

Near-term climate impacts are roughly linear in cumulative CO₂ emissions

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Understanding the relationship between CO₂ emissions and human well-being is central to informing climate policy. While global temperature change is proportional to cumulative CO₂ emissions, many human outcomes respond nonlinearly to climate variation. As a result, the magnitude of the effect of a quantum of CO₂ on these outcomes is ambiguous. Here we demonstrate that the impact of climate change on many important outcomes is, in fact, approximately linear in cumulative CO₂ emissions. Analyzing established response functions across economic growth, disease, mortality, and crop yields, we show that local warming is generally insufficient to alter the local derivatives of these response functions. Therefore, the marginal effect of CO₂ emissions does not substantially change over policy-relevant ranges of emissions. Thus, there is no level of CO₂ emissions that is irrelevant to human well-being: each ton emitted directly translates into reduced GDP growth, increased disease, altered temperature-related mortality, and reduced crop yields.

The Earth's climate is a dynamic system defined by nonlinearities and feedbacks¹. Despite this fact, some basic linear proportionalities have emerged in our understanding of climate change. Chief among these is the recognition that global warming is linearly proportional to cumulative CO₂ emissions². This linear relationship is an emergent property, not a physical law. Increasing CO₂ emissions both weakens carbon sinks and saturates radiative forcing, and the cancellation of these opposing nonlinear processes yields an approximately linear response^{3–5}.

The linearity of global warming in cumulative emissions, along with the well-mixed nature of CO₂ such that emissions everywhere have the same effect, have yielded a number of key insights. These include the justification for net zero emissions as a climate goal^{5,6} and the IPCC's statement² that "every tonne of CO₂ emissions adds to global warming". Subsequently, other Earth system processes have been shown to be approximately proportional to cumulative CO₂ emissions, including sea ice loss⁷ and extreme event intensity^{8–10}.

However, many downstream human climate impacts respond nonlinearly to local climate variability¹¹. For example, GDP growth increases with temperature in cool countries, peaks around 13 °C, and then declines in warmer countries^{12,13}. Dengue risk rises with temperature to a peak around 28 °C and then declines¹⁴, due to physiological effects of temperature on disease vectors¹⁵. Human mortality rates and agricultural yields experience benefits from mild temperatures before being

30 damaged by extreme temperatures above critical thresholds^{16–21}.

31 Collectively, these nonlinear human responses raise important policy-relevant questions about the
32 relationship between greenhouse gas emissions and human well-being. If substantial effects on
33 well-being require crossing some critical threshold in local climate exposure, it would be possible
34 for climate policy to alter global temperature but have no appreciable effect on human outcomes.
35 It would also allow individual actors to claim that their contributions to global warming were
36 irrelevant to human outcomes unless all actors acted in concert to reduce emissions. Empirical
37 evidence suggests that this perception is widespread, with members of the public believing that
38 mitigation only delivers benefits if some threshold of global emissions reduction is met²².

39 Here we show that, at a national or global scale, many important temperature-dependent climate
40 impacts scale directly and proportionately to cumulative CO₂ emissions over policy-relevant ranges
41 of emissions. We develop a theoretical framework to understand the circumstances in which
42 nonlinear response functions can generate climate damages that are quasi-linear in cumulative
43 CO₂ emissions. The key question is whether the local derivative of the response function changes
44 substantially with climate change.

45 We then analyze established response functions for GDP growth, infectious disease, mortality, and
46 crop yields. In each case, we re-estimate the response function and combine it with an ensemble
47 of climate model simulations to assess how the outcome changes as a function of cumulative CO₂
48 emissions (Methods). We show that the average local derivatives of the response functions do
49 not substantially change as CO₂ emissions increase. Thus, to first order, these human outcomes
50 respond quasi-linearly to cumulative CO₂ emissions. We conclude by discussing potential situations
51 in which linearity may not hold and policy implications of the findings.

52 **Theoretical framework**

53 Many important human outcomes are sensitive to the climate. Specifically, for some outcome y_{it}
54 such as GDP growth or mortality rates in location i at time t , there is some local response function
55 f_i that maps local temperature exposure to the outcome:

$$y_{it} = f_i(T_{it}) \quad (1)$$

56 This function is typically estimated in empirical settings using longitudinal data on climate vari-
57 ables of interest and outcomes across locations, exploiting within-location variation for causal
58 identification¹¹.

59 Then, to quantify the large-scale impacts of increasing CO₂ emissions on human well-being, we
60 are concerned with global damage functions D that map an aggregate outcome Y to global mean
61 warming $\Delta\bar{T}$ relative to some baseline global temperature $\bar{T}_0$:

$$D(\Delta\bar{T}) = Y(\bar{T}_0 + \Delta\bar{T}) - Y(\bar{T}_0) \quad (2)$$

62 The local response function and the global damage function are related but distinct. We can express
63 the global aggregated outcome Y as an exposure-weighted average of the local outcomes y , with

weights π_i (population, GDP, cropped area, etc. depending on context):

$$Y_t = \sum_i \pi_i y_{it} = \sum_i \pi_i f_i(T_{it}) \quad (3)$$

Next, consider a linear scaling coefficient α_i that relates local temperature change to global temperature change (i.e., $T_{it} = \alpha_i \bar{T}_t$). The linear scaling of local temperature to local temperature has been established in substantial previous work^{8,23}. Using this global-to-local relationship, the global damage function can be constructed as:

$$\hat{D}(\Delta \bar{T}) = \sum_i \pi_i [f_i(T_{i0} + \alpha_i \Delta \bar{T}) - f_i(T_{i0})] \quad (4)$$

We propose that the linear of the global damage function then depends on whether the derivative of local functions is roughly constant. If the derivative of the outcome with respect to climate change is constant, climate damages are linear in global warming and thus CO₂ emissions. If the derivative changes, however, there may be important nonlinearities that must be accounted for. We formalize this by taking the derivative of the global damage function:

$$M(\Delta \bar{T}) = \frac{d\hat{D}}{d\Delta \bar{T}} = \sum_i \pi_i \alpha_i f'_i(T_{i0} + \alpha_i \Delta \bar{T}) \quad (5)$$

The derivative of the global damage function can thus be expressed as the exposure-weighted (π_i), warming-pattern-weighted (α_i) average of the local derivatives (f'_i), with each local derivative evaluated at each location's projected temperature under warming $\Delta \bar{T}$.

