Article

The economic commitment of climate change

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Global projections of macroeconomic climate-change damages typically consider impacts from average annual and national temperatures over long time horizons[1–6]. Here we use recent empirical findings from more than 1,600 regions worldwide over the past 40 years to project sub-national damages from temperature and precipitation, including daily variability and extremes[7,8]. Using an empirical approach that provides a robust lower bound on the persistence of impacts on economic growth, we find that the world economy is committed to an income reduction of 19% within the next 26 years independent of future emission choices (relative to a baseline without climate impacts, likely range of 11–29% accounting for physical climate and empirical uncertainty). These damages already outweigh the mitigation costs required to limit global warming to 2 °C by sixfold over this near-term time frame and thereafter diverge strongly dependent on emission choices. Committed damages arise predominantly through changes in average temperature, but accounting for further climatic components raises estimates by approximately 50% and leads to stronger regional heterogeneity. Committed losses are projected for all regions except those at very high latitudes, at which reductions in temperature variability bring benefits. The largest losses are committed at lower latitudes in regions with lower cumulative historical emissions and lower present-day income.

Projections of the macroeconomic damage caused by future climate change are crucial to informing public and policy debates about adaptation, mitigation and climate justice. On the one hand, adaptation against climate impacts must be justified and planned on the basis of an understanding of their future magnitude and spatial distribution[9]. This is also of importance in the context of climate justice[10], as well as to key societal actors, including governments, central banks and private businesses, which increasingly require the inclusion of climate risks in their macroeconomic forecasts to aid adaptive decision-making[11,12]. On the other hand, climate mitigation policy such as the Paris Climate Agreement is often evaluated by balancing the costs of its implementation against the benefits of avoiding projected physical damages. This evaluation occurs both formally through cost–benefit analyses[1,4–6], as well as informally through public perception of mitigation and damage costs[13].

Projections of future damages meet challenges when informing these debates, in particular the human biases relating to uncertainty and remoteness that are raised by long-term perspectives[14]. Here we aim to overcome such challenges by assessing the extent of economic damages from climate change to which the world is already committed by historical emissions and socio-economic inertia (the range of future emission scenarios that are considered socio-economically plausible[15]). Such a focus on the near term limits the large uncertainties about diverging future emission trajectories, the resulting long-term climate response and the validity of applying historically observed climate–economic relations over long timescales during which socio-technical conditions may change considerably. As such, this focus aims to simplify the communication and maximize the credibility of projected economic damages from future climate change.

In projecting the future economic damages from climate change, we make use of recent advances in climate econometrics that provide evidence for impacts on sub-national economic growth from numerous components of the distribution of daily temperature and precipitation[3,7,8]. Using fixed-effects panel regression models to control for potential confounders, these studies exploit within-region variation in local temperature and precipitation in a panel of more than 1,600 regions worldwide, comprising climate and income data over the past 40 years, to identify the plausibly causal effects of changes in several climate variables on economic productivity[16,17]. Specifically, macroeconomic impacts have been identified from changing daily temperature variability, total annual precipitation, the annual number of wet days and extreme daily rainfall that occur in addition to those already identified from changing average temperature[2,3,18]. Moreover, regional heterogeneity in these effects based on the prevailing local climatic conditions has been found using interactions terms. The selection of these climate variables follows micro-level evidence for mechanisms related to the impacts of average temperatures on labour and agricultural productivity[2], of temperature variability on agricultural productivity and health[7], as well as of precipitation on agricultural productivity, labour outcomes and flood damages[8] (see Extended Data Table 1 for an overview, including more detailed references). References 7,8 contain a more detailed motivation for the use of these particular climate variables and provide extensive empirical tests about the robustness and nature of their effects on economic output, which are summarized in Methods. By accounting for these extra climatic variables at the sub-national level, we aim for a more comprehensive description of climate impacts with greater detail across both time and space.

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Constraining the persistence of impacts

A key determinant and source of discrepancy in estimates of the magnitude of future climate damages is the extent to which the impact of a climate variable on economic growth rates persists. The two extreme cases in which these impacts persist indefinitely or only instantaneously are commonly referred to as growth or level effects[19,20] (see Methods section 'Empirical model specification: fixed-effects distributed lag models' for mathematical definitions). Recent work shows that future damages from climate change depend strongly on whether growth or level effects are assumed[20]. Following refs. 2,18, we provide constraints on this persistence by using distributed lag models to test the significance of delayed effects separately for each climate variable. Notably, and in contrast to refs. 2,18, we use climate variables in their first-differenced form following ref. 3, implying a dependence of the growth rate on a change in climate variables. This choice means that a baseline specification without any lags constitutes a model prior of purely level effects, in which a permanent change in the climate has only an instantaneous effect on the growth rate[3,19,21]. By including lags, one can then test whether any effects may persist further. This is in contrast to the specification used by refs. 2,18, in which climate variables are used without taking the first difference, implying a dependence of the growth rate on the level of climate variables. In this alternative case, the baseline specification without any lags constitutes a model prior of pure growth effects, in which a change in climate has an infinitely persistent effect on the growth rate. Consequently, including further lags in this alternative case tests whether the initial growth impact is recovered[18,19,21]. Both of these specifications suffer from the limiting possibility that, if too few lags are included, one might falsely accept the model prior. The limitations of including a very large number of lags, including loss of data and increasing statistical uncertainty with an increasing number of parameters, mean that such a possibility is likely. By choosing a specification in which the model prior is one of level effects, our approach is therefore conservative by design, avoiding assumptions of infinite persistence of climate impacts on growth and instead providing a lower bound on this persistence based on what is observable empirically (see Methods section 'Empirical model specification: fixed-effects distributed lag models' for further exposition of this framework). The conservative nature of such a choice is probably the reason that ref. 19 finds much greater consistency between the impacts projected by models that use the first difference of climate variables, as opposed to their levels.

We begin our empirical analysis of the persistence of climate impacts on growth using ten lags of the first-differenced climate variables in fixed-effects distributed lag models. We detect substantial effects on economic growth at time lags of up to approximately 8–10 years for the temperature terms and up to approximately 4 years for the precipitation terms (Extended Data Fig. 1 and Extended Data Table 2). Furthermore, evaluation by means of information criteria indicates that the inclusion of all five climate variables and the use of these numbers of lags provide a preferable trade-off between best-fitting the data and including further terms that could cause overfitting, in comparison with model specifications excluding climate variables or including more or fewer lags (Extended Data Fig. 3, Supplementary Methods Section 1 and Supplementary Table 1). We therefore remove statistically insignificant terms at later lags (Supplementary Figs. 1–3 and Supplementary Tables 2–4). Further tests using Monte Carlo simulations demonstrate that the empirical models are robust to autocorrelation in the lagged climate variables (Supplementary Methods Section 2 and Supplementary Figs. 4 and 5), that information criteria provide an effective indicator for lag selection (Supplementary Methods Section 2 and Supplementary Fig. 6), that the results are robust to concerns of imperfect multicollinearity between climate variables and that including several climate variables is actually necessary to isolate their separate effects (Supplementary Methods Section 3 and Supplementary Fig. 7). We provide a further robustness check using a restricted distributed lag model to limit oscillations in the lagged parameter estimates that may result from autocorrelation, finding that it provides similar estimates of cumulative marginal effects to the unrestricted model (Supplementary Methods Section 4 and Supplementary Figs. 8 and 9). Finally, to explicitly account for any outstanding uncertainty arising from the precise choice of the number of lags, we include empirical models with marginally different numbers of lags in the error-sampling procedure of our projection of future damages. On the basis of the lag-selection procedure (the significance of lagged terms in Extended Data Fig. 1 and Extended Data Table 2, as well as information criteria in Extended Data Fig. 3), we sample from models with eight to ten lags for temperature and four for precipitation (models shown in Supplementary Figs. 1–3 and Supplementary Tables 2–4). In summary, this empirical approach to constrain the persistence of climate impacts on economic growth rates is conservative by design in avoiding assumptions of infinite persistence, but nevertheless provides a lower bound on the extent of impact persistence that is robust to the numerous tests outlined above.

Committed damages until mid-century

We combine these empirical economic response functions (Supplementary Figs. 1–3 and Supplementary Tables 2–4) with an ensemble of 21 climate models (see Supplementary Table 5) from the Coupled Model Intercomparison Project Phase 6 (CMIP-6)[22] to project the macroeconomic damages from these components of physical climate change (see Methods for further details). Bias-adjusted climate models that provide a highly accurate reproduction of observed climatological patterns with limited uncertainty (Supplementary Table 6) are used to avoid introducing biases in the projections. Following a well-developed literature[2,3,19], these projections do not aim to provide a prediction of future economic growth. Instead, they are a projection of the exogenous impact of future climate conditions on the economy relative to the baselines specified by socio-economic projections, based on the plausibly causal relationships inferred by the empirical models and assuming ceteris paribus. Other exogenous factors relevant for the prediction of economic output are purposefully assumed constant.

A Monte Carlo procedure that samples from climate model projections, empirical models with different numbers of lags and model parameter estimates (obtained by 1,000 block-bootstrap resamples of each of the regressions in Supplementary Figs. 1–3 and Supplementary Tables 2–4) is used to estimate the combined uncertainty from these sources. Given these uncertainty distributions, we find that projected global damages are statistically indistinguishable across the two most extreme emission scenarios until 2049 (at the 5% significance level; Fig. 1). As such, the climate damages occurring before this time constitute those to which the world is already committed owing to the combination of past emissions and the range of future emission scenarios that are considered socio-economically plausible[15]. These committed damages comprise a permanent income reduction of 19% on average globally (population-weighted average) in comparison with a baseline without climate-change impacts (with a likely range of 11–29%, following the likelihood classification adopted by the Intergovernmental Panel on Climate Change (IPCC); see caption of Fig. 1). Even though levels of income per capita generally still increase relative to those of today, this constitutes a permanent income reduction for most regions, including North America and Europe (each with median income reductions of approximately 11%) and with South Asia and Africa being the most strongly affected (each with median income reductions of approximately 22%; Fig. 1). Under a middle-of-the road scenario of future income development (SSP2, in which SSP stands for Shared Socio-economic Pathway), this corresponds to global annual damages in 2049 of 38 trillion in 2005 international dollars (likely range of 19–59 trillion 2005 international dollars). Compared with empirical specifications that assume pure growth or pure level effects,

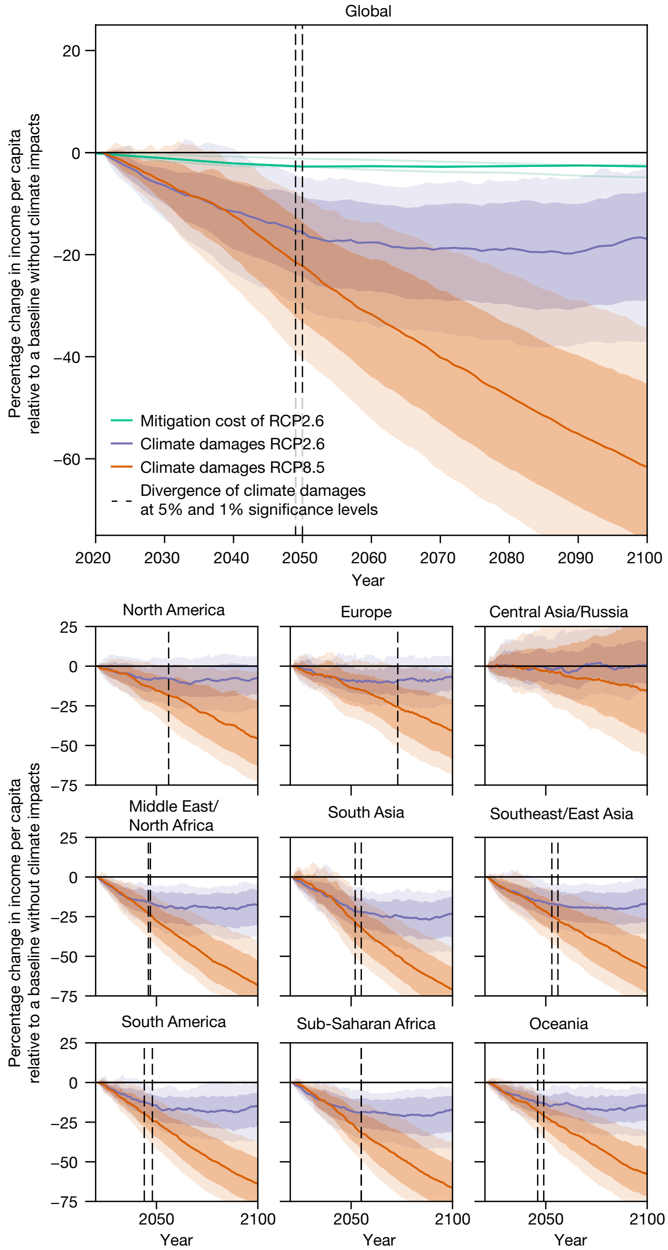

Fig. 1 | The commitment and divergence of economic climate damages versus mitigation costs. Estimates of the projected reduction in income per capita from changes in all climate variables based on empirical models of climate impacts on economic output with a robust lower bound on their persistence (Extended Data Fig. 1) under a low-emission scenario compatible with the 2 °C warming target and a high-emission scenario (SSP2-RCP2.6 and SSP5-RCP8.5, respectively) are shown in purple and orange, respectively. Shading represents the 34% and 10% confidence intervals reflecting the likely and very likely ranges, respectively (following the likelihood classification adopted by the IPCC), having estimated uncertainty from a Monte Carlo procedure, which samples the uncertainty from the choice of physical climate models, empirical models with different numbers of lags and bootstrapped estimates of the regression parameters shown in Supplementary Figs. 1–3. Vertical dashed lines show the time at which the climate damages of the two emission scenarios diverge at the 5% and 1% significance levels based on the distribution of differences between emission scenarios arising from the uncertainty sampling discussed above. Note that uncertainty in the difference of the two scenarios is smaller than the combined uncertainty of the two respective scenarios because samples of the uncertainty (climate model and empirical model choice, as well as model parameter bootstrap) are consistent across the two emission scenarios, hence the divergence of damages occurs while the uncertainty bounds of the two separate damage scenarios still overlap. Estimates of global mitigation costs from the three IAMs that provide results for the SSP2 baseline and SSP2-RCP2.6 scenario are shown in light green in the top panel, with the median of these estimates shown in bold.

our preferred specification that provides a robust lower bound on the extent of climate impact persistence produces damages between these two extreme assumptions (Extended Data Fig. 3).

Damages already outweigh mitigation costs

We compare the damages to which the world is committed over the next 25 years to estimates of the mitigation costs required to achieve the Paris Climate Agreement. Taking estimates of mitigation costs from the three integrated assessment models (IAMs) in the IPCC AR6 database[23] that provide results under comparable scenarios (SSP2 baseline and SSP2-RCP2.6, in which RCP stands for Representative Concentration Pathway), we find that the median committed climate damages are larger than the median mitigation costs in 2050 (six trillion in 2005 international dollars) by a factor of approximately six (note that estimates of mitigation costs are only provided every 10 years by the IAMs and so a comparison in 2049 is not possible). This comparison simply aims to compare the magnitude of future damages against mitigation costs, rather than to conduct a formal cost–benefit analysis of transitioning from one emission path to another. Formal cost–benefit analyses typically find that the net benefits of mitigation only emerge after 2050 (ref. 5), which may lead some to conclude that physical damages from climate change are simply not large enough to outweigh mitigation costs until the second half of the century. Our simple comparison of their magnitudes makes clear that damages are actually already considerably larger than mitigation costs and the delayed emergence of net mitigation benefits results primarily from the fact that damages across different emission paths are indistinguishable until mid-century (Fig. 1).

Although these near-term damages constitute those to which the world is already committed, we note that damage estimates diverge strongly across emission scenarios after 2049, conveying the clear benefits of mitigation from a purely economic point of view that have been emphasized in previous studies[4,24]. As well as the uncertainties assessed in Fig. 1, these conclusions are robust to structural choices, such as the timescale with which changes in the moderating variables of the empirical models are estimated (Supplementary Figs. 10 and 11), as well as the order in which one accounts for the intertemporal and international components of currency comparison (Supplementary Fig. 12; see Methods for further details).

Damages from variability and extremes

Committed damages primarily arise through changes in average temperature (Fig. 2). This reflects the fact that projected changes in average temperature are larger than those in other climate variables when expressed as a function of their historical interannual variability (Extended Data Fig. 4). Because the historical variability is that on which the empirical models are estimated, larger projected changes in comparison with this variability probably lead to larger future impacts in a purely statistical sense. From a mechanistic perspective, one may plausibly interpret this result as implying that future changes in average temperature are the most unprecedented from the perspective of the historical fluctuations to which the economy is accustomed and therefore will cause the most damage. This insight may prove useful in terms of guiding adaptation measures to the sources of greatest damage.

Nevertheless, future damages based on empirical models that consider changes in annual average temperature only and exclude the other climate variables constitute income reductions of only 13% in 2049

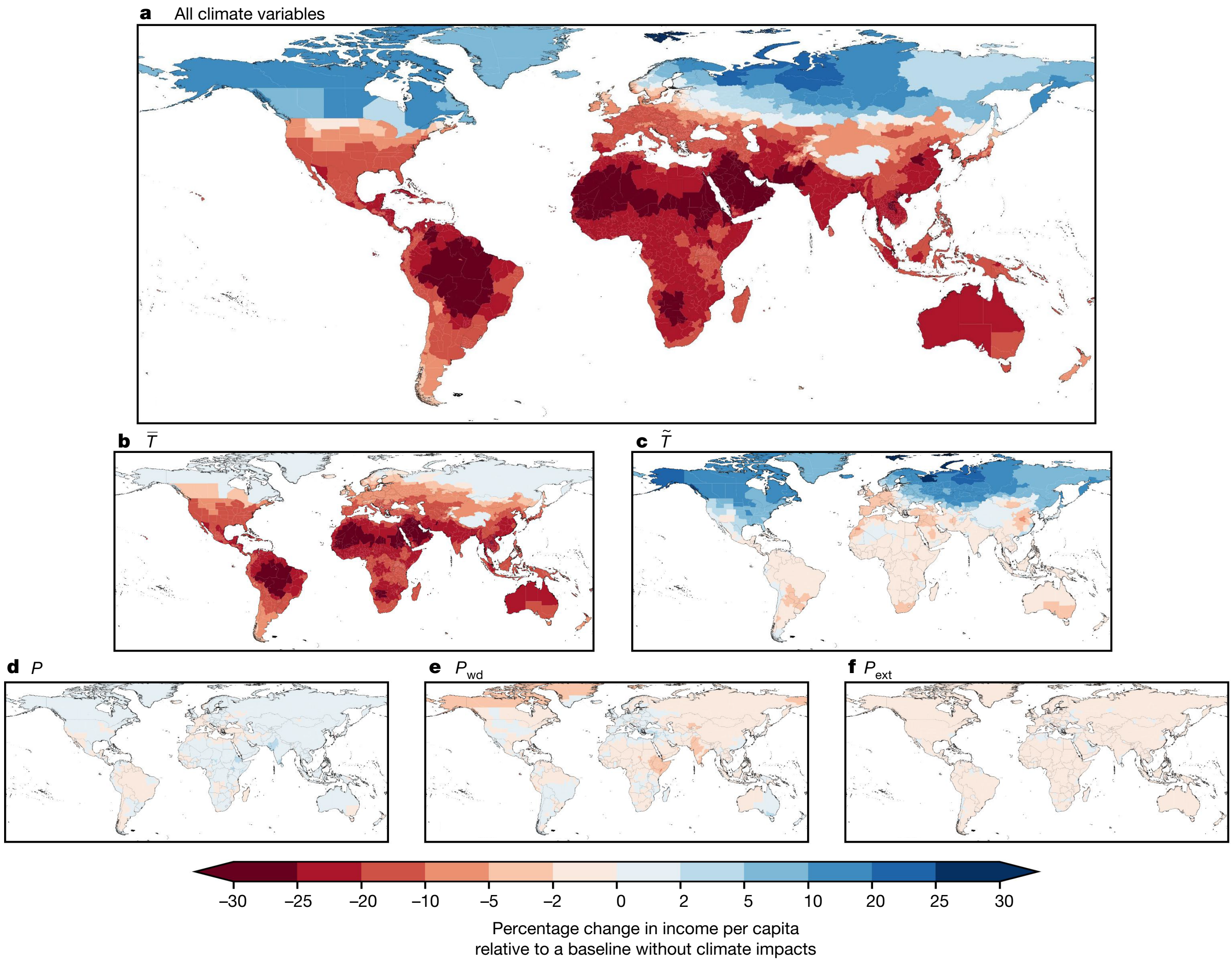

Fig. 2 | The committed economic damages of climate change by sub-national region and climatic component. Estimates of the median projected reduction in sub-national income per capita across emission scenarios (SSP2-RCP2.6 and SSP2-RCP8.5) as well as climate model, empirical model and model parameter uncertainty in the year in which climate damages diverge at the 5% level (2049, as identified in Fig. 1). **a**, Impacts arising from all climate variables. **b**–**f**, Impacts arising separately from changes in annual mean temperature (**b**), daily temperature variability (**c**), total annual precipitation (**d**), the annual number of wet days (>1 mm) (**e**) and extreme daily rainfall (**f**) (see Methods for further definitions). Data on national administrative boundaries are obtained from the GADM database version 3.6 and are freely available for academic use (https://gadm.org/).

