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Review

# Conflict in a changing climate

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**Abstract.** A growing body of research illuminates the role that changes in climate have had on violent conflict and social instability in the recent past. Across a diversity of contexts, high temperatures and irregular rainfall have been causally linked to a range of conflict outcomes. These findings can be paired with climate model output to generate projections of the impact future climate change may have on conflicts such as crime and civil war. However, there are large degrees of uncertainty in such projections, arising from *(i)* the statistical uncertainty involved in regression analysis, *(ii)* divergent climate model predictions, and *(iii)* the unknown ability of human societies to adapt to future climate change. In this article, we review the empirical evidence of the climate-conflict relationship, provide insight into the likely extent and feasibility of adaptation to climate change as it pertains to human conflict, and discuss new methods that can be used to provide projections that capture these three sources of uncertainty.

## 1 Introduction

Changes in climate have the potential to upset social stability. While the role of climatological factors in historical and ongoing violent conflicts has been long debated, a growing interdisciplinary literature demonstrates that the frequency and intensity of conflicts ranging from violent criminal acts to large-scale civil wars are often exacerbated by climate variation. Many pathways through which these effects manifest have been proposed. Climate variation may restrict the supply of natural resources, have psychological impacts on aggressive behavior, or directly increase poverty, each of which in turn can incite conflict. In this article, we review evidence of these impacts and discuss what our current knowledge implies for projections of conflict under anthropogenic climate change. While a robust relationship between historical climate disturbances and conflict outcomes has been established, there remain important challenges to mobilizing these findings into precise expectations of the

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future. To improve predictions of future outcomes, research efforts should be focused on identifying the mechanisms through which climate drives conflict, and the extent to which societies could adapt to changing environmental conditions.

## 2 Historical evidence

A natural first step to projecting the effect of future climate change on conflict is to examine the nature of this relationship in the past. A long history of study on the association between climate and social instability across disciplines as diverse as archaeology, geography, economics and political science provides a base of evidence upon which such climate impacts may be estimated. Much of the earliest work was qualitative in nature, focusing on relationships between environmental change and civil conflict using case studies. In a review, [1] demonstrates that many of these case studies identify a scarcity model in which climate leads to resource shortages, which in turn incite conflict.

In recent years, modern econometric methods and increased data availability have fueled a wave of quantitative evidence on this topic, complementing earlier qualitative work. Empirical studies compare conflict data across space and time, seeking evidence for or against the role of climate in triggering or prolonging conflict and crime. Initial reviews of this literature found that the causal link between climate and conflict was inconclusive, documenting contradictory results across contexts, methodological approaches, and data sources [2–4]. However, more recent reviews have concluded that a significant and robust relationship between climate variation and conflict exists across a diversity of spatial and temporal scales [5–7]. As detailed in [5] and [8], these differing views of the literature stem from the recent reviews' exploitation of increased data availability, inclusion of significantly more studies, adoption of clear methodological standards, consideration of statistical uncertainty, and exclusion of qualitative work.[1]

While acknowledging the distinct character that relationships between climate and conflict have in diverse settings, in our review of the historical evidence we follow [7] in seeking commonalities across quantitative and methodologically sound studies that plausibly identify the causal effect that past climate variation has had on a range of conflict outcomes. U.S.

### 2.1 The empirical challenge

Climatic variation does not alone cause conflict, but rather modifies the conditions under which social interactions occur, thus potentially changing the frequency or intensity of social unrest. The challenge facing quantitative assessments of the climate-conflict link lies in separating the causal effect of climate from all other complex and interacting drivers of conflict, such as economic hardship, social norms, and political institutions. For example, Mexican homicide rates in 2012 were more than twice those in the U.S., while average temperatures in the former nation also exceed those in the latter [15]. However, attributing this differential to climate alone is clearly problematic; among many other confounding factors, homicides in Mexico have been dramatically affected by recent political efforts to combat the drug trade [16], an influence likely not a consequence of temperature.

To isolate the role of climate in conflict, in an ideal experiment we would observe two identical societies and "treat" one with a changing climate, such as increased

[1] For details on the divergence between these literature reviews, see [5,6,8] and [9]. For efforts to reconcile seemingly contradictory findings, see [10,11] and [12].

temperature or higher frequency of drought. Leaving the second population as an unaltered "control", any difference in conflict outcomes across the two societies could be justifiably attributed to climate change, as no other factors differ across populations. Absent such an experiment, there are two common approaches to approximating this scenario. First, cross-sectional studies compare conflict outcomes *across* locations, assuming that populations are identical to one another once observable conflict covariates, such as economic and political indicators, are controlled for by including these variables in a statistical regression. However, many potential drivers of conflict, such as religion and culture, are both difficult to measure and correlated with climate. Because the full suite of conflict determinants are unknown and unmeasured, it is likely impossible that any cross-sectional study can explicitly account for all important differences. Thus, the analyst risks conflating the role of climate with these other unobserved factors.

Recent work generally follows an alternative approach. These studies rely on panel data to exploit variation in climate across time *within* a population, allowing one population to serve both as "control" (before a change in climate) and as "treatment" (after a change in climate). As long as the time gap between treatment and control is small enough, the assumption that all other correlates of conflict are independent from climate variation can be plausibly supported, and the estimated effect of the climate variable of interest can be seen as causal. The drawback of this approach, however, is that only high-frequency climate variation can be used: the more gradual the climate shift, the more implausible the claim that a human population at the start and end of the change in climate are directly comparable along the many unobservable dimensions that affect conflict.[2] Thus, while future climate change is likely to occur gradually over many decades, this approach relies on climate changes that are very short-run in nature – a challenge described as the *frequency-identification tradeoff* by [5].[3]

In this review, we replicate and expand results from the meta-analysis in [7], which includes only studies that use this latter approach to identify a causal effect of climate on various types of conflict. These studies estimate models of the generic form[4]

$$conflict\_variable_{it} = \beta \times climate\_variable_{it} + \mu_i + \theta_t + \varepsilon_{it} \tag{1}$$

where $\varepsilon$ is an error term and $\beta$ is the parameter of interest. In this model, $\beta$ captures the impact of climate variability on a conflict outcome within a location over time, ensuring the same population is used as both treatment and control, as discussed above. This is achieved by including a vector of location-specific constants, $\mu_i$, which are commonly known as location fixed effects. These control for all average differences in conflict across locations due to time-invariant factors such as culture, history and institutions. Additionally, the time fixed effects $\theta_t$ control for temporal shocks to conflict that affect all locations $i$ simultaneously, such as macroeconomic shocks, common policy changes or demographic shifts. Lagged effects of climate are relevant in cases

[2] Some authors call high-frequency climate variation "weather", referring to long-run average conditions as "climate".

[3] Note that the applicability of the impacts of short-run climate variation to questions of long-run climate change depends upon the extent of adaptation future societies are likely to invest in. As discussed in Sect. 3, evidence of adaptation in the crime and conflict literature is limited – [17] and [18] both show that populations in hotter average climates do not appear to have adapted at all with respect to crime. Moreover, gradual changes in climate have also been shown to impact conflict outcomes, suggesting adaptation has been limited [19,20]. See [21] for details.

[4] Some studies use nonlinear functions of climate variables to capture differential impacts across the support of temperature or precipitation (e.g. [22]).

