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ARE WE ADAPTING TO CLIMATE CHANGE?

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ABSTRACT

We study whether the sensitivity of economic, health, and livelihood outcomes to climate extremes has declined over the last half century, consistent with adaptation. Understanding whether such adaptation is already occurring is central to anticipating future climate damages, to calibrating the level of ambition needed for emissions mitigation efforts, and to understanding additional investments in adaptation that could be required to avoid additional damages. Using comprehensive panel data across diverse geographies and outcomes, including data on mortality, agricultural productivity, crime, conflict, economic output, and damages from flooding and tropical cyclones, we find limited systematic evidence of adaptation to date. Across 21 outcomes we study, six show a statistically significant declining sensitivity to a changing climate, five show an increasing sensitivity, and the remainder show no statistically significant change. Our results do not imply that specific documented adaptation efforts are ineffective or certain locations have not adapted, but instead that the net effects of existing actions have largely not been successful in meaningfully reducing climate impacts in aggregate. To avoid ongoing and future damages from warming, our results suggest a need to identify promising adaptation strategies and understand how they can be scaled.

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1 Introduction

Rapidly accumulating greenhouse gases in the atmosphere have warmed the planet roughly 1.3°C degrees over the last century and could warm it by that much again or more over the next century (1). Even rapid decarbonization will have a limited effect on near-term warming and associated climatic changes. It is thus inescapable that human society will have to face, at least in the near term, a planet that will continue to warm, perhaps substantially.

How a changing climate will impact society is a first order scientific and policy question. Answering this question is central to calibrating the level of ambition needed for emissions mitigation efforts, to understanding the scale and manner of additional investments in adaptation that could be required to avoid additional damages, and to anticipating the magnitude of remaining "loss and damage" if mitigation and adaptation fail. A voluminous literature using historical data demonstrates how a changing climate can affect a diverse array of societal outcomes, including physical and mental health, energy use, agricultural and labor productivity, cognition, infrastructure, civil and interpersonal conflict, migration, and economic output, among many other outcomes (2–13). Whether these documented past relationships between climate and societal outcomes are a good guide for the impacts of future climate change depends substantially on whether and how humans themselves respond.

One view, perhaps most popular among economists, is that humans are clever and will figure out how to adapt as climate conditions change, with such adaptation limiting future damages and rendering past impacts a poor guide for future impacts. An alternate view is that human societies are surprisingly poorly adapted even to our current climate, as evidenced by the large damages from extreme climate events that are readily observed, and thus that we should not expect that future adaptation will be nearly enough to limit damages from future climate change. The underlying question is empirical: are we adapting to a climate that is changing, and if so, where and how fast?

Here we use a broad array of longitudinal datasets from around to world to quantify the speed of recent adaptation to climate. Following the IPCC, we consider adaptation as any response that improves an outcome or reduces damage, and we take a broad view of actions and behaviors that could constitute adaptation. These could include actions taken directly in response to climate exposure (e.g. purchasing flood insurance or drought-tolerant seeds, or building sea walls), or societal changes that are not a direct response to climate itself but that reduce the impact of climate shocks (e.g. medical services that get people to the hospital faster, or income growth that allows people to live in sturdier homes). To quantify the net effect of these and any other adaptive actions that could have taken place, we estimate whether the sensitivity of a range of societal outcomes to a fixed change in climate has changed over time. This intuitive notion of adaptation, common in the empirical adaptation literature (3, 14), has the advantage of parsimoniously capturing the individual or interacting impacts of a broad range of possible adaptation actions that might have taken place, without having to directly observe which actions occurred or measure their individual impacts. Our approach to measuring adaptation is complementary to a number of alternative approaches, including cataloging what adaptation actions individuals or communities have taken or report to have taken (e.g. (15)), or studying whether responses to climate differ as a function of some adaptation-relevant variable (e.g. income; see below for a discussion of these other approaches, and tradeoffs among them).

Specifically, for outcomes that are affected by changes in temperature, we study whether the estimated impact of 1°C increase in temperature on that outcome has changed over time. For other climate variables not directly linked to temperature (heavy precipitation, tropical cyclones), we similarly study whether the impact of a fixed change in the climate variable on a given societal outcome has changed over time. In either setting, we estimate time-period-specific response functions that relate changes in the climate variable to changes in the outcome of interest, and then quantify adaptation progress by estimating whether the derivative of the response function with respect to the climate variable is changing over time. For linear response functions, this derivative is just the period-specific estimated slope coefficients. For non-linear response functions, we compute the exposure-weighted average derivative in each period of interest. We also separately evaluate whether sensitivities have changed differentially at different parts of the response function, as this sheds additional light on the climate conditions under which adaptation has or has not been successful. For instance, extreme cold temperatures and extreme hot temperatures are both known to increase mortality, but progress against one (for instance, from better access to wintertime heating) might not imply progress against the other.

We estimate changing sensitivities across a broad set of geographies and sectors, including agriculture, health, conflict and violence, and aggregate economic output, using a range of exposures including extreme temperatures, rainfall, and tropical cyclones. Where possible we build directly on established climate-society relationships, updating datasets and re-analyzing them under common statistical frameworks. The datasets we use and papers we build upon are listed in Table A1. We restrict analysis to settings with at least 20 years of panel data – i.e., repeated observations of outcomes and climate for specific units over time – and estimate the time-varying effects of a given climate variable on a given outcome using standard, flexible panel econometric approaches that seek to isolate variation in the climate variable from a broad set of time-invariant or time-varying confounding variables that could be correlated with both climate and the outcome.

We then distinguish and quantify two broad ways in which societal sensitivity to a given climate threat could change over time (Fig A1). In the first, the impact of a specific climate exposure could change over time – for instance, fewer people could end up at the hospital on a 30°C day in a recent period relative to an earlier period, perhaps because their homes are now air conditioned. We call this "changing responses". In the second, which we call "changing exposures", people or productive units (e.g. people, firms, or agricultural fields) could have changing exposure to climate threats because they have spatially relocated – for instance, if people have moved to cooler parts of a country from hotter parts, reducing the number of 30°C days they experience. Exposure could also change because the climate itself has changed in a given location, for instance if a warming climate brings more 30C days in given location. In either case, if response functions are non-linear, changing exposures can change average societal sensitivity by altering the proportion of the population exposed to different climate extremes; if response functions are linear, then changing exposures have no effect on average sensitivity and any change in sensitivity will be driven by changing responses.

We emphasize that our overall approach seeks to answer the question "are we adapting to climate change", which is subtly distinct from the question "are we adapting to climate". An approach to estimating the latter would be to integrate under a response function relative to some chosen baseline climate and calculate the total societal burden of sub-optimal climate – e.g count up the total number of excess deaths on days hotter or colder than a chosen moderate temperature – and then study how this value changed over time. In this study, we instead calculate the exposure-weighted derivative of that response function and answer whether the impact of a fixed change in climate (as estimated by this derivative) has itself changed over time. Both questions are important. Our approach is meant to guide our understanding of how future *changes* in climate might impact society – the central concern in the calculation of the social cost of carbon, among other quantities – and whether such damage estimates need to account for recent trends in societal sensitivity.

Briefly, across a broad range of outcomes and climate relevant exposures, we find limited evidence that sensitivities to climate have declined in a way consistent with adaptation. Only in about one quarter (6 of 21) of settings we study do we identify meaningful, ongoing, statistically significant declines in the overall sensitivity of an outcome to a fixed change in climate. These include US maize and EU wheat yield sensitivity to temperature, and the sensitivity of EU mortality, US income, US violent crime, and US injury mortality to temperature. However, some of these improvements are driven either by much higher sensitivities early on in the study period with little recent progress (e.g. US maize), or are improvements that have slowed or even begun to reverse in most recent decades (e.g. US crime and US injury mortality).

For another quarter of outcomes (5 of 21), we find that sensitivity to a given change in climate has increased rather than decreased over time, amplifying the negative impacts of a changing climate. These include soy and maize yields in Brazil, African civil conflict, and suicide in the US. For the remaining half of outcomes (10 of 21), we find no statistically significant change in sensitivity over time. This does not necessarily mean that sensitivities are not changing in these settings, but instead that confidence intervals are such that we cannot rule out meaningful increases or decreases in sensitivity, nor rule out no change in sensitivity for these outcomes. We conclude by proposing and discussing eight reasons for observed (lack of) adaptation, and highlight promising future research directions.

Data and methods

Estimating adaptation We study adaptation by using panel data (repeated observation of units over time) to estimate whether the sensitivity of a given outcome y to variation in a climate variable C has changed over time across locations i and years t. In the simplest linear setting, we estimate:

$$y_{it} = \sum_{d \in D} \mathbf{D_d}(\beta_d C_{it} + \lambda_d Z_{it}) + \alpha_i + \delta_t + \varepsilon_{it} \tag{1}$$

where $\mathbf{D_d}$ is a vector of decadal dummies equal to one when year t falls into decade d. Coefficients of interest β_d estimate the decade-varying effects of C on y, controlling in some settings for other time-varying climate variables Z (e.g. controlling for precipitation in a regression of agricultural yields on temperature) and fixed effects for unit and time. In sub-annual data - e.g monthly US mortality data – we additionally control for location-by-month FE to account for local seasonality. In data with large numbers of subnational units across large countries – e.g county or district level data – we additionally control for subnational time FE or subnational time trends, following closely where possible the original papers on which our estimates and data build.

In many of our settings, existing literature indicates a non-linear relationship between a climate variable C and outcome y. In these settings, we follow this existing literature as closely as possible, estimating non-linear relationships between C and y and allowing these to vary by decade. Specifically:

- For agricultural yields, we follow refs (4, 16) and estimate piecewise linear functions that model log yields as a linear function of growing degree days between 0-30°C (GDD) and extreme degree days >30°C (EDD), where these days are cumulated over the growing season, and a quadratic in precipitation:

$$y_{it} = \beta_1 GDD_{it} + \beta_2 EDD_{it} + g(P_{it}) + FE \quad (2)$$

- For all mortality outcomes where temperature is the climate variable of interest, we follow ref (12) and model mortality rates as a fourth-order polynomial in cumulative daily temperature exposure and a quadratic in cumulative precipitation:

  $$y_{it} = f(T_{it}) + g(P_{it}) + FE \quad (3)$$

  Estimated response functions are interpretable much like commonly-used binned models, with the mortality effect of an additional day at a given temperature T^* relative to some base temperature T_b calculated as $\hat{f}(T^*) - \hat{f}(T_b)$, where $\hat{f}$ is the estimated quartic polynomial. We use this same functional form for temperature and US violent crime.

- For the impact of temperature on GDP, we follow ref (5) and model GDP growth as a quadratic in annual temperature and quadratic in annual precipitation.

- For tropical cyclone impacts on GDP or mortality, we follow existing studies (17, 18) and model outcomes as a linear function of TC wind exposure in the same year and the previous 15 years, and calculate cumulative impacts up through year 15. For GDP impacts, we use estimated TC windfield data from (19). For mortalilty impacts in the US, we use data from ref (18).

Using these estimates, we then quantify adaptation in two ways. First, following existing literature, we track what we term "point sensitivities", or the estimated effect of a given extreme exposure relative to a specified mild exposure – for instance, the effect on mortality of a 30°C day relative to a 20°C day. In a binned exposure model, this is simply the point estimate of the impact of an additional day in a given bin. In a polynomial model $y = f(C)$, it is evaluated as $\hat{f}(C_e) - \hat{f}(C_b)$, where C_e is the extreme temperature of interest and C_b is a typically mild (e.g., mortality minimizing) temperature. These sensitivities have been the focus of influential past work, e.g. ref (14).

Second, as our primary measure of adaptation, we compute what we term "total sensitivity", or the exposure-weighted derivative of an estimated response function, weighted by the population exposure to the climate variable of interest. For our outcomes that respond to temperature, this derivative measures the estimated impact of +1°C temperature increase on the outcome and population of interest. For linear response functions, total sensitivity is equivalent to the period-specific linear coefficient. For non-linear response functions, total sensitivity will depend on the shape of the response function as well as the amount of exposure at each point in the function, each of which is allowed to change by decade. For instance, to compute the total sensitivity of mortality to temperature in the US in the 1980s, we take the estimated temperature-mortality response function in the 1980s and evaluate its derivative at the population-weighted temperature distribution in the 1980s. Computing total sensitivities in our piecewise linear agricultural functions requires an additional step, where we take the derivative of Equation 2 with respect to temperature:

$$\frac{\partial y}{\partial C} = \frac{\partial y}{\partial GDD}\frac{\partial GDD}{\partial C} + \frac{\partial y}{\partial EDD}\frac{\partial EDD}{\partial C} \tag{4}$$

where the first partial derivatives in each term come from estimating Equation 2, and the second partial derivatives are estimated in separate regressions of either GDD or EDD on daily average temperature, using crop area as weights. This enables changes in the locations of where crops are grown to affect the average GDD and EDD exposure of a crop, and thus to affect the estimated total sensitivity.

