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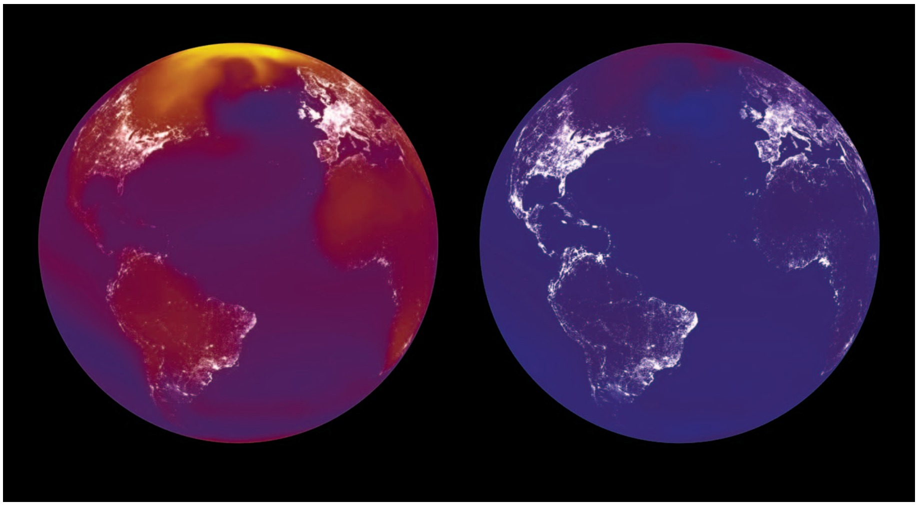
REVIEW SUMMARY

SOCIAL SCIENCES

Social and economic impacts of climate

Tamma A. Carleton* and Solomon M. Hsiang*†

BACKGROUND: For centuries, thinkers have considered whether and how climatic conditions influence the nature of societies and the performance of economies. A multidisciplinary renaissance of quantitative empirical research has begun to illuminate key linkages in the coupling of these complex natural and human systems, uncovering notable effects of climate on health, agriculture, economics, conflict, migration, and demographics.



Two globes depict two possible futures for how the climate might change and how those changes are likely to affect humanity, based on recent empirical findings. Base colors are temperature change under "Business as usual" (left, RCP 8.5) and "stringent emissions mitigation" (right, RCP 2.6). Overlaid are composite satellite images of nighttime lights with rescaled intensity reflecting changes in economic productivity in each climate scenario.

ADVANCES: Past scholars of climate-society interactions were limited to theorizing on the basis of anecdotal evidence; advances in computing, data availability, and study design now allow researchers to draw generalizable causal inferences tying climatic events to social outcomes. This endeavor has demonstrated that a range of climate factors have substantial influence on societies and economies, both past and present, with important implications for the future.

Temperature, in particular, exerts remarkable influence over human systems at many social scales; heat induces mortality, has lasting impact on fetuses and infants, and incites aggression and violence while lowering human productivity. High temperatures also damage crops, inflate electricity demand, and may trigger population movements within and across national borders. Tropical cyclones cause mortality, damage assets, and reduce economic output for long periods. Precipitation extremes harm economies and populations predominately in agriculturally dependent settings. These effects are often quantitatively substantial; for example, we compute that temperature depresses current U.S. maize yields roughly 48%, warming trends since 1980 elevated conflict risk in Africa by 11%, and future warming may slow global economic growth rates by 0.28 percentage points year^{-1}.

Much research aims to forecast impacts of future climate change, but we point out that society may also benefit from attending to ongoing impacts of climate in the present, because current climatic conditions impose economic and social burdens on populations today that rival in magnitude the projected end-of-century impacts of climate change. For instance, we calculate that current temperature climatologies slow global economic growth roughly 0.25 percentage points year^{-1}, comparable to the additional slowing of 0.28 percentage points year^{-1} projected from future warming.

Both current and future losses can theoretically be avoided if populations adapt to fully insulate themselves from the climate—why this has not already occurred everywhere remains a critical open question. For example, clear patterns of adaptation in health impacts and in response to tropical cyclones contrast strongly with limited adaptation in agricultural and macroeconomic responses to temperature. Although some theories suggest these various levels of adaptation ought to be economically optimal, in the sense that costs of additional adaptive actions should exactly balance the benefits of avoided climate-related losses, there is no evidence that allows us to determine how closely observed "adaptation gaps" reflect optimal investments or constrained suboptimal adaptation that should be addressed through policy.

OUTLOOK: Recent findings provide insight into the historical evolution of the global economy; they should inform how we respond to modern climatic conditions, and they can guide how we understand the consequences of future climate changes. Although climate is clearly not the only factor that affects social and economic outcomes, new quantitative measurements reveal that it is a major factor, often with first-order consequences. Research over the coming decade will seek to understand the numerous mechanisms that drive these effects, with the hope that policy may interfere with the most damaging pathways of influence.

Both current and future generations will benefit from near-term investigations. "Cracking the code" on when, where, and why adaptation is or is not successful will generate major social benefits today and in the future. In addition, calculations used to design global climate change policies require as input "damage functions" that describe how social and economic losses accrue under different climatic conditions, essential elements that now can (and should) be calibrated to real-world relationships. Designing effective, efficient, and fair policies to manage anthropogenic climate change requires that we possess a quantitative grasp of how different investments today may affect economic and social possibilities in the future. ■

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REVIEW

SOCIAL SCIENCES

Social and economic impacts of climate

Tamma A. Carleton[1,2]* and Solomon M. Hsiang[2,3]*†

For centuries, thinkers have considered whether and how climatic conditions—such as temperature, rainfall, and violent storms—influence the nature of societies and the performance of economies. A multidisciplinary renaissance of quantitative empirical research is illuminating important linkages in the coupled climate-human system. We highlight key methodological innovations and results describing effects of climate on health, economics, conflict, migration, and demographics. Because of persistent "adaptation gaps," current climate conditions continue to play a substantial role in shaping modern society, and future climate changes will likely have additional impact. For example, we compute that temperature depresses current U.S. maize yields by ~48%, warming since 1980 elevated conflict risk in Africa by ~11%, and future warming may slow global economic growth rates by ~0.28 percentage points per year. In general, we estimate that the economic and social burden of current climates tends to be comparable in magnitude to the additional projected impact caused by future anthropogenic climate changes. Overall, findings from this literature point to climate as an important influence on the historical evolution of the global economy, they should inform how we respond to modern climatic conditions, and they can guide how we predict the consequences of future climate changes.

Does climate affect our society? Or do human willpower and ingenuity render climate largely irrelevant to our affairs, as we overcome environmental challenges with resilience and innovation? If climate affects our lives, how much does it matter and why? Thinkers have asked these questions for generations, wondering whether climatic differences between regions could be partially responsible for differences in politics, economies, and culture, and whether large-scale social transformations, such as the rise of golden ages and the fall of empires, could be triggered by climatic changes. Over the last decade, an innovative community of researchers has taken a rigorous quantitative approach to these questions—mixing data and methods from the climate, social, and statistical sciences—making unprecedented and exciting progress. In this article, we review recent advances, findings, and open questions in this emerging interdisciplinary field.

Our focus is recent progress, but consideration of the social impact of climate is as old as the academy. Aristotle developed a climate classification system in which the tropics were described as an uninhabitable "torrid zone" (*1*), and Montesquieu argued that climate played a fundamental causal role in determining the structure and prosperity of different societies (*2*). In the late 19th century, theories on the impact of climate and other geographical factors led to a collection of ideas known as "environmental determinism," the notion that environmental conditions played the primary role in shaping social, economic and political outcomes, with little scope for leadership, innovation, institutions, or social will to alter societal trajectories. Some of these hypotheses were invoked to justify European colonialism as responsible paternalism—colonial advocates argued that climatically caused "morally inferior" character traits could be remedied through oversight by "advanced" societies that had already matured in more conducive climes (*3*).

The association of environmental determinism with colonial ambition had a chilling effect on this line of research in much of the social sciences during the late 20th century. Nonetheless, research continued among engineers and ergonomists interested in optimizing military and industrial performance using laboratory experiments to test the effects of environmental conditions on human performance (*4*, *5*).

Beginning in the 1970s, concern over booming populations led to a blossoming of theoretical work in resource economics. A key realization was that environmental conditions might influence economic performance and could be modeled as "natural capital," analogous to physical capital (e.g., machines) or human capital (e.g., education), and could be similarly developed or degraded (*6*).

At the turn of the 21st century, this economic approach, supported by advances in computing, led to the development of theoretical-numerical "integrated assessment models" that provide insights into how the global climate might be managed to maximize future "global welfare" under different assumptions (*7*–*9*). At the core of these models are theoretical "damage functions" that describe how global mean temperature translates into economic and social costs (*10*). Because these models are now used to design global policies (*11*, *12*), much of the current empirical research summarized here is framed as providing an empirical basis for global climate policy calculations (*13*, *14*).

A research agenda running parallel to climate change policy design is aimed at understanding how current climatic events, such as droughts or tropical cyclones, shape social outcomes today, irrespective of possible future climatic changes. This strand of work aims to minimize current social costs of climate events and promote economic development (*15*, *16*), either by identifying cost-effective risk-management strategies or minimizing harm through reactive instruments or policies, such as weather index insurance (*17*). As with climate change management, success in this arena depends critically on our quantitative understanding of the causal effect that climatic conditions have on populations.

Quantifying climatic influence on societies and economies

Recent advances in empirically measuring the effect of climate on society have been rapid, catalyzed by growth in computing power, access to data, and advances in the statistical theory of causal inference for non-experimental studies (*18*). Progress has been particularly explosive over the last decade, with exponential growth in publication volume due to innovations specific to studying the climate-human system, such as new methods to map climatic data onto social data and the development of spatiotemporal statistical models. For an in-depth treatment of the following techniques and innovations, we refer readers to reference (*19*).

Breaking down the problem

Climate is the joint probability distribution over several weather parameters, such as temperature or wind speed, that can be expected to occur at a given location during a specific interval of time (Fig. 1, A and B). To understand how alterations in this distribution affect populations, modern approaches separate the influence of climate into two pathways: through information regarding what environmental conditions might occur and through directly altering what actually happens (*19*). The "informational" pathway operates because individuals' expectations about their climate (Fig. 1A) may change how they act; for example, individuals who believe they live in a rainy climate may purchase umbrellas. The "direct" pathway operates because any change in the probability distribution of weather events must generate a change in the distribution of events that individuals actually experience (Fig. 1B); for example, individuals who live in a rainy climate will face rain more often. Informational effects result from individuals preparing for a distribution of weather events and corresponding

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direct effects that they expect. These adaptations may alter the overall direct effect of specific weather events (Fig. 1C)—for example, individuals who own umbrellas may use them to stay drier when an actual rainstorm occurs—a distinction that can be accounted for when examining these relationships empirically.

Figure 1 depicts these two ways that climate and social outcomes are linked. Weather events (Fig. 1B) are drawn from the probability distribution that defines the climate (Fig. 1A). Each event generates some direct effect on a population, where these direct effects can be described by a dose-response function $f(X)$ where specific "doses" of a weather parameter X (e.g., rain) generate "responses" within the population (e.g., getting wet; see arrow from Fig. 1, B to D). This sequence of direct effects combine with nonclimatic influences on the social outcome to produce the distribution of observed social data (Fig. 1 D and E). If the climate shifts (pink in Fig. 1A), this will alter the distribution of weather (Fig. 1B) and its corresponding social impacts. A direct effect (e.g., experiencing more rainfall) occurs, but the information effect (e.g., buying umbrellas) may also cause populations to adapt such that the structure of the dose-response function changes (Fig. 1C), leading to a shift in the distribution of outcomes that is a combination and interaction of these two effects (Fig. 1E). The core of the empirical challenge is to credibly reconstruct the dose-response function for pairings of weather variables and social outcomes, while simultaneously accounting for the possibility that adaptations alter this relationship.

Mapping climate data onto societies and economies

The first step in analysis is to collapse large quantities of high-dimensional climate data into measures that efficiently summarize the dimensions of climate that are influential on specific aspects of populations. This procedure is challenging because most weather data are collected by physical scientists with the goal of answering physical science questions, so existing structures used to organize these spatially and temporally varying data do not map directly onto social systems. Often, devising a suitable approach for "translating" physical data into a socially meaningful measure X is the critical innovation that allows researchers to study an entire class of phenomena (*19*). For example, the construction of data describing extreme heat-hours, measured in units of "degree days" and properly aggregated across space, led to strikingly consistent measurement of the effect of temperature on crop yields (*20*–*23*) and electricity demand (*24*, *25*). In another example, tropical cyclone track data were converted into surface wind-exposure of populations to understand the human and economic damage of these storms (*26*). In other work, researchers gain insight from developing new measures of human exposure to the El Niño–Southern Oscillation (ENSO) (*27*), drought indices (*28*–*30*), daily temperature distributions (*31*, *32*), rainfall variability (*33*), crop exposure to vapor pressure deficients (*34*), and trade or neighbor network exposure to multiple variables (*35*–*37*).