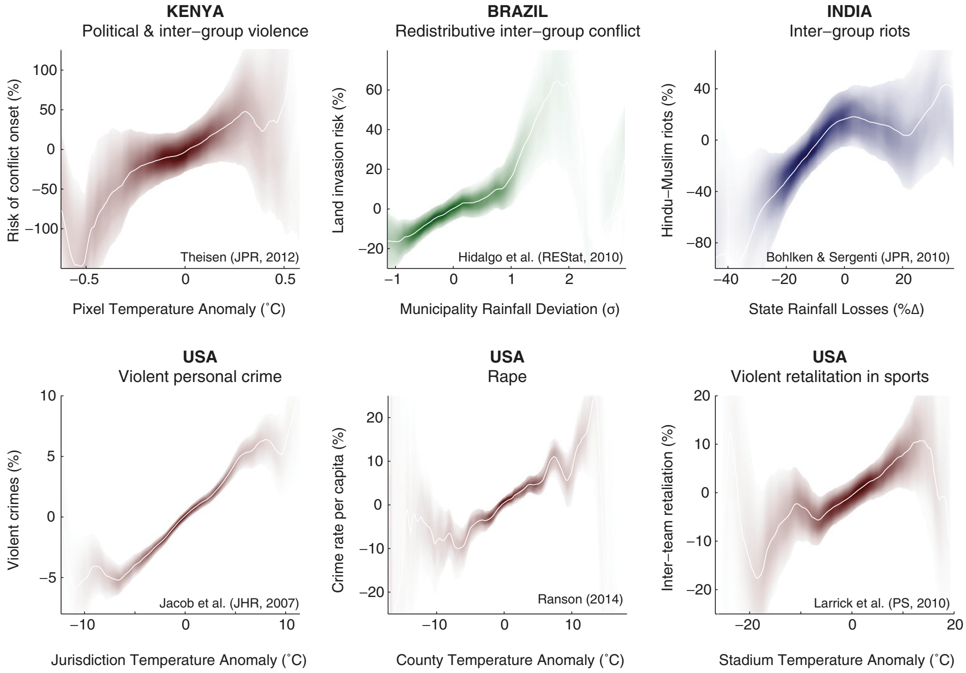


**Fig. 1.** Empirical studies indicating that climate variables have a large effect on the risk of violence or social instability throughout a variety of modern contexts. These are examples from studies of modern data that identify the causal effect of climatological variables on human conflict. Relationships are shown with nonparametric watercolor regressions, where the color intensity of 95% confidence intervals depicts the likelihood that the true regression line passes through a given value (darker is more likely), and the white line denotes the conditional mean. Results are from a replication of findings in [7].

where shocks have a delayed or persistent effect on conflict, and these can be addressed by including climate shocks from previous time periods as independent variables (e.g. [23,24]). To interpret $\hat{\beta}$ causally, one must assume that the timing of climatic variations at a given location are independent of the timing of changes in potentially confounding variables. Stated formally, we require $E[\varepsilon_{it} climate\_variable_{it}|\mu_i, \theta_t] = 0$, i.e. all unexplained variation is orthogonal to climatic variation once all time-invariant unobservables and population-wide temporal shocks are accounted for. Variations on the model in Eq. (1) have become the standard in the newly growing empirical climate-conflict literature, providing a large body of evidence on the causal effect of climate on conflict across a diversity of settings.

## 2.2 What has been studied?

Recent empirical work has explored the impacts of many facets of climatic change on a range of conflict outcomes across spatial and temporal scales. Using examples from this literature, Fig. 1 demonstrates that in settings as divergent as ethnic riots in India and violent retaliation in sports in the U.S., a robust and large effect of climate variation on conflict outcomes has been identified. Perhaps the most dominant climatological factor in this literature is temperature: from domestic violence in Australia [25] to outbreak of civil conflict between armed groups in North and South Sudan [26], higher temperatures have repeatedly been shown to inflate average levels of conflict.

Precipitation can also be a critical driver, particularly in developing nations where economic outcomes are closely tied to agriculture, such as India [27] and Brazil [22]. Other studies address distinct climate variables: [28] identify the positive impact of droughts on civil conflict in Sub-Saharan Africa, [29] show that the El Niño Southern Oscillation increases the probability of civil conflict throughout the tropics, while [30] find no effect of storms or floods on the onset of armed conflict throughout the world.

We follow [7] and categorize the diversity of conflict types into two broad classes. First, *interpersonal* conflict captures conflict between individuals, such as crime, rape, robbery, and policy brutality. Studies in this category generally find that high temperatures increase crime rates, with a particularly large and robust effect on violent crimes. For example, [31] demonstrate that the probability of violent retaliation during sporting events rises on hot days in the U.S., while [27] show that high temperatures increase both property and violent crime in India. While there is not a consistent effect of rainfall on interpersonal conflict, in some developing countries such as India [27,32,33] and Tanzania [34], rainfall shocks that damage agricultural yields appear to increase both violent and property crimes.

The second class of conflict is *intergroup* conflict, which encompasses interactions between collections of individuals, such as wars, riots, and political violence. High temperatures are found to exacerbate the risk of many types of collective violence, from gang murders in Mexico [15] to country-level institutional change in sub-Saharan Africa [35]. Effects are only detected, however, in low or middle income nations, where average temperatures are higher and economic output is more closely tied to climate via agricultural production. In these same countries, negative rainfall shocks have been shown to increase intergroup conflicts such as Hindu-Muslim riots in India [36], organized political conflict in sub-Saharan Africa [37] and coups across the world [38]. In some cases, large positive rainfall shocks can also increase collective conflict [22,39], suggesting a nonlinear response tied to the adverse impacts of both extremes of the rainfall distribution on agricultural income.

While each study addresses a specific population with vulnerability to particular types of climate shocks, comparison of effects across studies may help illuminate shared underlying processes linking climate and conflict throughout the literature. However, to compare magnitudes of effects across such diverse settings, a standardization of effect sizes is useful to account for the distinct climates and baseline conflict prevalence in every study. For example, [17] and [27] measure the impact of temperature on murder in the U.S. and India, respectively. [17] finds that one extra day between 90°F and 99°F, relative to a day in the 60–69°F range, causes 0.5% more murders. [27] find that a positive temperature shock (defined as one standard deviation above the mean) increases murders per 100,000 people by 3.7%. To compare these two findings, the differential modeling of temperature, as well as the average climate (much cooler in the U.S.) and baseline murder rates (much higher in India), should be taken into account. This can be achieved by creating a standardized coefficient that converts climate measures into standard deviations and normalizes the conflict rate by the average risk of conflict in the observed sample:

$$\beta_{standardized} = \beta_{reported} \times \frac{\sigma(climate)}{\text{avg}(\Pr(conflict))} \tag{2}$$

$\beta_{standardized}$ is the change in the relative risk of conflict caused by a one standard deviation change in the climate variable, where $\sigma(climate)$ is the within-location standard deviation of the climate variable of interest and $\text{avg}(\Pr(conflict)$ is the baseline conflict risk [7]. This standardized coefficient allows for comparison of the magnitude of climatic effects not just across study locations, but also across conflict types and climate variables, facilitating unification of a broad and diverse literature.

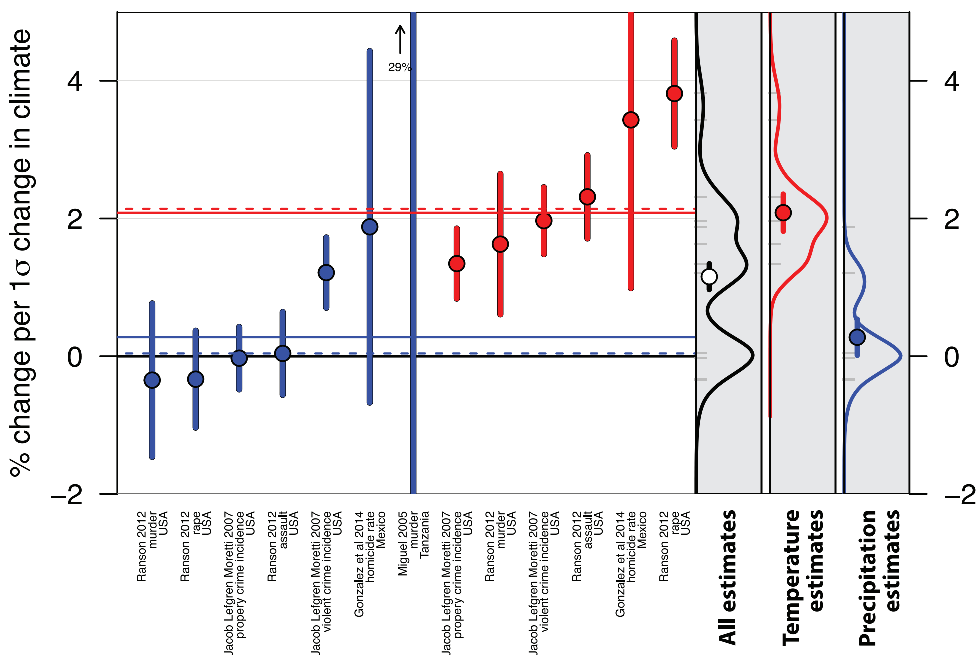


**Fig. 2.** Reanalysis of interpersonal conflict estimates. Colors indicate temperature (red) or rainfall loss (blue). Point estimates are the cumulative effect from a two period distributed lag model, with effect size distributions given for temperature and precipitation separately at right. Solid blue and red horizontal lines give precision-weighted mean effects for precipitation and temperature, respectively, and dotted lines the corresponding medians. The panels on the right show the precision-weighted mean effect (circles) and the distribution of study results (gray ticks); probability distributions are the posterior for the expected distribution of an additional study (solid lines). Results are from a replication of findings in [7].

