Climate damage projections beyond annual temperature

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ABSTRACT

Recent studies have linked variability and extremes in temperature and precipitation to lower economic growth, but global GDP projections under climate change remain focused on annual temperatures. Here we combine empirical dose-response functions for temperature variability, rainfall deviations, and extreme precipitation with 33 CMIP6 models to examine GDP impacts under different warming levels. We find that at +3℃, global average losses amount to 8% of GDP, with the worst effects (up to 13%) in poorer, low-latitude countries. Relative to annual temperature damages, the additional GDP impacts of projecting variability and extremes are smaller and dominated by inter-annual variability, especially in lower latitudes. However, accounting for variability and extremes when estimating temperature dose-response functions raises global GDP losses by over 1%-pt. Since tail risks for economic growth are substantial, our results emphasize the need for region-specific risk assessments and reducing uncertainties around future variability and extremes, particularly for developing countries.

Spatial projections of economic damages from climate change are key for evaluating the benefits of climate mitigation, identifying effects on vulnerable communities, and informing discussions around adaptation needs and loss and damage financing. On a global or country level, such assessments have focused on how projected changes in annual mean temperatures affect gross domestic product (GDP)[1–3]. However, the widespread losses in recent years driven by flooding and drought suggest that precipitation variability and extremes are similarly important[4]. Anthropogenic forcing is overall increasing both the frequency and intensity of precipitation extremes and variability on multiple scales, altering daily temperature patterns, and driving an overall increase in precipitation over land[5,6]. Continued global warming is expected to exacerbate these trends, potentially with uneven impacts across regions[4,7,8]. Therefore, the inclusion of precipitation, variability, and extremes can improve the precision, comprehensiveness, and interpretability of climate change damage estimations[9].

Economic damages from climate change can be assessed either bottom-up by quantifying, valuating and aggregating specific impacts (e.g., crop failures or labor supply changes) — or top-down by identifying the statistical relationship between observed climatic shifts and aggregate economic growth. While both approaches come with different advantages and limitations, top-down approaches usually neglect climatic shifts beyond annual temperature changes[10]. To address this shortcoming, recent studies have estimated the relationship between macro-level income and a wider range of climatic indicators, such as total precipitation[11–13], temperature variability[14,15], or temperature and precipitation extremes and anomalies[12,16,17]. However, these studies do not provide a forward-looking assessment of how much the inclusion of these climate indicators alters previous economic assessments of climate change—which is highly relevant for policy-making and future adaptation. A notable exception is the study by[13] which projects annual precipitation along with temperature for a range of socioeconomic and climate outcomes and investigates the effects on inequality. A comprehensive assessment of the projected economic impacts of intense periods of precipitation and temperature anomalies, however, is still missing.

In this study, we draw upon recent advances in estimating coherent dose-response functions, which relate shifts in various climate indicators (total precipitation, temperature variability, precipitation anomalies and extremes) to GDP changes[12]. Combining these functions with projections from 33 models of the 6th phase of the Coupled Model Intercomparison Project (CMIP6), we investigate how the inclusion of these indicators affects our understanding of future economic impacts at different global warming levels. Variability and extremes introduce substantial climatic and associated economic uncertainties, and we conduct a variance decomposition to determine the main drivers of uncertainty across different levels of global warming. Furthermore, we explore how the inclusion of variability and extremes in empirical regressions alters the dose-response function for annual mean temperature, which the extant literature has estimated controlling only for annual precipitation[1,2,18–20].

Results

Projecting GDP impacts for precipitation and temperature indicators

Compared to annual temperature, future changes in precipitation patterns and temperature variability under climate change are subject to high uncertainties[6,21,22]. To capture these uncertainties, we build upon previous analysis employing projections from a wide range of CMIP6 models to analyze several climate indicators besides annual mean temperature and annual precipitation[8]. These additional indicators include i) day-to-day temperature variability (how much daily temperatures on average deviate from monthly means); ii) extreme precipitation (the annual sum of precipitation on days with exceptionally high precipitation exceeding the historical 99.9th percentile); iii) monthly precipitation deviation (how much monthly precipitation deviates from historical means throughout the year); and iv) the number of "wet days" with precipitation above 1mm/d. These indicators have been linked to forcing from greenhouse gases[12,14] as well as to income growth using a global sample[12]. Considering all of these in one coherent estimation framework is crucial because variability and extremes correlate strongly with annual temperature and precipitation as well as among each other (see Figure S1 in the **Supplementary Information**). Therefore, combining dose-response functions from different estimations risks double-counting impacts. Notably, the coherent estimation framework we use does not explicitly model damages from droughts and heatwaves as separate impact channels, although these may be captured partially through other indicators, such as precipitation deviations or annual temperature spikes.

Figure 1 illustrates our approach for the example of extreme precipitation impacts on economic output for New York State under +3°C of global warming relative to pre-industrial levels. Based on how a given CMIP6 model and scenario project the respective climate indicator (Figure 1a), we compare the GDP impacts in a given year against the average impacts if the climate were to remain constant at levels of a recent baseline period (Figure 1b)[2,16]. For each model and scenario, the baseline period is selected as the 41-year period during which global warming equals the historical warming between 1979–2019 (+0.84°C), which is the climatic baseline used for estimating the dose-response functions deployed here (for more details, see **Methods**)[12]. We then repeat this procedure for different CMIP6 models and potential damage parameter estimates based on statistical uncertainty and aggregate results to the national level. This yields a distribution of GDP impacts for each country that features the years in each model and scenario that are associated with the same level of global warming, such as +3°C (Figure 1c). Therefore, the main sources of uncertainty in our GDP impact distribution, for a given global warming level and territory, are i) inter-annual variation for the same CMIP6 model and scenario since the magnitude of extremes can vary strongly from year to year (Figure 1a), ii) statistical uncertainty in the dose-response functions (Figure 1b), and iii) projection differences between CMIP6 models (Figure 1c).

Global results

Figure 2a displays the mean impact on global GDP and the uncertainty range for all variables combined, as well as the separate impacts from annual temperature, annual precipitation, and the four variability and extremes indicators. Global GDP is estimated to be 2.4% lower (lower/upper decile: 0.9 - 4.1%) at +1.5°C of global warming relative to pre-industrial levels over 1850–1900, compared to a world with no further climate change beyond recent levels. At +3°C, global GDP decreases by 7.9% (4.1 - 11.8%). When disaggregated by climate indicator, global impacts are strongly determined by the change in annual mean temperature, which accounts for a GDP reduction of 8.1% at +3°C. This estimate is consistent with recent top-down studies focusing exclusively on damages from annual temperature changes and projecting impacts of around 7–14% of GDP per capita loss by the end of the century under RCP8.5, which implies a global warming level of over +4°C[6,18,19]. For context, such an impact exceeds the GDP loss of the COVID pandemic when global output growth plummeted from +2.6% in 2019 to -3.1% in 2020 or the effect of the global financial crisis in 2009 when global output shrunk by -1.3%[23]. While other studies have come to even higher damage estimations[2], this is primarily driven by their assumption that temperature changes impact long-run growth trajectories persistently[10,24,25].

