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A top-down approach to projecting market impacts of climate change

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To evaluate policies to reduce greenhouse-gas emissions, economic models require estimates of how future climate change will affect well-being. So far, nearly all estimates of the economic impacts of future warming have been developed by combining estimates of impacts in individual sectors of the economy[1,2]. Recent work has used variation in warming over time and space to produce top-down estimates of how past climate and weather shocks have affected economic output[3–5]. Here we propose a statistical framework for converting these top-down estimates of past economic costs of regional warming into projections of the economic cost of future global warming. Combining the latest physical climate models, socioeconomic projections, and economic estimates of past impacts, we find that future warming could raise the expected rate of economic growth in richer countries, reduce the expected rate of economic growth in poorer countries, and increase the variability of growth by increasing the climate's variability. This study suggests we should rethink the focus on global impacts and the use of deterministic frameworks for modelling impacts and policy.

Cost–benefit integrated assessment models link the climate and the economy to calculate the optimal carbon tax or the social cost of carbon. The 'damage function' or 'impact function' is the crucial link that translates future warming into economic consequences. Right from the beginning of climate–economy modelling, the damage function was recognized as perhaps the most uncertain relation in these models[6,7]. Modellers typically derive this relation by assuming that cumulative warming reduces economic output, assuming a functional form relating that output loss to global mean surface temperature, and calibrating that function to estimates of impacts in particular economic sectors (such as agriculture or tourism) at low to moderate levels of warming[1,2,8–10]. However, recent work has shown that basic assumptions about the functional form of damages are crucial to policy evaluations[11–18], leading some prominent economists to question the policy relevance of existing integrated assessment models, given their uncertain underpinnings[19,20].

In contrast to this traditional 'bottom-up' approach to constructing a damage function from sectoral estimates of climate impacts, we develop and apply a new 'top-down', macroeconomic-based approach for constructing an impact function from historical climate–economy relationships and from climate models' simulations of future outcomes. Conventional approaches begin from assumptions about nonlinearities, but the limited history of warming prevents us from estimating nonlinear economic responses. Instead of introducing assumptions about nonlinearities with difficult-to-quantify uncertainties, we focus on extrapolating observed historical relationships so that our impact functions can provide a clear, empirically grounded baseline which future work might extend through further assumptions. Our results are therefore most relevant to relatively small changes in climate.

An emerging economics literature has begun analysing how climatic variables affect the broader economy[3,4,21–23]. In particular, recent work estimates how year-to-year variations in countries' temperature and precipitation have affected their annual economic growth since 1950 and also how changes in countries' average temperature and precipitation have affected their longer-run economic growth[5]. Through the former channel, future climate change could affect a country's 'short-run' growth by changing the interannual variability (that is, year-to-year variance) of its climate, and through the latter channel, future climate change could affect a country's 'medium-run' growth by changing its average climate (defined in our study as ten-year means). Ref. 5 finds that temperature and precipitation primarily affect the rate of output growth, not (as integrated assessment models have assumed) the level of output; that the magnitude and even the sign of these effects depend on countries' per-capita income; and that the relationships are approximately linear. We use adapted versions of these historical relations to develop impact functions for climate change (see Methods). Most cost–benefit integrated assessment models simulate only global mean surface temperature, not country-level temperature or precipitation. We therefore relate economic outcomes to global mean surface temperature by using physical climate models to simulate the spatially heterogeneous implications of future global climate change.

Our key contribution is our interdisciplinary statistical framework for converting historical estimates into probability distributions for the economic impacts of future climate change. Recently, ref. 24 heuristically transported the country-level impact estimates from ref. 5 to a global integrated assessment model to estimate the optimal carbon tax. We instead extend the approach of ref. 5 to develop distributions for impacts that can be directly implemented in future global or regional integrated assessment settings. In contrast to the heuristic implementation in ref. 24, our statistical framework uses a full physical climate model to connect the estimates of country-level impacts in ref. 5 to global temperature, allows impacts to vary continuously with income, and preserves the distinction between climate and weather shocks.