### 2.3 Synthesis of findings

Following [7], we bring together 56 studies that empirically estimate the relationship between climate and conflict using panel models of the general form in Eq. (1). [7] demonstrate that while there is a striking degree of commonality in effects across these studies, there is also some evidence of publication bias, perhaps due to author selection of specifications eliciting positive effects. Because this concern largely arises through authors using different lag structures and nonlinearities for climate effects, here we only present results in which we can use a single standardized specification estimating both contemporaneous and lagged terms for all climate variables. When authors did not present results for such a specification, we either obtained the original data and reanalyzed the results, or contacted authors and received author-run reanalysis. In the left panels of Figs. 2 and 3, we show the distribution of the standardized cumulative effects, calculated as in Eq. (2), for interpersonal and intergroup conflict, respectively. Each point estimate and confidence interval represents one study's standardized cumulative effect of contemporaneous and lagged climate variables, with blue indicating a rainfall estimate and red representing temperature. These figures suggest that, despite some heterogeneity, intergroup conflicts respond robustly to both positive temperature and negative precipitation shocks, while interpersonal conflict reveals a significant, yet smaller, temperature effect.

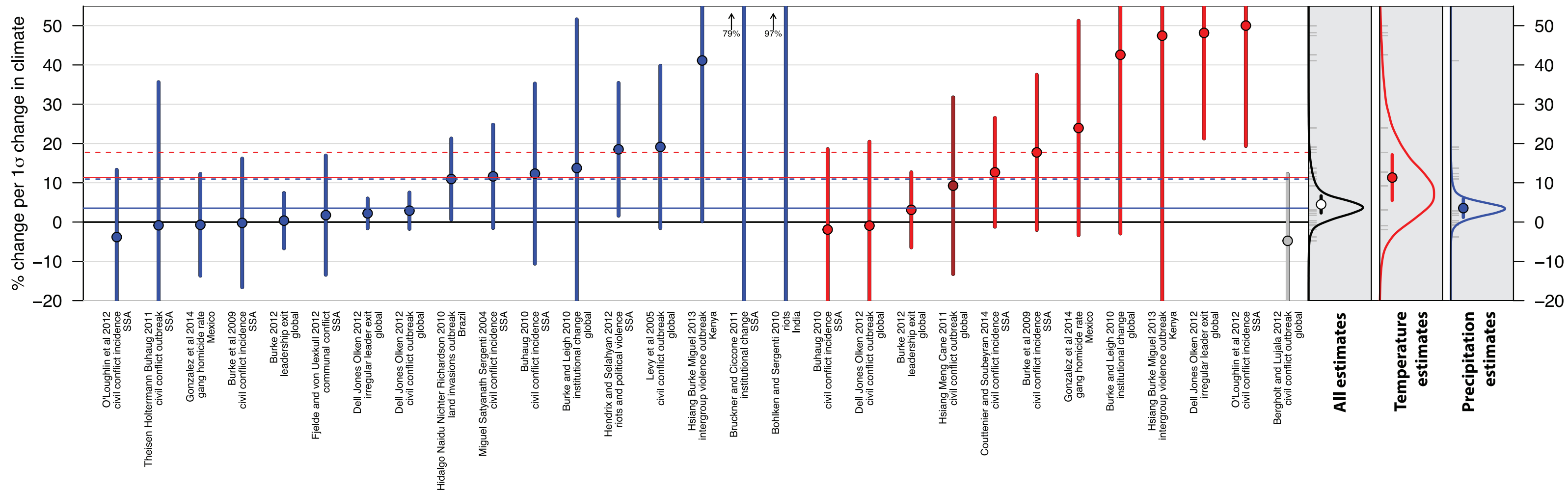


**Fig. 3.** Reanalysis of intergroup conflict estimates. Colors are as in Fig. 2, with additional colors indicating ENSO (brown) and storms (grey). Point estimates are the cumulative effect from a two period distributed lag model, with effect size distributions now given for temperature and precipitation separately at right. Solid blue and red lines give precision-weighted mean effects for precipitation and temperature, respectively, and dotted lines the corresponding medians. The panels on the right show the precision-weighted mean effect (circles) and the distribution of study results (gray ticks); probability distributions are the posterior for the expected distribution of an additional study (solid lines). Results are from a replication of findings in [7].

While the distribution of these standardized coefficients sheds light on the range of estimates for climate's impact on conflict across the literature, a further step is to determine whether there is a generalizable pattern across these findings. Using a hierarchical Bayesian approach to meta-analysis proposed in [40], we calculate the mean effect across studies and capture the heterogeneity in the distribution of individual study estimates. This approach explores whether "true" underlying effects likely differ across studies, or instead whether observed differences in estimated effects are more consistent with variation around an effect that is common across contexts.[5]

More precisely, we assume that the true standardized effect $\beta_j$ of each study $j$ is drawn from a population distribution of all possible studies:

$$\beta_j \sim N(\mu, \tau^2) \tag{3}$$

where $\mu$ is the common component across studies that describes the mean response of conflict to climate, and $\tau$ represents the degree of true heterogeneity across study contexts. As each estimate $\hat{\beta}_j$ has its own standard error $\hat{\sigma}_j$, both the within-study standard error and the between-study variance in $\hat{\beta}_j$'s affect estimates of $\mu$ and $\tau$. If $\tau$ is close to zero, true conflict responses to climate are likely quite similar across diverse populations and settings, and thus differences in coefficients across studies arise from sampling error only. Conversely, a large $\tau$ indicates that true differences across study estimates are large relative to sampling variability. Separately for interpersonal and intergroup climate, each for rainfall and temperature, we use Bayes' Rule to update estimates of $\mu$, $\tau$ and the $\beta_j$'s under a uniform prior. With 10,000 simulations, we generate the posterior distributions of each variable, thus characterizing both the commonality and heterogeneity in climate-conflict relationships across the existing literature.

The posterior distributions from the meta-analysis methodology discussed above are shown in the grey panels on the right of Figs. 2 and 3, run for all climate variables pooled (left panel), temperature only (center panel) and rainfall only (right panel). The circle with whiskers within each of these distributions is the estimated value of $\mu$, the common component across all studies. The two classes of conflict exhibit distinct responses. Interpersonal conflict effects are relatively small in magnitude, but precisely estimated, while intergroup conflict estimates are wide-ranging in magnitude and precision. Temperature effects are markedly larger than those for precipitation in both conflict classes. Overall, however, there is a clear consistency across studies demonstrating a robust impact of climate on conflict. For interpersonal conflict, the meta-analysis means $\mu$ show that on average, a $1\sigma$ increase in temperature increases conflict outcomes by 2.1%, around seven times larger than the $0.3\%/\sigma$ effect of rainfall, although both effects are statistically significant. Higher temperatures have a much larger effect on intergroup conflict, with an average $11.3\%/\sigma$ impact and a large dispersion in the posterior distribution of $\beta_j$'s. For each $1\sigma$ fall in precipitation, intergroup conflict rises on average by 3.5%; again, a smaller but statistically significant result. While there are unambiguous differences in this relationship based on the population and scale of analysis, the magnitude and statistical significance of the common component in each category of impacts provides strong evidence of a shared underlying process linking climate to conflict across many distinct settings.