Unlike annual temperature changes, increases in annual precipitation in many areas lead to a small *positive* impact on global GDP (0.2% under +3°C warming). In contrast, the distribution for the combined impact of the variability and extremes indicators remains centered around zero. While this seemingly suggests a lack of signal, this is not the case when projections are disaggregated by individual indicators (Figure 2b). On average, extreme precipitation reduces global GDP by 0.2% (0.1 - 0.5%) at +3°C, with 97% of our impact distribution indicating economic losses. This is caused by an overall increase in extreme precipitation around the globe, particularly in Sub-Saharan Africa, Northern parts of South America, and South-East Asia[12]. Notably, these impacts are over one order of magnitude lower than annual temperature damages. This is somewhat expected because extremes have a lower temporal and spatial correlation than annual mean temperature. Therefore, aggregation from daily, location-specific events to annual indicators and country-level projections reduces signals more strongly compared

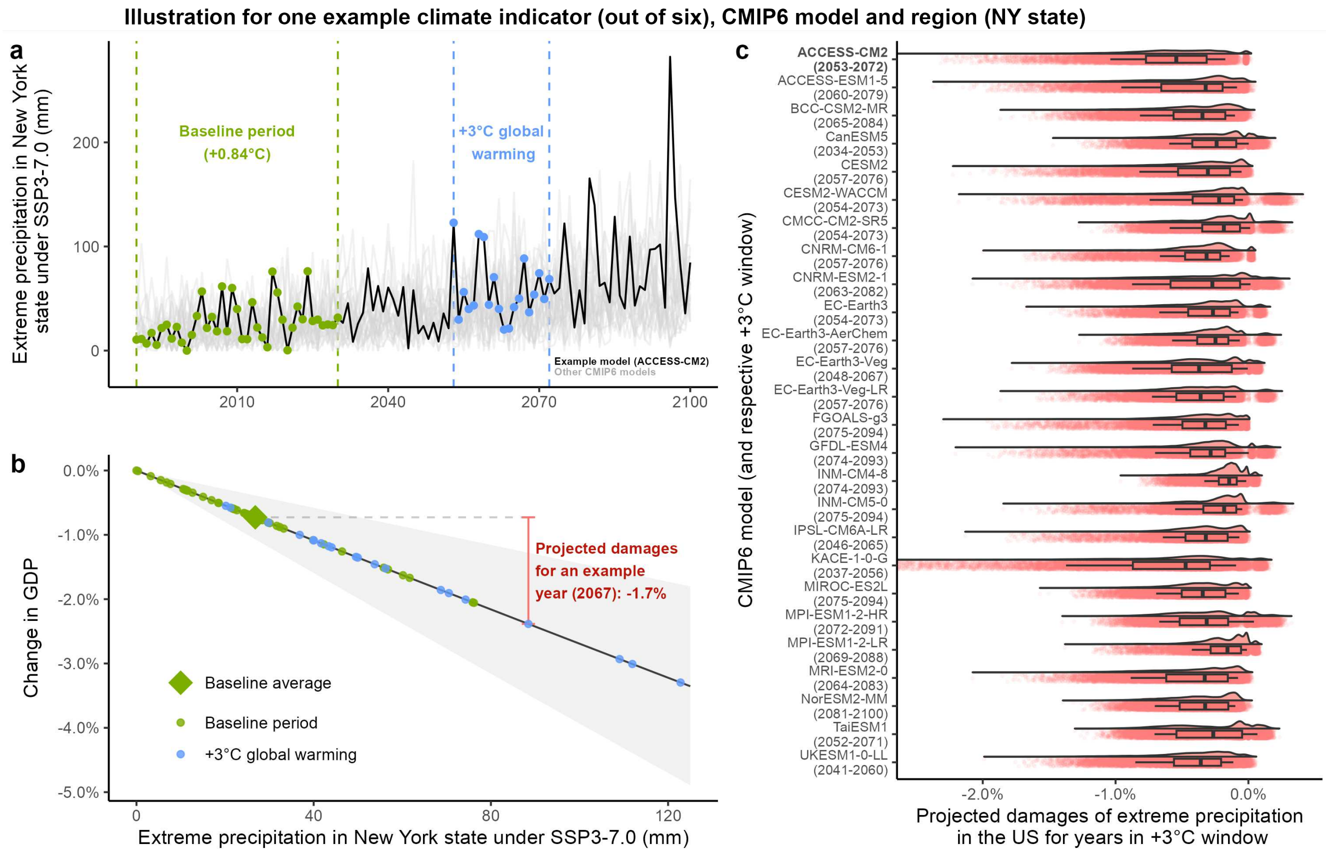

Figure 1. Illustrative example of GDP impact projections for one example indicator (extreme precipitation) and region (New York state) under +3°C global warming. **(a)** Projected extreme precipitation in New York state under SSP3-7.0 for all CMIP6 models used (grey) and an example model highlighted for illustrative purposes (ACCESS-CM2, black). Vertical dashed lines denote the baseline period in which the example model reaches the historical global warming level over 1979–2019, i.e., +0.84°C (green), and the 20-year window in which it reaches +3°C (blue). **(b)** Dose-response function for extreme precipitation (black line) and 95% confidence interval (grey area). Blue and green dots represent the extreme precipitation levels for New York state from Panel a for the baseline period and the +3°C global warming level window, as well as the corresponding values of the dose-response function, with the green diamond denoting the average across baseline years. The red error bar illustrates the difference between the dose-response function for an example year in the +3°C global warming level window (2067) and the baseline average, which corresponds to the damages from extreme precipitation projected for this year. Note that the dose-response function is linear in log-scale and hence is slightly non-linear in % of GDP, which is displayed here. **(c)** Damage projection distributions (density and boxplots) for the United States under +3°C global warming by CMIP6 model. Boxplot hinges and whiskers denote upper/lower quartiles and deciles, respectively. The x-axis is capped at -2.5% for visual purposes only because KACE-1-0-G and ACCESS-CM2 yield outlier damages of up to 4%. For more details on the methodology, see **Methods**.

to annual mean temperature[11,12]. However, a 0.2% GDP loss due to extreme precipitation at the global level and for an average year still represents a tenth of the damages caused by the catastrophic 2022 floods in Pakistan, which were estimated at -2.2% of GDP[26]. Moreover, magnitudes are comparable to recent bottom-up assessments of drought damages, projecting a 0.14% GDP loss for Europe under +3°C[27]. Losses from extreme precipitation, however, are compensated, on average, by a positive impact of day-to-day temperature variability, which for +3°C warming amounts to +0.2% of global GDP (-0.1%, +0.5%), with 78% of the impact distribution implying global economic gains. The reason is a significant decrease of temperature variability in higher latitudes (due to lower temperature advection), while there is a moderate increase in the Global South, potentially driven by soil drying processes and vegetation coverage[14,28]. For the monthly precipitation deviation and the number of wet days, global GDP impacts remain limited and uncertainty ranges centered around zero even for +3°C of warming.