The condition for linearity, then, is that $\hat{D}(\Delta \bar{T})$ is approximately linear if and only if $M(\Delta \bar{T})$ is approximately constant in $\Delta \bar{T}$. This, in turn, depends on the degree to which local derivatives f'_i are approximately constant in local temperature $\alpha_i \Delta \bar{T}$.

We propose two general situations, each pertaining to a certain category of response function, in which $M(\Delta \bar{T})$ is approximately constant because local derivatives are approximately constant in local climate change. The first pertains to *globally* nonlinear response functions, where different locations lie in different positions along a single unifying response function (Fig. 1a). The second pertains to *locally* nonlinear response functions, where a given location experiences nonlinear changes in outcomes across their distribution of exposures, yet exposures are distributed about the nonlinearity such that shifts in the distribution yield roughly linear changes in the outcome (Fig. 1c).

Globally nonlinear climate impacts

Several societal outcomes exhibit globally nonlinear responses to temperature, such that all locations share the same overall curve, with differences in response to a temperature change depending upon that location's baseline average temperature (Fig. 1a). GDP growth increases with annual mean temperature in cool countries and decreases with temperature in warm countries^{12,13} (Fig. 2a). Dengue incidence exhibits a similar inverted curve, with higher monthly temperatures increasing dengue in most places and decreasing it in the warmest regions¹⁴ (Fig. 2d). Climate change

is projected to reduce GDP growth and increase dengue incidence by shifting outcomes along these global response functions. Climate change can produce approximately linear responses in these outcomes if the change in local derivatives is small over the policy-relevant range in global temperature change.

We use panel regression with fixed effects to re-estimate the temperature-GDP relationship using country-level temperature and economic data over 1960–2019, controlling for long-term trends in temperature and GDP as well as cross-sectional differences in both average temperature and average GDP. We find the inverted U-shape that has been well-established by previous work^{12,13} (Fig. 2a), with a peak around 13 °C. We combine this empirical response function with climate model projections of country-level temperatures from the SSP2-4.5 and SSP3-7.0 emissions scenarios to project climate change effects on economic growth.

We first compute how countries' local derivatives change as emissions increase by evaluating their changing locations on the overall response functions (e.g., lines in Fig. 2a). At cumulative emissions of 3000 GtCO₂ (2031 in SSP3-7.0), 1 °C of local warming increases GDP growth in Norway by 1.5 percentage points (p.p.) and decreases growth in India by 1.2 p.p. (Fig. 2b). At 4000 GtCO₂ (2048 in SSP3-7.0), 1 °C of local warming increases growth in Norway by 1.4 p.p. and decreases it by 1.3 p.p. in India. Over a large span of emissions, then, the marginal effects of temperature on economic growth differ by less than 10%.

When averaging globally, the change in economic growth due to global warming scales consistently and linearly with cumulative emissions (Fig. 2c). Each additional 1000 GtCO₂ is associated with a ~0.6 p.p. reduction in global economic growth in both the SSP2-4.5 and SSP3-7.0 scenarios. A simple linear regression of global growth change on cumulative emissions fits both scenarios with $R^2 \geq 0.93$.

One difficulty when assessing damages to GDP growth is that a one-time reduction in growth can lead to a permanent divergence in GDP levels^{12,24–26}. Thus, when growth losses are integrated over time into total GDP losses, there is a nonlinear response to cumulative emissions that diverges across scenarios (Fig. S1). Critically, however, this nonlinearity does not emerge because the instantaneous marginal effect of emissions changes over time—this marginal effect in fact remains strikingly consistent over time (Fig. 2c).

We turn next to dengue, a widespread infectious disease that is highly sensitive to local climate conditions. Using monthly data on dengue incidence and temperature from tropical regions in the Americas and Asia from Childs et al.¹⁴, we derive a nonlinear response function for dengue that follows an inverted U-shape similar to GDP growth (Fig. 2d). For most countries such as Bolivia and Brazil, warmer temperatures increase dengue incidence, but for the warmest places like Cambodia, temperatures are warmer than optimal and additional warming reduces dengue (Fig. 2e). These marginal effects are only slightly altered by climate change as countries climb the overall response function (Fig. 2d, e).

Across near-term ranges of cumulative emissions, from 2500 GtCO₂ to 4000 GtCO₂, additional emissions linearly increase global dengue incidence (Fig. 2f). Each additional 1000 GtCO₂ is associated with a 3.4% increase in dengue incidence in both SSP2-4.5 and SSP3-7.0. A linear model fits the mean projection in both scenarios with $R^2 \geq 0.9$.

Our main analysis projects impacts through 2050, both to mirror the IPCC's assessment of the response of global warming to cumulative emissions² and to focus on policy-relevant ranges of cumulative emissions. Extending the projections to 2100 does not change the results for growth impacts, which remain extremely linear in cumulative emissions (Fig. S2a). However, for dengue, high cumulative emissions (>5000 GtCO₂) lead to a marked plateau in the incidence increase, because more countries approach or exceed the optimal temperature at which point the marginal effect becomes flat or negative (Fig. S2b).