Using research design to identify causal effects

Once societally relevant measures of climate exposure X are constructed, measuring the causal effect of a weather event on a societal outcome requires that we compare what actually occurred to a counterfactual outcome that would have occurred had the weather been different (*18*, *19*). For example, simply observing that 10 individuals are admitted to a hospital on a hot day does not imply all 10 admissions were caused by the heat; it might be the case that nine of those individuals would have gone to the hospital anyway, regardless of the temperature.

In an ideal experiment designed to measure the effect of climate on a social outcome, we would take two populations that are identical in every way and expose one to a "control" climate while exposing the other to a "treatment" climate. The control population serves as the counterfactual for the treatment population, and the difference in outcomes would be the effect of the climate treatment. In general, this experiment is infeasible, forcing researchers to rely on "natural experiments" or quasi-experiments.

Early researchers, stretching back to Montesquieu, tried to approximate this ideal experiment, implementing cross-sectional analyses in which different populations inhabiting different climates are compared to one another and their differences are attributed to their climates. For example, a researcher might observe that Nigeria has higher crime rates and is hotter than Norway, concluding that higher temperatures lead to crime. This comparison and conclusion are flawed as there are numerous dimensions along which Norway and Nigeria differ—such as geography, history, culture, politics, social institutions—which make Nigeria an unsuitable "treatment" comparison for a Norwegian "control." Some researchers have tried to adjust their analyses to account for important factors known to influence their outcome

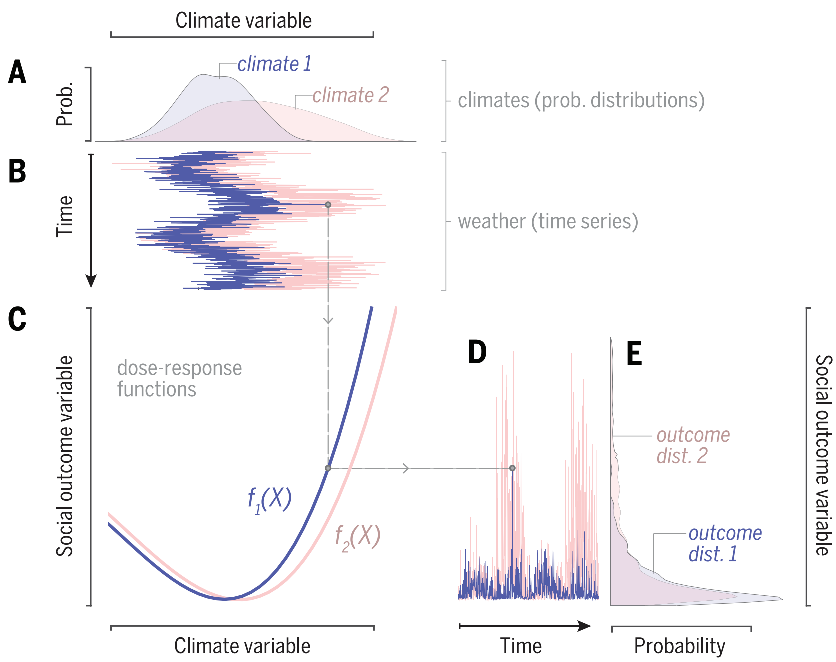

Fig. 1. Breaking down the influence of climate into analytical components. Climate affects the distribution of social outcomes by altering the distribution of weather events and how populations prepare and respond to these events. (**A**) Climate is defined as a probability distribution over weather events, such as the distribution *climate 1* (blue) characterizing the probability of the event *climate variable* = X, e.g., the likelihood of a rainy day. *climate 2* (pink) characterizes a climate distribution that is shifted to the right and more variable. (**B**) Weather events over time are realized from each climate, experienced by individuals on the ground, and observed as time series. (**C**) Statistical analysis recovers "dose-response" functions $f(X)$ that describe social outcomes as a response to each weather "dosage." If populations adapt to their climates (*climate 1* and *climate 2*), then they may respond differently to physically similar weather events, producing dose-response functions that differ [blue = $f_1(X)$, pink = $f_2(X)$]—e.g., if individuals in rainy climates own umbrellas, they may get less wet than populations in normally dry climes (who own few umbrellas) when both populations experience a day with *rainfall* = X. (**D**) Mapping a sequence of weather events through dose-response functions (gray dashed line) generates time series of social outcomes attributable to climatological conditions, accounting both for different distributions of weather events and corresponding adaptations. Signals in an outcome resulting from political, economic, cultural, and other drivers of outcomes might be superimposed on these time series (not shown). (**E**) Different distributions of expected social outcomes can then be attributable to the two climates (*outcome distribution 1* and *outcome distribution 2*), e.g., how much individuals in each climate were soaked by rain over the course of a year.

of interest, but for many complex social outcomes, such as economic growth or civil conflict, it is impossible to know if all relevant factors have been accounted for, and thus unknowable whether a result is plausibly causal.

Recent work recognizes this weakness of cross-sectional analysis and does not compare different populations to one another. Instead, it leverages the insight that the most comparable group for a certain population is itself, at a moment earlier or later in time. Thus, these longitudinal studies follow individual populations over time and examine how they respond to changes in the climatic conditions that they face. When using this approach, researchers have confidence that fundamental factors that influence societies, such as geography and political institutions, are "held fixed" because the population is not changing. In essence, a population just before an event serves as the "control" for that same population right after the event "treatment." Comparing outcomes before and after the climatic event, while accounting for secular trends, provides insight into its effect.

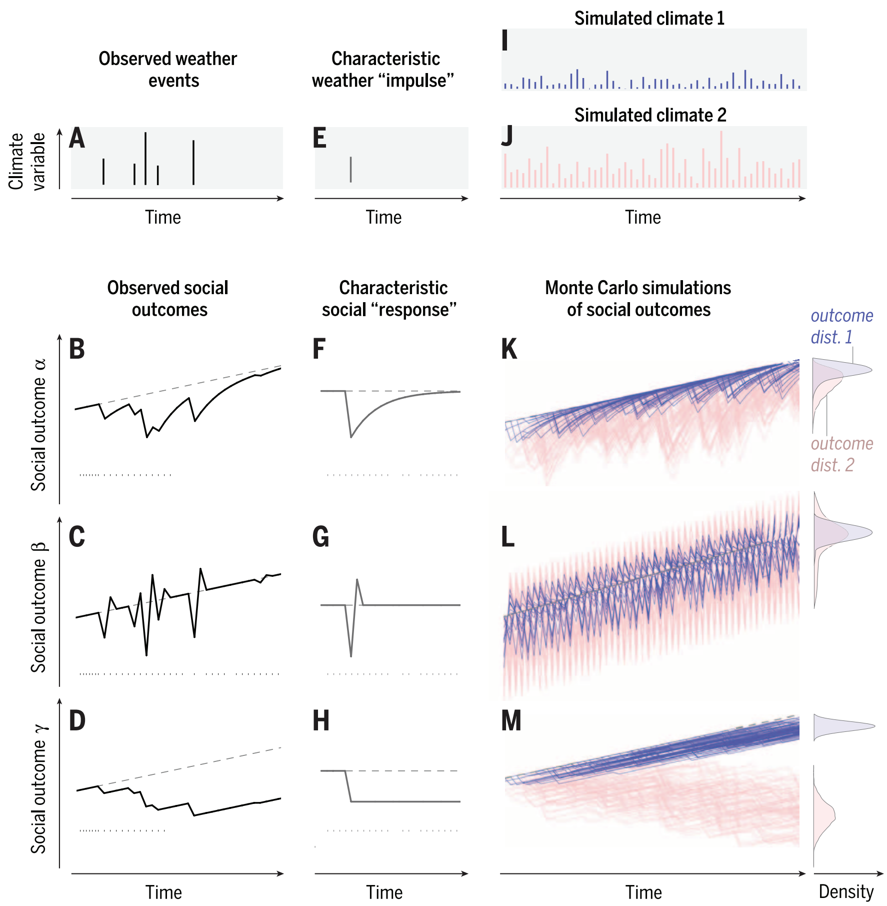

Fig. 2. The dynamics of societal responses to climate determine how alterations to a climate influence social outcomes. Modern approaches "hold nonclimatic factors fixed" by studying a single population over time and identifying social responses to sequential climatic events. Because societal responses may persist (or reverse) after a climatic event ends, continuing through another event that generates another overlapping response, a characteristic impulse-response function can only be recovered from the original data by deconvolution. (**A**) Time series of a single population's exposure to weather events each period of magnitude *X*, indicated as the height of bars (analogous to Fig. 1B). (**B** to **D**) Example time series of three different social outcomes (solid line) that vary relative to baseline trends (dashed line) in response to weather events in (A). (**E**) A characteristic single weather "impulse" of normalized magnitude. (**F** to **H**) Characteristic impulse-response functions describing how each social outcome responds to the weather impulse in (E), recovered from deconvolving data in (A) to (D). Impulse-responses illustrate different classes of behavior: (F) persistent but decaying effects (e.g., cold-related mortality; see Fig. 4A); (G) "temporal displacement" or "harvesting," where delayed responses partially compensate for initial responses (e.g., heat effect on births; see Fig. 4C); and (H) permanent effects (e.g., cyclone effects on GDP; see Fig. 4D). (**I** and **J**) Simulations of weather drawn from two distinct climate distributions. (**K** to **M**) Monte-Carlo simulations of social outcomes based on sampling weather from climate distribution 1 [blue, from (I)] and climate distribution 2 [pink, from (J)] and convolving these impulses with the characteristic impulse-response of of each social outcome from (F) to (H). Distributions of social outcomes under each simulated climate are shown to the right of each panel (analogous to Fig. 1E).

In practice, this approach is complicated by the multiplicity of states that exist for weather and climate, and because societies experience constant variation in both (as suggested by Fig. 1), it is sometimes difficult to determine if an observed social outcome is the result of current conditions or of climatic events in the past. This challenge is solved by deconvolution of the outcome as a series of responses to continuous climatic conditions. Having observed time series of climatic events or "impulses" (Fig. 2A) and resulting outcomes (Fig. 2, B to D), one can search for the characteristic impulse-response function that best fits how a single climatic event of unit "dosage" (Fig. 2E) generates a response in the outcome (formally, the impulse-response function describes intertemporal structure of the dose-response function). Figure 2, F to H, displays the characteristic responses that would have been recovered from the different types of outcome data in Fig. 2, B to D (these simulated responses have been constructed to illustrate three types of real behavior recovered by previous studies).

Considering the different structures of these responses is important for understanding the response of social systems to different types of climatic factors. For example, it has been shown that extreme heat reduces the number of children born exactly 9 months later but elevates births 11 to 13 months later, as some of the successful conceptions that would have occurred during the hot period, but did not, end up occurring in the near future (*38*). In these cases, where climatic events simply displace the timing of societal outcomes (a pattern illustrated in Fig. 2G), changes in the distribution of climatic events may have a smaller net effect than one would predict if this dynamic response were not accounted for. Although we do not illustrate it here, it is worth noting that different locations in the dose-response function (Fig. 1C) may have different dynamics over time (Fig. 2)—for example, cold days cause delayed excess mortality by causing individuals to become ill (analogous to Fig. 2F), whereas hot days generate essentially all excess mortality immediately (*39*).

Using statistical results to translate climate into outcomes

Once the full structure of a dose-response function, along with its dynamic properties, is identified for a specific population across different weather and climate conditions, researchers can simulate how a population might respond to distributions of weather events that differ slightly from historically experienced distributions (Fig. 2, I and J)—with repeated simulations enabling probabilistic assessment (Fig. 2, K to M). Gradually distorting the climatological distribution of weather events in such calculations, while adjusting response functions to account for measured patterns of adaptation, allows us to estimate how a shift in the climate may translate into a shift in the distribution of expected social outcomes (*19*).

Effects of climate on societies

Recent application of the tools described above demonstrate that societies are influenced by the climate in numerous dimensions and at many scales. Individuals face conditions that compromise personal health, while entire trade networks or countries can be weakened under adverse climate variation. The linkages between individuals within societal groups can themselves even be fractured by climatic conditions, triggering violence or migrant flows, for example. We review major findings at all these scales, examining effects on human health, economic conditions, social interactions (including violence), and demographic responses (including migration).