To explore what drives the uncertainty in our results, we decompose the variance in GDP impacts from each climate indicator into statistical dose-response function uncertainty, climate model uncertainty, and inter-annual variation, as shown in Figure 2c (for details, see **Methods**). For annual temperature damages, uncertainty is primarily driven by the dose-response function, particularly at higher levels of global warming. This stands in stark contrast with annual precipitation and variability and extremes, for which inter-annual variation drives impact uncertainty. Moreover, disagreement between CMIP6 models plays either a comparable or a larger role than dose-response function uncertainty for these additional indicators and is particularly pronounced for day-to-day temperature variability (see Figure 2d). More importantly, the share of climate model uncertainty in total GDP impact variance decreases for annual temperature impacts—whereas it increases for all variability and extremes indicators, indicating that for a stronger global warming signal, GDP impact projections do not converge between models.

Country-level results

Since global aggregates risk masking heterogeneities across regions, Figure 3a displays the combined country-level GDP impacts from all six climate indicators under +3°C of warming. Notably, all countries are expected to suffer from GDP losses, in line with recent evidence that climate change might not benefit cooler countries economically, as previously suggested[19]. Impacts are more severe in the Global South and highest in Africa and the Middle East, where higher initial temperatures make countries particularly vulnerable to additional warming. Figure 3b shows the combined GDP impact of all four variability and extremes indicators, i.e., excluding annual temperature and precipitation, and reveals a clear North-South divide. While for higher latitudes, the decrease in temperature variability mitigates overall GDP damages to some extent, variability and extremes exacerbate GDP losses in most parts of the Global South. However, these effects vary substantially across the full distribution of projected impacts for each country (Figure 3c).

Annual temperature is the only indicator where negative impacts arise for at least 90% of our impact distribution for all countries (upper dotted line in Figure 3c). Annual precipitation increases benefit most countries on average, but for many countries, less than two-thirds of the distribution support the sign of expected impacts (lower dotted line). For day-to-day temperature variability, we find a clear divide between relatively certain gains for a small group of high-income countries and less certain, smaller losses for many lower-income countries. While extreme precipitation is projected to increase in most regions, projected damages are highest and least uncertain for middle- and high-income countries in higher latitudes, in line with recent studies on forced changes in precipitation extremes[29]. In contrast, low-income countries are more likely to be adversely impacted by changes in precipitation deviation and the number of wet days, but high uncertainties limit the conclusions that can be drawn. Notably, the uncertainties about GDP impacts are lowest for high-income countries irrespective of the impact channel, potentially due to their position in higher latitudes, where warming is strongest, and hence the signal of climate change emerges earlier from the inherent variability of the climate system[30].

Overall impact of including variability and extremes

The results in the previous sections seemingly suggest that including variability and extremes in GDP impact projections exacerbates disparities between higher- and lower-income countries (Figure 3), but does not substantially alter the implications of climate change for global GDP (Figure 2). However, providing an apples-to-apples comparison with the recent climate economics literature requires calculating damages based on the current status quo approach, which i) projects only damages from annual temperature changes, and ii) estimates the relationship between income growth and annual temperature controlling only for annual precipitation[1,2,18–20]. Figure 4a illustrates the resulting global GDP impacts following this "status quo" methodology (in blue) compared to our approach (in red), which i) projects damages for all six indicators, and ii) controls for all of our climate indicators when estimating the temperature dose-response function. Our results show that including variability and extremes leads to higher global damages, with a mean difference of 1.5%-pts (7.9% instead of 6.4%) at +3°C of global warming.

The main reason for this increase is that controlling for variability and extremes, instead of only for annual precipitation, increases the estimated effect of mean temperature changes (see Figure 4b). The marginal GDP impact of a +1°C rise in annual temperature increases by over 0.5%-pts irrespective of the initial level of temperature when all climate indicators are included as control variables (red line). Most of this effect is driven by including temperature variability, which leads to higher estimated

