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Day-to-day temperature variability reduces economic growth

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Elevated annual average temperature has been found to impact macro-economic growth. However, various fundamental elements of the economy are affected by deviations of daily temperature from seasonal expectations which are not well reflected in annual averages. Here we show that increases in seasonally adjusted day-to-day temperature variability reduce macro-economic growth independent of and in addition to changes in annual average temperature. Combining observed day-to-day temperature variability with subnational economic data for 1,537 regions worldwide over 40 years in fixed-effects panel models, we find that an extra degree of variability results in a five percentage-point reduction in regional growth rates on average. The impact of day-to-day variability is modulated by seasonal temperature difference and income, resulting in highest vulnerability in low-latitude, low-income regions (12 percentage-point reduction). These findings illuminate a new, global-impact channel in the climate–economy relationship that demands a more comprehensive assessment in both climate and integrated assessment models.

The importance of understanding the impacts of climate on society has grown in recent decades, as climates change at geologically unprecedented rates across the globe[1–4]. Anthropogenic greenhouse gas emissions have been the dominant driver of global climate change[5–9], and the societal consequences are predicted to be predominantly negative[10]. The extent to which society should limit its impact on the climate poses a difficult challenge for policymakers. From a cost–benefit perspective, the solution hinges on balancing the predicted risk and societal costs of a changing climate with the costs of mitigating those changes. A sound understanding of the different socio-climatic interactions is vital for assessing where the optimal balance lies.

A growing body of empirical studies compares changes in climate observations with those in economic and social data, thereby providing numerous insights into the impacts of weather extremes and a changing climate[11–15]. Climatic conditions have been shown to affect agricultural output[16], conflict[17], electricity consumption[18,19], migration[20], and well-being and suicide rates[21]. Evidence for increasing economic damages from extreme events such as hurricanes[22] and other natural disasters[23] is also growing. Quantitative insights into the effects of changing climatic conditions and weather shocks on macro-economic growth have also been made. Recent econometric analyses exploit spatiotemporal variation in climate variables and growth and have found that average annual temperature has a significant effect on economic growth[11,24–28]. These results imply considerable economic losses and increasing global inequality as a result of historical and future climate change[25,29].

Despite this progress, most empirical assessments of the impacts of climate on macro-economic growth are subject to limitations. In particular, most studies only consider changes in annual averages of climate variables. Yet, productivity losses due to heat stress are experienced on an instantaneous daily basis[25], and as such, annual averages are unlikely to reflect the full extent of these heat-stress days. This has been addressed to some degree at the micro-economic level via degree days[30,31], which sum the extent to which daily temperature crosses predefined thresholds over the course of a year.

However, measures of both annual average temperature as well as degree days do not reflect the degree of variability in daily realizations of temperature, which is likely to be inherently challenging for economic agents. An extensive body of empirical studies demonstrates that uncertainty, measured as variability or volatility, poses an inherent limitation on macro-economic outcomes when realized across a variety of non-climate factors and timescales. For example, gross domestic product (GDP) is reduced by its own temporal fluctuations[32], by government-spending volatility[32] and by exchange-rate volatility[33]. Food-price volatility also reduces agricultural output[34] and welfare measures[35]. The key explanation for these effects is that investment risks increase with volatility[36–38]. Fundamentally, greater variability reduces the ability of economic agents to plan and function effectively, and this is likely to be true of their daily exposure to weather variables.

In particular, there is empirical evidence that variability of daily temperature from seasonal expectations has significant impacts on crop yields[39–42], human health[43,44], sales and operational costs in retail[45] and asset prices as a result of investor expectations[46]. The aggregated effect of day-to-day temperature variability across these fundamental elements of the economy thus has the potential to impact growth at the macro-economic level.

In this Article, we test whether the degree of variability in realizations of temperature has an effect on macro-economic outcomes by assessing historical changes to economic data and day-to-day temperature variability on a global scale. We measure day-to-day variability as the intra-monthly standard deviation of daily temperature, and then average these standard deviations across months of a given year to yield an annual measure (Methods, equation (1), Fig. 1). This approach follows findings that indicate that the

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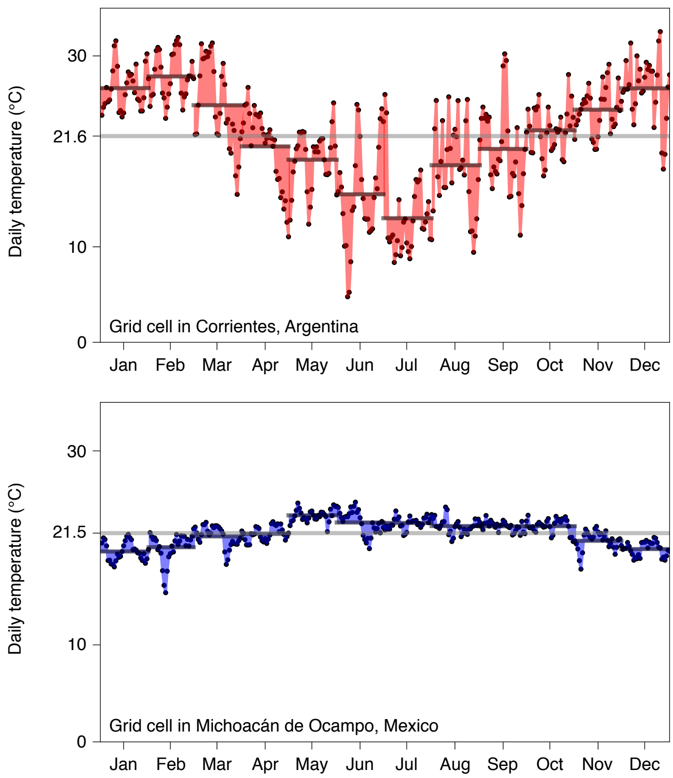

Fig. 1 | Day-to-day temperature variability, as measured by deviations of daily temperature from monthly means, can be considerably different for two regions with equal average annual temperature. Representative time series are shown for 2012 from two grid cells in the ERA5 dataset. Annual average temperature is denoted by the horizontal grey line, and deviations of daily temperature from monthly means are coloured.

intra-monthly standard deviation of daily temperature is a better measure of day-to-day variability than absolute changes between days[47]. Intra-monthly standard deviations were found to be less sensitive to changes in observational procedures and to correlate best with a variety of alternative definitions of day-to-day variability[47]. Moreover, this approach removes the seasonal temperature cycle, allowing us to focus on variability away from the seasonal expectations of economic agents to which they have probably already adapted. We focus on variability from year-specific monthly means rather than from long-term climatological monthly means as this facilitates a more distinct interpretation between the effects of changes to variability and changes to mean conditions.