Health impacts: Mortality

As individuals, each of us is constantly exposed to temperature, and under extreme heat or cold, our bodies struggle to successfully thermoregulate, sometimes leading to severe cardiovascular, respiratory, and cerebrovascular effects that can result in death (*40*, *41*). Both hot and cold environmental temperatures increase death rates (Fig. 3, A and B): In Delhi, deaths increase by 3.2% per °C above 20°C (*42*), and in the United States, days above 90°F (32.2°C) and below 20°F (−6.7°C) increase male mortality rates by 2 and 1.4%, respectively (*39*). Effects of high temperature are rapid and acute but decay quickly, sometimes depressing mortality in following days, as some of the same individuals would have died in subsequent days had an extreme heat event not occurred (*39*) (red line in Fig. 4A).

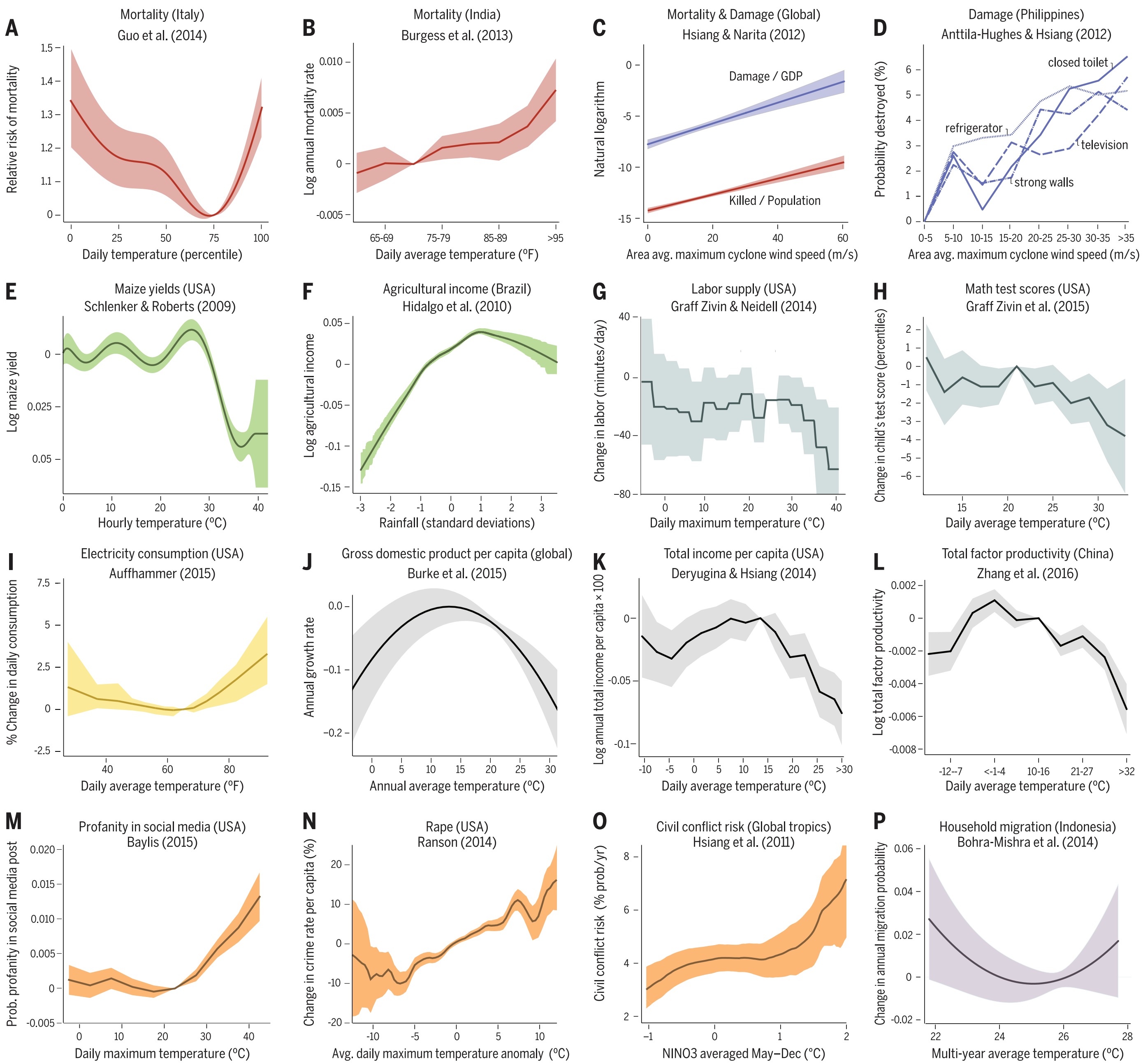

Fig. 3. Empirical studies demonstrate that climate variables influence social and economic outcomes in many sectors and contexts. (**A** to **P**) Examples of dose-response functions estimating the causal effect of climatological events on various social outcomes. Reproduced from authors' original estimation; titles list the outcome variable and location studied. Colors indicate categories of outcome variables: red, mortality (*44*, *46*); blue, cyclone damage to assets (*48*, *116*); green, agriculture (*21*, *153*); teal, labor productivity (*96*, *97*); yellow, electricity (*25*); gray, aggregate economic indicators (*32*, *100*, *125*); orange, aggression, violence, and conflict (*27*, *130*, *134*, *136*); purple, migration (*171*). Climate variables differ by study but include temperature, cyclone wind speed, rainfall anomalies, and ENSO measures. Response functions only identify relative changes and are either normalized to "zero effect" at a designated climatic event, such as a minimum valued outcome, or the sample mean of an outcome. Shaded areas are confidence intervals, as computed by original authors.

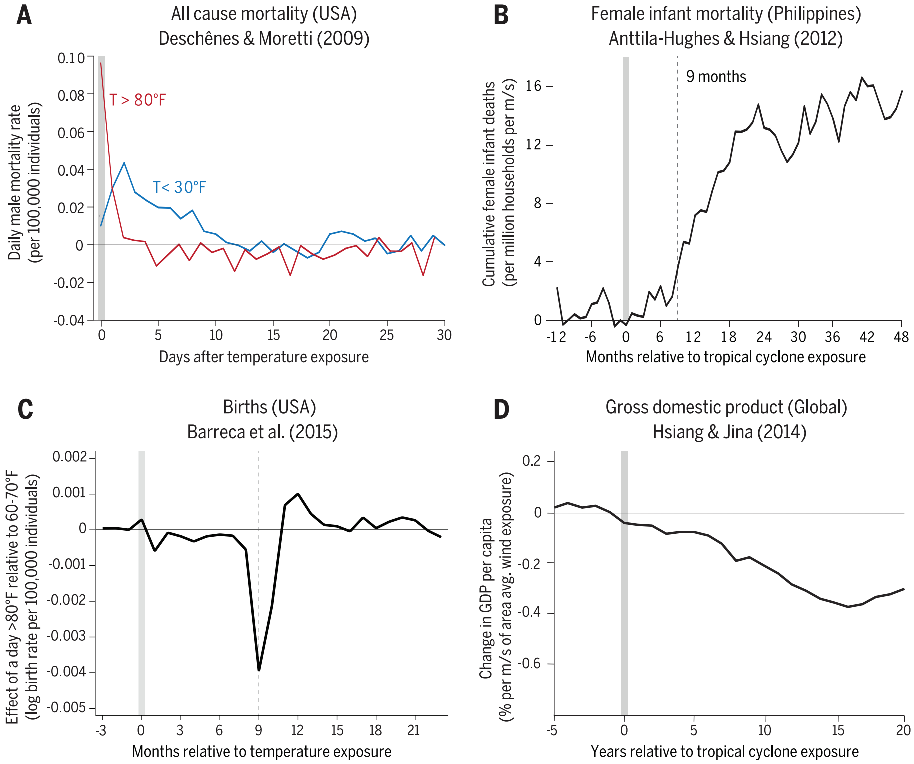

Fig. 4. Distinct dynamic characteristics of impulse-response functions uncovered in empirical studies. Examples of impulse-response functions from studies identifying dynamic relationships between climate variables and social outcomes, as illustrated schematically in Fig. 2, F to H. Vertical gray shaded bars indicates the timing of a unit climate "impulse." (**A**) Male mortality rates in the United States increase on both hot and cold days, but hot-day responses rapidly decay and tend to be small and negative for multiple weeks—indicating temporal displacement—whereas cold days generate a more gradual and enduring mortality effect (*39*). (**B**) Tropical cyclones increase female infant deaths but with a delayed effect that grows rapidly roughly a year after exposure (*49*). (**C**) Birth rates in the United States fall 8 to 10 months after a hot day, but this decline is partially compensated for by an increase during months 11 to 13 (*38*). (**D**) GDP in countries exposed to tropical cyclones falls gradually but persistently during the 15 years following exposure (*116*).

In contrast, cold days have delayed and smaller—albeit enduring—effects lasting up to a month as some individuals become ill, such as contracting influenza, and fail to recover (blue line in Fig. 4A).

Evidence suggests that adaptations moderate these direct mortality effects. For example, in the United States, mortality from extreme heat declined 80% over the course of the 20th century as air conditioner adoption soared (*43*) (Fig. 5D). Remarkably, mortality responses are highly consistent across contexts, when "hot" and "cold" conditions are defined relative to what populations are accustomed to (*44*), suggesting that populations cope with regional climates in a consistent way. Anthropogenic climate change is projected to increase heat-related mortality but decrease cold-related mortality, redistributing mortality rates across locations (*45*), but with an overall net increase in total mortality rates (*31*, *46*). In a cost-analysis of climate change in the United States, these deaths accounted for the largest share of losses across all impacts (*45*). Effects of humidity exacerbate these patterns (*45*, *47*), and mortality impacts in poor agricultural contexts are more extreme (*46*).

Climatic factors other than temperature also influence mortality. Tropical cyclones directly cause mortality—for example, through trauma or drowning—with immediate deaths in storms increasing exponentially with wind-speed exposure (*48*) (Fig. 3C). Populations regularly exposed to storms appear to adapt somewhat, as their mortality rates are lower than those of more naïve populations when both experience physically comparable events (*48*) (Fig. 5A. However, these immediate deaths may be minor in magnitude compared to "economic" deaths that occur in the wake of a cyclone (*48*, *49*). For example, in the Philippines, changing economic conditions in the years after a cyclone lowers incomes and corresponding spending on food and health care, causing mortality among female infants roughly 15 times as high as direct mortality across all age groups (*49*) (Fig. 4B). Extreme rainfall events outside tropical storms also influence mortality—in agriculturally dependent contexts, infants born in arid areas face elevated risk of death when exposed to droughts (*46*, *50*), while flooding has been linked to death throughout Europe (*51*).

Health impacts: Morbidity

Many injuries to human health caused by climate are nonfatal. One means of detecting these effects is to measure the impact of climatic events on hospital admissions. Admissions for respiratory and cardiovascular diseases respond to temperature similarly to mortality, with impacts at both high and low daily temperatures (*52*, *53*). The precise spatial and temporal resolution of these hospital- or city-level studies allows authors to account for key temperature correlates, such as air pollution and humidity, which also influence hospitalizations. This adjustment is important, as failing to account for particulate matter and ozone may exaggerate the effect of temperature by up to a factor of 2 (*52*, *54*). Even without hospital-level data, evidence using cause-of-death records can illuminate key morbidity effects; for example, humidity is an important driver of influenza, a notable cause of hospitalization and mortality in temperate climates (*55*).

A major component of morbidity affected by the climate is vector-borne disease. For example, malaria and dengue fever infect about 200 million and 50 million people globally each year (*56*), respectively, and the life-cycles of mosquito vectors transmitting these illnesses are strongly influenced by climate. Temperature nonlinearly influences the reproduction of parasites, extreme temperatures lower mosquito survival rates, and open water critical for mosquito breeding is constrained by rainfall (*57*, *58*). These climatic factors affect the intensity of infection in areas where malaria and dengue are already endemic (*59*), as well as affect where the disease may spread to (*60*). These dynamics make measurement of climate-disease interaction challenging: Some studies aim to recover incidence as nonlinear functions of temperature and rainfall (*61*, *62*), while others parameterize ecological models of vector transmission, using model output as indices to predict cases with data (*63*) or simulation (*64*). Anthropogenic climate change is likely to shift disease ranges and increase exposure globally, but changing temperatures, rainfall, and intervention strategies complicate projections (*60*, *65*); more research in this area is needed to link climate, ecological models, and social data.