For non-linear responses, a full understanding of adaptation involes joint examination of point sensitivities and total sensitivities. Total sensitivity alone is an incomplete measure - for instance, it is in principle possible that a non-linear function could change shape substantially with no change in its average derivative*. However, individual point sensitivities – e.g., the effect of a hot day on mortality – are also an imperfect guide, and could provide an incomplete and even misleading picture of the overall climate sensitivity of an outcome and how it is changing over time, given non-zero sensitivities at other parts of the temperature distribution. Indeed, our findings suggest that changes in sensitivities at more moderate temperatures can have outsized impacts on the total sensitivity of an outcome to climate, given that exposures to these more moderate temperatures are substantially more common than exposures to extremes. Thus for non-linear functions, our main measure of adaptation (total sensitivities) and the range of adaptive actions that changes in this measure might represent can only be fully understood by also examining point sensitivities, and we thus compute and discuss them jointly. To compute p-values on comparisons between estimated decadal sensitivities for a given outcome, we bootstrap regressions 1000 times (sampling spatial units with replacement) and compute p-values from the comparison of the resulting distributions of decadal parameter estimates.

To quantitatively compare the speed of adaptation across settings, we estimate a variant of Equation 1 where we interact climate variables with year to estimate the annual change in sensitivity.

*E.g consider two response functions $y = x^2$ and $y = x^4$, with a mean-zero normally-distributed x. Each would have identical total sensitivities but very different point sensitivities.

In the simplest linear setting, this is:

$$y_{it} = \beta_1 C_{it} + \beta_2 C_{it} * year_t + \lambda_1 Z_{it} + \lambda_2 Z_{it} * year_t + \alpha_i + \delta_t + \varepsilon_{it} \tag{5}$$

Using these estimates, we then compute the change in total sensitivity over time by calculating the annual change in the (exposure-weighted) derivative $\partial y/\partial C$ implied by Equation 5; for linear functions, this is just β_2. Finally, we convert this to percentage change sensitivity over time by dividing annual change in total sensitivity by the average total sensitivity, the latter estimated by running a pooled version of Equation 5 (with no interactions) on the full sample for each outcome and estimating the total sensitivity in that pooled regression. To compute a confidence interval on this value, we again bootstrap each regression 1000 times, sampling spatial units with replacement.

Adaptation decomposition We decompose changes in total sensitivity over time into "changing responses" and "changing exposures". The former captures any change in the impact of a fixed exposure over time - e.g., a change in the impact of a 30°C day on mortality. The latter captures any change in total sensitivity due to changing exposure to the climate variable of interest, holding fixed the response of that variable to a given climate exposure. Exposures could change because productive units (individuals, firms, agricultural plots) are moving around in space, because the climate itself is changing, or both (Fig A1). When response functions are linear, changing exposures will have no effect on total sensitivity – by definition, the slope of the response is the same at all points in the climate distribution – and adaptation is driven only by changing responses. When response functions are non-linear, total sensitivity can be driven by either changing exposures or changing responses.

To distinguish which is driving an observed change in sensitivity, we estimate period-specific response functions and exposures and iteratively fix one at its base value while varying the other. For instance, for the temperature-mortality relationship in the US, where the 1970s are our first full decade of data, we estimate changing responses by estimate decade specific response functions $y = f_d(T)$ (where $d \in$ 1970s, 1980s,.. 2010s) and then evaluating the derivative of each of these response functions at the 1970s population-weighted temperature distribution We then estimate changing exposures by fixing the response function at it's 1970 estimate and allowing the population weighted exposure to change over time.

Comparison to other approaches Our approach to measuring adaptation is complementary to a number of alternative approaches that have been taken. One such approach attempts to comprehensively catalog the actions people take or say they are taking in response to climate change (e.g.

ref (15)). Our approach instead evaluates whether the sum of those actions (observed and unobserved) are effective. Another popular alternative approach studies whether observed responses to climate differ as a function of putative adaptation drivers – asking, for instance, whether the effect of extreme heat on mortality is lower in wealthier regions. If correctly specified, this approach offers a plausible way to anticipate future climate impacts net of adaptation, given predicted changes in moderating variables, and also enables an implicit estimation of adaptation costs under some assumptions (12). Our approach cannot back out adaptation costs as this method can, but has a few notable advantages. First, it does not require having to take a stand on which among a large set of correlated moderating variables is the key moderator of past or future climate impacts. Second, it does not require having to make important assumptions about how variation in these moderators affects the realized pace of adaptation. For instance, observed cross-sectional variation in climate sensitivities (say, due to income) could be the result of years, decades, or centuries of changes in beliefs and behaviors, adaptive investments in technology or infrastructure, changes to regulation or even institutions, or some other slowly-evolving factor that reduced sensitivity to climate. Instead we are able to ask, given all observed and unobserved changes in adaptation-relevant moderators (e.g. income) and mediators (e.g. beliefs, infrastructure), how have climate sensitivities changed?

Our approach is closest to a more limited set of studies that have also looked at changing societal sensitivities to climate over time, particularly in the health domain (14, 20–22). These studies tend to focus on changes at specific points in the temperature distribution - for instance, the impact of a 30°C day on mortality. In addition to examining these changing point sensitivities, we also quantify whether the overall sensitivity across the temperature distribution is changing. Because sensitivities can (and often do) change differentially at different points in the temperature distribution, this approach provides a more complete picture of how a given outcome will respond to marginal warming, and for what types of exposures adaptation actions have or have not been successful in reducing impacts.

2 Results

Agriculture Climate impacts in agriculture have been studied for several decades, with a general tendency for studies to focus on crop yields but with a growing number also considering related outcomes such as livestock productivity, total farm revenue or GDP, worker productivity, and total factor productivity (TFP) (4, 23–26). A small subset of studies have considered whether sensitivities have changed over time, with reported increases in sensitivity for some cases (24, 25, 27) and decreases for others (28).

Here we consider crop yields across major producing countries in both temperate and tropical locations, as well as total global agricultural TFP. Our data include both irrigated and non-irrigated areas in each country, and so will account for any average mitigating effect of irrigation on temperature sensitivity (26, 29, 30), as well as any effect that changing use of irrigation over time will have on changes in sensitivity. For all yield outcomes we consider piecewise linear responses that allow the effect of warming at extreme temperatures to differ from those at more moderate temperatures.

Consistent with prior work using these datasets, we estimate on average a negative impact of warming for all outcomes investigated, including maize in the US, EU, and Brazil; wheat in the US, EU, and India; soybean in US and Brazil, and global ag TFP (Fig 1, Fig A2). This negative effect is in some cases a combination of positive effects of warming at moderate temperatures and negative effects at heat extremes, such as for US soybeans. For other crops, such as Brazil soybeans, warming at both moderate and extreme temperatures appears harmful to yields.

Most crops as well as global ag TFP show little evidence of a significant change in sensitivity over time (see Fig A2 for statistical tests of changing sensitivity). One exception is Brazil, where sensitivity appears to have increased in recent decades. For both maize and soybean, sensitivity in the 2010s was roughly twice as negative as in the 1970s in Brazil. Some of this may be due to greater measurement error of weather in prior decades, leading to underestimation of sensitivity in earlier decades (see Discussion). The increased sensitivity may also reflect real increases in heat impacts as the region has transitioned to a much more intensive, but still largely rainfed, production system. Crops in other regions (e.g. the US) show higher sensitivity early in the period but no clear trend over the past 50 years.

Changes in total sensitivity over time, where they were observed, were driven more by changing responses than changing exposures (Fig A3). The effect of changing exposures was minimal or slightly negative in most cases, suggesting that any movement of cropped area to more moderate climates within a given country was offset by the impact of a warming climate on the frequency of moderate and hot days. Changing responses offset the effect of these changing exposures in some settings (EU wheat and maize), but amplified them in other settings (Brazil maize and soybean).

Mortality A large body of research documents the impact of extreme hot and cold temperatures on all-cause and cause-specific mortality, but findings are mixed as to whether the effect of temperature extremes on mortality is changing over time. Studies suggest declining sensitivity of mortality to extreme hot temperatures but not necessarily extreme cold temperatures in the

US (14, 31), a declining sensitivity to extreme heat in some wealthy countries and cities but not in others (20, 32), declining sensitivities to moderate heat but not extreme heat in Europe (33), and a declining impact of cold temperatures but increasing impact of hot temperatures on mortality in Colombia (34). Recent reviews and cross country studies similarly suggest generally positive but sometimes uneven progress in reducing the effects of extreme temperatures on mortality (21, 22, 35).

Using county-level data from the US since 1968, we find an increasing and then declining sensitivity of mortality to cold temperatures (Fig 2), with the effect of a -10°C or a 0°C day on mortality about 25-30% lower than in the most recent decade relative to its peak in the 1990s (Fig A4). For extreme heat, we find that the effect of a 30°C or 35°C day on all-cause mortality declined through the 2000s, consistent with existing evidence (14), but that it has rebounded since, with the effect of either a 30°C or 35°C day in the most recent decade higher than in the previous two decades and only slightly lower than the effect in the 1970s and 1980s, and not significantly different (Fig A4; see Fig A8 for a comparison with results from ref (14)). Results are similar using models with nonparametric temperature bins (counts of days in different temperature intervals) rather than polynomials (Fig A6).

We find that the total sensitivity of mortality to warming (the estimated effect of +1°C temperature increase) is negative in all time periods, a result of populations in our historical sample being substantially more frequently exposed to extreme cold than extreme heat. However, total sensitivity in the most recent decade was substantially and significantly more positive than in any previous decade in our sample, a combination of a declining sensitivity to cold, a stable or increasing sensitivity to extreme heat, and increased exposure to hotter temperatures, the latter substantially driven by population growth in warmer locations in the US (Fig A4, Fig A5), which led to substantial increases in exposure to extreme temperatures relative to had populations not moved. Therefore, while our findings are consistent with the broader finding that near-term warming will reduce rather than increase overall temperature-related mortality in the US (12, 36), they also indicate that current trends are quickly eliminating this mortality benefit and that these changes might be underestimated by current models (see Fig A8).

In three decades of annual district-level data from 37 European countries, we also find fairly mixed evidence of changing sensitivity to either extreme cold or extreme heat. Data suggest that the effect of the coldest days on mortality is perhaps rising. The effect of the hottest days is falling from its peak in the 2000s but is now equivalent to effects observed in the 1990s, although larger confidence intervals make precise statements challenging (Fig A4). Overall patterns are robust to iteratively dropping the most populous countries from the sample (Fig A9). Estimated total sensitivity of mortality to temperature in Europe is negative, as in the US, but not significantly different than zero and is not discernibly trending over time in the annual data. Our results are thus again consistent with studies finding some near term benefits of warming for mortality in Europe (12), and studies that have found in more recent data that the "mortality minimizing temperature" has increased over time in Europe, limiting the impacts of moderate heat (33).

For a smaller sample of 17 European countries, we obtained weekly district-level mortality data back to 2000, allowing us to evaluate changing sensitivity in more granular data. We again find small increases in sensitivity to extreme cold and modest declines in sensitivity to extreme heat over time (Fig A10), consistent with annual data. Given suggestion in the literature that France in particular responded with adaptive measures following the deadly 2003 European heat wave (37), we re-estimate models with only French data, which extend back to the 1980s. Consistent with earlier papers, we find a substantial decline in heat-related mortality in the most recent decade relative to earlier decades, consistent with adaptation (Fig A10, right panels). Importantly, however, we find that prior to the 2010s, French mortality was substantially more sensitive to heat relative to elsewhere in Europe, and that recent progress in reducing this sensitivity in France has only brought this sensitivity down to levels observed elsewhere in Europe. Our findings are thus consistent with studies that find that extreme heat continues to be a substantial public health threat across much of Europe (32, 33, 38).

Finally, we study the impact of tropical cyclone winds on all-cause mortality in the US, using state level monthly mortality data back to the 1950s, following ref (18). As shown in that paper, excess mortality increases for many years after exposure to TC winds. These long-term indirect deaths are likely driven by the complex chain of events that follow a tropical cyclone (such as disruptions in healthcare access and economic losses) and are, therefore, distinct from direct deaths occurring during the geophysical event, potentially requiring different adaptive strategies. We compare estimates of cumulative excess mortality 15 years after TC exposure, finding limited change over time in cumulative mortality from TC exposure (Fig 2g). Populations have on average moved toward rather than away from more TC-exposed states, modestly increasing population-average sensitivity relative to had population shares remained at 1950 levels (see ref (18), Fig 4k).

Economic output, income, and productivity Previous work using a half-century of data on economic output from a global sample of countries documented a non-linear relationship between temperature and per capita economic growth (5), with marginal warming beneficial in the coldest countries and harmful in countries with average temperatures above about 13°C . In updated data, we find that this relationship has not changed over time (3a-b). The sign of the estimated total sensitivity (average marginal effect) depends on whether GDP or population is used as weights. Using GDP weights, the effect of +1°C warming is positive but not statistically significant early in the period, but becomes increasingly negative through time ($p < 0.01$, Fig A11). Using population weights, the marginal effect is negative and statistically significant, and is also becoming increasingly negative through time ($p < 0.01$). Population-weighted sensitivities are more negative that GDP-weighted sensitivities because much of the world's population lives in warmer regions (where marginal effects of warming are negative) while much of global GDP is currently produced in countries with moderate climates.

