

The economic commitment of climate change

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The economic commitment of climate change

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1 **Global projections of macroeconomic climate-change damages typically consider impacts**
2 **from average annual and national temperatures over long-time horizons. Here, we utilize**
3 **recent empirical findings from more than 1600 regions worldwide over the past 40 years**
4 **to project sub-national damages from temperature and precipitation including daily**
5 **variability and extremes. Using an empirical approach which provides a robust lower-**
6 **bound on the persistence of impacts on economic growth, we find that the world economy**
7 **is committed to an income reduction of 19% within the next 26 years due to historical**
8 **carbon emissions and socioeconomic inertia (relative to a baseline without climate**
9 **impacts, likely range of 11-29% accounting for physical climate and empirical**
10 **uncertainty). These damages already outweigh the mitigation costs required to limit**
11 **global warming to two degrees by sixfold over this near-term timeframe, and thereafter**
12 **diverge strongly dependent on emission choices. Committed damages arise**
13 **predominantly through changes in average temperature, but accounting for further**
14 **climatic components raises estimates by approximately fifty percent and leads to stronger**
15 **regional heterogeneity. Committed losses are projected for all regions except those at very**
16 **high latitudes, where reductions in temperature variability bring benefits. The largest**
17 **losses are committed at lower latitudes in regions with lower cumulative historical**
18 **emissions and lower present-day income.**

19 Projections of the macroeconomic damage caused by future climate change are crucial to
20 informing public and policy debates regarding adaptation, mitigation and climate justice. On
21 the one hand, adaptation against climate impacts must be justified and planned on the basis of
22 an understanding of their future magnitude and spatial distribution¹. This is also of importance
23 in the context of climate justice², as well as to key societal actors including governments,
24 central banks and private businesses which increasingly require the inclusion of climate risks
25 in their macroeconomic forecasts to aid adaptive decision making^{3,4}. On the other hand, climate
26 mitigation policy such as the Paris Climate Agreement is often evaluated by balancing the costs
27 of its implementation against the benefits of avoiding projected physical damages. This
28 evaluation occurs both formally via cost-benefit analyses⁵⁻⁸, as well as informally via public
29 perception of mitigation and damage costs⁹.

30 Projections of future damages meet challenges when informing these debates, in particular the
31 human biases relating to uncertainty and remoteness which are raised by long-term
32 perspectives¹⁰. Here we aim to overcome such challenges, by assessing the extent of economic
33 damages from climate change to which the world is already committed by historical emissions
34 and socioeconomic inertia (the range of future emission scenarios which are considered
35 socioeconomically plausible¹¹). Such a focus on the near-term limits the large uncertainties
36 regarding diverging future emission trajectories, the resulting long-term climate response, and
37 the validity of applying historically observed climate-economic relations over long timescales
38 during which socio-technical conditions may change considerably. As such, this focus aims to
39 simplify the communication and maximize the credibility of projected economic damages from
40 future climate change.

41 In projecting the future economic damages from climate change, we make use of recent
42 advances in climate econometrics which provide evidence for impacts on sub-national
43 economic growth from numerous components of the distribution of daily temperature and

44 precipitation¹²⁻¹⁴. Using fixed effects panel regression models to control for potential
45 confounders, these studies exploit within-region variation in local temperature and
46 precipitation in a panel of more than 1600 regions worldwide, comprising climate and income
47 data over the past 40 years to identify the plausibly causal effects of changes in several climate
48 variables on economic productivity^{15,16}. Specifically, macroeconomic impacts have been
49 identified from changing daily temperature variability, total annual precipitation, the annual
50 number of wet days and extreme daily rainfall which occur in addition to those already
51 identified from changing average temperature^{12,17,18}. Moreover, regional heterogeneity in these
52 effects based on the prevailing local climatic conditions has been found using interactions
53 terms. The selection of these climate variables follows micro-level evidence for mechanisms
54 related to the impacts of average temperatures on labor and agricultural productivity¹⁷, of
55 temperature variability on agricultural productivity and health¹³, as well as of precipitation on
56 agricultural, labor outcomes, and flood damages¹⁴ (see Table S1 for an overview including
57 more detailed references). Refs. ^{13,14} contain a more detailed motivation for the use of these
58 particular climate variables and provide extensive empirical tests regarding the robustness and
59 nature of their effects on economic output which are summarized in our methods section. By
60 accounting for these additional climatic variables at the sub-national level, we aim for a more
61 comprehensive description of climate impacts with greater detail across both time and space.

62 **A robust lower bound on the persistence of climate impacts on growth**

63 A key determinant and source of discrepancy in estimates of the magnitude of future climate
64 damages is the extent to which the impact of a climate variable on economic growth rates
65 persists. The two extreme cases in which these impacts persist indefinitely or only
66 instantaneously are commonly referred to as growth or level effects^{19,20} (see methods section
67 “Empirical specification – fixed-effects distributed lag model” for definitions). Recent work
68 shows that future damages from climate change depend strongly on whether growth or level

69 effects are assumed²⁰. Following refs. (^{17,18}), we provide constraints on this persistence by
70 using distributed lag models to test the significance of delayed effects separately for each
71 climate variable. Importantly and in contrast to refs (^{17,18}), we use climate variables in their
72 first-differenced form following ref. ¹², implying a dependence of the growth rate on a change
73 in climate variables. This choice means that a baseline specification without any lags
74 constitutes a model prior of purely level effects, in which a permanent change in the climate
75 has only an instantaneous effect on the growth rate^{12,19,21}. By including lags, one can then test
76 whether any effects may persist further. This is in contrast to the specification used by refs.
77 ^{17,18} in which climate variables are used without taking the first difference, implying a
78 dependence of the growth rate on the level of climate variables. In this alternative case, the
79 baseline specification without any lags constitutes a model prior of pure growth effects, in
80 which a change in climate has an infinitely persistent effect on the growth rate. Consequently,
81 including further lags in this alternative case tests whether the initial growth impact is
82 recovered^{18,19,21}. Both of these specifications suffer from the limiting possibility that if too few
83 lags are included, one might falsely accept the model prior. The limitations of including a very
84 large number of lags, including loss of data and increasing statistical uncertainty with an
85 increasing number of parameters, means that such a possibility is likely. By choosing a
86 specification in which the model prior is one of level effects, our approach is therefore
87 conservative by design, avoiding assumptions of infinite persistence of climate impacts on
88 growth and instead providing a lower-bound on this persistence based on what is observable
89 empirically (see methods section “Empirical specification – fixed-effects distributed lag
90 model” for further exposition of this framework). The conservative nature of such a choice is
91 likely the reason that ref. ¹⁹ finds much greater consistency between the impacts projected by
92 models which use the first difference of climate variables as opposed to their levels.

93 We begin our empirical analysis of the persistence of climate impacts on growth using ten lags
94 of the first-differenced climate variables in fixed-effects distributed lag models. We detect
95 significant effects on economic growth at time lags of up to approximately eight to ten years
96 for the temperature terms, and up to approximately four years for the precipitation terms
97 (Extended Data Figure 1, Table S2). Furthermore, evaluation by means of Information Criteria
98 indicates that the inclusion of all five climate variables and the use of these numbers of lags
99 provide a preferable trade-off between best-fitting the data and including additional terms
100 which could cause overfitting, in comparison to model specifications excluding climate
101 variables or including more or fewer lags (Supplementary Methods Section S1, Fig. S1 and
102 Table S3). We therefore remove insignificant terms at later lags (Figs. S2-4, Tables S4-6).
103 Further tests using Monte-Carlo simulations demonstrate that the empirical models are robust
104 to autocorrelation in the lagged climate variables (Supplementary Methods Section S2, Figs.
105 S5& S6), that Information Criteria provide an effective indicator for lag selection
106 (Supplementary Methods Section S2, Fig. S7), that the results are robust to concerns of
107 imperfect multi-collinearity between climate variables and that including several climate
108 variables is actually necessary to isolate their separate effects (Supplementary Methods Section
109 S3, Fig. S8). We provide a further robustness check using a restricted distributed lag model to
110 limit oscillations in the lagged parameter estimates which may result from autocorrelation,
111 finding that it provides similar estimates of cumulative marginal effects to the un-restricted
112 model (Supplementary Methods Section S4, Figs. S9 and S10). Finally, to explicitly account
113 for any outstanding uncertainty arising from the precise choice of the number of lags, we
114 include empirical models with marginally different numbers of lags in the error sampling
115 procedure of our projection of future damages. Based on the lag selection procedure (the
116 significance of lagged terms in Extended Data Figure 1 and Table S2, as well as Information
117 Criteria in Fig. S1), we sample from models with eight to ten lags for temperature and four for

