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The effect of rainfall changes on economic production

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Macro-economic assessments of climate impacts lack an analysis of the distribution of daily rainfall, which can resolve both complex societal impact channels and anthropogenically forced changes[1–6]. Here, using a global panel of subnational economic output for 1,554 regions worldwide over the past 40 years, we show that economic growth rates are reduced by increases in the number of wet days and in extreme daily rainfall, in addition to responding nonlinearly to the total annual and to the standardized monthly deviations of rainfall. Furthermore, high-income nations and the services and manufacturing sectors are most strongly hindered by both measures of daily rainfall, complementing previous work that emphasized the beneficial effects of additional total annual rainfall in low-income, agriculturally dependent economies[4,7]. By assessing the distribution of rainfall at multiple timescales and the effects on different sectors, we uncover channels through which climatic conditions can affect the economy. These results suggest that anthropogenic intensification of daily rainfall extremes[8–10] will have negative global economic consequences that require further assessment by those who wish to evaluate the costs of anthropogenic climate change.

Considerable changes to Earth's hydrological cycle are anticipated owing to anthropogenic climate change. The resulting effects on rainfall are heterogeneous across a variety of timescales and characteristics, reflecting the complex physical processes that underlie them. For example, daily rainfall extremes have increased globally[8,9] owing to the relationship between atmospheric water vapour content and temperature[10]. Conversely, seasonal and annual averages are changing heterogeneously, with both regional wetting and drying, largely as a result of dynamical changes in the atmospheric circulation[11–13]. Considering variability[14] and seasonality[15] adds further nuance to the anticipated response of rainfall to anthropogenic influence. Quantifying the costs of these complex changes remains an important barrier to a comprehensive assessment of the costs of climate change, particularly as rainfall has extensive potential for societal impacts. Alterations to water availability can subsequently affect agricultural productivity[16,17], metropolitan labour outcomes[17,18] and the onset of conflict[17,19]; in addition to which flash flooding can cause extensive damages[20] and economic disruption[21].

In contrast to this micro-level evidence, most macro-economic assessments of the costs of climate change have found precipitation changes to affect economic growth rates insignificantly[1–3]. Two recent studies have provided some reconciliation, identifying macro-economic effects of rainfall when using a higher spatial resolution[4,5]. However, these studies have not assessed rainfall at the range of timescales necessary to capture either the variety of societal impact channels or the complex physical changes resulting from anthropogenic forcing. By focusing on annual totals[1–4] and monthly means[5], recent findings are unlikely to realistically capture future costs. This problem is exacerbated by the fact that fundamental elements of the economy are known to respond to daily realizations of weather variables[2], meaning that higher-order moments of the distribution of daily rainfall may be important determinants of economic growth rates, as has been shown for the variability of daily temperature[6].

To address these issues, we assess higher-order moments of the annual distribution of daily rainfall in conjunction with subnational economic output. The distribution of daily rainfall is highly non-Gaussian (Fig. 1) and we therefore take a threshold approach. We count both the number of days and the amount of rainfall on days falling above a wide range of critical thresholds to flexibly identify different possible impact channels. Thresholds are set either as constants or as percentiles of the historical distribution (1979–2019) of local daily rainfall (Methods). The second approach allows us to implicitly account for local adaptation to prevailing rainfall conditions. Furthermore, we calculate the total annual rainfall and standardized monthly rainfall anomalies to assess the results of previous studies and their relation to the daily measures introduced here (see Extended Data Fig. 1 for maps of the principal rainfall measures considered). Standardized monthly rainfall anomalies constitute an annual sum of monthly rainfall anomalies from their climatological means, weighted by their historical contribution to the annual rainfall, as defined in ref. [5] and shown in equation (4) in Methods. Our primary source of climate data is the surface precipitation rate from the European Centre for Medium-Range Weather Forecasts Reanalysis 5 (ERA-5) of historical observations, owing to its global coverage, high spatial and temporal resolution, and high-degree of correlation with ground-based measurements of rainfall at the daily timescale[22].

We combine these rainfall measures with data on subnational economic production from 1,554 regions across 77 countries[3] resulting

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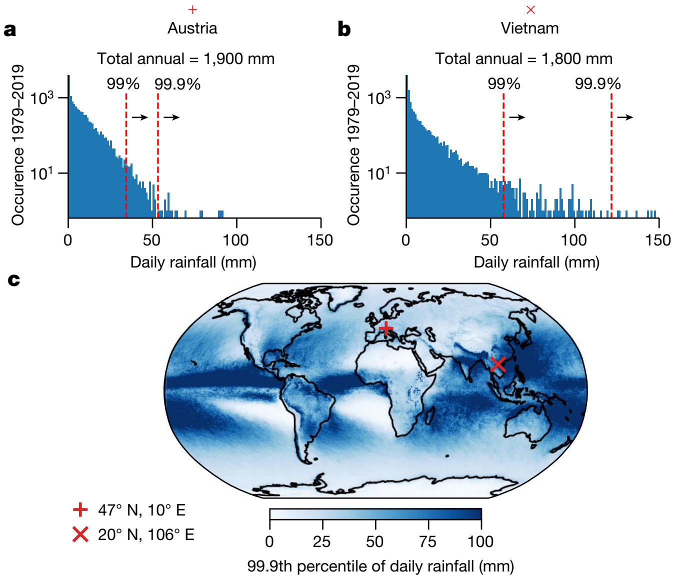

Fig. 1 | Assessing the distribution of daily rainfall via thresholds. a, **b**, The distribution of daily rainfall from grid cells in Austria (**a**) and Vietnam (**b**) differs considerably, despite similar average annual totals (data are from the ERA-5 reanalysis of historical observations). The 99th and 99.9th percentiles of the historical distribution (1979–2019), as used to calculate extreme daily rainfall, are denoted by the vertical red lines. **c**, The spatial distribution of the 99.9th percentile of daily rainfall. The two locations are marked with a red plus and cross, respectively.

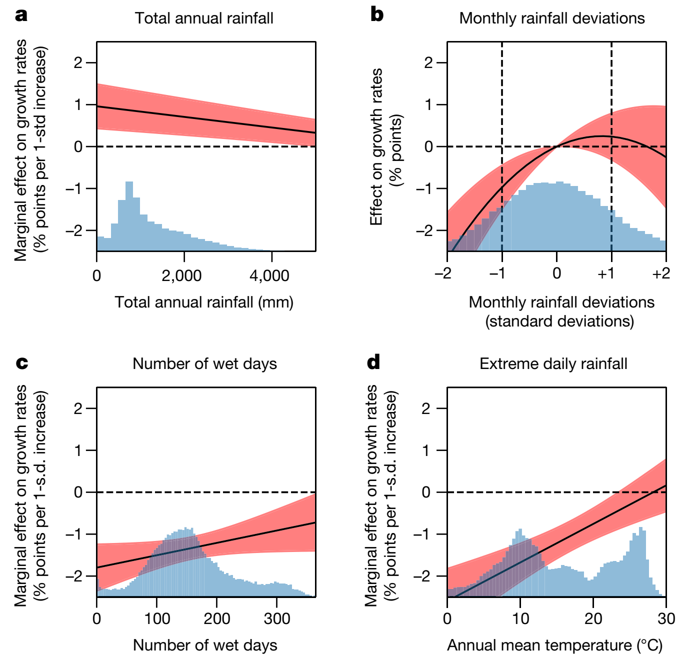

Fig. 2 | The effect of four rainfall measures on economic growth rates. a, The marginal effects of a 1-s.d. increase in the total annual rainfall, as a function of total annual rainfall. **b**, The effects of standardized monthly deviations of rainfall (an annual sum of anomalies of monthly rainfall from their climatological means, weighted by their historical contribution to the total annual rainfall; see equation (4) in Methods). **c**, The marginal effects of a 1-s.d. increase in the number of wet days, as a function of the number of wet days. **d**, The marginal effects of a 1-s.d. increase in extreme daily rainfall (the annual sum of rainfall on days exceeding the 99.9th percentile of the historical distribution (1979–2019)), as a function of the annual mean temperature. The 95% confidence intervals are shown in red, having clustered standard errors by region. The main regression supporting these results includes 30,121 observations (see Extended Data Table 1 for further details). The distributions of observations of the moderating variable are shown as blue histograms.