Health impacts: Early life

Climatic conditions experienced during early stages of life can have outsized impact because altered early development affects long-run health and well-being (*66*). For example, in-utero exposure to high temperatures can lower birth weight (*67*), and exposure to tropical cyclones leads to a variety of birth complications (*68*). Mechanisms explaining these in-utero effects remain elusive, as it is challenging to separate effects on gestational length and nutrient accumulation (*67*), and because climate shocks occurring at different points in the gestational period likely operate through distinct channels. For example, high temperatures at conception lead to fetal losses that, through selection, improve outcomes for babies who do survive (*69*), whereas high temperatures in the third trimester have unambiguously negative impacts (*70*).

Regardless of mechanism, in-utero health insults have later-life economic consequences, such as lowered income (*33*, *70*). In developing-country

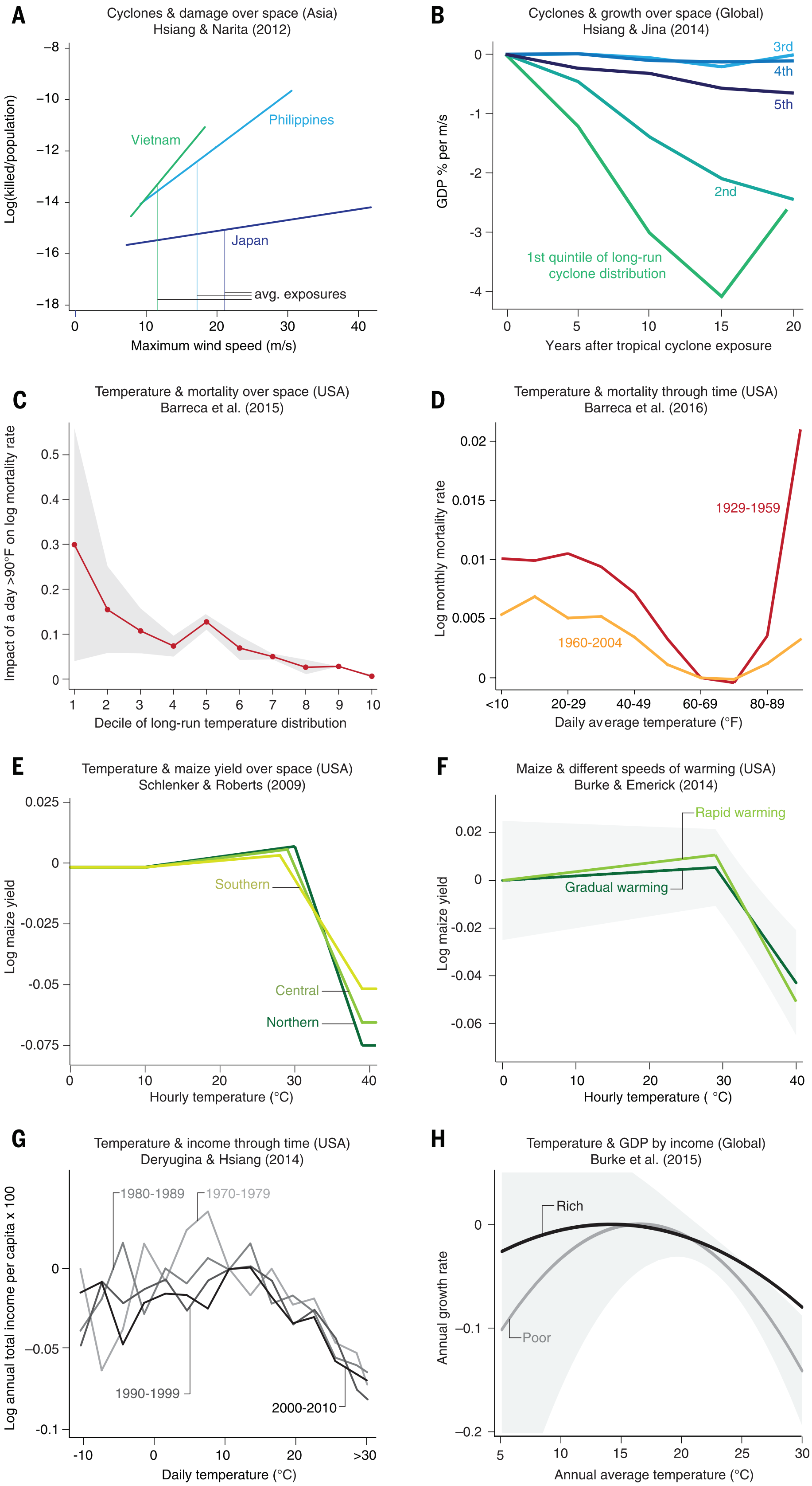

Fig. 5. Responses to physically similar events in different contexts may indicate the presence or absence of effective adaptations. Comparison of response functions over time and across space can indicate where populations have been successful in adaptation and where an "adaptation gap" might persist. Global cyclone losses indicate adaptation: (**A**) mortality rates increase with cyclone intensity more in countries where average exposure (thin vertical line) is lower (48) and (**B**) effects of cyclones on GDP over time are most negative in countries with the lowest levels of historical experience—rank indicates quintile of exposure (116). Temperature-induced mortality in the United States exhibits adaptation: (**C**) locations that have hotter long-run climates tend to have smaller effects (185) and (**D**) sensitivities have declined over time (43). Maize yields in the United States indicate limited adaptation: (**E**) Hot and cool climates exhibit similar effects of heat (21), and (**F**) yields are equally affected by rapid and slow changes in temperature (23). Aggregate income exhibits limited adaptation: (**G**) County-level losses from high temperatures have not changed over time in the United States (32), and (**H**) country-level GDP reductions are slightly less severe in rich nations than in poor countries but are not statistically different (100). Shaded areas are confidence intervals, as computed by original authors.

contexts, adverse rainfall in the year of birth lowers adult female health outcomes and educational attainment (71), and droughts experienced by toddlers lower childhood growth and education (30, 72). These rainfall-related impacts likely operate through agricultural income loss and lowered nutrition; however, our understanding of these channels is generally weak, and work is needed to parse out direct physiological impacts from economic factors and behavioral responses.

Economic impacts: Agricultural yields

Study of the direct effect of climate on economic outcomes began in agriculture, where the importance of climatic factors is clearest (73). Despite centuries of agricultural experience, a surprising recent finding is the importance of temperature, often dominating rainfall, in the production of staple crops (21, 74–76). Highly nonlinear yield losses on the hottest days drive much of this effect (21) (Fig. 3E), a relationship recovered in the United States (21), Africa (20), Europe (77), Southeast Asia (78), and India (46, 79). Crops are most sensitive to temperatures during specific phases of the growth cycle (76, 78). Although temperature impacts generally outweigh those of rainfall, low and very high total seasonal rainfall levels do damage yields in many contexts (21, 33) (Fig. 3F), an effect that is partially attenuated when water storage and irrigation are widely available (76, 78, 80, 81). Similarly, within a single growing season, farms that experience a small number of extremely rainy days suffer damaged yields, relative to the same quantity of rain distributed evenly across growing days (33). These various dose-response functions have been recovered and replicated for major global crops like maize, rice, soy, and wheat, but less is known about effects on regional crops like millet and cassava—which can be critical in poor rural regions—and specialty crops like fruits and vegetables, with some notable exceptions (20, 82, 83). A body of research in dairy science suggests that both temperature and humidity nonlinearly affect milk yields (84–86) while linearly lowering cattle pregnancy rates (87), but little is known outside of highly managed livestock operations in industrialized countries.

Effective adaptation to climate in agriculture appears modest, as dose-response functions change little across time and space (21, 88) (Fig. 5E), even when warming effects are gradual (23) (Fig. 5F). Furthermore, large but temporary climate events, like the U.S. Dust Bowl, have had persistent multidecadal impacts on farm values (89). These findings contrast with historical narratives of farmer adaptability, such as the 200-year-long spread of agriculture into previously nonarable land (90, 91) and adjustment of cultivars in response to drought (92). These two views of agriculture adaptability remain unreconciled, and identifying obstacles to adaptation, such as poor incentives (93) or high adaptation costs (88), are a critical area for future research.

Economic impacts: Labor supply and productivity

Agricultural effects cannot explain many patterns in the overall economic response to climate, leading to the hypothesis that effects on labor are another important channel of influence (26). A growing body of evidence now supports this theory (94). Heat stress can lower work intensity (95), reduce cognitive performance (96), and voluntarily shorten work hours in sectors of the economy most exposed to outdoor temperature, such as construction and agriculture (97) (Fig. 3, G and H). Impacts on manufacturing production have been identified in both high- and low-income contexts (98, 99), although understanding the full impact of this effect is made challenging by reallocation of labor within an economy (35). Patterns in the overall macroeconomic responses to temperature (discussed below) are consistent with labor effects playing an important role (26, 32, 100) (Fig. 3, J to L), where individuals are each affected modestly but a large number of affected individuals might generate substantive aggregate impacts on output, and possibly on growth (100). Theory suggests that labor productivity losses might be exacerbated by market reactions that reduce the intensity of labor used in economic activities (101) and slow downstream production (102). Investments in climate control for work environments can offset some of these labor productivity effects (98), but at substantial cost, such as expenditures on energy.

Economic impacts: Energy supply and demand

The relationship between climate and energy is unique. Energy systems are directly affected by climate—high temperatures provoke demand surges while straining supply and transmission—and they also serve a critical role supporting adaptation by enabling cooling, heating, irrigation, trade, and so forth. Simultaneously, energy use is the largest contributor to anthropogenic climate change.

The effect of temperature on energy demand is highly nonlinear. Households and firms use energy heavily for indoor climate, based on the weather and available infrastructure (103, 104). Almost universally, energy demands fall with rising cool temperatures and increase steeply at high temperatures, leading to a U-shaped relationship (Fig. 3I) (24, 31, 105). Investments in new energy-intensive infrastructure, such as heaters, may respond to climate more slowly as households and industry adopt expensive technology based on their beliefs about their climates. Evidence from the United States (106), Mexico (105), and China (107) indicates that electricity demands on hot days rise fastest in locations that tend to be hot, presumably because more buildings in these locations have air conditioners that are all used simultaneously on hot days.

Engineering models and simple thermodynamics suggest that electricity supply and transmission systems should suffer efficiency losses at high temperatures (108), but these effects are empirically challenging to measure in the presence of fluctuating demand. Evidence indicates that river-water temperatures can influence electricity prices (109), nuclear power capacity utilization may fall with high temperature (110), and droughts can shift generation away from hydropower and toward carbon-intensive fuel sources (111, 112), but it is unclear whether these findings generalize.

Projections under climate change generally indicate that energy demand will grow on net, even though fewer days will require energy for heating. Sensitivity to high temperatures will likely grow as air conditioner use expands owing to improvements in technology, rising incomes, and investments specifically motivated by warming (105, 107). These investments may affect energy prices by substantially elevating peak demand (45), but better understanding of these issues is required to support long-term energy planning.

Economic impacts: Trade

The current structure of the global economy represents a spatial equilibrium in which the location of populations and sites of economic production are all determined by the functioning and friction of markets through which individuals trade with one another and the factors that make locations more or less productive. Analyses of climatic influence on migration can be interpreted as a reallocation of labor across these locations, perhaps in response to changing economic conditions, which we discuss below. Yet, given an approximately fixed distribution of populations across locations, climate may also affect how populations decide to trade with one another. For example, global wind patterns and ocean currents have strongly influenced patterns of trade historically because of the role these factors play in the cost of shipping along different routes (113, 114). High temperatures that reduce productivity lower the quantity of goods exported from a country, both in agriculture (36) and manufacturing (115), and cyclone strikes that lower national incomes tend to reduce imports (116). In large integrated trade networks, the spatial distribution of climatic conditions can affect market prices (45, 117), presumably through effects on both supply costs and demand, and should theoretically determine the location of different economic activities (118, 119).

These reallocations across space and time can, in some contexts, mitigate the direct damages of climate. For example, outdoor labor supply shifts to cooler hours of the day during heat waves (97), water storage weakens the link between rainfall and agricultural productivity (81), unskilled labor moves from agriculture to manufacturing when crops are hit by high temperatures (35), and grain inventories adjust to smooth weather impacts on farm profits (36). However, these adjustments may be limited—historical evidence of intertemporal substitution is minimal for aggregate incomes (32, 100) and cyclone damages (116), and in the future, sequential periods of similar extreme conditions may make such reallocations over time more difficult. Reallocation across space may also be constrained in the future—current simulations disagree as to whether adjustment of trade patterns under climate change will dampen or amplify its overall social costs (45, 119, 120). Investigation of substitution patterns across both space and time is a key area for future work.