(Extended Data Fig. 5a, likely range 5–21%). This suggests that accounting for the other components of the distribution of temperature and precipitation raises net damages by nearly 50%. This increase arises through the further damages that these climatic components cause, but also because their inclusion reveals a stronger negative economic response to average temperatures (Extended Data Fig. 5b). The latter finding is consistent with our Monte Carlo simulations, which suggest that the magnitude of the effect of average temperature on economic growth is underestimated unless accounting for the impacts of other correlated climate variables (Supplementary Fig. 7).

In terms of the relative contributions of the different climatic components to overall damages, we find that accounting for daily temperature variability causes the largest increase in overall damages relative to empirical frameworks that only consider changes in annual average temperature (4.9 percentage points, likely range 2.4–8.7 percentage points, equivalent to approximately 10 trillion international dollars). Accounting for precipitation causes smaller increases in overall damages, which are—nevertheless—equivalent to approximately 1.2 trillion international dollars: 0.01 percentage points (−0.37–0.33 percentage points), 0.34 percentage points (0.07–0.90 percentage points) and 0.36 percentage points (0.13–0.65 percentage points) from total annual precipitation, the number of wet days and extreme daily precipitation, respectively. Moreover, climate models seem to underestimate future changes in temperature variability[25] and extreme precipitation[26,27] in response to anthropogenic forcing as compared with that observed historically, suggesting that the true impacts from these variables may be larger.

The distribution of committed damages

The spatial distribution of committed damages (Fig. 2a) reflects a complex interplay between the patterns of future change in several climatic components and those of historical economic vulnerability to changes in those variables. Damages resulting from increasing annual mean temperature (Fig. 2b) are negative almost everywhere globally, and larger at lower latitudes in regions in which temperatures are already higher and economic vulnerability to temperature increases is greatest (see the response heterogeneity to mean temperature embodied in Extended Data Fig. 1a). This occurs despite the amplified warming projected at higher latitudes[28], suggesting that regional heterogeneity

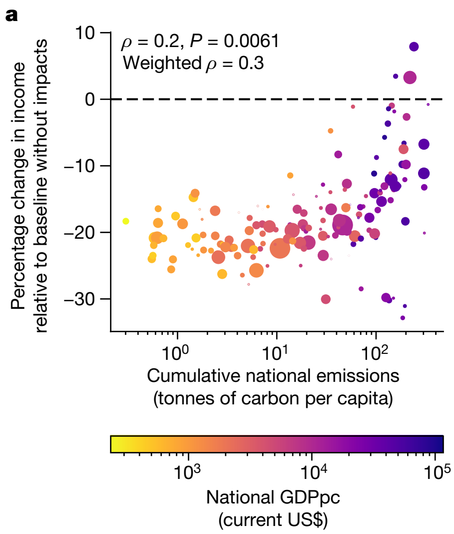

Fig. 3 | The injustice of committed climate damages by cumulative historical emissions and income. Estimates of the median projected change in national income per capita across emission scenarios (RCP2.6 and RCP8.5) as well as climate model, empirical model and model parameter uncertainty in the year in which climate damages diverge at the 5% level (2049, as identified in Fig. 1) are plotted against cumulative national emissions per capita in 2020 (from the Global Carbon Project) and coloured by national income per capita in 2020 (from the World Bank) in **a** and vice versa in **b**. In each panel, the size of each scatter point is weighted by the national population in 2020 (from the World Bank). Inset numbers indicate the Spearman's rank correlation ρ and P-values for a hypothesis test whose null hypothesis is of no correlation, as well as the Spearman's rank correlation weighted by national population.

in economic vulnerability to temperature changes outweighs heterogeneity in the magnitude of future warming (Supplementary Fig. 13a). Economic damages owing to daily temperature variability (Fig. 2c) exhibit a strong latitudinal polarisation, primarily reflecting the physical response of daily variability to greenhouse forcing in which increases in variability across lower latitudes (and Europe) contrast decreases at high latitudes[25] (Supplementary Fig. 13b). These two temperature terms are the dominant determinants of the pattern of overall damages (Fig. 2a), which exhibits a strong polarity with damages across most of the globe except at the highest northern latitudes. Future changes in total annual precipitation mainly bring economic benefits except in regions of drying, such as the Mediterranean and central South America (Fig. 2d and Supplementary Fig. 13c), but these benefits are opposed by changes in the number of wet days, which produce damages with a similar pattern of opposite sign (Fig. 2e and Supplementary Fig. 13d). By contrast, changes in extreme daily rainfall produce damages in all regions, reflecting the intensification of daily rainfall extremes over global land areas[29,30] (Fig. 2f and Supplementary Fig. 13e).

The spatial distribution of committed damages implies considerable injustice along two dimensions: culpability for the historical emissions that have caused climate change and pre-existing levels of socio-economic welfare. Spearman's rank correlations indicate that committed damages are significantly larger in countries with smaller historical cumulative emissions, as well as in regions with lower current income per capita (Fig. 3). This implies that those countries that will suffer the most from the damages already committed are those that are least responsible for climate change and which also have the least resources to adapt to it.

To further quantify this heterogeneity, we assess the difference in committed damages between the upper and lower quartiles of regions when ranked by present income levels and historical cumulative emissions (using a population weighting to both define the quartiles and estimate the group averages). On average, the quartile of countries with lower income are committed to an income loss that is 8.9 percentage points (or 61%) greater than the upper quartile (Extended Data Fig. 6), with a likely range of 3.8–14.7 percentage points across the uncertainty sampling of our damage projections (following the likelihood classification adopted by the IPCC). Similarly, the quartile of countries with lower historical cumulative emissions are committed to an income loss that is 6.9 percentage points (or 40%) greater than the upper quartile, with a likely range of 0.27–12 percentage points. These patterns reemphasize the prevalence of injustice in climate impacts[31–33] in the context of the damages to which the world is already committed by historical emissions and socio-economic inertia.

Contextualizing the magnitude of damages

The magnitude of projected economic damages exceeds previous literature estimates[2,3], arising from several developments made on previous approaches. Our estimates are larger than those of ref. 2 (see first row of Extended Data Table 3), primarily because of the facts that sub-national estimates typically show a steeper temperature response (see also refs. 3,34) and that accounting for other climatic components raises damage estimates (Extended Data Fig. 5). However, we note that our empirical approach using first-differenced climate variables is conservative compared with that of ref. 2 in regard to the persistence of climate impacts on growth (see introduction and Methods section 'Empirical model specification: fixed-effects distributed lag models'), an important determinant of the magnitude of long-term damages[19,21]. Using a similar empirical specification to ref. 2, which assumes infinite persistence while maintaining the rest of our approach (sub-national data and further climate variables), produces considerably larger damages (purple curve of Extended Data Fig. 3). Compared with studies that do take the first difference of climate variables[3,35], our estimates are also larger (see second and third rows of Extended Data Table 3). The inclusion of further climate variables (Extended Data Fig. 5) and a sufficient number of lags to more adequately capture the extent of impact persistence (Extended Data Figs. 1 and 2) are the main sources of this difference, as is the use of specifications that capture nonlinearities in the temperature response when compared with ref. 35. In summary, our estimates develop on previous studies by incorporating the latest data and empirical insights[7,8], as well as in providing a robust empirical lower bound on the persistence of impacts on economic growth, which constitutes a middle ground between the extremes of the growth-versus-levels debate[19,21] (Extended Data Fig. 3).

Compared with the fraction of variance explained by the empirical models historically (<5%), the projection of reductions in income of 19% may seem large. This arises owing to the fact that projected changes in climatic conditions are much larger than those that were experienced historically, particularly for changes in average temperature (Extended Data Fig. 4). As such, any assessment of future climate-change impacts necessarily requires an extrapolation outside the range of the historical data on which the empirical impact models were evaluated. Nevertheless, these models constitute the most state-of-the-art methods for inference of plausibly causal climate impacts based on observed data. Moreover, we take explicit steps to limit out-of-sample extrapolation by capping the moderating variables of the interaction terms at the 95th percentile of the historical distribution (see Methods). This avoids extrapolating the marginal effects outside what was observed historically. Given the nonlinear response of economic output to annual mean temperature (Extended Data Fig. 1 and Extended Data Table 2), this is a conservative choice that limits the magnitude of damages that we project. Furthermore, back-of-the-envelope calculations indicate that the projected damages are consistent with the magnitude and patterns of historical economic development (see Supplementary Discussion Section 5).

Missing impacts and spatial spillovers

Despite assessing several climatic components from which economic impacts have recently been identified[3,7,8], this assessment of aggregate climate damages should not be considered comprehensive. Important channels such as impacts from heatwaves[31], sea-level rise[36], tropical cyclones[37] and tipping points[38,39], as well as non-market damages such as those to ecosystems[40] and human health[41], are not considered in these estimates. Sea-level rise is unlikely to be feasibly incorporated into empirical assessments such as this because historical sea-level variability is mostly small. Non-market damages are inherently intractable within our estimates of impacts on aggregate monetary output and estimates of these impacts could arguably be considered as extra to those identified here. Recent empirical work suggests that accounting for these channels would probably raise estimates of these committed damages, with larger damages continuing to arise in the global south[31,36–42].

Moreover, our main empirical analysis does not explicitly evaluate the potential for impacts in local regions to produce effects that 'spill over' into other regions. Such effects may further mitigate or amplify the impacts we estimate, for example, if companies relocate production from one affected region to another or if impacts propagate along supply chains. The current literature indicates that trade plays a substantial role in propagating spillover effects[43,44], making their assessment at the sub-national level challenging without available data on sub-national trade dependencies. Studies accounting for only spatially adjacent neighbours indicate that negative impacts in one region induce further negative impacts in neighbouring regions[45–48], suggesting that our projected damages are probably conservative by excluding these effects. In Supplementary Fig. 14, we assess spillovers from neighbouring regions using a spatial-lag model. For simplicity, this analysis excludes temporal lags, focusing only on contemporaneous effects. The results show that accounting for spatial spillovers can amplify the overall magnitude, and also the heterogeneity, of impacts. Consistent with previous literature, this indicates that the overall magnitude (Fig. 1) and heterogeneity (Fig. 3) of damages that we project in our main specification may be conservative without explicitly accounting for spillovers. We note that further analysis that addresses both spatially and trade-connected spillovers, while also accounting for delayed impacts using temporal lags, would be necessary to adequately address this question fully. These approaches offer fruitful avenues for further research but are beyond the scope of this manuscript, which primarily aims to explore the impacts of different climate conditions and their persistence.

Policy implications

We find that the economic damages resulting from climate change until 2049 are those to which the world economy is already committed and that these greatly outweigh the costs required to mitigate emissions in line with the 2 °C target of the Paris Climate Agreement (Fig. 1). This assessment is complementary to formal analyses of the net costs and benefits associated with moving from one emission path to another, which typically find that net benefits of mitigation only emerge in the second half of the century[5]. Our simple comparison of the magnitude of damages and mitigation costs makes clear that this is primarily because damages are indistinguishable across emissions scenarios—that is, committed—until mid-century (Fig. 1) and that they are actually already much larger than mitigation costs. For simplicity, and owing to the availability of data, we compare damages to mitigation costs at the global level. Regional estimates of mitigation costs may shed further light on the national incentives for mitigation to which our results already hint, of relevance for international climate policy. Although these damages are committed from a mitigation perspective, adaptation may provide an opportunity to reduce them. Moreover, the strong divergence of damages after mid-century reemphasizes the clear benefits of mitigation from a purely economic perspective, as highlighted in previous studies[1,4,6,24].

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-024-07219-0.

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Methods

Historical climate data

Historical daily 2-m temperature and precipitation totals (in mm) are obtained for the period 1979–2019 from the W5E5 database. The W5E5 dataset comes from ERA-5, a state-of-the-art reanalysis of historical observations, but has been bias-adjusted by applying version 2.0 of the WATCH Forcing Data to ERA-5 reanalysis data and precipitation data from version 2.3 of the Global Precipitation Climatology Project to better reflect ground-based measurements[49–51]. We obtain these data on a 0.5° × 0.5° grid from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) database. Notably, these historical data have been used to bias-adjust future climate projections from CMIP-6 (see the following section), ensuring consistency between the distribution of historical daily weather on which our empirical models were estimated and the climate projections used to estimate future damages. These data are publicly available from the ISIMIP database. See refs. 7,8 for robustness tests of the empirical models to the choice of climate data reanalysis products.

Future climate data

Daily 2-m temperature and precipitation totals (in mm) are taken from 21 climate models participating in CMIP-6 under a high (RCP8.5) and a low (RCP2.6) greenhouse gas emission scenario from 2015 to 2100. The data have been bias-adjusted and statistically downscaled to a common half-degree grid to reflect the historical distribution of daily temperature and precipitation of the W5E5 dataset using the trend-preserving method developed by the ISIMIP[50,52]. As such, the climate model data reproduce observed climatological patterns exceptionally well (Supplementary Table 5). Gridded data are publicly available from the ISIMIP database.

Historical economic data

Historical economic data come from the DOSE database of sub-national economic output[53]. We use a recent revision to the DOSE dataset that provides data across 83 countries, 1,660 sub-national regions with varying temporal coverage from 1960 to 2019. Sub-national units constitute the first administrative division below national, for example, states for the USA and provinces for China. Data come from measures of gross regional product per capita (GRPpc) or income per capita in local currencies, reflecting the values reported in national statistical agencies, yearbooks and, in some cases, academic literature. We follow previous literature[3,7,8,54] and assess real sub-national output per capita by first converting values from local currencies to US dollars to account for diverging national inflationary tendencies and then account for US inflation using a US deflator. Alternatively, one might first account for national inflation and then convert between currencies. Supplementary Fig. 12 demonstrates that our conclusions are consistent when accounting for price changes in the reversed order, although the magnitude of estimated damages varies. See the documentation of the DOSE dataset for further discussion of these choices. Conversions between currencies are conducted using exchange rates from the FRED database of the Federal Reserve Bank of St. Louis[55] and the national deflators from the World Bank[56].

Future socio-economic data

Baseline gridded gross domestic product (GDP) and population data for the period 2015–2100 are taken from the middle-of-the-road scenario SSP2 (ref. 15). Population data have been downscaled to a half-degree grid by the ISIMIP following the methodologies of refs. 57,58, which we then aggregate to the sub-national level of our economic data using the spatial aggregation procedure described below. Because current methodologies for downscaling the GDP of the SSPs use downscaled population to do so, per-capita estimates of GDP with a realistic distribution at the sub-national level are not readily available for the SSPs. We therefore use national-level GDP per capita (GDPpc) projections for all sub-national regions of a given country, assuming homogeneity within countries in terms of baseline GDPpc. Here we use projections that have been updated to account for the impact of the COVID-19 pandemic on the trajectory of future income, while remaining consistent with the long-term development of the SSPs[59]. The choice of baseline SSP alters the magnitude of projected climate damages in monetary terms, but when assessed in terms of percentage change from the baseline, the choice of socio-economic scenario is inconsequential. Gridded SSP population data and national-level GDPpc data are publicly available from the ISIMIP database. Sub-national estimates as used in this study are available in the code and data replication files.

Climate variables

Following recent literature[3,7,8], we calculate an array of climate variables for which substantial impacts on macroeconomic output have been identified empirically, supported by further evidence at the micro level for plausible underlying mechanisms. See refs. 7,8 for an extensive motivation for the use of these particular climate variables and for detailed empirical tests on the nature and robustness of their effects on economic output. To summarize, these studies have found evidence for independent impacts on economic growth rates from annual average temperature, daily temperature variability, total annual precipitation, the annual number of wet days and extreme daily rainfall. Assessments of daily temperature variability were motivated by evidence of impacts on agricultural output and human health, as well as macroeconomic literature on the impacts of volatility on growth when manifest in different dimensions, such as government spending, exchange rates and even output itself[7]. Assessments of precipitation impacts were motivated by evidence of impacts on agricultural productivity, metropolitan labour outcomes and conflict, as well as damages caused by flash flooding[8]. See Extended Data Table 1 for detailed references to empirical studies of these physical mechanisms. Marked impacts of daily temperature variability, total annual precipitation, the number of wet days and extreme daily rainfall on macroeconomic output were identified robustly across different climate datasets, spatial aggregation schemes, specifications of regional time trends and error-clustering approaches. They were also found to be robust to the consideration of temperature extremes[7,8]. Furthermore, these climate variables were identified as having independent effects on economic output[7,8], which we further explain here using Monte Carlo simulations to demonstrate the robustness of the results to concerns of imperfect multicollinearity between climate variables (Supplementary Methods Section 2), as well as by using information criteria (Supplementary Table 1) to demonstrate that including several lagged climate variables provides a preferable trade-off between optimally describing the data and limiting the possibility of overfitting.

We calculate these variables from the distribution of daily, d, temperature, $T_{x,d}$, and precipitation, $P_{x,d}$, at the grid-cell, x, level for both the historical and future climate data. As well as annual mean temperature, $\overline{T}_{x,y}$, and annual total precipitation, $P_{x,y}$, we calculate annual, y, measures of daily temperature variability, $\widetilde{T}_{x,y}$:

$$\widetilde{T}_{x,y}=\frac{1}{12}\sum_{m=1}^{12}\sqrt{\frac{1}{D_m}\sum_{d=1}^{D_m}(T_{x,d,m,y}-\overline{T}_{x,m})^2}, \quad (1)$$

the number of wet days, $\mathrm{Pwd}_{x,y}$:

$$\mathrm{Pwd}_{x,y}=\sum_{d=1}^{D_y}H(P_{x,d}-1\ \mathrm{mm}) \quad (2)$$

and extreme daily rainfall:

$$\text{Pext}_{x,y} = \sum_{d=1}^{D_y} H\left(P_{x,d} - P99.9_x\right) \times P_{x,d}, \tag{3}$$

in which $T_{x,d,m,y}$ is the grid-cell-specific daily temperature in month m and year y, $\overline{T}_{x,m,y}$ is the year and grid-cell-specific monthly, m, mean temperature, D_m and D_y the number of days in a given month m or year y, respectively, H the Heaviside step function, 1 mm the threshold used to define wet days and $P99.9_x$ is the 99.9th percentile of historical (1979–2019) daily precipitation at the grid-cell level. Units of the climate measures are degrees Celsius for annual mean temperature and daily temperature variability, millimetres for total annual precipitation and extreme daily precipitation, and simply the number of days for the annual number of wet days.