Locally nonlinear climate impacts

A second category of response functions is those for which individual locations experience nonlinear changes in outcomes over their own ranges of exposure (Fig. 1c). For example, all-cause mortality rises at both cold and hot temperatures within European subnational regions (Fig. 3a), and maize yields rapidly decline at temperatures above 30 °C in U.S. counties (Fig. 3d).

In these cases, the key question is whether climate change shifts the local exposure distribution sufficiently to create a substantial difference in the exposure-weighted average derivative of the outcome. If the change in the overall exposure distribution is small relative to the nonlinearity in the response function (Fig. 1c), the marginal effect of each increment of warming will be similar (Fig. 1c, 1d).

We begin with the relationship between temperature and weekly mortality rates in 924 subnational regions of Europe established in our previous work¹⁸. As expected given the concave relationship (Fig. 3a), increases in daily temperature in the summer lead to increases in mortality and increases in temperature in the winter lead to decreases (Fig. 3b). Given the greater number of deaths due to cold than heat^{17,19}, the overall derivative of mortality with respect to temperature in Europe is negative (gray line in Fig. 3b).

Projecting future changes in mortality yields two compensating responses: Summer mortality linearly increases with cumulative emissions and winter mortality linearly decreases (Fig. 3c). Each 1000 GtCO₂ in cumulative emissions increases summer mortality rates by 1.3% and decreases winter mortality rates by 1.7% in SSP3-7.0. The net effect of these is ambiguous or slightly negative (gray line in Fig. 3c), but the underlying compensating changes are substantial. A linear fit explains more than 82% of the variance in the projections in both winter and summer. Extending these projections to 2100 leads to slightly more curvature in the projections, but they remain consistently proportional to cumulative CO₂ emissions with only slight increases in the marginal effects at high emissions totals (Fig. S2).

Figure 3c shows Europe-wide projections, but this linearity also holds within individual countries, as shown for three examples in Fig. S3. This result suggests that the emergent linearity is not due to spatially aggregating over many nonlinear responses, but instead that each location independently sees little change in its exposure-weighted derivative of the response (Fig. 3b).

Finally, we examine heat-related losses in U.S. maize yields. We follow Schlenker and Roberts²⁰ and Burke et al.²⁷ in regressing annual yields on a piecewise linear function of mild temperatures ("growing degree days", GDDs, defined as temperatures between 0-30 °C) and extreme temperatures ("extreme degree days", EDDs, temperatures over 30 °C). We find the canonical response in which mild temperatures slightly increase yields and extreme temperatures strongly decrease them (Fig.

3d).

Because the regression model is piecewise linear (which performs equally well as much more flexible polynomial specifications²⁰), the primary question for the projections is whether GDDs or EDDs themselves change nonlinearly with CO₂ emissions. We find that they do not. Figure 3e shows that EDDs increase proportionally to cumulative CO₂ emissions, with >20 more EDDs per year per 1000 GtCO₂. We find little change in GDDs, perhaps because warming causes increases in days above 0 °C at the low end to compensate for days now exceeding 30 °C at the high end (Fig. S4).

The linear increase in EDDs with warming, combined with a linear response of yields to EDDs, yields a linear response of maize yields to cumulative CO₂ emissions (Fig. 3f). Each 1000 GtCO₂ translates to a 10% reduction in yields in SSP2-4.5 and an 8% reduction in SSP3-7.0.

The R² on the linear fit is lower for these projections, around 51%. This may be due to large internal variability over the next 25 years; when the projections are extended to 2100, a linear fit explains a striking 94% of the variation in the SSP3-7.0 yield projection (Fig. S2).

Locally linear climate impacts

A final category of response functions for which the conclusion is more trivial is those for which the local response is linear. This appears to hold for several response functions in the literature, including the effect of temperature on emergency department visits in California²⁸, violent crime in the US²⁹, and suicides in the US and Mexico³⁰. In these cases, each increment of emissions should be expected to translate proportionally into damages, regardless of the level of global warming or historical emissions.

Potential situations in which linearity does not hold

The goal of this analysis is to illustrate that there are some key impacts for which emitting more CO₂, regardless of the amount, directly translates to greater damage. This finding emphatically does not deny the presence of other nonlinearities in the climate system.

Cryosphere. If climate change causes catastrophic collapse of marine ice sheets or ice cliffs³¹, rapid sea level rise could be triggered by specific emissions thresholds. In this case, only mitigation in the near term could avoid irreversible sea level rise³², meaning that the marginal effects of CO₂ emissions today are relatively higher than in the future.

Ocean circulation. If climate change leads to rapid regime shifts in thermohaline circulation patterns such as the Atlantic Meridional Overturning Circulation (AMOC), there could be cascading global climate impacts that are poorly constrained by empirical response functions³³. Similar to cryosphere impacts, in this case, the marginal effects of near-term CO₂ emissions or mitigation might be higher than CO₂ emissions in the long run after AMOC collapse has already occurred.

Compound extreme events. If the effect of some climate exposure depends on other exposures, such as sequential heat extremes³⁴, rainfall following wildfires³⁵, or simultaneous global breadbasket failure³⁶, then the net damages from climate change may compound in nonlinear ways. In this case, the marginal effects of CO₂ emissions might grow over time rather than being higher in the short term.

Importantly, however, in each of these categories, there is relative little causal empirical evidence on how they would affect human outcomes. By contrast, the impacts we focus on have been subject to decades of empirical assessment and form the basis of federal climate cost-benefit analysis and other policy-relevant tools^{13,16,37,38}. As a result, they are particularly relevant to understanding how historical and near-term climate policy decisions translate into changes in human welfare.

