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Supplementary information

The economic commitment of climate change

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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

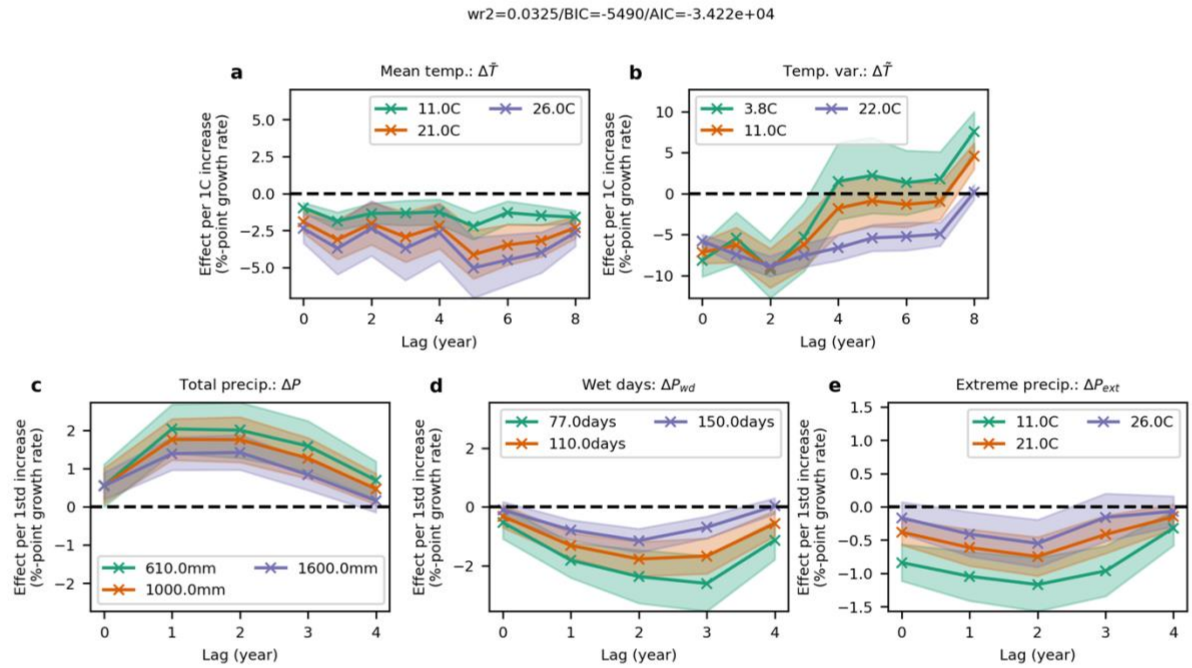
Section S5: The magnitude of damages in the context of historical economic development

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.

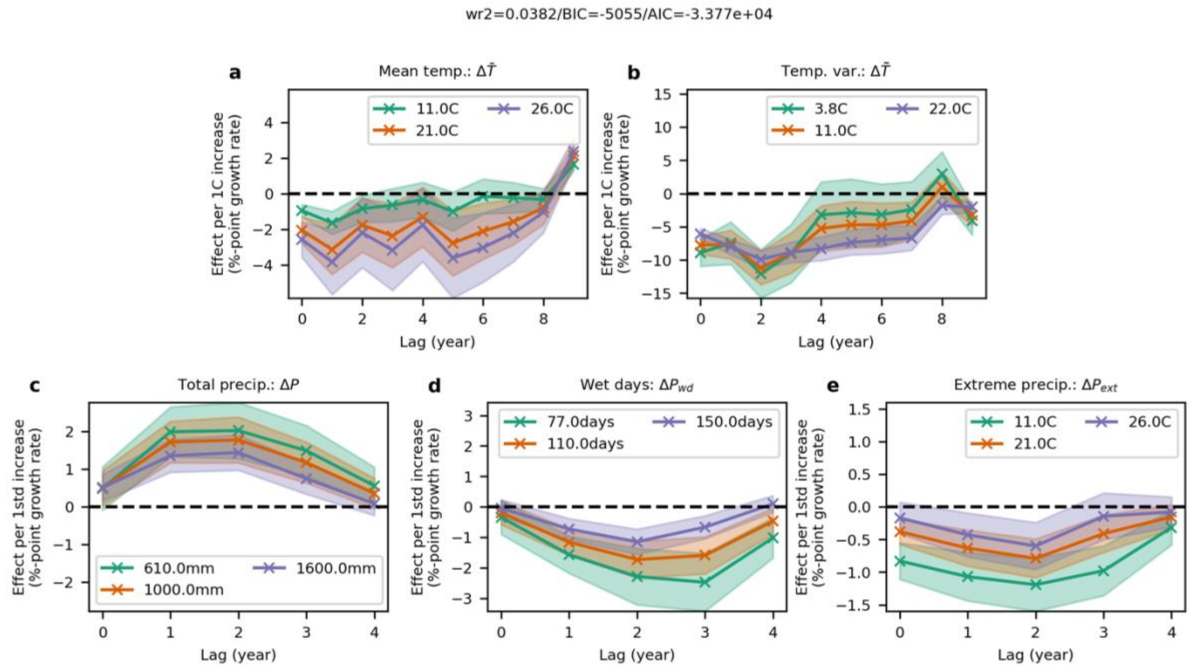
The world has experienced approximately 1C of global warming historically since 1970[17], and CMIP6 climate models project approximately another 1C of global warming by 2050 (compared to 2020) under SSP585 (see IPCC AR6 WG1[18], Figure4.2). This makes for a convenient and approximate comparison of the 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.