## 2.4 Mechanisms

The empirical literature reviewed above estimates a "reduced form" effect of climate on conflict – i.e. a cumulative effect across multiple potentially interacting pathways –

[5] For a more detailed exposition of this methodology, see [7].

but is often silent on the particular pathway(s) through which the effect takes place. While many mechanisms have been suggested, few studies can isolate a single channel. To fix ideas, suppose there are multiple mechanisms, indexed by $i$, through which a climate variable affects a conflict outcome. Empirical estimates described in Sect. 2 generally identify the following cumulative effect across all pathways:

$$\beta = \frac{\mathrm{d}\, conflict\_variable}{\mathrm{d}\, climate\_variable} = \sum_i \frac{\partial\, conflict\_variable}{\partial\, pathway_i} \cdot \frac{d\, pathway_i}{d\, climate\_variable}. \quad (4)$$

To accurately measure the causal effect of climate on conflict, understanding the mechanism through which this occurs is not necessary. However, identifying these pathways can be helpful for quantifying and forecasting the degree to which humans may adapt over time. While the empirical estimates we have are accurate descriptions of past responses, knowledge of how these effects may be tempered or exacerbated through changes in each pathway can inform climate change policy for the future. To meet this need, many studies attempt to uncover plausible pathways, and two central mechanisms have been repeatedly supported.

First, there is a body of evidence suggesting a channel of shifting economic incentives. Under this theory, a temporary reduction in productivity due to a climate shock lowers the opportunity cost of conflict, thus increasing outcomes such as crime or civil unrest [41]. For example, [42] argue that negative rainfall events increase the risk of civil conflict in Africa via temporarily low agricultural productivity, and [43] hypothesize that drought in Somalia increases local violent conflicts via livestock market effects. Climatic events similar in structure to those that increase conflict risk (hot and dry, or very wet) have been repeatedly shown to also reduce productivity in agriculture [22,29,44–47] as well as nonagricultural incomes [48–52], supporting the possibility of an economic channel.

Further evidence demonstrates that the pattern in which climate affects income is similar to that which drives conflict. For example, in Brazilian municipalities, [22] shows that the nonlinear inverted-U shaped relationship between agricultural income and rainfall almost exactly mirrors the U-shaped relationship between land invasions and rainfall. Similarly, [29] match patterns of conflict and income responses to climate, showing that both correlate with the timing of ENSO only in the tropics and not at higher latitudes. In other examples, studies match the timing of climatic events that affect conflict with the timing of climatic events that are thought to be economically important [27,53,54]. In sum, these findings provide suggestive evidence that an economic productivity channel is likely to be a meaningful pathway between climate and conflict.

A second commonly discussed channel for temperature effects is psychological. Neural structures react to ambient temperature changes in order to regulate internal body temperature [55]. In particular, levels of the neurotransmitter serotonin have been shown to fall as temperature rises. Because serotonin is associated with aggressive behavior, it is hypothesized that serotonin depletion can induce violent acts under heat stress [56,57]. Other neurotransmitters, neuromodulators and hormones, such as testosterone, norepinephrine and cholesterol may also tie temperature to violent behavior, but are understudied [58,59].

Empirical support for this psychological channel is found primarily in studies of interpersonal conflict that exploit climate shocks at time scales too short for an economic pathway to be established. For example, [60] find that domestic violence increases on hot days in the U.S., [61] and [17] report that assaults, rapes, and murders increase during hot weeks and months (respectively) in the U.S., and [15] demonstrate that homicide and suicide in Mexico both respond to higher temperatures with similar patterns that appear unrelated to economic conditions. In an experimental setting, [62] show that Dutch police officers were more likely to use deadly force against threatening opponents during training simulations in hotter weather. Although unable to directly test the psychological mechanism, all of these studies point to the presence of a short-run direct effect of climate on aggressive behavior that is plausibly related to hypothesized roles of neurotransmitters in body temperature regulation.

## 3 Adaptation

These two mechanisms, which likely operate to different degrees in distinct contexts, suggest varied means of adaptation. In cases where an income channel is plausible, such as in developing countries where income is strongly tied to agriculture, sensitivities to temperature could decline over time if countries or regions experience rapid income growth. Conversely, in cases where a psychological channel is more likely, such as in the short-run response of interpersonal violence to temperature, adaptation may take the form of acclimatization. That is, continuous exposure to higher average temperatures may mitigate the neurological stress induced by a heat shock, making populations in hotter climates less responsive (in terms of conflict outcomes) than populations in temperate locations. In this section, we review existing evidence of adaptation, with particular attention to the identification of income effects and acclimatization.

Three basic approaches have been implemented to identify the extent to which populations adapt to climate after repeated exposure. The first strategy, which is fairly common in the literature, is to study whether estimates of coefficients of interest in Eq. (1) vary over time. A second, newer approach studies how populations have responded to longer and slower-moving changes in climate over time. Finally, the third approach contrasts climate response functions across locations with different average characteristics. This latter approach facilitates a distinction between income and acclimatization channels, but is accompanied by the common challenges of conducting causal inference with cross-sectional comparisons, as different responses may be due to many unobservable characteristics that vary across space.

### 3.1 Long-run evolution of short-run sensitivity

A first approach for studying adaptation uses the same high-frequency climate events used in Sect. 2 to study whether climate responses in a given population change over time. For example, [17] estimates the impact of daily climate variation on monthly crimes in U.S. counties separately for 5 different decades, starting in 1960 and ending in 2009. Using these high-frequency data, the author generates a separate causal impact of climate for each of these ten-year periods, and compares coefficients to test for the presence of gradual adaptation that could lower the response severity over time. Because there has been general warming over these 50 years throughout the U.S. [63], a decline in response functions in later decades would suggest adaptation. Ranson finds no evidence of this, as each of the five regressions generate nearly identical results. Similarly, in their study of crime and climate in India, [27] estimate the impact of climate variation separately for three decades over which significant urbanization, economic growth and technological modernization took place in the country. They find that the effect of rainfall shortages on crime is surprisingly stable across time, but that temperature damages for both property and violent crime do fall significantly from $9\%/\sigma$ in the 1970s to $4.2\%/\sigma$ in the 1990s, suggesting adaptation is occurring. Given the divergent findings in these two contexts, more applications of this method to new settings could help determine the extent to which conflict responses can adapt to future climate change.

### 3.2 Examining long-run sensitivity to gradual change

A second strategy enables identification of any type of adaptation that may have occurred in response to somewhat longer-run historical changes in climate. This approach examines how gradual trends in conflict and gradual trends in climate are correlated over time in a given location, and compares this result to a coefficient estimated from a typical higher-frequency panel data model as in Eq. (1). Evidence of adaptation manifests as long-run responses that are less severe than those in the short run: smaller impacts of low-frequency climate shifts suggest adaptation through time. In one of the first uses of this "long difference" method in the climate impacts literature, [64] demonstrate that the effects of climate on agricultural yields in the U.S. over multiple decades are nearly identical to those derived from the short-run model. They therefore conclude that there is little evidence of adaptation in American agriculture.[6]

In the only direct application of this method to conflict outcomes, [7] use pixel-level data on local conflict in East Africa between 1991 and 2009, a setting and dataset first studied by [13]. For each pixel, the authors compute gradual trends in both temperature and conflict by subtracting the 1991–1995 average values from 2005–2009 average values. Local temperature trends range from pixels with no warming at all to pixels with more than 2°C warming, as shown in the left panel of Fig. 4. They then regress, at the pixel level, this gradual change in conflict on the gradual change in climate. The right panel of Fig. 4 compares the point estimate from this long difference approach with the coefficient from a regression of the form in Eq. (1). As was found in [64], the long-run coefficient is indistinguishable from the short-run estimate, suggesting a lack of adaptation across the 20 year period studied. Extending the difference period over which averages are taken to 1991–1999 and 2001–2009 only increases the long-differences estimate, reinforcing the finding of no adaptation.