Economic impacts: Economy-wide effects

Rather than examining individual or sectoral responses to climate, an alternative "top down" approach examines how the macro-economy as a whole responds to climatic conditions. This approach is usually implemented by examining total income or gross domestic product (GDP) per capita as the outcome of interest. Recent work has shown that low rainfall slows national incomes greatly in Africa (*121*, *122*), ENSO modulates a see-saw–like oscillation in total agricultural income between tropical and temperate countries (*123*), tropical cyclone strikes slow GDP growth for roughly 15 years in proportion to the intensity of the storm (*116*) (Fig. 4D), and temperatures have a nonlinear effect on economic production, such that output is maximized around 13°C (*100*) (Fig. 3, J to L). The roughly linear effects of cyclones and nonlinear effects of temperature at the macro level are fully consistent with the structure of effects measured in micro-level analyses (*32*, *49*, *124*, *125*). Determining the persistence of these GDP losses is important because enduring losses may accumulate and compound, leading to larger long-run losses (*100*, *116*)—this could occur if climatic events alter investment behavior (*100*) or capital depreciation (*45*, *126*). However, existing data and approaches have had difficulty constraining the overall persistence of these effects (*100*, *127*).

Perhaps remarkably, effects of temperature and cyclones are globally generalizable in the sense that they have been recovered using subsamples of data from around the world, including both rich and poor countries (*32*, *100*, *116*, *125*). Early analyses focused on large negative effects of temperature on GDP in poor countries (*26*, *128*), although later studies demonstrated that almost identical responses appeared in rich countries as well (*32*, *100*) (Fig. 5H). This finding—in conjunction with the result that the effects of temperature on income in the United States remained essentially unchanged from 1960 to 2010 (*32*, *100*) (Fig. 5G) and gradual warming has effects identical to those of short-lived warming (*128*)—leads naturally to the conclusion that effective adaptation to temperature, at the macro level, is limited. Across a variety of contexts, once temperatures are higher than the optimum, each increase in temperatures by 1°C lowers economic production by roughly 1 to 1.7%. The single finding that suggests some effective adaptation at the macro level is that cyclone-prone countries experience GDP losses (per cyclone) much smaller than countries where storms are infrequent (*116*) (Fig. 5B).

Social interactions: Women and girls

Under economic pressure from climate, the terms and bargaining positions in personal relationships may change. These bargaining interactions are often gender-based, causing women and girls to experience these changes differently. For example, in sub-Saharan Africa, evidence suggests some women suffering income shortfalls during drought engage in "transactional" intercourse, leading to increased probability of HIV infection (*129*); in the Philippines, female infants conceived after a tropical cyclone have elevated risk of mortality (Fig. 4B), particularly if they have older brothers (*49*); and in Indonesia, girls born in drought years exhibit lower long-run health and education, as diminished family resources are more often allocated toward investment in boys (*71*).

Social interactions: Interpersonal violence and aggression

Evidence from numerous contexts repeatedly finds that interpersonal violence increases with temperatures and sometimes low rainfall (*130*, *131*). This response manifests in low-level aggression, such as horn honking (*132*), antisocial behavior toward service employees (*133*), and the use of profanity in social media (*134*) (Fig. 3M), as well as in outright violence, such as retaliation in sports (*135*) and violent crimes: rape, murder, robbery, and assault (*136*–*138*) (Fig. 3N). The effect of temperature is strikingly linear with almost no delay, suggesting it might be driven by a physiological mechanism (*139*–*141*). Effects of rainfall on interpersonal violence appear primarily in some poor agricultural contexts, such as rural India (*138*, *142*, *143*) and Tanzania (*144*), suggesting that damage to agricultural yields may be a mediating factor.

Social interactions: Intergroup violence

Climatic conditions also influence relationships between groups, changing the risk of large-scale conflict (*130*, *131*). Cold events during cold epochs, such as feudal Europe and dynastic China (*145*–*148*), or periods of low rainfall (*149*–*151*), produced instability and upheaval—probably related to crop failures. During the modern warm period, hotter conditions increase collective violence in settings as diverse as insurgency in India (*152*), land invasions in Brazil (*153*), and civil war intensity in Somalia (*154*). This relationship is linear, with violence rising roughly 11% per standard deviation in temperature, exhibits some evidence of adaptation through rising incomes (*155*), and has an unknown mechanism (*131*). Rainfall extremes also increase intergroup conflict in agricultural contexts (*28*, *121*, *153*, *156*), as does El Niño (*27*) (Fig. 3O).

Social interactions: Institutional breakdown and state failure

Governing institutions may falter under sufficiently strong climatological stress. Patterns such as the forcible removal of rulers (*157*–*160*) can be tied to fluctuations in climate, but attributing societal collapse to climate is more difficult because there are fewer events. Nonetheless, several historical cases are compelling, such as the collapse of the Akkadian (*161*), Mayan (*162*), and Angkor (*163*) empires, dynastic changes in China (*164*), and major transitions in Europe (*165*).

Demographic effects: Migration

Human mobility is likely an important strategy to cope with climatic changes, but it is challenging to characterize as climate appears to have two opposing influences: Deteriorating economic conditions and safety motivate migration while simultaneously undercutting household resources needed to migrate (*166*, *167*). Net effects are mixed; for example, urbanization and outmigration from agriculturally dependent areas may increase as temperatures hit crop-damaging levels and moisture declines (*89*, *168*–*172*) (Fig. 3P), but nonagricultural workers in Mexico move in response to temperature more rapidly than farm laborers (*173*), and some of the poorest countries show no emigration response (*167*). In Africa, flows from urban to foreign locations appear responsive to weather (*174*), but U.S.-bound migration from urban Mexico is unaffected by heat waves (*175*). Climatological natural disasters that influence incomes, such as hurricanes and flooding, appear to have limited impact on total migration in low-income contexts (*171*, *176*, *177*) and cause simultaneous inflow and outflow of migrants in the United States (*178*, *179*). Overall, the wide-ranging climatic effects on migration are not well understood and remain an area of active investigation.

Demographic effects: Population structure and growth

Because climatic events affect subgroups within a population differently, such as women or the poor, it is thought that repeated exposure of the population may gradually distort its demographic structure. For example, recent findings suggest that male fetuses are less likely to survive challenging climatic events, such as extreme heat, leading to disproportionately female cohorts of surviving infants born just after hot years (*69*, *180*). Demographic distortions may also occur through nonfatal mechanisms, such as the disproportionate migration of wealthy older individuals away from U.S. counties struck by cyclones simultaneous with the movement of young and low-income individuals into these same counties (*178*, *179*). These seemingly small individual effects might grow to be substantial after repeated exposure, but the full scale and scope of climatological influence on equilibrium demographic structure remain unknown.

New findings also suggest that overall population growth may be directly influenced by the climate through altering sexual behavior or fertility rates. Birth rates are abnormally lower 9 months after extreme heat events in both sub-Saharan Africa (*69*) and the United States (*38*) (Fig. 4C), although identifying the mechanism driving this effect is challenging. Remarkably, these results appear to explain a large fraction of birth seasonality across climates, and projections for the United States suggest that warming will reduce birth rates 3% (*38*).

Attributing current and future effects of climate

The results above describe the structure of the dose-response functions that govern how populations respond to individual climatic events, where these relationships were isolated from data containing overlapping signals of numerous

Table 1. Attribution of climate impacts.

Study	Social impact	Sample region	Sample period	Effects of current climate distribution	Effects of climate trends to date	Future impacts of climate change
Agriculture						
Auffhammer *et al*. 2012 (*76*)	Rice yield	India	1966–2002		Between 1966 and 2002, trends in temperature, monsoon characteristics, and rainfall lowered yields by 5.7% on average	
Lobell and Field 2007 (*197*)	Major crop yields	Global	1961–2002		By 2002, trends in temperature since 1981 caused annual losses of 40 megatons or $5 billion	
Lobell *et al*. 2011 (*184*)	Major crop yields	Global	1960–2008		Between 1980 and 2002, trends in temperature and precipitation lowered maize and wheat yields by 3.8 and 5.5%; rice and soy were unaffected	
Schlenker and Lobell 2010 (*20*)	Major crop yields	Sub-Saharan Africa	1961–2007			Predicted climate change‡ by 2050 lowers annual yields by 22% for maize, 17% for sorghum and millet, 18% for groundnut, and 17% for cassava
Schlenker and Roberts 2009 (*21*)	Maize yield	Eastern USA	1950–2008	Relative to an optimal season at 29°C, realized temperatures lower annual yields by 48% on average*		Predicted climate change† by 2100 lowers annual yields by 63 to 82%
Welch *et al*. 2010 (*78*)	Rice yield	South Asia	1979–2004		Between 1979 and 2004, trends in temperature and solar radiation lowered yield growth by 0 to 0.76%	
Income						
Burke *et al*. 2015 (*100*)	Income	Global	1960–2010	Relative to each country's optimal annual temperature, realized temperatures lower the annual global growth rate by 0.25 percentage points on average*	Between 1980 and 2010, trends in temperature lowered the annual global growth rate by 0.002 percentage points on average*	Predicted climate change§ by 2100 lowers global GDP by 23% and between 2010 and 2100 lowers the global annual growth rate by 0.28 percentage points on average
Deryugina and Hsiang 2015 (*32*)	Income	USA	1969–2011	Relative to each county's optimal annual temperature, realized county temperatures lowered the U.S. growth rate between 1970 and 2011 by 1.69 percentage points on average		Predicted climate change§ by 2100 lowers the U.S. annual growth rate by 0.06 to 0.16 percentage points
Hsiang and Jina 2014 (*116*)	GDP growth	Global	1950–2008	Relative to a world without cyclones, realized cyclones lowered the global annual growth rate between 1970 and 2008 by 1.27 percentage points		Predicted climate change‡ by 2090 induces damages valued at $9.7 trillion in net present value
Zhang *et al*. 2016 (*125*)	Total factor productivity (TFP)	China	1998–2007	Relative to a full year at 50° to 60°F, realized temperatures lower TFP by 31% on average*		Predicted climate change† by 2050 lowers annual TFP by 4.18%

Continued on the next page

Study	Social impact	Sample region	Sample period	Effects of current climate distribution	Effects of climate trends to date	Future impacts of climate change
Health						
Anttila-Hughes and Hsiang 2012 (49)	Mortality rate, total deaths	Philippines	1950–2008	Realized typhoon-induced "economic" deaths account for 13% of the overall infant mortality rate		
Burke *et al*. 2015 (129)	HIV rate	Sub-Saharan Africa	2003–2009	Rainfall shocks account for 14 to 21% of cross-country variation in HIV prevalence		
Deschênes and Greenstone 2011 (31)	Mortality rate, energy use	USA	1968–2002	Relative to a full year at 50° to 60°F, realized temperatures increase mortality rates by 11.2% and energy use by 29% on average*		Predicted climate change† by 2100 increases annual mortality rates by 3% and energy use by 11%
Conflict						
Burke *et al*. 2009 (183)	Civil conflict	Sub-Saharan Africa	1981–2002	Relative to each country's optimal annual temperature, realized temperatures increase annual incidence of war by 29.3% on average*	Between 1981 and 2006, trends in temperature increased the annual incidence of war by 11.1% on average*	Predicted climate change‡ by 2030 increases annual incidence of war by 54%
Hsiang *et al*. 2011 (27)	Civil conflict	Global	1950–2004	Relative to the optimal state, realized ENSO conditions had a role in 21% of all civil conflicts between 1950 and 2004		
Ranson 2014 (136)	Violent crime	USA	1980–2009	Relative to each county's optimal monthly temperature, realized temperatures increase crime rates by 6.1% for rape, 2.4% for murder, and 3.6% for aggravated assault on average*		Predicted climate change‡ between 2010 and 2099 increases total crime cases by 180,000 for rape, 22,000 for murder, and 2.3 million for aggravated assault

*New calculation generated either from reanalysis of the authors' data, or from analysis of statistics provided in the authors' paper. See supplementary materials for detailed descriptions of each calculation. †‡§Climate change impacts are predicted using the Intergovernmental Panel on Climate Change A1F1†, A1B‡, or RCP 8.5§ future climate change scenarios.

sequential climatic events. By mapping distributions of multiple climatic events back onto these empirically recovered dose-response functions, we can reconstruct distributions of predicted outcomes attributable to these weather distributions (as illustrated in Figs. 1 and 2). Comparison of outcome distributions resulting from different climatologies allows us to estimate the first-order effects of any arbitrary change in the climate (19). In principle, with sufficient information on patterns of adaptation to climate (i.e., the "informational" channel that caused the dose-response function in Fig. 1C to change), these comparisons can account for the full range of adaptations observed in the real world; although in practice, such adjustments tend to be relatively minor (45, 48, 88, 181), in part because they are mathematically second-order (19, 48), a notion that is consistent with observation that the informational effect tends to be modest in magnitude across numerous contexts (23, 32, 136, 182), especially once the costs of adaptive adjustments are accounted for (19, 88).