We calculate our measure from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis fifth generation (ERA5) climate data for the years 1979–2018 and combine it with a regional economic dataset, recently introduced by ref. [27], to yield roughly 29,000 year–region observations of day-to-day temperature variability and economic growth, measured as the first difference of the logarithm of gross regional product. By conducting our analysis at the regional level, not only do we increase our statistical power, but we also reduce the weakening of climate and economic signals that occurs by aggregating over spatially heterogenous variables[28,48]. Following the most recent climate–econometric literature, we then apply fixed-effects panel regression models to exploit within-region changes of day-to-day temperature variability and regional growth from one year to the next (Methods). This allows us to flexibly control for contemporaneous global shocks, omitted biases between regions and region-specific trends in growth and climate, hence strengthening the inference of causality in our findings.

Impact of day-to-day temperature variability

We find that day-to-day temperature variability has a negative linear effect on regional growth rates. An extra degree Celsius of day-to-day temperature variability in a given year and region reduces the regional growth rate by at least five percentage points, hereon referred to as the marginal losses (Table 1: columns (1)–(4), row 1). We further find that the magnitude of the response is modulated by the seasonal temperature difference, when accounted for as an interaction term in our regressions (Table 1: columns (5)–(8), rows 1 and 2 and Extended Data Fig. 1). We define the seasonal temperature difference as the historical average of the difference between maximum and minimum monthly temperature of a given year. This nonlinearity implies heterogenous marginal effects that are dependent on the underlying climatic conditions. Specifically, countries which experience smaller seasonal temperature differences are affected more by a given change in day-to-day temperature variability (Extended Data Fig. 1). For example, in regions of northern Russia or Canada, where average monthly temperature varies by over 40 °C within a year, losses per extra degree of day-to-day temperature variability can be as small as three percentage points. On the contrary, marginal losses can be greater than 10 percentage points in regions of Colombia or Indonesia, where seasonal temperature differences are less than 3 °C. This suggests that exposure to greater changes in temperature over the course of the year cultivates resilience against day-to-day variability.

Moreover, the dependence of the effect on the seasonal temperature difference has strong implications for its geographical distribution, shown in Fig. 2. Marginal losses from an increase in day-to-day temperature variability are largest in low-latitude and coastal regions as these regions typically experience small seasonal temperature changes and are hence less resilient to variability in daily temperature. This amplifies the pattern of low latitude, high climate vulnerability shown in previous work[25] and adds another dimension of coastal/continental vulnerability which is important for the United States and Europe.

Independence of changes in annual average temperature

The effect of day-to-day variability and its interaction with the seasonal temperature difference is significant and remarkably stable under the inclusion of various other climate measures in the regression models (Table 1: columns (2)–(4) and (6)–(8), rows 1 and 2). We consider total yearly precipitation, linear and quadratic annual average temperature, the first difference of annual average temperature and its one-year lag; and interactions between these variables. These controls cover the findings of recent analyses of the effect of annual average temperature on economic growth[25,27,28]. In particular, our results replicate previous findings of a nonlinear effect of annual average temperature levels (Table 1: columns (2) and (6), rows 3 and 4)[25,28], which is outperformed by the effect of annual average temperature changes and its interaction with the annual average temperature level (Table 1: columns (4) and (8), rows 5–8)[27]. In all cases, no significant effect of total precipitation is observed.

Importantly, the effect of day-to-day temperature variability on regional growth rates is unaffected by the inclusion of annual average temperature under all specifications. This implies that it constitutes an additional effect to that of annual average temperature already identified in previous studies; that is, an effect which has previously been unaccounted for in the temperature–growth relationship. Two years with equal annual average temperature may therefore experience a different overall impact due to differences in the day-to-day variability of temperature.

We include these additional climate variables as controls and continue to focus on the effect of day-to-day temperature

Table 1 | Regression results from different panel-regression-model specifications for the effect of climate variables on regional growth rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\tilde{T}_{r,y}$	−0.0538*** (0.0045)	−0.0596*** (0.0047)	−0.0541*** (0.0046)	−0.0563*** (0.0046)	−0.117*** (0.015)	−0.123*** (0.015)	−0.115*** (0.015)	−0.116*** (0.015)
$\tilde{T}_r.\tilde{T}_{r,y}$					0.00198*** (0.00049)	0.002*** (0.0005)	0.00192*** (0.0005)	0.00189*** (0.0005)
$\bar{T}_{r,y}$		−0.00283 (0.0023)		−0.00722 (0.0041)		−0.00143 (0.0024)		−0.00668 (0.0042)
$\bar{T}_r.\bar{T}_{r,y}$		−0.000788** (0.00024)		−0.0000406 (0.00038)		−0.000883*** (0.00024)		−0.0000629 (0.00038)
$\delta\bar{T}_{r,y}$			0.000956 (0.002)	0.00548 (0.0036)			0.00217 (0.0021)	0.00634 (0.0036)
$\bar{T}_r.\delta\bar{T}_{r,y}$			−0.00093*** (0.0002)	−0.000898** (0.00032)			−0.00102*** (0.0002)	−0.000975** (0.00033)
$\delta\bar{T}_{r,y-1}$			−0.00137 (0.0021)	0.00083 (0.0025)			−0.000307 (0.0021)	0.00171 (0.0025)
$\bar{T}_r.\delta\bar{T}_{r,y-1}$			−0.000683*** (0.00019)	−0.000651** (0.00023)			−0.000746*** (0.0002)	−0.000706** (0.00023)
$P_{r,y}$		0.000152 (0.00013)	0.000264* (0.00013)	0.000248 (0.00013)		0.000149 (0.00013)	0.000257 (0.00013)	0.000241 (0.00013)
N	29,603	29,603	28,872	28,872	29,603	29,603	28,872	28,872
adjusted R^2	0.221	0.223	0.226	0.226	0.222	0.223	0.226	0.226
BIC	−33,570	−33,601	−33,221	−33,208	−33,580	−33,611	−33,229	−33,216