in over 30,000 observations over the past 40 years (see Methods for details). Using data at the subnational level allows for a more detailed spatial description of both climate and economic variables, which has been shown to help identify impacts in economic data[3–5]. This is particularly crucial for assessments of rainfall, for which spatial variability is considerably larger than for temperature[4]. We explicitly evaluate the spatial autocorrelation of these rainfall measures (Supplementary Fig. 1) at the subnational level of our economic data, the results of which suggest that the level of spatial detail used here is appropriate to address the problem of spatial aggregation (Supplementary Section 1). We then apply fixed-effects panel regression models to estimate the effect of these aspects of the distribution of daily rainfall on economic production. This approach uses within-region changes in climate variables from one year to the next to assess their impact on economic outcomes. As such, it allows us to account for unobserved differences between regions, contemporaneous global shocks and regional time trends (Methods), strengthening the identification of causal effects between changes in rainfall and economic production.

Main findings

Assessing the distribution of daily rainfall across a range of thresholds, we identify four distinct effects on economic production. Confirming previous studies, we identify quadratic effects of both total annual rainfall[4] and monthly rainfall deviations[5] on economic growth rates. Greater annual rainfall benefits economic growth, but these benefits diminish with greater climatological rainfall totals (Fig. 2a, Extended Data Table 1). This is consistent with the interpretation of net water supply as an economic good[23] with diminishing marginal utility. Furthermore, economic growth rates are strongly concave with monthly rainfall deviations (Fig. 2b, Extended Data Table 1), such that negative rainfall shocks away from historical monthly means cause strong and significant losses. The response to positive rainfall shocks is weaker and less statistically significant, consistent with previous assessments[5]. This suggests that economies are adapted to their prevailing rainfall conditions at the monthly timescale, and that drought away from these norms is inherently damaging. To the best of our knowledge, our results provide the first confirmation of this effect at the global scale.

Importantly, we identify two further effects of rainfall that have previously been unaccounted for. First, we find that increases in the number of days with rainfall exceeding 1 mm result in strong reductions in growth rates (Fig. 2c, Extended Data Table 1), with similar but less statistically significant results for thresholds between 0.1 mm and 3 mm (Supplementary Table 1). This suggests that days with any considerable amount of rainfall constitute suboptimal economic conditions, and we refer to this measure as the number of wet days from hereon. We note that the marginal effect from an increase in the number of wet days is smaller in regions where the number is already higher (Fig. 2c, Extended Data Table 1), which suggests adaptation based on prolonged exposure to wet days.

Second, we find that increases in extreme daily rainfall cause further reductions in growth rates (Fig. 2d, Extended Data Table 1), where extreme daily rainfall is measured as the annual sum of rainfall on days exceeding the 99.9th percentile of the historical distribution (1979–2019) (see equation (2) in Methods). This suggests that increases in both the number and severity of extreme rainfall days within a given year reduce economic productivity. This response is also identifiable with larger standard errors using either lower percentiles of the historical distribution (95th and 99th (Supplementary Table 2, Supplementary Fig. 2)) or absolute thresholds at similar magnitudes (Supplementary Table 3). The improved precision using percentile-based measures suggests the presence of regional adaptation to heavy rainfall conditions.