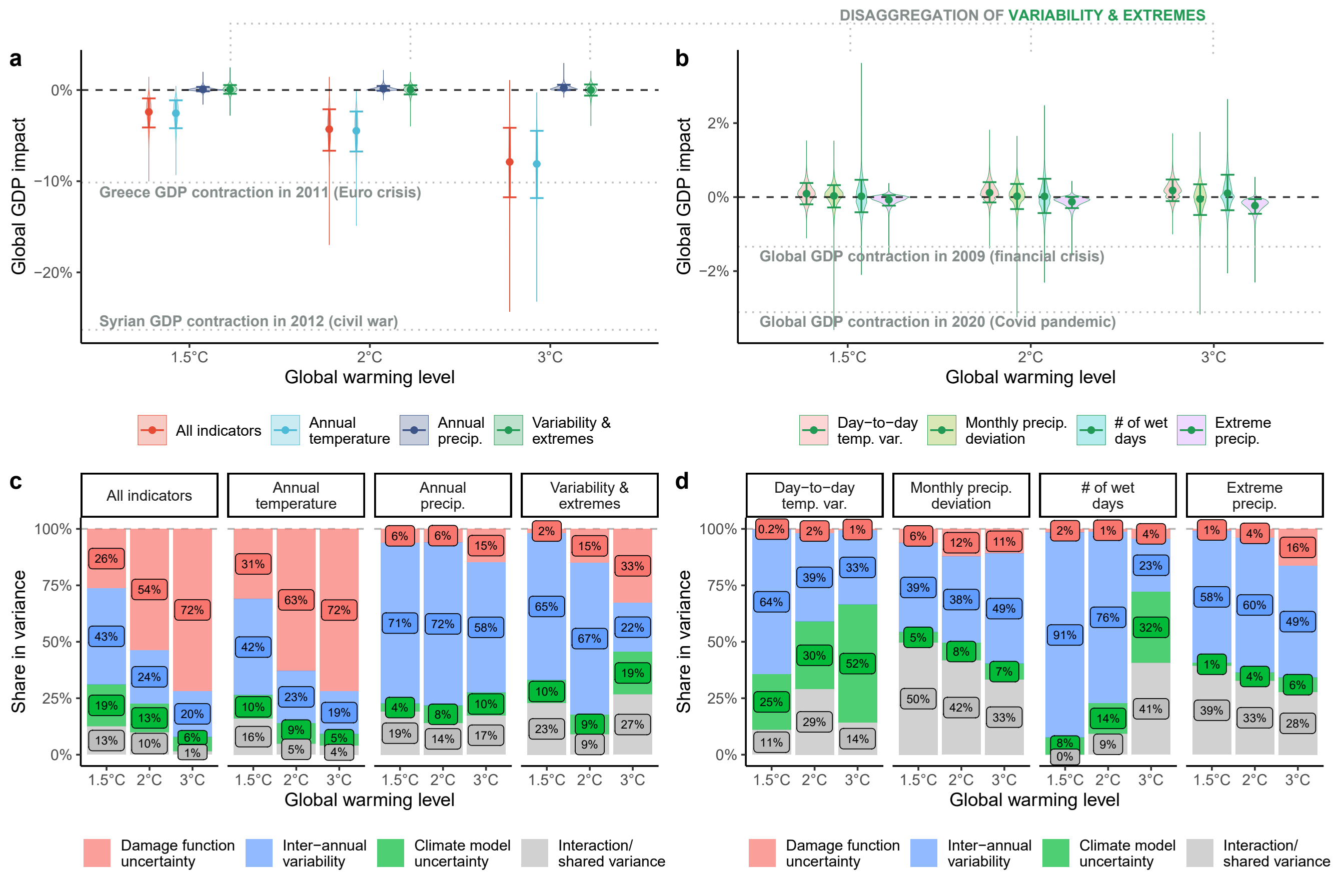

Figure 2. Distribution and variance decomposition of global GDP impacts under different global warming levels. **(a)** Distribution of global GDP impacts conditional on different global warming levels. Points and error bars denote the mean and upper-to-lower-decile range, respectively. "Variability & extremes" are composed of the four climate indicators displayed in Panel b. Dashed horizontal lines denote example year-to-year growth rates in real GDP from the World Bank's World Development Indicators database[23]. **(b)** Same as Panel a, with "variability & extremes" impacts disaggregated by climate indicator. **(c)** Variance decomposition for the GDP impacts of all climate indicators under consideration and disaggregated by impact channel, conditional on the respective level of global warming. Variance decompositions can be carried out by impact channel because impacts in the underlying regression model are additive and hence can be projected out separately. Residual variance arising from interactions between the uncertainty drivers that cannot be attributed solely to one of the three uncertainty drivers is displayed in grey. For the sake of simplicity, if the interaction term is negative, we take the absolute value and rescale to 100% to capture this "shared variance" regardless, but we show charts without this simplification in the **Supplementary Information** (for details, see **Methods**). **(d)** Same as Panel c, with "variability & extremes" disaggregated by climate indicator.

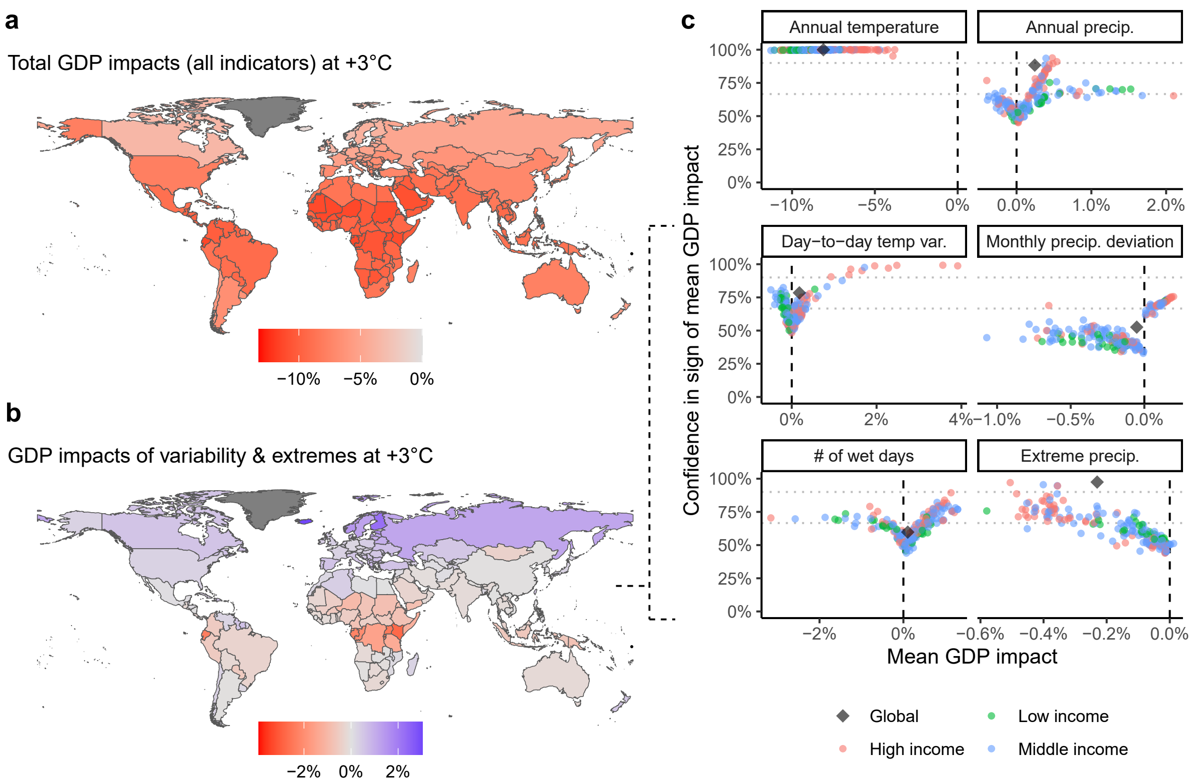

Figure 3. Country-level GDP impacts and uncertainty under +3°C of global warming. **(a)** Mean of the GDP impact distribution at +3°C of global warming, displayed for sovereign countries only (other territories marked in dark grey) and considering all impact channels displayed in Panel c. **(b)** Same as Panel a but only considering impacts of "variability & extremes" indicators (the bottom four indicators displayed in Panel c). **(c)** Mean GDP impact (x-axis) and share of the impact distribution agreeing with the mean's sign (y-axis) for all sovereign countries at +3°C of global warming. Grey diamond denotes the result for the global economy. Income-based country groups follow the World Bank's classification, with "Middle income" comprising both lower and upper-middle-income countries for conciseness. Horizontal dotted lines denote thresholds for 66% and 90% likelihood following IPCC uncertainty guidance terminology[6].

temperature impacts particularly for colder regions (dotted line). Therefore, the positive impacts of temperature variability shown above in Figure 3 obscure that in fact, including this parameter leads to *higher* global damages since it disentangles potential benefits of reduced variability from the negative effects of temperature increases. As a result, we find that including other climate indicators exacerbates GDP impacts across the globe (see Figure 4c). Importantly, the inclusion of climate indicators beyond annual precipitation has not been discussed in recent studies about sources of potential non-robustness when estimating damages from annual temperature changes empirically[20], whereas our results suggest that the implications could be substantial.