We also calculated weighted standard deviations of monthly rainfall totals as also used in ref. 8 but do not include them in our projections as we find that, when accounting for delayed effects, their effect becomes statistically indistinct and is better captured by changes in total annual rainfall.

Spatial aggregation

We aggregate grid-cell-level historical and future climate measures, as well as grid-cell-level future GDPpc and population, to the level of the first administrative unit below national level of the GADM database, using an area-weighting algorithm that estimates the portion of each grid cell falling within an administrative boundary. We use this as our baseline specification following previous findings that the effect of area or population weighting at the sub-national level is negligible[7,8].

Empirical model specification: fixed-effects distributed lag models

Following a wide range of climate econometric literature[16,60], we use panel regression models with a selection of fixed effects and time trends to isolate plausibly exogenous variation with which to maximize confidence in a causal interpretation of the effects of climate on economic growth rates. The use of region fixed effects, μ_r, accounts for unobserved time-invariant differences between regions, such as prevailing climatic norms and growth rates owing to historical and geopolitical factors. The use of yearly fixed effects, η_y, accounts for regionally invariant annual shocks to the global climate or economy such as the El Niño–Southern Oscillation or global recessions. In our baseline specification, we also include region-specific linear time trends, $k_r y$, to exclude the possibility of spurious correlations resulting from common slow-moving trends in climate and growth.

The persistence of climate impacts on economic growth rates is a key determinant of the long-term magnitude of damages. Methods for inferring the extent of persistence in impacts on growth rates have typically used lagged climate variables to evaluate the presence of delayed effects or catch-up dynamics[2,18]. For example, consider starting from a model in which a climate condition, $C_{r,y}$, (for example, annual mean temperature) affects the growth rate, $\Delta\text{lgrp}_{r,y}$ (the first difference of the logarithm of gross regional product) of region r in year y:

$$\Delta\text{lgrp}_{r,y} = \mu_r + \eta_y + k_r y + \alpha C_{r,y} + \varepsilon_{r,y}, \tag{4}$$

which we refer to as a 'pure growth effects' model in the main text. Typically, further lags are included,

$$\Delta\text{lgrp}_{r,y} = \mu_r + \eta_y + k_r y + \sum_{L=0}^{\text{NL}} \alpha_L C_{r,y-L} + \varepsilon_{r,y}, \tag{5}$$

and the cumulative effect of all lagged terms is evaluated to assess the extent to which climate impacts on growth rates persist. Following ref. 18, in the case that,

$$\sum_{L=0}^{\text{NL}} \alpha_L < 0 \text{ for } \alpha_0 < 0 \text{ or } \sum_{L=0}^{\text{NL}} \alpha_L > 0 \text{ for } \alpha_0 > 0, \tag{6}$$

the implication is that impacts on the growth rate persist up to NL years after the initial shock (possibly to a weaker or a stronger extent), whereas if

$$\sum_{L=0}^{\text{NL}} \alpha_L = 0, \tag{7}$$

then the initial impact on the growth rate is recovered after NL years and the effect is only one on the level of output. However, we note that such approaches are limited by the fact that, when including an insufficient number of lags to detect a recovery of the growth rates, one may find equation (6) to be satisfied and incorrectly assume that a change in climatic conditions affects the growth rate indefinitely. In practice, given a limited record of historical data, including too few lags to confidently conclude in an infinitely persistent impact on the growth rate is likely, particularly over the long timescales over which future climate damages are often projected[2,24]. To avoid this issue, we instead begin our analysis with a model for which the level of output, $\text{lgrp}_{r,y}$, depends on the level of a climate variable, $C_{r,y}$:

$$\text{lgrp}_{r,y} = \mu_r + \eta_y + k_r y + \alpha C_{r,y} + \varepsilon_{r,y}. \tag{8}$$

Given the non-stationarity of the level of output, we follow the literature[19] and estimate such an equation in first-differenced form as,

$$\Delta\text{lgrp}_{r,y} = \mu_r + \eta_y + k_r y + \alpha \Delta C_{r,y} + \varepsilon_{r,y}, \tag{8}$$

which we refer to as a model of 'pure level effects' in the main text. This model constitutes a baseline specification in which a permanent change in the climate variable produces an instantaneous impact on the growth rate and a permanent effect only on the level of output. By including lagged variables in this specification,

$$\Delta\text{lgrp}_{r,y} = \mu_r + \eta_y + k_r y + \sum_{L=0}^{\text{NL}} \alpha_L \Delta C_{r,y-L} + \varepsilon_{r,y}, \tag{9}$$

we are able to test whether the impacts on the growth rate persist any further than instantaneously by evaluating whether $\alpha_L > 0$ are statistically significantly different from zero. Even though this framework is also limited by the possibility of including too few lags, the choice of a baseline model specification in which impacts on the growth rate do not persist means that, in the case of including too few lags, the framework reverts to the baseline specification of level effects. As such, this framework is conservative with respect to the persistence of impacts and the magnitude of future damages. It naturally avoids assumptions of infinite persistence and we are able to interpret any persistence that we identify with equation (9) as a lower bound on the extent of climate impact persistence on growth rates. See the main text for further discussion of this specification choice, in particular about its conservative nature compared with previous literature estimates, such as refs. 2,18.

We allow the response to climatic changes to vary across regions, using interactions of the climate variables with historical average (1979–2019) climatic conditions reflecting heterogenous effects identified in previous work[7,8]. Following this previous work, the moderating variables of these interaction terms constitute the historical average of either the variable itself or of the seasonal temperature difference, $\hat{T}_r$, or annual mean temperature, $\overline{T}_r$, in the case of daily temperature variability[7] and extreme daily rainfall, respectively[8].

The resulting regression equation with N and M lagged variables, respectively, reads:

$$\begin{aligned}\Delta \mathrm{lgrp}_{r,y} = {} & \mu_r + \eta_y + k_r y + \sum_{L=0}^{N} (\alpha_{1,L} \Delta \overline{T}_{r,y-L} + \alpha_{2,L} \Delta \overline{T}_{r,y-L} \times \overline{T}_r) \\ & + \sum_{L=0}^{N} (\alpha_{3,L} \Delta \widetilde{T}_{r,y-L} + \alpha_{4,L} \Delta \widetilde{T}_{r,y-L} \times \hat{T}_r) \\ & + \sum_{L=0}^{M} (\alpha_{5,L} \Delta P_{r,y-L} + \alpha_{6,L} \Delta P_{r,y-L} \times P_r) \\ & + \sum_{L=0}^{M} (\alpha_{7,L} \Delta \mathrm{Pwd}_{r,y-L} + \alpha_{8,L} \Delta \mathrm{Pwd}_{r,y-L} \times \mathrm{Pwd}_r) \\ & + \sum_{L=0}^{M} (\alpha_{9,L} \Delta \mathrm{Pext}_{r,y-L} + \alpha_{10,L} \Delta \mathrm{Pext}_{r,y-L} \times \overline{T}_r) + \epsilon_{r,y}\end{aligned} \quad (10)$$

in which $\Delta \mathrm{lgrp}_{r,y}$ is the annual, regional GRPpc growth rate, measured as the first difference of the logarithm of real GRPpc, following previous work[2,3,7,8,18,19]. Fixed-effects regressions were run using the fixest package in R (ref. 61).

Estimates of the coefficients of interest $\alpha_{i,L}$ are shown in Extended Data Fig. 1 for $N = M = 10$ lags and for our preferred choice of the number of lags in Supplementary Figs. 1–3. In Extended Data Fig. 1, errors are shown clustered at the regional level, but for the construction of damage projections, we block-bootstrap the regressions by region 1,000 times to provide a range of parameter estimates with which to sample the projection uncertainty (following refs. 2,31).

Spatial-lag model

In Supplementary Fig. 14, we present the results from a spatial-lag model that explores the potential for climate impacts to 'spill over' into spatially neighbouring regions. We measure the distance between centroids of each pair of sub-national regions and construct spatial lags that take the average of the first-differenced climate variables and their interaction terms over neighbouring regions that are at distances of 0–500, 500–1,000, 1,000–1,500 and 1,500–2000 km (spatial lags, 'SL', 1 to 4). For simplicity, we then assess a spatial-lag model without temporal lags to assess spatial spillovers of contemporaneous climate impacts. This model takes the form:

$$\begin{aligned}\Delta \mathrm{lgrp}_{r,y} = {} & \mu_r + \eta_y + k_r y + \sum_{\mathrm{SL}=0}^{N} (\alpha_{1,\mathrm{SL}} \Delta \overline{T}_{r-\mathrm{SL},y} + \alpha_{2,\mathrm{SL}} \Delta \overline{T}_{r-\mathrm{SL},y} \times \overline{T}_{r-\mathrm{SL}}) \\ & + \sum_{\mathrm{SL}=0}^{N} (\alpha_{3,\mathrm{SL}} \Delta \widetilde{T}_{r-\mathrm{SL},y} + \alpha_{4,\mathrm{SL}} \Delta \widetilde{T}_{r-\mathrm{SL},y} \times \hat{T}_{r-\mathrm{SL}}) \\ & + \sum_{\mathrm{SL}=0}^{N} (\alpha_{5,\mathrm{SL}} \Delta P_{r-\mathrm{SL},y} + \alpha_{6,\mathrm{SL}} \Delta P_{r-\mathrm{SL},y} \times P_{r-\mathrm{SL}}) \\ & + \sum_{\mathrm{SL}=0}^{N} (\alpha_{7,\mathrm{SL}} \Delta \mathrm{Pwd}_{r-\mathrm{SL},y} + \alpha_{8,\mathrm{SL}} \Delta \mathrm{Pwd}_{r-\mathrm{SL},y} \times \mathrm{Pwd}_{r-\mathrm{SL}}) \\ & + \sum_{\mathrm{SL}=0}^{N} (\alpha_{9,\mathrm{SL}} \Delta \mathrm{Pext}_{r-\mathrm{SL},y} + \alpha_{10,\mathrm{SL}} \Delta \mathrm{Pext}_{r-\mathrm{SL},y} \times \overline{T}_{r-\mathrm{SL}}) + \epsilon_{r,y},\end{aligned} \quad (11)$$

in which SL indicates the spatial lag of each climate variable and interaction term. In Supplementary Fig. 14, we plot the cumulative marginal effect of each climate variable at different baseline climate conditions by summing the coefficients for each climate variable and interaction term, for example, for average temperature impacts as:

$$\mathrm{ME} = \sum_{\mathrm{SL}=0}^{N} (\alpha_{1,\mathrm{SL}} + \alpha_{2,\mathrm{SL}} \overline{T}_{r-\mathrm{SL}}). \quad (12)$$

These cumulative marginal effects can be regarded as the overall spatially dependent impact to an individual region given a one-unit shock to a climate variable in that region and all neighbouring regions at a given value of the moderating variable of the interaction term.

Constructing projections of economic damage from future climate change

We construct projections of future climate damages by applying the coefficients estimated in equation (10) and shown in Supplementary Tables 2–4 (when including only lags with statistically significant effects in specifications that limit overfitting; see Supplementary Methods Section 1) to projections of future climate change from the CMIP-6 models. Year-on-year changes in each primary climate variable of interest are calculated to reflect the year-to-year variations used in the empirical models. 30-year moving averages of the moderating variables of the interaction terms are calculated to reflect the long-term average of climatic conditions that were used for the moderating variables in the empirical models. By using moving averages in the projections, we account for the changing vulnerability to climate shocks based on the evolving long-term conditions (Supplementary Figs. 10 and 11 show that the results are robust to the precise choice of the window of this moving average). Although these climate variables are not differenced, the fact that the bias-adjusted climate models reproduce observed climatological patterns across regions for these moderating variables very accurately (Supplementary Table 6) with limited spread across models (<3%) precludes the possibility that any considerable bias or uncertainty is introduced by this methodological choice. However, we impose caps on these moderating variables at the 95th percentile at which they were observed in the historical data to prevent extrapolation of the marginal effects outside the range in which the regressions were estimated. This is a conservative choice that limits the magnitude of our damage projections.

Time series of primary climate variables and moderating climate variables are then combined with estimates of the empirical model parameters to evaluate the regression coefficients in equation (10), producing a time series of annual GRPpc growth-rate reductions for a given emission scenario, climate model and set of empirical model parameters. The resulting time series of growth-rate impacts reflects those occurring owing to future climate change. By contrast, a future scenario with no climate change would be one in which climate variables do not change (other than with random year-to-year fluctuations) and hence the time-averaged evaluation of equation (10) would be zero. Our approach therefore implicitly compares the future climate-change scenario to this no-climate-change baseline scenario.

The time series of growth-rate impacts owing to future climate change in region r and year y, $\delta_{r,y}$, are then added to the future baseline growth rates, $\pi_{r,y}$ (in log-diff form), obtained from the SSP2 scenario to yield trajectories of damaged GRPpc growth rates, $\rho_{r,y}$. These trajectories are aggregated over time to estimate the future trajectory of GRPpc with future climate impacts:

$$\begin{aligned}\mathrm{GRPpc}_{r,Y} & = \mathrm{GRPpc}_{r,2020} \sum_{y=2020}^{Y} \rho_{r,y} \\ & = \mathrm{GRPpc}_{r,2020} \sum_{y=2020}^{Y} (1 + \pi_{r,y} + \delta_{r,y}),\end{aligned} \quad (13)$$

in which $\mathrm{GRPpc}_{r,y=2020}$ is the initial log level of GRPpc. We begin damage estimates in 2020 to reflect the damages occurring since the end of the period for which we estimate the empirical models (1979–2019) and to match the timing of mitigation-cost estimates from most IAMs (see below).

For each emission scenario, this procedure is repeated 1,000 times while randomly sampling from the selection of climate models, the selection of empirical models with different numbers of lags (shown in Supplementary Figs. 1–3 and Supplementary Tables 2–4) and bootstrapped estimates of the regression parameters. The result is an ensemble of future GRPpc trajectories that reflect uncertainty from both physical climate change and the structural and sampling uncertainty of the empirical models.

Estimates of mitigation costs

We obtain IPCC estimates of the aggregate costs of emission mitigation from the AR6 Scenario Explorer and Database hosted by IIASA[23]. Specifically, we search the AR6 Scenarios Database World v1.1 for IAMs that provided estimates of global GDP and population under both a SSP2 baseline and a SSP2-RCP2.6 scenario to maintain consistency with the socio-economic and emission scenarios of the climate damage projections. We find five IAMs that provide data for these scenarios, namely, MESSAGE-GLOBIOM 1.0, REMIND-MAgPIE 1.5, AIM/GCE 2.0, GCAM 4.2 and WITCH-GLOBIOM 3.1. Of these five IAMs, we use the results only from the first three that passed the IPCC vetting procedure for reproducing historical emission and climate trajectories. We then estimate global mitigation costs as the percentage difference in global per capita GDP between the SSP2 baseline and the SSP2-RCP2.6 emission scenario. In the case of one of these IAMs, estimates of mitigation costs begin in 2020, whereas in the case of two others, mitigation costs begin in 2010. The mitigation cost estimates before 2020 in these two IAMs are mostly negligible, and our choice to begin comparison with damage estimates in 2020 is conservative with respect to the relative weight of climate damages compared with mitigation costs for these two IAMs.

Data availability

Data on economic production and ERA-5 climate data are publicly available at https://doi.org/10.5281/zenodo.4681306 (ref. 62) and https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, respectively. Data on mitigation costs are publicly available at https://data.ene.iiasa.ac.at/ar6/#/downloads. Processed climate and economic data, as well as all other necessary data for reproduction of the results, are available at the public repository https://doi.org/10.5281/zenodo.10562951 (ref. 63).

Code availability

All code necessary for reproduction of the results is available at the public repository https://doi.org/10.5281/zenodo.10562951 (ref. 63).