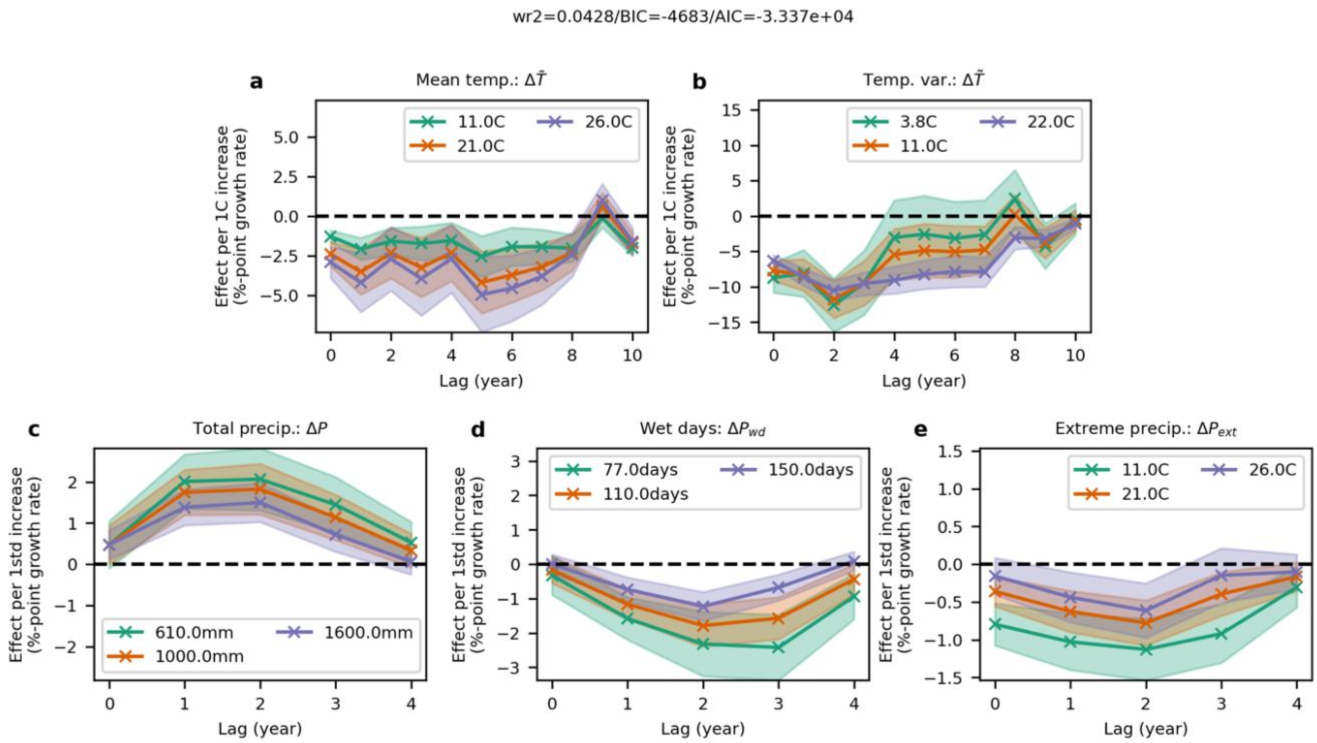
Nevertheless, these “back-of-the-envelope” calculations demonstrate that the magnitude of damages which we project is consistent with historical developments, given that: a) historical economic development is much larger than the historical damages implied by our analysis, b) richer regions grew historically 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.



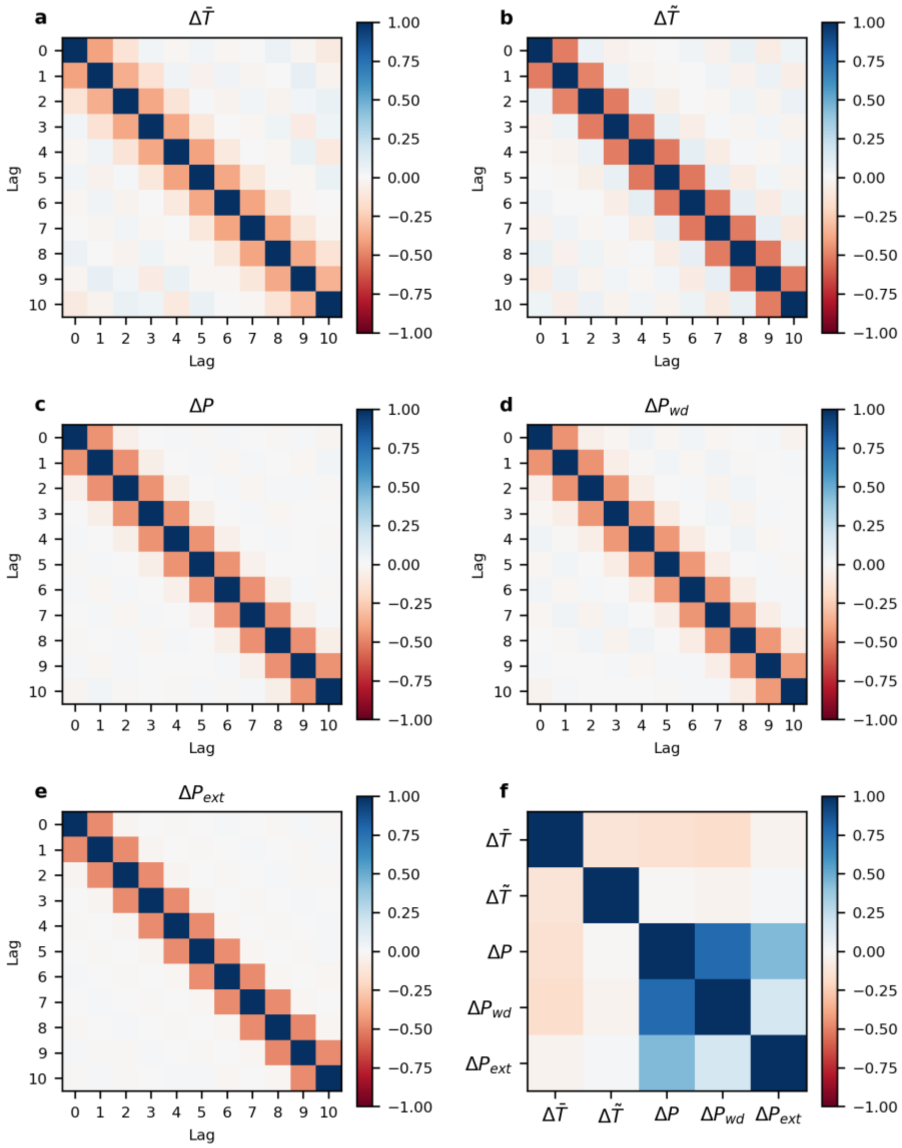
Supplementary Figure 1. Results of a panel fixed effects distributed lag model with eight lags for temperature terms and four for precipitation terms. As Extended Data Figure 1 but using eight lags for the temperature terms and four lags for the precipitation terms.