By using this approach to "reconstitute" distributions of impacts from climate, researchers are now beginning to provide first-order answers to three questions that originally motivated this research agenda: How much does the current climate affect outcomes that we observe in the current world? How much has recent warming affected outcomes? And how are projected changes in the climate expected to alter social outcomes?

The current climate

Most analyses do not explicitly report how much the distribution of a social outcome examined is driven by climatic factors, but such results are implicitly computed and relied upon in every deconvolution or regression analysis, and estimating the total effect of current climate distributions provides perspective on the magnitude of contemporary impacts. In column 5 of Table 1 we tabulate estimates from studies that do report such results, as well as compute some new estimates based on reported values and available data. To compute the total effect of the current climate, one can use the sample of data analyzed and the empirical relationship recovered by the analysis to (i) compute the distribution of outcomes predicted by the current distribution of climatic events; and (ii) compare this to the distribution of outcomes obtained if the same population were exposed to their best possible environmental conditions continuously, where "best possible" is based on the nature of the estimated empirical relationship (see supplementary materials for details). Essentially, to create this benchmark we imagine a world in which climate could be managed as other aspects of societies and economies are, such as the allocation of law enforcement or capital investments. For example, in their analysis of the effect of ENSO on civil conflict, Hsiang *et al.* (27) estimate average conflict rates predicted by historical ENSO conditions and compare them to conflict rates that would be predicted if the world were to experience La Niña–like conditions, the climate state with least conflict, continuously. This thought experiment is clearly impossible to confirm, as societies cannot uniformly be exposed to an optimal climate; however, it is a useful and precisely defined benchmark for considering the overall magnitude of effects resulting from observed climates.

In general, modern climates have substantial influence on social and economic outcomes. For example, historical temperatures in the United States are estimated to currently suppress maize yields by roughly 48% relative to ideal growing conditions (*21*); raise average murder rates by 2% and assault rates by 4% relative to the coolest conditions experienced in each county and month (*136*); increase residential energy consumption by 29% and elevate mortality rates by 11% on net (*31*); and reduce GDP growth by roughly 1.7 percentage points year^{-1} (*32*). Temperatures contribute to 29% of civil conflicts in sub-Saharan Africa (*183*), and 13% of infant mortality in the Philippines is attributable to tropical cyclones (*49*). Globally, ENSO has elevated civil conflict rates by 21% relative to constant low-conflict conditions (*27*), while temperature and tropical cyclones reduce global economic growth by roughly 0.25 and 1.3 percentage points year^{-1}, respectively (*100*, *116*).

Climate change to date

Only a few agricultural studies estimate the social effect of recent already-observed anthropogenic climate trends. In Table 1, column 6, we show that, relative to an unchanged climate, trends in various climatic variables that occurred at the end of the 20th century have lowered rice yield growth rates in South Asia by up to 0.76% annually (*78*) and reduced global maize and wheat production 3.8% and 5.5%, respectively, whereas global gains and losses for soy and rice roughly balance one another out (*184*). Based on calculations using data from (*100*) and (*183*), we estimate that warming trends since 1980 have slowed global average GDP growth by 0.002 percentage points per year and increased the incidence of civil conflict in Sub-Saharan Africa by ~11% (see supplementary materials for details).

Future climate change

Projected impacts of future "business-as-usual" climate changes, relative to a counterfactual of no climate change, are generally much larger than impacts of warming that have already occurred and tend to be comparable to the baseline impact of climate on social and economic outcomes today (Table 1, column 7). For example, crop yields in Africa are likely to decline 17 to 22% for maize, sorghum, millet, and groundnuts by 2050 (*20*); yields for major crops in the United States are likely to decline 15 to 20% by 2050 (*21*, *23*, *45*) and 63 to 82% by 2100 (*21*, *45*), although accounting for estimated effects of CO_2 fertilization may keep expected losses nearer to 15% (*45*). Projected estimates suggest that armed conflict in Africa may rise roughly 50% by 2030 (*183*), while violent and property crimes in the United States may increase roughly 3 and 1%, respectively (*45*, *136*). Warming by end of century is projected to increase U.S. mortality rates 3 to 9% and electricity consumption 11% (*31*, *45*). The growth rate of overall economic production is projected to fall roughly 0.12 percentage points year^{-1} in the United States (*32*) and 0.28 percentage points year^{-1} globally (*100*) during the next century owing to the effects of rising temperature, with additional projected losses due to cyclones costing roughly $9.7 trillion dollars in present discounted value (*116*). Notably, these impact projections are all constructed on the basis of historically observed responses to environmental conditions, and the actual impact of future changes might be less disruptive if, for example, adaptive technologies improve dramatically in the future. Alternatively, future impacts could be worse than described here if current adaptive strategies, such as irrigation using fossil aquifers, are unsustainable or societal responses become highly nonlinear once the environment shifts to conditions beyond recent experience.

Critical challenge: Understanding "adaptation gaps"

Overall, new empirical measurements suggest that current climatic conditions impose substantial economic and social burdens on modern populations and that future climate change will further increase these ongoing costs considerably. These losses could be avoided, in theory, if populations could costlessly and fully adapt to these dimensions of their climate—why this has not occurred to date remains an important open question, with potentially large gains for both present and future populations should it be solved.

Given information on the climatically determined probability distribution of potential weather events, populations may take actions or make investments that will reduce the influence of these events when they actually occur. As depicted in Fig. 1, this adaptation can be detected implicitly by observing how the dose-response function linking climate variables to outcomes changes. More highly adapted populations will have flatter responses (*48*), such that changes in climatic variables have less influence on an outcome. An alternative approach to detecting adaptation is explicit measurement of outcomes that are themselves thought to be adaptations, such as investing in crop switching after a drought (*89*). Notably, measurement of adaptation using either approach is made possible by the use of intertemporal changes in climatic variables, whether over short time scales (e.g., days) or long time scales (*23*) (e.g. decades)—and we note that in contrast to widely cited heuristics, short-term weather variation can be used to exactly measure the influence of long-term climate changes under the right conditions, even when populations adapt to knowledge of their climate (*19*).

Comparison of adaptation results across different sectors reveals striking dissimilarities: In some cases, adaptation appears remarkably effective at minimizing damages, whereas in other cases, we observe essentially no adaptation, leading to seemingly costly "adaptation gaps." For example, populations regularly exposed to cyclones experience substantially smaller losses than naïve populations when exposed to physically similar events (*48*, *49*, *116*) (Fig. 5, A and B). Similarly, mortality on hot days in hot climates is lower than in similar populations in cooler climates (*44*, *185*) (Fig. 5C), and heat-related mortality has declined over time with rising availability of air-conditioning and other technologies (*43*) (Fig. 5D). In sharp contrast, violence and crop yields in hot and cool locations respond almost identically to temperature in the United States (*21*, *136*) (Fig. 5E), and the temperature sensitivity of agriculture (*23*), crime (*136*), and economic productivity (*32*, *100*) has changed little over multiple decades, even though populations are presumably innovating and adjusting to climate over this time period (Fig. 5, F and G). At a global scale, it has been widely hypothesized that wealthy populations will adapt effectively to future climate changes because they have greater resources, have access to wider arrays of technology, and tend to have stronger governments (*8*, *186*, *187*), but data from the present largely suggest that overall economic activity in wealthy countries actually responds to temperature (in percentage terms) similarly to economic activity in poor countries (Fig. 5, G and H)— although there is suggestive but statistically insignificant evidence that wealthy countries might be adapting slightly more effectively. In puzzling incongruity, wealthy countries appear substantially more adapted than poor countries, in terms of some outcomes, to tropical cyclones (*48*) and ENSO (*27*).

To date, it is not well understood why populations adapt so effectively in some dimensions with respect to certain aspects of the climate while entirely failing to adapt in other contexts. Existing evidence suggests that high costs of adaptation (*48*, *88*, *105*), incentives to adapt (*48*, *93*), limited access to credit for financing adaptations (*46*), limited rationality when planning for future risks (*16*, *188*), incorrect or limited information about the benefits of adaptation (*89*, *189*), perverse political incentives (*190*, *191*) or weak government institutions (*187*, *192*), constraints to sharing risk among individuals and groups (*193*), and access to technologies (*90*, *185*) might play substantial roles, although existing evidence is primarily suggestive as it relies on cross-sectional associations. To better understand what constrains adaptation, future work will likely need to exploit natural experiments where specific potential constraints (or costs) are exogenously eliminated; if the link between an outcome and climate disappears, it can be more confidently inferred that the altered constraint was playing a critical role in limiting adaptation (*43*, *152*).

It is theoretically possible that existing adaptation gaps are "economically optimal" in the sense that the costs of additional adaptive actions and investments exactly balance their benefits, which are avoided climate-related social losses (*48*). Many patterns of adaptation described above seem qualitatively consistent with this notion of optimality; for example, cyclone-prone locations benefit more from investments in cyclone shelters because they are used more often, so cost-benefit analyses would predict more shelters in locations that are more cyclone-prone. However, many patterns seem inconsistent with optimality, such as the persistent sensitivity of crop yields to temperature (*23*, *182*), but could be reconciled as optimal if adaptation technologies are extraordinarily costly. In general, there is no quantitative evidence that allows us to determine how closely current adaptation gaps reflect optimal investments or are bound at suboptimal levels by the market failures and other constraints described above.

Because the persistence of adaptation gaps has such large impacts on current and future well-being around the globe, understanding its cause is likely the most pressing current research question. Identifying the causes of these gaps and determining whether they are optimal is critical for designing policies that can support and accelerate adaptation in the numerous contexts where it lags. For example, if current adaptation gaps are optimal, then policy should focus on improving the cost-effectiveness of adaptation technologies (*48*) rather than on correcting market failures. Such policies, if carefully designed and effectively implemented, could both substantially benefit current generations that presently suffer large economic and social burdens from the modern climate, and also benefit future generations that would otherwise continue bearing these burdens along with all additional costs of climate change.

Discussion

The endeavor to understand the impact of climate on society is unlocking promise. Climate has imposed varied environmental constraints on humanity for millennia, and new understanding provides insight into the role of climate in global historical development. More urgently, current climatic conditions and variations are constantly shaping and reshaping human well-being today, thus understanding these processes allow us to better prepare for and respond to the climate that we experience now. Finally, designing effective, efficient, and fair policies to manage anthropogenic climate change requires, critically, that we develop a quantitative grasp of how different investments today may affect economic and social possibilities in the future.

Advances in data, computing, and methods have triggered rapid progress in our ability to empirically measure how climatic conditions affect human well-being and productivity around the world. Although climate is clearly not the only factor that affects social and economic outcomes, quantitative measurements reveal that it is a major factor, often with first-order consequences. Notably, these results suggest that the magnitude of influence that current climatic conditions have on social outcomes is generally comparable to (and sometimes larger than) the projected effects of future warming. Collectively, these findings suggest that both local climatic conditions and the state of the global climate can be thought of as forms of "natural capital" that play an important role in supporting human welfare and are inputs to economic production.

An insight that emerges from these findings is the notion that current climate patterns may be an important source of inequality. Populations endowed with different distributions of climatic conditions face different environmental constraints that may lead to different distributions of outcomes. In a thought experiment where we hold all other factors constant, these recent findings directly suggest that hotter locations with more extreme rainfall patterns and more major disturbances, such as ENSO and tropical cyclones, will generally face additional health costs, lower productivity, and additional economic costs, greater population movement, and higher rates of violence. To first order, this idea is broadly consistent with cross-sectional patterns (*194*); however, as described earlier, it is not yet possible to ensure that the "all other factors constant" assumption holds when comparing outcomes across different populations, so we cannot directly test these cross-sectional predictions empirically. Nonetheless, such inferences, with important repercussions for present and future inequality, would follow logically from these results.