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Additional information

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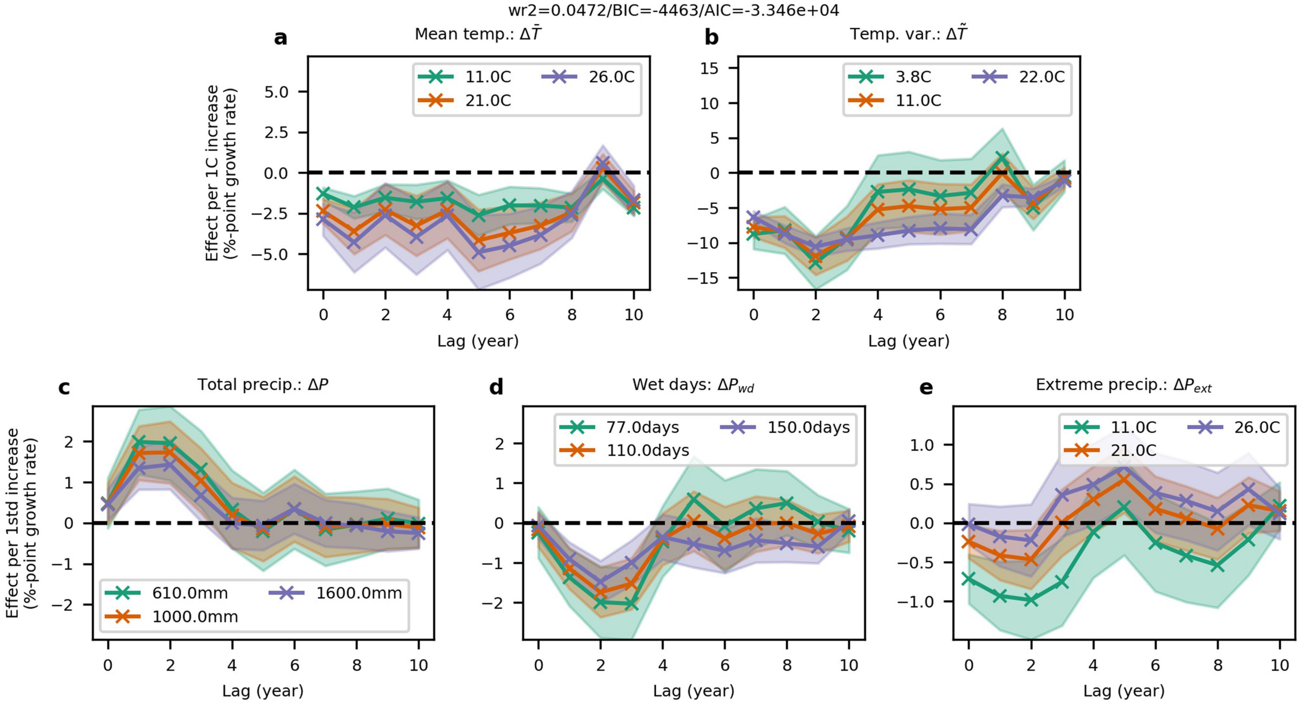
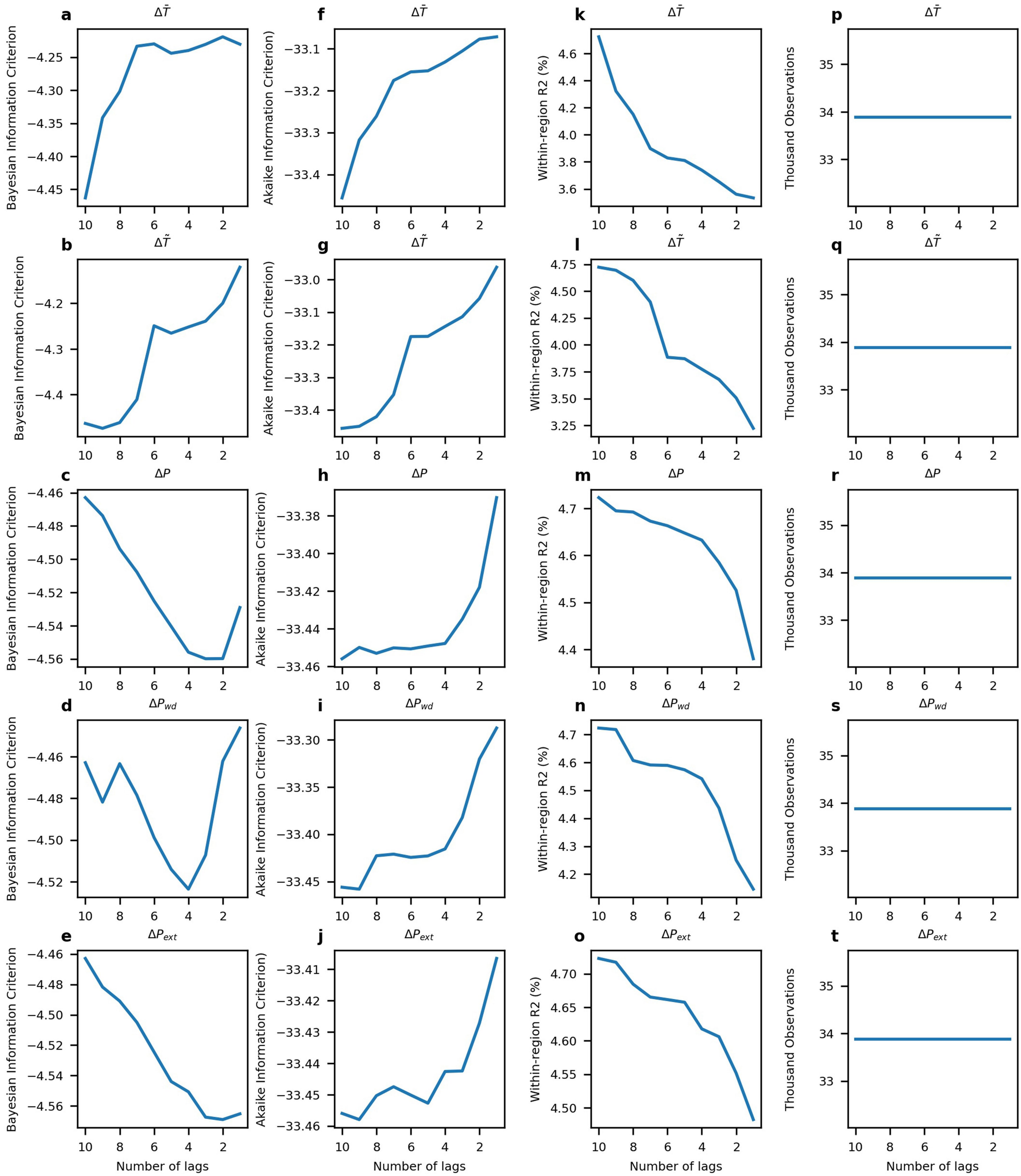
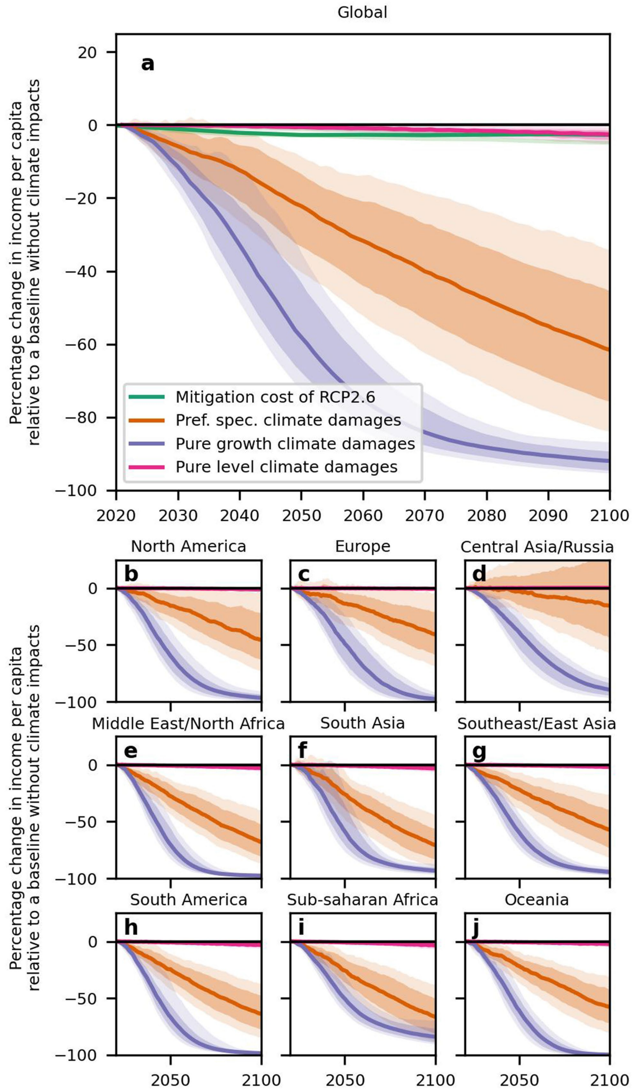


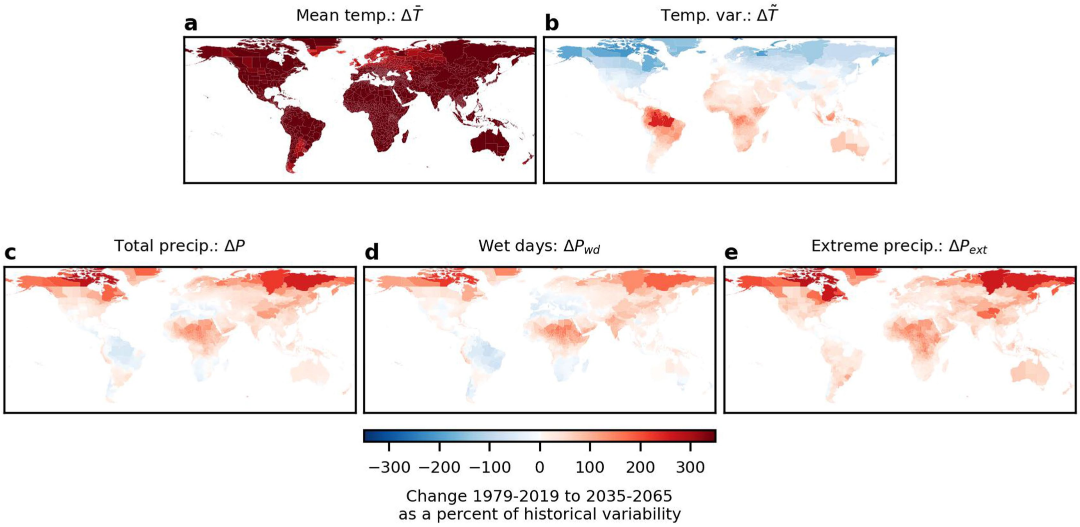
Extended Data Fig. 1 | Constraining the persistence of historical climate impacts on economic growth rates. The results of a panel-based fixed-effects distributed lag model for the effects of annual mean temperature (**a**), daily temperature variability (**b**), total annual precipitation (**c**), the number of wet days (**d**) and extreme daily precipitation (**e**) on sub-national economic growth rates. Point estimates show the effects of a 1 °C or one standard deviation increase (for temperature and precipitation variables, respectively) at the lower quartile, median and upper quartile of the relevant moderating variable (green, orange and purple, respectively) at different lagged periods after the initial shock (note that these are not cumulative effects). Climate variables are used in their first-differenced form (see main text for discussion) and the moderating climate variables are the annual mean temperature, seasonal temperature difference, total annual precipitation, number of wet days and annual mean temperature, respectively, in panels **a**–**e** (see Methods for further discussion). Error bars show the 95% confidence intervals having clustered standard errors by region. The within-region R^2, Bayesian and Akaike information criteria for the model are shown at the top of the figure. This figure shows results with ten lags for each variable to demonstrate the observed levels of persistence, but our preferred specifications remove later lags based on the statistical significance of terms shown above and the information criteria shown in Extended Data Fig. 2. The resulting models without later lags are shown in Supplementary Figs. 1–3.



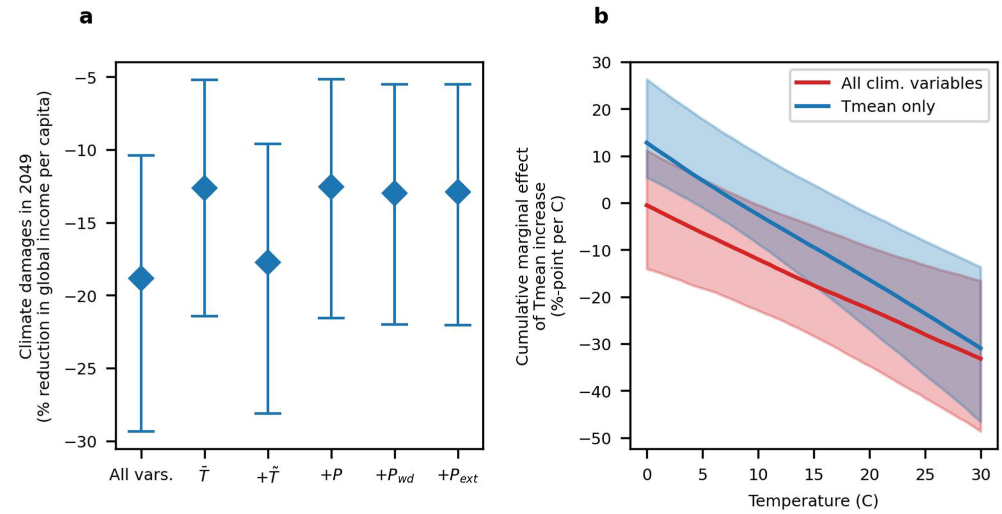
Extended Data Fig. 2 | Incremental lag-selection procedure using information criteria and within-region R^2. Starting from a panel-based fixed-effects distributed lag model estimating the effects of climate on economic growth using the real historical data (as in equation (4)) with ten lags for all climate variables (as shown in Extended Data Fig. 1), lags are incrementally removed for one climate variable at a time. The resulting Bayesian and Akaike information criteria are shown in **a**–**e** and **f**–**j**, respectively, and the within-region R^2 and number of observations in **k**–**o** and **p**–**t**, respectively. Different rows show the results when removing lags from different climate variables, ordered from top to bottom as annual mean temperature, daily temperature variability, total annual precipitation, the number of wet days and extreme annual precipitation. Information criteria show minima at approximately four lags for precipitation variables and ten to eight for temperature variables, indicating that including these numbers of lags does not lead to overfitting. See Supplementary Table 1 for an assessment using information criteria to determine whether including further climate variables causes overfitting.



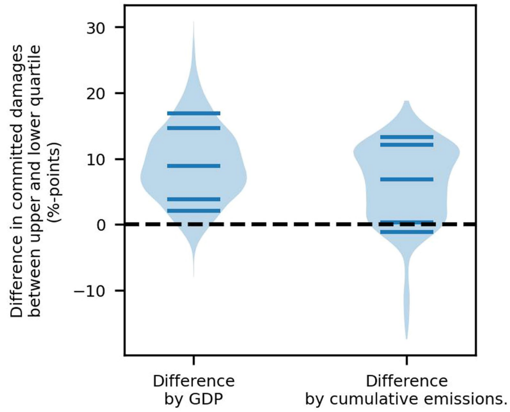
Extended Data Fig. 3 | Damages in our preferred specification that provides a robust lower bound on the persistence of climate impacts on economic growth versus damages in specifications of pure growth or pure level effects. Estimates of future damages as shown in Fig. 1 but under the emission scenario RCP8.5 for three separate empirical specifications: in orange our preferred specification, which provides an empirical lower bound on the persistence of climate impacts on economic growth rates while avoiding assumptions of infinite persistence (see main text for further discussion); in purple a specification of 'pure growth effects' in which the first difference of climate variables is not taken and no lagged climate variables are included (the baseline specification of ref. 2); and in pink a specification of 'pure level effects' in which the first difference of climate variables is taken but no lagged terms are included.



Extended Data Fig. 4 | Climate changes in different variables as a function of historical interannual variability. Changes in each climate variable of interest from 1979–2019 to 2035–2065 under the high-emission scenario SSP5-RCP8.5, expressed as a percentage of the historical variability of each measure. Historical variability is estimated as the standard deviation of each detrended climate variable over the period 1979–2019 during which the empirical models were identified (detrending is appropriate because of the inclusion of region-specific linear time trends in the empirical models). See Supplementary Fig. 13 for changes expressed in standard units. Data on national administrative boundaries are obtained from the GADM database version 3.6 and are freely available for academic use (https://gadm.org/).



Extended Data Fig. 5 | Contribution of different climate variables to overall committed damages. a, Climate damages in 2049 when using empirical models that account for all climate variables, changes in annual mean temperature only or changes in both annual mean temperature and one other climate variable (daily temperature variability, total annual precipitation, the number of wet days and extreme daily precipitation, respectively). **b**, The cumulative marginal effects of an increase in annual mean temperature of 1 °C, at different baseline temperatures, estimated from empirical models including all climate variables or annual mean temperature only. Estimates and uncertainty bars represent the median and 95% confidence intervals obtained from 1,000 block-bootstrap resamples from each of three different empirical models using eight, nine or ten lags of temperature terms.



Extended Data Fig. 6 | The difference in committed damages between the upper and lower quartiles of countries when ranked by GDP and cumulative historical emissions. Quartiles are defined using a population weighting, as are the average committed damages across each quartile group. The violin plots indicate the distribution of differences between quartiles across the two extreme emission scenarios (RCP2.6 and RCP8.5) and the uncertainty sampling procedure outlined in Methods, which accounts for uncertainty arising from the choice of lags in the empirical models, uncertainty in the empirical model parameter estimates, as well as the climate model projections. Bars indicate the median, as well as the 10th and 90th percentiles and upper and lower sixths of the distribution reflecting the very likely and likely ranges following the likelihood classification adopted by the IPCC.

Extended Data Table 1 | A summary of several physical mechanisms that plausibly underlie the impact of the different climate variables on macroeconomic growth, with references to empirical evidence

Climate variable	Physical mechanisms	References
Average annual temperature	Labour productivity and supply; agricultural productivity	Dasgupta et al. (2021)[62];Lobell et al. (2013)[63], Zhao et al. (2017)[64]
Daily temperature variability	Agricultural productivity; physical health; mental health	Wheeler et al. (2000)[65], Rowhani et al. (2011)[66], Ceglar et al. (2016)[67]; Shi et al. (2015)[68]; Xue et al. (2019)[69]
Total annual precipitation	Agricultural productivity; metropolitan labour outcomes; conflict	Liang et al. (2017)[70]; Desbreaux et al. (2019)[71]; Damania et al. (2020)[72]
Number of wet days	Travel disruption	Lacking
Extreme daily precipitation	Flood damages; disruption	Davenport et al. (2021)[73], Dave et al. (2021)[74]

This summary is not intended to be an exhaustive list of all mechanisms or references. In the case of most climate variables, several plausible physical mechanisms supported by empirical evidence exist. The only exception here is the number of wet days, for which plausible mechanisms are listed but empirical evidence does not yet exist (as far as the authors are aware). The use of the number of wet days in the main empirical models is therefore guided primarily by the empirical evidence indicating robust impacts on economic growth[8]. References 64–76 in the table.

Extended Data Table 2 | Regression results for the historical effects of different climate variables on sub-national economic growth rates in the period 1979–2019

Variable	Formula	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10
Annual mean temperature	$\Delta T_{r,y}$	-0.17	-0.57	-0.78	-0.23	-0.79	-0.96	-0.23	-0.71	-1.8**	-1.1*	-2.5***
		(0.32)	(0.5)	(0.54)	(0.57)	(0.57)	(0.65)	(0.67)	(0.73)	(0.63)	(0.48)	(0.35)
	$\Delta \bar{T}_{r,y}.\bar{T}_r$	-0.0011***	-0.0014**	-0.00072	-0.0015**	-0.00072	-0.0015**	-0.0017***	-0.0012**	-0.00029	0.00065*	0.00029
		(0.00029)	(0.00049)	(0.00051)	(0.00055)	(0.00047)	(0.0005)	(0.00046)	(0.00047)	(0.0004)	(0.00032)	(0.00023)
Daily temp. variability	$\Delta \tilde{T}_{r,y}$	-9.3***	-8.1***	-13***	-9.3***	-1.5	-1.2	-2.4	-1.8	3.3	-5.3**	-0.34
		(1.3)	(2)	(2.3)	(2.7)	(3.1)	(3.2)	(3)	(2.9)	(2.5)	(1.9)	(1.3)
	$\Delta \tilde{T}_{r,y}.\hat{T}_r$	0.0013*	-0.0003	0.0013	-0.00011	-0.0034**	-0.0032*	-0.0025*	-0.0029*	-0.003**	0.00079	-0.00037
		(0.00054)	(0.00083)	(0.00087)	(0.0011)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.00078)	(0.00057)
Total annual precipitation	$\Delta P_{r,y}$	0.002	0.0094***	0.009***	0.0068**	0.0021	-0.0012	0.0013	-0.001	-0.0001	0.0012	0.0005
		(0.0016)	(0.002)	(0.0023)	(0.0024)	(0.0024)	(0.0025)	(0.0025)	(0.0023)	(0.0021)	(0.0019)	(0.0015)
	$\Delta P_{r,y}.P_r$	-1.4e-09	-2.6e-08**	-2.1e-08*	-2.6e-08**	-1.4e-08	6.3e-09	4.6e-10	6.4e-09	-1.2e-09	-1.3e-08	-9.4e-09
		(6.9e-09)	(8.5e-09)	(9.7e-09)	(9.8e-09)	(1e-08)	(1e-08)	(1e-08)	(9.3e-09)	(8.6e-09)	(7.8e-09)	(6.1e-09)
Annual no. wet days	$\Delta Pwd_{r,y}$	-0.028	-0.12**	-0.17**	-0.2***	-0.038	0.12	0.037	0.079	0.1*	0.045	-0.03
		(0.038)	(0.043)	(0.055)	(0.055)	(0.052)	(0.065)	(0.068)	(0.058)	(0.048)	(0.04)	(0.032)
	$\Delta Pwd_{r,y}.Pwd_r$	1.5e-06	4.1e-06	4.5e-06	9.2e-06*	9.6e-07	-1e-05*	-5.5e-06	-7.1e-06	-9e-06**	-5.6e-06*	2.2e-06
		(2.3e-06)	(2.7e-06)	(3.6e-06)	(3.6e-06)	(3.4e-06)	(4.1e-06)	(4.1e-06)	(3.6e-06)	(3e-06)	(2.5e-06)	(1.9e-06)
Precipitation extremes	$\Delta Pext_{r,y}$	-0.023***	-0.028***	-0.029***	-0.029**	-0.01	-0.0032	-0.013	-0.017	-0.019*	-0.013	0.0054
		(0.0053)	(0.0073)	(0.0084)	(0.0094)	(0.0098)	(0.01)	(0.011)	(0.01)	(0.0093)	(0.0079)	(0.0052)
	$\Delta Pext_{r,y}.\bar{T}_r$	8.8e-06***	9.6e-06**	9.6e-06*	1.4e-05**	7.7e-06	6.5e-06	8e-06	8.8e-06	8.7e-06	8.1e-06*	-1.2e-06
		(2.5e-06)	(3.4e-06)	(4e-06)	(4.6e-06)	(4.7e-06)	(4.9e-06)	(4.9e-06)	(4.8e-06)	(4.5e-06)	(4e-06)	(2.7e-06)
R^2	0.291											
wR^2	0.0472											
BIC	-4.46e+03											
AIC	-3.35e+04											
N	34855											

Numbers show the point estimates for the effect of each climate variable and their interaction term on sub-national economic growth rates (in percentage points), having estimated equation (4) with ten lags for each climate variable (that is, each table entry denotes a specific regression coefficient $\alpha_{X,L}$ of the same model as indicated in equation (4)). Standard errors are shown in parentheses and *, ** and *** denote significance at the 5%, 1% and 0.1% levels, respectively, having clustered standard errors by region. Formulas for climate variables and their interaction terms are denoted as in equation (4). Note that an interpretation of the significance of the effects of a given climate variable requires an assessment of both the coefficient of the climate variable itself as well as its interaction term. Extended Data Fig. 1 provides the opportunity for such an interpretation by plotting the estimated marginal effects with confidence intervals. The R^2, within-region R^2 (the R^2 along the temporal dimension), Akaike information criterion (AIC), Bayesian information criterion (BIC) and number of observations are also shown.