Coefficients from eight regression models are shown. $\tilde{T}$, day-to-day temperature variability; $\hat{T}$, seasonal temperature difference; $\bar{T}$, annual average temperature level; $\delta\bar{T}$, annual average temperature change; P, total annual precipitation; N, number of observations. Subscripts r and y denote region and year, while $y-1$ indicates the one-year lag of a variable. Coefficients describe the estimated effect of a one-unit change in the climatic variable on the regional growth rate. On the basis of the adjusted R^2 and BIC, we select model 7 as our preferred specification. Standard errors are clustered at the regional level and shown in parentheses. *P<0.05, **P<0.01, ***P<0.001.

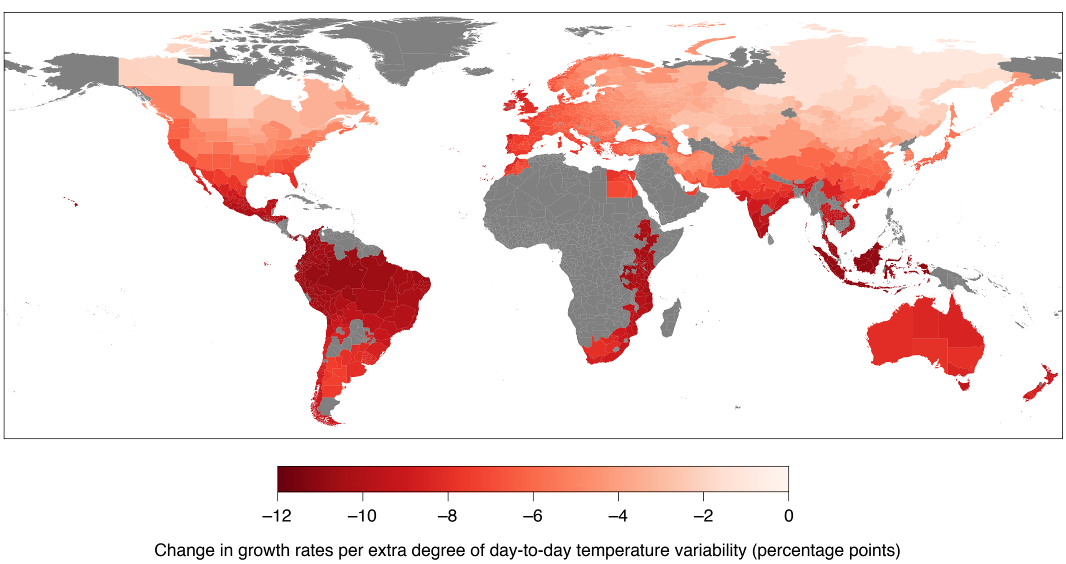

Fig. 2 | The effect of an extra degree of day-to-day temperature variability on regional growth rates varies geographically. The reduction is larger for regions that experience small seasonal temperature differences, implying a strong latitudinal dependence. Marginal changes are estimated from the model specification shown in Table 1, column (7). Grey regions indicate lack of economic data.

variability. On the basis of the adjusted R^2 value and Bayesian information criterion (BIC) we select the model of column (7) (Table 1) as our preferred specification and continue to use the specification and results therein in further robustness checks and plots of the marginal effects of day-to-day variability.

Impact mechanisms and channels

It is of conceptual interest whether the observed effect of day-to-day temperature variability predominantly reflects the inherently damaging effects of greater variability in the realization of weather variables or merely potential nonlinearities in the response to the