Projections of climate changes based on these empirical results also inform questions of inequality, as predicted future impacts are highly unevenly distributed across locations, often because the effects of climate are nonlinear and different populations have different baseline climates, such that incremental warming has heterogeneous effects. For example, warming is expected to increase productivity in cool locations while decreasing productivity in warm locations, leading to projections where current patterns of inequality increase, sometimes dramatically (*32*, *45*, *100*).

Recent advances in this literature point toward two areas of future work with important policy consequences. First, "cracking the code" on when, where, and why adaptation is or is not successful promises major social benefits. New evidence suggests that (i) there are some cases where populations are able to adapt such that they partially neutralize the effects of climate; (ii) there are many cases where adaptation does not occur; and (iii) the social and economic benefits of successful, low-cost, and widespread adaptation are potentially very large for both current and future populations, especially in many low-income countries. Understanding what causes this "adaptation gap" can help policy address it; for example, if adaptation technologies are expensive (*48*, *88*), then policy should focus on their research and development. Second, models used to understand the costs and benefits of different global climate change policies take as inputs various "damage functions" that describe how social and economic losses accrue under different future climate change scenarios (*11*). Historically, these damage functions were theoretical constructs whose structures were based on modeling intuition informed by some data (*10*, *195*), but the recent explosion of empirical work suggests that these global policy models can now be calibrated to real-world relationships that characterize the many social impacts of climate (*45*, *196*).

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SUPPLEMENTARY MATERIALS

www.sciencemag.org/content/353/6304/aad9837/suppl/DC1
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Editor's Summary

Social and Economic Impacts of Climate
Supplementary Materials

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Computations for climate impact attribution (Table 1)

Most entries in Table 1 were taken directly from the text of individual studies (see footnote in table). Here we describe novel calculations for values in cases where attribution was not done by the authors, but either original data were available or summary statistics and estimation results reported in the original study were sufficient to calculate attribution values. In all cases, even when analyses examine the impacts of multiple different climate variables, our calculations focus on temperature. We take this approach because the magnitude of the effect of temperature dominates in most studies included in the table, and because historical and future trends in temperature are much more certain than are trends in other climate variables.

1 Effects of the current climate distribution (Table 1, Column 5)

Our general approach to compute the total impact of the current climate distribution is the same for all studies. We take the following steps:

1. **Calculate $\hat{\mathbf{y}}^{\mathbf{actual}}$:** Apply the estimated empirical relationship in each study the actual climate observed in the authors' data, predicting outcomes under actual climate.

2. **Calculate $\hat{\mathbf{y}}^{\mathbf{optimal}}$:** Apply the estimated empirical relationship in each study to some "optimal" counterfactual climate, predicting outcomes under a counterfactual climate.

3. **Compare:** Calculate $\hat{\mathbf{y}}^{\mathbf{actual}} - \hat{\mathbf{y}}^{\mathbf{optimal}}$, normalizing the difference by predicted levels of outcomes under the "optimal" counterfactual climate.

For example, with linear models we set optimal temperature to be the minimum temperature experienced for a given panel unit (Figure 1 A), and for quadratic response functions we set optimal temperature to be the temperature for a given panel unit that maximizes the predicted level of the social outcome (Figure 1 B). For binned models we set the optimum temperature to be the omitted bin value.

It is important to note that while we describe these computations from the point of view of an "optimal" temperature versus the actual realized temperature, it is equivalent to think of this exercise as the value of fully adapting to temperatures within a population's historical experience. That is, predicted outcomes for a population continuously experiencing an optimal temperature are equivalent to those realized under a flat dose-response function, where changes in temperature have no impact on social outcomes.

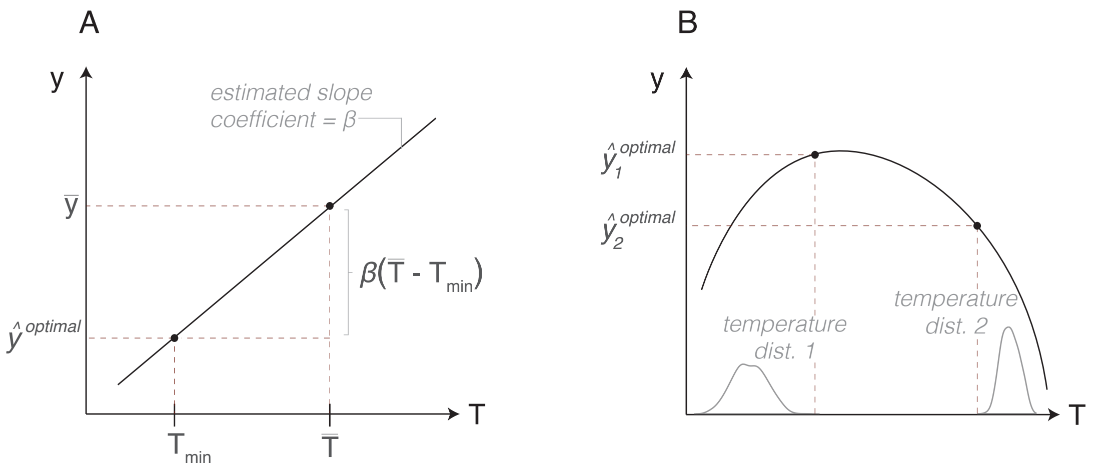

Figure 1: Identifying optimal counterfactual temperatures with (A) a linear dose-response function and (B) a quadratic dose-response function.

Calculation details for each study marked with ($*$) in Column 5 of Table 1 are analyzed are below.

1. **Schlenker & Roberts (2009) - Maize yields in the U.S.** (*1*). We reanalyze the authors' original data using their main degree-days specification, for maize yields only, where i indicates county, s indicates state, and t indicates year:

$$log(yield_{it}) = \beta_1 DD_{0-29} + \beta_2 DD_{>29} + \delta_1 precip_{it} + \delta_2 precip_{it}^2 + c_i + d_s \times t + d_s \times t^2 + \varepsilon_{it}$$

Where DD_{0-29} and $DD_{>29}$ are growing season degree days as described in (*1*) with a single threshold value of 29°C, $precip_{it}$ is total precipitation, c_i are county fixed effects, and $d_s \times t$ and $d_s \times t^2$ are state-specific time trends.

We estimate $\hat{\beta}_1 = 0.00019$ and $\hat{\beta}_2 = -0.006$, consistent with the authors' original result. We use these coefficients to recover predicted values for every county-year observation using observed values of DD_{0-29} and $DD_{>29}$, and exponentiate these values to obtain predicted levels of yields in units of bushels/acre; this is $\hat{y}_{it}^{actual}$. We then compute the counterfactual damage value $\hat{y}^{optimal}$ by setting $DD_{0-29} = 184 \times 29$ and $DD_{>29} = 0$, since in ref. (*1*) there are 184 days in the growing season for maize and because 29°C is the optimal growing season temperature based on the estimated response function (*1*). Conceptually, this simulation mimics an experimental setting in which maize is grown in a greenhouse where temperature is set at 29°C continuously throughout the growing season.

We calculate the difference in damages between counterfactual and actual climate distributions as $\hat{\Delta} y_{it} = \hat{y}_{it}^{optimal} - \hat{y}_{it}^{actual} = \hat{y}^{optimal} - \hat{y}_{it}^{actual}$, where the last equality comes from the fact that optimal climate is 29°C for all counties in all years so that predicted outcomes under optimal climate do not change over space or time. In each year, we normalize this damage by the level of predicted yields in the optimal climate, to get the ratio $\frac{\hat{\Delta} y_{it}}{\hat{y}^{optimal}}$, which is the fraction of potential optimal yields that are lost annually due to realized climate. Our reported value is the weighted average of this ratio, where weights in each year across counties are the county's area planted to corn:

$$fractional\_yield\_losses = \frac{1}{\tau} \sum_t \left[\frac{\sum_i \frac{\hat{\Delta} y_{it}}{\hat{y}^{optimal}} \times A_{it}}{\sum_i A_{it}} \right]$$

Where A_{it} is the area planted to maize in each county-year, and τ is the total number of years in the panel (1950-2005). This value is the average (across all counties and all years in the sample) share of optimal bushels/acre that are lost each year due to realized temperatures.

2. **Burke et al. 2009 - Civil conflict in Sub-Saharan Africa** (*2*). We reanalyze the authors' original data using their Model 3, for war incidence only:

$$war\_incidence_{it} = \beta_1 T_{it} + \beta_2 T_{it-1} + \delta_1 precip_{it} + \delta_2 precip_{it-1} + \gamma X_{it} + c_i + d_i \times t + \varepsilon_{it}$$

Where i indicates country, t indicates year, T is annual average temperature, $precip$ is total precipitation, X includes all controls in Model 3 in ref. (*2*), and $d_i \times t$ are country-specific time trends.

From this estimated relationship (we estimate $\hat{\beta}_1 = 0.0489$ and $\hat{\beta}_2 = 0.0206$, consistent with the authors' original result), we follow a similar process as for Schlenker & Roberts, but set the optimal temperature in the counterfactual (called $T_i^{optimal}$) as the minimum temperature each country is observed to experience in the sample, since the estimated relationship in Burke et al. is linear (see Figure 1 A). We calculate $\hat{y}_{it}^{actual} = \hat{\beta}_1 T_{it}^{actual}$ and $\hat{y}_{it}^{optimal} = \hat{\beta}_1 T_i^{optimal}$. The difference in war incidence between actual and counterfactual climate distributions is $\hat{\Delta} y_{it} = \hat{y}_{it}^{actual} - \hat{y}_{it}^{optimal} = \hat{y}_{it}^{actual} - \hat{y}_i^{optimal}$. While the model includes lags, because the lag coefficient is often large but never statistically significant, and does not change the magnitude of the contemporaneous coefficient (either in our reanalysis or in Burke et al.'s reported results), we report estimates using the contemporaneous effect only.

To normalize these damages, we need to calculate the baseline risk at the optimal (within-country minimum) temperature. This is not straightforward, because the fixed effects estimation identifies only the slope, and not the level, of the linear response function. To calculate baseline risk, we exploit the fact that the OLS hyperplane passes through the sample mean. Because this is a linear model, we can back out the level of y predicted at $T_i^{optimal}$ as $\bar{y}_i - \hat{\beta}_1 \times (\bar{T}_i - T_i^{optimal})$, as shown in Figure 1 A. Using this normalization, relative damages in each country-year are $\frac{\hat{\Delta} y_{it}}{\bar{y}_i - \hat{\beta}_1 \times (\bar{T}_i - T_i^{optimal})}$, where $\bar{y}_i$ and $\bar{T}_i$ are mean war incidence and mean annual temperature over the sample for country i. Because this is a linear probability model, when this denominator value is predicted as negative, we set it to zero. Our reported value is the average increase in the annual incidence of war under realized temperatures, relative to baseline risk under optimal temperatures:[1]

$$fractional\_excess\_war\_risk = \frac{\sum_i \sum_t \hat{\Delta} y_{it}}{T \times \sum_i \left[\bar{y}_i - \hat{\beta}_1 \times (\bar{T}_i - T_i^{optimal})\right]}$$

3. **Ranson 2014 - Crime in the U.S.** (*4*). We reanalyze the author's original data for rates of rape, murder, and aggravated assault using a linear approximation of the author's nonparametric regression on monthly average maximum temperature, as the estimated nonparametric responses in the original paper are very close to linear over most of the support (e.g. see Figure 3 panel n in the main text). We follow a nearly identical procedure to that discussed above for Burke et al. 2009. We include lags, as Ranson does, county-by-month-of-year (c_{im}) and county-by-year (d_{it}) fixed

[1]Note that we do not take the ratio before averaging because the denominator is zero for some countries. Thus, the interpretation of our final number is the cumulative elevated risk due to temperature, as a percent of the cumulative risk at the optimal temperature, accumulated across all countries in the sample. This is analogous to the "Annual Conflict Risk" (ACR) measure used in Hsiang, Meng & Cane (2011) (*3*), i.e. average probability of war in a randomly selected country.

effects. Following Ranson, we weight the regression by county population.

$$crime\_rate_{imt} = \beta_1 T_{i,m,t} + \beta_2 T_{i,m-1,t} + \delta_1 precip_{i,m,t} + \delta_2 precip_{i,m-1,t} + c_{im} + d_{it} + \varepsilon_{it}$$

Where i indicates country, m indicates month-of-year, t indicates year, T is monthly maximum temperature, and $precip$ is total monthly precipitation. We estimate that $\hat{\beta}_{1,rape} = 0.028, \hat{\beta}_{1,murder} = 0.0028, \hat{\beta}_{1,assault} = 0.351$. In this calculation, we define optimal temperature as each county's minimum value of observed maximum temperature for each month over all years of the sample, because the observations are at the county-month level (e.g. county i will have a January optimal that is distinct from its July optimal). We also account for cumulative effects of the contemporaneous and one-month-lagged temperature effect, as these lagged variables are often statistically significant in both our reanalysis and in Ranson's original study. Thus, each month's optimal temperature exposure is the current month's optimal temperature in addition to the previous month's optimal temperature. We use the same normalization discussed above to get the average risk of crime, relative to the level of crime predicted at each county's minimum temperature. We population weight this average to generate an estimate of the excess crime risk for an average American:

$$fractional\_excess\_crime\_risk = \frac{\sum_t \sum_i \hat{\Delta} y_{i,m,t} \times w_{i,m,t}}{\tau \times \sum_i \left((\bar{y}_{i,m,t} - [\hat{\beta}_1(\bar{T}_{i,m,t} - T^{optimal}_{i,m,t}) + \hat{\beta}_2(\bar{T}_{i,m-1,t} - T^{optimal}_{i,m-1,t})]) \times w_{i,m,t} \right)}$$

Where τ is the total number of monthly observations in the panel and $w_{i,m,t}$ is the population weight.[2]

[2] As with our calculation for Burke et al. (2009), note that here we do not take the ratio before averaging because the denominator is zero for some counties.