Figure 1 illustrates the components of our statistical framework (expanded in Methods). We begin with time series of economic, population and climate variables by country over the latter half of the twentieth century (box A). Adapting the fixed-effects estimation procedure of ref. 5, we estimate how a change in a single year's temperature and precipitation affects economic growth for poorer and richer countries, and we also follow ref. 5 in using long differences to estimate how longer-run changes in temperature and precipitation affect economic growth. These regressions generate

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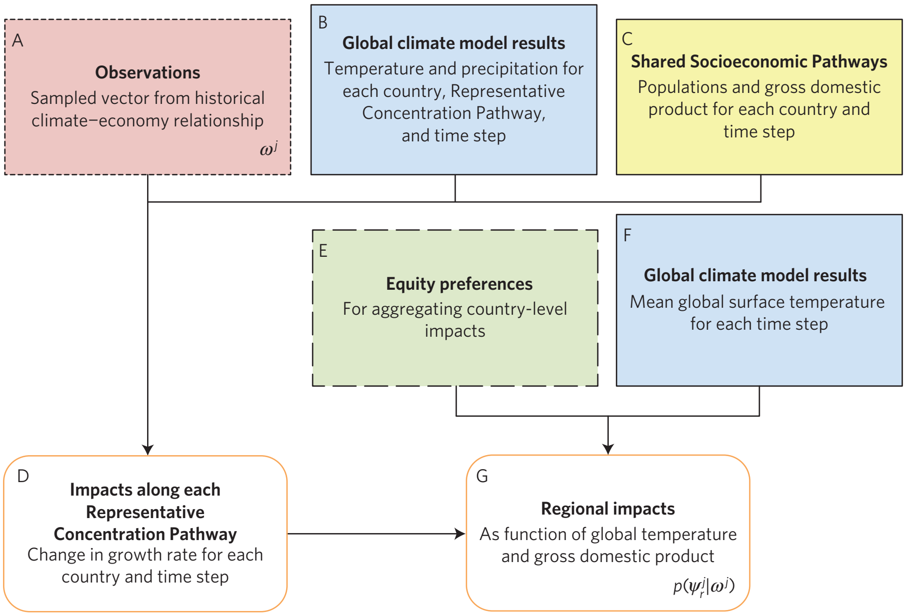

Figure 1 | Schematic of methodology for calculating regional impacts of climate change. Regional impacts (box G) are found by combining historical relationships between country-level climate and economic growth (box A), physical climate simulations (boxes B and F), projections of economic output and population (box C), projections of impacts for each country per time step (box D), and aversion to inequality in consumption across countries (box E). White boxes depict variables calculated within our statistical framework. Coloured boxes depict inputs: each colour corresponds to a different source; solid borders indicate inputs that are projections of future variables; dotted borders indicate inputs that are data from past years; and dashed borders indicate inputs that are ethical (or preference) parameters. Mathematical representations are shown in the corners of boxes A and G. See Methods and Supplementary Information for full explanations.

distributions for parameters governing the economic impacts of past climate and weather shocks. We then combine these distributions with physical climate models' projections of future temperature and precipitation (box B) and with benchmark socioeconomic projections for population and economic variables (box C) to obtain probability distributions for future climate impacts in each country (box D). We aggregate these country-level impacts to the global scale by applying ethical criteria that may weight impacts by the income of each country (box E). To provide a damage distribution useful for integrated assessment models, the final step summarizes the projected relationship between regional or global growth and global temperature change, with global temperature at each time step obtained from the same physical climate models used to project country-level climate variables (box F). The product of this final step is a set of probability distributions for the parameters governing how average global growth and the year-to-year variance of global growth change with global warming (box G).

Figure 2a,b depicts the expected value of each country's distribution for the 'medium-run' effects of global warming on each country's average economic growth (Fig. 2a) and for the 'short-run' effects of global warming on the year-to-year variance of each country's economic growth (Fig. 2b), calculated holding GDP and population fixed at year 2010 values. Figure 2c,d shows the standardized variables produced by dividing each country's expected value by its standard deviation. Strongly positive values in Fig. 2a indicate that warming increases average growth (a favourable outcome for countries), whereas strongly positive values in Fig. 2b indicate that warming increases the variance of growth (which could be a favourable or unfavourable outcome depending on preferences and on how that variability is managed). Values greater than 1 (less than −1) in Fig. 2c,d suggest that the bulk of the estimated distributions are above (below) zero.