Conclusion

Our results show that across a range of important outcomes, greater CO₂ emissions directly translate into linear changes in these outcomes. These results are conceptually consistent with the well-understood linearity of global warming in cumulative emissions, which has also been extended to local processes like extreme event intensity and sea ice loss. Our results demonstrate that, despite nonlinearity in many human outcomes, these local climate changes do translate approximately proportionately into changes in outcomes. Further, the fact that CO₂ is well-mixed in the atmosphere means that CO₂ has the approximately the same warming effect regardless of where it is emitted, and implies that this finding generalizes to all substantial emitters.

Our results bear directly on recent policy debates about the effect of emissions restrictions on human well-being. Specifically, they demonstrate that there is no *de minimis* level of emissions at which CO₂ has no effect on damage; more emissions equal more across a wide range of emissions totals. Given this fact, reductions in CO₂ emissions directly translate into avoided climate damages.

Methods

Across all climate impacts we analyze, we take the same general approach. First, we re-estimate an established historical response function using data on local climate and human outcomes. Second, we project future climate exposures using an ensemble of climate models from the sixth phase of the Coupled Model Intercomparison Project (CMIP6). Finally, by combining these projections with the historical response function, we quantify how human outcomes change as a function of the greenhouse gas emissions trajectory associated with the given climate scenario.

For each response function, we use panel regression with fixed effects in both time and space to remove both unit-specific average confounders and time-varying confounders. This strategy allows us to isolate plausibly exogenous variation in climate conditions to identify the causal effect of climate on a human outcome^{11,39,40}.

GDP growth

For GDP growth, we follow Burke et al.¹² and model country-level growth y as a quadratic function of annual mean temperature and precipitation. For country i in year t , we estimate:

$$y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \psi_1 P_{it} + \psi_2 P_{it}^2 + \mu_i + \delta_t + \theta_{i1}t + \theta_{i2}t^2 + \epsilon_{it} \quad (6)$$

The country fixed effect μ_i removes all time-averaged factors specific to each country (e.g. the fact that Nigeria is on average warmer than Norway) and the year fixed effect δ_t removes all globally averaged shocks (e.g., global financial crises). The country-specific linear and quadratic time trends $(\theta_{i1}t + \theta_{i2}t^2)$ further remove time-varying factors that may correlate with trends in temperature.

Dengue

For dengue, we follow Childs et al.¹⁴ and model monthly dengue incidence in subnational regions in the Americas and Asia as a third-order polynomial in both monthly temperature and precipitation. For region i in country c in month m of year y , we estimate:

$$d_{icmy} = \sum_{j=1}^L [f(\mathbf{T}_{ic(m-j)y})] + \mathbf{P}_{icmy} + \mu_i + \delta_{cy} + \lambda_{cm} + \epsilon_{icmy} \quad (7)$$

We include three monthly lags of temperature ($L=3$) to account for delayed effects, as in the original paper. μ_i is a region fixed effect, δ_{cy} is a country-year fixed effect, and λ_{cm} is a country-month fixed effect.

The temperature and precipitation vectors are made up of polynomial terms from order 1 through 3 to account for nonlinearity in the climate-dengue relationship. Each nonlinear term is calculated first at the daily scale and then averaged monthly, rather than taking a polynomial in monthly average temperature. For days $m(d)$ within month m , each temperature and precipitation vector is calculated as:

$$f(\mathbf{T}_{icmy}) = \beta_1 \frac{1}{31} \sum_{d=1}^{31} T_{icm(d)y} + \beta_2 \frac{1}{31} \sum_{d=1}^{31} T_{icm(d)y}^2 + \beta_3 \frac{1}{31} \sum_{d=1}^{31} T_{icm(d)y}^3 \quad (8)$$

264 Mortality

265 For European mortality, we follow Callahan et al.¹⁸ and model weekly all-cause mortality rates in
 266 European subnational regions as a nonlinear function of weekly accumulated temperature, including
 267 both contemporaneous and lagged effects. Specifically, for region i in week w of year y , we estimate:

$$M_{iwy} = \sum_{j=0}^L [f(\mathbf{T}_{i(w-j)y}) + f(\mathbf{T}_{i(w-j)y}) \times \bar{T}_i] + \mu_{iy} + \delta_{iw} + \epsilon_{iwy} \quad (9)$$

268 The lagged terms account for delayed mortality effects as well as “displacement” effects as extreme
 269 temperatures accelerate the deaths of people who would have died soon anyway. We include
 270 three lags ($L=3$) in our specification, following the original paper. The interaction term with
 271 regional mean temperature ($\bar{T}$) allows the effect of temperature to vary based on baseline climate,
 272 an important signal of adaptation^{17,18}. μ_{iy} is a region-year fixed effect and δ_{iw} is a region-week
 273 fixed effect.

274 To account for the effects of individual daily high temperatures, we calculate the temperature vectors
 275 as the sum of daily polynomial terms within each week, using a fourth-order polynomial:

$$f(\mathbf{T}_{iwy}) = \beta_1 \sum_{d=1}^7 T_{iw(d)y} + \beta_2 \sum_{d=1}^7 T_{iw(d)y}^2 + \beta_3 \sum_{d=1}^7 T_{iw(d)y}^3 + \beta_4 \sum_{d=1}^7 T_{iw(d)y}^4 \quad (10)$$

276 Crop yields

277 For U.S. maize yields, we follow Schlenker and Roberts²⁰ and Burke et al.²⁷ and model yields
 278 in county i and year t as a piecewise linear function of growing degree days (GDD) and extreme
 279 degree days (EDD), as well as annual accumulated precipitation:

$$y_{it} = \beta_1 GDD_{it} + \beta_2 EDD_{it} + \theta_1 P + \theta_2 P_{it}^2 + \mu_i + \delta_t + \epsilon_{it} \quad (11)$$

280 Growing degree days are defined as the annual sum of degrees between 0 °C and 30 °C, and extreme
 281 degree days as the sum of degrees over 30 °C. We first calculate hourly temperatures for each day
 282 using a sinusoidal interpolation applied to daily max and min temperatures, and then calculate
 283 degree days from hourly temperatures²⁸. All calculations are performed only for March through
 284 August to represent the growing season²⁰. μ_i is a county fixed effect and δ_t is a year fixed effect.