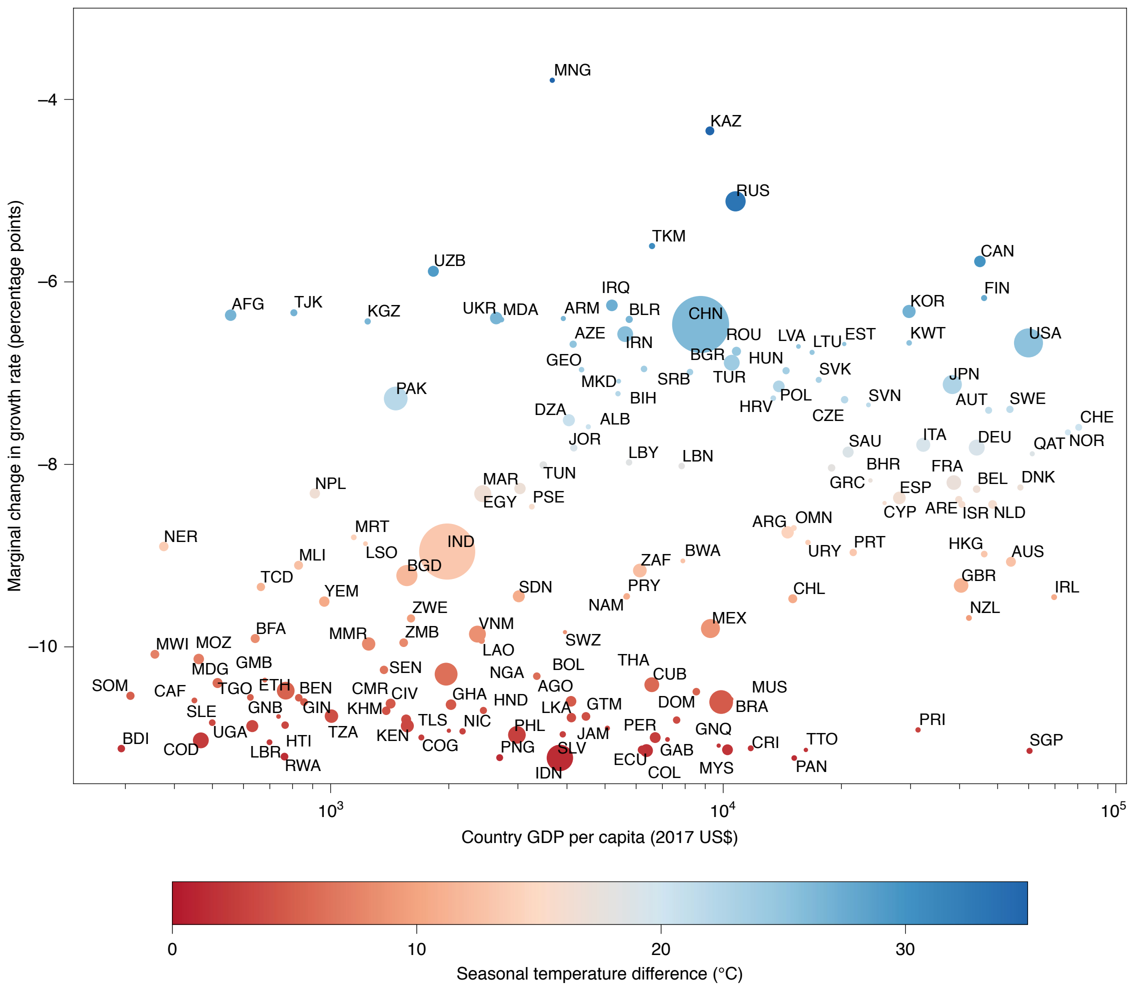

Fig. 3 | The reduction in regional growth rates per extra degree of day-to-day temperature variability (marginal change) is larger in countries with lower GDP per capita (2017 values), since they tend to experience smaller seasonal temperature differences. The size of scatter points indicates country population (2017 values) and the colour denotes the average seasonal temperature difference of the country. Marginal changes are estimated from the model specification shown in Table 1, column (7). For country name abbreviations, see ref. [56].

frequency of heat-stress days. To distinguish between these possible mechanisms, we calculate the degree days above 30 °C and 25 °C in regions of our sample and include them in the regression models as an additional control for the frequency of heat-stress days (section 1 in the Supplementary Information). The effect of day-to-day temperature variability is unaltered by the inclusion of these measures, suggesting that it predominantly reflects the inherently damaging effects of greater variability in temperature realizations (Supplementary Table 1).

Moreover, we find that day-to-day temperature variability in spring, summer and autumn has significant effects of similar magnitudes on annual regional growth rates (Supplementary Table 2). This suggests that the effect of variability is independent of the proximity of the underlying temperature level to heat-stress thresholds, thereby providing further evidence that greater variability is inherently damaging (further discussion in section 2 in the Supplementary Information). Interestingly, the effect of day-to-day variability in winter on annual regional growth rates is statistically insignificant and of negligible magnitude. A possible explanation for the absence of an effect in winter months is that economic agents may be sheltered from the effects of weather and its variability by adapting their behaviour to avoid already harsh winter weather conditions (that is, by reducing the extent of outdoor operations).

The degree to which day-to-day temperature variability affects different economic sectors is also of considerable conceptual and practical interest. We exploit the sectoral detail of our economic dataset to show that the effects of day-to-day variability are approximately equal across the agricultural, manufacturing and services sectors (Supplementary Table 3). This suggests that a broad range of economic channels are sensitive to changes in day-to-day temperature variability.

Robustness of results

We conduct a number of further robustness tests on the observed effect of day-to-day temperature variability. The use of different climate re-analysis datasets tests the consistency of the assimilation and interpolation techniques applied by re-analyses to the observational data (Supplementary Table 4). Weighting climate data by population rather than by area tests the sensitivity of the results to the regional aggregation of climate data (Supplementary Table 5). The inclusion of region-specific time trends accounts for possible regional trends in economic growth and climate (Supplementary Table 6). The exclusion of the United States, China or major oil producers from the dataset precludes the possibility that the effect is dominated by the response of a particularly large economy or industry (Supplementary Table 7). Across these robustness tests,

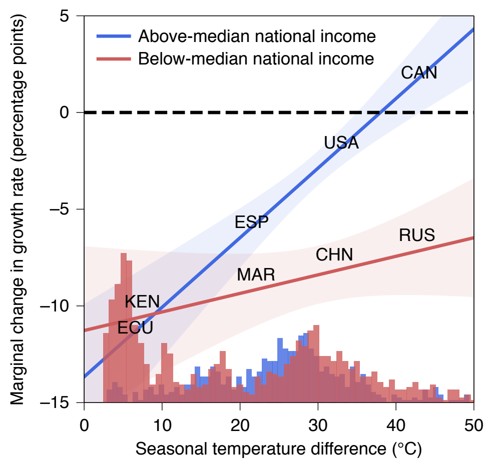

Fig. 4 | The change in regional growth rates per extra degree of day-to-day temperature variability (marginal change) estimated separately for countries with above- and below-median income per capita. For both sets of countries, regional marginal losses are dependent on the seasonal temperature difference, but, in regions with below-median national income, marginal losses are generally larger than in their higher-income counterparts. Moreover, in higher-income regions the marginal losses show a stronger dependence on the seasonal temperature difference (shown by the greater slope). This suggests both that higher income directly shields against day-to-day variability and that it facilitates better adaptation in response to historical exposure to large seasonal temperature differences. The positions of selected representative countries are shown along their respective curves. Marginal losses are estimated from the regression results shown in columns 1 and 2 of Supplementary Table 9. Two-sided 95% confidence intervals are shaded. Histograms show the distribution of data for the above- (blue) and below-median (red) income regions. For country name abbreviations, see ref. [56].

the effect of day-to-day temperature variability and its interaction with the seasonal temperature difference remains significant and remarkably stable.