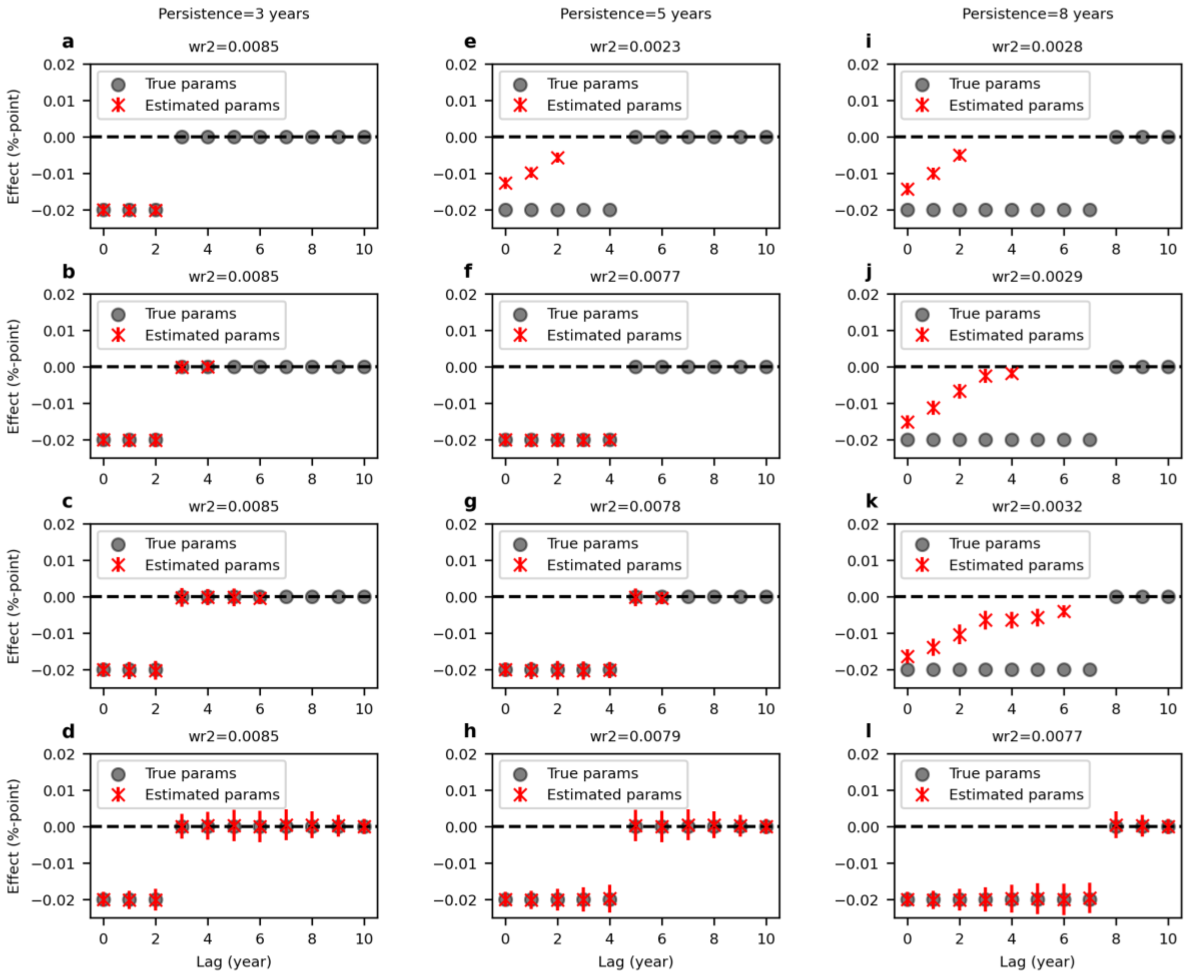
Supplementary Figure 2. Results of a panel fixed effects distributed lag model with nine lags for temperature terms and four for precipitation terms. As Extended Data Figure 1 but using nine lags for the temperature terms and four lags for the precipitation terms.