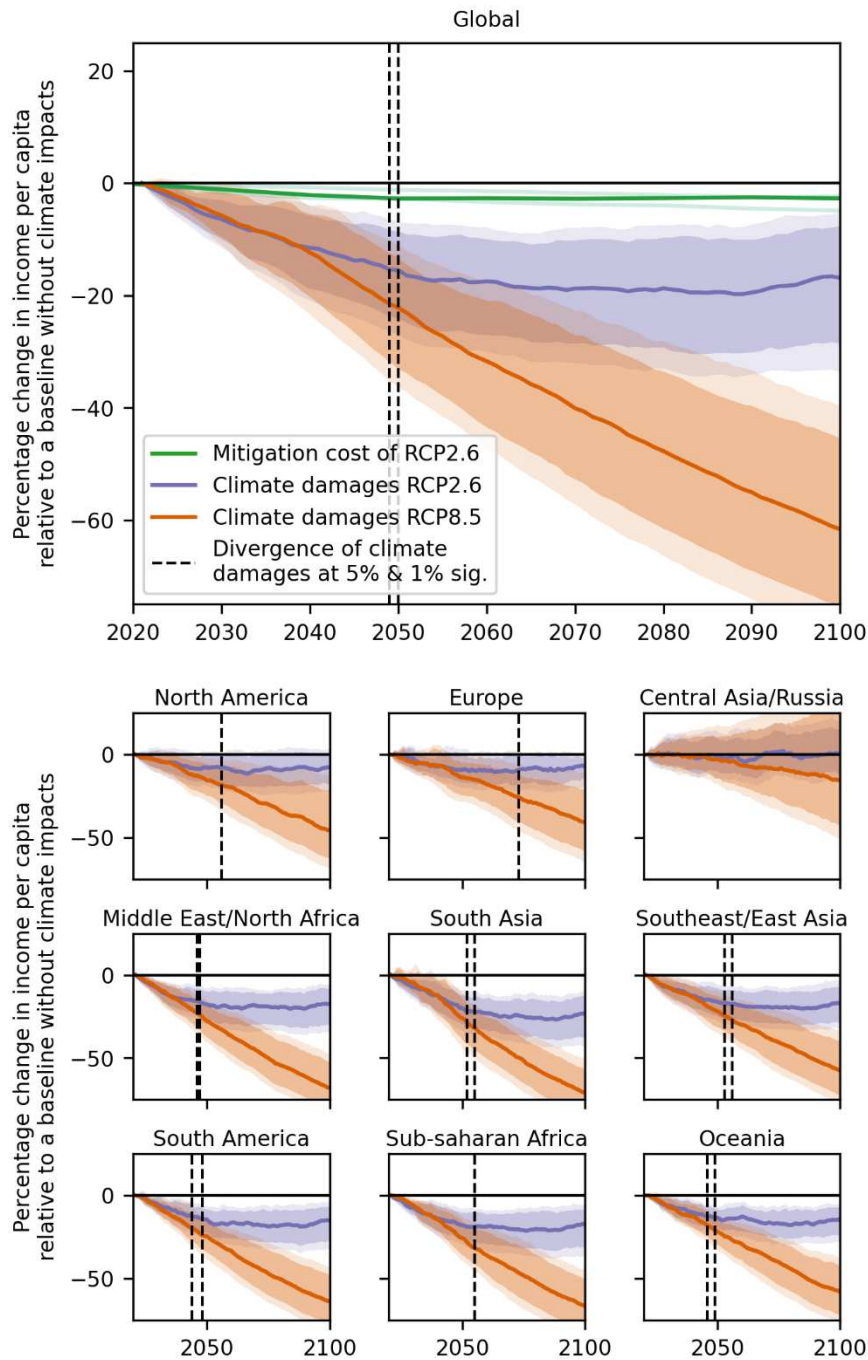
118 precipitation (models shown in Figs. S2-S4 and Tables S3-S5). In summary, this empirical
119 approach to constrain the persistence of climate impacts on economic growth rates is
120 conservative by design in avoiding assumptions of infinite persistence, but nevertheless
121 provides a lower bound on the extent of impact persistence which is robust to the numerous
122 tests outlined above.

123 **Economic damages until mid-century are committed and diverge thereafter**

124 We combine these empirical economic response functions (Figs. S2-S4 and Tables S3-5) with
125 an ensemble of twenty-one climate models (see Table S7) from the Coupled Model
126 Intercomparison Project phase-6 (CMIP-6)²² to project the macroeconomic damages from
127 these multiple components of physical climate change (see methods for further details). Bias-
128 adjusted climate models which provide a highly accurate reproduction of observed
129 climatological patterns with limited uncertainty (Table S8) are used to avoid introducing biases
130 in the projections. Following a well-developed literature^{12,17,19}, these projections do not aim to
131 provide a prediction of future economic growth. Instead, they are a projection of the exogenous
132 impact of future climate conditions on the economy relative to the baselines specified by
133 socioeconomic projections, based on the plausibly causal relationships inferred by the
134 empirical models, and assuming *ceteris paribus*. Other exogenous factors relevant for the
135 prediction of economic output are purposefully assumed constant.

136 A Monte-Carlo procedure which samples from climate model projections, empirical models
137 with different numbers of lags, and model parameter estimates (obtained by 1000 block-
138 bootstrap resamples of each of the regressions in Figs. S2-S4 and Tables S3-5) is used to
139 estimate the combined uncertainty from these multiple sources. Given these uncertainty
140 distributions, we find that projected global damages are statistically indistinguishable across
141 the two most extreme emission scenarios until 2049 (at the 5% significance level, Fig. 1). As
142 such, the climate damages occurring before this time constitute those to which the world is

143 already committed due to the combination of past emissions and the range of future emission
144 scenarios which are considered socioeconomically plausible¹¹. These committed damages
145 comprise a permanent income reduction of 19% on average globally (population weighted
146 average) in comparison to a baseline without climate change impacts (with a likely range of
147 11-29%, following the likelihood classification adopted by the Intergovernmental Panel on
148 Climate Change (IPCC), see caption of Fig. 1). Even though levels of income per capita
149 generally still increase relative to those today, this constitutes a permanent income reduction
150 for the majority of regions, including North America and Europe (each with median income
151 reductions of approximately 11%) and with South Asia and Africa being the most strongly
152 affected (each with median income reductions of approximately 22%; Fig. 1). Under a middle-
153 of-the road scenario of future income development (SSP2), this corresponds to global annual
154 damages in 2049 of 38 trillion in 2005 International Dollars (likely range of 19-59 trillion 2005
155 International Dollars). Compared to empirical specifications which assume pure growth or pure
156 level effects, our preferred specification which provides a robust lower-bound on the extent of
157 climate impact persistence produces damages between these two extreme assumptions
158 (Extended Data Fig. 2).