Climate and economic variables exhibit spatial autocorrelation (section 5 in the Supplementary Information and Supplementary Figs. 1 and 2), which might pose an additional concern when assessing standard errors in statistical models. The varying size of subnational regions within our dataset means that there is not a clear administrative level at which errors should be clustered to account for this; climate variables may be correlated across all regions of the same small European country but are not across all different states of the United States, China or Russia (further discussion in section 5 in the Supplementary Information). We therefore present alternative error clustering specifications in Supplementary Table 8. Under even the most conservative error estimations, in which errors are simultaneously clustered by both country and year, the effect of day-to-day temperature variability remains statistically significant.

Heterogeneity of the effect by income

The distribution of vulnerability to changes in day-to-day temperature variability is influenced by the dependence of the effect on the seasonal temperature difference. As shown in Fig. 2, this implies that marginal losses from an increase in day-to-day temperature variability are largest in low-latitude and coastal regions. Since lower-income countries tend to reside at lower latitudes, they are also some of the most vulnerable to changes in day-to-day temperature variability, with important implications for global inequality and sustainable development (Fig. 3).

However, the greater vulnerability of lower-income regions is not just driven by their location at lower latitudes. By partitioning our data on the basis of median national income and re-evaluating the analysis separately on each dataset (Methods; Extended Data Fig. 2), we find that marginal losses from an increase in day-to-day temperature variability are generally larger for regions in low-income nations compared with those in higher-income nations, with the difference being more pronounced in higher-latitude countries (Fig. 4). This provides some evidence that lower-income regions are more vulnerable to increases in day-to-day temperature variability due to their low income itself, in addition to their relative lack of exposure, and hence resilience, to large seasonal temperature changes. Moreover, in high-income regions the effect of day-to-day variability shows a stronger response to the seasonal temperature difference, suggesting that higher income enables regions to better utilize their exposure to large historical seasonal temperature differences to adapt to the effects of greater day-to-day variability. This heterogeneity by national income is consistent with empirical evidence that the negative effects of variability (in the context of commodity prices) are smaller in higher-income nations with well-developed financial sectors as these can provide better insurance and risk-management practices[49].

When partitioned at the regional rather than the national level, the marginal losses of lower-income regions are greater, but the response is not significantly different from that of higher-income regions (Extended Data Fig. 3). The fact that the effects of climate are differentiable by income at the national but not at the regional level is intuitive given that adaptation is likely to be coordinated between regions of a given country. This is largely due to the greater opportunities for adaptation (such as via cultural practices, provision of public goods and transfer of ideas and capital) within countries than between them[50]. Adaptation to the impact of day-to-day temperature variability is therefore dependent on national income as well as long-term exposure of economic agents to large seasonal temperature differences. These patterns of low income, high climate vulnerability reinforce those already found in the impact of annual average temperature and emphasize the relevance of inequality for climate impacts and global mitigation efforts.

Long-term impact and implications for climate policy

An ongoing debate in the climate–economics literature exists over whether impacts estimated from spatiotemporal (that is, panel) regressions have persistent or instantaneous effects on growth rates; whether they are growth or level effects[14,26,28]. This has important implications for the effect of changes in climate on the long-term size of the economy[11,24] and hence for optimal climate policy[51–53]. Following recent econometric literature[24–27], we use a distributed-lag model to address this question with regard to the effect of changes in day-to-day temperature variability on economic growth (section 7 in the Supplementary Information). The analysis shows that the negative impacts of day-to-day variability persist for at least two years following the initial shock (Supplementary Table 10 and Supplementary Fig. 3). There is evidence of a partial growth recovery in the third year, beyond which estimates of the long run effect are still negative but statistically less significant. This suggests that the negative effects of greater day-to-day temperature variability are not fully recovered in the medium term, in accordance with the conclusions of previous studies on the effect of weather shocks on growth[24,25].

Regardless of the question of persistence, day-to-day temperature variability has a significant impact on economic growth that is independent of both the annual mean and the frequency of extreme temperature. This suggests that the effect reflects the inherently damaging consequences of greater variability in the realization of weather variables. Across our sample (1979–2018), historical deviations of day-to-day temperature variability from regional means have been 0.2 °C on average (Supplementary Table 11, within-region standard deviation of day-to-day temperature variability). This translates to economic growth effects of approximately one percentage point under our central econometric specification (Table 1, column (3)). This value is larger than, but comparable with, the average effect size of GDP volatility on national growth rates (0.3–0.5 percentage points[32]) and of average annual temperature on national (0.69 percentage points[24]) and regional growth rates (0.69 percentage points[27]) as identified in previous studies (note that one can expect larger effect sizes on regional rather than national growth rates due to the greater volatility in output at the regional rather than national level). Spill-over effects may potentially attenuate or aggravate these effects, but a thorough assessment of their role requires explicit assessment of the trade, financial and infrastructure networks through which they may propagate (such as in refs. [54,55]) and as such is beyond the scope of this work.

The effect of day-to-day temperature variability on macroeconomic growth thus constitutes a previously unidentified impact channel of considerable magnitude in the climate–economy relationship. This should therefore be considered by policymakers and climate and integrated assessment modellers who wish to consider the broader effects of future climate change on the economy. Doing so may have knock-on implications for the social cost of carbon and for determining optimum levels of mitigation.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-020-00985-5.

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Methods

Climate data. Our primary source of climate data is the ERA5 re-analysis dataset[57]. We use daily 2 m air temperature and daily total precipitation for the historical period 1979–2018. As a robustness check against the assimilation and interpolation techniques applied to the observational data by ERA5, we also use the daily temperature at surface and daily total precipitation from the WFDEI (Water and Global Change (WATCH) Forcing Data methodology applied to ERA-Interim data)[58] and EWEMBI (EarthH2Observe, WFDEI and ERA-Interim data merged and bias-corrected for the Inter-Sectoral Impact Model Inter-Comparison Project (ISIMIP))[59] reanalysis datasets. The WFDEI and EWEMBI datasets cover the period 1979–2018. In all cases, climate data are obtained as daily time series on a 0.5° grid. The mean and standard deviation of daily temperature, the degree days above 30 °C, and 25 °C, (section 1 in the Supplementary Information) and the sum of daily precipitation within each month are calculated at the grid-cell level.