Related work has shown a similar non-linear relationship between temperature and per capita incomes in the US (39). We reproduce this relationship in updated data, finding that the negative effect of a hot day on annual incomes has gotten smaller over time, but that the negative effect of cold days has also declined (Fig 3c-d). The net effect has reduced the total sensitivity of US incomes to temperature ($p < 0.01$, Fig A11), with effects in the most recent period 20-30% smaller than in earlier periods.

Using global data on GDP growth and tropical cyclone (TC) exposure between 1965-2019, with wind field data from ref (19), we replicate and update results from earlier work (17) and document large cumulative effects of TC exposure on subsequent growth in GDP. We find no evidence that the cumulative impact of TC exposure on GDP growth has declined over time (Fig 3c), and point estimates suggest that this impact has increased but differences are only marginally statistically significant (Fig A11).

Finally, we reproduce results on the relationship between extreme precipitation and flood damages in the US, using data from 1988-2017 and following the empirical approach of ref (13), who documented a log-linear relationship between flood damages and standardized precipitation anomalies. As in that study, we find that the impact of precipitation increases on (log) flood damages were marginally higher in the final period (2008-2017) as compared to the early period (1988-1997), again suggesting limited adaptation over our study period (Fig 3d). Because damages are measured in logs, differential impacts over time are not driven by secular changes in the value of capital (buildings, infrastructure) that can be destroyed in a storm.

Crime, violence, and injury We revisit earlier findings on the relationship between temperature and conflict in Africa (10), using 1-degree gridded data on annual temperature and civil conflict (40) from the African continent between 1990-2019. Following earlier work, we estimate linear models between temperature and conflict, dividing estimated coefficients by period-specific baseline conflict risk to account for the fact that average rates of conflict are changing over time.

We find that the impacts of temperature on conflict are substantially and statistically significantly higher in the most recent decade relative to earlier decades (Fig 4a, Fig A12). Because we are normalizing coefficients by decade-specific baseline rates, this finding is not a mechanical result of recent increases in the average risk of conflict.

Building on a range of earlier work (41, 42), we also revisit the relationship between violent crime and temperature in the US, using county-month FBI data on violent crime (43) back to 1980. Consistent with this work, we find a roughly linear relationship between temperature and the rate of violent crime. However, we see clear evidence that the impact of hot days on crime has fallen substantially over time (Fig 4b), which has reduced the total sensitivity of violent crime to temperature by about one-third since the 1980s (Fig A12), although declines have appear to level off in the last 20 years.

Finally, using cause-specific US mortality data back to 1968, we study two specific types of mortality identified in prior literature as having a relationship with temperature that is plausibly distinct from the U-shaped all-cause relationship shown in Fig 2: unintentional injuries and suicides (9, 44, 45). Unintentional injury mortality in our data includes traffic fatalities, drug overdoses, poisonings, and workplace accidents. For unintentional injuries, we find a somewhat mixed picture: a meaningful decline in the impact of hot days on injury mortality beginning in the 1990s, with total sensitivity since 1990 about one-third lower than pre-1990, but roughly stable in the decades since 1990 and a statistically significant increase in the most recent decade relative to the 2000s (Fig 4c, Fig A12). The decline in total sensitivity to warming is also driven in part by a modest increase in the sensitivity of injury mortality to extreme cold temperatures.

For suicide, we similarly find a decline in the impact of hot days on suicide risk starting in the 1990s, but also find that the benefit of colder days in terms of reduced suicide mortality have also increased meaningfully in recent decades (Fig 4d). The net effect of these changes is a modest but statistically significant increase in total sensitivity of suicide to a 1°C increase in temperature (Fig A12).

Summary of results To compare adaptation progress across all studied outcomes, we estimate the annual percentage change in total sensitivity for each outcome across each of their particular study periods, and compute whether the observed change is statistically distinguishable from zero (Figure 5). The sign of the annual change in sensitivity depicted in the figure is set such that negative estimates are settings in which we conclude that adaptation is occurring, i.e. where the harmful impacts of a given change in a climate variable are being reduced (e.g. EU wheat yields and temperature) or the benefits are increasing (e.g. EU mortality and temperature). Positive estimates are settings where the harmful impacts of a given change in a climate variable are being amplified (e.g. African conflict and temperature, Brazilian soy and temperature). Colors denote the statistical confidence with which we can say whether observed changes are unlikely to be observed by chance, and match the signs as just described.

Across 21 outcomes, we estimate that 6 show statistically significant evidence of adaptation (28% of outcomes, shown in blue), measured as a change in total sensitivity that reduces the negative impact of a climate exposure. These include US maize and EU wheat yield sensitivity to temperature, and the sensitivity of EU mortality, US income, US violent crime, and US injury mortality to temperature. However, some of these improvements are driven either by much higher sensitivities early on in the study period with little recent progress (e.g. US maize), have slowed or even reversed in most recent decades (e.g. US crime and US injury mortality, see Fig A12), or are driven by a combination of decreasing sensitivity to extreme heat and increasing sensitivity to extreme cold (e.g. EU weekly mortality). In this latter case, both changes result in a reduced sensitivity to +1°C of warming, but only one change is desirable on its own.

For 5 out of 21 outcomes shown in red, we find changes over time in total sensitivity that have increased the negative impact of a climate exposure. These include soy and maize yields in Brazil, African civil conflict, and suicide in the US. For the remaining 10 outcomes (grey), we find no statistically significant change in sensitivity over time. This does not necessarily mean that sensitivities are not changing in these settings, but instead that confidence intervals are such that we cannot rule out meaningful increases or decreases in sensitivity, nor rule out no change in sensitivity for these outcomes.

3 Discussion

Across a broad range of outcomes and climate relevant exposures, we find limited evidence that sensitivities to climate have declined in a way consistent with adaptation. Only in about one quarter of settings we study do we identify meaningful, ongoing, statistically significant declines in the overall sensitivity of an outcome to a fixed change in climate. In all other settings, we see clear evidence that sensitivities increasing or we do not have strong evidence that they are increasing or decreasing. A key methodological insight across settings is the importance of looking across the entire temperature distribution in order to assess how sensitivities of a given outcome to temperature are changing. Demonstrable changes in sensitivity at one end of the temperature distribution could be offset by changes somewhere else in the distribution, as we find consistently across many different settings, and accounting for the net effect of these different changes can alter both quantitative and qualitative findings about the speed and nature of adaptation.

Relationship with existing adaptation estimates Our work is related to a large body of existing work that has estimated how climate sensitivities vary as a function of cross-sectional (spatial) variation in adaptation-relevant factors, for instance finding evidence that the sensitivity of agricultural yields to extreme heat is lower in places with more irrigation (26, 29), that mortality is less sensitive to extreme heat in places that are wealthier and/or more frequently exposed to extreme heat (12), and that crime goes up less on hot days in wealthier neighborhoods (46). Our findings of limited adaptation over time are not necessarily inconsistent with these findings, either quantitatively or qualitatively (see Fig A8 for a comparison in the US mortality context; estimates differ in magnitude but not in sign). Cross-sectional sensitivity gradients could reflect the outcome of longer-run processes that do not emerge on decadal time scales – for instance, recognition of the health or productivity impacts of a changed (new) climate, or time lags in investments in the built environment needed to reduce sensitivity to a changed climate. The benefit of projecting future impacts with models that specify the (cross-sectional) climatic or societal factors that shape climate impacts is that these factors themselves can be projected, allowing future impact projections that account for adaptation. The challenge is that the longer-run adaptations they imply might be slow to emerge on impact-relevant time-scales. Better reconciling cross-sectional versus time-series differences in sensitivities is a key area for future work.

Similarly, our findings are not inconsistent with other work that has found a substantial decline in the sensitivity of certain outcomes to specific temperature exposures – e.g., the century-long decline in the sensitivity of mortality to hot temperatures (14), or a decline in the sensitivity of mortality to moderate heat in Europe since 2000 (33). Our estimates of recent sensitivities are quantitatively similar to that work, but suggest that previous progress against extreme heat in particular has stalled or progressed slowly in both the US and Europe.

Finally, our broader results are consistent with more qualitative synthesis work that seeks to characterize adaptation actions being taken around the world. This work finds that existing implemented human adaptation efforts have been fragmented and incremental, with little evidence of "transformational" adaptation likely to substantially reduce impacts (15). Our results are, largely, a quantitative confirmation of these findings.

Explaining and interpreting limited adaptation What explains the relatively limited observed adaptation in our data? We discuss eight explanations why sensitivities of a given outcome to a climatic exposure could change (or not) over time, and whether and where these explanations are likely to be relevant to our findings.

The first two explanations focus on how the measurement of climate exposures might affect inferences about adaptation. First, classical measurement error in independent variables attenuates regression coefficient estimates, and so if this measurement error is trending over time – for instance, if data on temperature or cyclones have gotten more accurate over time – then that could make more recent estimates larger in absolute value, even absent changes in the "true" sensitivity of an outcome to climate. While this possibility cannot be ruled out, it is unlikely to explain many of our results. For US temperature data, we rely on a temperature product constructed from a fixed set of weather stations, and so our results will not be affected by improvements over time in station coverage. Similarly, at global scale, the number of temperature stations routinely reporting to international monitoring networks has actually declined in recent decades (47), perhaps implying that the simplest measurement error stories (e.g. better measurement through expanded monitor networks) are unlikely to be driving our results. Finally, TC records are notoriously incomplete, especially before the second half of the 20th century (48). However, records of specifically landfalling cyclones – the cyclones that drive the impacts we observe – are generally considered complete back to at least the 1930s, likely reducing measurement error in our setting (49). Additionally, our TC exposure metrics are based on mathematical models of wind fields which are applied consistently to TC track data and do not vary in time (18, 19).

A second explanation is the role of possible changes in other environmental variables that are relevant for measured outcomes. These could be variables whose impact interacts with a climate variable of interest (e.g., if the effect of a hot day on mortality is higher if average air pollution is also higher), and/or variables that cause impacts independently but which are more frequently co-occuring with a climate variable of interest – for instance, if a hot day is more humid or more likely to have wildfire smoke in recent years, amplifying mortality, or if a given windspeed during a tropical storm is now associated with more storm surge or more rainfall, influencing economic damages. These changes or interactions, to the extent they are occurring, would be implicitly reflected in our sensitivity estimates. A key analytic question is then whether this inclusion is a benefit or a shortcoming of our approach. To the extent that these changes or interactions reflect phenomena that are likely to continue under future warming, then arguably our sensitivity estimates provide accurate estimates of near-term impacts of changes in the measured climate variable of interest. If recent correlations or interactions between measured and unmeasured variables are likely to change substantially in the future, then our sensitivity estimates using recent data could be a poor guide for future impacts.

Our results are unlikely to be driven by a third explanation about changes over time in the amount of people or property available to be lost to a hazard – commonly called "exposure". For instance, the monetized damage from floods could rise over time simply because the value of assets that are exposed to floods has gone up. This is a common concern when trying to estimate changes in impacts of societal exposures over time. Our results are unlikely to be driven by this concern because we consistently use either scale-invariant measures of outcomes – per capita income growth, log-transformed flood damages and agricultural yields, or mortality rates – or we normalize estimated effect sizes by differences in baseline rates over time (for the case of civil conflict). Our results do capture (and are meant to capture) the related phenomenon of population movements and their influence on average sensitivities – for instance, if more people move to hot locations from cold locations, then the average effect of warming on mortality will rise. Our estimates capture the impact of these "changing exposures", and show that in most settings they are relatively modest relative to changing responses conditional on exposure.

A fourth explanation for changing sensitivities is if agents are adopting profit- or livelihood-maximizing technologies or practices that amplify productivity when climatic conditions are favorable, at the cost of increasing sensitivity (the difference between favorable and unfavorable conditions) when conditions are unfavorable. This tradeoff is perhaps most salient in agriculture where, for instance, increased sowing density of maize in the US (25) or increased fertilizer use in Brazil have increased overall productivity while also increasing the gap between output in favorable climate years versus unfavorable ones. This gap can also be amplified by policies that insure agents against losses in bad years, as has again been observed in agriculture (50). In both settings, climate is just one of many factors over which farmers are optimizing, and the net effect of this optimization is to increase overall output while also increasing sensitivity. It is unclear the extent to which this explanation is relevant in non-agricultural contexts.

A fifth and related explanation concerns "competing risks", or the possibility that declines in the importance of other health- or productivity-limiting factors could amplify the importance of climatic variation. In a health setting, declines in the importance of non-climate related causes of death could increase the relative impact of climate-related causes of death (with the opposite also possible). In agriculture, highly nutrient-constrained systems might be less affected by a drought because there is little productivity to lose. Thus, secular changes in these competing risks could drive changes in observed climate sensitivities. As in the previous explanation, this explanation offers another setting in which changes in non-climate related factors can increase climate sensitivities.