159

160

Figure 1. The commitment and divergence of economic climate damages vs mitigation

161

costs. Estimates of the projected reduction in income per capita from changes in all climate

162

variables based on empirical models of climate impacts on economic output with a robust

163

lower-bound on their persistence (Extended Data Fig. 1) under a low-emission scenario

164

compatible with the 2C warming target and a high-emission scenario (SSP2-RCP2.6 and

165

SSP5-RCP8.5 respectively) are shown in purple and orange respectively. Shading represents

166 the 17% and 10% confidence intervals reflecting the *likely* and *very likely* ranges respectively
167 (following the likelihood classification adopted by the Intergovernmental Panel on Climate
168 Change), having estimated uncertainty from a Monte-Carlo procedure which samples the
169 uncertainty from both the choice of physical climate models, empirical models with different
170 numbers of lags, and bootstrapped estimates of the regression parameters shown in Figs. S2-
171 S4. Vertical dashed lines show the time at which the climate damages of the two emission
172 scenarios diverge at the 5% and 1% significance level based on the distribution of differences
173 between emission scenarios arising from the uncertainty sampling discussed above. Note that
174 uncertainty in the *difference* of the two scenarios is smaller than the combined uncertainty of
175 the two respective scenarios because samples of the uncertainty (climate model and empirical
176 model choice as well as model parameter bootstrap) are consistent across the two emission
177 scenarios; hence the divergence of damages occurs while the uncertainty bounds of the two
178 separate damage scenarios still overlap. Estimates of global mitigation costs from the three
179 Integrated Assessment Models which provide results for the SSP2 baseline and SSP2-RCP2.6
180 scenario are shown in light green in the upper panel, with the median of these estimates
181 shown in bold.

182

183 **Committed damages outweigh the mitigation costs required to limit warming to 2C**
184 **before mid-century**

185 We compare the damages to which the world is committed over the next 26 years to estimates
186 of the mitigation costs required to achieve the Paris Climate Agreement. Taking estimates of
187 mitigation costs from the three Integrated Assessment Models (IAMs) in the IPCC AR6
188 database²³ which provide estimates under comparable scenarios (SSP2 baseline, and SSP2-
189 RCP2.6), we find that the median committed climate damages outweigh the median mitigation
190 costs in 2050 (six trillion in 2005 International dollars) approximately sixfold (note estimates
191 of mitigation costs are only provided every 10 years by the IAMs and so a comparison in 2049
192 is not possible). These results emphasise that climate damages strongly outweigh mitigation
193 costs already over the next 25 years, a perspective which may complement formal cost-benefit
194 analyses which find that the net benefits of mitigation only emerge after 2050⁷. While these
195 near-term damages constitute those to which the world is already committed, we note that
196 damage estimates diverge strongly across emission scenarios after 2049, conveying the clear
197 benefits of mitigation from a purely economic point of view which have been emphasised in
198 previous studies^{5,24}. In addition to the uncertainties assessed in Fig. 1, these conclusions are
199 robust to structural choices such as the timescale with which changes in the moderating
200 variables of the empirical models are estimated (Figs. S11 & S12), as well as the order in which
201 one accounts for the inter-temporal and inter-national components of currency comparison
202 (Fig. S13, see methods for further detail).

203 **Accounting for additional climatic components raises net damages**

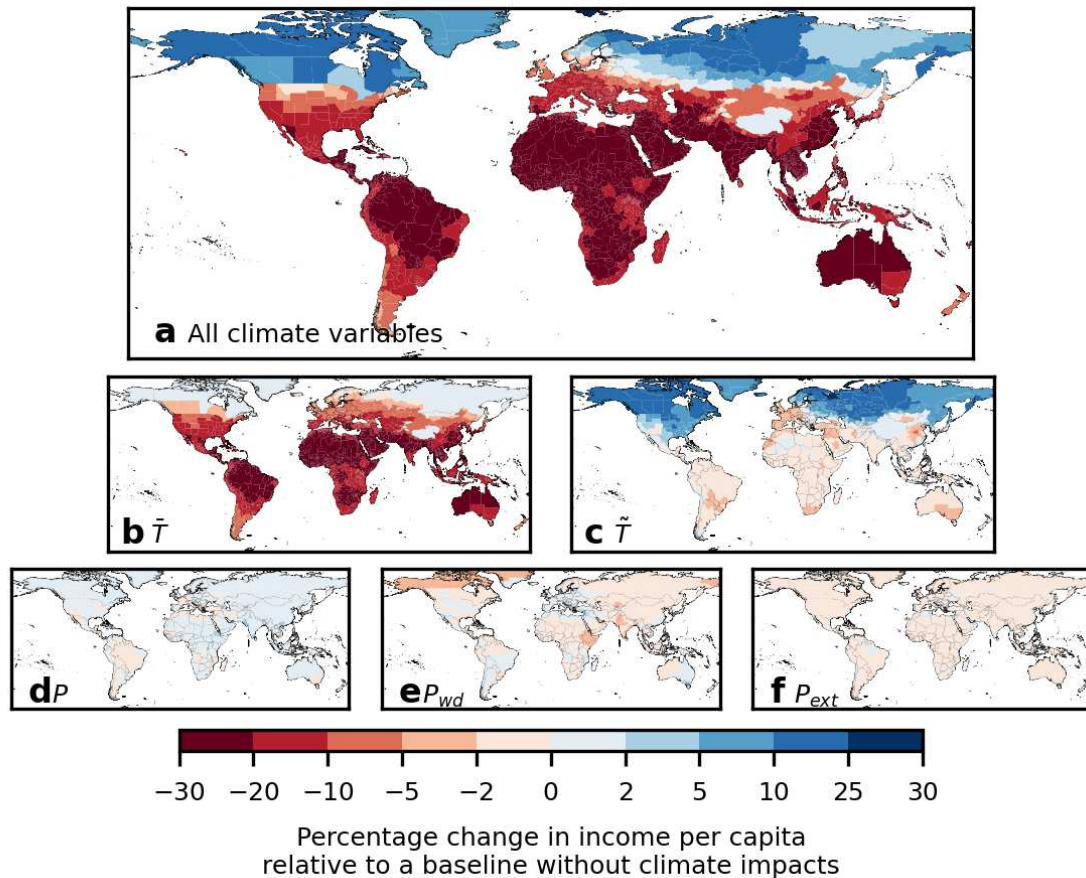
204 Committed damages primarily arise through changes in average temperature (Fig. 2). This
205 reflects the fact that projected changes in average temperature are larger than those in other
206 climate variables when expressed as a function of their historical interannual variability (Fig.
207 S14). Since the historical variability is that on which the empirical models are estimated, larger

208 projected changes in comparison to this variability are likely to lead to larger future impacts in
209 a purely statistical sense. From a mechanistic perspective, one may plausibly interpret this
210 result as implying that future changes in average temperature are the most unprecedented from
211 the perspective of the historical fluctuations to which the economy is accustomed, and therefore
212 will cause the most damage. This insight may prove useful in terms of guiding adaptation
213 measures to the sources of greatest damage.

214 Nevertheless, future damages based on empirical models which consider changes in annual
215 average temperature only and exclude the other climate variables constitute income reductions
216 of only 13% in 2049 (Fig. S16a, likely range 5-21%). This suggests that accounting for the
217 other components of the distribution of temperature and precipitation raises net damages by
218 nearly fifty percent. This increase arises through the additional damages which these climatic
219 components cause, but also because their inclusion reveals a stronger negative economic
220 response to average temperatures (Fig. S16b). The latter finding is consistent with our Monte-
221 Carlo simulations which suggest that the magnitude of the effect of average temperature on
222 economic growth is underestimated unless accounting for the impacts of other correlated
223 climate variables (Fig. S8).

224 In terms of the relative contributions of the different climatic components to overall damages,
225 we find that accounting for daily temperature variability causes the largest increase in overall
226 damages relative to empirical frameworks which only consider changes in annual average
227 temperature (4.9%-points, likely range 2.4-8.7%-points, equivalent to approximately 10 trillion
228 International Dollars). Accounting for precipitation causes smaller increases in overall
229 damages which are nevertheless equivalent to approximately 1.2 trillion International Dollars:
230 0.01%-points (-0.37-0.33%-points), 0.34%-points (0.07-0.90%-points) and 0.36%-points
231 (0.13-0.65%-points) from total annual precipitation, the number of wet days and extreme daily
232 precipitation respectively. Moreover, climate models appear to underestimate future changes

233 in temperature variability²⁵ and extreme precipitation^{26,27} in response to anthropogenic forcing
234 as compared to that observed historically, suggesting that the true impacts from these variables
235 may be larger.