Spatial aggregation. Grid-cell monthly climate variables, as described above, are then aggregated to the regional level. Regions are taken to be the highest administrative unit within a country, as indicated in the GADM Database of Global Administrative Areas[60]. This administrative unit corresponds to, for example, states in the United States, provinces in China and federal subjects in Russia. The aggregation of data from grid cell to regional level is weighted by area. The weightings for a given grid cell are estimated by equally distributing 100 points across the grid cell and taking the proportion of these which fall within the region. This aggregation scheme was chosen as a base-line methodology (rather than weighting by population) as it is not clear that human elements of the economy should necessarily respond more considerably than non-human elements to day-to-day temperature variability. As a robustness check, climate data are alternatively aggregated by population. Gridded population data from the History Database of the Global Environment version 3.2.1 are averaged over the years 1979–2018 and used for this purpose. Aggregating by population rather than by area does not considerably alter the results (Supplementary Table 5).

Day-to-day temperature variability and yearly aggregation. To compare climate variables with macro-economic data, an assessment must be made at the yearly level. The regional intra-monthly standard deviation of temperature is therefore averaged across the months of a given year to yield an annual measure of day-to-day temperature variability, the full calculation of which is shown in equation (1).

$$\tilde{T}_{r,y} = \frac{1}{12}\sum_{m}^{12}\frac{1}{\sum_{x}^{N_r} w_{r,x}}\sum_{x}^{N_r} w_{r,x}\sqrt{\frac{1}{D_{m,y}}\sum_{d}^{D_{m,y}}\left(T_{x,d,y}-\bar{T}_{x,m,y}\right)^2} \qquad (1)$$

$\tilde{T}_{r,y}$ is our measure of day-to-day temperature variability in a given year, y, and region, r, calculated from the temperature, $T_{x,d,y}$, on a given grid cell, x, of that region and day, d, of that year. $\bar{T}_{x,m,y}$ is the average temperature of that grid cell in month, m, of that year. $D_{m,y}$ is the number of days in the month of a given year. N_r is the number of grid cells which at least partially fall within a given region. $w_{r,x}$ is the proportion of a grid cell that falls within a given region (or in the case of aggregation by population, it is the product of this proportion with the population of that grid cell). As to the control variables, regional average monthly temperature is averaged across months to yield a regional annual average temperature, whereas regional monthly degree days and precipitation are summed to yield regional annual measures.

Seasonal temperature difference. The regional seasonal temperature difference for a given year is calculated as the difference between the maximum and minimum regional average monthly temperature of a given year. This is then averaged across years (1979–2018) to yield the historical-average seasonal temperature difference.

Economic data. As a measure of economic activity, we use data on economic output at the subnational level, referred to as gross regional product, for 1,537 regions in 76 countries spanning the years 1979–2018. These data were assimilated from various statistical agencies of central or federal governments and yearbooks and have been converted from country-specific currencies to US dollars using exchange rates from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis. This conversion avoids diverging national inflationary tendencies. Data on sectoral gross regional product are also available, denoting the share of agriculture, manufacturing and service sectors, respectively. For a detailed description of this data source, see the Appendix of ref. [27]. Data on gross national product and national population for Fig. 3 are obtained from the World Bank[61,62]. The resulting combination of economic and climate data yielded 29,603 observations to be used in the regression models.

Partitioning data by income. For Fig. 4, data are partitioned into above- and below-median income on the basis of national averages of gross regional product per capita in 2008, the year in which we have best data coverage across regions (or the year nearest to 2008 if the region lacks data in that year). Data are alternatively partitioned at the regional level, also using gross regional product per capita in 2008, or the closest year with data. The two alternative partitions are shown in Extended Data Fig. 2 and the results based on these datasets in Supplementary Table 9.

Regression models. We apply fixed-effects panel regression models to estimate the effect of the annual measure of day-to-day temperature variability, $\tilde{T}_{r,y}$, on economic growth. Following the econometric literature[11,13,24,25,27], the first difference of the logarithm of gross regional product, g, is used, allowing the regression coefficients to be interpreted as an estimation of the percentage-point change in regional growth rates per unit change of the explanatory variable[13,23]. In its simplest form, the regression model reads:

$$g_{r,y} = \alpha_1\tilde{T}_{r,y} + \mu_r + \eta_y + \varepsilon_{r,y}; \qquad (2)$$

with $g_{r,y}$ describing the growth rate of region r in year y and $\tilde{T}_{r,y}$ being the annual aggregate of day-to-day temperature variability in that year. Regional and yearly fixed effects are denoted by μ_r and η_y respectively; $\varepsilon_{r,y}$ is the region–year error. Regional fixed effects are regional dummy variables which account for unobserved, time-invariant differences between regions such as institutional and cultural differences. The problem of omitted-variable bias that arises in inter-regional comparisons is therefore avoided. Year fixed effects act as global dummy variables for each year, therefore accounting for contemporaneous global shocks to both climate and economic data, such as El Niño events or global recessions. For our main modelling specification, we add a term that interacts day-to-day temperature variability with the average seasonal temperature difference, $\hat{T}_r$:

$$g_{r,y} = \alpha_1\tilde{T}_{r,y} + \alpha_2\tilde{T}_{r,y}\hat{T}_r + \mu_r + \eta_y + \varepsilon_{r,y}. \qquad (3)$$