A sixth explanation concerns what might be termed "incidental" or "indirect" adaptation, resulting from the fortuitous climate benefits of new technologies or practices aimed at raising overall productivity or improving health and general comfort. This is yet another way in which changes in non-climate-related factors might alter climate sensitivities. Many documented examples exist in the health domain, including widespread adoption of air conditioning (14) (arguably adopted for home comfort rather than as a mortality-reducing tool), stricter gun laws that decreased temperature-related homicides (51), or the expansion of community health centers that reduced temperature-related mortality (52). Existing evidence on these indirect adaptations makes it clear that absence of adaptation in the aggregate does not imply that adaptation is not occurring at smaller scales. Many such secular changes in society are likely reducing sensitivities, even if those are not (yet) leading to substantial aggregate benefits.

A seventh explanation, likely important in many settings, is the role of information: individuals might not recognize that they're being exposed, might not realize that exposure is impacting them, or might not know how to respond. A host of recent papers highlight the importance of adequate information for climate adaptation, including the ability of improved forecasts of extreme heat and cold to reduce mortality and accidents (53, 54), of improved cyclone forecasts to reduce economic damages (55), and improved seasonal forecasts for agriculture to increase productivity (56).

A final set of likely explanations for why climate sensitivities can change, or why they have not changed, is the range of forces that shape the existence, adoption and use of "direct" adaptive measures – i.e. technologies or practices whose direct purpose is to reduce climate sensitivity. Examples include the creation and adoption of drought-tolerant crop varieties or expansion of irrigation in agriculture, or the choice to stay inside on a hot day in response to a public health messaging about the risks of extreme heat. A standard economic model suggests that adoption of these technologies and practices have both benefits and costs, and individuals, firms or communities will adopt them up to the point that the benefits of an additional adaptation action just equal the costs of that action. Under this model of adaptation, we would not expect sensitivities to change unless the costs or benefits of adaptation have changed – and in many real-world settings, perhaps they have not appreciably changed. Difficulty in innovating and disseminating new technologies could keep adaptation costs high (or infinite, if no relevant technology exists). For instance, multiple studies highlight the complex challenges and long time lags involved in developing new climate resilient crop varieties (57), and arguably we have no demonstrated technology or practice for limiting the impact of hot temperatures on conflict. Costs could also remain high due to existing market failures or frictions – for instance, an inability to borrow or insure – and a growing literature highlights the existence and importance of these frictions for various types of climate adaptation and disaster recovery (56, 58–60).These frictions intersect with low incomes in much of the world, including even in wealthier countries – for instance, low income households in the US often reduce their use of air conditioning on hot days because it is too expensive to run (60). Maintaining incomes through cash transfers have been shown to help households to maintain consumption and productivity in the face of climate shocks (61, 62).

We emphasize that the optimal climate sensitivity across each of our settings is unlikely to be zero. Even absent other competing goals, the cost of completely eliminating the impacts of climatic variation likely exceed the benefits. But competing goals are also important, and the goal of most human activities is not to reduce climate sensitivity but rather to improve other outcomes, e.g. incomes, productivity, or happiness. Sometimes pursuing these other goals can reduce sensitivity (AC increases comfort and reduces mortality), but sometimes it increases sensitivity (increased planting density increases average yields but raises yield sensitivity to drought). Sometimes both could be happening and the net effect could be no change in sensitivity. Nevertheless, existing sensitivities imply very large economic and livelihood losses from climatic variation in today's climate, and even larger losses under future climate change, representing a substantial fraction of global economic output and a meaningful contribution to global and local health burdens (3, 12, 18, 63). The combination of these large existing and projected losses, and a rapidly growing body of research that shows that adaptation is substantially constrained in many settings, suggests that current levels of adaptation are likely too low. If this is correct, and substantial aggregate damages from a warming climate are to be reduced, then a critical task will be to uncover which adaptation actions are successful and cost effective, what might constrain their adoption, and how these constraints can be lessened and adaptation actions scaled.

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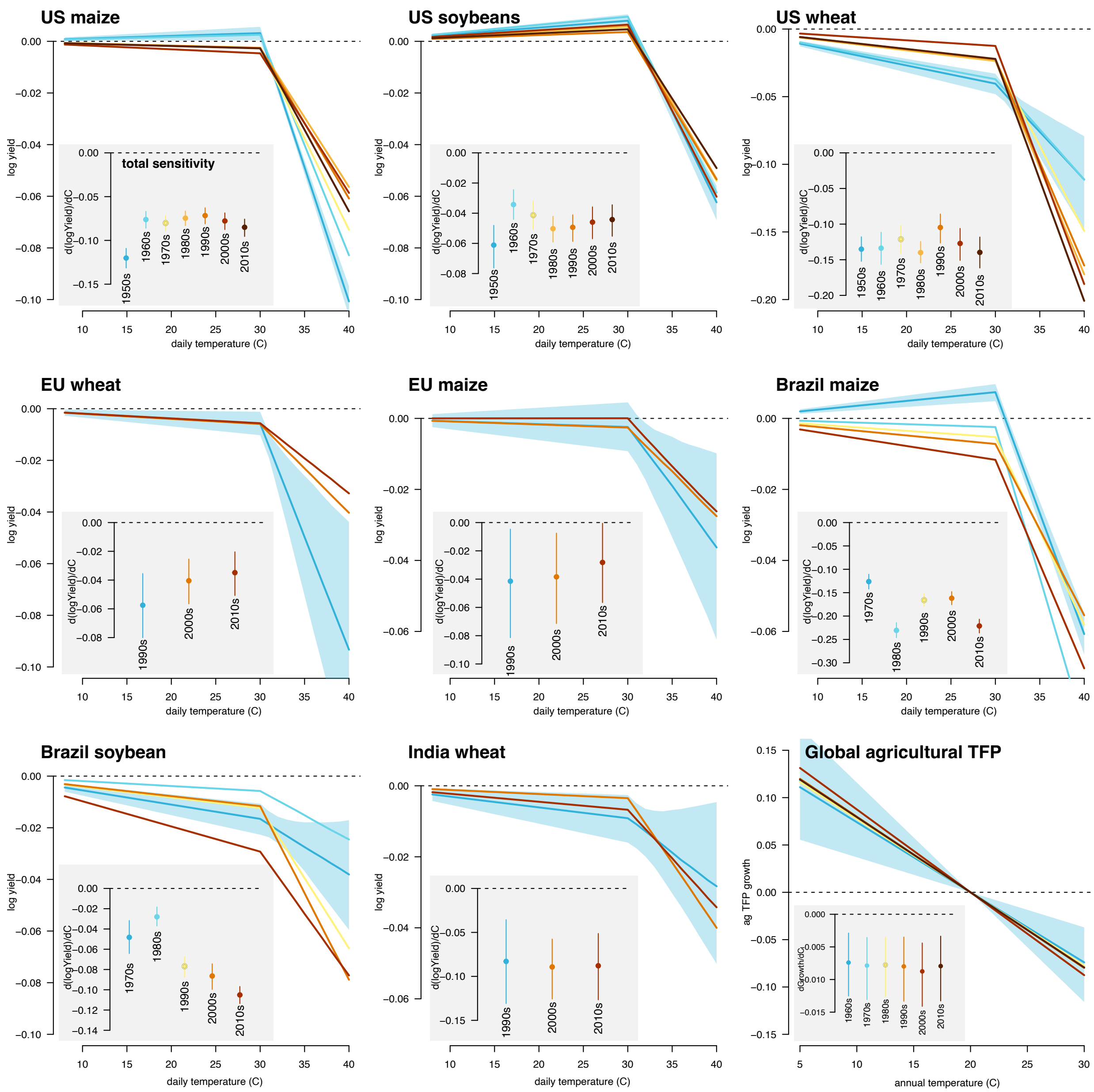

Figure 1: **Sensitivity of agricultural yields to temperature over time**. Each panel shows decadal sensitivity for the country-crop combo denoted in the panel title, with kinked lines showing the estimated piecewise linear response function to degree days between 0-30°C and above 30°C , by decade for each crop, with the confidence interval shown for the first period response function. Colors correspond to decades as labeled in panel insets. Inset panels show estimates of the "total sensitivity" (or estimated effect of a +1°C increase in temperature). Corresponding p-values on whether sensitivities differ over time are given in Fig A2. The final plot shows the sensitivity of global agricultural total factor productivity (TFP) to annual temperature. Most settings show stable or increasing sensitivity of yields to temperature, with declines in sensitivity to extreme heat offset by declining benefits from moderate (<30°C) temperatures.

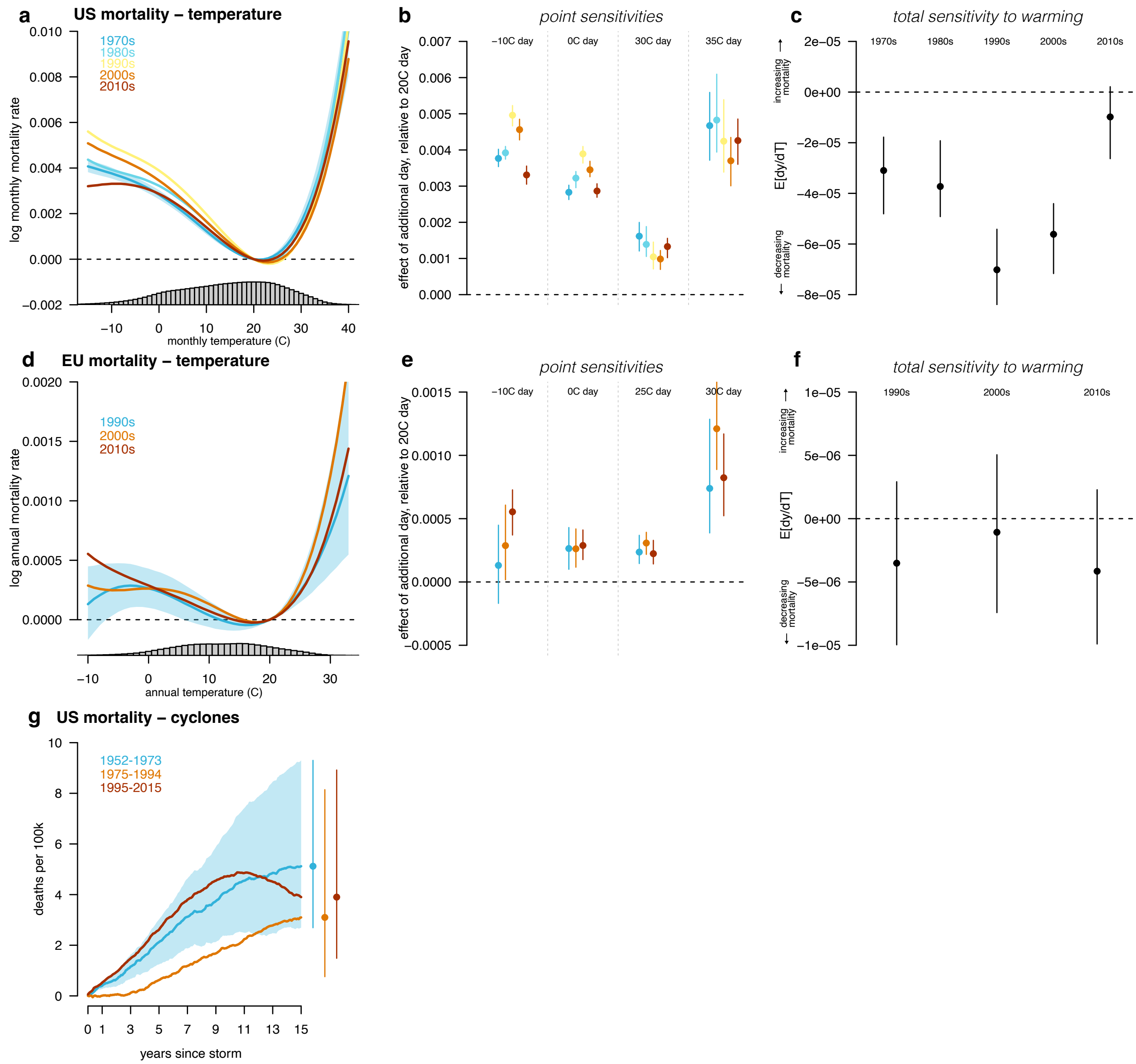

Figure 2: **Sensitivity of mortality to temperature and tropical cyclones**. **a-c**. Temperature-mortality relationship in the US over 1968-2019, using monthly data at the county level. **a** Temperature-mortality response functions by decade, with histograms at bottom showing population-weighted temperature exposure. Confidence intervals are shown for the first period. **b** Effect of an additional cold or hot day on monthly mortality by decade, relative to a day at 20°C . **c** "Total sensitivity" to +1°C warming over time, measured as the exposure-weighted derivative of the decadal response functions shown. Overall sensitivity to +1°C of marginal warming is negative, because populations are currently much more exposed to extreme cold than extreme heat. Corresponding p-values on whether sensitivities differ over time are given in Fig A2. **d-f** Same, for temperature-mortality relationships in EU countries over 1990-2019, using annual data at the district level. **g** Relationship between cumulative mortality and tropical cyclone (TC) exposure in the US using monthly data at the state level, 1952-2015, adapted from ref (18). Each line shows cumulative excess mortality out 15 years following TC exposure, for 20 year periods starting in the 1950s. Estimates at right show period-specific cumulative mortality estimates at 15 years after exposure.