### 3.3 Identifying potential adaptation pathways

In the third methodology, the potential mediating role of economic and psychological factors are explored more directly, for instance by comparing climate responses across populations with different income levels. Specifically, estimates of $\hat{\beta}$ from a regression of the type shown in Eq. (1) are calculated separately for different spatial units (e.g. a U.S. county) or temporal periods (e.g. a decade). These estimates are then correlated with hypothesized drivers of adaptation, such as income and average temperature, that also vary across spatial units. For example, evidence that violent crime in wealthier counties in the U.S. is less sensitive to temperature than in poorer counties would suggest that income might facilitate adaptation, in so far as crime responds to temperature.

[6] Similarly, [65] use this approach to claim that poor nations continue to suffer negative economic damages from high temperature over long time periods of gradual warming.

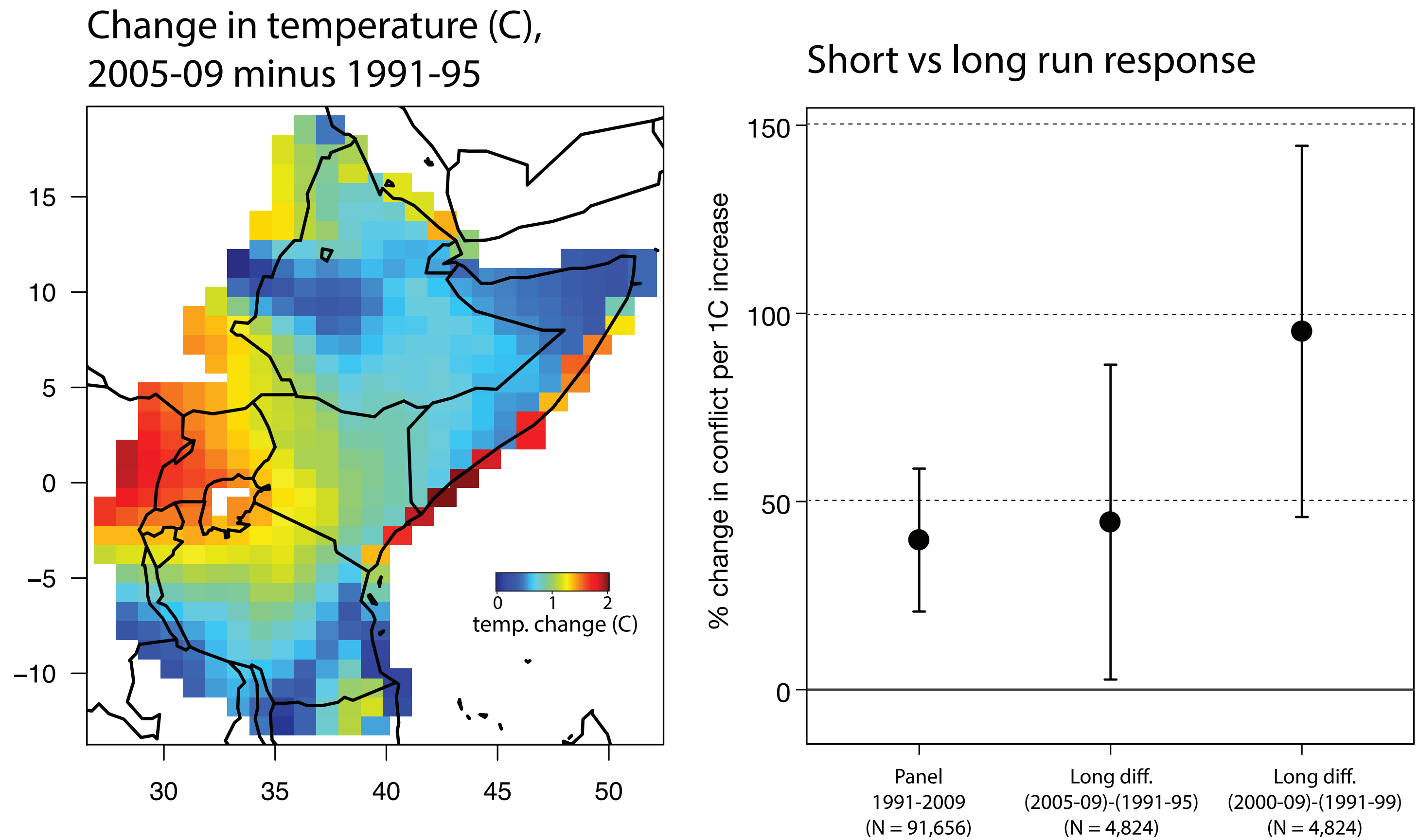


**Fig. 4.** Calculations using data from [13] to demonstrate how adaptation to longer run changes in temperature can be studied. Left panel: multi-decadal change in average temperature (°C) across East Africa. Right panel: comparing panel estimates of how conflict responds to temperature using an annual panel approach (as in Eq. (1)) and using a "long differences" estimate that compares trends in conflict at each location with trends in temperature (from left panel). Results are from a replication of findings in [7].

Nevertheless, there are many confounding factors in this approach that may bias estimates of the causes of adaptation. For example, locations with higher average income may have better police forces, more established rule of law, or may be cooler on average, all factors that could be driving differential climate responses. Cross-sectional regressions generate results that conflate all of these factors with income. This same challenge arises for estimates of acclimatization: similar correlates of average climate and conflict can bias the estimate of adaptation. However, this approach may be informative, albeit should be interpreted cautiously, and has been implemented in various forms throughout the climate impacts literature. In what follows we explore explicitly whether both acclimatization and differential impacts by income are apparent in the data.

### 3.3.1 Acclimatization in cross-section

The underlying idea behind acclimatization is the possibility that if populations have adapted to a particular climate (e.g. the hot and humid tropics), then they may be less vulnerable to short-run climate variability (e.g. a hot summer with extreme rainfall). If such adaptation has occurred in the past, populations inhabiting more adverse climates, all else equal, should exhibit smaller conflict responses to climate shocks than those in more temperate locations. In one example of this approach, [17] tests whether hot days in hotter locations in the U.S. are less influential on crime than hot days in cooler locations. The author divides the U.S. into four climate zones based on long-term mean annual maximum daily temperature, and then estimates a regression of the form in Eq. (1), separately for each zone. His results demonstrate little to no acclimatization: high temperatures have a very similar effect on crime across all climate zones. Similarly, [18] and [66] provide two time series analyses using hourly violent crime data in Minneapolis, MN and Dallas, TX to identify a curvilinear relationship between temperature and aggravated assaults. The authors find a similar nonlinear response function in both the hot location of Dallas, TX as well as the cooler Minneapolis, MN, and show that the relationship is moderated by the time of day identically in both cities. While these findings cannot prove that populations do not adapt to long-term climate conditions since the identifying variation is still high-frequency under this methodology, they do suggest that long term exposure may not always lead to more effective short-term adaptation.

### 3.3.2 Rising income

If adaptation costs are the main impediment to mitigating the impact of climate on conflict outcomes, higher income regions should have lower marginal effects, as agents are able to invest in adaptive measures. As discussed above, much of the literature proposes the presence of an economic channel through which climate variables impact conflict, suggesting that income may be an important means of adaptation. This stands somewhat in contrast to the broader climate impacts literature, which provides mixed evidence that income ameliorates climate damages for a host of non-conflict-related outcomes. For example, [67] find that the Philippines' average typhoon climate depresses incomes by 6.6%, and that this effect is the same for rich and poor households; and [68] show that both rich and poor countries alike suffer nonlinear economic productivity damages as temperatures rise.

Few studies in the conflict literature have directly studied the potential mediating role of income. An exception is [53], who studies whether the rollout of a large governmental workfare program (where civilians were guaranteed employment) ameliorates the role of temperature and precipitation on insurgency violence in India. He finds that monsoon season rainfall significantly increases the risk of conflict and the intensity of existing violence, but that the National Rural Employment Guarantee (NREGA) scheme, a country-wide workfare program that generated 2.76 billion person-days of employment in 2010–2011, completely removes the previously identified impact of rainfall shocks on both the incidence and intensity of insurgency. Similarly, [15] uses the rollout of the governmental cash transfer program *Progresa* in Mexico between 2002 and 2010 to identify the effect of monetary transfers on the temperature-conflict relationship. The authors find evidence that these income transfers can mitigate the effects of temperature on intergroup conflict to some degree, but not the effects on interpersonal violence [15]. Extrapolated to other contexts, these results suggest rising incomes in the future could lessen conflict's sensitivity to temperature, but the magnitude of this across different settings remains unknown.