To separate the effect of day-to-day temperature variability from that of annual average temperature as analysed in previous studies[24,25,27], we also consider terms for a nonlinear effect of annual average temperature, $\bar{T}$, and annual average temperature change, $\delta(\bar{T})$, (including interaction terms and lagged effects) in further model variants. We also include yearly total precipitation, P, as a control:

$$g_{r,y} = \alpha_1\tilde{T}_{r,y} + \alpha_2\tilde{T}_{r,y}\hat{T}_r + \alpha_3\bar{T}_{r,y} + \alpha_4\bar{T}_r\bar{T}_{r,y} + \alpha_9 P_{r,y} + \mu_r + \eta_y + \varepsilon_{r,y} \qquad (4)$$

and

$$\begin{aligned} g_{r,y} = {} & \alpha_1\tilde{T}_{r,y} + \alpha_2\tilde{T}_{r,y}\hat{T}_r + \alpha_5\delta(\bar{T}_{r,y}) + \alpha_6\bar{T}_r\delta(\bar{T}_{r,y}) + \alpha_7\delta(\bar{T}_{r,y-1}) \\ & + \alpha_8\bar{T}_r\delta(\bar{T}_{r,y-1}) + \alpha_9 P_{r,y} + \mu_r + \eta_y + \varepsilon_{r,y}, \end{aligned} \qquad (5)$$

as well as a variant in which we include both annual temperature levels and annual temperature changes:

$$\begin{aligned} g_{r,y} = {} & \alpha_1\tilde{T}_{r,y} + \alpha_2\tilde{T}_{r,y}\hat{T}_r + \alpha_3\bar{T}_{r,y} + \alpha_4\bar{T}_r\bar{T}_{r,y} + \alpha_5\delta(\bar{T}_{r,y}) + \alpha_6\bar{T}_r\delta(\bar{T}_{r,y}) \\ & + \alpha_7\delta(\bar{T}_{r,y-1}) + \alpha_8\bar{T}_r\delta(\bar{T}_{r,y-1}) + \alpha_9 P_{r,y} + \mu_r + \eta_y + \varepsilon_{r,y}. \end{aligned} \qquad (6)$$

The results of the different regression model specifications are shown in the columns of Table 1. The estimated parameters α_i are reported as the numbers in these columns. In further robustness checks we also include region-specific time trends to account for regional economic or climate trends; these take either a linear ($\kappa_r y$) or quadratic ($\kappa_r y + \lambda_r y^2$) form. These trends are not included in our main specification because significant trends in day-to-day variability are not present in all regions of our sample and the brevity of the time series of economic growth in certain regions (less than 10 years in some cases) might make their inclusion inappropriate due to overfitting. Region-specific trends are instead included in robustness tests, as a result of which none of the major results are altered (Supplementary Table 6).

Marginal effects. The marginal effect of a change in day-to-day temperature variability is the change in the regional growth rates that we estimate would occur from an increase in day-to-day temperature variability of 1 °C. This is calculated as the first derivative of the growth rate with respect to the day-to-day temperature variability, given an equation describing the regression model specification. For example, for the specification shown in equation (2), the marginal effect would simply be the constant α_1. In all other regression model specifications, equations (2–5), the marginal effects would be:

$$ME_r = \alpha_1 + \alpha_2\hat{T}_r. \qquad (7)$$

The effect of a 1 °C increase of day-to-day temperature variability is therefore dependent on the average regional seasonal temperature difference, $\hat{T}_r$.

Data availability

ERA5 data are publicly available from the European Centre for Medium-Range Weather Forecasts (https://www.ecmwf.int/). The 0.5 × 0.5° resolution version used in this analysis and the EWEMBI and WATCH climate datasets are available from the Inter-Sectoral Impact Model Intercomparison Project (https://www.isimip.org/) or from the corresponding author upon request. Source data are provided with this paper. All other data are publicly available at https://doi.org/10.5281/zenodo.4323163 (ref. [63]).

Code availability

All code used for analysis and plotting are publicly available at https://doi.org/10.5281/zenodo.4323163 (ref. [63]).

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Author contributions

M. Kalkuhl provided the economic data. A.L. proposed the climate measure. M. Kotz processed the climate and economic data. M. Kotz and L.W. designed the regression models. All authors contributed to the interpretation of the results. M. Kotz and L.W. wrote the manuscript, with all authors providing feedback.

Competing interests

The authors declare no competing interests.