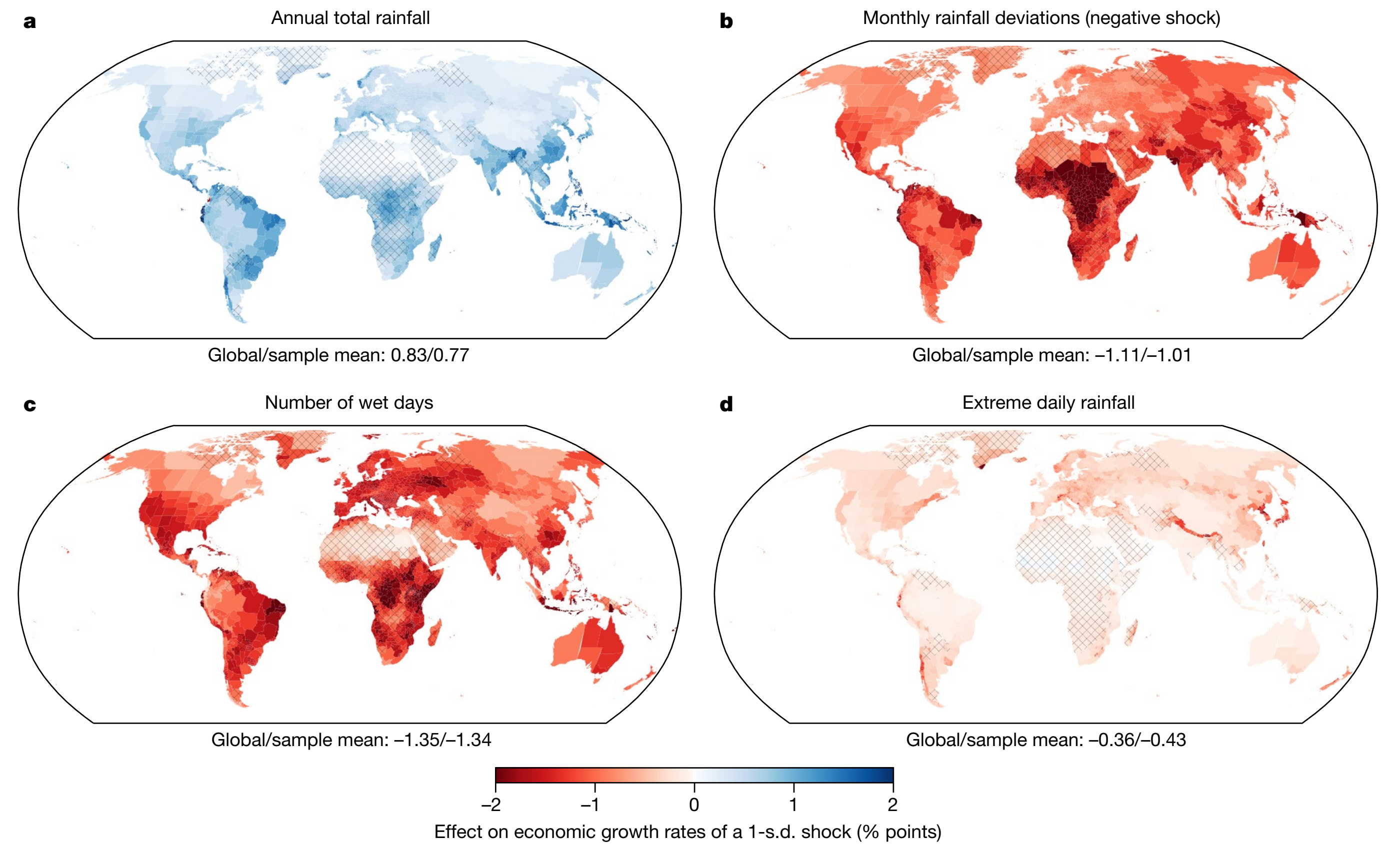

Fig. 3 | Regional estimates of the historical effect on economic growth rates of a 1-s.d. shock in each of the four rainfall measures. These estimates are obtained via the product of the region-specific marginal effects and the region-specific standard deviation for each rainfall measure (from annual variability over the historical period 1979–2019; see Extended Data Fig. 2 and Methods for details). Note that for all rainfall measures except the monthly deviations, the magnitudes of a positive or negative 1-s.d. shock are equivalent but of opposite sign. As such, shocks constitute a 1-s.d. increase in each measure, other than for the monthly deviations in which a 1-s.d. decrease is shown (see Supplementary Fig. 5 for the impact of a positive shock of monthly rainfall deviations). The hatching indicates regions outside of our sample of economic data; here historical effects have been extrapolated using historical climate data and the estimated marginal effects. Global and sample means of impacts across regions are given in each panel.

Furthermore, the marginal effects of increases in extreme daily rainfall show a regional heterogeneity that is best described by the annual mean temperature (this heterogeneity may also be described less precisely by either latitude or the seasonal temperature difference, see Supplementary Table 4). This implies further regional adaptation, although through a mechanism that is less clear.

These effects from rainfall are separately identifiable when included as competing independent variables on economic growth rates (see equation (5) in Methods), suggesting that they constitute independent, additive effects. We explore the extent of this independence by sequentially excluding certain measures (Supplementary Table 5) and assessing each measure individually (Supplementary Table 6). The effect of the annual total is increased to some extent by the exclusion of the monthly deviations, and the monthly deviations are skewed more positively with the exclusion of the annual total (Supplementary Table 5). This suggests that to some degree they are competing, interdependent measures that capture the same effects on economic growth rates. Conversely, the effects of the daily measures are decreased by the exclusion of the annual and monthly measures, and vice versa (Supplementary Table 5). This suggests that they are complementary measures, which although partially colinear, assist one another in identifying their separate effects on economic growth rates. Other than the annual total, all measures remain strongly significant when assessed individually, albeit with marginally reduced effect sizes (Supplementary Table 6). However, the inclusion of all measures improves the description of our statistical model (within-region R^2 of 0.014 rather than of about 0.009, see Supplementary Table 6) and we therefore continue to include them in our preferred specification. Moreover, these effects of rainfall are identified while accounting for the effects of temperature as found in previous studies[3,6] (Extended Data Table 1), and additionally for daily temperature extremes (Supplementary Table 7) and standardized monthly temperature deviations (Supplementary Table 8), which suggests that they constitute additional effects.

These findings complement previous narratives by showing that although greater rainfall may be beneficial[4], this is only true if it does not also cause increases in the number of wet days or in the extent of extreme daily rainfall. We encourage the use of these additional measures in further assessments of the economic effects of rainfall, as they may resolve contradictory findings from country-level studies that show both benefits and losses when assessing rainfall only through annual totals[24,25]. Moreover, measures of extreme daily rainfall may also provide helpful insights for assessments of the direct impact of fluvial floods on economic growth which, so far, have come to contradictory conclusions[26,27].

Robustness, seasonality and persistence

We conduct a number of robustness tests of these main results, which are presented in Supplementary Section 2. The results are recovered consistently when accounting for different levels of spatial autocorrelation in rainfall measures (Supplementary Fig. 1, Extended Data Table 1), across two alternative precipitation datasets (Supplementary Tables 9, 10), when aggregating climate data by use of population weights rather