Extended Data Table 3 | A comparison of the magnitude of estimated economic damage from future climate change across recent panel-based empirical studies

Study	Resolution	Number of climate variables	Baseline specification of growth- or level-effects	Number of lags	Damages by 2100 under RCP8.5
Burke et al. (2015)[2]	National	One	Growth	None	25%
Kahn et al. (2019)[35]	National	One	Level	Four	7.2%
Kalkuhl & Wenz (2020)[3]	Sub-national	One	Level	One	14.2%
This study	Sub-national	Five	Level	Eight-ten/four	61.6%

All studies use fixed-effects panel regressions. The first four columns describe differences in the underlying data and empirical specification. The third column shows the nature of the baseline specification without lags with regards to growth or level effects (see main text for further discussion). The last column compares projections of future economic damage under RCP8.5 by 2100 as reported by the respective study.

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Supplementary information

The economic commitment of climate change

In the format provided by the authors and unedited

Supplementary Information for:

The economic commitment of climate change

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Supplementary overview

This document provides supplementary information for the manuscript "The economic commitment of climate change". Within can be found:

1. Supplementary methods on robustness tests of the empirical models:
    1. Section S1: Limiting overfitting
    2. Section S2: Robustness to autocorrelation in the climate variables
    3. Section S3: Robustness to cross-correlation in the climate variables
    4. Section S4: Restricted distributed lag model.
2. Supplementary Discussion
    1. Section S5: The magnitude of damages in the context of historical economic development
3. Supplementary Figures 1-14.
4. Supplementary Tables 1-6.

References herein are listed separately to those appearing in the main manuscript.

Supplementary Methods:

Robustness tests of the empirical models

Section S1: Limiting overfitting

Our empirical models contain five climate variables, each included with a number of lags. These choices are made to reflect previous literature which identified multiple climatic conditions with significant impacts on economic output[1–3], as well as to identify the extent of persistence with which these climatic conditions impact growth (see main text and methods). The use of a large number of independent variables may raise concerns that the empirical models may overfit the data and as such provide inaccurate estimations of the impacts from future climate change. We assess this possibility by using the Bayesian and Aikake Information Criteria (BIC and AIC) to compare empirical models with and without different climate variables and when including different numbers of lags. BIC and AIC are evaluated using a trade-off between the maximized likelihood function and penalties for additional model terms which could result in overfitting. As such, they can be used to assess the relative strength of different models in terms of best describing the data and limiting the possibility of overfitting.

Section S1.1: Limiting overfitting with regards to multiple climate variables

Supplementary Table 1 compares our main model including all climate variables to models which sequentially exclude individual climate variables. In general, the BIC and AIC indicate a preference for the original model with all climate variables compared to models which lack other variables. This indicates that the model with all climate variables provides the best trade-off between best describing the data and including additional terms which could cause overfitting. The only exception here is that when removing the measure of extreme daily rainfall, the BIC indicates a preference for the model without extreme daily rainfall, whereas the AIC indicates a preference for the model with extreme daily rainfall. BIC is a more conservative measure[4] which provides superior performance in selecting the true model from a set of alternatives[5]. Given the epistemological inexistence of a "true model" of the reality of climate impacts, the fact that AIC is often superior in selecting models which will generalise better to new data[5] (i.e. projecting impacts under climate change), and the fact that the parameters of the extreme daily rainfall metric are statistically significant (Extended Data Figure 1, Extended Data Table 2, Supplementary Figures 1-3, and Supplementary Tables 2-4), we continue to include extreme daily rainfall in our empirical model.

Section 1.2: Limiting overfitting due to the inclusion of lagged variables

Extended Data Figure 1 compares models with different numbers of lags to assess the extent to which including lags may cause overfitting. The analysis begins with a model with ten lags for each climate variable, and sequentially excludes lags from one climate variable at a time. The BIC and AIC show minima at approximately four lags for precipitation variables, supporting the choice of four lags which was made when considering the statistical significance of the lagged terms (Extended Data Figure 1, Extended Data Table 2). For the temperature terms, minima in AIC and BIC are found at approximately eight to ten lags, further supporting the choice of lags made based on statistical significance (Extended Data Figure 1, Extended Data Table 2).

These analyses indicate that including all climate variables with four lags for precipitation and eight to ten for temperature terms provides the best trade-off between describing the data and including more terms which could cause overfitting. Moreover, the Monte-Carlo simulations outlined in Section S2 demonstrate that Information Criteria can act as an effective indicator for selecting an appropriate number of lags (see Section S2 and Supplementary Figure 6).

Section S1.3 Alternative methods to limit overfitting

AIC and BIC metrics support our choice of climate variables and number of lags, indicating that they provide a preferable trade-off between maximizing variance and limiting overfitting. Alternative methods exist which could fulfil similar functions in selecting models which optimize this trade-off. In particular, cross-validation provides an asymptotically equivalent approach[6], which may be particularly attractive in the context of prediction problems. Cross-validation splits the available data into two parts, first training the empirical model with one set before testing it on the other. This yields a direct evaluation of the ability of the empirical model to predict new data.

The aim of this paper, however, is not to accurately predict economic growth, but to project the exogenous impact of future climate conditions on the economy, based on robustly inferred causal relationships, and assuming ceteris paribus (compare previous climate-economy literature, e.g. refs. ([1,7,8])). That is, factors important for predicting economic growth such as technological development, wars, pandemics and financial crises are assumed constant. As a consequence, the main objective of the model selection procedure is to provide a robust identification strategy for causal inference[9–11]. In particular, our empirical model is based on a careful selection of fixed-effects and regional time-trends to isolate variation in climate and economic growth which are plausibly exogenous, and a careful choice of climate variables in their first-differenced form with a number of lags to provide a lower-bound on the persistence of impacts on growth (see main text section "A robust lower bound on the persistence of climate impacts on growth" and methods section "Empirical models – fixed-effects distributed lag models"). Given this emphasis on inference rather than prediction in the identification of plausibly causal empirical models and the projection of exogenous impacts; the asymptotic equivalence of Information Criteria and cross-validation for model selection[6]; and the fact that AIC and BIC indicate that our empirical models already provide a preferable trade-off between maximizing variance and limiting overfitting, we do not pursue cross-validation as a further method for model selection. Cross-validation nevertheless offers an interesting avenue for further work on the prediction of economic growth in the context of climate impacts which is beyond the scope of this manuscript.

Section S2: Robustness to autocorrelation in the climate variables

When using lagged climate variables, the presence of autocorrelation (Supplementary Figure 4) may raise concerns regarding imperfect multicollinearity in the empirical models. Developing upon the methodology used by ref. [12], we conduct Monte-Carlo simulations in which real climate data is randomly reassigned to different regions and a known effect is artificially added to the economic data to test whether this produces biased or imprecise parameter estimates (Supplementary Figure 5a-d).

Specifically, we choose an effect, α, of 2%-points per degree C increase in temperature to mimic the magnitude of effect sizes which we detect in the real data (Extended Data Figure 1). Moreover, we allow this effect to persist for a number of years after the initial shock which we refer to as the persistence time, *p*. The original time series of economic growth, $g_{r,y}$, is updated based on the newly assigned temperature time series, $\bar{T}_{r,y}$, according to the equation,

$$\tilde{g}_{r,y} = g_{r,y} + \alpha(\bar{T}_{r,y} - \bar{T}_{r,y-p}) \ . \qquad \text{(S1)}$$

This procedure is repeated 100 times to produce an ensemble of artificial datasets with known effects of temperature changes on economic growth which preserve the structure of the temperature time-series, including its autocorrelation. We then run panel fixed effects distributed lag models of the same structure as outlined in equation (10) in the Methods section (but in this case including only a single climate variable as independent variable without interaction terms), to test the efficacy of the models in obtaining the true parameter estimates in the presence of autocorrelation.

The results are shown in Supplementary Figure 5 for models with different numbers of lags applied to artificial data in which effects of different persistence times have been added. Results indicate that despite the presence of autocorrelation in the temperature time series (Supplementary Figure 4), the empirical models obtain accurate and precise estimates of the true regression parameters. We further quantify the systematic and random errors in these model estimates explicitly by measuring the percentage difference between the cumulative true parameters (as added to the data) and estimated parameters (as obtained from the empirical models), as well as the standard deviation of parameter estimates across Monte-Carlo simulations. These estimates are shown in Supplementary Figure 6 alongside Information Criteria from the empirical models estimated on the artificial datasets. Results demonstrate that despite the presence of autocorrelation, random error is very small, although it increases with the number of lags, in particular when this number greatly exceeds the persistence times (Supplementary Figure 5i-l & 6a-c). By contrast, including an insufficient number of lags to adequately capture the extent of impact persistence can systematically underestimate the cumulative impact of a climatic change (Supplementary Figure 5i-l & Figure 6a-c), a direct result of the conservative nature of our empirical specification using the first difference of climate variables as outlined in the main text.

As well as demonstrating the robustness of the empirical models in the presence of autocorrelation, these results also indicate that Information Criteria typically used for model selection may provide a useful diagnostic for an incremental model selection when reducing the number of lags from a larger initial number (Supplementary Figure 6d-f). This further supports the use of Information Criteria for selecting an appropriate number of lags, as used in Extended Data Figure 2 and outlined in Section S1. While these tests focus on the role of annual mean temperature only, the results generalize to other variables as made clear in the second set of Monte-Carlo simulations described in Section S3 and shown in Supplementary Figure 7.

Section S3: Robustness to cross-correlation in the climate variables

A second set of Monte-Carlo simulations aims to test the robustness of the empirical models to cross correlations between different climate variables (Supplementary Figure 4f). The simulation procedure follows the same as that outlined above, but effects from all five climate variables are added into the data simultaneously following equivalent procedures as in equation (S1). Importantly, time series of the different climate variables are re-assigned together to preserve their cross-correlative structure. Effect sizes and persistence times are chosen to reflect those observed in the real data for each variable, corresponding to $\alpha = 2$, 5, 0.008, 0.2 and 0.02 per unit increase of each climate variable for annual mean temperature, daily temperature variability, total annual precipitation, annual number of wet days and extreme daily rainfall respectively (these appear different to the magnitudes shown in Extended Data Figure 1 for precipitation variables because effect sizes in this figure have been scaled by the within-region standard deviation of each precipitation variable), and to p=8, 8, 4, 4, and 4 for the respective variables. Panel fixed effects distributed lag models are then applied to the artificial datasets as outlined in equation (10) in the Methods section, in one case including only individual climate variables as independent variables, and in the other case including all climate variables simultaneously. The results shown in Figure 7 indicate that cross correlations between climate variables only produce biased estimates when climate variables are assessed individually; simultaneously including all variables in the models is necessary to adequately capture the effect of individual variables.

Section S4: Restricted distributed lag model

Minor oscillations in the point estimates for the effects of annual mean temperature may indicate the influence of autocorrelation (Extended Data Figure 1). While the results of our Monte-Carlo simulations suggest that such influence is negligible (Supplementary Figures 5 and 6), we nevertheless investigate whether the use of a restricted distributed lag model limits these effects[13,14].

Restricted distributed lag models are often used to limit the potential oscillations and imprecision caused by autocorrelation in the independent variables, by constraining the lagged parameters to follow a particular function[15]. Motivated by the distribution of unrestricted lags observed with ten lags for all climate variables (Extended Data Figure 1), which generally grow and then decay at varying rates, we choose a quadratic function to approximate the distribution.

Given a single variable distributed lag model with lag coefficients, β_L, and the assumption of a quadratic distribution of these coefficients,

$$\beta_L = \vartheta_0 + \vartheta_1 L + \vartheta_2 L^2, \qquad \text{(S2)}$$

the distributed lag model may be simplified according to the following transformation:

$$g_{r,y} = \sum_{L=0}^{NL} \beta_L \, \bar{T}_{r,y-L} + \mu_r + \eta_y + \varepsilon_{r,y} \qquad \text{(S3)}$$

$$g_{r,y} = \sum_{L=0}^{NL} \vartheta_0 \, \bar{T}_{r,y-L} + \sum_{L=0}^{NL} \vartheta_1 L \, \bar{T}_{r,y-L} + \sum_{L=0}^{NL} \vartheta_2 L^2 \, \bar{T}_{r,y-L} + \mu_r + \eta_y + \varepsilon_{r,y} \qquad \text{(S4)}$$

$$g_{r,y} = \vartheta_0 Z0_{r,y} + \vartheta_1 Z1_{r,y} + \vartheta_2 Z2_{r,y} + \mu_r + \eta_y + \varepsilon_{r,y}, \qquad \text{(S5)}$$

where

$$Z0_{r,y} = \sum_{L=0}^{NL} \bar{T}_{r,y-L},\ Z1_{r,y} = \sum_{L=0}^{NL} L.\bar{T}_{r,y-L},\ Z2_{r,y} = \sum_{L=0}^{NL} L^2\bar{T}_{r,y-L}. \quad \text{(S6)}$$

This simplifying transformation reduces the number of parameters required to estimate the distribution of lagged effects, limiting imprecision and smoothing oscillatory behavior which are potentially introduced by autocorrelation in the independent variable. We apply the above transformation to all independent variables in equation (10) of the main manuscript (i.e., all climate variables and their interaction terms), estimate panel fixed-effects regressions on these transformed variables, and then display the estimated distribution of lagged effects in Supplementary Figure 8.

Using a quadratic lag distribution reduces oscillations (Supplementary Fig 8) but provides cumulative effects of a similar magnitude to the un-restricted model for annual mean temperature (Supplementary Fig 9a). This likely reflects the fact that, even when severe, imperfect multicollinearity causes correlated parameter biases[13] which consequently do not introduce errors in out of sample predictions[16]. In this context, this implies that if oscillatory biases in the lagged parameters were present due to autocorrelation (which Supplementary Methods Section S2 suggests is not the case), then these biases would anyway be correlated in such a way as not to introduce bias to the cumulative lagged effects (because if one lag is biased larger, another will be biased smaller). This suggests that our initial un-restricted lag model is suitable for projecting future damages which depend primarily on the cumulative lagged effects. We therefore continue to use the un-restricted model as our main specification, also due to its more flexible form which appears to provide a better description of the lag distribution for the temperature variability and extreme rainfall variables in particular (compare Extended Data Figure 1 to Supplementary Figure 8, and further see Supplementary Figure 9).

Supplementary Discussion

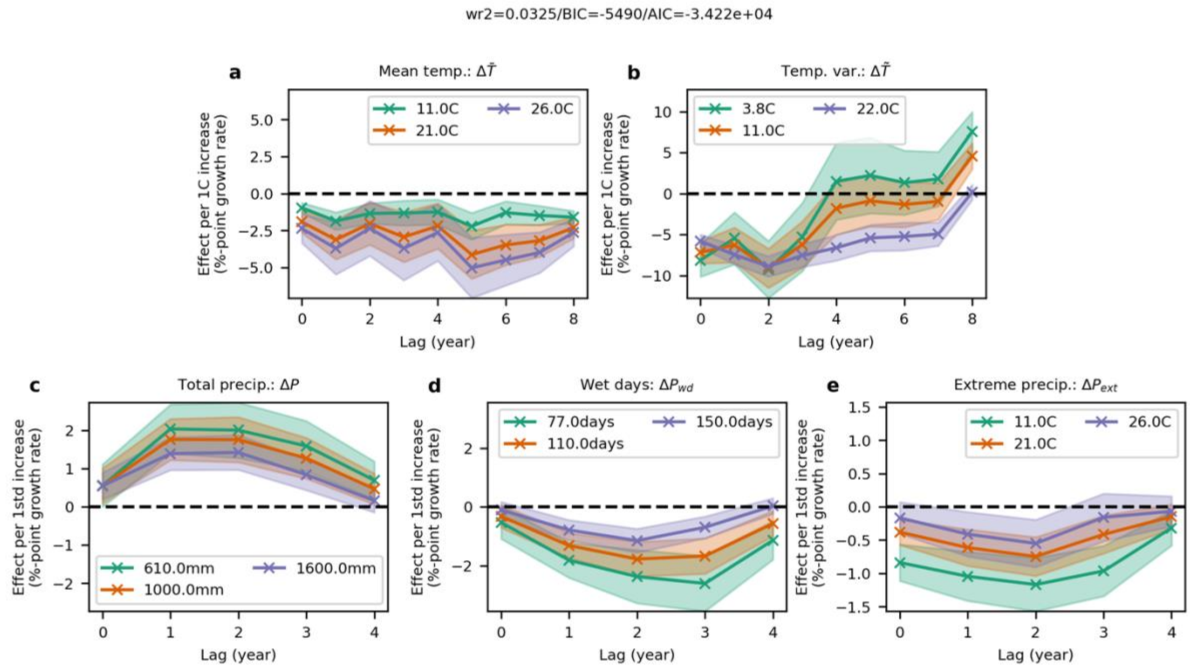
Section S5: The magnitude of damages in the context of historical economic development

We here provide a discussion of the plausibility of the magnitude of projected climate damages, in light of the historical damages which they imply, and the background of historical economic development. In particular, this discussion addresses whether magnitudes and patterns of historical economic development make the magnitude and heterogeneity of damages which we project implausible. These discussions can be considered as "back-of-the-envelope" calculations, to estimate and compare approximate magnitudes.

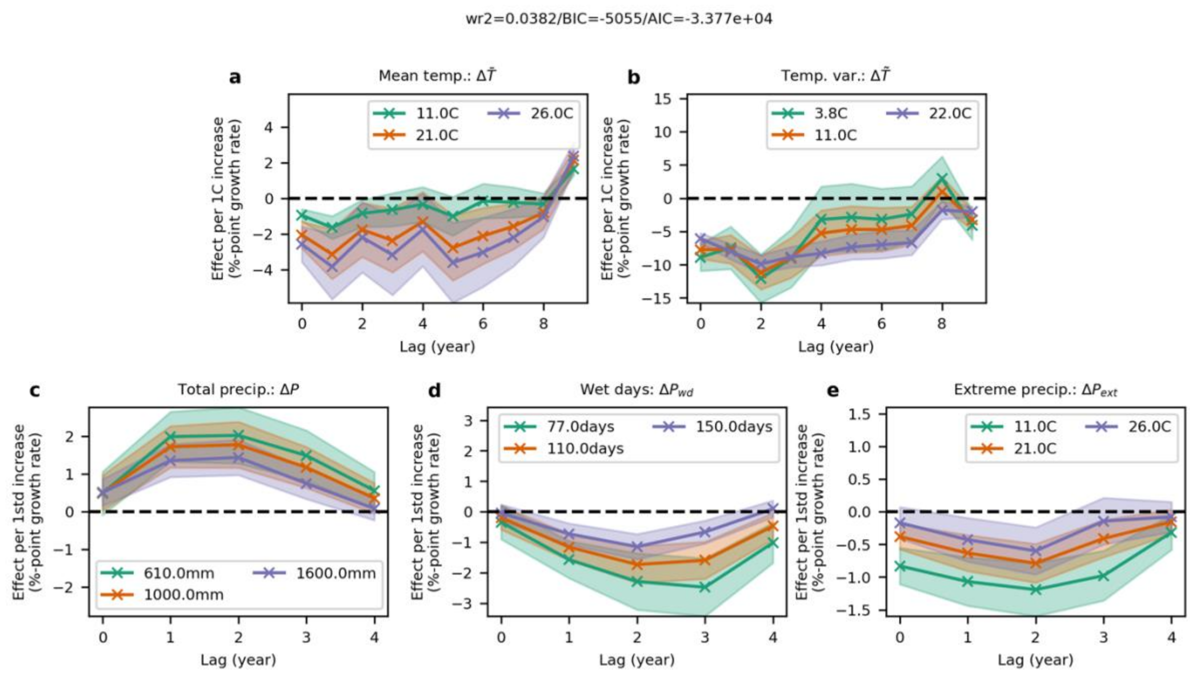
The world has experienced approximately 1C of global warming historically since 1970[17], and CMIP6 climate models project approximately another 1C of global warming by 2050 (compared to 2020) under SSP585 (see IPCC AR6 WG1[18], Figure4.2). This makes for a convenient and approximate comparison of the future damages which we project against those which we should have experienced historically since 1970, allowing a contextualisation against the background of historical economic development. We calculate an approximate 20% reduction in global GDP from the additional 1C of global warming projected under SSP585 (Figure1), with differences between the upper and lower quartile of the income distribution of approximately 10%-points (Supplementary Figure 17), meaning a maximal impact of 30% reduction in developing countries compared to 10% reduction in more wealthy countries. Let us assume that the historical 1C of global warming produced damages of similar magnitudes, although in reality they were likely smaller due to the non-linear response to average temperature which is more negative as regions warm (Extended Data Figure 1). We can then compare the magnitude of these damages to the background economic development which occurred between 1970 and 2020. Average growth rates of GDP per capita were approximately 1.8% over the past 50 years[19], implying an average growth in GDP per capita of over 140% since 1970. Taking the bottom quartile of countries by World Bank income per capita (using 2015 values) gives average growth rates of 0.84% annually over the past 50 years, whereas the upper quartile of countries gives average growth rates of 1.41% annually (note that this is consistent with evidence that absolute income convergence has not occurred historically, see refs. [20–22]). These imply overall income per capita growth of 52% and 101% in the lower- and upper-income quartiles respectively over the past 50 years (noting that the greatest income growth has occurred for countries in the middle quartiles).