Additional information

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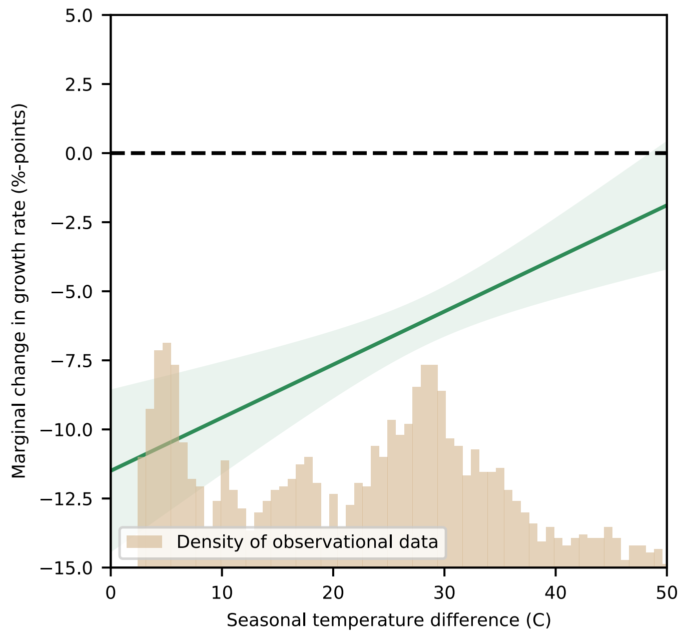
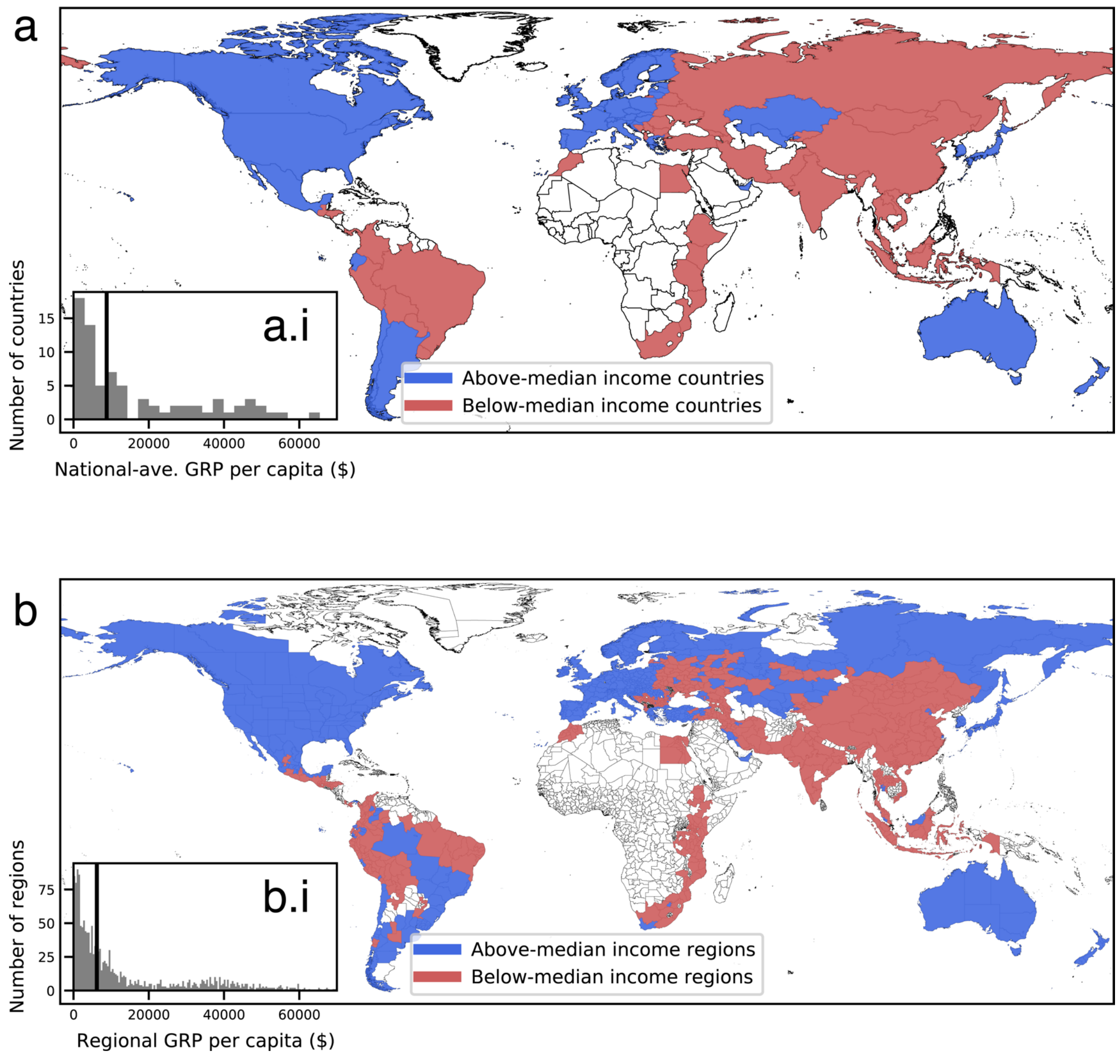
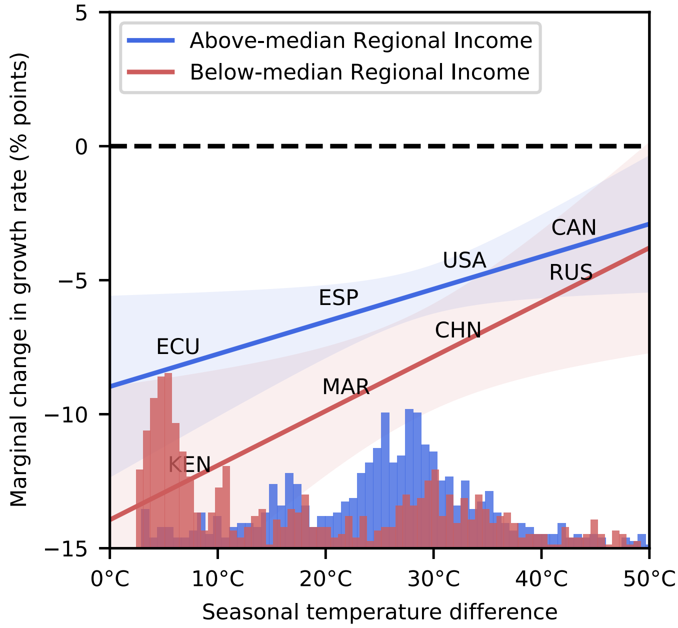


Extended Data Fig. 1 | Marginal effects of day-to-day temperature variability on regional economic growth rates. Marginal effects of a 1° Celsius increase of day-to-day temperature variability on regional growth rates, as estimated by model (7) in Table 1. Regions which are accustomed to smaller seasonal temperature differences suffer greater marginal losses (greater negative marginal changes) from a 1 degree increase of day-to-day temperature variability. 95% confidence intervals are shown shaded, and the histograms show the distribution of the data used to estimate the model.



Extended Data Fig. 2 | Partitioning of the data by per-capita income. Partitioning data based on above- and below-median national (**a**) and regional (**b**) averages of regional income (GRP) per capita. Data from 2008, the year in which we have best coverage across regions, or the closest year to this for which data are available, are used. Histograms of the distribution of national average (a.i) and regional (b.i) GRP per capita are shown with the median income indicated by a vertical black line. Partitions from (**a**) are used to estimate the results shown in Fig. 4, those from (**b**) are used to estimate the results shown in Extend Data Fig. 3.



Extended Data Fig. 3 | Marginal effects of high and low-income regions. Marginal effects of a 1 degree increase of day-to-day temperature variability on regional growth rates, estimated for regions with below- and above-median regional income. When partitioned based on regional-income, the difference between the response of high- and low-income regions is not significant, although above-median income regions generally experience smaller marginal losses. The results shown here are based on the partition shown in Extended Data Fig. 2b and, and the models used to estimate the marginal effects are those shown in Supplementary Table 9.