236

237 **Figure 2. The committed economic damages of climate change by sub-national region**

238 **and climatic component.** Estimates of the median projected reduction in sub-national

239 income per capita across emission scenarios (SSP2-RCP2.6 and SSP2-RCP8.5) as well as

240 climate model, empirical model and model parameter uncertainty in the year at which climate

241 damages diverge at the 5% level (2049, as identified in Fig. 1). Panel (a) shows the impacts

242 arising from all climate variables, while panels (b-f) show the impacts arising separately from

243 changes in annual mean temperature, daily temperature variability, total annual precipitation,

244 the annual number of wet days (>1mm) and extreme daily rainfall respectively (see methods

245 for further definitions).

246

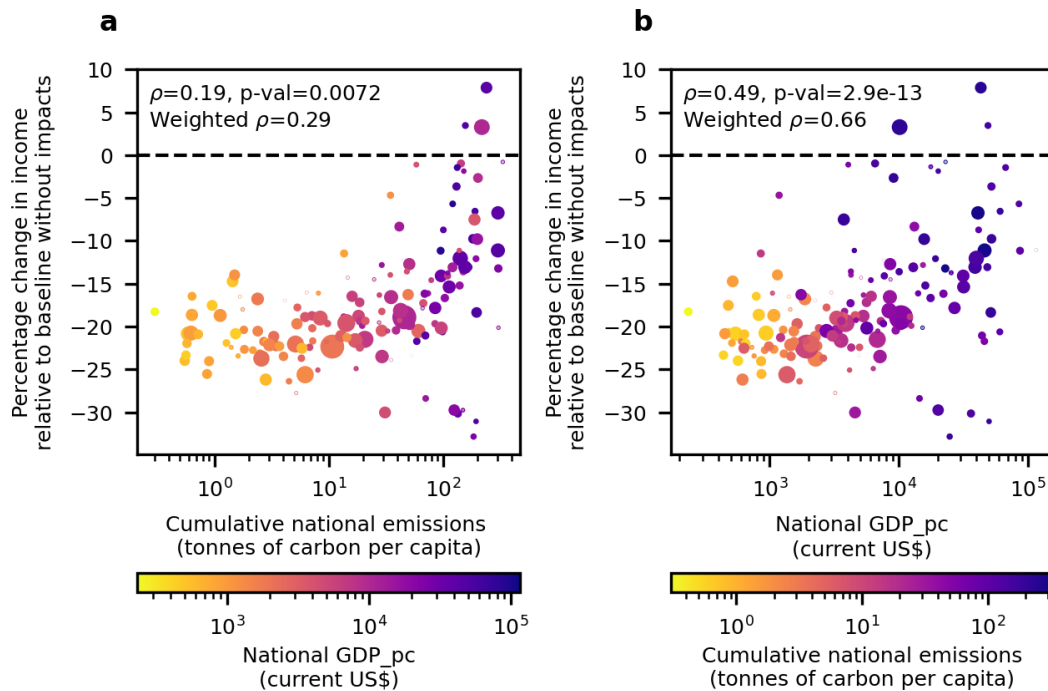
247 **Heterogeneity of committed economic climate damages**

248 The spatial distribution of committed damages (Fig. 2a) reflects a complex interplay between
249 the patterns of future change in multiple climatic components and those of historical economic
250 vulnerability to changes in those variables. Damages due to increasing annual mean
251 temperature (Fig. 2b) are negative almost everywhere globally, and larger at lower latitudes in
252 regions where temperatures are already higher and economic vulnerability to temperature
253 increases is greatest (see the response heterogeneity to mean temperature embodied in
254 Extended Data Fig. 1a). This occurs despite the amplified warming projected at higher
255 latitudes²⁸, suggesting that regional heterogeneity in economic vulnerability to temperature
256 changes outweighs heterogeneity in the magnitude of future warming (Fig. S15a). Economic
257 damages due to daily temperature variability (Fig. 2c) exhibit a strong latitudinal polarisation,
258 primarily reflecting the physical response of daily variability to greenhouse forcing in which
259 increases in variability across lower latitudes (and Europe) contrast decreases at high latitudes
260 (Fig S15b)²⁵. These two temperature terms are the predominant determinants of the pattern of
261 overall damages (Fig. 2a), which exhibits a strong polarity with damages across most of the
262 globe except at the highest northern latitudes. Future changes in total annual precipitation
263 mainly bring economic benefits except in regions of drying such as the Mediterranean and
264 central South America (Fig. 2d, Fig. S15c), but these benefits are opposed by changes in the
265 number of wet days, which produce damages with a similar pattern of opposite sign (Fig. 2e,
266 Fig. S15d). By contrast, changes in extreme daily rainfall produce damages in all regions,
267 reflecting the intensification of daily rainfall extremes over global land areas^{29,30} (Fig. 2f, Fig.
268 S15e).

269 The spatial distribution of committed damages implies considerable injustice along two
270 dimensions: culpability for the historical emissions which have caused climate change, and
271 pre-existing levels of socio-economic welfare. Spearman's rank correlations indicate that

272 committed damages are significantly larger in countries with smaller historical cumulative
273 emissions, as well as in regions with lower current income per capita (Fig. 3). This implies that
274 those countries which will suffer the most from the damages which are already committed are
275 those which are least responsible for climate change, and which also have the least resources
276 to adapt to it.

277 To further quantify this heterogeneity, we assess the difference in committed damages between
278 the upper and lower quartiles of regions when ranked by present income levels and historical
279 cumulative emissions (using a population weighting to both define the quartiles and estimate
280 the group averages). On average, the quartile of countries with lower income are committed to
281 an income loss which is 8.9 percentage-points (or 61%) greater than the upper quartile (Fig.
282 S17), with a likely range of 3.8-14.7 percentage-points across the uncertainty sampling of our
283 damage projections (following the likelihood classification adopted by the IPCC). Similarly,
284 the quartile of countries with lower historical cumulative emissions are committed to an income
285 loss which is 6.9 percentage-points (or 40%) greater than the upper quartile, with a likely range
286 of 0.27-12 percentage-points. These patterns re-emphasise the prevalence of injustice in
287 climate impacts³¹⁻³³ in the context of the damages to which the world is already committed by
288 historical emissions and socio-economic inertia.



289

290 **Figure 3. The injustice of committed climate damages by cumulative historical**

291 **emissions and income.** Estimates of the median projected change in national income per
 292 capita across emission scenarios (RCP2.6 and RCP8.5) as well as climate model, empirical
 293 model and model parameter uncertainty in the year at which climate damages diverge at the
 294 5% level (2049, as identified in Fig. 1), are plotted against national cumulative emissions per
 295 capita in 2020 (from the Global Carbon Project) and coloured by national income per capita
 296 in 2020 (from the World Bank) in panel (a), and vice versa in panel (b). In each panel, the
 297 size of each scatter point is weighted by the national population in 2020 (from the World
 298 Bank). Inset figures indicate the Spearman's rank correlation, ρ , and p-values for a
 299 hypothesis test whose null hypothesis is of no correlation, as well as the Spearman's rank
 300 correlation weighted by national population.

301

302 **Discussion**

303 The magnitude of projected economic damages exceeds previous literature estimates^{12,17},
304 arising from a number of developments made upon previous approaches. Our estimates are
305 larger than those of ref.¹⁷ (see first row of Extended Data Table 1) primarily due to the facts
306 that sub-national estimates typically show a steeper temperature response (see also refs.^{12,34})
307 and that accounting for other climatic components raises damage estimates (Fig. S16).
308 However, we note that our empirical approach using first-differenced climate variables is
309 conservative compared to that of ref.¹⁷ with regards to the persistence of climate impacts on
310 growth (see introduction and methods section “Empirical specification – fixed-effects
311 distributed lag model”), an important determinant of the magnitude of long-term damages^{19,21}.
312 Using a similar empirical specification to ref.¹⁷ which assumes infinite persistence while
313 maintaining the rest of our approach (sub-national data and additional climate variables),
314 produces considerably larger damages (purple curve of Extended Data Fig. 2). Compared to
315 studies which do take the first-difference of climate variables^{12,35}, our estimates are also larger
316 (see second and third rows of Extended Data Table 1). The inclusion of additional climate
317 variables (Fig. S16) and a sufficient number lags to more adequately capture the extent of
318 impact persistence (Extended Data Fig. 1) are major sources of this difference, as is the use of
319 specifications which capture non-linearities in the temperature response when compared to ref.
320³⁵. In summary, our estimates develop upon previous studies by incorporating the latest data
321 and empirical insights^{13,14}, as well as in providing a robust empirical lower-bound on the
322 persistence of impacts on economic growth, which constitutes a middle ground between the
323 extremes of the growth-vs-levels debate^{19,21} (Extended Data Fig. 2).