Even given the approximate nature of these calculations, it becomes quite clear that while considerable, the implied damages of historical climate change (20%) are unlikely to have had consequences which are inconsistent with historical economic development (an increase in income per capita of 140%) or obviously noticeable without an appropriate no-climate-change counterfactual to which to compare. Moreover, poorer regions have actually seen lower growth rates than richer regions historically. Our estimates indicate that climate change may have played a role in this, and that the gap between them would have been smaller (approx. 52+30=82% vs 101+10=111%) without climate change. However, the observation of lower growth rates in poor versus rich countries can in no way be interpreted as causal evidence of historical climate damages because of the large unobserved biases which influence differences across countries which are unrelated to climate. There is no counterfactual world without climate change from which we can measure whether poorer and richer countries are *actually* 30% and 10% worse off than they would have been without climate change. Therefore, we must rely on the empirical approaches such as the one taken here based on fixed-effects panel regressions to identify impacts which are plausibly causal.

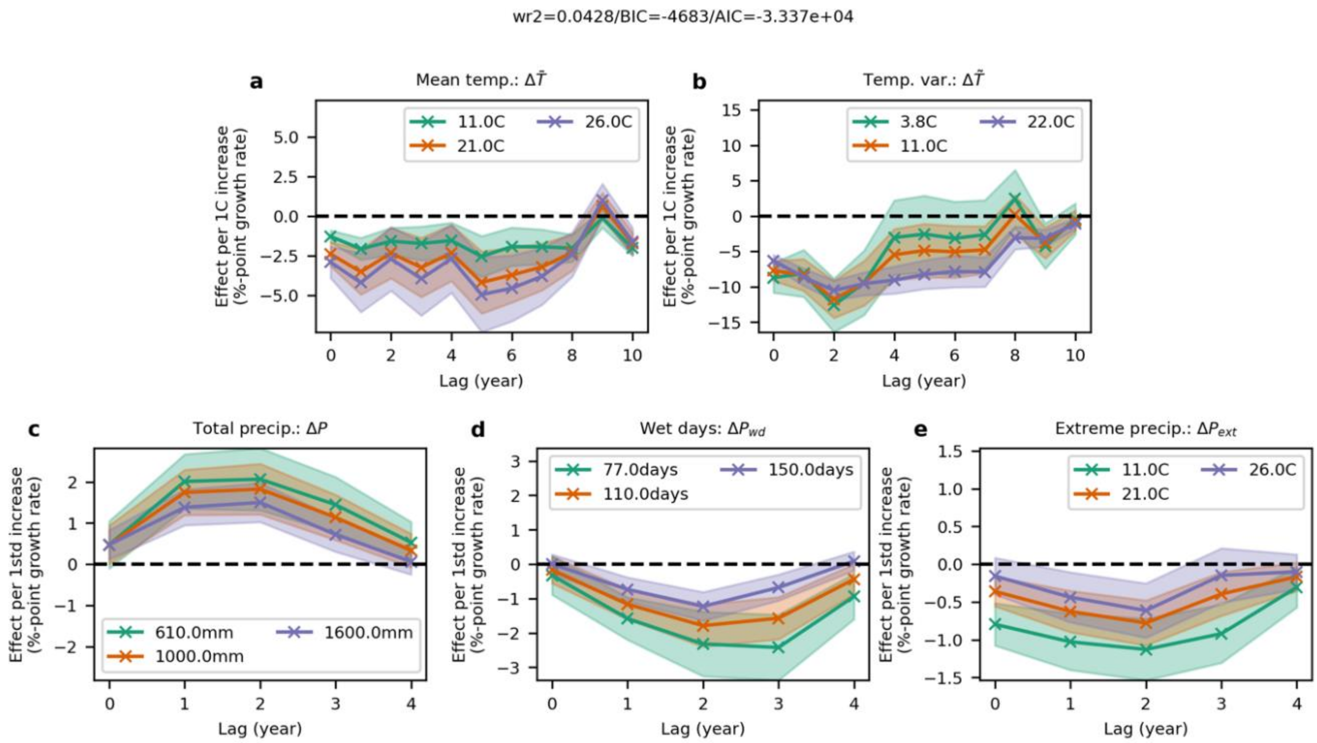
Nevertheless, these “back-of-the-envelope” calculations demonstrate that the magnitude of damages which we project is consistent with historical developments, given that: a) historical economic development is much larger than the historical damages implied by our analysis, b) richer regions grew historically at faster rates than poorer regions, consistent with the pattern of climate damages we show, and in which historical climate change therefore potentially played a contributing role.



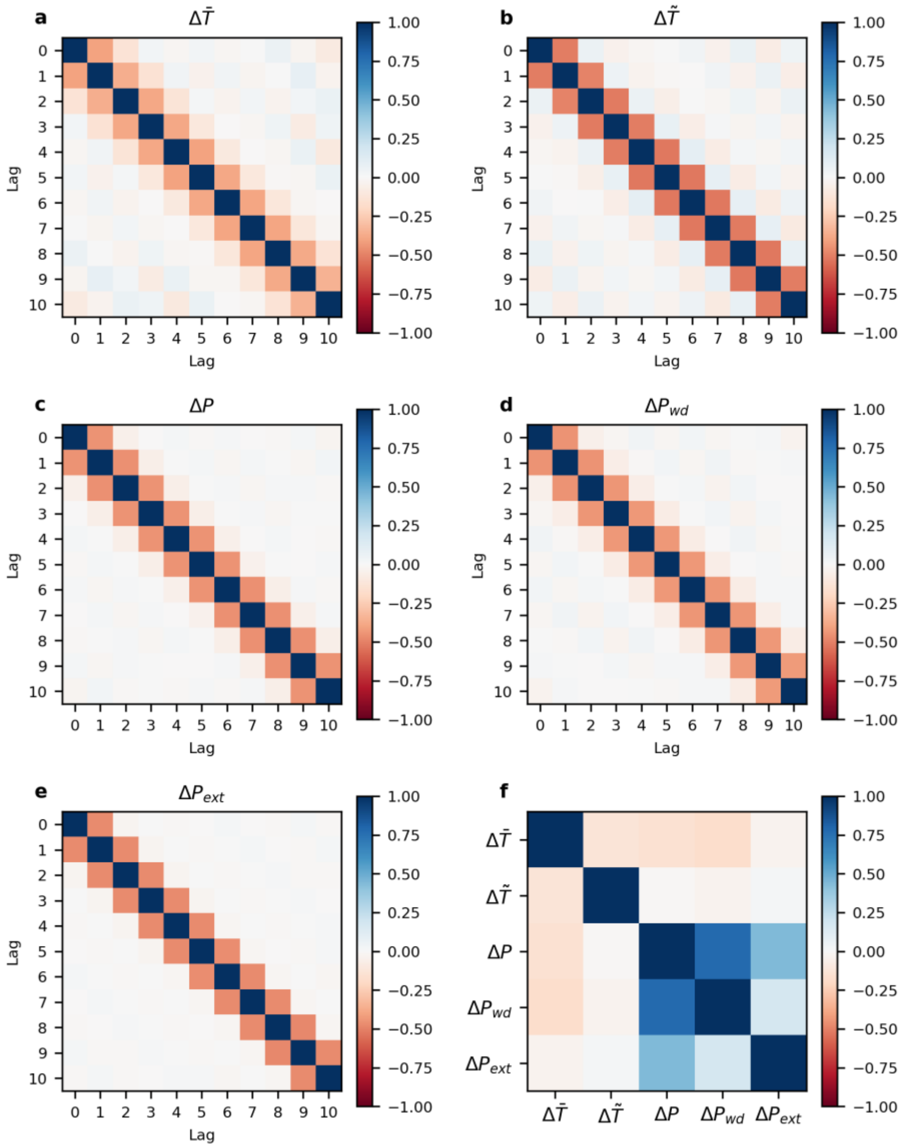
Supplementary Figure 1. Results of a panel fixed effects distributed lag model with eight lags for temperature terms and four for precipitation terms. As Extended Data Figure 1 but using eight lags for the temperature terms and four lags for the precipitation terms.



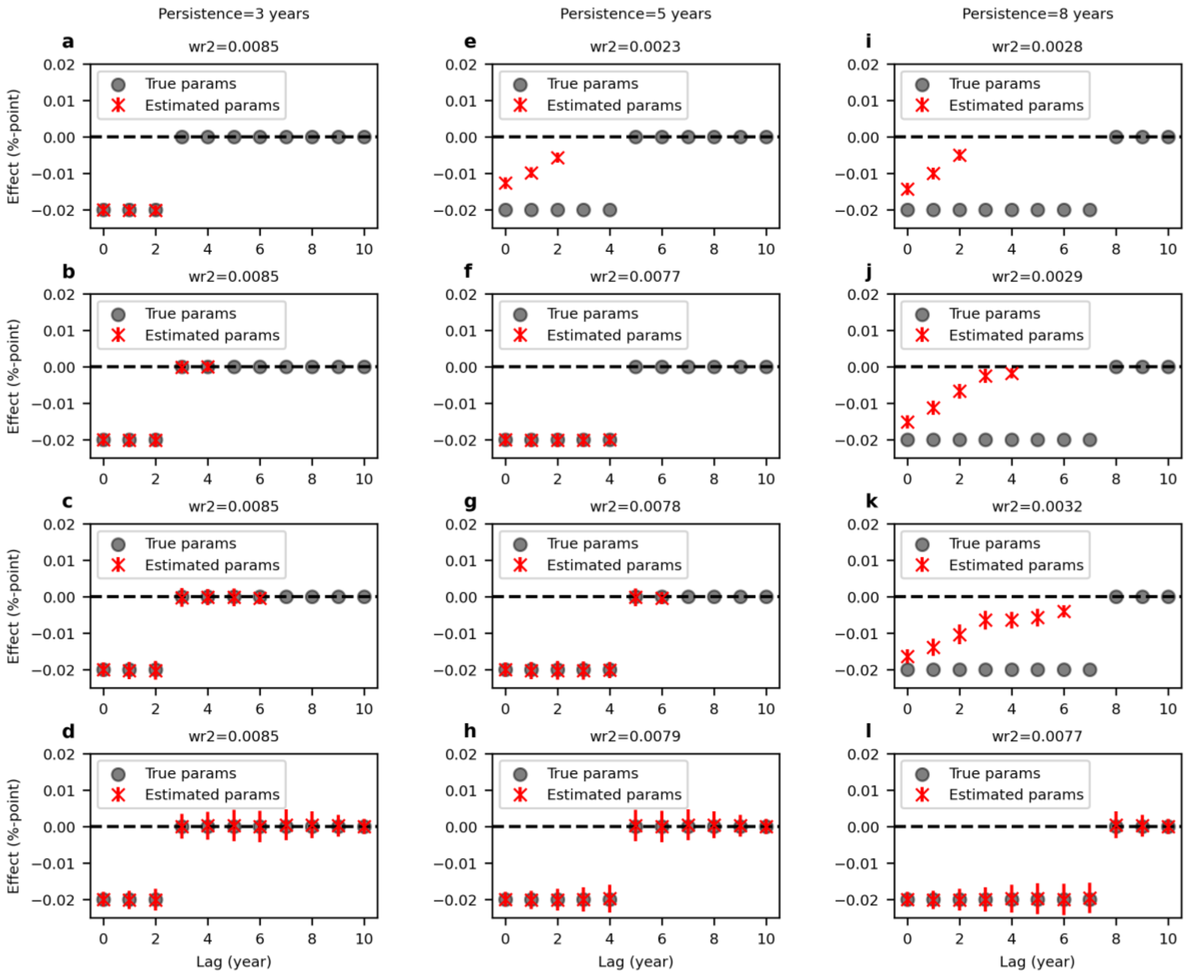
Supplementary Figure 2. Results of a panel fixed effects distributed lag model with nine lags for temperature terms and four for precipitation terms. As Extended Data Figure 1 but using nine lags for the temperature terms and four lags for the precipitation terms.



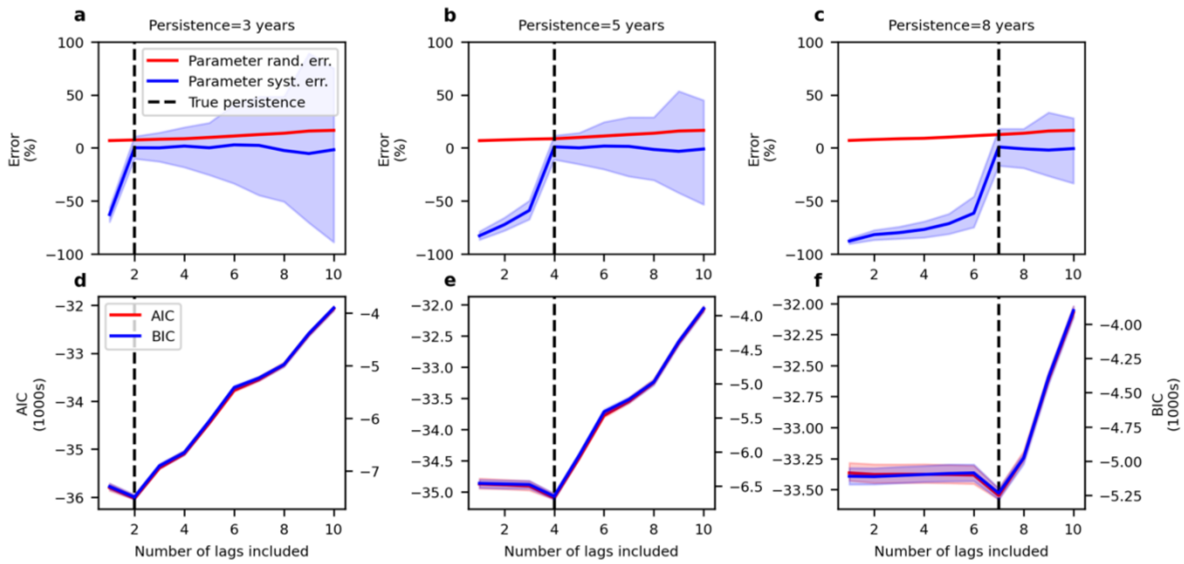
Supplementary Figure 3. Results of a panel fixed effects distributed lag model with ten lags for temperature terms and four for precipitation terms. As Extended Data Figure 1 but using ten lags for the temperature terms and four lags for the precipitation terms.



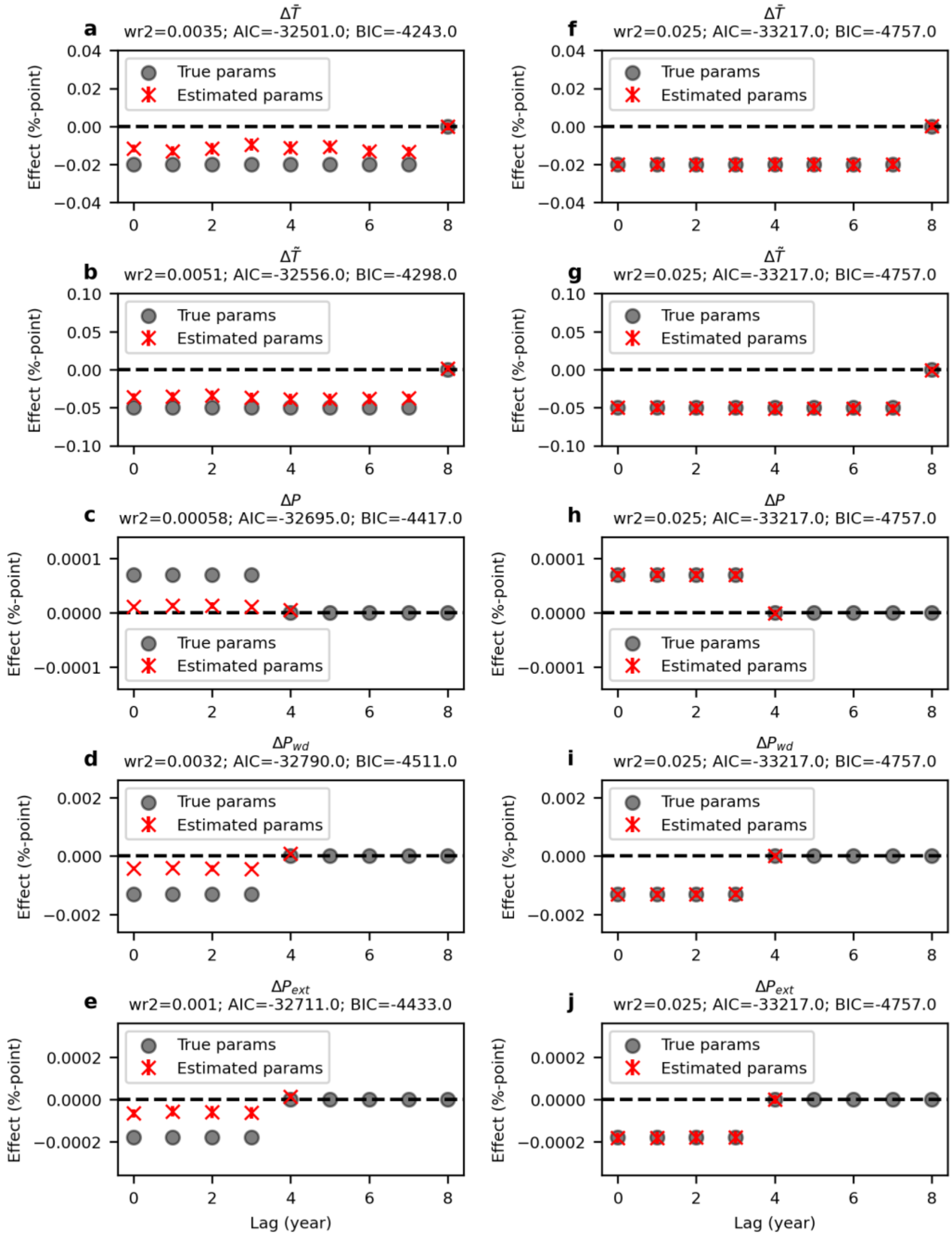
Supplementary Figure 4. Assessing auto- and cross-correlations in the climate variables identified as drivers of climate impacts on economic output. (a-e) Correlation matrices between lagged variables to assess auto-correlation in annual mean temperature, $\Delta\overline{\mathrm{T}}$, daily temperature variability, $\Delta\tilde{T}$, total annual precipitation, ΔP, the annual number of wet days, ΔP_{wd}, and the measure of extreme daily precipitation, ΔP_{ext}, (see methods for further details of these definitions). (f) Correlation matrices between the different climate variables. All values show the average Pearson correlation obtained from each of the 1660 regions on which the effects of climatic changes on economic output are estimated. Note that in all cases, climate variables are assessed in their first differenced form to reflect the way in which they are used in the empirical models.