285 Climate model projections

286 All projections are performed using an ensemble of CMIP6 global climate model (GCM) simula-
 287 tions from the SSP2-4.5 and SSP3-7.0 emissions scenarios. In all cases, we calculate temperature
 288 exposures from the GCMs that mirror the response function analysis, and project how the outcome
 289 of interest changes by applying the empirical coefficients to the projected exposure changes.

290 Because different variables are required for different response functions (e.g., annual average
 291 temperature for GDP growth vs. daily max and min temperature for crops), the number of models
 292 used for each projection differs slightly, but ranges from 16 for agriculture to 23 for GDP growth.

293 We quantify uncertainty in the projections by resampling uncertainty from the response functions

294 and calculating a separate projection for each response function sample and each climate model.
295 The uncertainty ranges shown in the figures thus incorporate both uncertainty in the historical
296 response function and uncertainty in the physical climate response to forcing.

297 **Acknowledgements**

298 We thank Lisa Rennels for helpful discussions. Some of this research was performed using
299 Indiana University high-performance computing systems, which were supported in part by Lilly
300 Endowment, Inc., through its support for the Indiana University Pervasive Technology Institute.

301 **Author contributions**

302 All authors conceived the analysis. C.W.C. performed the analysis and wrote the first draft of the
303 manuscript with all authors providing feedback on analysis, interpretation of results, and writing.

304 **Competing interests**

305 The authors declare no competing interests.

306 **Data and code availability**

307 All data and code will be made available upon publication at a permanent repository.

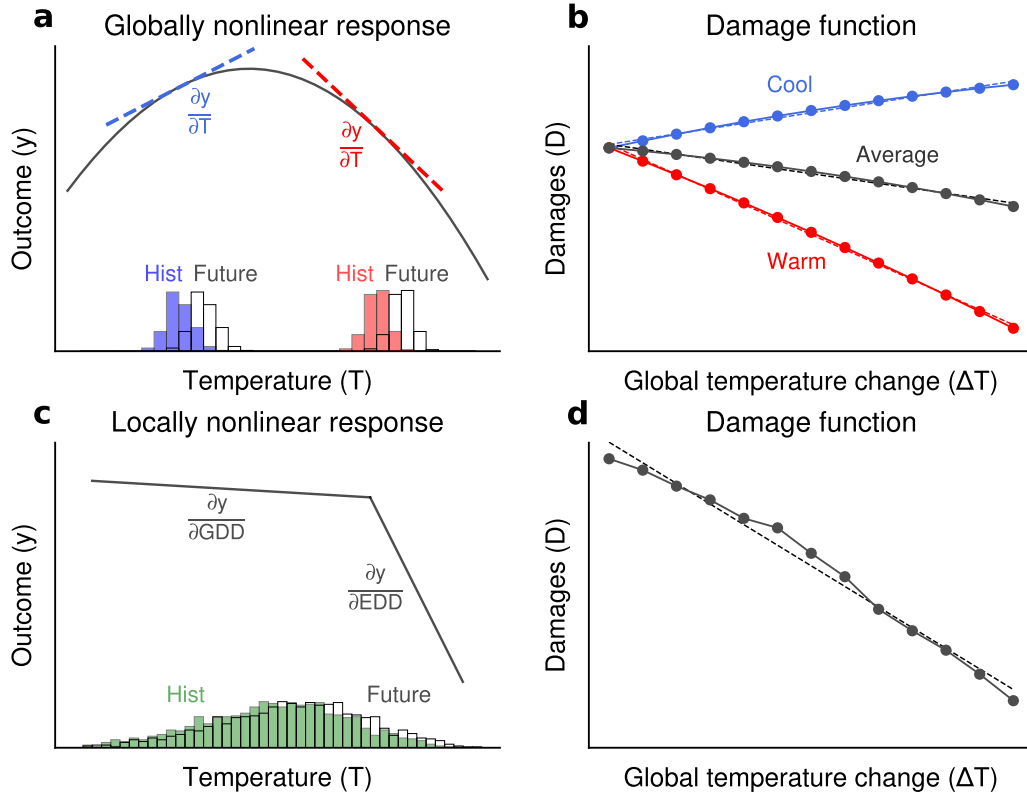


Figure 1: Schematic responses of nonlinear climate impacts to global warming. a) Globally nonlinear response of an outcome y to temperature T , with different regions occupying different locations on a single global function. Blue and red distributions show hypothetical “cool” and “warm” countries, with black distributions showing them with an additional several degrees of warming. b) Damages in the cool (blue) and warm (red) countries to future temperature change, and the average of these two responses (black), calculated based on the response function in (a). c) Locally nonlinear response of an outcome to temperature, with the response spanning the full distribution of within-location temperature exposure. Green distribution shows a hypothetical location’s distribution and black shows its hypothetical future distribution with global warming. d) Damages in that location as a result of future temperature change. In (b) and (d), thick lines show damages calculated directly from the response function and dashed lines show linear fits to these damages as a function of temperature change.