324

325 Compared to the fraction of variance explained by the empirical models historically (<5%), the
326 projection of reductions in income of 19% may appear large. This arises due to the fact that

327 projected changes in climatic conditions are much larger than those which were experienced
328 historically, particularly for changes in average temperature (Fig. S14). As such, any
329 assessment of future climate change impacts necessarily requires an extrapolation outside of
330 the range of the historical data on which the empirical impact models were evaluated.
331 Nevertheless, these models constitute the most state-of-the-art methods for inference of
332 plausibly causal climate impacts based on observed data. Moreover, we take explicit steps to
333 limit out-of-sample extrapolation by capping the moderating variables of the interaction terms
334 at the 95th percentile of the historical distribution (see methods). This avoids extrapolating the
335 marginal effects outside of what was observed historically. Given the non-linear response of
336 economic output to annual mean temperature (Extended Data. Fig.1, Table S2), this is a
337 conservative choice which limits the magnitude of damages which we project.

338

339 Despite assessing multiple climatic components from which economic impacts have recently
340 been identified¹²⁻¹⁴, this assessment of aggregate climate damages should not be considered
341 comprehensive. Important channels such as impacts from heatwaves³¹, sea-level rise³⁶, tropical
342 cyclones³⁷ and tipping points^{38,39}, as well as non-market damages such as those to ecosystems⁴⁰
343 and human health⁴¹ are not considered in these estimates. Sea-level rise is unlikely to be
344 feasibly incorporated into empirical assessments such as this since historical sea level
345 variability is mostly insignificant. Non-market damages are inherently intractable within our
346 estimates of impacts on aggregate monetary output and estimates of these impacts could
347 arguably be considered as additional to those identified here. Recent empirical work suggests
348 that accounting for these channels would likely raise estimates of these committed damages
349 with larger damages continuing to arise in the global south^{31,36-41}.

350

351 We find that the economic damages due to climate change until 2049 are those to which the
352 world economy is already committed, and that these greatly outweigh the costs required to
353 mitigate emissions in line with the 2C target of the Paris Climate Agreement (Fig. 1). For
354 simplicity and due to the availability of data, we compare damages to mitigation costs at the
355 global level. Regional estimates of mitigation costs may shed further light on the national
356 incentives for mitigation to which our results already hint, of relevance for international climate
357 policy. While these damages are committed from a mitigation perspective, adaptation may
358 provide an opportunity to reduce them. Moreover, the strong divergence of damages after mid-
359 century reemphasises the clear benefits of mitigation from a purely economic perspective as
360 emphasised in previous studies^{5,6,8,24}.

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446 **Methods**

447 **Historical climate data**

448 Historical daily 2-m temperature and precipitation totals (in mm) are obtained for the period
449 1979-2019 from the W5E5 database. W5E5 stems from ERA-5, a state-of-the-art reanalysis of
450 historical observations, but has been bias-adjusted by applying version 2.0 of the WATCH
451 Forcing Data to ERA-5 reanalysis data, and precipitation data from version 2.3 of the Global
452 Precipitation Climatology Project to better reflect ground-based measurements⁴²⁻⁴⁴. We obtain
453 this data on a 0.5-by-0.5-degree grid from the Inter-Sectoral Impact Model Intercomparison
454 Project (ISIMIP) database. Importantly, this historical data has been used to bias-adjust future
455 climate projections from CMIP-6 (see the following section), ensuring consistency between
456 the distribution of historical daily weather on which our empirical models were estimated, and
457 the climate projections used to estimate future damages. These data are publicly available from
458 the ISIMIP database. See refs. ^{13,14} for robustness tests of the empirical models to the choice of
459 climate data reanalysis products.

460 **Future climate data**

461 Daily 2-m temperature and precipitation totals (in mm) are taken from 21 climate models
462 participating
463 in CMIP-6 under a high (RCP8.5) and a low (RCP2.6) greenhouse gas emission scenario
464 from 2015-2100. The data have been bias-adjusted and statistically downscaled to a common
465 half-degree grid to reflect the historical distribution of daily temperature and precipitation of
466 the W5E5 dataset using the trend-preserving method developed by ISIMIP^{43,45}. As such, the
467 climate model data reproduces observed climatological patterns exceptionally well (Table
468 S8). Gridded data are publicly available from the ISIMIP database.

469 **Historical economic data**

470 Historical economic data stem from the DOSE database of sub-national economic output⁴⁶. We
471 use a recent update to DOSE which provides data across 83 countries, 1660 sub-national
472 regions with varying temporal coverage from 1960-2019. Sub-national units constitute the first
473 administrative division below national, e.g., states for the USA and provinces for China. Data
474 stem from measures of gross-regional product per capita (GRPpc) or income per-capita in local
475 currencies, reflecting the values reported in national statistical agencies, yearbooks and, in
476 some cases, academic literature. We follow previous literature^{12-14,47} and assess real sub-
477 national output per capita by first converting values from local currencies to US dollars to
478 account for diverging national inflationary tendencies, and then account for US inflation using
479 a US deflator. Alternatively, one might first account for national inflation and then convert
480 between currencies. Fig. S13 demonstrates that our conclusions are consistent when accounting
481 for price changes in the reversed order, although the magnitude of estimated damages varies.
482 See the documentation of DOSE for further discussion of these choices. Conversions between
483 currencies are conducted using exchange rates from the FRED database of the Federal Reserve
484 Bank of St Louis⁴⁸ and the national deflators from the World Bank⁴⁹.

485 **Future socioeconomic data**

486 Baseline gridded GDP and population data for the period 2015-2100 are taken from the middle-
487 of-the-road Shared Socioeconomic Pathway scenario SSP2¹¹. Population data have been
488 downscaled to a half-degree grid by ISIMIP following the methodologies of refs.^{50,51}, which
489 we then aggregate to the sub-national level of our economic data using the spatial aggregation
490 procedure described below. Since current methodologies for downscaling GDP of the SSPs use
491 downscaled population to do so, per capita estimates of GDP with a realistic distribution at the
492 sub-national level are not readily available for the SSPs. We therefore use national-level GDP
493 per capita projections for all sub-national regions of a given country, assuming homogeneity
494 within countries in terms of baseline GDP per-capita. Here, we use projections which have

495 been updated to account for the impact of the Covid-19 pandemic on the trajectory of future
496 income, while remaining consistent with the long-term development of the SSPs⁵². The choice
497 of baseline SSP alters the magnitude of projected climate damages in monetary terms, but when
498 assessed in terms of percentage change from the baseline, the choice of socioeconomic scenario
499 is inconsequential. Gridded SSP population data and national level GDP per capita data are
500 publicly available from the ISIMIP database. Sub-national estimates as used in this study are
501 available in the code and data replication files.