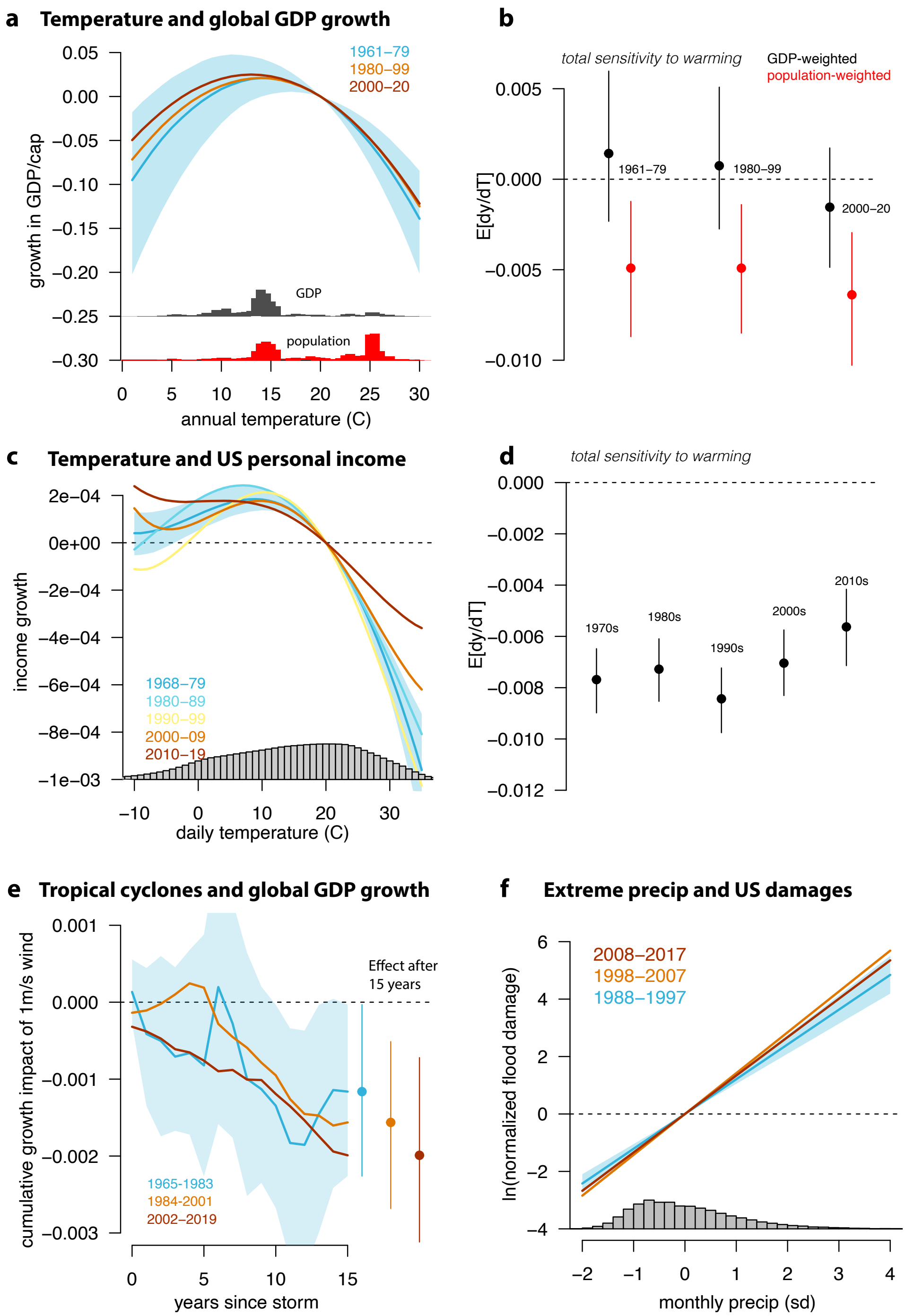

Figure 3: **Changes in climate impacts on income and economic output over time.** **a-b** Temperature and growth in per capita GDP, 1961-2019, following refs (5, 63). **a** Period specific response functions colored by period, with the confidence interval shown for the first period. Distributions at bottom show GDP- or population-weighted temperature observations. **b** Estimated period-specific average sensitivity, as estimated by computing the average derivative of the period specific response functions in (a), using either population (red) or GDP weights (black). **c-d** Temperature and personal income in the US, 1968-2019, following ref (39). Average sensitivities in (d) calculated using the population-weighted daily temperature distribution shown at the bottom of panel (c). **e** Tropical cyclone winds and GDP growth, 1950-2019, following ref (17). **f** Precipitation and flood damages in the US, 1988-2017, following ref (13).

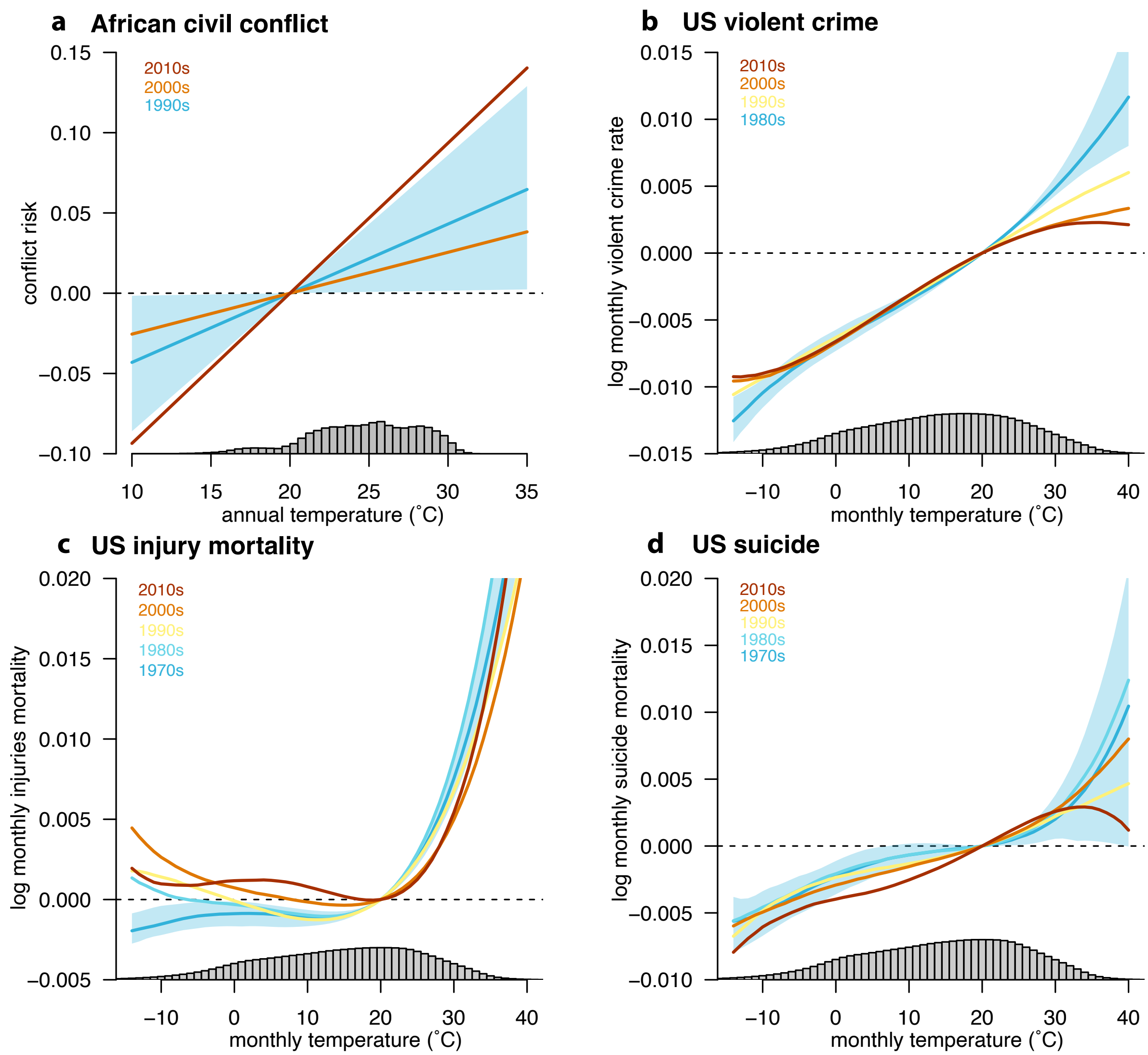

Figure 4: **Changes in climate impacts on conflict, violence, and injury. a** Temperature and African civil conflict at the annual 1∘ grid-cell level, 1989-2019. **b** Temperature and US violent crime at the county-month level, 1980-2019. **c** Temperature and US unintentional injury mortality at the county-month level, 1968-2019. Unintentional injuries include traffic fatalities, overdoses and poisionings, and workplace accidents. **d** Temperature and US suicide at the county-month level, 1968-2019. Each panel shows period specific response functions colored by period, with the confidence interval shown for the first period. Histograms at bottom show distribution of temperature exposure in each sample.

	outcome	period	exposure	ΔTotal sensitivity (%/yr)
Agriculture	US maize	1950–2019	+1°C growing season	–0.5
	US soybeans	1950–2019	+1°C growing season	–0.1
	US wheat	1950–2019	+1°C growing season	–0.1
	EU wheat	1990–2019	+1°C growing season	–1.9
	EU maize	1990–2019	+1°C growing season	–2.3
	Brazil soy	1970–2019	+1°C growing season	2.3
	Brazil maize	1970–2019	+1°C growing season	0.8
	India wheat	1990–2019	+1°C growing season	–0.7
	Global Ag TFP	1960–2019	+1°C growing season	0.2
Mortality	US mortality – temperature	1968–2019	+1°C monthly	–0.7
	EU mortality – temperature (annual)	1990–2019	+1°C annual	–5.3
	EU mortality – temperature (weekly)	2000–2019	+1°C weekly	–7.4
	US mortality – cyclones	1952–2015	+1 m/s wind speed	4.8
Output	Global GDP – temperature	1961–2019	+1°C annual	–0.0
	US income – temperature	1968–2019	+1°C annual	–0.5
	Global GDP – cyclones	1965–2019	+1 m/s wind speed	1.3
	US damages – floods	1988–2017	+1sd monthly rainfall	0.4
Violence	African conflict	1989–2019	+1°C annual	3.4
	US violent crime	1980–2019	+1°C monthly	–1.3
	US injury mortality	1968–2019	+1°C monthly	–2.4
	US suicide	1968–2019	+1°C monthly	0.6

Key:

	p-value, change==0			
	<0.01	*<0.05*	*<0.1*	*>0.1*
Sensitivity worsening				
Sensitivity improving				

Figure 5: **Summary of adaptation findings across outcomes show no consistent evidence of adaptation.** We summarize adaptation as the percentage change in total sensitivity per year over the listed study period. Total sensitivity is measured as the exposure-weighted derivative of the outcome with respect to the exposure listed in the third column, and signs indicate whether adaptations are reducing any harmful impact of the climate exposure over time (negative) or amplifying a harmful impact over time (positive). Statistical significance of the annual change is denoted by the color shading, as shown in the key at bottom; darker shades indicates higher confidence that the estimated effect is unlikely to happen by chance. Six out of 21 outcomes show a statistically significant decline in the impact of a given climate change, five show an increase, and the remaining 10 show no statistically significant change.