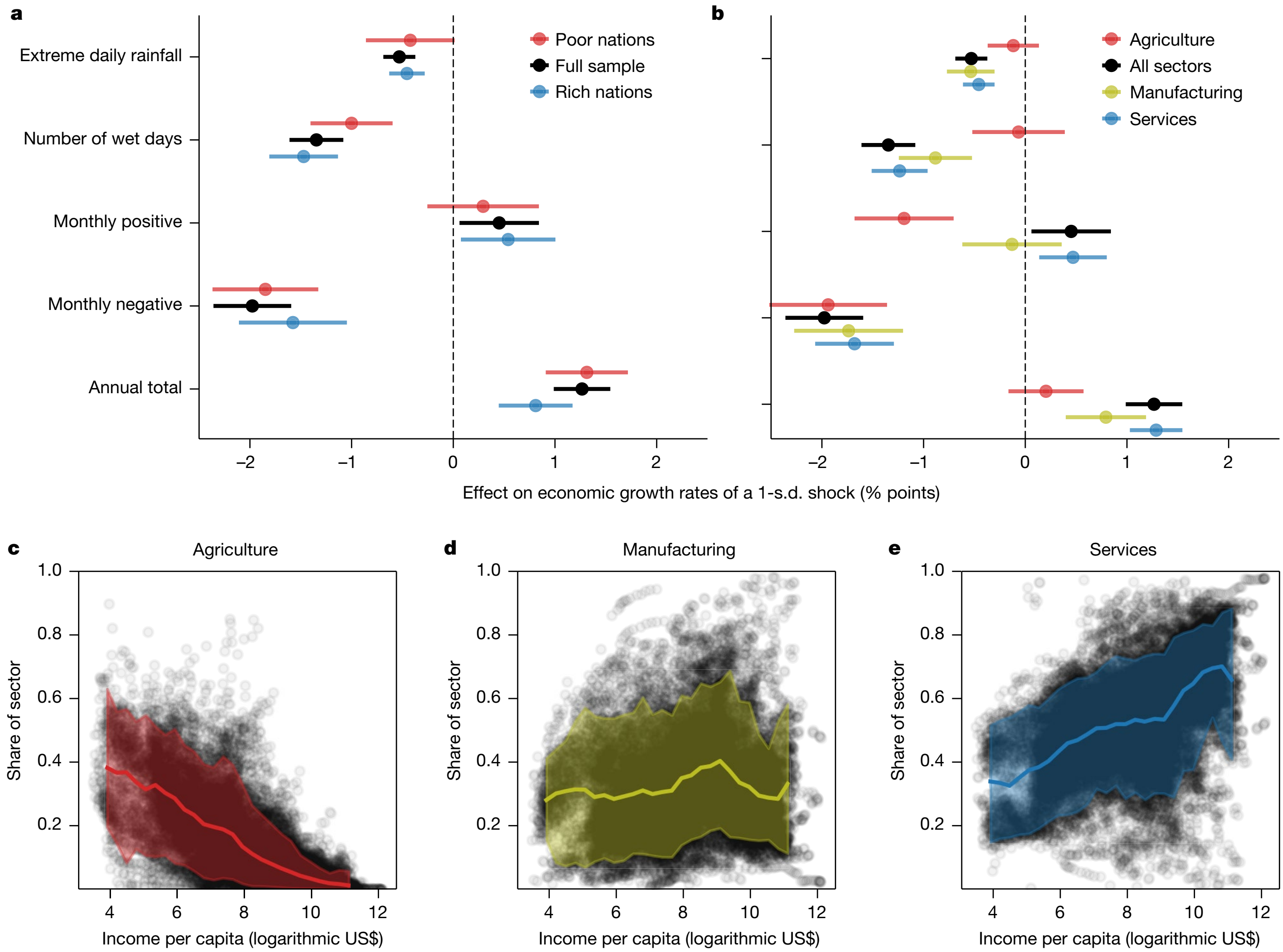

Fig. 4 | Assessing the heterogeneity of the effect of rainfall by income and sector. a, **b**, Estimates of the effect on economic growth rates of a 1-s.d. shock in each rainfall measure, when partitioning data based on national income per capita (**a**) and assessing sector specific economic output (**b**). The 95% confidence intervals of the estimates are shown as bars, having clustered standard errors by region. **c**–**e**, The share of the agriculture (**c**), manufacturing (**d**) and services (**e**) sectors as a function of income per capita for each region and year are shown in black. The median and 5th and 95th percentiles of these shares are shown in colour for bins of width of approximately 0.3 logarithmic US dollars.

than by area (Supplementary Table 11) and when accounting for linear or quadratic region-specific time trends (Supplementary Table 12).

Given the strong seasonal characteristics of rainfall, we further stratify our assessment of the number of wet days and extreme daily rainfall by season. The effects of both measures are strongest in winter and autumn, showing little response in summer and spring. This seasonal heterogeneity is robustly identified when using either annual (Supplementary Table 13) or season-specific (Supplementary Table 14) thresholds, when explicitly accounting for snowfall (Supplementary Table 15, Supplementary Fig. 3), and despite greater daily rainfall (both extremes and number of wet days) in summer than winter across most of the global land mass (Supplementary Fig. 4). These results suggest that the effect arises due to a seasonal economic vulnerability rather than owing to differing seasonal characteristics of rainfall (see Supplementary Section 3 for further discussion). Moreover, it is consistent with the already identified modulating effect of annual mean temperature on the impact of extreme rainfall (Fig. 2d) such that both hotter seasons and years reduce vulnerability. Further research into the mechanisms behind this pattern may provide insights into adaptation planning against the effects of extreme rainfall.

The persistence of climate impacts on economic growth is a strong determinant of long-term damages with important implications for optimal climate policy[1–3,28,29]. Following the literature[1–3], we assess the presence of persistent or rebound effects in the impact of the rainfall measures introduced here using a distributed lag model. We find no evidence for rebound effects in the short term, instead identifying some persistence in the effect of the annual total and number of wet days (Supplementary Table 16).

Spatial heterogeneity

To assess the spatial heterogeneity in the magnitude of historical impacts from these aspects of the distribution of rainfall, we multiply regional estimates of the marginal effects with the historical standard deviation of each measure (from annual variability over the historical period, 1979–2019; Methods, Fig. 3). Using the identified marginal effects and historical climate data, we are able to extrapolate these estimates out of our economic sample (results for these regions are hatched in Fig. 3). Economic impacts in the historical period have been largest from the number of wet days and negative monthly rainfall deviations. These impacts have also been fairly balanced across regions within the economic sample but show the smallest values for the number of wet days in desert regions where interannual variability is low (Extended Data Fig. 2). Conversely, impacts from the total annual and extreme daily rainfall have been smaller and show greater regional heterogeneity. On the one hand, effects from the total annual rainfall have been strongest at low latitudes and across coastal regions where interannual variability is large (Extended Data Fig. 2). On the other hand, effects from extreme daily rainfall have been strongest at higher latitudes and across coastal and mountainous regions, resulting in large impacts in key industrial regions such as the coastal United States, central Europe, China, Korea and Japan.

Sectoral and income heterogeneity

To shed light on the impact channels associated with these measures, we re-assess their effects separately on sectoral economic output and on the above- and below-median national income countries of our dataset (hereon referred to as rich and poor; see Methods for details on the partitioning of the data by income) (Fig. 4). Owing to the interdependence between the effects of the annual total and the monthly rainfall deviations, we assess their effects separately (the results of the daily measures are still estimated with the inclusion of all other rainfall measures).

In their response to deviations of monthly rainfall, rich and poor countries are similar (Fig. 4a, Extended Data Fig. 3b). However, poor countries show greater sensitivity to the annual total rainfall (+62%, with respect to the other income group), whereas rich countries show greater sensitivity to the number of wet days (+47%) and a much more statistically significant response to extreme daily rainfall (Fig. 4a, Extended Data Fig. 3c, d). Interestingly, agricultural output shows little to no response to both measures of daily rainfall, whereas the services and manufacturing sectors respond to these measures strongly (Fig. 4b, Extended Data Fig. 4). This offers a possible explanation for the greater sensitivity of rich nations to daily rainfall, given their smaller dependence on agriculture and greater dependence on services (Fig. 4c–e)[30]. Agricultural output shows little dependence on the total annual rainfall in our assessment, showing only a strong negative response to both negative and positive rainfall shocks at the monthly timescale (Fig. 4b, Extended Data Fig. 4). However, price effects may mask some of the response of agriculture when assessed using monetary output instead of physical measures of agricultural output such as net primary production[17]. The manufacturing and services sectors by contrast show strong responses to rainfall across all timescales and measures.

In addition to these heterogeneous effects, the economic response to changes in the number of wet days shows a strong, nonlinear dependence on the regional income level when accounted for as an interaction term in the regression model (Methods, Supplementary Table 17, Supplementary Fig. 6). This suggests a more complex pattern of adaptation to impacts from the changing number of wet days. Accounting for such dependence considerably improves the description of the statistical model (R^2, Supplementary Table 17) and does not alter the conclusions drawn in Fig. 4 (see caption of Supplementary Fig. 6).

Concluding remarks

These results demonstrate that focusing on the beneficial effects of greater annual rainfall for agriculturally dependent low-income countries alone[4,7] provides an incomplete picture of the economic effects of rainfall changes. Increases in extreme daily rainfall and the number of wet days are adverse for economic growth, particularly in high-income countries and via the manufacturing and services sectors.

The most robust prediction of future rainfall change under anthropogenic climate change is the intensification of daily rainfall extremes across the globe[8–10]. The identification of an adverse effect on economic growth rates from this aspect of the distribution of rainfall is therefore a crucial step towards assessing the costs of anthropogenic climate change. Our results suggest that accounting for this aspect will raise estimates of these costs compared with previous work[2,3,28,29]. Considerable changes are also projected from global climate models for the other aspects of rainfall but are likely to be regionally heterogeneous and are subject to greater uncertainty[12,13]. Our results suggest that these changes would cause further regional economic losses and gains that are at present difficult to quantify. In the historical period, effects from these aspects of the distribution of rainfall have been larger than those of extreme daily rainfall. Further work is therefore required to quantify the economic consequences of future changes in rainfall, comprehensively accounting for both the magnitude and uncertainty of impacts from all the channels identified here.

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/s41586-021-04283-8.