502 **Climate variables**

503 Following recent literature¹²⁻¹⁴ we calculate an array of climate variables for which significant
504 impacts on macro-economic output have been identified empirically, supported by further
505 evidence at the micro-level for plausible underlying mechanisms. Please see refs. ^{13,14} for an
506 extensive motivation for the use of these particular climate variables and for detailed empirical
507 tests regarding the nature and robustness of their effects on economic output. To summarize,
508 these studies have found evidence for independent impacts on economic growth rates from
509 annual average temperature, daily temperature variability, total annual precipitation, the annual
510 number of wet days and extreme daily rainfall. Assessments of daily temperature variability
511 were motivated by evidence of impacts on agricultural output and human health, as well as
512 macroeconomic literature on the impacts of volatility on growth when manifest in different
513 dimensions such as government spending, exchange rates and even output itself¹³. Assessments
514 of precipitation impacts were motivated by evidence of impacts on agricultural productivity,
515 metropolitan labor outcomes and conflict, as well as damages caused by flash flooding¹⁴. See
516 Table S1 for detailed references to empirical studies of these physical mechanisms. Significant
517 impacts of daily temperature variability, total annual precipitation, the number of wet days and
518 extreme daily rainfall on macroeconomic output were identified robustly across different
519 climate data-sets, spatial aggregation schemes, specifications of regional time-trends, and

520 error-clustering approaches. They were also found to be robust to the consideration of
 521 temperature extremes^{13,14}. Furthermore, these climate variables were identified as having
 522 independent effects on economic output^{13,14}, which we further elucidate here using Monte-
 523 Carlo simulations to demonstrate the robustness of the results to concerns of imperfect multi-
 524 collinearity between climate variables (Supplementary Methods Section S2), as well as by
 525 using Information Criteria (Table S3) to demonstrate that including several lagged climate
 526 variables provides a preferable trade-off between optimally describing the data and limiting the
 527 possibility of overfitting.

528 We calculate these variables from the distribution of daily, d , temperature, $T_{x,d}$, and
 529 precipitation, $P_{x,d}$, at the grid-cell, x , level for both the historical and future climate data. In
 530 addition to annual mean temperature, $\bar{T}_{x,y}$, and annual total precipitation, $P_{x,y}$, we calculate
 531 annual, y , measures of daily temperature variability, $\tilde{T}_{x,y}$:

$$532 \quad \tilde{T}_{x,y} = \frac{1}{12} \sum_{m=1}^{12} \sqrt{\frac{1}{D_m} \sum_{d=1}^{D_m} (T_{x,d,m,y} - \bar{T}_{x,m})^2}, \quad (1)$$

533 the number of wet days, $Pwd_{x,y}$:

$$534 \quad Pwd_{x,y} = \sum_{d=1}^{D_y} H(P_{x,d} - 1mm), \quad (2)$$

535 and extreme daily rainfall:

$$536 \quad Pext_{x,y} = \sum_{d=1}^{D_y} H(P_{x,d} - P99.9_x) \cdot P_{x,d}, \quad (3)$$

537 where $T_{x,d,m,y}$ is the grid-cell specific daily temperature in month m and year y , $\bar{T}_{x,m,y}$ is the
 538 year and grid-cell specific monthly, m , mean temperature, H the Heaviside step function, 1mm
 539 the threshold used to define wet days, and $P99.9_x$, the 99.9th percentile of historical (1979-
 540 2019) daily precipitation at the grid-cell level. Units of the climate measures are degrees
 541 Celsius for annual mean temperature and daily temperature variability, millimeters for total
 542 annual precipitation and extreme daily precipitation, and simply the number of days for the
 543 annual number of wet days.

544 We additionally calculated weighted standard deviations of monthly rainfall totals as also used
545 in ref. ¹⁴, but do not include them in our projections as we find that when accounting for delayed
546 effects their effect becomes statistically indistinct and is better captured by changes in total
547 annual rainfall.

548 **Spatial aggregation**

549 We aggregate grid-cell level historical and future climate measures, as well as grid-cell level
550 future GDPpc and population, to the level of the first administrative unit below national level
551 of the GADM database using an area-weighting algorithm which estimates the portion of each
552 grid-cell falling within an administrative boundary. We use this as our base-line specification
553 following previous findings that the effect of area or population weighting at the sub-national
554 level is negligible^{13,14}.

555 **Empirical model specification – fixed-effects distributed lag models**

556 Following a wide-range of climate econometric literature^{15,53}, we use panel regression models
557 with a selection of fixed-effects and time-trends to isolate plausibly exogenous variation with
558 which to maximise confidence in a causal interpretation of the effects of climate on economic
559 growth rates. The use of region fixed effects, μ_r , accounts for unobserved time-invariant
560 differences between regions such as prevailing climatic norms and growth rates due to
561 historical and geo-political factors. The use of yearly fixed effects, η_y , accounts for regionally
562 invariant annual shocks to the global climate or economy such as the El-Nino Southern
563 Oscillation or global recessions. In our base-line specification we also include region-specific
564 linear time trends, $k_r y$, to exclude the possibility of spurious correlations due to common slow-
565 moving trends in climate and growth.

566 The persistence of climate impacts on economic growth rates is a key determinant of the long-
567 term magnitude of damages. Methods for inferring the extent of persistence in impacts on
568 growth rates have typically used lagged climate variables to evaluate the presence of delayed

569 effects or catch up dynamics^{17,18}. For example, consider starting from a model in which a
 570 climate condition, $C_{r,y}$, (e.g. annual mean temperature) impacts the growth rate, $\Delta lgrp_{r,y}$ (the
 571 first difference of the logarithm of gross-regional product) of region r in year y :

$$572 \Delta lgrp_{r,y} = \mu_r + \eta_y + k_r y + \alpha C_{r,y} + \varepsilon_{r,y}, \quad (4)$$

573 which we refer to as a “pure growth-effects” model in the main text. Typically, additional lags
 574 are included,

$$575 \Delta lgrp_{r,y} = \mu_r + \eta_y + k_r y + \sum_{L=0}^{NL} \alpha_L C_{r,y-L} + \varepsilon_{r,y}, \quad (5)$$

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

$$578 \sum_{L=0}^{NL} \alpha_L < 0 \text{ for } \alpha_0 < 0; \text{ or } \sum_{L=0}^{NL} \alpha_L > 0 \text{ for } \alpha_0 > 0 \quad (6)$$

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

$$581 \sum_{L=0}^{NL} \alpha_L = 0, \quad (7)$$

582 then the initial impact on the growth rate is recovered after NL years and the effect is only one
 583 on the level of output. However, we note that such approaches are limited by the fact that when
 584 including an insufficient number of lags to detect a recovery of the growth rates, one may find
 585 equation (6) to be satisfied and incorrectly assume that a change in climatic conditions impacts
 586 the growth rate indefinitely. In practice, given a limited record of historical data, including too
 587 few lags to confidently conclude in an infinitely persistent impact on the growth rate is likely,
 588 particularly not over the long-timescales over which future climate damages are often
 589 projected^{17,24}. To avoid this issue, we instead begin our analysis with a model in which the

590 level of output, $lgrp_{r,y}$, depends on the level of a climate variable, $C_{r,y}$:

$$591 lgrp_{r,y} = \mu_r + \eta_y + k_r y + \alpha C_{r,y} + \varepsilon_{r,y}. \quad (8)$$

592 Given the non-stationarity of the level of output, we follow the literature¹⁹ and estimate such
 593 an equation in first-differenced form as,

594 $\Delta lgrpr_{r,y} = \mu_r + \eta_y + k_r y + \alpha \Delta C_{r,y} + \varepsilon_{r,y}$. (8)

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

599 $\Delta lgrpr_{r,y} = \mu_r + \eta_y + k_r y + \sum_{L=0}^{NL} \alpha_L \Delta C_{r,y-L} + \varepsilon_{r,y}$, (9)

600 we are able to test whether the impacts on the growth rate persist any further than
601 instantaneously by evaluating whether $\alpha_{L>0}$ are statistically significantly different from zero.
602 Even though this framework is also limited by the possibility of including too few lags, the
603 choice of a baseline model specification in which impacts on the growth rate do not persist
604 means that in the case of including too few lags, the framework reverts to the baseline
605 specification of level-effects. As such, this framework is conservative with respect to the
606 persistence of impacts and the magnitude of future damages. It naturally avoids assumptions
607 of infinite persistence and we are able to interpret any persistence which we do identify with
608 equation (9) as a lower-bound on the extent of climate impact persistence on growth rates. See
609 the main text for further discussion of this specification choice, in particular regarding its
610 conservative nature compared to previous literature estimates such as refs. ^{17,18}.

