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Observed heavy precipitation increase confirms theory and early models

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Environmental phenomena are often observed first, and then explained quantitatively. The complexity of processes, the range of scales involved, and the lack of first principles make it challenging to predict conditions beyond the ones observed. Here we use the intensification of heavy precipitation as a counterexample, where seemingly complex and potentially computationally intractable processes manifest themselves to first order in simple ways: heavy precipitation intensification is now emerging in the observed record across many regions of the world, confirming both theory and model predictions made decades ago. As the anthropogenic climate signal strengthens, there will be more opportunities to test climate predictions for other variables against observations and across a hierarchy of different models and theoretical concepts.

Many processes across a large range of scales determine the global water cycle, and as a consequence, the response of precipitation to increased greenhouse gas concentrations is complex. Even for a specific location, light and heavy rainfall rates often respond differently to warming. This behavior is commonly illustrated with a simple schematic (Fig. 1a) suggesting that the wettest days become more frequent at the expense of days with light or no precipitation[1,2]. Such schematics are powerful and often so widely used that in the end no one remembers where they came from. Here we trace back this schematic and show how different lines of evidence emerged that gave rise to it. More than 25 years after it was first proposed (Fig. 1b), the emerging climate change signal in observed heavy precipitation allows us to test its validity and to complement it with an equally simple updated version purely based on observations from two continents.

Theory and early model results

Climate science is sometimes criticized for providing explanations for seemingly unexpected observed phenomena such as the warming hiatus[3,4] only *a posteriori*. We argue that the evidence for heavy rainfall changes unfolded quite the opposite way: starting with theory, followed by model experiments and only decades later supported by robust observational evidence.

It started in 1834 when the French scientist Benoît Clapeyron suggested a thermodynamic law[5], complemented by Rudolf Clausius[6] in 1850, which states that warmer air has a higher water vapour holding capacity. This thermodynamic law, referred to as the Clausius–Clapeyron relationship, is at the core of our understanding of the response of the hydrological cycle to a warming atmosphere. Living during an unusually cold period in Europe, Clapeyron and Clausius hardly anticipated that their work would be highly cited in literature on heavy rainfall in a warming climate almost two hundred years later.

More than one hundred years after the theoretical principle had been postulated, the first computers allowed scientists to numerically simulate the atmosphere and later the atmosphere-ocean system. Already some of those first numerical model simulations of the climate system in the 1960s and 1970s suggested that with higher CO_2 concentrations, not only would the temperatures increase but so would the absolute humidity and thereby potentially the global mean precipitation[7]. However, only in the late 1980s did the first scientists point out that heavy rainfall responds differently to a warming atmosphere than annual precipitation averages[8–11]. Interestingly, this behavior had not been observed so far but was predicted by early generations of general circulation models (GCMs). This is remarkable since in many respects those climate models were quite different to contemporary ones.

In 1989 when Noda and Tokioka first suggested an increase in the frequency of heavy rainfall rates[8] (Fig. 1b), they used a GCM in which mountain ranges like the Alps were simply disregarded, and ocean straits neglected so that major islands like Japan were modelled as peninsulas. The atmospheric model had a horizontal resolution of 4° by 5° rather than a few tens of kilometers as seen in today's models. Instead of the 80 vertical layers in the atmosphere of some of today's pioneering GCMs, just 5 were modelled. Where contemporary studies use thousands of years of model data from the Coupled Model Intercomparison Project phase 5 (CMIP5)[12], they analysed only 10 days worth, which today would be rejected as too short a period for robust results. Nevertheless, their conclusions still hold today and are broadly consistent with the response in leading-edge high resolution global and regional climate models. There were many open questions at that time, for instance regarding the changes in large-scale versus convective precipitation. Noda and Tokioka argued that the simulated precipitation increase relates to enhanced convective rainfall that was partly compensated by reduced large-scale precipitation[8]. Their conclusions were consistent with earlier studies[13,14] which described the potential for enhanced moist convective activity in $2\times CO_2$ experiments but did not highlight it. In the early 1990s, their findings suggesting wide-spread heavy rainfall intensification were backed up by more comprehensive analyses of a series of detailed model experiments[10,11]. Even then, all authors were exceptionally careful in formulating their conclusions, highlighting numerous caveats due to the coarse resolution and stating that the model deficiencies precluded "the quantitative interpretation of simulated changes in daily rainfall intensity in terms relevant to the real world". One study even discussed their "scientific dilemma" of whether it would be "appropriate to go public with results" in which they had "limited confidence" (ref. 9).

Growing observational evidence

Alongside these models, in the early 1990s, the first indications for observed changes in precipitation were published — for example,

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a trend to more frequent heavy rainfall events across the US and Japan[15]. By today's standard the robustness of some of these results would be considered poor, since their US analysis was based on only 14 stations. Thus, the IPCC Second Assessment Report[16] still concluded in 1995 that no clear large-scale pattern of heavy rainfall intensification had emerged.

Today, there are many studies that provide observational evidence for heavy rainfall intensifications in different regions[17–21]. However, in contrast to illustrative time series of temperature, sea ice extent or glacier melt, the observation-based figures of the heavy precipitation intensification are often hard to interpret for non-experts. Observed maps of station trends show a lot of natural climate variability, and robust global evidence is based on complex statistical methods such as histograms of trends in the location parameter of a non-stationary extreme value distribution[20]. Due to this complexity, the intensification of heavy precipitation is often illustrated to lay audiences with schematics rather than with observation-based evidence.