Figure 2a shows that, holding income fixed at year 2010 GDP per capita, a degree of warming over the course of a decade tends to increase growth by 1–3 percentage points in much of the world. Figure 2c shows that the possibility of climate damages (that is, negative impacts) often lies 1–2 standard deviations below the expected value. However, there are notable exceptions to this rule. In many parts of sub-Saharan African and south Asia, a degree of warming reduces growth by up to 2 percentage points. These effects are primarily driven by the interaction between GDP per capita and temperature. In the Supplementary Information we show that the combined impacts map roughly tracks a map of GDP per capita and that precipitation channels are quantitatively small compared to temperature channels (and are even beneficial in much of sub-Saharan Africa). Global warming has heterogeneous climatic manifestations across these countries, but its effects on any given country's market output are primarily determined by that country's income level. Richer countries' economies can benefit from warming, even as poorer countries are harmed.

These medium-run effects contrast with the effects on the variance of short-run economic growth. To match the identifying variation underlying the panel regression in ref. 5, we model future short-run weather impacts as driven by deviations of temperature and precipitation from agents' forecasts (see Methods). Figure 2b,d shows that, holding income fixed at year 2010 GDP per capita, an additional degree of cumulative warming around the globe tends to increase the variability of growth in much of central and eastern Asia by 10–20% and to increase the variability of growth in much of the Americas and central Africa by up to 10%. In contrast, an additional degree of global mean surface temperature tends to decrease the variability of growth in west Africa by 10–20%, and to decrease the variability of growth in many Mediterranean countries by up to 10%. In the Supplementary Information we show that, in contrast to the medium-run case, a country's short-run precipitation channel often affects the variability of growth as strongly as does its temperature channel. The ratio of annual to decadal variability of precipitation is greater than for temperature in some regions, leading to precipitation and temperature having more equal effects on short-run variability. This is most evident in monsoon regions