611 We allow the response to climatic changes to vary across regions, using interactions of the
612 climate variables with historical average (1979-2019) climatic conditions reflecting
613 heterogenous effects identified in previous work ^{13,14}. Following this previous work, the
614 moderating variables of these interaction terms constitute the historical average of either the
615 variable itself or of the seasonal temperature difference, \hat{T}_r , or annual mean temperature, \bar{T}_r , in
616 the case of daily temperature variability ¹³ and extreme daily rainfall, respectively ¹⁴.

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

$$\begin{aligned}
618 \quad \Delta lgrp_{r,y} &= \mu_r + \eta_y + k_r y + \sum_{L=0}^N (\alpha_{1,L} \Delta \bar{T}_{r,y-L} + \alpha_{2,L} \Delta \bar{T}_{r,y-L} \cdot \bar{T}_r) + \\
619 \quad &\sum_{L=0}^N (\alpha_{3,L} \Delta \tilde{T}_{r,y-L} + \alpha_{4,L} \Delta \tilde{T}_{r,y-L} \cdot \hat{T}_r) + \sum_{L=0}^M (\alpha_{5,L} \Delta P_{r,y-L} + \alpha_{6,L} \Delta P_{r,y-L} \cdot P_r) + \\
620 \quad &\sum_{L=0}^M (\alpha_{7,L} \Delta Pwd_{r,y-L} + \alpha_{8,L} \Delta Pwd_{r,y-L} \cdot Pwd_r) + \\
621 \quad &\sum_{L=0}^M (\alpha_{9,L} \Delta Pext_{r,y-L} + \alpha_{10,L} \Delta Pext_{r,y-L} \cdot \bar{T}_r) + \epsilon_{r,y} \tag{10}
\end{aligned}$$

622 where $\Delta lgrp_{r,y}$ is the annual, regional GRPpc growth rate, measured as the first difference of
623 the logarithm of real GRPpc, following previous work^{12-14,17-19}.

624 Estimates of the coefficients of interest $\alpha_{i,L}$ are shown in Extended Data Fig. 1 for N=M=10
625 lags and for our preferred choice of the number of lags in Figs. S2-S4. In Extended Data Fig.
626 1 errors are shown clustered at the regional level, but for the construction of damage projections
627 we block-bootstrap the regressions by region 1000 times to provide a range of parameter
628 estimates with which to sample the projection uncertainty (following refs. ^{17,31}).

629 **Constructing projections of economic damage from future climate change**

630 We construct projections of future climate damages by applying the coefficients estimated in
631 equation (10) and shown in Tables S3-5 (when including only lags with significant effects in
632 specifications which limit overfitting, see Supplementary Methods Section S1) to projections
633 of future climate change from the CMIP-6 models. Year-on-year changes in each primary
634 climate variable of interest are calculated to reflect the year-to-year variations used in the
635 empirical models. 30-year moving averages of the moderating variables of the interaction terms
636 are calculated to reflect the long-term average of climatic conditions which were used for the
637 moderating variables in the empirical models. By using moving averages in the projections, we
638 account for the changing vulnerability to climate shocks based on the evolving long-term
639 conditions (Figs. S11 & S12 show that the results are robust to the precise choice of the window
640 of this moving average). While these climate variables are not differenced, the fact that the
641 bias-adjusted climate models reproduce observed climatological patterns across regions for
642 these moderating variables very accurately (Table S8) with limited spread across models (<3%)

643 precludes the possibility that any considerable bias or uncertainty is introduced by this
644 methodological choice. However, we impose caps on these moderating variables at the 95th
645 percentile at which they were observed in the historical data, in order to prevent extrapolation
646 of the marginal effects outside of the range in which the regressions were estimated. This is a
647 conservative choice which limits the magnitude of our damage projections.

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

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

$$662 \quad GRPpc_{r,Y} = GRPpc_{r,2020} \sum_{y=2020}^Y \rho_{r,y} = GRPpc_{r,2020} \sum_{y=2020}^Y (1 + \pi_{r,y} + \delta_{r,y})$$

663 (11)

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

668 For each emission scenario, this procedure is repeated 1000 times while randomly sampling
669 from the selection of climate models, the selection of empirical models with different numbers
670 of lags (shown in Figs. S2-S4 and Table S4-S6), and bootstrapped estimates of the regression
671 parameters. The result is an ensemble of future GRPpc trajectories which reflect uncertainty
672 from both physical climate change and the structural and sampling uncertainty of the empirical
673 models.

674 **Estimates of mitigation costs**

675 We obtain IPCC estimates of the aggregate costs of emission mitigation from the AR6 Scenario
676 Explorer and Database hosted by IIASA²³. Specifically, we search the AR6 Scenarios Database
677 World v1.1 for Integrated Assessment Models (IAMs) which provided estimates of global GDP
678 and population under both an SSP2 baseline and SSP2-RCP2.6 scenario in order to maintain
679 consistency with the socio-economic and emission scenarios of the climate damage projections.
680 We find five IAMs which provide data for these scenarios, namely MESSAGE-GLOBIOM
681 1.0, REMIND-MAgPIE 1.5, AIM/GCE 2.0, GCAM 4.2, and WITCH-GLOBIOM 3.1. Of these
682 five, we use results only from the first three which passed the IPCC vetting procedure for
683 reproducing historical emission and climate trajectories. We then estimate global mitigation
684 costs as the percentage difference in global per capita GDP between the SSP2 baseline and the
685 SSP2-RCP2.6 emission scenario. In the case of one of these IAMs, estimates of mitigation
686 costs begin in 2020 while in the case of two others mitigation costs begin in 2010. The
687 mitigation cost estimates prior to 2020 in these two IAMs are mostly negligible, and our choice
688 to begin comparison to damage estimates in 2020 is conservative with respect to the relative
689 weight of climate damages compared to mitigation costs for these two IAMs.

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716

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719 **Author contributions**

720 All authors contributed to the design of the analysis. MK conducted the analysis and
721 produced the figures. All authors contributed to the interpretation and presentation of the
722 results. MK and LW wrote the manuscript.

723 **Competing interest declaration**

724 We have no competing interests to declare.

725 **Additional information**

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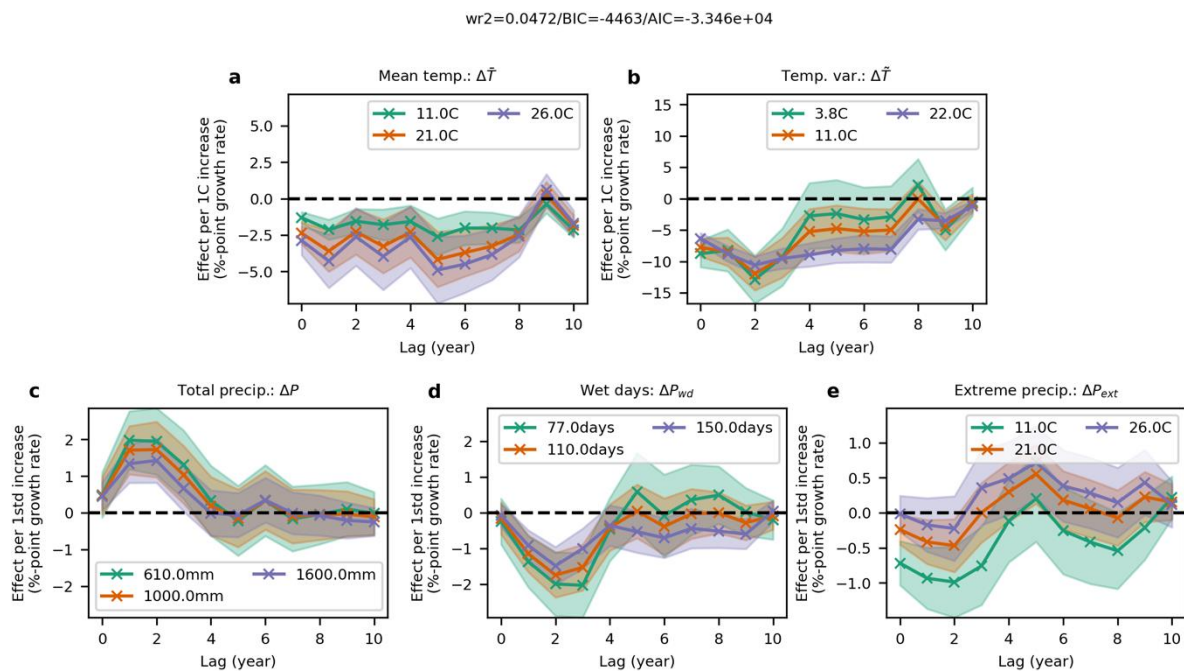
727 **Data availability**

728 Data on economic production and ERA-5 climate data are both publicly available at
729 <http://doi.org/10.5281/zenodo.4681306>, and
730 <https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5> respectively. Data on
731 mitigation costs are publicly available at <https://data.ene.iiasa.ac.at/ar6/#/downloads>. All
732 secondary data will be made available at a public repository upon publication.