As a first step in providing broader evidence on whether higher incomes are associated with lower sensitivities to temperature, we study whether results from the 56 studies discussed in Sect. 2 differ meaningfully by income. We use Penn World Tables purchasing power parity adjusted income data to calculate the average income in the mean year of the study period for the location studied in each analysis. In Fig. 5, we plot the standardized effects of each study, $\hat{\beta}_{standardized}$ in Eq. (2), against the log of real average income, along with a linear regression line that is precision-weighted to down-weight observations from studies in which the marginal effect of climate was imprecisely estimated.[7] As expected, the effect of temperature on conflict declines as income rises, suggesting that income may effectively facilitate adaptation. For intergroup conflict, the slope is $-6.12$, suggesting that for a 10% increase in income, the marginal effect of temperature falls by $0.6\%/\sigma$. Given that the intergroup mean effect of temperature is $11.3\%/\sigma$, this suggests a small adaptive effect of income in the cross-section. However, interpersonal conflict reveals a temperature slope of $-2.63$; the marginal effect in this case falls by $0.3\%/\sigma$ from a mean of 2.1 for each 10% gain in income, which is a slightly larger relative effect. In contrast, Fig. 5 shows no evidence supporting the claim that income lowers precipitation sensitivities. In sum, we find evidence that higher income levels may have an ameliorating effect on some temperature-conflict relationships, but that this mediating effect is not apparent in the large number of studies that examine precipitation responses.

### 3.4 Adaptation and projections

Understanding adaptation is crucial for extrapolating estimates of historical climate responses to future time periods, with the accuracy of any projected future impacts depending critically on whether future societies respond similarly to changes in climate as past societies. This in turn depends on the feasibility and costs of adaptation: if available and cost-effective adaptive measures allow populations to alleviate the negative impacts of new climatic conditions, estimated historical sensitivities may overstate future impacts under climate change. While this argument is a common one, it is also possible that future conflict outcomes could respond more severely to climate change than the causal estimates reviewed in Sect. 2 would suggest. This could be

[7] Because the number of studies limits the power of the regression, we include estimated effects from all original author-preferred specifications in this analysis, rather than our own reanalyzed effects. However, the reanalysis regression line is also shown in gray in Fig. 5, and is not significantly different from the model using all author specifications.

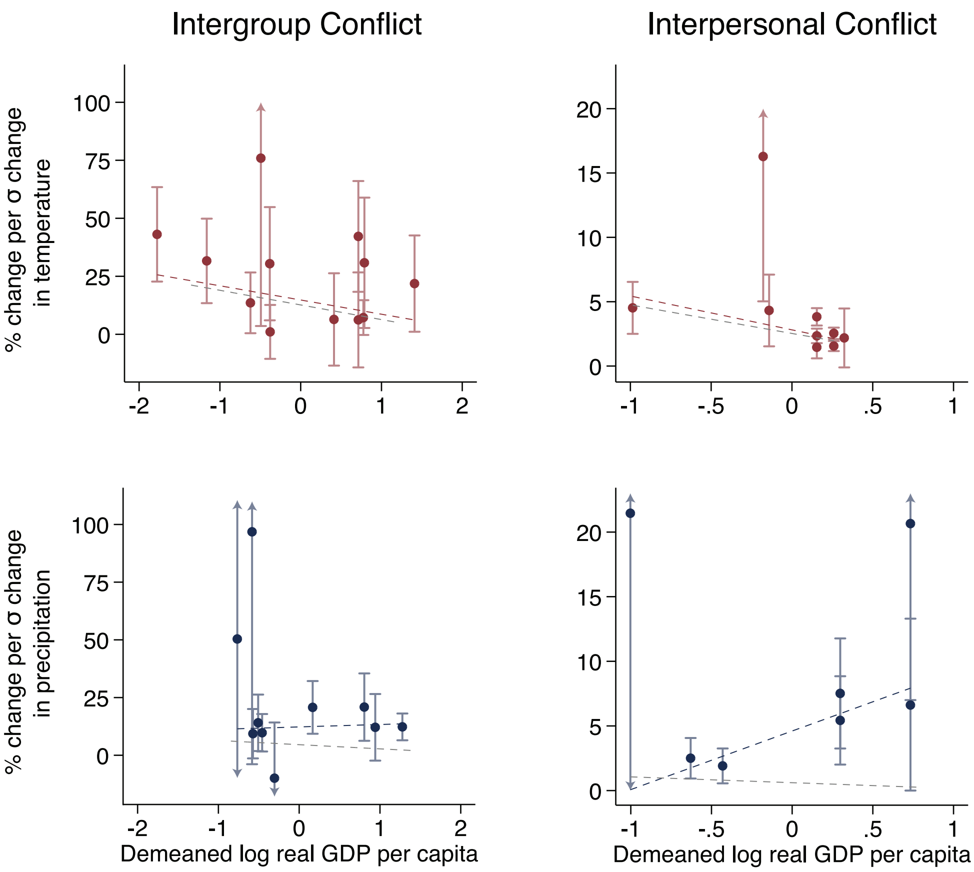


**Fig. 5.** New analysis using standardized effects from the studies reviewed in [7] paired with Penn World Tables real income data from the mean year in each study sample. These figures show the correlation between income and the marginal damage of climate on conflict, for intergroup conflict (left panels) and interpersonal conflict (right panels), temperature (top panels) and precipitation (bottom panels). The colored dashed lines are precision-weighted linear regressions using authors' preferred specifications, gray dashed lines are precision-weighted linear regressions using estimated effects from our standardized reanalysis of the original data.

the case if adaptation strategies employed in response to the high-frequency events studied in the empirical literature are infeasible under a long-run gradual shift in climate. For example, suppose rainfall in a developing country is strongly tied to income via agricultural output, and that income shocks can affect crime rates, as has been argued (e.g. [27,32,42]). A farmer may be able to drill a new well during a drought year to limit crop losses due to rainfall shortages, dampening the effect these losses may potentially have on conflict outcomes. However, this strategy becomes obsolete after repeated rain failure and well drilling exhaust available aquifers, rendering future drought impacts more acute. Due to uncertainty regarding these types of effects, both the degree of potential adaptation and its influence on the magnitude of future relative to past impacts remain highly debated.

In this section we have described the muted evidence of adaptation to climate within the conflict literature, with some studies identifying factors that appear to ameliorate climate's effect on conflict, and others finding little evidence that conflict's response differs meaningfully over space or time. We discuss the projection of future climate impacts in the following section, highlighting the importance of improving our understanding of the likely extent and feasibility of adaptation.

## 4 Projections of conflict under climate change

As shown above, empirical evidence from recent history indicates a robust link between climate variability and a host of conflict outcomes. There have been a variety of attempts to extrapolate these findings forward to predict changes in conflict under anthropogenic climate change, relative to a baseline of stable climatic conditions. In essence, these extrapolations pair an estimate from one of the empirical frameworks described in Sect. 2 with climate model-derived predicted changes in temperature and rainfall over some future time period. This pairing then provides a point estimate (and confidence interval) of changes in conflict caused by the altered climate. For example, [17] uses his findings from a version of Eq. (1) to predict that between 2010 and 2099, climate change will increase the number of murders in the U.S. by 22,000 and the number of aggravated assaults by 1.2 million. Similarly, [14] project an increase of 54% in armed conflict incidence in Africa by 2030, which translates into 393,000 additional battle deaths. As rainfall variability and annual mean temperatures are both predicted to rise under climate change in coming years [63], these positive and potentially large impacts are plausible for a range of conflict outcomes.