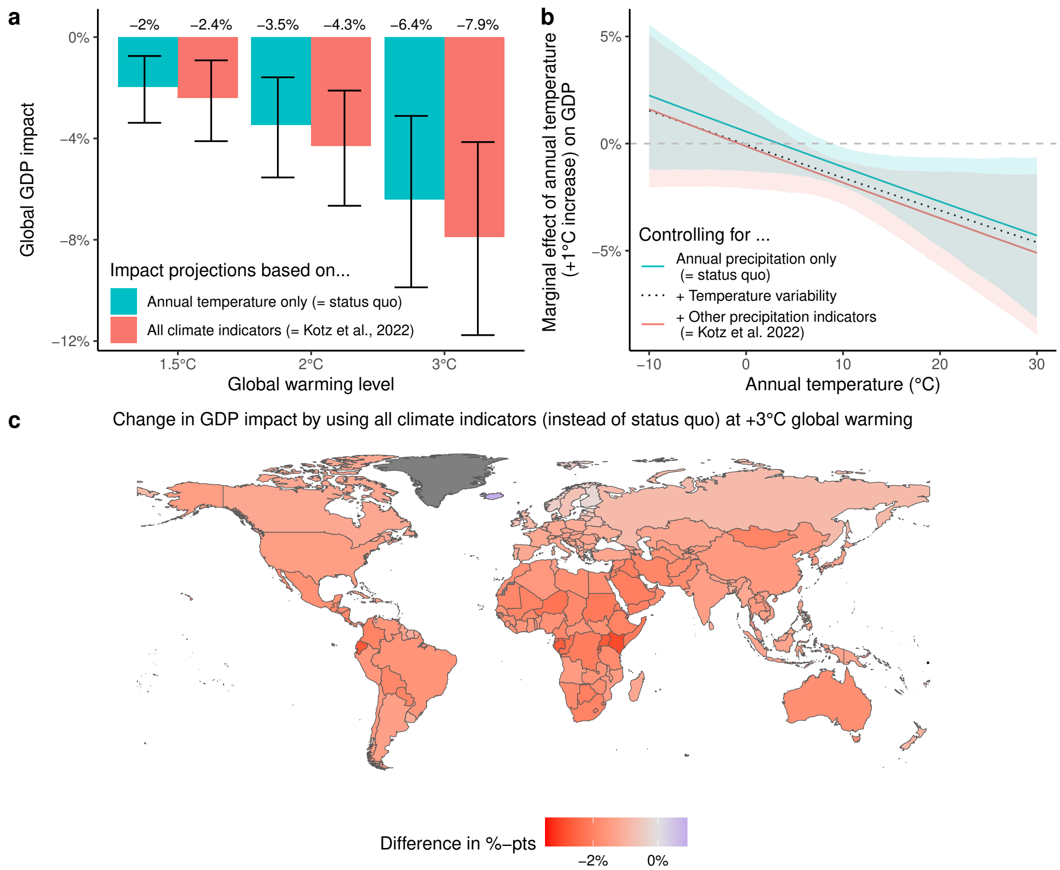

Figure 4. Comparison with impact projections based on considering annual temperature only (= status quo). **(a)** Bars/value labels and error bars denote the mean and upper-to-lower-decile range across the GDP impact distribution, respectively. "Status quo" projects impacts from annual temperature only and additionally considers annual precipitation as a control variable when estimating the dose-response function. "All climate indicators" uses all indicators displayed in Figure 3 Panel c, both for projections and for estimating dose-response functions. **(b)** Marginal GDP impact of a +1°C increase in a territory's annual temperature for different initial temperature levels (x-axis) with 95% confidence intervals (shaded area). Estimated using Equation S1 and the regression models in Table S4 (columns 1, 2 and 5) in the **Supplementary Information**. "+ Temperature variability" uses a dose-response function estimated by controlling for annual precipitation and day-to-day temperature variability (no confidence interval shown for visual conciseness). Remaining labels correspond to the ones in Panel a. **(c)** Difference in mean GDP impacts between our main approach and the "status quo" approach at +3°C displayed for sovereign countries only (other territories marked in dark grey).

Exposure to tail risks

Aside from average impacts and the uncertainty around them, prudent risk management by policymakers also requires information about tail risks. Figure 5a displays the percentage of the current global population living in countries that have a non-negligible chance (at least 5%) of suffering from damages exceeding different thresholds (x-axis) under different levels of global warming (color), both for our main approach (solid line) and the "status quo" approach (dotted line). Even at only +1.5°C global warming, tail risks are substantial, with about 69% of the global population living in countries with a non-negligible risk of suffering GDP damages of 5% or higher if all climate indicators are included—a number that increases to 100% of the global population at +3°C. Comparing results based on all climate indicators and the "status quo" approach (Figure 5b) reveals that including variability and extremes increases tail risks considerably. While under the "status quo", 5% of the global population is projected to face damages of at least 15% with a likelihood of at least 5% at +3°C of warming, this increases to 43% of the population when variability and extremes are included. The share of the global population facing catastrophic impacts of 20% or higher with a 5%-chance rises from 0% to 2%.

Disaggregating these results by individual climate indicators (see Figure S6 in the **Supplementary Information**) highlights that the high climatic uncertainties for some of the climate indicators lead to sizable tails that might represent either real risks or noise. For extreme precipitation, where the signal is clearest, 15% of the global population lives in countries that have a 5%-chance of suffering GDP losses beyond 1% at +3°C of warming—whereas at +1.5°C, this would hold for only 1% of the global population. However, the conclusions from Figure 4d, i.e., the increase in global exposure to catastrophic climate change damages, is primarily driven by higher temperature damages if underlying regression models control for more climate indicators than just annual precipitation.

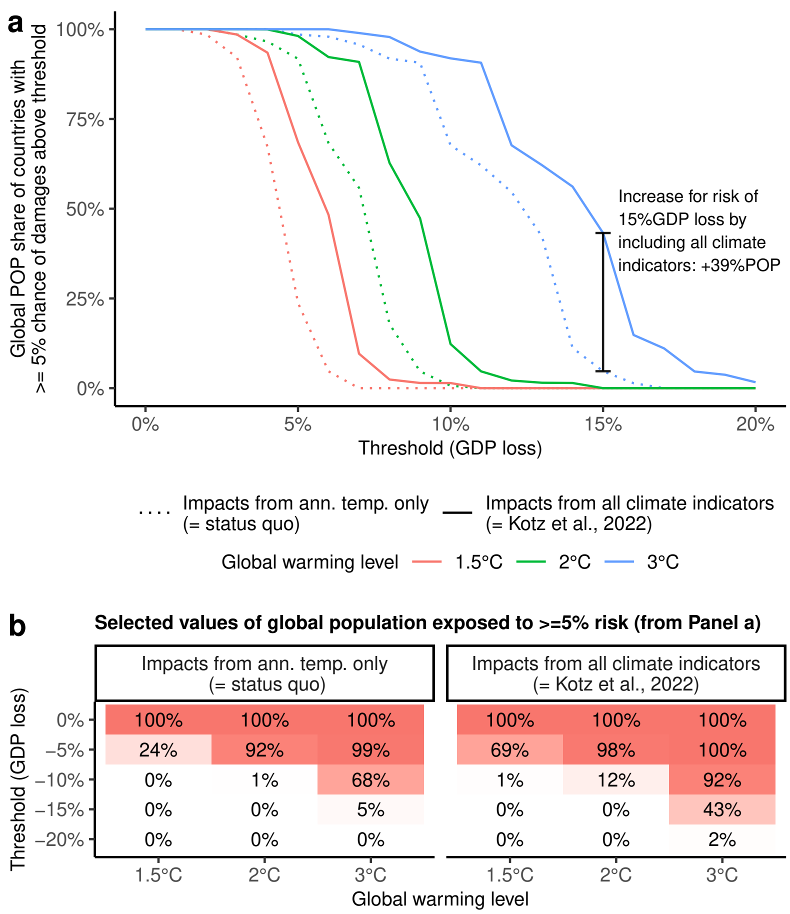

Figure 5. Exposure of global population to tail risks (5th percentile) of GDP losses. **(a)** Share of the current global population that lives in countries whose projected GDP impacts for a given warming level (color) exceeds the respective threshold (x-axis) for at least 5% of the GDP impact distribution. Dotted and solid lines denote the values based on the "status quo" approach and our main approach using all climate indicators, respectively. The black error bar provides a reading example of the chart to illustrate by how much the global population exposed to a 5% risk of 15% GDP losses at +3°C increases when all climate indicators are included. **(b)** Table with selected values of the exposed share of the current global population from Panel a. Cell color based on position in value range between 0% (white) and 100% (red).