Appendix

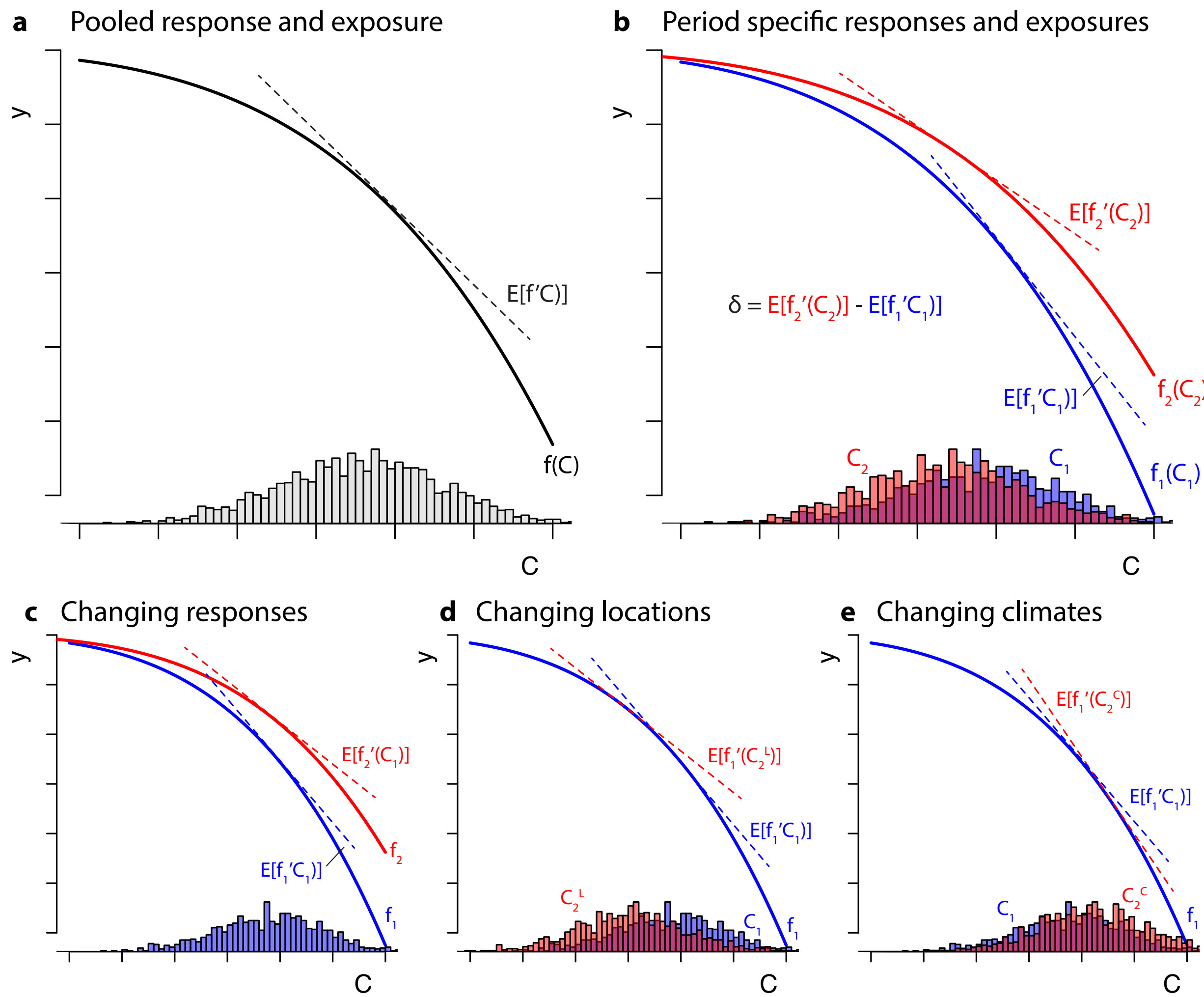

Figure A1: **Understanding changes in societal sensitivity to climate over time**. **a.** A societal outcome y is related to a climate variable C via an estimated response function $y = f(C)$. We describe sensitivity ("total sensitivity") as the average slope of this response function, which is computed as the exposure weighted average derivative $E[f'(C)]$. **b.** With a non-linear response function, overall sensitivity could change between two time periods due to a changing response function ($f_1 \rightarrow f_2$), changing exposure distributions ($C_1 \rightarrow C_2$), or both. Our primary measure of adaptation is whether the per-period average sensitivity is changing, $\delta = E[f_2'(C_2)] - E[f_1'(C_1)]$. We then decompose this change in sensitivity into two main components: "changing responses", or changes in the response function over time for a fixed exposure (**c**); and "changing exposures", which is itself made up of two components: "changing locations", or changes in exposure distributions due to spatial relocation of productive units (people, plants, etc) under a fixed response function and climate (**d**); and "changing climates", or changes in exposure distributions due to a warming climate, with population movements and response functions held fixed (**e**). C_2^L describes the period 2 exposure distribution if the climate was exactly as it was in period 1, yet productive units had spatially relocated to their observed locations in period 2. C_2^C describes the period 2 exposure distribution if the location of productive units was exactly as it was in period 1, yet the climate in each location had changed to its observed period 2 values.

Table A1: Data sources and References

Sector	**Country**	**Years**	**Reference**	**Reference paper**	**Climate dataset**
Agriculture	US	1950-2019	NASS (2023)	Schlenker and Roberts (2009) (4)	PRISM
Agriculture	Brazil	1974-2022	IBGE (2022)		ERA5
Agriculture	India	1990-2020	ICRISAT (2023)		ERA5
Agriculture	EU	1980-2020	European Commission-Directorate-General for Agriculture and Rural Development (2023)		E-OBS
Conflict	Global	1990-2020	UCDP (2023)	Brosché and Sundberg (2023) (40)	BEST
Crime	US	1980-2019	OpenICPSR (2023) (43)		PRISM
Mortality	European Union	1960-2020	Eurostat (2023)	Carleton et al (2022) (12)	E-OBS
Mortality	France	1980-2019	INSEE (2023)		E-OBS
Mortality (county)	US	1968-2020	CDC WONDER (2023)		PRISM
Mortality (state)	US	1930-2015	US Vital Statistics		PRISM
Population	European Union	1960-2020	Eurostat (2023)	Carleton et al (2022) (12)	E-OBS
Population	US	1968-2020	US census Bureau (2023)		PRISM

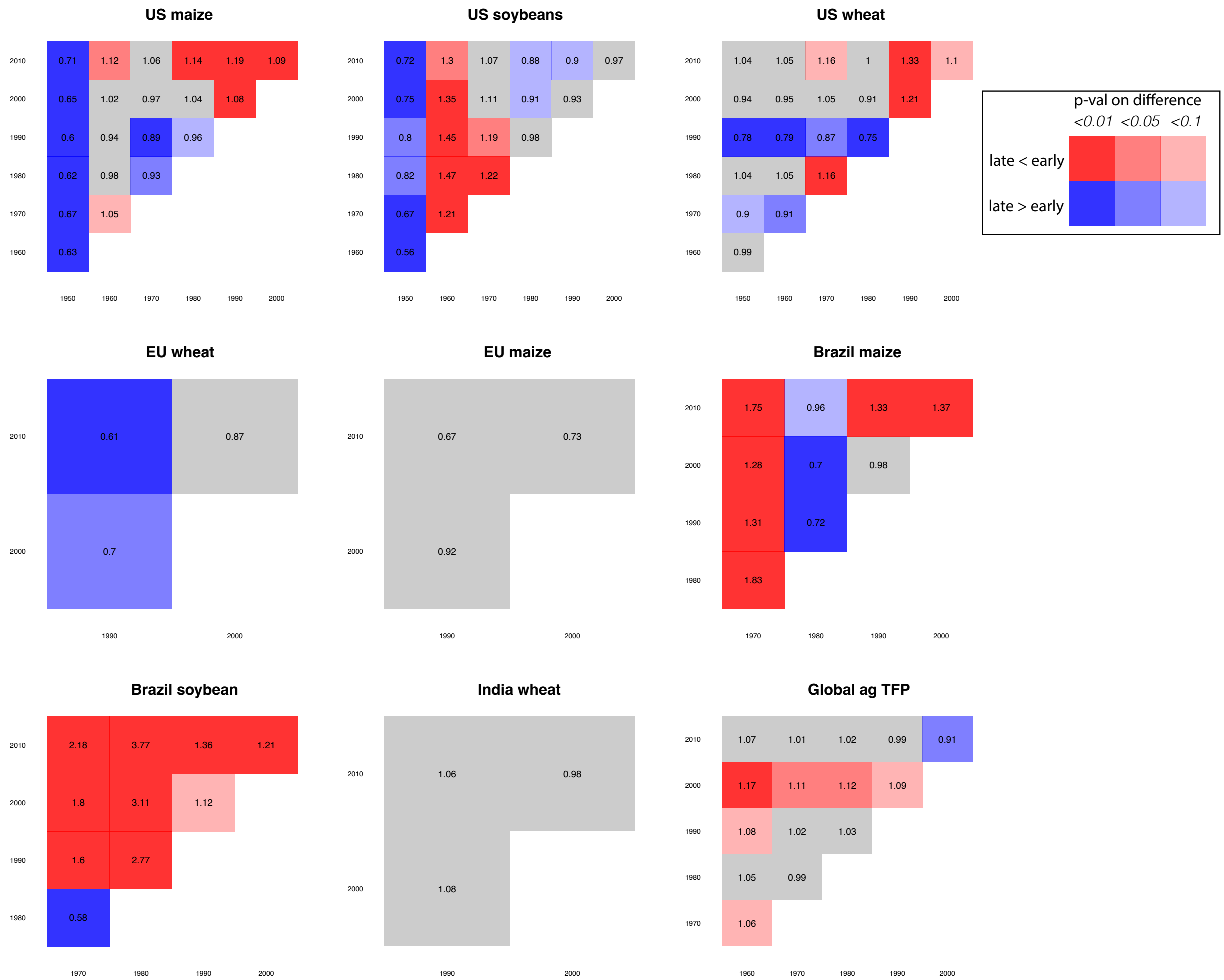

Figure A2: **Statistical tests on whether climate sensitivity is changing over time for temperature-agriculture relationships shown in Fig 1**. Each panel shows tests of whether climate sensitivities are quantitatively and statistically different between periods. Key is shown at right. Heatmaps in each panel show pairwise tests of equivalence in sensitivity between periods, with period years labeled on rows and columns. Boxes are shaded blue if the sensitivity in the later period is more positive than the earlier comparison period, and red if the later period is more negative. Darker shading indicates higher significance levels, as calculated using the p-value on a two-sided test that the sensitivities are the same. Grey shading indicates $p >= 0.1$ in a two-sided test. Numerical values within the boxes report the ratio between the sensitivity in the later period and the sensitivity in the earlier period. Ratio values are not reported if the sensitivities in the two comparison periods differ in sign.

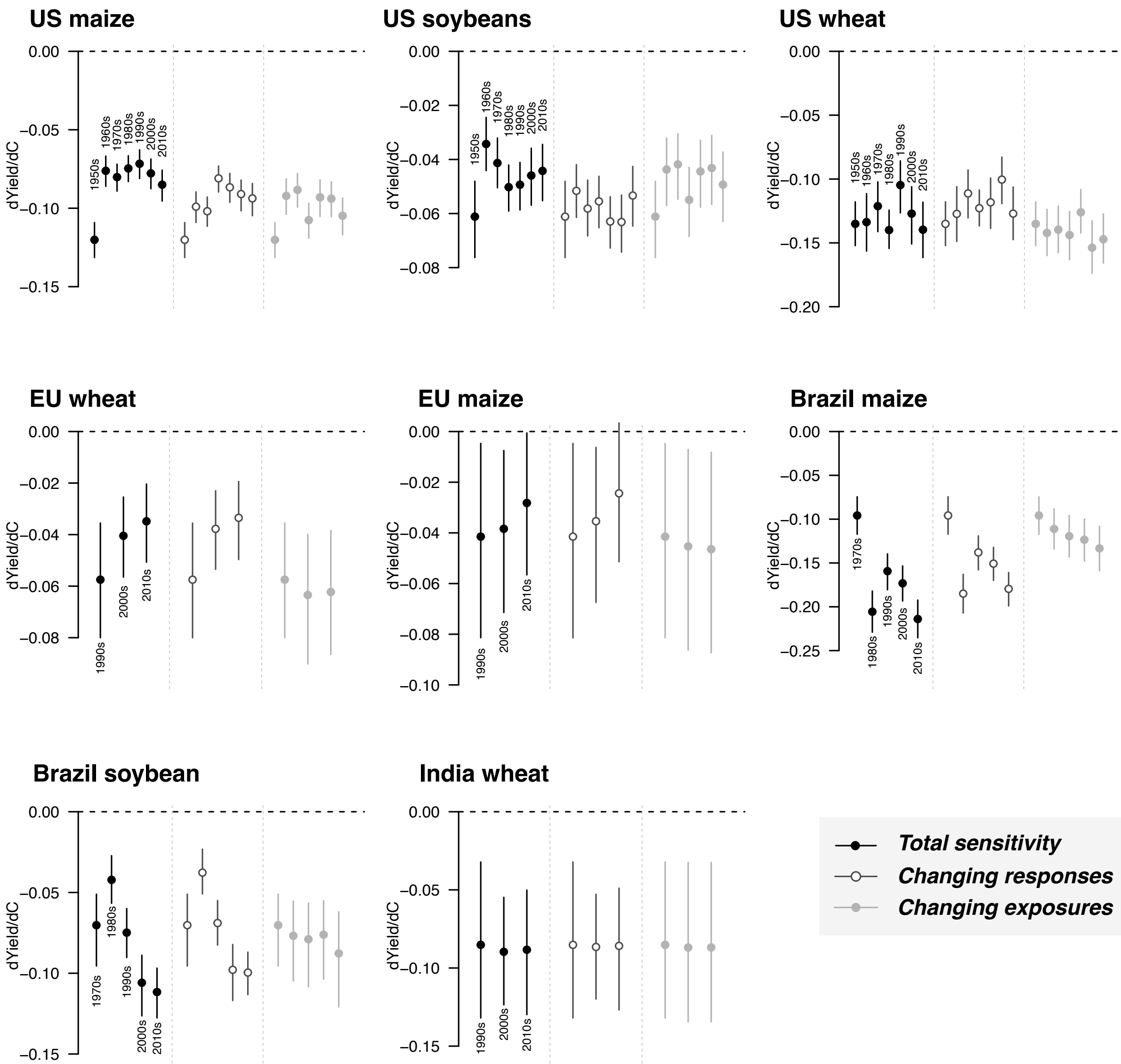

Figure A3: **Decomposing changes in agricultural yield sensitivity to temperature**. We decompose decadal estimates of “total sensitivity” (black dots and whiskers) into changes resulting from changing response to a given exposure holding the distribution of temperature exposure at beginning-period levels (grey open circles) and changes resulting from changing exposures holding responses fixed at beginning-period responses (light grey filled circles).