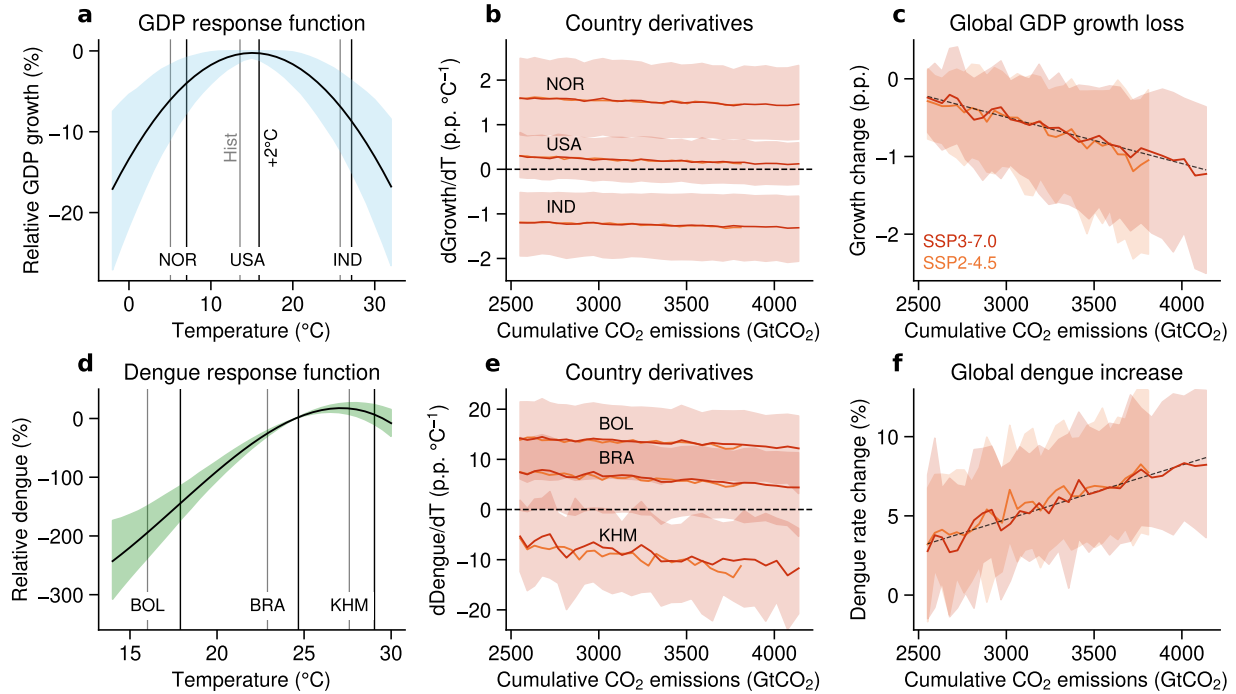


Figure 2: Linear response of global climate impacts to cumulative CO₂ emissions. a) Response of GDP growth to annual mean temperature, following Burke et al.¹². Lines show example country temperatures historically (gray) and after 2 °C of warming relative to 1850-1900 (black). NOR = Norway, USA = United States, IND = India. b) Country-level derivatives for each example in country in (a), using climate model projections from the SSP2-4.5 and SSP3-7.0 emissions scenario between 2021 and 2050. c) Global average GDP growth change due to climate change between 2021 and 2050. d) Response of dengue incidence to monthly mean temperature, following Childs et al.¹⁴, with example countries similar to (a). BOL = Bolivia, BRA = Brazil, KHM = Cambodia. e) Country-level derivatives of dengue response with regard to temperature for the three examples shown in (a). f) Global average dengue rate change due to climate change between 2021 and 2050. In all plots, solid lines shows average response and shading shows 90% confidence interval. In (c) and (f), dashed black lines show linear fit to SSP3-7.0 average projection.