Discussion

Taken together, our results illustrate that, unlike annual temperature impacts, damage projections of variability and extremes remain severely constrained by the large climatic uncertainties involved since the signal of climate change emerges only at high warming levels. This highlights the need for a scientific effort to improve projections of temperature variability and precipitation in climate models, e.g., by leveraging empirical temperature-scaling relationships to narrow uncertainties[31]. Such efforts should focus particularly on low-income countries, which are expected to suffer the most but also exhibit the largest uncertainties in impact projections. For policymakers, dedicating more resources to modeling precipitation and climatic extremes, particularly for the Global South, could yield useful progress in reducing uncertainty about expected local, regional, and global impacts. While the overall impacts of variability and extremes remain substantially below those of annual temperature changes, they are likely to exacerbate global disparities further, in line with recent research on precipitation impacts[13].

For scholars studying the economic effects of climate change, our results suggest a potential downward bias in temperature damage estimates by not disentangling the impacts of changes in temperature means and temperature variability. As temperature impacts dominate overall GDP loss projections, future studies estimating such dose-response functions should test how the inclusion of variability and extremes indicators that have been linked to economic growth alters their findings. Importantly, such biases could also be caused by other climate indicators not explicitly considered here, such as heatwaves or droughts. Furthermore, since the signal clarity is much higher for extreme precipitation and day-to-day temperature variability, these indicators seem more suitable to be included in climate-economy calculations, such as the social cost of carbon.

While our results rest on strong empirical foundations and a wide range of state-of-the-art climate models, there are several reasons why actual GDP impacts may exceed our projections. First, the dose-response functions used here do not explicitly cover some important climate extremes, most notably heat events[16] and droughts[27]. Second, to be conservative, we abstract from the possibility that climatic shifts do not only change GDP growth in a given year but alter a country's long-run growth trajectory persistently. While such persistence in GDP losses remains empirically debated[1,2,12,20,32], it would increase damage estimates substantially[24,25] . Third, aggregation across time and space is more likely to reduce signals in precipitation patterns due to their lower spatial and temporal correlation compared to annual mean temperature[11,12]. For these reasons, our results should be seen as an important first step, but they certainly do not exclude the possibility of larger GDP losses. Furthermore, econometric-based dose-response functions like the ones used here have several limitations, e.g., the risk of conflating weather impacts with climatic shifts or the extrapolation of impacts to warming levels that go far beyond historical observations[33]—-particularly given the unclear role of adaptation[19]. In addition, specification questions can further exacerbate socio-economic uncertainties[20] and uniform dose-response functions for aggregate GDP can mask heterogeneities between countries, sectors and income segments, with precipitation affecting agriculture and poorer households particularly[13]. Moreover, considering impacts in % of GDP implicitly assigns a lower weight to poorer regions within countries that are disproportionately exposed to climate change risks[34].

Nevertheless, our study highlights the sizable risks of omitting climate indicators beyond annual mean temperature from damage projections and identifies the most promising fields for additional research. Building on our work, researchers could integrate further climate indicators excluded here, particularly heat and droughts, into a comprehensive assessment of climate change impacts or improve our understanding of potential adaptation, which remains a key limitation for GDP impact projections[10]. Aside from improvements in climate modeling, this would also require more empirical studies to robustly identify the link between economic growth and different climatic extremes.

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Author contributions statement

All authors conceived the study. F.B. prepared the underlying climate data and conducted the bias correction. P.W. and J.R. performed the data aggregation and developed the projection methodology. P.W. carried out the impact projections, analyzed and visualized the results, and wrote the manuscript. All authors reviewed the manuscript.

Additional information

No authors declared any conflict of interest.

Methods

Climatic data We take daily temperature and precipitation projections from a total of 33 CMIP6 models to calculate annual climate, extreme and variability indicators for the 1850–2100 period, building on previous country-based analyses of projected changes in climate extremes at different global warming levels[8]. We use three pairs of representative concentration pathways (RCPs) and shared socioeconomic pathways (SSPs); two of them covering lower emissions and slower warming throughout this century with continued strong economic growth and convergence (SSP1-1.9 and SSP1-2.6) and a third one with higher warming, high inequality and generally lower GDP growth (SSP3-7.0). As not all three RCP-SSP pairs are available for all CMIP6 models, we arrive at a total of $N = 71$ model-scenario pairings, for each of which we use one realization only (see Table S1 in the **Supplementary Information**). Time series switch between historical scenarios and the respective RCP-SSP pair in 2015. Consistent with our source of empirically calibrated dose-response functions using ERA5 data[12], we calculate annual average temperature T, annual total precipitation RA as well as four climate indicators using the equations listed below before downscaling and re-gridding annual temperature and precipitation indicators from 2.5° to 0.25° (i.e., the grid resolution of ERA5).

For *day-to-day temperature variability*:

$$\tilde{T}_{x,t} = \frac{1}{12}\sum_{a=1}^{12}\left(\frac{1}{D_a}\sum_{d=1}^{D_a}(T_{x,d,a,t} - \bar{T}_{x,a,t})^2\right)^{0.5} \tag{1}$$

where $T_{x,d,a,t}$ is the temperature for grid cell x of day d of month a in year t and $D_a \in \{28, 29, 30, 31\}$ is the number of days in the respective month a. $\bar{T}_{x,a,t}$ denotes the mean temperature in month a of year t for the respective grid cell.

For *extreme precipitation* (based on the 99.9th percentile):

$$\hat{RD}_{x,t} = \sum_{d=1}^{365} R_{x,d,t} \times I(R_{x,d,t} > R_{x,99p9,base}) \tag{2}$$

where $R_{x,d,t}$ is the precipitation of grid cell x on day d of year t, $I()$ is an indicator function, and $R_{x,99p9,base}$ denotes the 99.9th percentile of daily precipitation in grid cell x over a historical baseline period.

For *number of wet days* with precipitation exceeding 1mm/d:

$$RD_{x,t} = \sum_{d=1}^{365} I(R_{x,d,t} > 1\text{mm/d}) \tag{3}$$

Grid cell-level annual climate indicators are then aggregated to the subnational region level (ADM1) using the geospatial data from the Database of Global Administrative Areas (GADM, v3.6) and area-weighting.

For *monthly precipitation deviation*, which we calculate only at the ADM1-level and not at the grid cell level, consistent with ref.[12]:

$$RM_{i,t} = \sum_{a=1}^{12} \frac{R_{i,a,t} - \bar{R}_{r,a,base}}{\sigma_{i,a,base}} \times \frac{\bar{R}_{i,a,base}}{\bar{RA}_{i,base}} \tag{4}$$

where $R_{i,a,t}$ denotes precipitation totals in month a of year t for a given ADM1-level region i. Variables denoted by a bar represent averages across the baseline period, either for the full year or for a specific month, while $\sigma_{i,a,base}$ denotes the month-specific standard deviation across the baseline period for region i. As for all other climate indicators, region-level monthly precipitation $R_{i,a,t}$ is derived from grid cell-level values based on area-weighting.