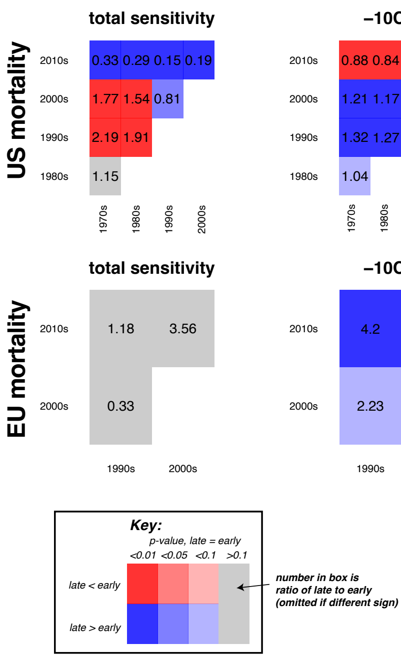

Figure A4: **Statistical tests on whether climate sensitivity is changing over time for temperature-mortality relationships shown in Fig 2**. Each panel shows tests of whether climate sensitivities are quantitatively and statistically different between periods. Key is shown at right. Heatmaps in each panel show pairwise tests of equivalence in sensitivity between periods, with period years labeled on rows and columns. Boxes are shaded blue if the sensitivity in the later period is more positive than the earlier comparison period, and red if the later period is more negative. Darker shading indicates higher significance levels, as calculated using the p-value on a two-sided test that the sensitivities are the same. Grey shading indicates $p >= 0.1$ in a two-sided test. Numerical values within the boxes report the ratio between the sensitivity in the later period and the sensitivity in the earlier period. Ratio values are not reported if the sensitivities in the two comparison periods differ in sign.

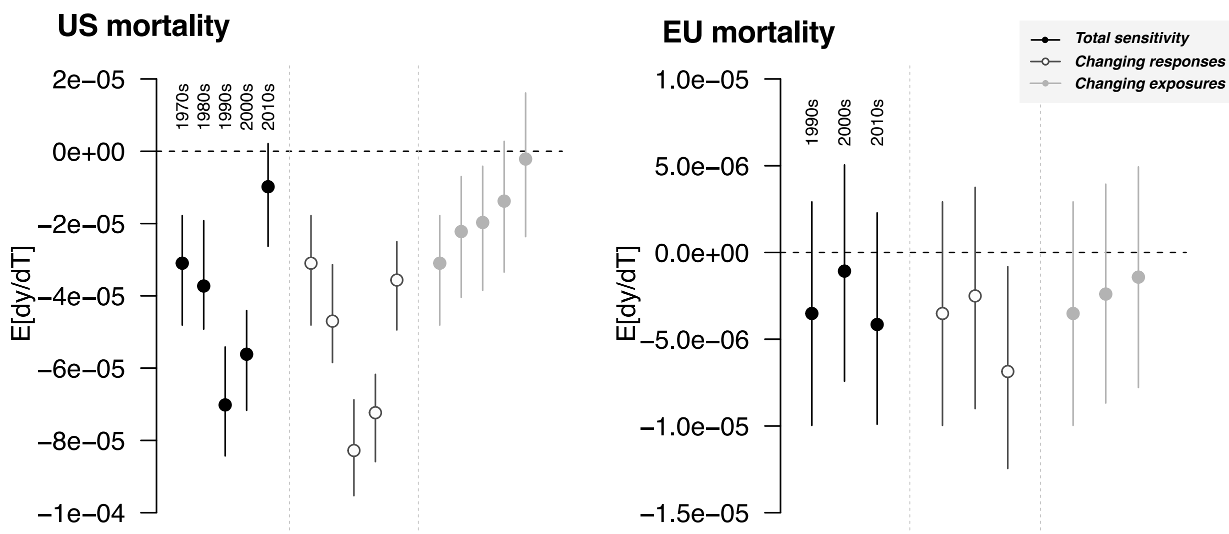

Figure A5: **Decomposing changes in mortality sensitivity to temperature**. We decompose decadal estimates of "total sensitivity" (black dots and whiskers) into changes resulting from changing response to a given exposure holding the distribution of temperature exposure at beginning-period levels (grey open circles) and changes resulting from changing exposures holding responses fixed at beginning-period responses (light grey filled circles). Changing sensitivities in the US are driven substantially by changing responses, with recent increases in sensitivity driven by a reduction in cold sensitivity and increasing or stable heat sensitivities; changing exposures have also increased sensitivity, due to a combination of population movements to warmer regions and a warming climate. EU changes in sensitivity have been more muted.

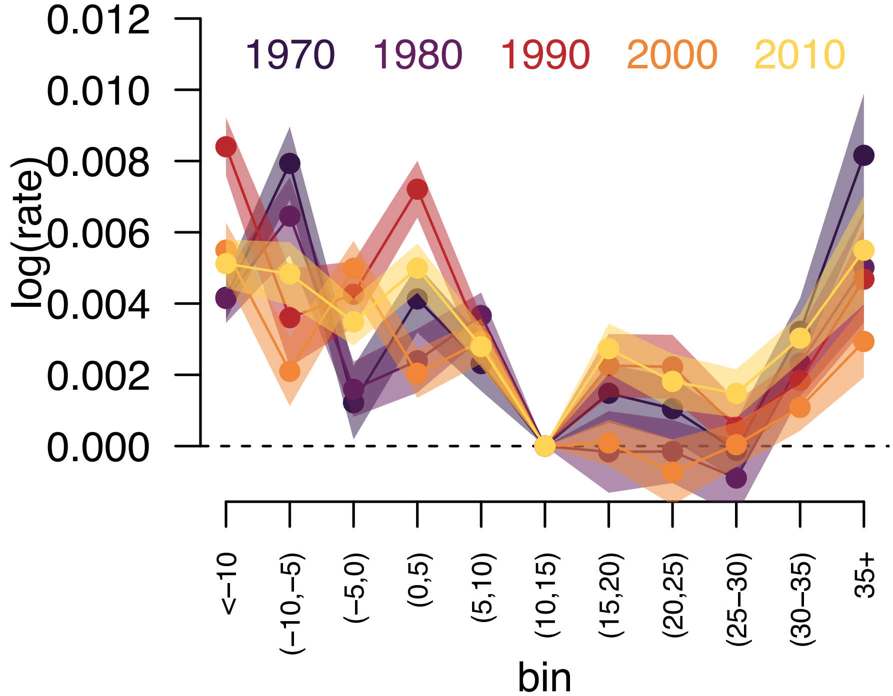

Figure A6: **US all-cause mortality response to temperature by decade, estimated using a binned model**. Each color shows a response function by decade with confidence interval. Consistent with polynomial models, effect of extreme heat fell through the 2000s and then rebounded.

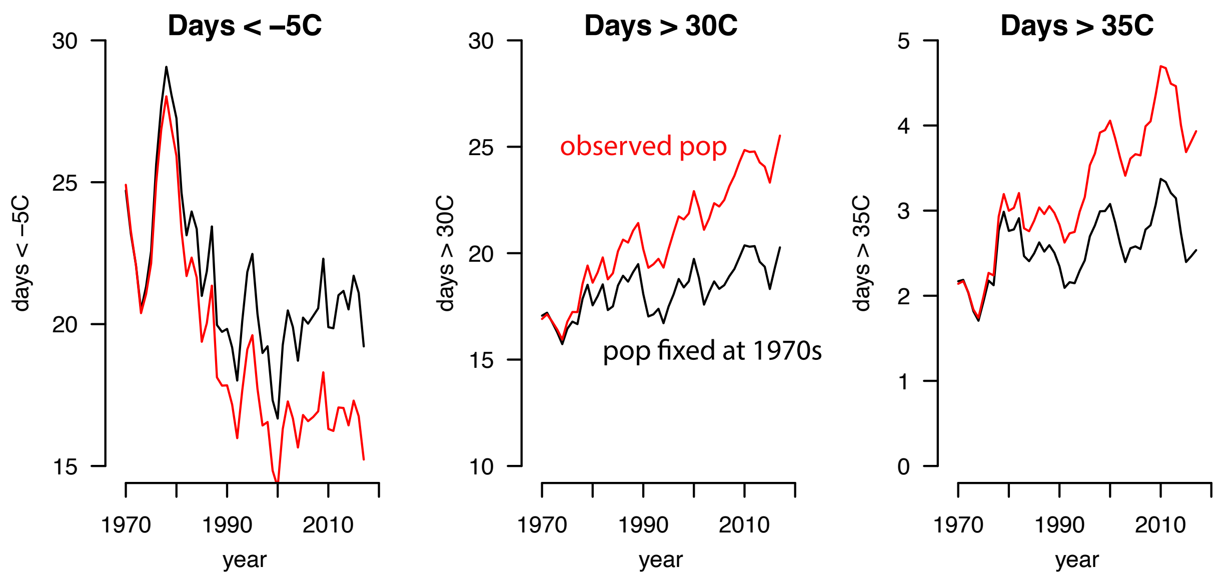

Figure A7: **Increasing exposure to extreme heat in the US as a function of population growth in warmer areas**. Panels show population-weighted average annual exposure to extreme cold (days <-5°C) and extreme heat (days >30°C or 35°C), either as observed in the data (red lines) or as estimated would have occurred had the spatial distribution of population remained fixed at its 1970 locations.

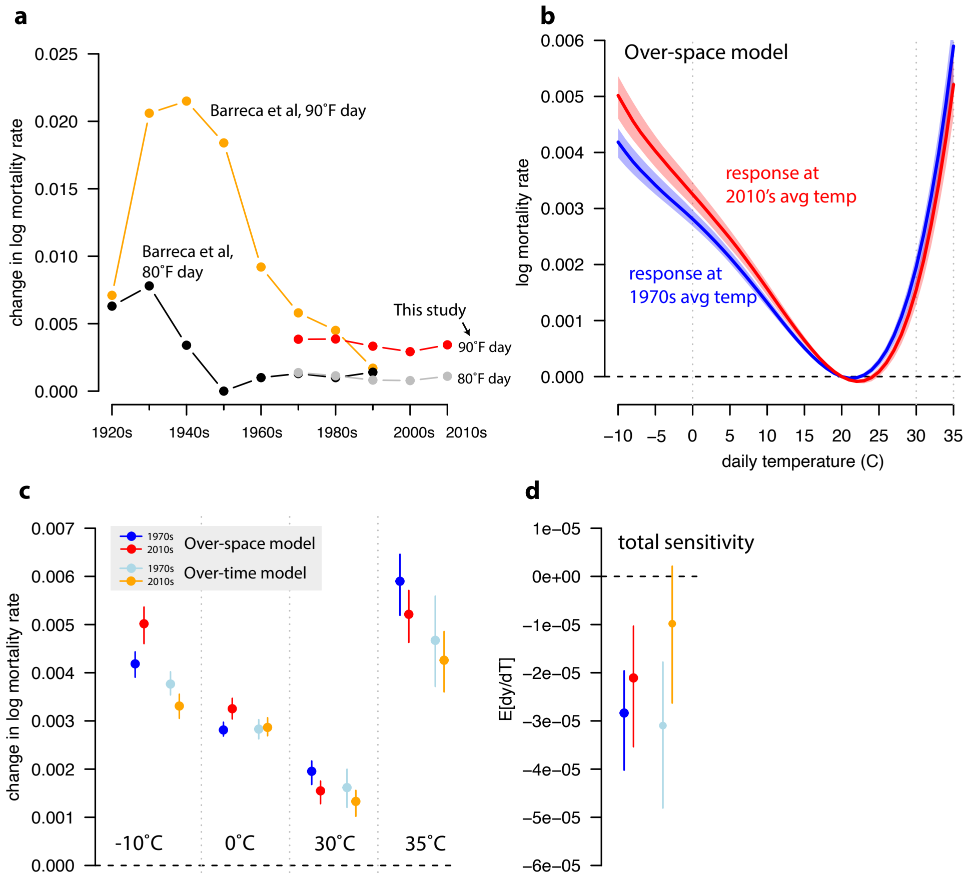

Figure A8: **Comparison of US temperature-mortality estimates from this study versus other recent work**. **a** Comparison of estimated impact of an additional 80°F (black lines) and 90°F day (orange lines) from Barreca et al (14) through 2004, vs estimates of impacts at those temperatures from this study through 2019 (red and grey lines). Estimates are largely similar for overlapping periods, although suggest less decline in impacts on the hottest days. **b-d** Contrasting with this study's "over-time" model, we estimate an "over-space" model that allows the impact of daily temperatures to depend on a location's long-run average temperature, following (12). **b**. Estimated temperature-mortality relationships from the "over-space" model in the 1970s (blue) and 2010s (red), given the observed +1.85°C (pop-weighted) long-run average temperature increase over the period. **c**. Estimated changes in point sensitivities (impacts on mortality for an additional day at -10°C , 0°C , 30°C , 35°C relative to 20°C) in the 1970s vs 2010s, for the over-space and over-time models; colors given in legend. Both models show qualitatively similar declines in sensitivities at hot temperatures, but differing changes at cold temperatures. **d**. Estimated changes in total sensitivity for the two models across the two periods. Total sensitivity in the over-time model has become less negative more rapidly, due in part to estimated declines in cold sensitivity from that model (versus increases in cold sensitivity from the over-space model); the over-space model would project statistically significant declines in mortality from an additional +1°C warming today, whereas the over-time model would project gains that were half as big and not statistically significant.