4. **Burke et al. 2015 - Global GDP growth** (*5*). We reanalyze the authors' original data using their preferred specification:

$$g_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \delta_1 precip_{it} + \delta_2 precip_{it}^2 + c_i + d_i \times t + d_i \times t^2 + \varepsilon_{it}$$

Where g_{it} is growth in GDP per capita in country i and year t, T_{it} is country average annual temperature, $precip_{it}$ is total country annual precipitation, c_i are country fixed effects, and $d_i \times t$ and $d_i \times t^2$ are country-specific quadratic time trends. We estimate $\hat{\beta}_1 = 0.127$ and $\hat{\beta}_2 = -0.00049$, consistent with the authors' original result.

To get an optimal temperature for each country, we use $T_i^{optimal} = \underset{T_{it}:t \in S}{argmax} \left[\hat{\beta}_1 T_{it} + \hat{\beta}_2 T_{it}^2\right]$, where S is the set of years included in the original data. This value $T_i^{optimal}$ is the observed temperature for country i that minimizes growth rate damages, given the estimated relationship (see Figure 1 B). We compute $\hat{g}_{it}^{actual} = \hat{\beta}_1 T_{it}^{actual} + \hat{\beta}_2 (T_{it}^{actual})^2$ and $\hat{g}_{it}^{optimal} = \hat{\beta}_1 T_{it}^{optimal} + \hat{\beta}_2 (T_{it}^{optimal})^2$. The difference in growth rates between counterfactual and actual climates is then $\hat{\Delta} g_{it} = \hat{g}_{it}^{optimal} - \hat{g}_{it}^{actual}$.

This $\hat{\Delta} g_{it}$ is the difference growth rates across the two climate scenarios, measured in GDP per capita for each country-year. We transform this value into total dollars by multiplying by the level of GDP per capita (Y_{it}) and the population (pop_{it}) in country i and year t; we then sum to get global losses in dollars in year t:

$$unearned\_dollars\_of\_global\_GDP_t = \sum_i \hat{\Delta} g_{it} \times Y_{it} \times pop_{it}$$

We average across all years and divide by global GDP in each year to get the average change in the global growth rate:

$$Avg\_growth\_rate\_adjustment = \frac{1}{\tau}\sum_t \frac{unearned\_dollars\_of\_global\_GDP_t}{global\_GDP_t}$$
$$= \frac{1}{\tau}\sum_t \left[\frac{\sum_i \hat{\Delta} g_{it} \times Y_{it} \times pop_{it}}{\sum_i Y_{it} \times pop_{it}}\right]$$

5. **Deschenes & Greenstone 2011 - Mortality and energy consumption in the U.S.** (*6*). We do not have access to the original data, so we compute the effects of climate using the summary statistics and coefficient estimates reported in the paper. The authors use the binned temperature specifications shown below (where superscripts m and e indicate the mortality and energy regression coefficients, respectively). Let $\tilde{T}_j = \mathbb{1}(T \in \Omega^j)$, where $\Omega^j = [\underline{T}^j, \bar{T}^j)$ – that is, $\tilde{T}_j$ is an indicator function equal to 1 if temperature is in the set $[\underline{T}^j, \bar{T}^j)$, and $\tilde{P}_k$ is defined analogously for precipitation:

$$mortality\_rate_{it} = \sum_j \beta_j^m \tilde{T}_{itj} + \sum_k \delta_k^m \tilde{P}_{itk} + c_i^m + d_t^m + \gamma_{st}^m + \varepsilon_{it}^m$$
$$\log(energy\_demand_{st}) = \sum_j \beta_j^e \tilde{T}_{stj} + \sum_k \delta_k^e \tilde{P}_{stk} + \mathbf{X}_{st}\beta^e + c_s^e + \gamma_{dt}^e + \varepsilon_{it}^e$$

Where c_i are county fixed effects, γ_{st} are state-by-year fixed effects, γ_{dt} are census division-by-year fixed effects, and $\mathbf{X}_{st}$ is a vector of state-level covariates, including population and GDP (see Deschenes & Greenstone (2011) for details).

We use summary statistics on the average annual number of days that temperature falls into each bin across all panel units, as well as the estimated coefficients for each bin, to compute the total effect of climate. The number of days in each bin are taken from Figure 1 in Deschenes & Greenstone (2011). Note that because these average values are population-weighted across all the county-year observations in the sample, our estimates of the average excess mortality risk and excess energy demand will both be population-weighted averages. The mortality coefficients $\hat{\beta}_j^m$ are taken from Figure 2 and the residential energy use coefficients $\hat{\beta}_j^e$ are from Figure 3. Because the energy demand specification is log-linear, we report the log-transformation of the cumulative damages from days in every bin to get the average percent change in energy consumption due to temperature:

$$fractional\_change\_in\_energy\_demand = \exp\left(\sum_j \hat{\beta}_j^e \times \overline{\tilde{T}_j}\right) - 1$$

Where $\overline{\tilde{T}_j}$ is the mean value of $\tilde{T}_j$ across the sample. Mortality rates are not logged in the authors' specification. Thus, we compute the cumulative impacts across all bins, relative to the the predicted level at the optimum. As above, we estimate the predicted level of mortality at the optimum using the fact that the OLS hyperplane passes through the sample means.

$$fractional\_excess\_mortality\_risk = \frac{\sum_j \hat{\beta}_j^m \times \overline{\tilde{T}_j}}{\overline{y} - \sum_j \hat{\beta}_j^m \times \overline{\tilde{T}_j}}$$

Where $\overline{y}$ is the average mortality rate in the sample. As the original article did not provide the mean all-age mortality rate, we download the publicly available version of the outcome data and multiply each age-specific mortality rate in these data by the age-group population weights used in the original article to get a mean mortality rate of 859 per 100,000.

6. **Zhang et al. 2016 - TFP in China** (*7*). We follow an identical approach as above for energy consumption in Deschenes & Greenstone, as we do not have access to the original data and Zhang et al. use a binned temperature response function with the log of TFP on the left hand side. We use summary statistics for the average number of days in each bin shown in Figure 2, and TFP coefficients from Figure 4 of the original article. We calculate total losses of TFP as a percent of optimal:

$$fractional\_reduction\_of\_TFP = \exp\left(\sum_j \hat{\beta}_j \times \overline{\tilde{T}_j}\right) - 1$$

2 Effects of climate change to date (Table 1, Column 6)

Very few papers in the literature conduct warming-to-date attribution exercises. Nonetheless, for two papers where we have sufficient data, we compute estimates for the effect of warming temperature trends since 1980, following the approach outlined in (*8*) and (*9*). We do not consider trends in any other variables, although some other papers do report impacts of trends in variables such as precipitation (*8*) or pollution (*10*).

The approach outlined below to compute the total impact of recent warming trends is analogous to that employed above to measure the impact of the current climate distribution. Now, however, our two quantities are $\hat{\mathbf{y}}^{\mathbf{actual}}$ – the predicted social outcome under actual climate (including any warming that has occurred) – and $\hat{\mathbf{y}}^{\mathbf{detrended}}$ – the predicted social outcome under a counterfactual de-trended climate, where warming trends are removed. We then compare the difference between these quantities and normalize in an identical manner to the calculations in Section 1 of this supplement.

1. **Burke et al. (2009) - Civil conflict in Sub-Saharan Africa** (*2*). These data are country-year observations covering the years 1980-2006. For each country in the data, we estimate a linear trend in average annual temperature and predict temperatures in each year, calling these predicted values T^*_{it}. E.g., denote the predicted country-level temperature in country i during 1981 using this linear fit as $T^*_{i,1981}$.

   We then create a de-trended temperature residual for every country-year as follows, which is normalized to temperature in 1981 (see Figure 2):

$$T\_detrended_{it} = T_{it} - T^*_{it} + T^*_{i,1981}$$

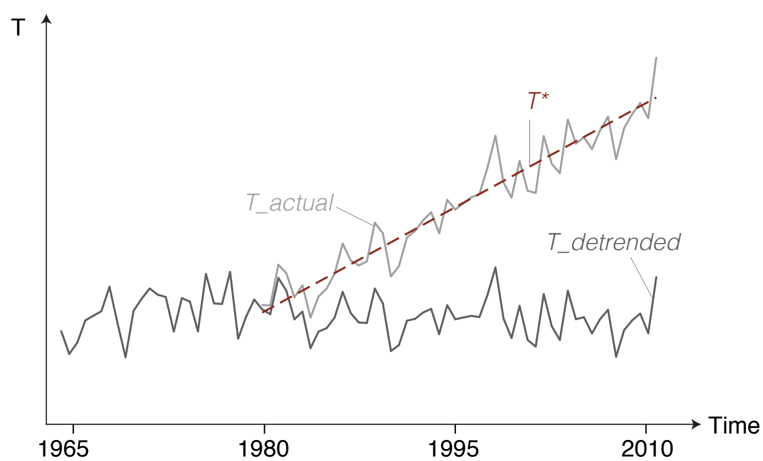

Figure 2: Identifying counterfactual de-trended temperatures

   We predict conflict levels using actual and de-trended temperature, using the coefficient estimates from our re-analysis of the originally reported empirical model. Excess conflict risk due to the trend, relative to the de-trended counterfactual, is the difference between these two predictions, which simplifies to $\hat{\Delta}y_{it} = \hat{\beta} \times (T_{it} - T\_detrended_{it})$. Integrating over countries and years provides total additional risk born due to recent warming. We report this number as a percent change relative to the total risk in the de-trended climate (recall Figure 1 A) and report the following total damages due to recent warming, relative to a counterfactual de-trended climate, as:

$$excess\_conflict\_risk\_from\_warming = \frac{\sum_i \sum_t \hat{\Delta} y_{it}}{\sum_i \sum_t \left[\bar{y}_i - \hat{\beta}_1 \times (\bar{T}_i - T\_detrended_{it})\right]}$$

Note that the values we report are averages over the 20+ years of warming in the sample obtained from Burke et al. (2009). Comparing outcomes just for years at the end of the sample leads to higher estimated impacts of warming, as the trend has been generally linear since 1980.

2. **Burke et al. (2015) - Global GDP growth** (*5*). These data are country-year observations covering the years 1960-2010. We estimate country-specific linear trends in temperature only using data after 1980 (inclusive) to generate T^*_{it} and $T\_detrended_{it}$, as above. We then calculate $\hat{\Delta} g_{it} = \left[\hat{\beta}_1 T^{actual}_{it} + \hat{\beta}_2 (T^{actual}_{it})^2\right] - \left[\hat{\beta}_1 T\_detrended_{it} + \hat{\beta}_2 (T\_detrended_{it})^2\right]$.

   As described in Section 1.4 of this supplement, we transform this value into total dollars of GDP, averaged across all years, and divide by global GDP in each year to get the average damages to the global average income growth rate:

$$\begin{aligned} Avg\_growth\_rate\_adjustment\_from\_warming &= \frac{1}{\tau} \sum_t \frac{unearned\_dollars\_of\_global\_GDP_t}{global\_GDP_t} \\ &= \frac{1}{\tau} \sum_t \left[\frac{\sum_i \hat{\Delta} g_{it} \times Y_{it} \times pop_{it}}{\sum_i Y_{it} \times pop_{it}}\right] \end{aligned}$$

Again, note that the values we report are averages over the damages each year from 1980 to 2010.

References and Notes

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