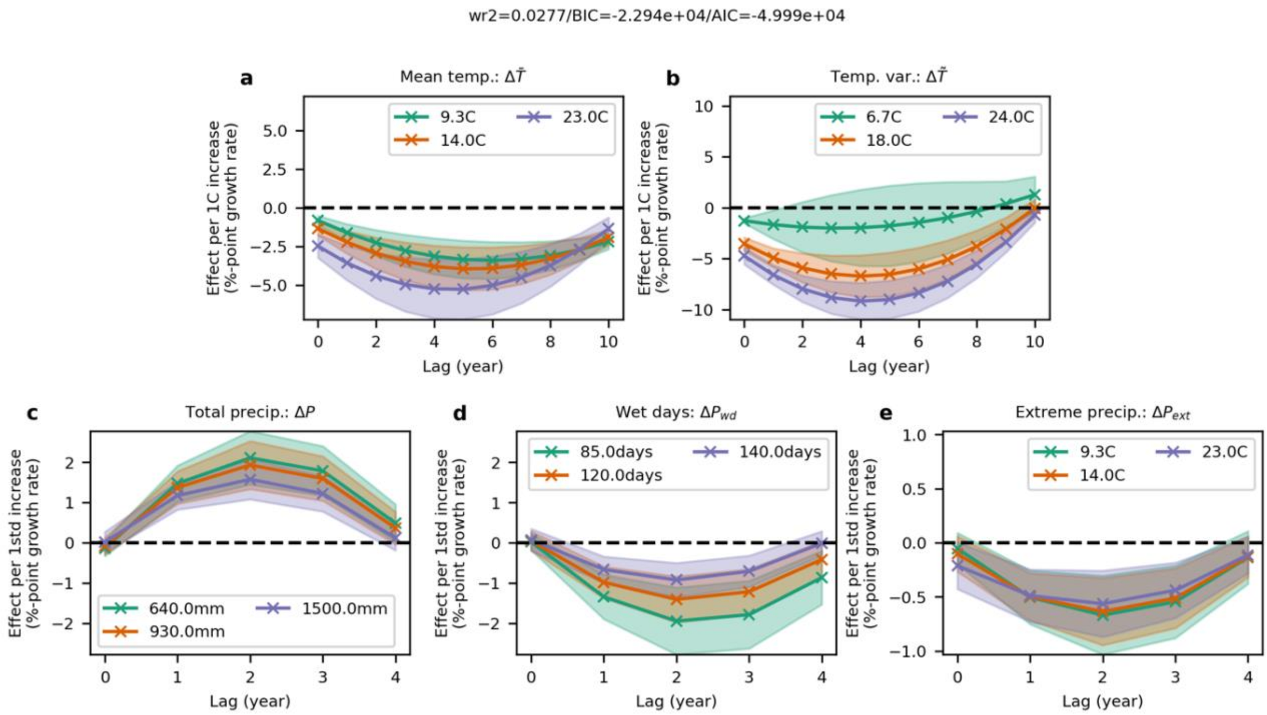
Supplementary Figure 5. Results of Monte-Carlo simulations to assess the robustness of the empirical models to autocorrelations in the climate time series, as well as to demonstrate the conservative nature of our approach which underestimates the magnitude of impacts when an insufficient number of lags are included. Grey circles indicate the true parameters describing the effect of a change in climate on economic growth rates as added into the data during the Monte-Carlo simulation procedure which randomly reassigned real temperature time series to different regions (see SI Methods Section S1). Red crosses indicate the average and vertical lines the standard deviation of estimates of these parameters from panel fixed-effects distributed lag models based on 100 Monte-Carlo simulations. Panels (a-d) show the results for an effect which persists for three years, when including an increasing number of lags (two, four, six, ten) in the regressions, while panels (e-h) and (i-l) show the equivalent results for an effect which persists for five and eight years respectively. The average within-region R-squared values (variance explained along the temporal dimension) across models of the different simulations are indicated above each panel.



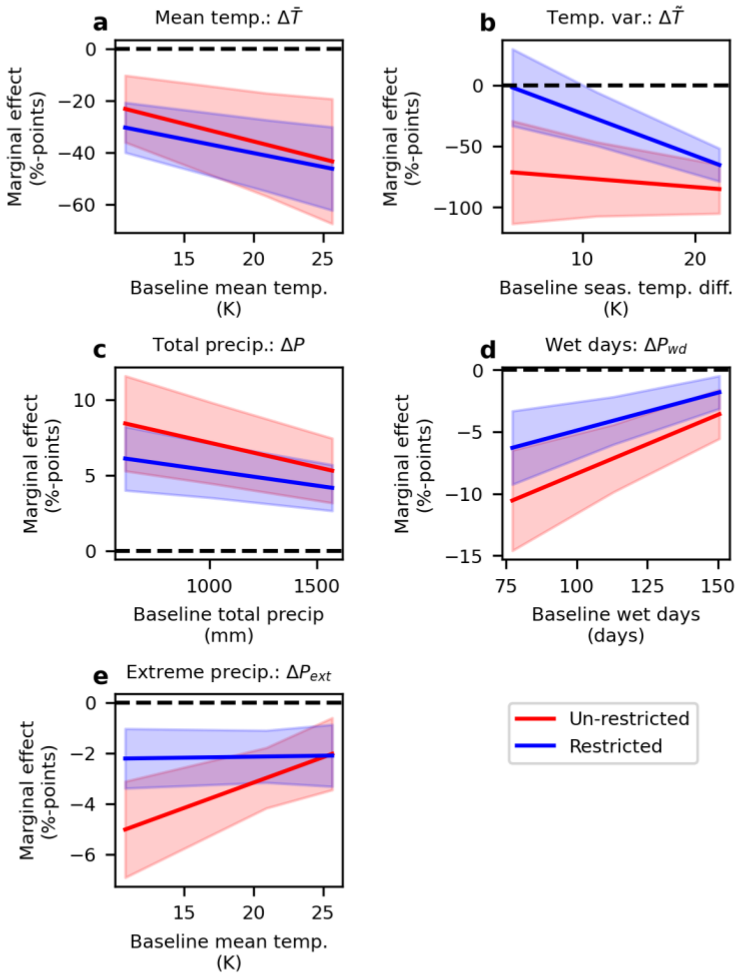
Supplementary Figure 6. Random and systematic errors in model parameter estimates, as well as Information Criteria at different levels of climate impact persistence and different numbers of lags as obtained from the results of Monte-Carlo simulations. Results of the same Monte-Carlo simulations presented in Supplementary Figure S5, in which effects of different persistence times (three, five and eight) are added into the economic data after a random reassignment of temperature time series and are then detected using different numbers of lags (one to ten) in panel fixed effects distributed lag models (see SI methods section S1). Panels (a-c) display the standard deviation of parameter estimates across Monte-Carlo simulations averaged across the lagged parameters, expressed as a percentage of the true parameter magnitude (in red); also shown is the percentage difference between the cumulative lagged parameter estimates and the true cumulative lagged parameters (blue). The first measure reflects random error, whereas the second measure reflects systematic error in the parameter estimates. In the case of the second measure, solid lines show the average and confidence intervals the 5th and 95th percentiles across the 100 Monte-Carlo simulations. Results indicate that an insufficient number of lags with respect to the true level of impact persistence causes an underestimation of the true effect, while the inclusion of a larger number of lags can increase random error. Panels (d-f) display the Akaike and Bayesian Information Criteria (AIC/BIC) which are typically used to select between alternative models by penalizing overfitting (note that lower values indicate a better model). Results show that a lag selection process based on information criteria and incremental model changes only provides useful indications for the appropriate number of lags when starting from a large initial number and then decreasing.



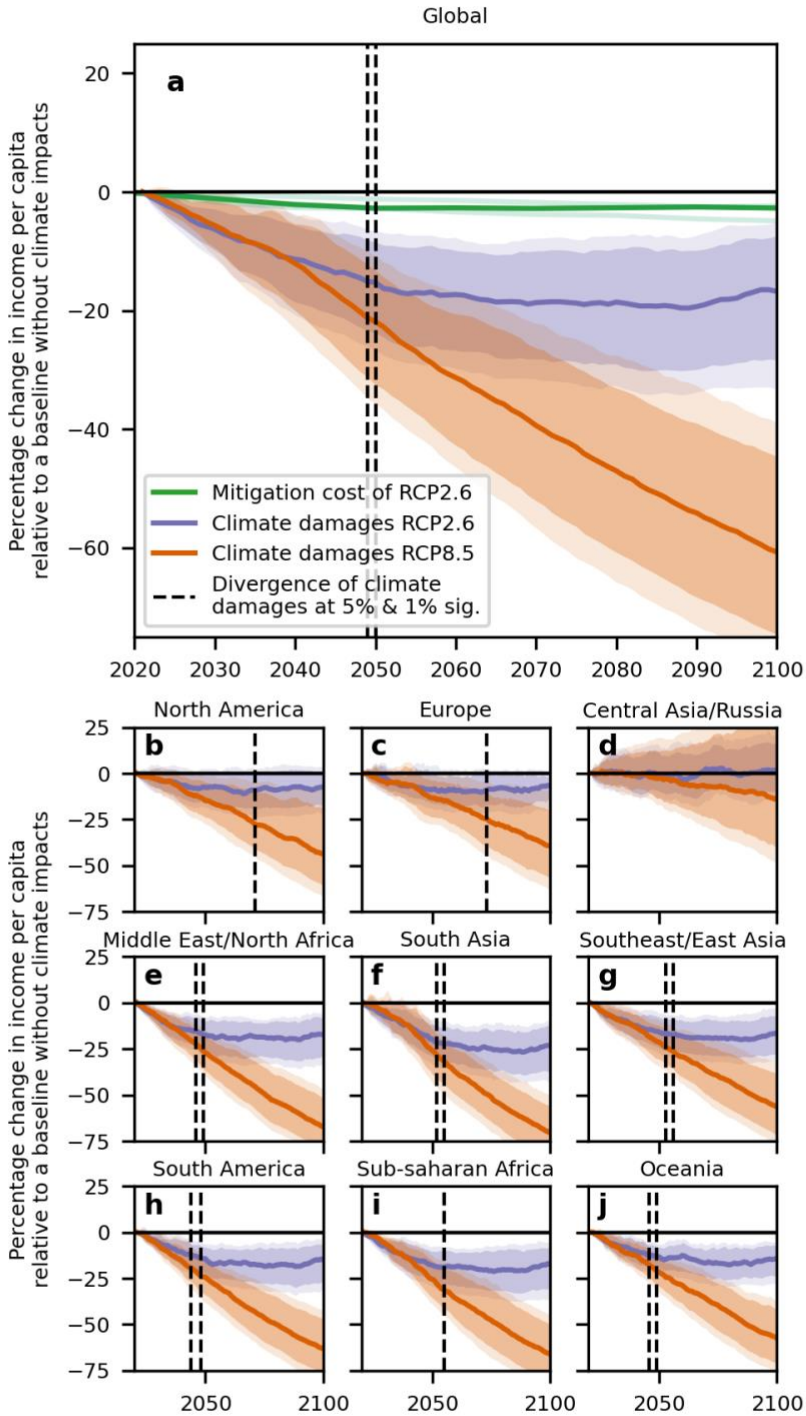
Supplementary Figure 7. Results of Monte-Carlo simulations to assess the robustness of the empirical models to imperfect multicollinearity arising from cross-correlations between different climate variables. Grey circles indicate the true parameters describing the effect of a change in climate on economic growth rates as added into the data during the Monte-Carlo simulation procedure which randomly reassigned real time series of all climate variables to different regions (see methods). The effect sizes and persistence of the effects of the different climate variables are chosen to mimic those identified in the real historical data (Extended Data Figure 1). Red crosses indicate the average and vertical lines the standard deviation of estimates of these parameters from fixed-effects panel regressions based on 100 Monte-Carlo simulations. Panels (a-e) show results from empirical models in which only a single climate variable was included as an independent variable, whereas panels (f-j) show results from models in which all climate variables were included simultaneously. The within-region R-squared values (variance explained along the temporal dimension; wr2), and Akaike and Bayesian Information Criteria on average across models of the different simulations (AIC, BIC) are given above each panel. Results of the simulations indicate that, given the real co-linearities between climate variables, including all climate variables simultaneously in the regressions is necessary to accurately capture the separate effects of the individual variables (compare left and right columns).



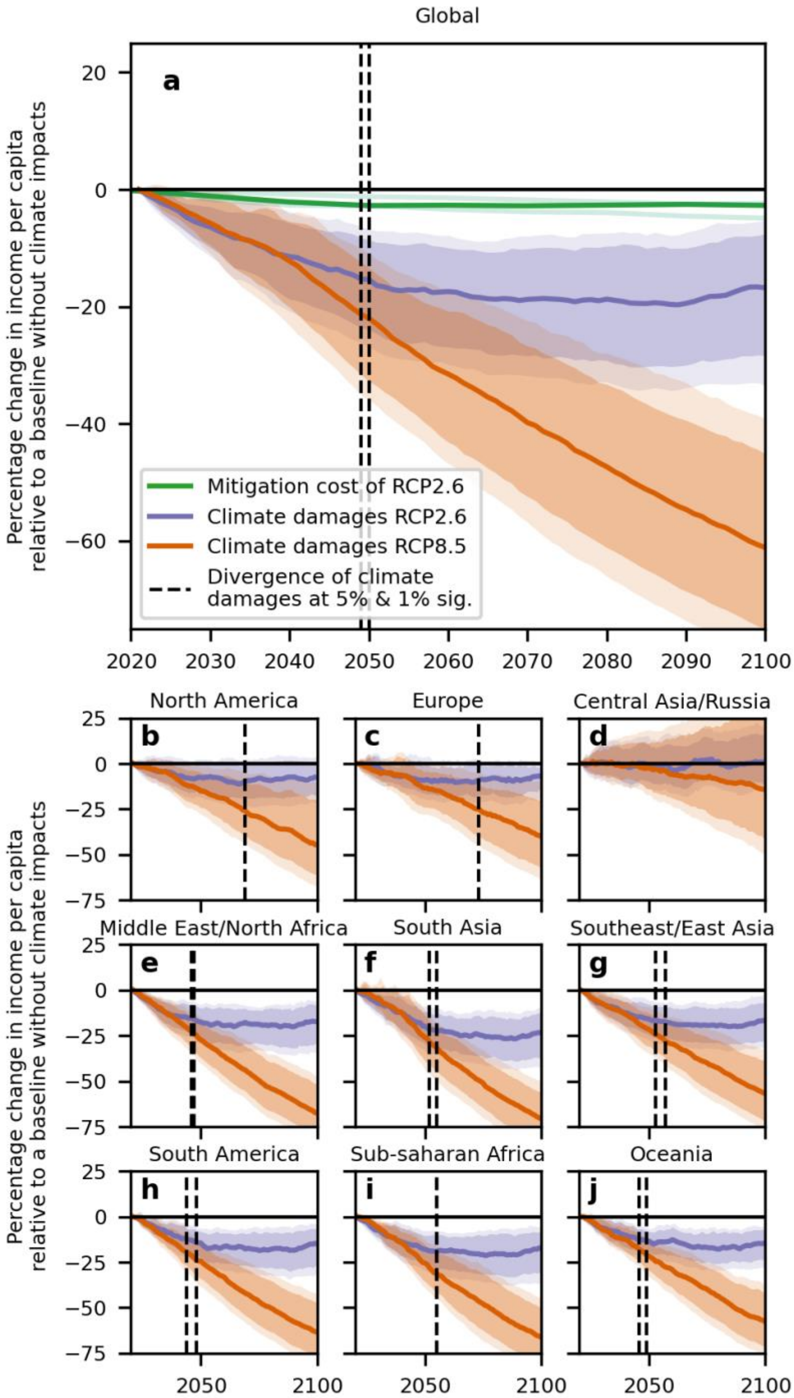
Supplementary Figure 8. Results of a panel fixed effects restricted distributed lag model for the effects of climatic changes on economic output using a quadratic lag distribution. See Supplementary Methods Section S3 for details of the transformation of lagged variables used to produce a quadratic distribution. Ten lags are used for temperature terms but only four for precipitation terms to enable an appropriate fitting of a quadratic function to the distribution of lagged effects observed in the un-restricted model shown in Extended Data Figure 1. Figure is otherwise structured as Extended Data Figure 1.



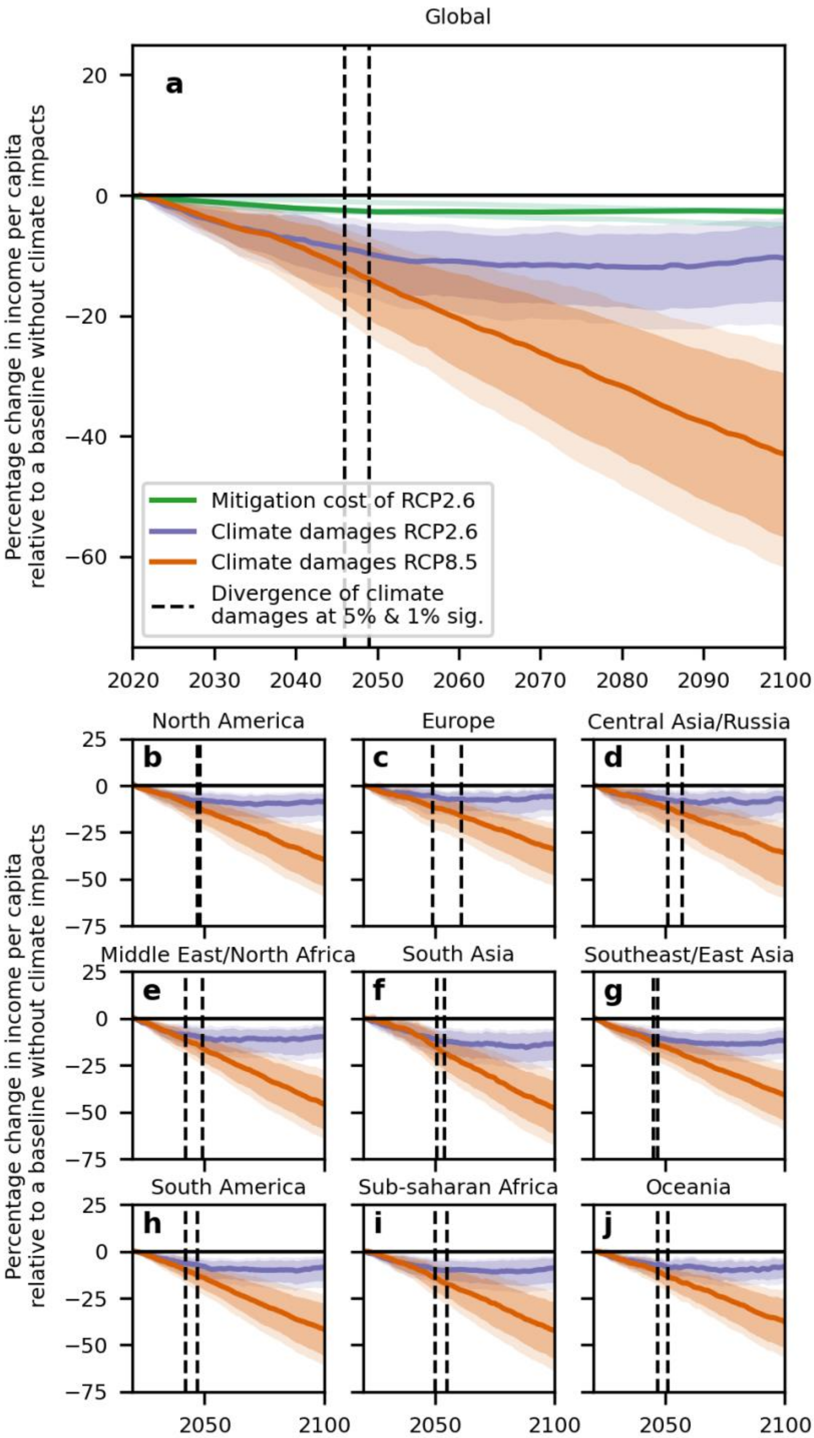
Supplementary Figure 9. Comparison of the cumulative marginal effects of climate variables on economic output when using a restricted and unrestricted distributed lag model. The cumulative marginal effects of annual mean temperature (a), daily temperature variability (b), total annual precipitation (c), the annual number of wet days (d) and extreme daily precipitation (e) are shown at different values of the moderating variable (x-axis) having been estimated from the restricted and un-restricted distributed lag models with ten lags for temperature and four lags for precipitation terms respectively, as shown in Supplementary Figures 3 & 8. Cumulative marginal effects are in most cases statistically indistinguishable between the models, with particularly close estimates for annual mean temperature (a) for which the restricted lag model was motivated (see main text). Larger differences between the cumulative marginal effects of the two models in the other climate variables likely arise when a quadratic function does not provide a good fit to the un-restricted distribution of lags, in particular for daily temperature variability (b) and extreme daily precipitation (e) which exhibit different lag distributions at different values of the moderating variables (see Extended Data Figure 1). This suggests that for these variables the more flexible un-restricted distributed lag model provides a better description of the delayed effects.