733 **Code availability**

734 Code used for the analysis will be made available at a public repository upon publication.

735



737

738 **Extended Data Figure 1. Constraining the persistence of historical climate impacts on**739 **economic growth rates.** The results of a panel fixed effects distributed lag model for the

740 effects of annual mean temperature (a), daily temperature variability (b), total annual

741 precipitation (c), the number of wet days (d) and extreme daily precipitation (e) on sub-

742 national economic growth rates. Point estimates show the effects of a one degree Celsius or

743 one standard deviation increase (for temperature and precipitation variables respectively) at

744 the lower quartile, median and upper quartile of the relevant moderating variable (green,

745 orange, purple, respectively) at different lagged periods after the initial shock (note that these

746 are not cumulative effects). Climate variables are used in their first-differenced form (see

747 main text for discussion), and the moderating climate variables are the annual mean

748 temperature, seasonal temperature difference, total annual precipitation, number of wet days,

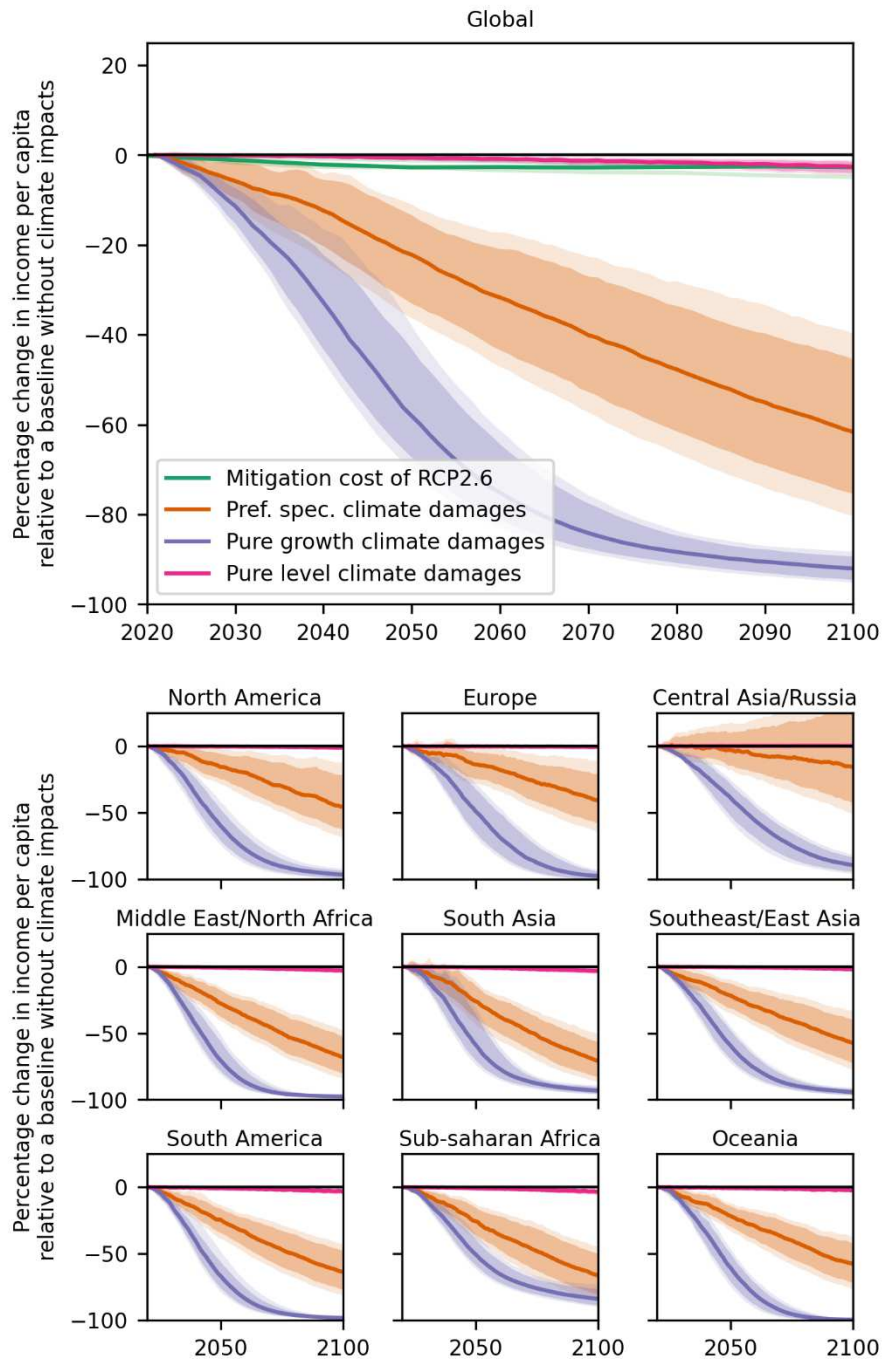
749 and annual mean temperature respectively in panels (a-e) (see methods for further

750 discussion). Error bars show the 95% confidence intervals having clustered standard errors by

751 region. The within-region R-squared, Bayesian and Akaike Information criteria for the model

752 are shown at the top of the figure. This figure shows results with ten lags for each variable to
753 demonstrate the observed levels of persistence, but our preferred specifications remove later
754 lags based on the significance of terms shown above and the Information Criteria shown in
755 Fig. S5. The resulting models without later lags are shown in Figs. S8-S10.

756



757

758 **Extended Data Figure 2. Damages in our preferred specification which provides a**

759 **robust lower-bound on the persistence of climate impacts on economic growth vs**

760 **damages in specifications of pure growth or pure level effects.** Estimates of future

761 damages as shown in Fig. 1 of the main manuscript, but under the emission scenario RCP8.5

762 for three separate empirical specifications: in orange our preferred specification which

763 provides an empirical lower-bound on the persistence of climate impacts on economic growth

764 rates while avoiding assumptions of infinite persistence (see main text for further discussion);
765 in purple a specification of “pure growth effects” in which the first difference of climate
766 variables is not taken and no lagged climate variables are included (the baseline specification
767 of ref ¹⁷); and in pink a specification of “pure level effects” in which the first difference of
768 climate variables is taken but no lagged terms are included.
769

Study	Empirical resolution	Number of climate variables considered	Baseline specification of growth or level effect	Number of lags in primary specification	Damages by 2100 under RCP8.5
Burke (2015) ¹⁷	National	One	Growth	None	~25%
Kahn (2019) ³⁵	National	One	Level	Four	7.2%
Kalkuhl & Wenz (2020) ¹²	Sub-national	One	Level	One	14.2%
This study	Sub-national	Five	Level	Eight-ten/four	61.6%

770

771 **Extended Data Table 1. A comparison of the magnitude of estimated economic damage**

772 **from future climate change across recent panel-based empirical studies.** All studies use

773 fixed effects panel regressions. The first four columns describe differences in the underlying

774 data and empirical specification. The third column shows the nature of the baseline

775 specification without lags with regards to growth or level effects (see main text for further

776 discussion). The last column compares projections of future economic damage under RCP-

777 8.5 by 2100 as reported by the respective study.

Supplementary Files

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

- [KotzLevermannWenzNatureSirevised3.pdf](#)