1. Dell, M., Jones, B. F. & Olken, B. A. Temperature shocks and economic growth: evidence from the last half century. *Am. Econ. J. Macroecon.* **4**, 66–95 (2012).
2. Burke, M., Hsiang, S. & Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **527**, 235–239 (2015).
3. Kalkuhl, M. & Wenz, L. The impact of climate conditions on economic production. Evidence from a global panel of regions. *J. Environ. Econ. Manage.* **103**, 102360 (2020).
4. Damania, R., Desbureaux, S. & Zaveri, E. Does rainfall matter for economic growth? Evidence from global sub-national data (1990–2014). *J. Environ. Econ. Manage.* **102**, 102335 (2020).
5. Holtermann, L. Precipitation anomalies, economic production, and the role of "first-nature" and "second-nature" geographies: a disaggregated analysis in high-income countries. *Glob. Environ. Change* **65**, 102167 (2020).
6. Kotz, M. et al. Day-to-day temperature variability reduces economic growth. *Nat. Clim. Change* **11**, 319–325 (2021).
7. Barrios, S., Bertinelli, L. & Strobl, E. Trends in rainfall and economic growth in Africa: a neglected cause of the African growth tragedy. *Rev. Econ. Stat.* **92**, 350–366 (2010).
8. Min, S. K. et al. Human contribution to more-intense precipitation extremes. *Nature* **470**, 378–381 (2011).
9. Madakumbura, G. D. et al. Anthropogenic influence on extreme precipitation over global land areas seen in multiple observational datasets. *Nat. Commun.* **12**, 3944 (2021).
10. Fischer, E. & Knutti, R. Observed heavy precipitation increase confirms theory and early models. *Nat. Clim. Change* **6**, 986–991 (2016).
11. Marvel, K. & Bonfils, C. External influences on global precipitation. *Proc. Natl Acad. Sci. USA* **110**, 19301–19306 (2013).
12. Chadwick, R. et al. Large rainfall changes consistently projected over substantial areas of tropical land. *Nat. Clim. Change* **6**, 177–181 (2016).
13. Lehmann, J., Mempel, F. & Coumou, D. Increased occurrence of record-wet and record-dry months reflect changes in mean rainfall. *Geophys. Res. Lett.* **45**, 13468–13476 (2018).
14. Zhang, W. et al. Increasing precipitation variability on daily-to-multiyear time scales in a warming world. *Sci. Adv.* **7**, eabf8021 (2021).
15. Feng, X., Porporato, A. & Rodriguez-Iturbe, I. Changes in rainfall seasonality in the tropics. *Nat. Clim. Change* **3**, 811–815 (2013).
16. liang, X. Z. et al. Determining climate effects on US total agricultural productivity. *Proc. Natl Acad. Sci. USA* **114**, E2285–E2292 (2017).
17. Damania, R. The economics of water scarcity and variability. *Oxf. Rev. Econ. Policy* **36**, 24–44 (2020).
18. Desbureaux, S. & Rodella, A. S. Drought in the city: the economic impact of water scarcity in Latin American metropolitan areas. *World Dev.* **114**, 13–27 (2019).
19. Hsiang, S. M., Burke, M. & Miguel, E. Quantifying the influence of climate on human conflict. *Science* https://doi.org/10.1126/science.1235367 (2013).
20. Davenport, F. V., Burke, M. & Diffenbaugh, N. S. Contribution of historical precipitation change to US flood damages. *Proc. Natl Acad. Sci. USA* **118**, e2017524118 (2021).
21. Willner, S. N., Otto, S. N. C. & Levermann, A. Global economic response to river floods. *Nat. Clim. Change* **8**, 594–598 (2018).
22. Beck, H. E. et al. Daily evaluation of 26 precipitation datasets using stage-IV gauge-radar data for the CONUS. *Hydrol. Earth Syst. Sci.* **23**, 207–224 (2019).
23. Garrick, D. E. et al. Valuing water for sustainable development. *Science* **358**, 1003–1005 (2017).
24. Ali, S. Climate change and economic growth in a rain-fed economy: How much does rainfall variability cost Ethiopia? *SSRN* https://doi.org/10.2139/ssrn.2018233 (2012).
25. Sangkhaphan, S. & Shu, Y. The effect of rainfall on economic growth in Thailand: a blessing for poor provinces. *Economies* **8**, 1–17 (2020).
26. Loayza, N. V., Olaberría, E., Rigolini, J. & Christiaensen, L. Natural disasters and growth: going beyond the averages. *World Dev.* **40**, 1317–1336 (2012).
27. Kirchene, H. et al. Long-term impacts of tropical cyclones and fluvial floods on economic growth—empirical evidence on transmission channels at different levels of development. *World Dev.* **144**, 105475 (2021).
28. Moore, F. C. & Diaz, D. B. Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Change* **5**, 127–131 (2015).
29. Kikstra, J. S. et al. The social cost of carbon dioxide under climate–economy feedbacks and temperature variability. *Environ. Res. Lett.* **16**, 094037 (2021).
30. Hidalgo, C. A., Klinger, B., Barabási, A.-L. & Hausmann, R. The product space conditions the development of nations. *Science* **317**, 482–487 (2007).

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Methods

Climate data

We use the surface precipitation rate and the 2-m air temperature from the ERA-5 reanalysis of historical observations as our primary climate data. The ERA-5 combines satellite and in situ observations with state-of-the-art assimilation and modelling techniques to provide estimates of climate variables with global coverage and at six-hourly resolution. Data are obtained at the daily timescale and on a regular 0.25° × 0.25° grid for the years 1979–2019. In addition, we use the surface precipitation rate from the Multi-Source Weighted-Ensemble Precipitation v.1.2 (MSWEP[31],) at the same temporal and spatial resolution and for the same years, and the Princeton Global Meteorological Forcing dataset (PGF[32],) at a daily timescale on a regular grid of resolution 0.5° × 0.5° for the years 1948–2016. The MSWEP combines precipitation data from a variety of sources (including multiple reanalyses, and satellite and ground-based observations) as a function of timescale and location. The PGF applies bias correction and forcing based on observational data to the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis of historical observations.

Economic data

Subnational economic data on macro-economic output per capita are obtained from DoSE —the Database of Subnational Economic output made publicly available by the Mercator Research Institute on Global Commons and Climate Change (MCC) and the Potsdam Institute for Climate Impact Research (PIK)[3,33]. The dataset has been introduced by ref. [3] and comprises annual gross regional product from 1,554 subnational regions across 77 countries with varying temporal coverage from 1901 to 2014. The data have been assembled from various sources, such as statistical agencies of central and federal governments as well as yearbooks. Values in local currencies have been converted to US dollars by means of exchange rates from the FRED database of the Federal Reserve Bank of St Louis to avoid diverging national inflationary tendencies. Following previous literature[1–6], subnational per-capita growth rates are estimated as the first difference of the logarithm of gross regional product per capita.