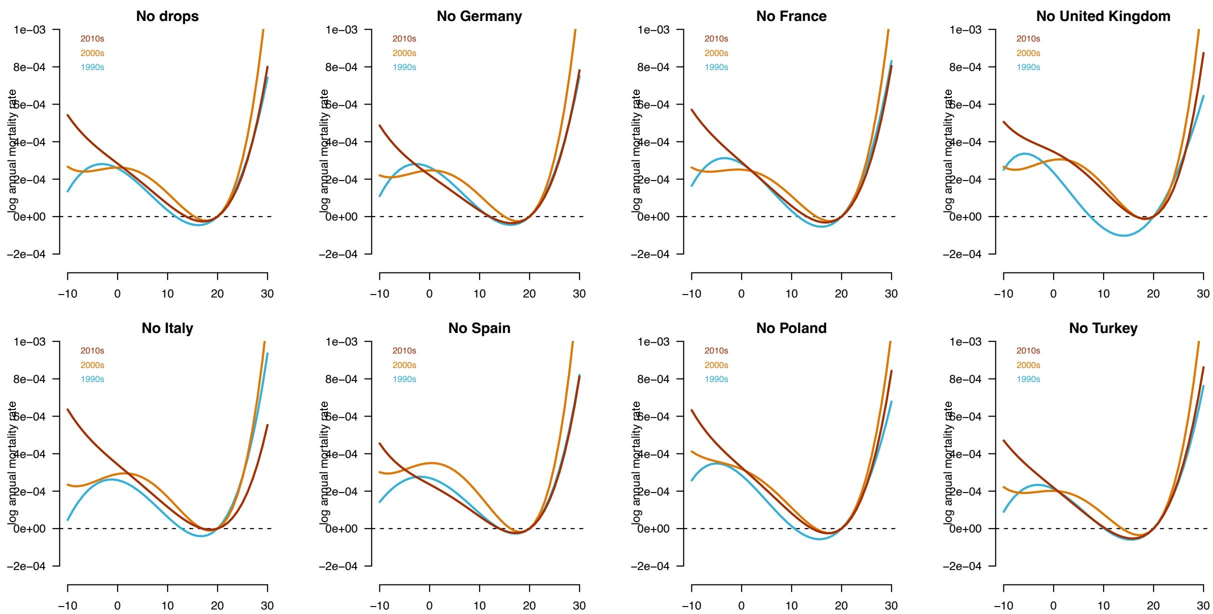

Figure A9: **EU mortality results are robust to dropping individual countries from the sample**. Results are as in Figure 2c, but with the country in the panel title dropped from the EU sample. Top left panel is the full sample result.

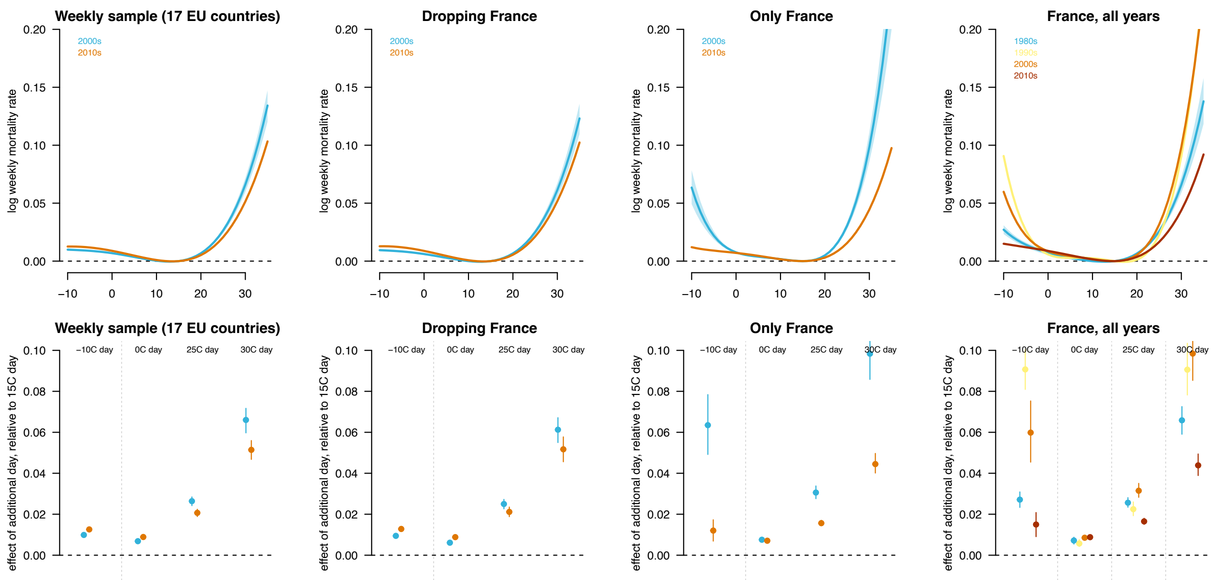

Figure A10: **EU mortality results using weekly data for 17 EU countries (2000-2019) and for France (1980-2019)**. First three columns use the 2000-2019 data across 17 countries, showing decadal temperature-mortality relationships (top row) and point sensitivities (bottom row). Columns show estimates for the 17 countries pooled, for that sample without France, and for only France. The last column extends the French data to 1980. France succeeded in reducing heat-related mortality in the most recent decade, but relative to a very high baseline in prior decades; sensitivities in the most recent decade now appear on par with the rest of the European sample.

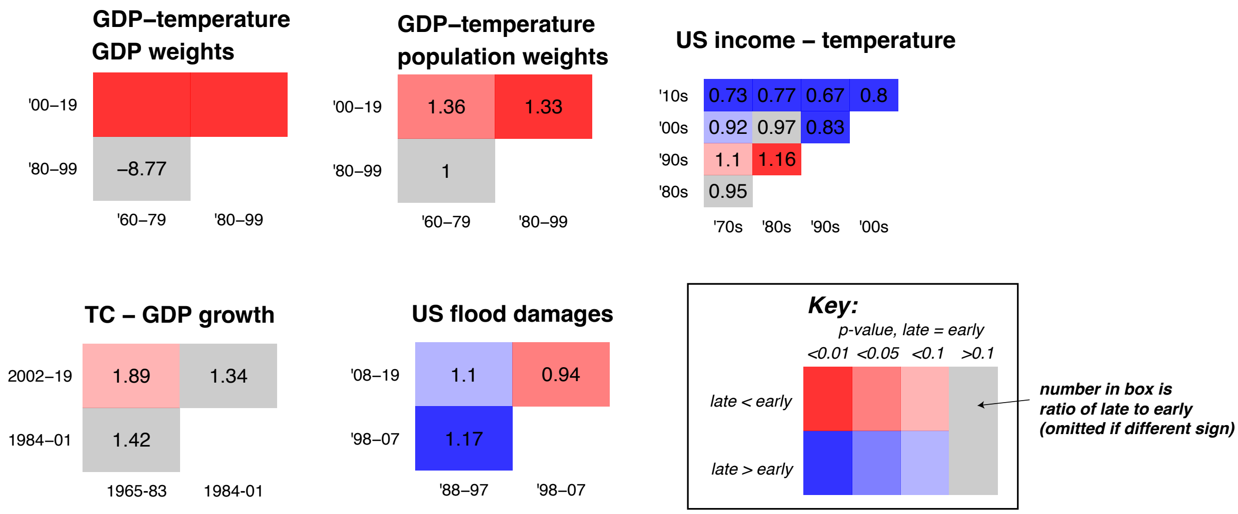

Figure A11: **Statistical tests on whether climate sensitivity is changing over time for climate-output relationships shown in Fig 3**. Each panel shows tests of whether climate sensitivities are quantitatively and statistically different between periods. Key is shown in bottom right. Heatmaps in each panel show pairwise tests of equivalence in sensitivity between periods, with period years labeled on rows and columns. Boxes are shaded blue if the sensitivity in the later period is more positive than the earlier comparison period, and red if the later period is more negative. Darker shading indicates higher significance levels, as calculated using the p-value on a two-sided test that the sensitivities are the same. Grey shading indicates $p >= 0.1$ in a two-sided test. Numerical values within the boxes report the ratio between the sensitivity in the later period and the sensitivity in the earlier period. Ratio values are not reported if the sensitivities in the two comparison periods differ in sign.

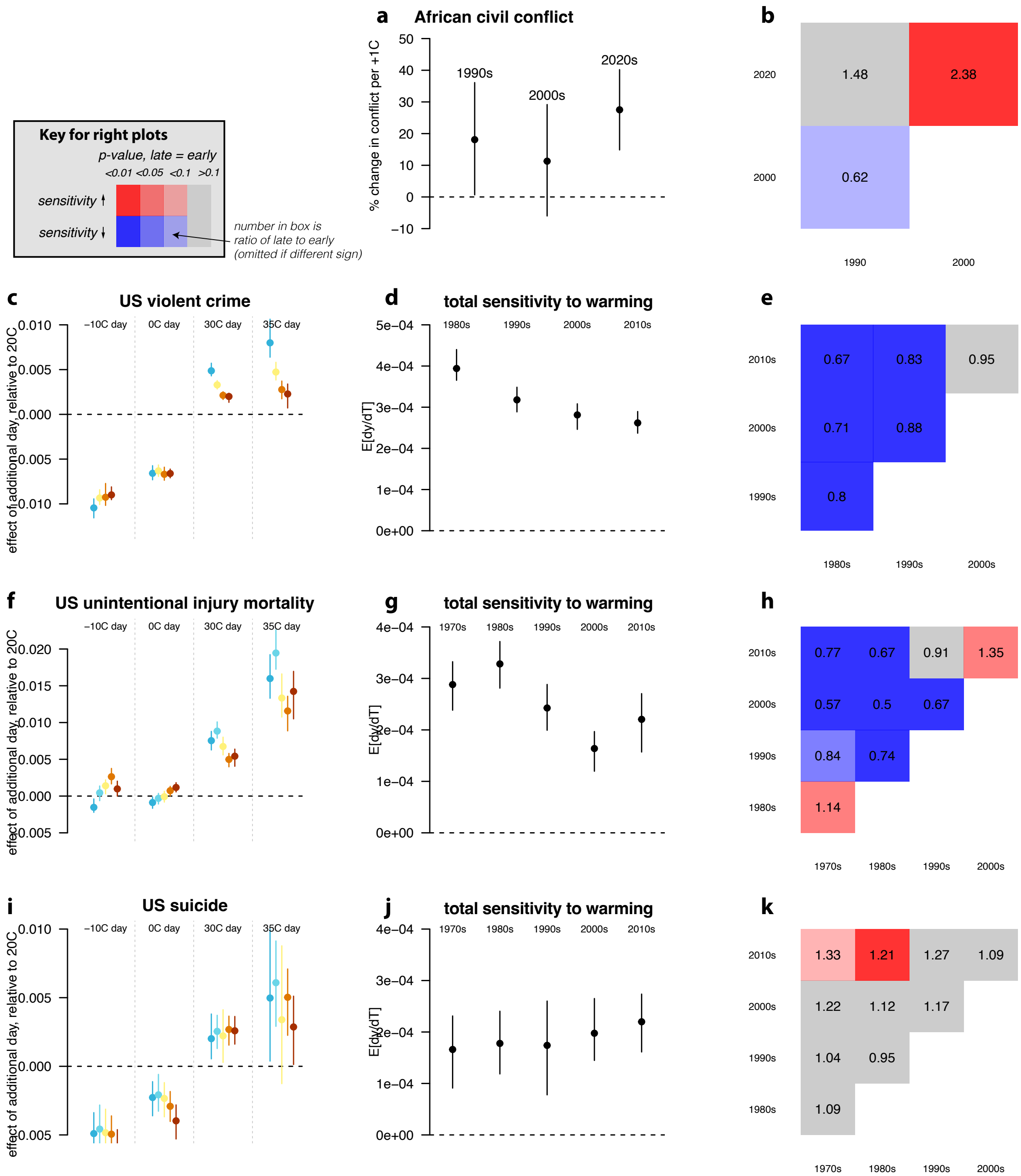

Figure A12: **Statistical tests on whether climate sensitivity is changing over time for climate-conflict relationships shown in Fig 4**. Each row shows results for a different outcome. Panels in the left column show the effect of an additional hot or cold day on the outcome, relative to a day spent at 20C, for responses with a non-linear response function; panel is omitted for African conflict (top row) which has a linear response function. Middle column reports changes in total sensitivity, right column the p-values on decadal changes in total sensitivity. Shading is as in previous plots, using key in upper left of plot.