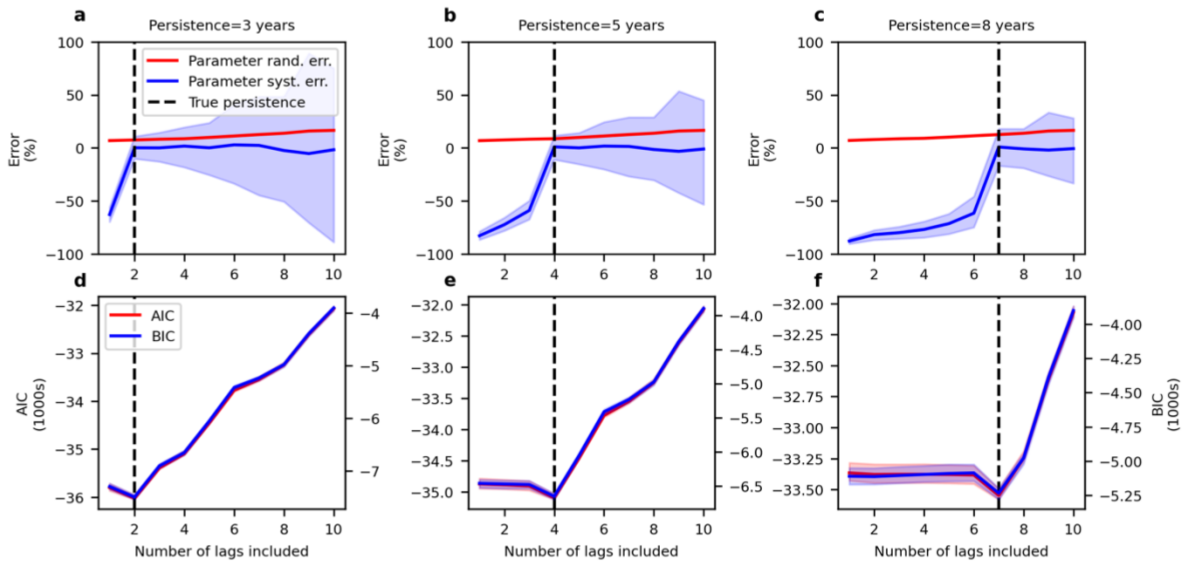
Supplementary Figure 3. Results of a panel fixed effects distributed lag model with ten lags for temperature terms and four for precipitation terms. As Extended Data Figure 1 but using ten lags for the temperature terms and four lags for the precipitation terms.



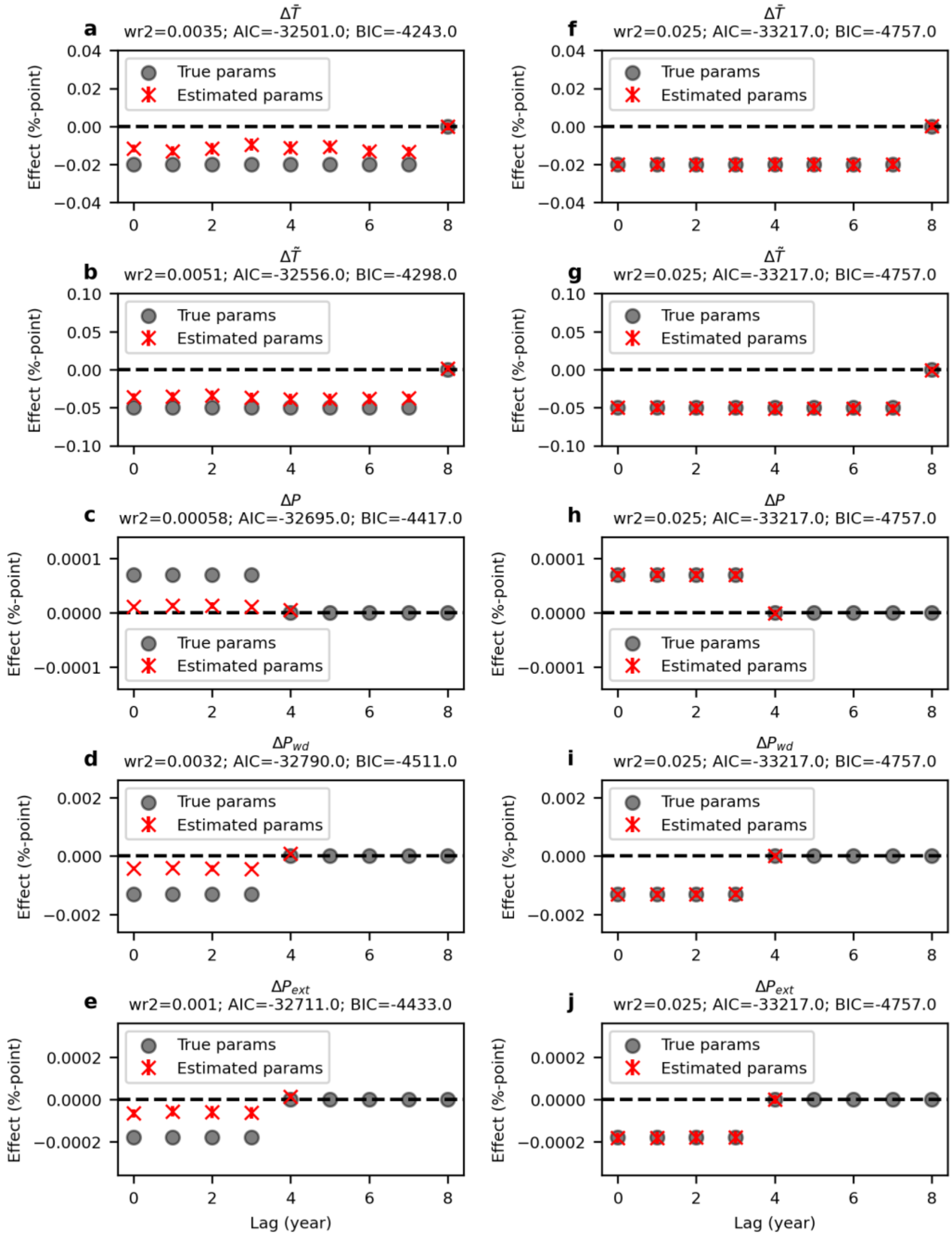
Supplementary Figure 4. Assessing auto- and cross-correlations in the climate variables identified as drivers of climate impacts on economic output. (a-e) Correlation matrices between lagged variables to assess auto-correlation in annual mean temperature, $\Delta\overline{\mathrm{T}}$, daily temperature 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.