Climate measures

We calculate multiple measures of the annual distribution of daily rainfall at the grid-cell level. These include annual and monthly totals, and measures in relation to a number of critical thresholds. Critical thresholds are set at a 0.1, 0.3, 1, 3, 10, 20, 30, 50, 70, 80 and 90 mm d^{-1}, or at the 50th, 70th, 80th, 90th, 95th, 99th and 99.9th percentiles of the historical (1979–2019) distribution of daily rainfall at the grid-cell level. We use the entire historical distribution to define the percentile-based thresholds given the importance of doing so for accurate assessment of extreme values[34]. The number of days, $\mathrm{RD}_{x,y}$, and the annual sum of rainfall on days exceeding these values, $\hat{\mathrm{RD}}_{x,y}$, are calculated for a given year, y, and for each threshold, R_C, according to:

$$\mathrm{RD}(R_C)_{x,y} = \sum_{d=1}^{D_y} H(R_{x,d} - R_C), \quad (1)$$

and

$$\hat{\mathrm{RD}}(R_C)_{x,y} = \sum_{d=1}^{D_y} R_{x,d} H(R_{x,d} - R_C), \quad (2)$$

where $R_{x,d,}$ is the rainfall on grid cell x and day d, D_y is the number of days in a given year and H is the Heaviside step function. This results in a total of 36 different threshold measures of the annual distribution of daily rainfall. The number of wet days, and the measure of extreme daily rainfall, for which we identify significant economic effects are denoted as $\mathrm{RD}(1\,\mathrm{mm})_{x,y}$ and $\hat{\mathrm{RD}}(99.9\%)_{x,y}$ respectively, using the above notation. Designed in this way, the second measure captures both the frequency and intensity of extreme exceedance, both of which are important under climate change[8–10,35].

As additional control variables, we calculate annual mean temperature, $\overline{T}$, and day-to-day temperature variability, $\widetilde{T}$, as defined in ref. [7]

$$\widetilde{T}_{x,y} = \frac{1}{12} \sum_{m=1}^{12} \sqrt{\frac{1}{D_m} \sum_{d=1}^{D_m} (T_{x,d,m,y} - \overline{T}_{x,m,y})^2}, \quad (3)$$

where $T_{x,d,m,y}$ is the temperature on grid cell x of day d of month m of year y, D_m is the number of days in a given month and $\overline{T}_{x,m,y}$ is the year and grid-cell specific monthly mean temperature.

Spatial aggregation

Grid-cell values of the annual and monthly totals, and the annual threshold measures are aggregated to the regional level using an area-weighted mean of grid cells that fall at least partially within the administrative boundaries, obtained from the Database of Global Administrative Areas (GADM). Weights are calculated using an algorithm that estimates the proportion of each grid cell falling at least partially inside the administrative boundary. In an alternative specification, a population-weighted mean is used for aggregation, using population data from Hyde 3.1, the History database of the Global Environment[36] (the results of which are shown in Supplementary Table 11).

Standardized monthly rainfall deviations

Regional, r, monthly, m, rainfall totals, $R_{r,m,y}$ are used to calculate an annual measure of standardized monthly rainfall deviations, $\mathrm{RM}_{r,y}$ as described in ref. [5] and as shown below:

$$\mathrm{RM}_{r,y} = \sum_{m=1}^{12} \frac{R_{r,m,y} - \overline{R}_{r,m}}{\sigma_{r,m}} \frac{\overline{R}_{r,m}}{\overline{\mathrm{RA}}_r} \quad (4)$$

where $\overline{R}_{r,m}$ is the historical mean, and $\sigma_{r,m}$ is the historical standard deviation, of monthly rainfall totals in that region and $\overline{\mathrm{RA}}_r$ is the historical mean of annual rainfall totals in that region. This measure represents an annual sum of monthly rainfall anomalies from their climatological means, weighted by the climatological contribution of monthly rainfall to the annual rainfall. This may be of particular interest in the context of increasing precipitation volatility at monthly to annual timescales[37].

Econometric models

We use fixed-effects panel regression models to estimate relationships between changes in annual climate measures, and subnational per-capita growth rates, $g_{r,y}$. In our baseline estimations, we include regional, μ_r, and yearly, η_y, fixed effects. The first flexibly accounts for unobserved, time-invariant differences between regions such as differing mean climate regimes and different baseline growth rates owing to geopolitical and historical factors. The second flexibly accounts for unobserved, spatially invariant annual shocks to both climate measures and economic growth rates owing to global phenomena such as the El Niño–Southern Oscillation or global economic recessions or pandemics. In additional specifications, we include region-specific linear, $k_r y$, or quadratic, $k_r y + \gamma_r y^2$ time trends (with region-specific slopes, k_r and γ_r), to exclude the possibility of spurious correlations due to common time trends (the results of which are shown in Supplementary Table 12).

As independent variables, we include annual total rainfall, $\mathrm{RA}_{r,y}$, and monthly rainfall deviations, $\mathrm{RM}_{r,y}$ quadratically, following the findings of previous studies[4,5]. We then separately include each of the 36 threshold measures of the distribution of daily rainfall. We identify statistically significant effects from two measures: the number of wet days $\mathrm{RD}(1\,\mathrm{mm})_{x,y}$ and the measure of extreme daily rainfall $\hat{\mathrm{RD}}(99.9\%)_{x,y}$. We note a quadratic effect of the number of wet days, and a dependence of the effect of extreme daily rainfall on the annual mean temperature, such that the main econometric specification reads:

$$\begin{aligned} g_{r,y} = {} & \alpha_1 \mathrm{RA}_{r,y} + \alpha_2 \mathrm{RA}^2_{r,y} + \alpha_3 \mathrm{RM}_{r,y} + \alpha_4 \mathrm{RM}^2_{r,y} \\ & + \alpha_5 \mathrm{RD(1mm)}_{r,y} + \alpha_6 \mathrm{RD(1mm)}^2_{r,y} \\ & + \alpha_7 \hat{\mathrm{RD}}(99.9\%)_{r,y} + \alpha_8 \hat{\mathrm{RD}}(99.9\%)_{r,y} \overline{T}_{r,y} \\ & + \alpha_9 \widetilde{T}_{r,y} + F(\overline{T}_{r,y}) + \mu_r + \eta_y + \varepsilon_{r,y} \end{aligned} \tag{5}$$

with regression coefficients, α_i, and region year error, $\varepsilon_{r,y}$. As additional controls, we include day-to-day temperature variability, $\alpha_9 \widetilde{T}_{r,y}$, and the function of the annual mean temperature, $F(\overline{T}_{r,y}) = \alpha_{10}(\overline{T}_{r,y} - \overline{T}_{r,y-1}) + \alpha_{11}\overline{T}_{r,y}(\overline{T}_{r,y} - \overline{T}_{r,y-1})$, specifiedin ref. [6] and ref. [3], respectively. By including all variables of interest in the same regression equation, we strengthen the interpretation of the effects as independent and additive[38]. When assessing heterogeneity of the effect of the number of wet days with income level, $\theta_{r,y}$ (as in Supplementary Table 17, Supplementary Fig. 6), we find that considering a nonlinear effect considerably increases the statistical power of the model (R^2, Supplementary Table 17) and therefore include the following additional terms in equation (5): $\alpha_{11}\mathrm{RD(1mm)}_{r,y}\theta_{r,y} + \alpha_{12}\mathrm{RD(1mm)}^2_{r,y}\theta_{r,y} + \alpha_{13}\mathrm{RD(1mm)}_{r,y}\theta^2_{r,y} + \alpha_{14}\mathrm{RD(1mm)}^2_{r,y}\theta_{r,y}$.