All approaches to projections based on historical findings face three key challenges. First, as discussed previously, causal estimates in this literature are derived from high-frequency climate variation, while future climate change is likely to manifest gradually. If slow-moving climate shifts allow societies time to adapt, future impacts could be smaller than those observed in studies of short-run historical variability. However, short-run effects could also be underestimates of longer-run climate impacts if adaptive measures available under one-off events are not feasible when the entire distribution of climate has shifted, as discussed above. Second, even if high-frequency climate variability and long-run climate change have exhibited similar impacts on conflict historically, climate change projections must assume that future societies will respond as have those of the past. It is possible that forces such as economic development, increased globalization, and changes in technology could fundamentally alter vulnerability to climate in ways that cannot be captured using data from the recent or distant past. While the fact that there remain strong impacts in the most developed and wealthiest nations in the world suggests that economic development alone is unlikely to eliminate a climate-conflict relationship, there are no means of accounting for unanticipated technological changes. In the absence of better alternatives, most studies assume commonality in behavior between current and future generations with respect to their climate response. Finally, climate change projections must account for statistical uncertainty arising from sampling variability in the empirical estimates *and* for model uncertainty arising from divergent projections provided by alternative climate models. In this section, we focus on this final challenge and its possible solutions, while also demonstrating the importance of incorporating adaptation directly into projections of the future.

### 4.1 "Back-of-the-envelope" projections

A simple approach to projecting impacts, common in the broader climate literature, is to multiply a causal estimate $\hat{\beta}$ by predicted changes in the climate variable of interest. For concreteness, assume a study estimates the model in Eq. (1), where the climate variable of interest is temperature. The coefficient of interest, $\hat{\beta}$, estimates the marginal change in the conflict rate given a 1°C increase in temperature and has a standard error $\hat{\sigma}_\beta$. Researchers then rely on climate model output to generate a predicted change in temperature $\Delta T$ over some time interval, e.g. between 2000 and 2080. The projected change in conflict due to climate change in this linear model is thus $\hat{\beta}\Delta T$.

Selection of $\Delta T$ from the large body of publicly available climate model output is not trivial, as there are multiple dimensions of uncertainty and thus many possible estimates of climate change values. First, all climate projections are conditional upon an emissions scenario, which depends in turn on assumptions about the future evolution of population, economic growth, and policy. Given a choice of emissions scenario, such as a "business-as-usual" trajectory (roughly represented by "Representative Concentration Pathway" (RCP) 8.5 in the recent Intergovernmental Panel on Climate (IPCC) Fifth Assessment Report (AR5)), there are then multiple climate models that provided projected changes in a range of climate variables. These projections can diverge due to different representations of the physical processes involved in climate change. In AR5 the IPCC gives a range of global mean surface temperature projections for 2081–2100 relative to 1986–2005 of 2.6 °C to 4.8 °C under RCP 8.5 based on an ensemble of over 30 climate models. Importantly, there is no agreed-upon way to rank output from different climate models, with an equal weighting across all models the existing benchmark approach in the climate literature. Nevertheless, much of the social science literature makes climate change predictions using very few of the available climate models, often simply selecting output from one model alone. For example, [69] point out that the best-cited studies that estimate the impact of climate on agricultural yields in the U.S. rely only on output from a single climate model – the Hadley Centre model – likely due to its ease of use. In contrast to this literature, conflict studies have begun to incorporate flexible ways of accounting for the uncertainty that arises both in the regression equation via $\hat{\sigma}_\beta$ and via climate model selection, leading to more realistic predictions of future outcomes. We review this approach and some examples of its implementation in the following section.

### 4.2 Incorporating climate uncertainty

Statistical analyses are often careful to describe uncertainty in estimated parameters that arises from sampling error; however, the climate impact projection $\hat{\beta}\Delta T$ necessarily merges statistical results ($\hat{\beta}$) with climate model results ($\Delta T$), which are themselves uncertain. To date, most studies account either for one or the other forms of uncertainty, but not both, suggesting that published projections are likely less precise than reported. The variance in a projection $\hat{\beta}\Delta T$ is

$$var(\hat{\beta}\Delta T) = E(\Delta T)^2 var(\hat{\beta}) + E(\hat{\beta})^2 var(\Delta T) + var(\hat{\beta}) var(\Delta T) \qquad (5)$$

where we assume climate projections and impact parameter estimates are independent. Most studies from the econometric literature only report the first term while studies from the geophysical literature usually report the second term. Both approaches understate the true uncertainty in these projections.

In a recent paper, a team of climate and social scientists outlined a simple analytical approach to incorporate both regression and climate model uncertainty in projections based on empirical impacts estimates [69]. The authors apply this methodology to seven influential climate impacts papers to demonstrate that in many cases the inclusion of both sources of uncertainty fundamentally alters projected impacts.

The approach combines bootstrapping (to capture regression uncertainty) with the employment of many climate models (to capture climate uncertainty). The first step is to bootstrap the main specification of a given study, sampling a large number of times (e.g. 1000 or more) with replacement. Then for each of 18 publicly available and commonly used climate models, each bootstrapped estimate is extrapolated to the future using the model's estimated change in the climate variable of interest. For example, let $\hat{\beta}_{ij}$ be the estimated coefficient for a climate variable in study $j$ and for bootstrap replication $i \in \{1, ...1000\}$. In a linear regression like Eq. (1), for model $m \in \{1, ..., 18\}$, the estimated future impact would be $\hat{\beta}_{ij}\Delta T_m$. Thus, with 1000 bootstrap draws, there would be 18,000 projected impacts for each study $j$. Finally, confidence intervals can be created by taking the 2.5th and 97.5th percentiles in the distribution of $\hat{\beta}_{ij}\Delta T_m$'s across all models to generate the range of values containing 95% of projected estimates. This method produces (weakly) wider confidence intervals on projected future impacts because it captures two key sources of uncertainty rather than just the one that is usually reported.

Increasingly, the approach established by [69] has been used in the conflict literature both for interpersonal and intergroup conflicts. In one of the earliest implementations of this method, [14] estimate the impact of current and lagged temperature on the incidence of civil war in Africa using data on conflict events between 1981 and 2002 across the continent. With 10,000 bootstrap runs of their regression model and 18 climate models projecting climate under the A1B "business-as-usual" scenario,[8] the authors generate likely ranges of impacts due to changes in average climate between 1980–1999 and 2020–2030. Their results are reproduced in Fig. 6. The authors estimate that in combination, temperature and precipitation changes by 2030 will cause a 54% increase in civil war incidence. However, this point estimate has a 6.2–119.4% confidence interval when both regression and model uncertainty are accounted for. Similarly, [17] estimates the impact of climate change on rates of criminal activity in the U.S. using county-level data for the years 1980 to 2009. With 1,000 bootstrap runs and 15 climate models, he generates ranges for the estimated number of additional crimes due to climate change (temperature and precipitation) between 2010 and 2099. He finds that total crimes are predicted to increase by 3.7–12.5 million, with heterogeneity across crime types. Murders increase by 12,000–33,000, aggravated assaults by 1.2–3.5 million, and robbery by 4,000–500,000. These ranges capture both varying degrees of uncertainty in the empirical estimate of climate on a given crime type, as well as the uncertainty in temperature and precipitation projections through the 21st century.

[70] build on the approach in [69] by weighting each climate model $m$ using a probability weight $w_m$, where weights are constructed so that the ensemble of weighted models reconstructs a best estimate for the probability distribution of the global climate sensitivity. This is a potentially important adjustment because the distribution of climate sensitivities in existing global climate models does not reflect the distribution that is estimated using other techniques (e.g. lower dimensional energy balance models) that are more tightly constrained by data. In particular, the raw distribution of temperature changes from climate models are "conservative" in the sense that the tail of the distribution is underrepresented. To correct for this, higher weights are assigned to climate models with global climate sensitivities in the tail of the distribution. The weight assigned to each model can be thought of as the probability that the

[8] A1B was the IPCC's Fourth Assessment Report's precedent to RCP 8.5 in the most recent report.