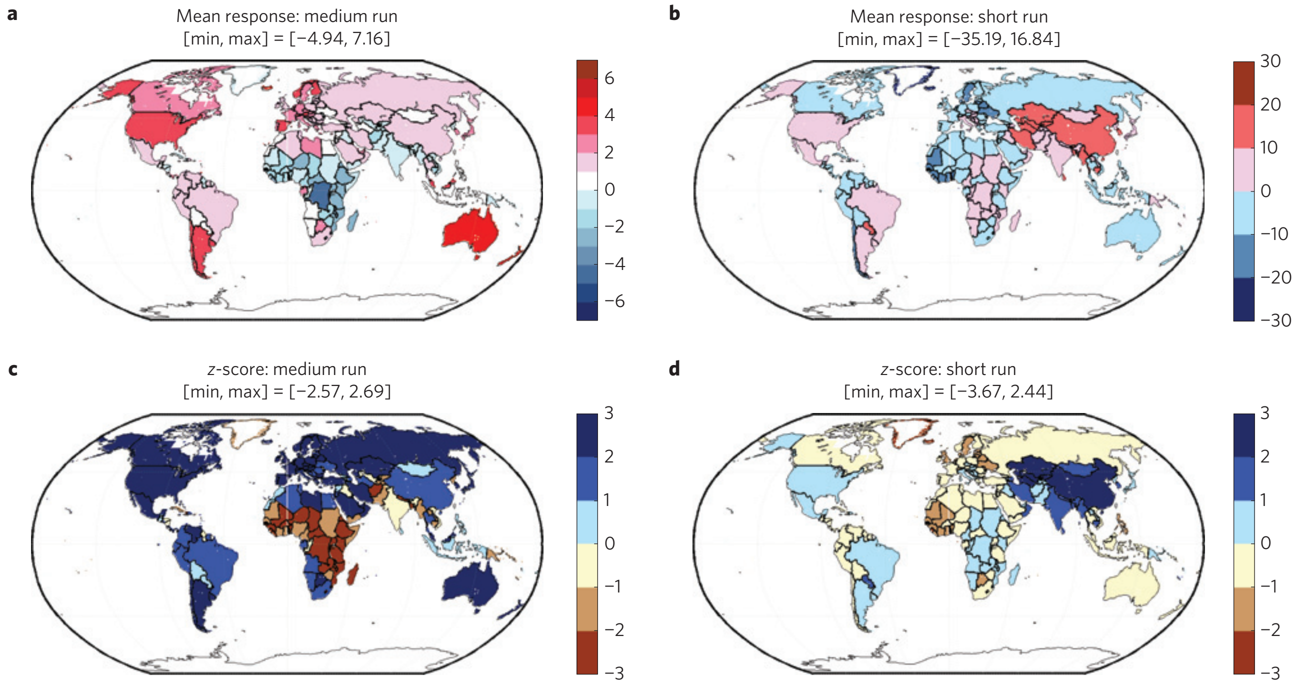

Figure 2 | Effects of climate on economic growth through changing averages and changing variability. a,**c**, Expected value (**a**) and *z*-score (**c**) for the estimated 'medium-run' effect of a 1 °C decadal increase in global mean surface temperature on the rate of economic growth (measured in percentage points; $\psi^M_{r,T}$ in equation (1) in Methods). **b**,**d**, Expected value (**b**) and *z*-score (**d**) for the estimated 'short-run' effect of a 1 °C increase in global mean surface temperature on the interannual variability of the rate of economic growth (measured as a percentage change; $\psi^S_{r,T}$ in equation (2) in Methods).

such as southeast Asia and parts of Africa, where failure and intensification of the monsoons can lead to greater forecast errors in precipitation[25].

Figure 3 reports the estimated distributions for the parameters relating global output growth to global warming using η, a value representing inequality aversion[26,27] (see Methods). As suggested by the heterogeneous effects depicted in Fig. 2, preferences over consumption inequality strongly affect the estimated global relationship. Figure 3a depicts the marginal distribution for the effect of warming at year 2010 global GDP per capita. Without any inequality weighting ($\eta = 0$), the effects are centred around zero, balancing the tension between rich countries' faster growth and poor countries' slower growth. However, complementary results in the Supplementary Information show that the interaction term (for global temperature and GDP per capita) is fairly large, tending to make global warming beneficial once the world has become wealthier on average. These results are largely in line with the benchmark DICE model, whose bottom-up impacts calibration does not use equity weighting: because its source studies also suggest that rich countries are less exposed to climate change, market channels are only a small component of the DICE damage function[1]. Most of the impacts in DICE instead arise from assumptions about potential catastrophic climate change[1].

If integrated assessment models explicitly represent many geographic regions, then their impact functions can neglect equity weighting within regions. However, many benchmark integrated assessment models include only a few regions, or even only a single global region. In these cases, spatial equity weighting must be embedded in their impact functions, giving us the change in the growth rate of consumption for a representative agent. At $\eta = 1$ (that is, log utility), additional warming is probably beneficial at year 2010 global per-capita income, but at the more conventional $\eta = 2$ (ref. 28), additional warming is probably detrimental, with the mode suggesting that 1 °C of warming reduces global growth by nearly a full percentage point. Larger values of η shift the distribution even further towards detrimental effects. In the Supplementary Information, we show that the interaction term shrinks as η increases, suggesting that future growth will not quickly convert warming from a detriment to a benefit for $\eta \geq 2$.

Figure 3b depicts the effects of warming on the variability of global output growth at year 2010 output per capita. We might expect that aggregating over a larger region tends to reduce both the variability of growth and the extent to which that variability changes with warming: growth and climate are more predictable at a global level than at the level of an individual country in the same way that population effects are more predictable than the effects on any individual. Indeed, we see these distributions are centred closer to zero, with the mode indicating a slight reduction in variability for extreme values of η (corresponding to the negative effects on variability seen in many of the poorest and richest countries) and indicating a 0.5–1% increase in variability for more common values of η. These results suggest that the effects of climate change on the interannual variability of growth are mitigated if regions insure each other either directly or through trade.