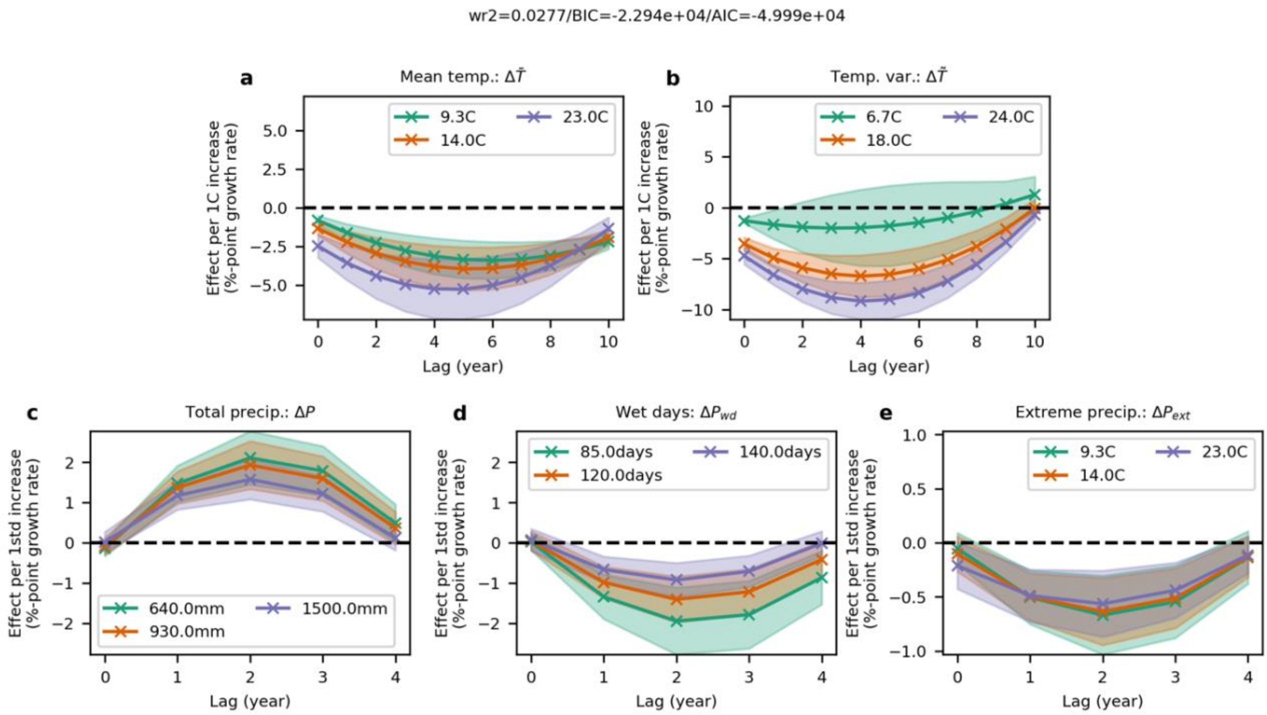
Supplementary Figure 5. Results of Monte-Carlo simulations to assess the robustness of the empirical models to autocorrelations in the climate time series, as well as to demonstrate the conservative nature of our approach which underestimates the magnitude of impacts when an insufficient number of lags 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.



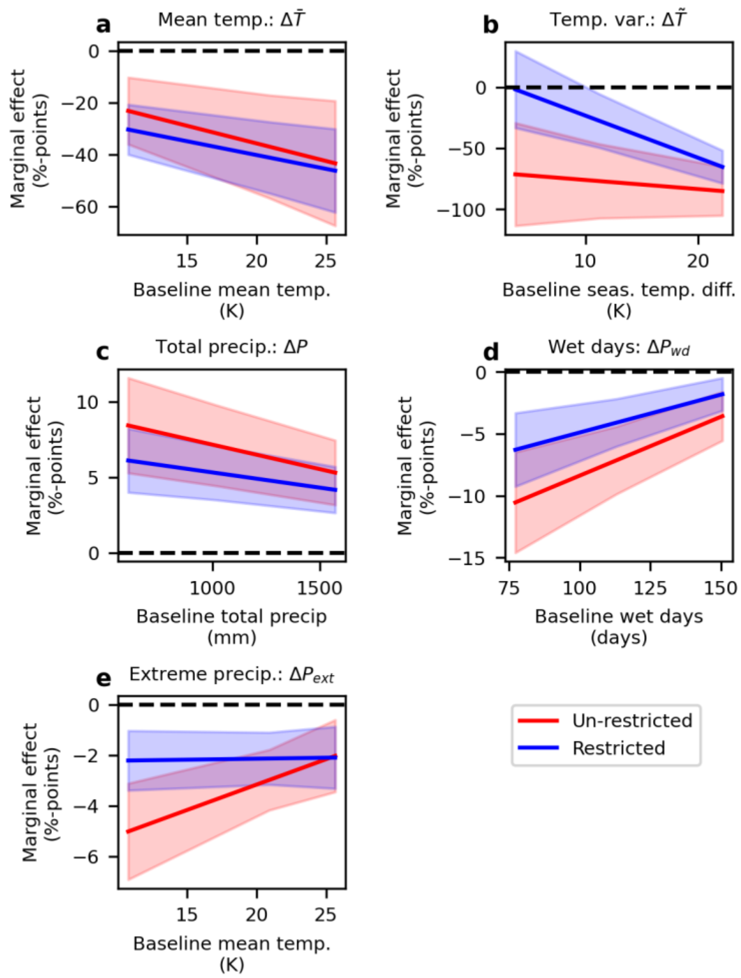
Supplementary Figure 6. Random and systematic errors in model parameter estimates, as well as Information Criteria at different levels of climate impact persistence and different numbers of lags as obtained from the results of Monte-Carlo simulations. Results of the same Monte-Carlo simulations presented 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.