For the baseline-dependent climate indicators $\hat{RD}$ and RM, our source of dose-response functions[12] uses 1979–2019 as the historical baseline period, during which global warming averaged +0.84°C according to Berkeley Earth data (the best estimate for the observed warming and, in a previous version, used in the IPCC AR6[6]). To maintain consistency, we identify climate model- and RCP-SSP pair-specific 41-year windows during which global warming is +0.84°C . Warming level windows are calculated following the approach by ref.[8] and displayed in Table S1 in the **Supplementary Information**. Then, we use this model- and scenario-specific 41-year window as the baseline period. This ensures that, despite model differences, all climate indicators are based on the same baseline in terms of global warming. However, percentile-based indicators, such as extreme precipitation defined by precipitation above the 99.9th percentile, can lead to artificial jumps beyond the reference period, meaning overestimated frequency increases. This is because the density is monotonically decreasing around the 99.9th percentile of the true distribution[35] , thus creating artificial jumps and exceedances outside the reference period[8,36]. To correct this, we use the bootstrap resampling procedure developed by ref.[36]. We estimate thresholds by excluding one year and adding a random year from the 41-year reference period in consecutive order. The thresholds found in each iteration are applied to the excluded year. We then average the 41 thresholds obtained through bootstrap resampling to use for future periods.

GDP impacts The dose-response function describing growth in GDP per capita (on a log-scale) is represented as a sum of functions specific to each climate indicator $C_{i,t}$ for ADM1-level region i in year t. These functions are denoted by $h^C(C_{i,t})$, where

$$C \in \{T, RA, \tilde{T}, \hat{RD}, RD, RM\}$$

For each climate indicator, we derive the functional form of h^C from the main specification by ref.[12], which jointly estimates the impact of all six indicators on GDP per capita growth using region and year fixed effects and is displayed in Table S4, column 5 in the **Supplementary Information**. For instance, for annual precipitation RA the relationship with GDP per capita growth is estimated as a quadratic relationship such that

$$h^{RA}(RA_{i,t}) = \beta_1^{RA} RA_{i,t} + \beta_2^{RA} RA_{i,t}^2 \tag{5}$$

where β_1^{RA} and β_2^{RA} are the respective regression coefficients. All dose-response functions are displayed in Figure S7 in the **Supplementary Information**.

To calculate the impacts of climate change, we compare annual economic impacts against the average impact during the historical baseline period for the same model-scenario pair, such that our impacts represent changes from a hypothetical scenario in which climate remains constant, following previous studies[2,13]. As a baseline period for GDP impacts, we again use the +0.84°C global warming level window for a given climate model m and RCP-SSP pair s for consistency with the calculation of our climate indicators. Therefore, annual impacts in % of GDP due to shifts in a given climate indicator C relative to the baseline period are calculated as follows

$$\delta_{i,t}^{C} = exp\left(h^C(C_{i,t})\right) - \frac{1}{41}\sum_{k\in K} exp\left(h^C(C_{i,k})\right) \tag{6}$$

where K is the model-scenario-specific baseline period corresponding to +0.84°C of global warming. Note that we exponentiate to convert log-scale impacts to % of GDP.

Importantly, the model specification by ref.[12] specifies the dose-response function annual temperature in first-differences compared to previous years and not in absolute levels:

$$\begin{aligned} h^T(T_{i,t}, T_{i,t-1}, T_{i,t-2}) = &\beta_1^T(T_{i,t} - T_{i,t-1}) + \beta_2^T(T_{i,t-1} - T_{i,t-2}) + \\ &\beta_3^T(T_{i,t} - T_{i,t-1})T_{i,t} + \beta_4^T(T_{i,t-1} - T_{i,t-2})T_{i,t-1} \end{aligned} \tag{7}$$

To translate this dose-response function into impact projections, we calculate cumulative impacts following ref.[18], such that annual temperature impacts due to warming compared to the baseline period are derived as follows:

$$\delta_{i,t}^{T} = exp\left(\sum_{j=k_0}^{t} h^T(T_{i,j}, T_{i,j-1}, T_{i,j-2})\right) - \frac{1}{41}\sum_{k\in K} exp\left(\sum_{j=k_0}^{k} h^T(T_{i,j}, T_{i,j-1}, T_{i,j-2})\right) \tag{8}$$

where k_0 denotes the first year in the model- and scenario-specific baseline period K.

For extreme precipitation $\hat{RD}$, the dose-response function estimated by ref.[12] interacts extreme rainfall with the annual mean temperature T because the marginal impact of extreme precipitation is found to be lower in warmer climates. Projecting this out under climate change, however, would make the strong assumption that global warming increases the resilience of countries to extreme precipitation worldwide. Since there is no evidence supporting such a positive feedback of warming and since the heterogeneity of extreme rainfall effects in ref.[12] is equally well-explained by a country's latitude (see R2 and Adjusted R2 in Table S4 of ref.[12]), which is time-constant, we hold temperature in the interaction constant at the average level during the baseline period such that

$$h^{\hat{RD}}(\hat{RD}_{i,t}) = \beta_1^{\hat{RD}} \hat{RD}_{i,t} + \beta_2^{\hat{RD}} \hat{RD}_{i,t} \frac{1}{41}\sum_{k\in K} T_{i,k} \tag{9}$$

Since impacts are additive in log-scale, the total impact from all six climate indicators combined can be calculated by using the sum of all impacts, i.e., $h^{RA}(\cdot) + \sum_{j=k_0}^{t} h^T(\cdot) + h^{\tilde{T}} + ...$ instead of the impacts from an individual climate indicator in Equation 6. Using only the dose-response functions for $\tilde{T}$, $\hat{RD}$, RD and RM yields the joint impact of variability and extremes.

When projecting damages of climate change, a core methodological choice is whether to assume that impacts affect GDP levels, such that the economy bounces back in the following year, or whether to assume that a part of damages persists and alters the long-run growth trajectory. Assuming persistence has a substantial impact on damage projection trajectories and the associated uncertainty[20,24,25]. Recent empirical analyses differ in methods and outcomes, with no consensus yet[1,2,10,20,32]. To be conservative, here we assume no persistence, noting that this leads to underestimated impact levels and uncertainty bands in projections if impacts, in fact, do persist over time. In addition, we follow ref.[25] in equating log-scale GDP per capita impacts with log-scale GDP impacts, i.e., assuming that any decrease in GDP per capita is caused by a climate change-induced reduction in economic output and not by an increase in population.