The impact estimates from our framework come with three caveats, all of which suggest that they are lower bounds. First, we assume that historical relations between aggregate output and climate continue to hold for future increments of warming—and do so in a linear fashion. However, the treatment effects estimated from past warming may not be constant at future higher levels of warming. Future work should disentangle the structural channels through which past climate variables have affected growth and assess the potential for nonlinear effects as new data become available. Second, by considering implications of climate change for national output, we ignore the considerable heterogeneity within nations. Combining imperfect insurance, equity weighting, and more geographically refined estimates would probably increase the estimated losses from climate change, but at present the resolution of global climate models limits such a project. Third, our impact estimates include only those channels present in past data. They

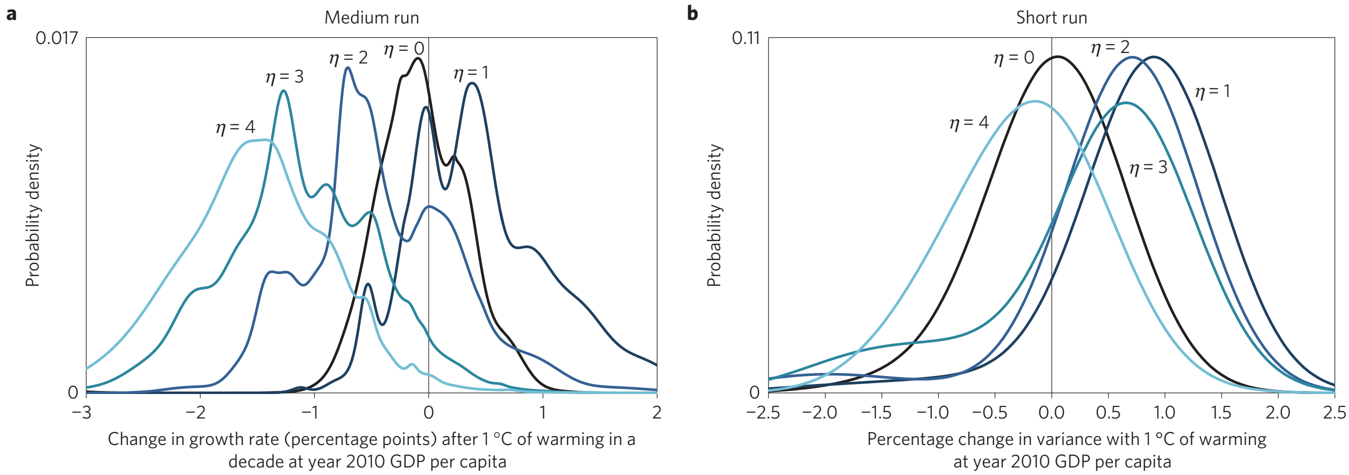

Figure 3 | Distribution of change in growth rate as a function of inequality aversion (η). a, At year 2010 GDP per capita, the estimated marginal probability density function for the change in the growth rate of global GDP per capita due to a 1 °C increase in average global mean temperature over a decade. **b**, At year 2010 GDP per capita, the estimated marginal probability density function for the change in the variance of the global growth rate due to a 1 °C increase in global mean temperature. Greater η implies stronger aversion to inequality of GDP per capita among countries.

therefore omit new impact channels such as sea level rise, changing water supplies, ocean acidification, and nonlinearities due to further shifts in extreme weather, and they also omit non-market channels, such as ecological disruption, that are not visible in past GDP data. Including additional damage channels may affect output or utility in rather different ways from the aggregate market channels studied here. A multipronged impacts relationship would reflect the multiple pathways by which climate matters, and probably highlight the crucial role for preferences over environmental goods beyond their value in economic production.

In conclusion, we have integrated economic and climatic time series, high-resolution physical climate modelling, and recently developed benchmark socioeconomic projections to produce 'top-down' estimates of climate impacts. Our estimates account for the heterogeneous effects of global warming on country-level temperature and precipitation, as well as for the observed sensitivity of country-level climate impacts to GDP per capita. Our projected climate impacts depend strongly on aversion to consumption inequality among nations. Optimal climate policy is likely to be sensitive not only to preferences for valuing impacts over time (as has been widely studied) but also to preferences for valuing impacts over space (which has been less commonly modelled)[29]. To investigate these and other questions, integrated assessment modellers can substitute our new 'top-down' estimates of climate impacts for the much-critiqued impact assumptions at the core of climate–economy models. Our estimates offer an independent impact assessment that relies on a different set of assumptions than those driving conventional 'bottom-up' estimates of climate impacts.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions

D.L. led the experimental design and writing of the manuscript. S.K. provided GFDL climate model data and contributed to the writing of the manuscript. Both authors helped to interpret the results.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to D.L.