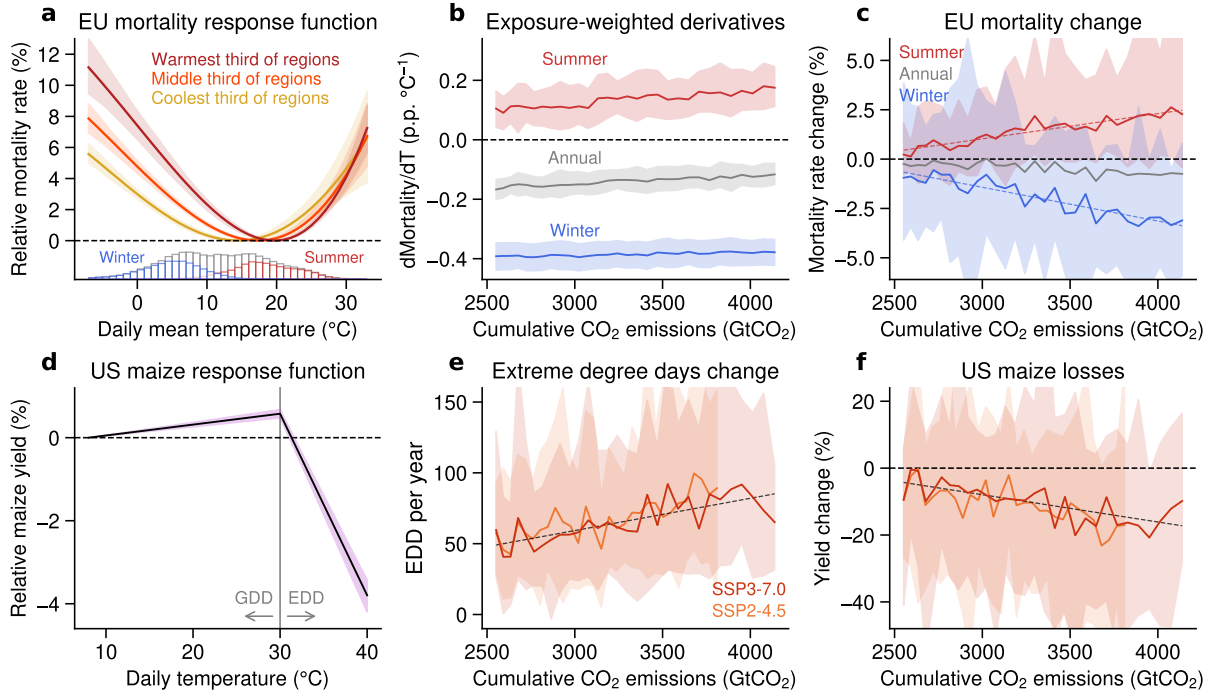


Figure 3: Linear response of local climate impacts to cumulative CO₂ emissions. **a)** Response of all-cause mortality to temperature in European subnational regions, following Callahan et al.¹⁸. Response functions are allowed to differ as a function of regional average temperature and are plotted at the lower, middle, and upper terciles of regional mean temperatures as examples. Lower histograms show the distributions of annual (gray), winter (blue), and summer (red) weekly average temperatures. Winter is defined as December through March and summer is defined as May through August. **b)** Average derivatives of mortality with respect to annual, winter, and summer temperatures as a function of cumulative CO₂ emissions between 2021–2050 in the SSP3-7.0 emissions scenario. **c)** Change in mortality as a function of cumulative emissions between 2021–2050 in SSP3-7.0, in winter (blue), summer (red), and across the entire year (gray). **d)** Response of annual maize yields in U.S. counties to temperature, modeled as a piecewise linear function of growing degree days (GDD) and extreme degree days (EDD), following Schlenker and Roberts²⁰ and Burke et al.²⁷. **e)** Change in annual EDDs as a function of cumulative CO₂ emissions over 2021–2025. **f)** Change in average maize yields across U.S. counties as a function of cumulative CO₂ emissions over 2021–2050. In all plots, solid lines shows average response and shading shows 90% confidence interval. In (c) and (f), light dashed lines show linear fit to average projection.

Supplementary Materials

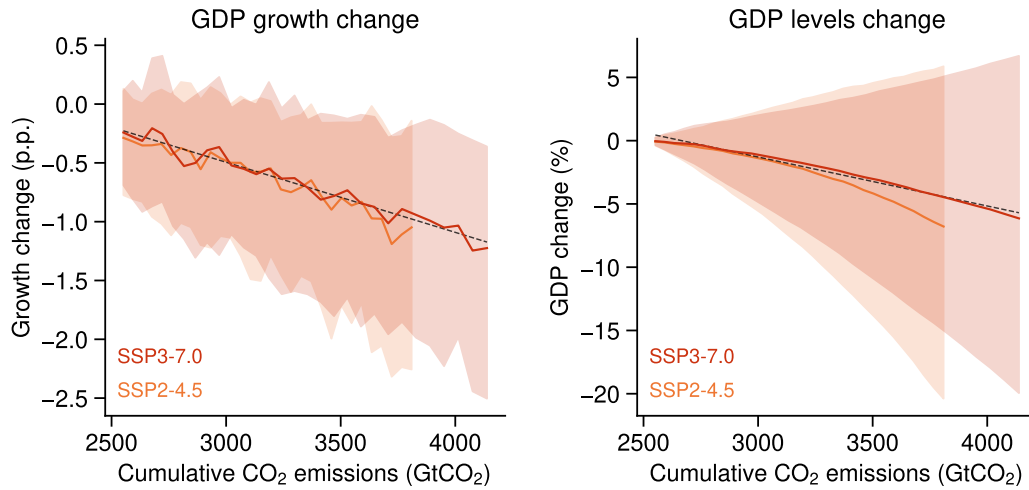


Figure S1: Changes in GDP growth vs. levels. Left panel is reproduced from main text Figure 2c: change in annual GDP growth as a function of cumulative CO₂ emissions. Right panel shows percent changes in GDP levels, after changes in GDP growth have been integrated back into counterfactual GDP levels. These changes are nonlinear and cumulative because even a one-time change in growth persistently diverts the economy from its counterfactual trajectory, leading to accumulating losses in GDP levels.