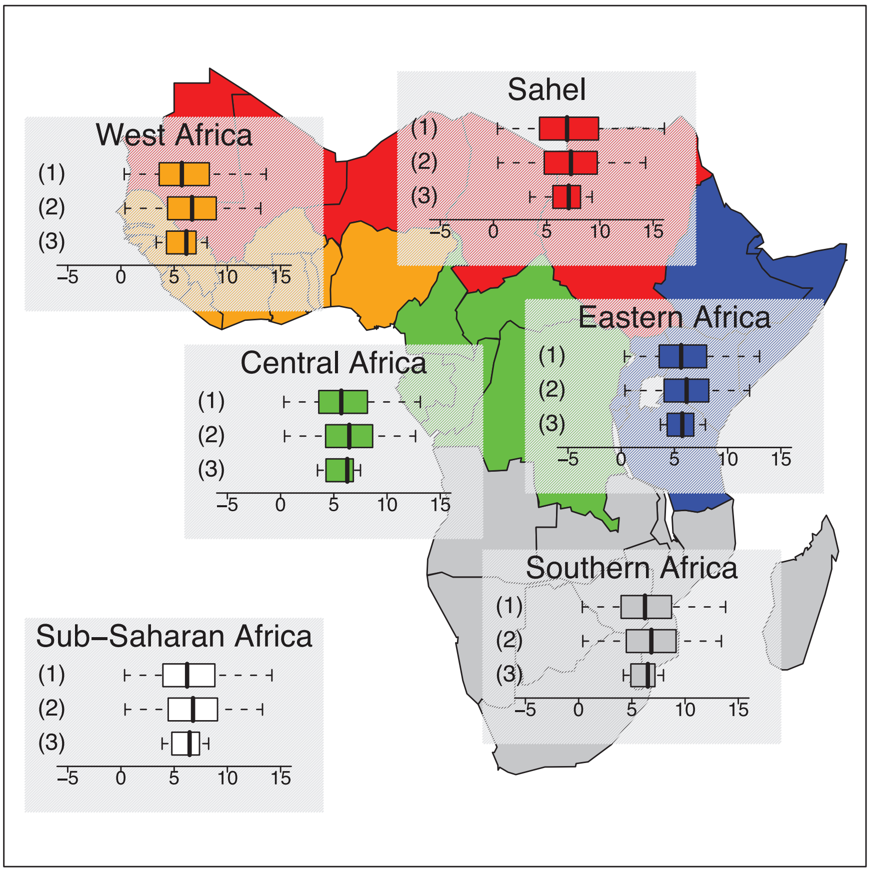


**Fig. 6.** Projected percentage point change in civil war for African regions and the continent as a whole by 2030, from [14]. Results are a combination of 18 climate model projections running the A1B scenario, and 10,000 bootstrap estimates of the historical relationship between climate and civil war in Africa. For each region, boxplot 1 represents projections including uncertainty in both climate model projections and in conflict response to climate, boxplot 2 represents uncertainty only in conflict response to climate, and boxplot 3 represents uncertainty only in climate projections. Dark vertical lines represent median projection, colored boxes the interquartile range, and whiskers the 5th–95th percentile of projections.

model represents what will actually occur in the future (the original approach in [69] assumes each model is equally likely) and thus the corrected probabilistic distribution of projections is the distribution of $\hat{\beta}_{ij}\Delta T_m$ weighted by $w_m$. This approach brings the distribution of projected conflict outcomes into alignment with the distribution of global climate sensitivities estimated by climate modelers.

### 4.3 Considering adaptation

These methods of projection have not yet been combined with estimates of expected adaptation. That is, while Sect. 3 discussed the potential ameliorating effect of income on the climate-conflict relationship, studies projecting future impacts do not account for the mitigating influence of income growth over time. To quantitatively explore the magnitude of this adaptive mechanism, we use results shown in Fig. 5 and a simple back-of-the-envelope climate projection to provide suggestive evidence of the adaptive potential of economic growth for future conflict outcomes. Recall that for intergroup and interpersonal conflicts, respectively, we estimate that a 10% increase in average income lowers the marginal effect of temperature on conflict by $0.6\%/\sigma$ and $0.3\%/\sigma$, using empirical studies reviewed in [7]. If we make the admittedly strong assumption that this association is causal, how might this result translate into future projected impacts? As the climate warms in coming decades, it may amplify baseline conflict rates, but as incomes rise over these same years, these effects may be attenuated. A projection that accounts for such adaptation must compare the magnitude of the direct climate effect ($14.78\%/\sigma$ on average across the intergroup studies with authors' original specifications, and $2.81\%/\sigma$ for interpersonal studies) with the adaptive impact of rising incomes.

We conduct this simple exercise and discuss our results for two example countries. First, consider Tanzania, a country with expected warming of $3\sigma$ by 2050, as calculated using an ensemble mean for 21 climate models running a "business-as-usual" emissions scenario [6]. Ignoring the adaptive effect of income, a simple projection of conflict impacts due to climate change by 2050 is a $3\sigma \times 14.78\%/\sigma = 44.3\%$ increase in the relative risk of intergroup conflict and a $3\sigma \times 2.81\%/\sigma = 8.43\%$ increase for interpersonal conflict. However, Tanzania's economy has been growing at an annual rate of 5.1% on average since 1989, the first year for which the World Bank provides data. If we assume this trend were to continue to 2050, national income will have grown by a factor of 4. Combining the impact of climate change with our estimated income adaptation effect and this income growth, the increase in relative risk is reduced to $11.4\%/\sigma$ for intergroup and to zero for interpersonal conflict, clearly an important adjustment. Now consider a slower growing country, The Netherlands, where annual economic growth has averaged 2.1% since 1989 and projected warming is $2\sigma$. Direct climate change damages induce a 29.6% increase in the relative risk of intergroup conflict and a 5.6% increase in interpersonal conflict by 2050. These impacts fall to 20.1% and 1.8% when we extrapolate historical income growth and adjust $\hat{\beta}$ using this approach.

These figures are a cursory estimate using a simple projection approach for climate and a basic cross-sectional linear regression to capture adaptation. They should thus not be interpreted literally, especially because the cross-sectional association between $\hat{\beta}$ and income in Fig. 5 might not be a causal relationship. Nonetheless, this thought experiment is useful because it illustrates the potentially important effect that adaptation might have on projections of conflict risk imposed by climate change. Future work should focus on identifying a causal effect of income growth on $\beta$ so that these adjustments to projections can be applied with greater confidence.

## 5 Conclusion

Findings from quantitative research in economics, political science and other social science disciplines employing modern econometric techniques and data from recent history indicate a robust link between climatological factors and a range of conflict outcomes in diverse settings throughout the world. While there are important differences in this relationship based on the population and scale of analysis, meta-analysis results indicate strong evidence of a shared underlying process tying climate to conflict across many distinct contexts.

Existing empirical evidence of climate's impact on conflict can be paired with climate model output to generate projections of the impact future climate change may have on conflicts ranging from violent crime to civil war. However, there are large degrees of uncertainty in such projections, arising from *(i)* the statistical uncertainty involved in regression analysis, *(ii)* divergent climate model predictions, and *(iii)* the unknown ability of human societies to adapt to future climate change. New methods can be used to provide projections that capture the first two sources of uncertainty; while these approaches generate more accurate assessments of the state of scientific knowledge, they tend to generate large confidence intervals for most conflict outcomes. Policy design should account for this higher level of uncertainty.

Addressing *(iii)* is a current major challenge in the literature, and a promising area for future research. All projections of future impacts based on empirical estimates from historical datasets rely on an important set of assumptions regarding the similarities between past, current and future societies. These assumptions manifest in the extent to which future populations can and will adapt, thus mitigating climate damages that we have observed in the past and present. Theoretically, human populations may be able to use adaptive strategies to break the pathways linking climate variability and conflict. However, evidence of adaptation is weak within the conflict literature and few studies have directly addressed the issue. Among existing analyses, there appears to be no amelioration of the sensitivities over time, although there is some evidence of reduced sensitivities for populations with higher incomes – but it is not known if this association is causal. Similarly there is little evidence for acclimatization, as locations with more adverse average climates do not exhibit less vulnerability to short-run climate shocks. More research in this area is clearly needed, yet as the literature currently stands, limited evidence of adaptation suggests that the significant impact of past climate variability on both interpersonal and intergroup conflict is likely to persist in the future, with climate change over the 21st century amplifying existing patterns of conflict.

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