Competing financial interests

The authors declare no competing financial interests.

Methods

We here describe the data and the statistical framework. The Supplementary Information provides mathematical and computational details, additional results (including decompositions and summary statistics), and robustness checks.

Global climate model simulations. For the medium-run estimation procedure, we use population-weighted temperature and precipitation for each country from 17 global climate models from the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report with available simulations for each of the four Representative Concentration Pathways[30]: BCC-CSM1-1, CCSM4, CESM1-CAM5, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GISS-E2-H, GISS-E2-R, HadGEM2-AO, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM, MIROC-ESM-CHEM, MRI-CGCM3, NorESM1-M and NorESM1-ME. For the short-run estimation, we do not want to conflate intermodel variability with interannual variability. We therefore use population-weighted temperature and precipitation from five simulations of the NOAA-GFDL CM2.5 model following the RCP8.5 pathway[31].

World Bank data set. Initial GDP per capita comes from the World Bank's purchasing power parity-adjusted, constant-dollars data set for the year 2010. That data set is in year 2005 dollars, which we rescale to year 2000 dollars using the current-dollars data set to match the units in the historical regressions following ref. 5. Year 2010 population also comes from a World Bank data set. In the global analyses, the initial log GDP per capita $\ln(y_{r0})$ is 9.0642.

Impacts framework. We seek distributions for the coefficients ψ in the following two relations:

$$I_r^M(\Delta T_t^g) = \psi_{r,T}^M \, \Delta T_t^g + \psi_{r,Ty}^M \, \Delta T_t^g \, \ln(y_{rt}/y_{r0}) \tag{1}$$

$$\mathrm{var}(I_r^S(T_t^g)) = \exp[\psi_{r,T}^S \, T_t^g + \psi_{r,Ty}^S \, T_t^g \, \ln(y_{rt}/y_{r0})] \tag{2}$$

where I_r^M and I_r^S give the medium- and short-run changes in growth rates in region r due to time t global mean surface temperature T_t^g and conditional on the log change in per-capita economic output (that is, in per-capita GDP) y_{rt} between the initial time and time t. ΔT_t^g is the change in global mean surface temperature between times $t-1$ and t, y_{rt} is per-capita GDP in region r at time t, and y_{r0} is per-capita GDP in region r in the initial period. Note that these equations describe future impacts. They are not regression equations for application to past data: as described below, we follow the fixed-effects specifications in ref. 5 when estimating historical relationships. We project a region's impacts as a function of global mean surface temperature rather than of regional climate because we aim to produce an impact function that will be useful for climate–economy integrated assessment models, which often simulate only a single global temperature index. At a region's initial GDP per capita y_{r0}, the coefficients $\psi_{r,T}^M$ and $\psi_{r,T}^S$ give the effect of, respectively, a 1 °C increase in decadal global mean temperature on medium-run growth and a 1 °C increase in global mean temperature on the variance of short-run growth (shown in Fig. 2). The coefficients $\psi_{r,Ty}^M$ and $\psi_{r,Ty}^S$ describe how temperature interacts with an e-fold (≈2.7-fold) increase in per-capita GDP.

Calculating probability distributions for $\boldsymbol{\psi_r^j}$. To obtain probability distributions for each vector of coefficients ψ_r^j in equations (1) and (2), we use the law of conditional probability:

$$p(\psi_r^j) = \int p(\psi_r^j|\omega^j)\, p(\omega^j)\, \mathrm{d}\omega^j$$

We adapt ref. 5 to obtain central estimates and standard errors for the historical relationship between the climate and the economy (see Supplementary Information). These parameters define the probability $p(\omega^j)$ of any sampled set of historical relationships defined by the vector ω^j. Combining this probability $p(\omega^j)$ with the conditional probability $p(\psi_r^j|\omega^j)$ (described below) allows us to calculate an unconditioned distribution for ψ_r^j, which includes the economic uncertainty about historical climate–economy relationships via $p(\omega^j)$ and also scientific uncertainty about how future global mean surface temperature relates to country-level climatic outcomes via $p(\psi_r^j|\omega^j)$.