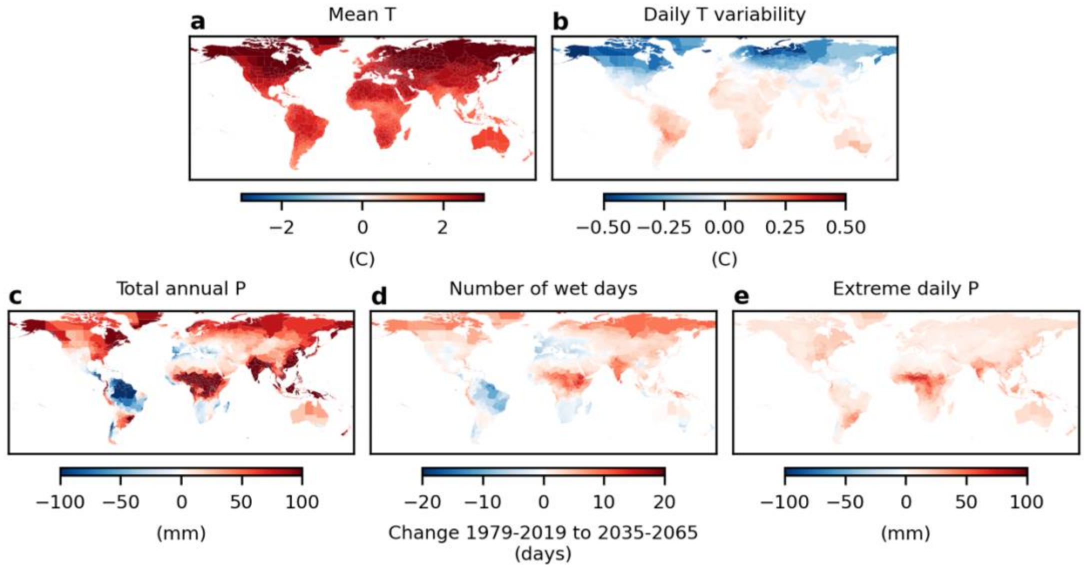
Supplementary Figure 10. Robustness test of the timescale with which changes in the moderating variable of the empirical models are estimated. As Figure 1 of the main manuscript but when evaluating changes in the moderating variables of the interaction terms in the empirical models based on 10-year averages rather than 30-year averages. See methods for further details.



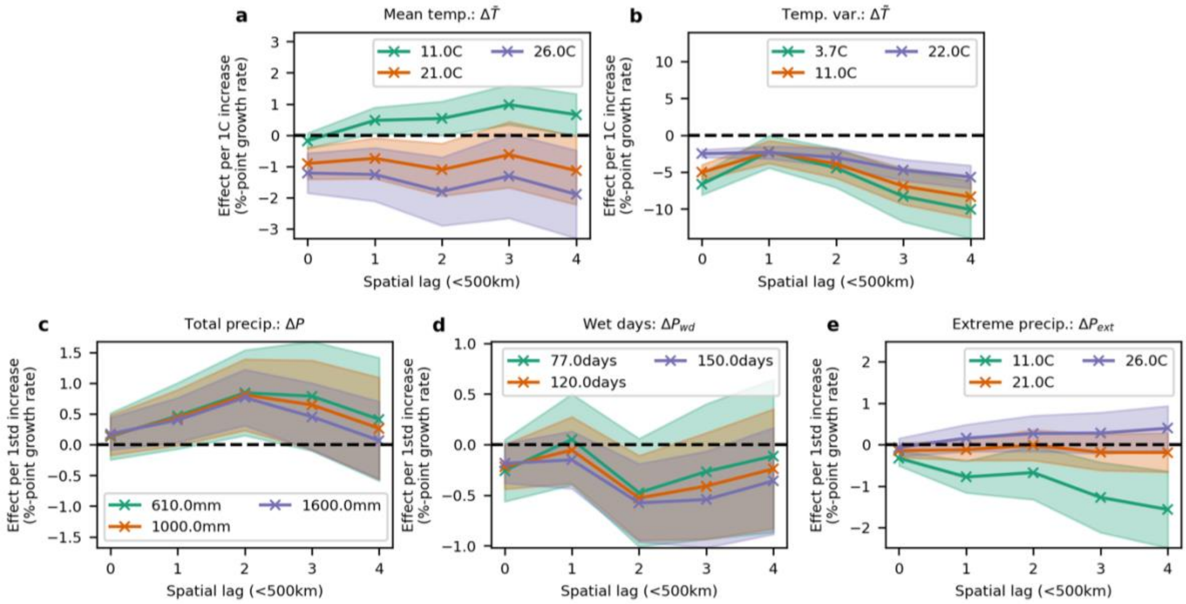
Supplementary Figure 11. Robustness test of the timescale with which changes in the moderating variable of the empirical models are estimated. As Figure 1 of the main manuscript but when evaluating changes in the moderating variables of the interaction terms in the empirical models based on 20-year averages rather than 30-year averages. See methods for further details.



Supplementary Figure 12. Robustness test of the choice of method used for accounting for sub-national price changes. As Figure 1 but having used results obtained from fixed-effects panel models applied to estimates of sub-national real output per capita based on the application of national-level GDP deflators prior to the use of currency conversions (see methods for further details).



Supplementary Figure 13. Climate changes in different variables. Changes in each climate variable of interest from 1979-2019 to 2035-2065 under the high-emission scenario SSP5-RCP8.5. Data on national administrative boundaries are obtained from the GADM database version 3.6 and are freely available for academic use (https://gadm.org/).



Supplementary Figure 14. Exploration of possible spill-over effects of contemporaneous climate impacts on spatially neighbouring regions. Panels (a-e) show the cumulative impacts of different climate variables on economic growth rates when including the spatially lagged-effects of climate shocks in neighbouring regions with centroids a distance of up to 500, 1000, 1500 and 2000km away (1, 2, 3 or 4 spatial lags, respectively). Spatial lags are constructed by taking the average of the first-differenced climate variables and their interaction terms over neighboring regions (see methods for detail). Due to data availability constraints, these models do not account for spill-overs which may occur via trade, and for simplicity they use no temporal lags of the climate variables, therefore only reflecting contemporaneous impacts. Error bars show the 95% confidence intervals having clustered standard errors by region. See the Methods section of the main manuscript for further details.

Climate measure removed	None (full model)	Daily temp. variability	Total annual rainfall	Annual number of wet days	Extreme daily precip.
AIC	-34220	-33690	-34140	-34080	-34188
BIC	-5490	-5111	-5489	-5435	-5537

Supplementary Table 1. Information criteria to assess model overfitting when removing additional climate variables. Akaike and Bayesian Information criteria to assess the relative strength of models which include either all climate variables or remove individual variables. The models here use eight lags for temperature and four for precipitation terms as indicated in Supplementary Figure 1 to be optimal for limiting overfitting in terms of lag selection. Lower information criteria indicate a better model in terms of explaining a greater amount of variance while limiting overfitting by penalising additional terms. Both criteria indicate that including all climate variables provides the best model in terms of limiting overfitting, except the more conservative BIC[4,5] measure when considering extreme daily precipitation.

Variable	Formula	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
Annual mean temperature	$\Delta\bar{T}_{r,y}$	0.051	-0.52	-0.62	0.4	-0.24	-0.18	1*	0.32	-0.85**
		(0.32)	(0.49)	(0.5)	(0.51)	(0.42)	(0.47)	(0.46)	(0.46)	(0.31)
	$\Delta\bar{T}_{r,y}.\bar{T}_r$	-0.094**	-0.12*	-0.067	-0.16**	-0.093*	-0.19***	-0.21***	-0.17***	-0.07**
		(0.029)	(0.049)	(0.05)	(0.055)	(0.044)	(0.048)	(0.042)	(0.037)	(0.026)
Daily temp. variaiblity	$\Delta\tilde{T}_{r,y}$	-8.6***	-5**	-9.3***	-4.8	3.2	3.8	2.7	3.2	9.1***
		(1.2)	(1.9)	(2.1)	(2.5)	(2.8)	(2.8)	(2.3)	(2)	(1.4)
	$\Delta\tilde{T}_{r,y}.\hat{T}_r$	0.13*	-0.11	0.021	-0.12	-0.44***	-0.42***	-0.36***	-0.37***	-0.4***
		(0.052)	(0.081)	(0.082)	(0.1)	(0.11)	(0.11)	(0.092)	(0.088)	(0.064)
Total annual precipitation	$\Delta P_{r,y}$	0.0022	0.0096***	0.0093***	0.0081***	0.0041**				
		(0.0014)	(0.0017)	(0.0019)	(0.0017)	(0.0013)				
	$\Delta P_{r,y}.P_r$	-4.6e-8	-2.6e-06***	-2.4e-06**	-3.1e-06***	-2.2e-06***				
		(6.2e-07)	(7e-07)	(8.6e-07)	(7.5e-07)	(5.5e-07)				
Annual no. wet days	$\Delta Pwd_{r,y}$	-0.064	-0.19***	-0.24***	-0.3***	-0.15***				
		(0.033)	(0.035)	(0.057)	(0.059)	(0.04)				
	$\Delta Pwd_{r,y}.Pwd_r$	3.8e-04	9.2e-04***	1.1e-03**	1.7e-03***	1e-03***				
		(2e-04)	(2.2e-04)	(3.6e-04)	(3.6e-04)	(2.4e-04)				
Precipitation extremes	$\Delta Pext_{r,y}$	-0.025***	-0.028***	-0.03***	-0.029***	-0.0094*				
		(0.0047)	(0.0061)	(0.0067)	(0.0064)	(0.0044)				
	$\Delta Pext_{r,y}.\bar{T}_r$	8.5e-04***	8e-04**	7.8e-04*	1e-03**	3.2e-04				
		(2.2e-04)	(2.9e-04)	(3.2e-04)	(3.1e-04)	(2.1e-04)				
R^2	0.277									
wR^2	0.0325									
BIC	-5.49e+03									
AIC	-3.42e+04									
N	34855									

Supplementary Table 2. Regression results for the historical effects of different climate variables on sub-national economic growth rates in the period 1979-2019. As Extended Data Table 2 but including eight time lags for the temperature terms four time lags for the precipitation terms.

Variable	Formula	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9
Annual mean temperature	$\Delta\bar{T}_{r,y}$	0.21	-0.064	0.12	1.2*	0.67	0.87	1.9***	1.2*	0.18	1.1***
		(0.32)	(0.5)	(0.51)	(0.53)	(0.46)	(0.53)	(0.56)	(0.58)	(0.45)	(0.29)
	$\Delta\bar{T}_{r,y}.\bar{T}_r$	-0.11***	-0.15**	-0.09	-0.17**	-0.095*	-0.17***	-0.19***	-0.13**	-0.048	0.048*
		(0.029)	(0.05)	(0.051)	(0.055)	(0.046)	(0.05)	(0.046)	(0.043)	(0.032)	(0.022)
Daily temp variability	$\Delta\tilde{T}_{r,y}$	-9.5***	-7.3***	-13***	-9.1***	-2.1	-1.9	-2.4	-1.5	3.9	-4.5***
		(1.2)	(1.9)	(2.2)	(2.6)	(2.9)	(3)	(2.7)	(2.5)	(2)	(1.3)
	$\Delta\tilde{T}_{r,y}.\hat{T}_r$	0.15**	-0.031	0.12	0.01	-0.28*	-0.24*	-0.21	-0.23*	-0.26**	0.11*
		(0.052)	(0.08)	(0.084)	(0.1)	(0.12)	(0.12)	(0.11)	(0.11)	(0.088)	(0.052)
Total annual precipitation	$\Delta P_{r,y}$	0.0019	0.0094***	0.0094***	0.0077***	0.0034**					
		(0.0015)	(0.0017)	(0.002)	(0.0017)	(0.0013)					
	$\Delta P_{r,y}.P_r$	9e-8	-2.6e-06***	-2.4e-06**	-3e-06***	-2e-06***					
		(6.4e-07)	(7.2e-07)	(8.7e-07)	(7.6e-07)	(5.4e-07)					
Annual no. wet days	$\Delta Pwd_{r,y}$	-0.043	-0.16***	-0.23***	-0.29***	-0.14***					
		(0.033)	(0.036)	(0.058)	(0.059)	(0.04)					
	$\Delta Pwd_{r,y}.Pwd_r$	2.7e-04	7.5e-04***	1e-03**	1.6e-03***	1e-03***					
		(2e-04)	(2.3e-04)	(3.7e-04)	(3.7e-04)	(2.4e-04)					
Precipitation extremes	$\Delta Pext_{r,y}$	-0.025***	-0.029***	-0.03***	-0.03***	-0.0092*					
		(0.0047)	(0.0061)	(0.0067)	(0.0064)	(0.0044)					
	$\Delta Pext_{r,y}.\bar{T}_r$	8.3e-04***	8.1e-04**	7.5e-04*	1e-03***	3e-03					
		(2.2e-04)	(2.9e-04)	(3.2e-04)	(3.1e-04)	(2.1e-04)					
R^2	0.283										
wR^2	0.0382										
BIC	-5.06e+03										
AIC	-3.38e+04										
N	34855										

Supplementary Table 3. Regression results for the historical effects of different climate variables on sub-national economic growth rates in the period 1979-2019. As Extended Data Table 2 but including nine time lags for the temperature terms and four time lags for the precipitation terms.

Variable	Formula	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8	Lag 9	Lag 10
Annual mean temperature	$\Delta\bar{T}_{r,y}$	-0.12	-0.54	-0.79	-0.13	-0.72	-0.82	-0.041	-0.6	-1.7**	-0.93	-2.3***
		(0.32)	(0.5)	(0.53)	(0.57)	(0.57)	(0.65)	(0.67)	(0.72)	(0.62)	(0.48)	(0.34)
	$\Delta\bar{T}_{r,y}.\bar{T}_r$	-0.11***	-0.14**	-0.074	-0.15**	-0.077	-0.16**	-0.18***	-0.13**	-0.027	0.074*	0.028
		(0.029)	(0.05)	(0.051)	(0.055)	(0.047)	(0.051)	(0.047)	(0.046)	(0.039)	(0.032)	(0.023)
Daily temp. variability	$\Delta\tilde{T}_{r,y}$	-9.2***	-8***	-13***	-9.4***	-1.8	-1.4	-2.2	-1.5	3.6	-4.5*	-0.28
		(1.3)	(2)	(2.2)	(2.7)	(3.1)	(3.2)	(3.1)	(2.9)	(2.5)	(1.9)	(1.3)
	$\Delta\tilde{T}_{r,y}.\hat{T}_r$	0.13*	-0.03	0.11	-7.9e-03	-0.33**	-0.31*	-0.25*	-0.29*	-0.3**	0.06	-0.035
		(0.054)	(0.083)	(0.086)	(0.1)	(0.12)	(0.13)	(0.12)	(0.12)	(0.11)	(0.078)	(0.056)
Total annual precipitation	$\Delta P_{r,y}$	0.0019	0.0095***	0.0095***	0.0075***	0.0032*						
		(0.0015)	(0.0017)	(0.002)	(0.0018)	(0.0013)						
	$\Delta P_{r,y}P_r$	6.5e-9	-2.6e-06***	-2.3e-06**	-3e-06***	-1.9e-06***						
		(6.5e-07)	(7.3e-07)	(8.9e-07)	(7.6e-07)	(5.5e-07)						
Annual no. wet days	$\Delta Pwd_{r,y}$	-0.044	-0.16***	-0.23***	-0.28***	-0.13***						
		(0.033)	(0.037)	(0.058)	(0.059)	(0.04)						
	$\Delta Pwd_{r,y}.Pwd_r$	2.9e-04	7.6e-04**	9.7e-04**	1.6e-03***	9.2e-04***						
		(2e-04)	(2.3e-04)	(3.6e-04)	(3.6e-04)	(2.4e-04)						
Precipitation extremes	$\Delta Pext_{r,y}$	-0.024***	-0.027***	-0.028***	-0.028***	-0.0085						
		(0.0047)	(0.0061)	(0.0067)	(0.0065)	(0.0044)						
	$\Delta Pext_{r,y}.\bar{T}_r$	8.1e-04***	7.4e-04*	6.5e-04*	9.7e-04**	2.6e-04						
		(2.2e-04)	(2.9e-04)	(3.2e-04)	(3.2e-04)	(2.1e-04)						
R^2	0.287											
wR^2	0.0428											
BIC	-4.68e+03											
AIC	-3.34e+04											
N	34855											

Supplementary Table 4. Regression results for the historical effects of different climate variables on sub-national economic growth rates in the period 1979-2019. As Extended Data Table 2 but including ten time lags for the temperature terms and four time lags for the precipitation terms.

GFDL-ESM4	CNRM-CM6-1	BCC-CSM2-MR	KACE-1-0-G
IPSL-CM6A-LR	CNRM-ESM2-1	CAMS-CSM1-0	NESM3
MPI-ESM1-2-HR	EC-Earth3	CESM2	TaiESM1
MRI-ESM2-0	MIROC6	FGOALS-g3	
UKESM1-0-LL	ACCESS-ESM1-5	IITM-ESM	
CanESM5	AWI-CM-1-1-MR	INM-CM5-0	

Supplementary Table 5. List of climate models from the Coupled Model Intercomparison Project phase-6 used to project future climate change.

Climate measure	Annual mean temperature	Seasonal temperature difference	Total annual rainfall	Annual number of wet days
Pearson correlation to observations	1.000	1.000	1.000	0.998
Average absolute percentage error to observations	0.2%	2.1%	1.2%	2.8%
Coefficient of variation across climate models	0.0038	0.018	0.018	0.030

Supplementary Table 6. Evaluation of systematic bias and uncertainty in bias-adjusted climate model output over the historical period 1979-2015. The first row shows Pearson correlations between regional climate data from the mean of the bias-adjusted CMIP-6[35,36] ensemble and the W5E5 observational dataset[37] for the different climate variables used as moderating variables of the interaction terms of the empirical models and in the projections of future damages. The second row shows the absolute percentage difference between the climate data from the two sources, averaged across regions. The third row shows the coefficient of variation (standard deviation divided by the mean) of each climate measure across climate models, averaged across regions.

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