Spatial aggregation of GDP impacts We aggregate GDP impacts from the subnational detail (ADM1) to the country level (ADM0) using GDP weighting. For GDP weights, we use 2010 GDP data downscaled to a 0.5° grid by ref.[37]. To deal with 105 outlier grid cells with raw GDP data exceeding \$1e20, we apply a ceiling at \$1e10, which is the next highest grid-cell GDP value in the dataset. Note that we hold this intra-country distribution of income constant across all years and SSPs. This simplification stems from the SSPs not directly informing spatial intra-country GDP per capita distributions and also serves to prevent our results from being driven by changes in the weighting scheme over time rather than climatic changes, which is standard practice in the literature[2]. To calculate GDP impacts at the global level, we weigh each country i with its share in global GDP in year t as per the respective SSP. Since the SSP Database does not provide GDP growth trajectories for a number of small sovereign countries, namely Andorra, Liechtenstein, Nauru, North Korea, San Marino, South Sudan and Tuvalu, these economies are not represented in our damage projections for the global economy, which, given their joint economic size, is unlikely to affect our conclusions.

GDP impact distribution For each CMIP6 model-scenario pair, we draw estimates for the dose-response function parameters $\beta_1^{RA}, \beta_2^{RA}, \beta_1^{T}, \ldots$ jointly from the multivariate Gaussian distribution estimated by ref.[12] (main specification, standard errors clustered at the country level). Combining 71 model-scenario pairings with $1,000$ draws for the dose-response function parameters, this provides us with $71,000$ different impact projection pathways for each territory. For each model-scenario pairing, we then identify the 20 years corresponding to a global warming level of +1°C, +1.5°C, +2°C, +3°C, and +4°C respectively, following the approach by ref.[8]. This provides us with a conditional distribution of GDP impacts for a given territory and warming level. Aside from reducing the importance of individual RCP-SSP scenarios, conditioning results on global warming levels also reduces the need to omit or down-weight 'hot models' in CMIP6, which project too much warming[38]. Since not all models reach all warming levels for the same RCP-SSP and some models are not available for some scenarios (see Table S1 in the **Supplementary Information**), we weight models inversely such that each CMIP6 model has the same sampling probability for each warming level following ref.[16]. All summary statistics of the distribution (means, percentiles, variances, ...) are calculated using these CMIP6 model weights.

Variance decomposition Following ref.[3], we attribute the observed variance in our GDP impact distribution to the sources of uncertainty. Let $\delta^C_{t,m,s,b}$ denote the global GDP impacts from climate indicator C in year t based on a CMIP6 model m under RCP-SSP scenario s using dose-response function parameter draw b. Let GWL be the set of all model-scenario-year combinations that imply a given global warming level. Then the conditional variance of impacts for a given warming level GWL can be decomposed as

$$\begin{aligned} Var(\delta^C_{t,m,s,b}|GWL) = & Var(\delta^C_{t,m,s,b}|GWL, m=m_0, t=t_0, s=s_0) + Var(\delta^C_{t,m,s,b}|GWL, m=m_0, b=b_0) + \\ & Var(\delta^C_{t,m,s,b}|GWL, t=t_0, s=s_0, b=b_0) + \Lambda \end{aligned} \tag{10}$$

where all variables with a zero subscript are median-like values and the first, second and third term capture the marginal variance due to dose-response function parameter draws, scenario-years, and CMIP6 models, respectively. Λ accounts for the interaction of these three variance components. For the median-like model m_0, we select ACCESS-CM2, which produces near-median results both for overall damages and for variability & extremes. However, we conduct robustness checks with two alternative model candidates in Figures S4 and S5 in the **Supplementary Information**. Similarly, b_0 is the dose-response function parameter draw that across all CMIP6 models and scenario-years produces the median GDP impact for a given climate indicator C at +3°C of global warming. Lastly, for each CMIP6 model, we set s_0 and t_0 to the scenario-year that yields the median GDP impacts for a given global warming level and climate indicator (note that scenario-years vary across warming levels such that we cannot choose s_0 and t_0 solely based on the +3°C warming level). The interaction term Λ is the residual between the total observed variance and the marginal variances. As this can be negative[3], we take the absolute value of Λ and rescale such that marginal variances and Λ add to 100% for simplicity, but we display results with negative interaction terms in Figure S3 in the **Supplementary Information**, resulting in identical conclusions.

Bias correction To ensure that our results are not driven by CMIP6 model bias, we bias-correct our climate indicators using the previously used change factor (CF) methodology[39]. The initial iteration of the CF approach involves using raw outputs from models and subtracting historical averages from future simulated values to generate climate anomalies. These anomalies are subsequently added to the corresponding historical average based on an observational dataset. This correction process, referred to as the "delta method", assumes consistent variability in both future and reference periods. For any climate indicator C out of the six indicators considered here, the formula for the bias-corrected value using the delta method is presented below:

$$C^{cor}_{x,t,m,s} = \bar{C}^{ERA5}_{x,ref} + \left(C_{x,t,m,s} - \bar{C}_{x,ref,m,s}\right) \tag{11}$$

In the formula, $C_{x,t,m,s}$ represents the raw climate indicator output of climate model m under scenario s in year t for grid cell x. $\bar{C}^{ERA5}_{x,ref}$ represents the average value of the same climate indicator in the observational dataset ERA5 during the historical reference period. $\bar{C}_{x,ref,m,s}$ represents the corresponding reference period average for the climate model m under scenario s (see Table S1 in the **Supplementary Information**). We bias-correct each annual indicator separately, and for the monthly precipitation deviation apply the delta method to the underlying monthly precipitation amounts. As a historical reference period, we utilize ERA5 data from 1950–1990, which corresponds to global warming of +0.38°C according to Berkeley Earth. Thus, for the model- and scenario-specific historical average $\bar{C}_{x,ref,m,s}$, we used a 41-year period that also corresponds to global warming of +0.38°C. The reason behind selecting 1950–1990 and hence +0.38°C of warming as a reference is to bias-correct the indicators using a period with less influence of anthropogenic forcing. To avoid implausible values resulting from the delta method, we impose zero lower bounds for all climate indicators that are, by definition, non-negative. In addition, the bias-corrected monthly precipitation deviation in some selected cases yields values that are one or two orders of magnitude above the maximum in the ERA5-based sample by ref.[12] or the maximum in our raw CMIP6 data. To address these outliers, we cap bias-corrected monthly precipitation deviation at the highest value observed for the raw CMIP6 data (i.e., 9.1), which affects only 353 ADM1-level model-scenario-year observations (out of approx. 64 million).

While our approach to correct for model bias ensures the highest consistency for each indicator with the ERA5 data used to estimate dose-response functions[12], it can also introduce inconsistencies between the different climate indicators derived from the same daily values of temperature or precipitation and, as outlined above, leads to outlier values in a few cases. Therefore, we use bias-corrected results only as a robustness check and display all our main results using the bias-corrected CMIP6 data in the **Supplementary Information**, noting that all conclusions drawn in this study hold when using the bias-corrected data instead.

Data & code availability. CMIP6 temperature and precipitation data are available at https://esgf-node.llnl.gov/projects/cmip6. Scripts to estimate the dose-response functions deployed here, as well as the underlying climate and economic data, are available from https://zenodo.org/record/5657457. All additional data and scripts required to replicate the analysis and to create the figures in this study will be made available upon acceptance.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- 230718SupplementaryInformation.pdf