflicts triggered by misunderstandings. Alternatively, if climatic changes and their economic consequences are inaccurately attributed to the actions of an individual or group (*63*, *122*–*125*)—for example, an inept political leader (*71*)—this may lead to violent actions that try to return economic conditions to normal by removing the "offending" population.

Selecting Climate Variables and Conflict Outcomes

Climate variables that have been analyzed previously, such as seasonal temperatures, precipitation, water availability indices, and climate indices, may be correlated with one another and autocorrelated across both time and space. For instance, temperature and precipitation time series tend to be negatively correlated in much of the tropics, and drought indices tend to be spatially correlated (*51*, *126*). Unfortunately, only a few of the existing studies account for the correlations between different variables, so it may be that some studies mistakenly measure the influence of an omitted climate variable by proxy [see (*126*) for a complete discussion of this issue]. Except for the experiments linking temperature to aggression (*27*, *28*), only a few studies demonstrate that a specific climate variable is more important for predicting conflict than other climate variables or that climatic changes during a specific season are more important than during other seasons. Furthermore, no study isolates a particular type of climatic change as the most influential, and no study has identified whether temporal or spatial autocorrelations in climatic variables are mechanistically important. Identifying the climatic variables, timing of events, and forms of autocorrelation that influence conflict will help us better understand the mechanisms linking climatic changes to conflict.

A similar situation exists with the choice of conflict outcomes. Most analyses simply document changes in the rate at which conflicts are reported in aggregate, but this approach provides only limited insight into how the evolution of conflict is affected by climatic variables. A path for future investigation is to link climate data with richer conflict data that describes different stages of the conflict "life cycle." For example, future studies could examine how often nonviolent group disputes become violent. Two studies cited in this paper (*28*, *36*) demonstrate the usefulness of selecting conflict variables other than total conflict rates. By examining the probability that an initial confrontation escalates rather than just counting the total number of conflicts, these studies demonstrate that high temperatures lead to more violence by increasing the likelihood that a small conflict escalates into a larger conflict.

Conclusion

Findings from a growing corpus of rigorous quantitative research across multiple disciplines suggest that past climatic events have exerted considerable influence on human conflict. This influence appears to extend across the world, throughout history, and at all scales of social organization. We do not conclude that climate is the sole, or even primary, driving force in conflict, but we do find that when large climate variations occur, they can have substantial effects on the incidence of conflict across a variety of contexts. The median effect of a 1σ change in climate variables generates a 14% change in the risk of intergroup conflict and a 4% change in interpersonal violence, across the studies that we review where it is possible to calculate standardized effects. If future populations respond similarly to past populations, then anthropogenic climate change has the potential to substantially increase conflict around the world, relative to a world without climate change.

Although there is marked convergence of quantitative findings across disciplines, many open questions remain. Existing research has successfully established a causal relationship between climate and conflict but is unable to fully explain the mechanisms. This fact motivates our proposed research agenda and urges caution when applying statistical estimates to future warming scenarios. Importantly, however, it does not imply that we lack evidence of a causal association. The studies in this analysis were selected for their ability to provide reliable causal inferences and they consistently point toward the existence of at least one causal pathway. To place the state of this research in perspective, it is worth recalling that statistical analyses identified the smoking of tobacco as a proximate cause of lung cancer by the 1930s (*127*), although the research community was unable to provide a detailed account of the mechanisms explaining the linkage until many decades later. So although future research will be critical in pinpointing why climate affects human conflict, disregarding the potential effect of anthropogenic climate change on human conflict in the interim is, in our view, a dangerously misguided interpretation of the available evidence.

Numerous competing theories have been proposed to explain the linkages between the climate and human conflict, but none have been convincingly rejected, and all appear to be consistent with at least some existing results. It seems likely that climatic changes influence conflict through multiple pathways that may differ between contexts, and innovative research to identify these mechanisms is a top research priority. Achieving this research objective holds great promise, as the policies and institutions necessary for conflict resolution can be built only if we understand why conflicts arise. The success of such institutions will be increasingly important in the coming decades, as changes in climatic conditions amplify the risk of human conflicts.

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Supplementary Materials

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