Historical effect sizes and marginal effects

The regression coefficients (α_x in equation (5)) describe the percentage-point effect on subnational growth rates of a one unit increase in each rainfall measure. Given the different magnitudes of each measure, the regression coefficients do not provide comparable estimates of the magnitude of each effect. Therefore, to assess the magnitude of the historical effect sizes for the three non-standardized measures ($\mathrm{RA}_{r,y}$, $\mathrm{RD(1mm)}_{r,y}$ and $\hat{\mathrm{RD}}(99.9\%)_{r,y}$), we multiply the marginal effects by the within-region standard deviation (from interannual variability over the period 1979–2019). In Figs. 2, 4, the sample average (either the global, or in Fig. 4a, the rich and poor, sample) of the within-region specific standard deviations are used, whereas in Fig. 3, region-specific values are used. The marginal effects of these measures are the first derivative of equation (5) with respect to the relevant measure, such that they read:

$$\mathrm{ME}_{\mathrm{RA}} = \alpha_1 + 2\alpha_2 \mathrm{RA}_{r,y}, \tag{6}$$

$$\mathrm{ME}_{\mathrm{RD(1mm)}} = \alpha_5 + 2\alpha_6 \mathrm{RD(1mm)}_{r,y}, \tag{7}$$

and

$$\mathrm{ME}_{\hat{\mathrm{RD}}(99\%)} = \alpha_7 + \alpha_8 \overline{T}_{r,y}. \tag{8}$$

These marginal effects are evaluated at the sample (for Figs. 2, 4) or regional (for Fig. 3) mean of the moderating variable, before multiplication by the relevant within-region standard deviation.

Owing to its standardization, the monthly rainfall deviations are by definition zero mean and as such have a marginal effect close to zero at the regional mean. Consequently, we instead assess the average historical effect size of this measure by simply evaluating the relevant part of equation (5) ($\alpha_3\mathrm{RM}_{r,y} + \alpha_4\mathrm{RM}^2_{r,y}$) at one within-region standard deviation. The within-region standard deviations are taken either as the average across regions in the sample (for Figs. 2, 4) or the region-specific value (for Fig. 3).

Partitioning data by income

To assess the heterogeneity of the effect of rainfall by income, we re-assess our results separately for nations with above- and below-medium income per capita. Following ref. [6], we partition nations based on their per-capita income in the year in which we have best data coverage across regions (2008) or the year closest to this.

Data availability

The data on economic production and the ERA-5 climate data are both publicly available at https://doi.org/10.5281/zenodo.4681306 and https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, respectively. Secondary data are available at the public repository for this publication: https://doi.org/10.5281/zenodo.5657457. The maps were created using Matplotlib v. 3.4.2 (https://matplotlib.org/), Cartopy v.0.18.0 (Met Office UK, https://pypi.python.org/pypi/Cartopy/0.18.0), Geopandas v. 0.6.1 (https://geopandas.org/) and GADM administrative boundaries (https://gadm.org/). Source data are provided with this paper.

Code availability

The code to reproduce the analysis is available at the public repository for this publication: https://doi.org/10.5281/zenodo.5657457.

31. Beck, H. E. et al. MSWEP: 3-hourly 0.25° global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data. *Hydrol. Earth Syst. Sci.* **21**, 589–615 (2017).
32. Sheffield, J., Goteti, G. & Wood, E. F. Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. *J. Clim.* **19**, 3088–3111 (2006).
33. Wenz, L., Kalkuhl, M. & Kotz, M. DOSE v.1. The MCC and PIK database of subnational economic output: documentation. *Zenodo* https://doi.org/10.5281/zenodo.4681306 (2021).
34. Bador, M., Alexander, L. V., Contractor, S. & Roca, R. Diverse estimates of annual maxima daily precipitation in 22 state-of-the-art quasi-global land observation datasets. *Environ. Res. Lett.* **51**, 035005 (2020).
35. Myhre, G. et al. Frequency of extreme precipitation increases extensively with event rareness under global warming. *Sci. Rep.* **9**, 16063 (2019).
36. Klein Goldewijk, K., Beusen, A., van Drecht, G. & de Vos, G. M. The HYDE 3.1 spatially explicit database of human induced land use change over the past 12,000 years. *Glob. Ecol. Biogeogr.* **20**, 73–86 (2011).
37. Swain, D. L. et al. Increasing precipitation volatility in twenty-first-century California. *Nat. Clim. Change* **8**, 427–433 (2018).
38. Auffhammer, M., Hsiang, S. M., Schlenker, W. & Sobel, A. Using weather data and climate model output in economic analyses of climate change. *Rev. Environ. Econ. Policy* **7**, 181–198 (2013).

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Competing interests The authors declare no competing interests.

Additional information

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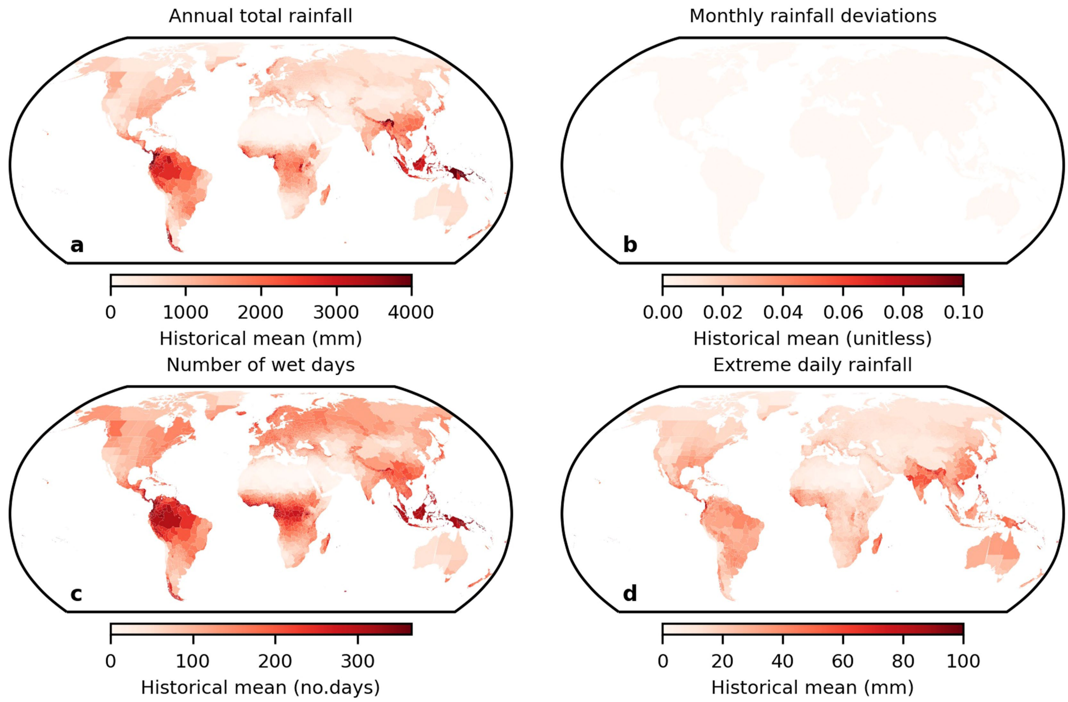
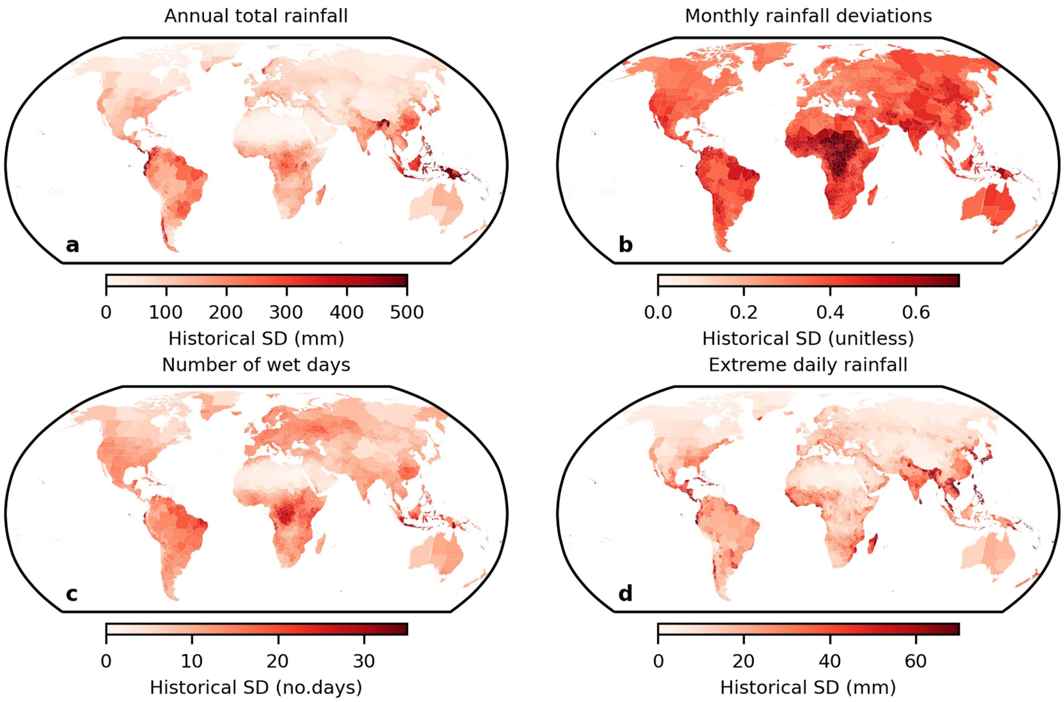
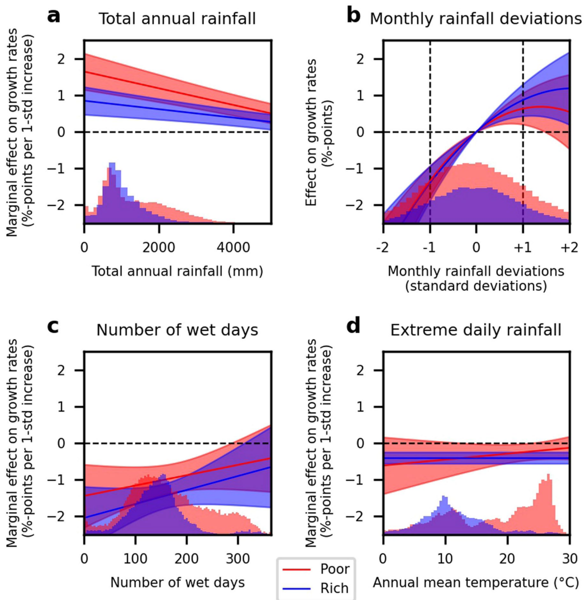