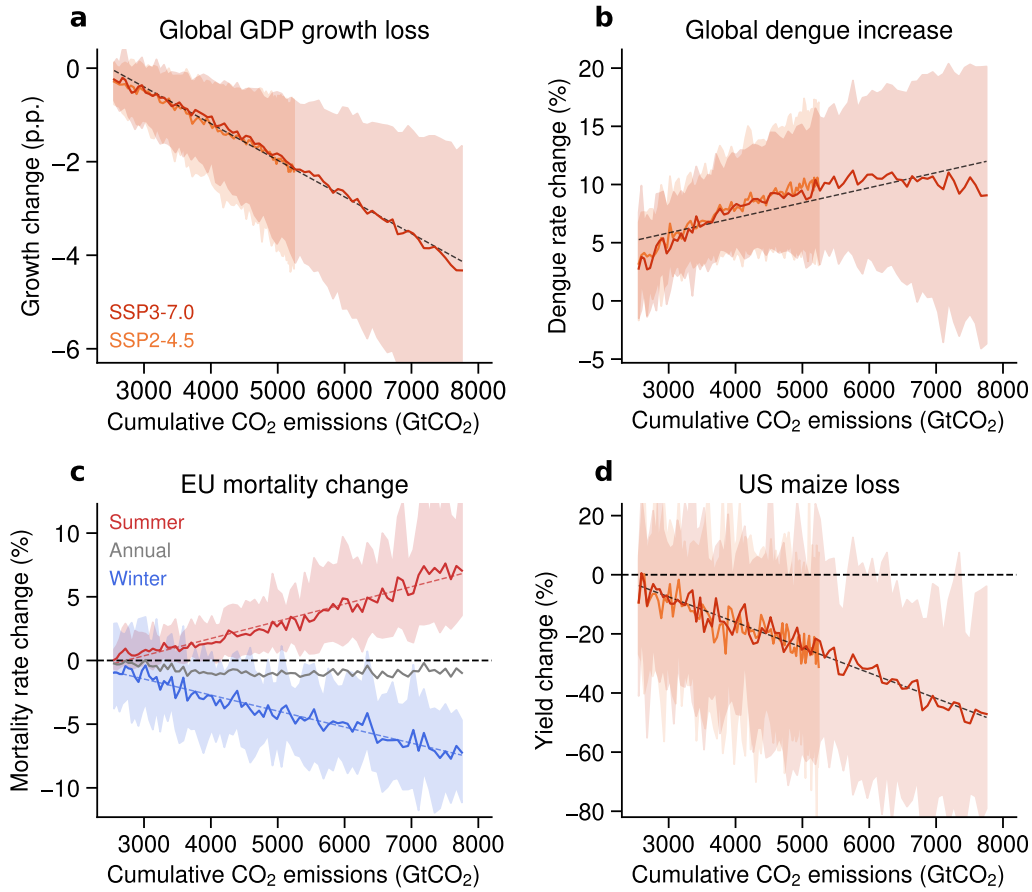


Figure S2: Damage projections through 2100. As in Fig. 2c and 2f, and 3c and 3f, but extending the damages calculation from 2050 to 2100.

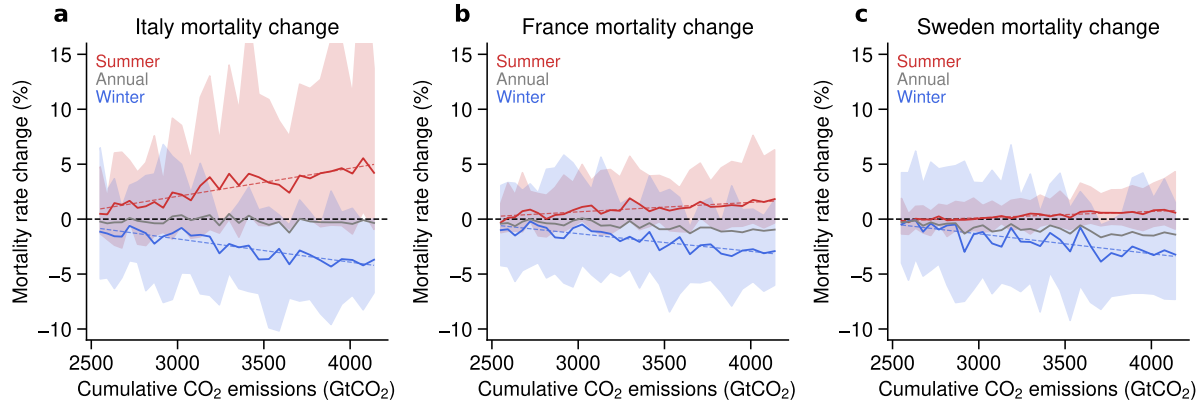


Figure S3: Country-specific mortality projections. As in Fig. 3c, but for three specific countries: a) Italy; b) France; and c) Sweden.

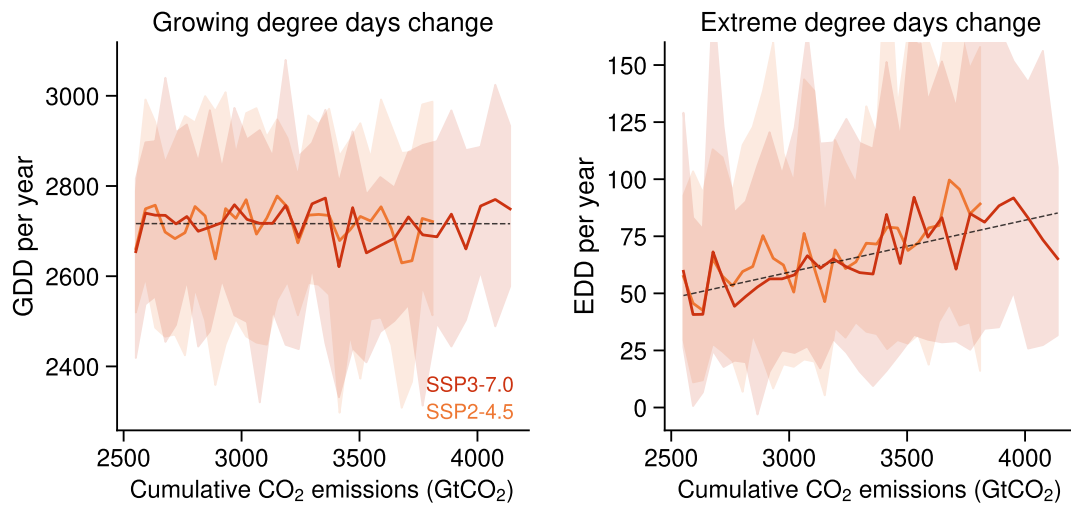


Figure S4: Changes in GDD and EDD. Left panel shows changes in growing degree days (days between 0 °C and 30 °C) as a function of cumulative emissions between 2021 and 2050. Right panel shows analogous changes in extreme degree days (days above 30 °C).

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