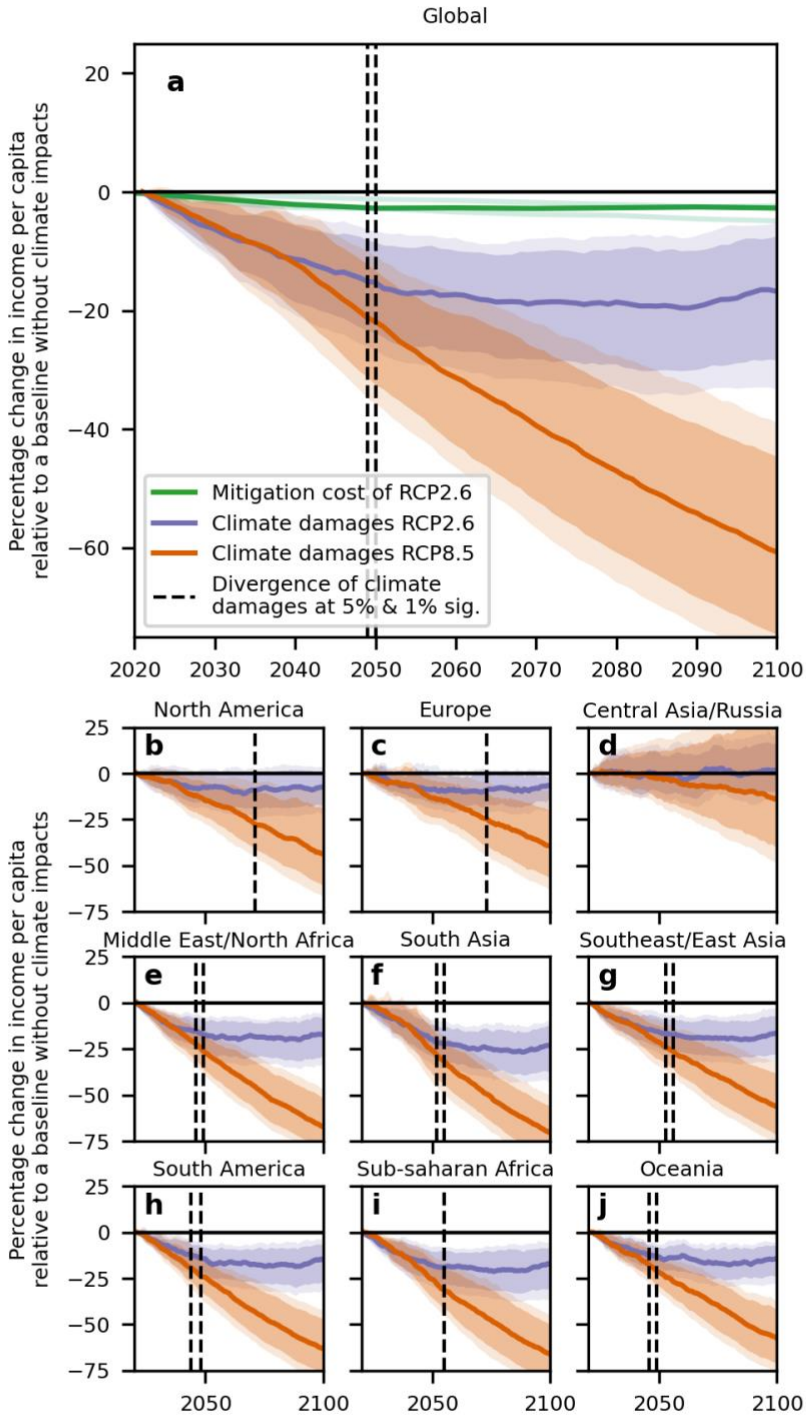
Supplementary Figure 7. Results of Monte-Carlo simulations to assess the robustness of the empirical models to imperfect multicollinearity arising from cross-correlations between different climate variables. Grey circles indicate the true parameters describing the effect of a change in climate on economic 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).