Figure 1 outlines how we calculate the conditional probability $p(\psi_r^j|\omega^j)$ by combining state-of-the-art physical climate simulations and socioeconomic projections to account for the spatially heterogeneous implications of global temperature change and for uncertainty about those implications. We begin with a sampled vector ω^j (box A) from historical climate–economy relationships, simulations of temperature and precipitation from physical climate models (box B), and population and GDP projections from the recently developed Shared Socioeconomic Pathways (SSPs; box C; ref. 32). All results in the main text use SSP2, which is the scenario of 'middle' challenges. Combining these country-level socioeconomic projections with the country-level climatic projections and each sampled ω^j yields projected impacts for each country (box D) at each decade (in the medium-run analysis) or each year (in the short-run analysis).

The medium-run and short-run specifications calculate these future country-level impacts differently. When estimating medium-run impacts from changing average weather outcomes, we convert each sampled vector ω^j into a sampled impacts trajectory by multiplying ω^j by each time step's changes in average temperature and precipitation and by their interactions with log GDP per capita. Medium-run impacts arise from the change in global mean surface temperature at each time step rather than the absolute value of temperature because we assume that impacts over this time frame arise primarily from further changes in average climate rather than from changes that have already happened and may have triggered adaptation.

In contrast, when estimating short-run impacts from changing the variability of the weather, we use forecast errors in place of actual changes in temperature and precipitation: we match the panel estimation framework from ref. 5 by assuming that agents are harmed by unexpected weather shocks. This approach differs from literature that assesses whether the climate becomes more variable as global temperature increases[33–36]. To separate uncertainty about future warming from weather that is surprising conditional on global warming, we assume that agents correctly anticipate the next year's global mean surface temperature. Agents then use a straightforward forecasting rule: a linear projection of time $t+1$ country-level temperature (or precipitation) on time t country-level temperature (or precipitation) and time $t+1$ global mean surface temperature. More complex forecasting methods exist in both the economics and climate science literatures, but the chosen rule is a reasonable heuristic for ordinary agents. In the Supplementary Information we assess robustness to the choice of forecasting rule. Within each simulation of CM2.5, agents estimate the linear projection's coefficients via an ordinary least squares regression of historical country-level temperature (or precipitation) on lagged country-level temperature (or precipitation) and on contemporaneous global mean surface temperature. Agents use data from all previous years to construct forecasts for the next year.

The final steps in calculating the conditional probability $p(\psi_r^j|\omega^j)$ are to convert these country-level impacts into regional impacts and then estimate regional impacts as a function of global mean surface temperature. When the regions of interest encompass more than one country, we aggregate the country-level impacts via a social welfare function that can exhibit aversion to unequal consumption over space (box E). This approach seeks the impacts that affect a regional representative agent in the same way as the combination of its heterogeneous country-level impacts. We employ the same type of power utility social welfare function used to aggregate consumption over time in standard integrated assessment models, where the parameter η controls the degree of inequality aversion[26,27]. We vary the parameter between 0 (no inequality aversion) and 4 (high inequality aversion). When aggregating outcomes over time, standard integrated assessment models use values between 1 and 2 (refs 8,37,38), and values between 2 and 4 have also been recommended as reasonable[39,40].

We estimate the parameter vector ψ_r^j that best fits a sampled ω^j by combining the simulated regional impacts with the same global climate models' simulations of global mean surface temperature (box F). The coefficients and standard errors produced by this estimation define a distribution for each region's desired impact coefficient ψ_r^j (box G), which provides us with the probability $p(\psi_r^j|\omega^j)$ of any given value of ψ_r^j given a sampled value of ω^j.

The conditional probability $p(\psi_r^j|\omega^j)$ captures uncertainty about how global warming affects country-level temperature and precipitation. This climatic uncertainty arises from variation across physical climate models and across emission scenarios; it does not include uncertainty generated by biases common to all physical climate models[41]. Uncertainty about the relationship between future country-level climatic outcomes and growth is captured by $p(\omega^j)$, which reflects variability in the late twentieth century data but does not reflect uncertainty about how the historical relationship may change at higher levels of warming. Combining $p(\psi_r^j|\omega^j)$ and $p(\omega^j)$ generates a distribution for the coefficients in the relationship describing impacts for region r as a function of global temperature, reflecting both uncertainty about the historical relationship between country-level climate and the economy and uncertainty about the future relationship between global warming and country-level climate.

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