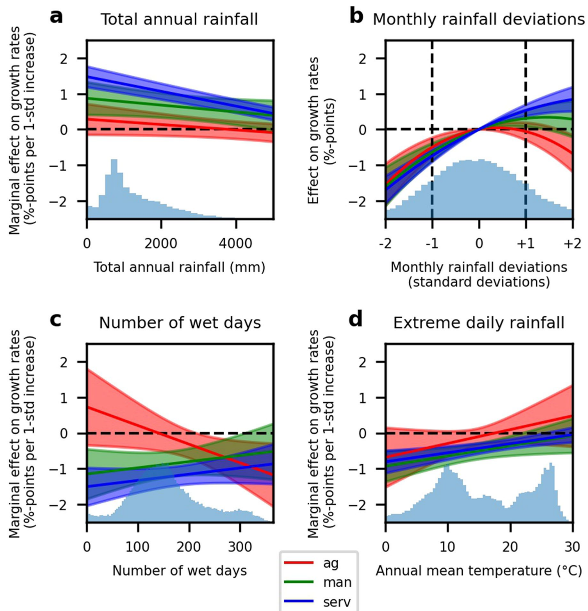
Extended Data Fig. 1 | Historical means of the four principal rainfall measures. Maps of the historical (1979–2019) means of each annual rainfall measure. **a**, The annual total rainfall. **b**, The monthly rainfall deviations (a weighted annual sum of anomalies of monthly rainfall from their climatological means which are, by definition, zero mean). **c**, The number of wet days. **d**, The extreme daily rainfall measure (the annual sum of rainfall on days exceeding the 99.9th percentile of the historical distribution).



Extended Data Fig. 2 | Historical variability of the four principal rainfall measures. Historical variability (the standard deviation of annual values over the years 1979–2019) for each measure of rainfall.



Extended Data Fig. 3 | Rich and poor differentiated response of economic growth to changes in rainfall. As Fig. 2 but having estimated economic responses to rainfall for rich and poor countries separately.



Extended Data Fig. 4 | Response of sectoral growth to changes in rainfall. As Fig. 2 but having estimated economic responses to rainfall for the agricultural ("ag"), manufacturing ("man") and services ("serv") sectors separately.

Extended Data Table 1 | Results of the main econometric specification for the effect of temperature and rainfall changes on economic growth rates

	Main results	
	Errors clustered:	
	Regionally	Nationally
T_var	-5.8e-02***	-5.8e-02***
	(4.5e-03)	(0.016)
D.T_mean	9.6e-04	9.6e-04
	(2e-03)	(4.8e-03)
L.D.T_mean	-2.3e-03	-2.3e-03
	(2.4e-03)	(5.9e-03)
D.T_mean:T_mean	-1.1e-03***	-1.1e-03**
	(2e-04)	(5.1e-04)
L.D.T_mean:L.T_mean	-6.5e-04***	-6.5e-04
	(2.1e-04)	(5.2e-04)
Annual rainfall	5.8e-05***	5.8e-05**
	(1.6e-05)	(2.7e-05)
Annual rainfall^2	-3.8e-09***	-3.8e-09**
	(9e-10)	(1.7e-09)
Monthly rainfall deviations	0.017**	0.017*
	(7.3e-03)	(0.01)
Monthly rainfall deviations^2	-2.8e-02***	-2.8e-02***
	(4.7e-03)	(9.9e-03)
No. wet days	-1.3e-03***	-1.3e-03**
	(2.1e-04)	(5.3e-04)
No. wet days^2	1.1e-06*	1.1e-06
	(5.8e-07)	(1.2e-06)
Extreme daily rainfall	-3.7e-04***	-3.7e-04***
	(5.6e-05)	(8.7e-05)
Extreme daily rainfall:T_mean	1.3e-05***	1.3e-05***
	(2.9e-06)	(3.7e-06)
Observations	30121	30121
R2	0.014	0.014
Adjusted R2	-4.1e-02	-4.1e-02
Note:	$*$p$<$0.1; $**$p$<$0.05; $***$p$<$0.01	

Numbers show the regression coefficients for the effect of each measure on growth rates, which constitute the %-point effect per unit increase in the given measure. Standard errors are shown below in parentheses. "T_var" and "T_mean" denote daily temperature variability and annual mean temperature, while the prefixes "D" and "L" denote the first difference and one-year lag of a variable.