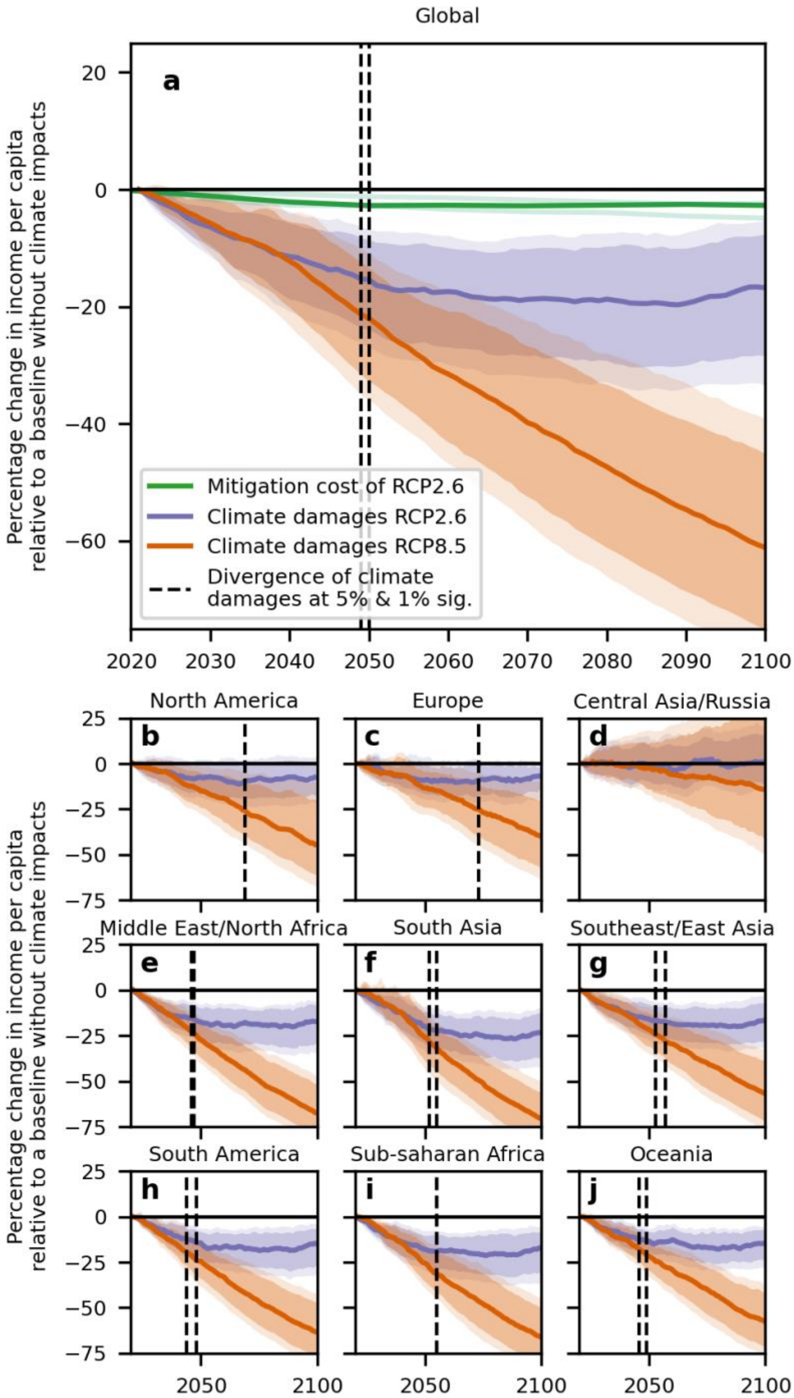
Supplementary Figure 8. Results of a panel fixed effects restricted distributed lag model for the effects of climatic changes on economic output using a quadratic lag distribution. See Supplementary Methods Section S3 for details of the transformation of lagged variables used to produce a quadratic distribution. 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.



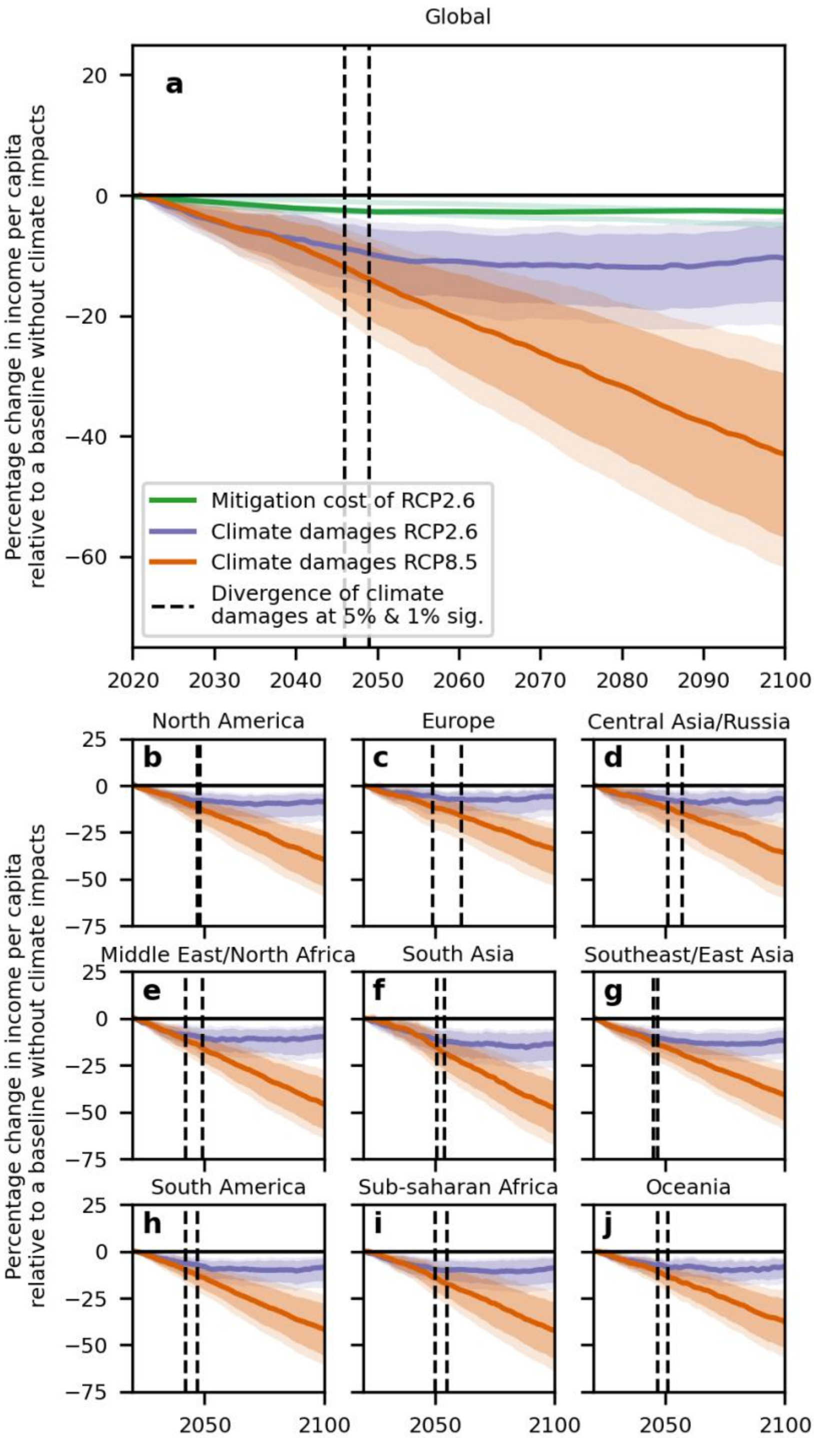
Supplementary Figure 9. Comparison of the cumulative marginal effects of climate variables on economic output when using a restricted and unrestricted distributed lag model. The cumulative marginal effects of annual mean temperature (a), daily temperature variability (b), total annual precipitation (c), 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.



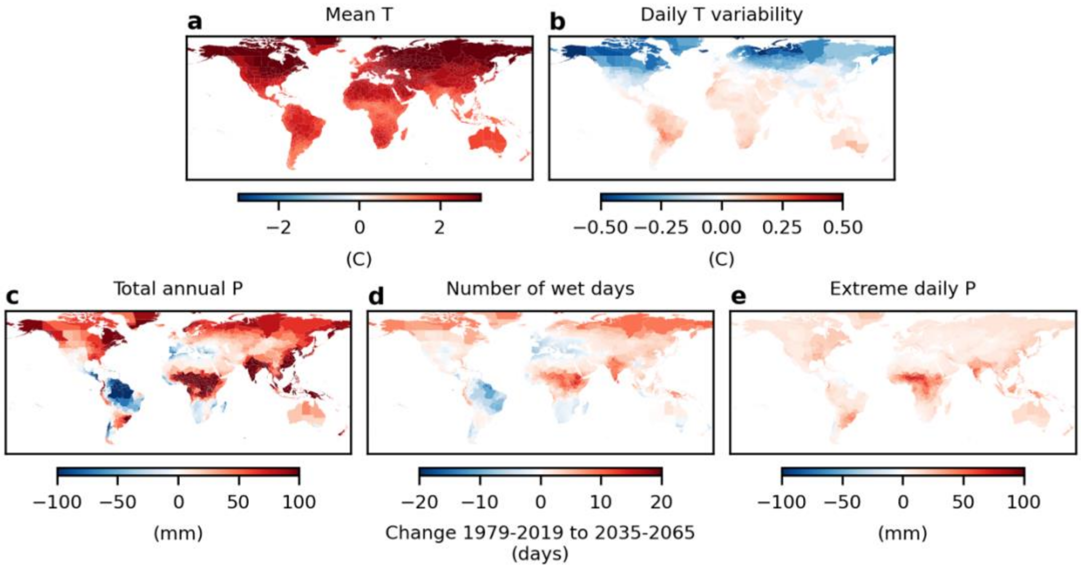
Supplementary Figure 10. Robustness test of the timescale with which changes in the moderating variable of the empirical models are estimated. As Figure 1 of the main manuscript but when evaluating changes in the moderating variables of the interaction terms in the empirical models based on 10-year averages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



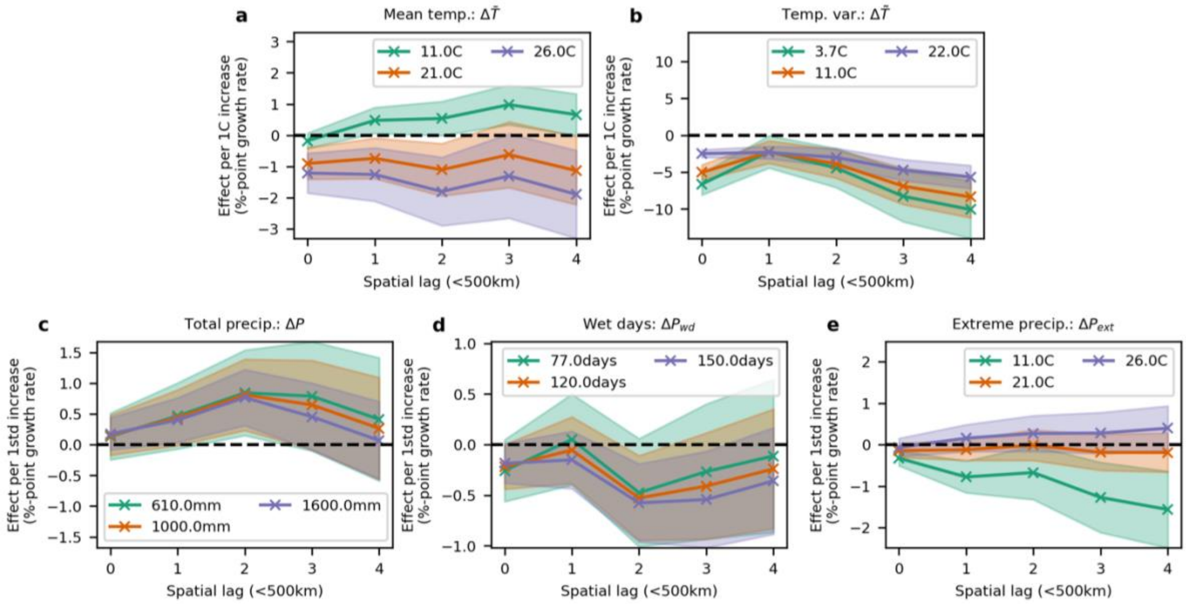
Supplementary Figure 11. Robustness test of the timescale with which changes in the moderating variable of the empirical models are estimated. As Figure 1 of the main manuscript but when evaluating changes in the moderating variables of the interaction terms in the empirical models based on 20-year averages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