The challenge of visualizing changes in heavy rainfall at the station or gridbox level is that the signal is obscured by high internal variability, due to the chaotic nature of weather and phenomena such as the El Niño Southern Oscillation. Therefore robust changes in extremes only become evident if aggregated in space. Here we propose a simple observation-based illustration for Europe and the US in order to complement the idealized schematic. To this end the frequency of daily precipitation data in the period 1981–2013 compared to the baseline period 1951–1980 is calculated for different all-day percentiles, and then averaged across the gridpoints of the ENSEMBLES gridded observational data set (Fig. 2a, light blue, EOBS version 12)[22] that contains continuous data, and across all stations of the European Climate Assessment (ECA)[22] (see Methods). The observations for Europe (Fig. 2a) confirm the schematic (Fig. 1a) and show more heavy precipitation days. The more intense the heavy rainfall event, the higher the relative increase in frequency (Fig. 2b). The findings imply that what was a 1-in-1000 day heavy rainfall in 1951–1980 occurred about 45% more often in the 1981– 2013 period, a frequency change consistent in sign but much more pronounced than a global model-based estimate[23]. The increase in heavy precipitation days is substantially larger than expected from internal variability only (grey shading). The observed increase in the gridded EOBS data (light blue) is very similar to ECA station average across the same domain (violet) and furthermore is remarkably consistent with expectations from Clausius–Clapeyron (Fig. 2b, dashed light blue line). The Clausius–Clapeyron scaling is here estimated by increasing EOBS precipitation on all days by 5.25% according to the observed warming of 0.75 °C in that region (see Methods). Likewise, the same approach applied to daily gridded precipitation data for the contiguous US east of 100° W yields a highly consistent result between observations and theory (Supplementary Fig. 1).

Consistency with newest model generation

The observed changes are also broadly consistent with the most recent generations of GCMs within the CMIP5 archive and regional climate models (RCM) run at 0.44° and 0.11° resolution within the EURO-CORDEX model intercomparison project[24,25] (Fig. 2c). For comparison with observations, the GCMs and RCMs were masked where EOBS has incomplete data coverage. The model response shows a substantial spread, with some RCMs showing only weak increases. The observations are at the high end of the range of GCMs and slightly above the range of RCMs, which is consistent with the argument that models tend to underestimate the observed changes in heavy rainfall intensity[26–28]. For the US the overestimation is less pronounced (Supplementary Fig. 1). However, the differences across models and the potential bias against observations need to be interpreted with caution. They may arise from a combination of at least

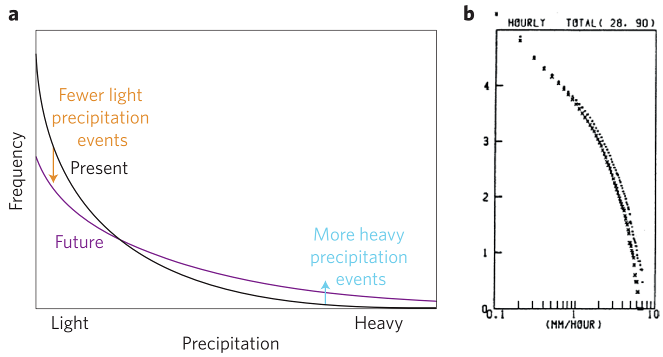

Figure 1 | Heavy rainfall intensification in theory and very coarse GCMs. **a**, Schematic illustrating the change in rainfall distribution redrawn after ref. 103 and Fig. 1.8 in ref. 104. **b**, Frequency distribution for precipitation rates (mm h^{-1}) for 1–10 January. This panel, a reproduction from Noda and Tokioka[8], shows the log-frequency of precipitation exceeding a given rate per hour in the $1\times CO_2$ (crosses) and $2\times CO_2$ simulations (dots) aggregated across each gridpoint between 20° N–90° N shown in ref. 8. The vertical axis shows the log-frequency where 1 corresponds to 10 (since $\log_{10}(10) = 1$), 2 corresponds to 100, and so on. Note data point outside the axes range.

five factors; (1) differences in warming between the two periods in models compared to observations, (2) internal variability in regional heavy precipitation, (3) different forced heavy rainfall response to the warming, (4) statistical effects of different grid resolutions, and (5) deficiencies in the observational datasets such as missing or changing station coverage and data inhomogeneities. An analysis of 21 realizations of the same GCM only differing in the initial atmospheric conditions suggests a large role for internal variability for the change between the two historical periods (Supplementary Fig. 4). We find that for a common warming level of 3 °C and if the RCM simulations are regridded to the GCM resolution, there is no systematic difference between GCMs and RCMs (Supplementary Figs 2,3 and Supplementary Discussion) suggesting that for daily data the results are not sensitive to model resolution. Model biases in the forced response of heavy precipitation may contribute but need to be interpreted with caution, and a detailed model evaluation is beyond the scope of this manuscript. Note that at the scales they resolve, RCMs and high resolution GCMs still provide added value in the representation of extreme precipitation amounts[29,30] and may regionally even simulate a modified response to increased greenhouse gas concentrations, for instance over topography[31].

Overall the observed changes in heavy precipitation are consistent across Europe and the US. In some other regions and particularly in parts of the tropics the observed signal is less evident[17–19]. This may be due to a lack of long-duration high-quality observational series, trends being masked by internal variability even at the continental scale or due to a lack of a heavy rainfall signal. According to both observations and models there are substantial latitudinal differences in the sensitivity of precipitation extremes to warming[20,32–34]. In some regions, heavy rainfall events relate to large-scale dynamic features[35,36] such as frontal systems, which implies that dynamical changes such as the expansion of the Hadley cells or shifts in the storm tracks may substantially alter the heavy precipitation response[37]. In this Perspective we do not disentangle whether the wettest days become more frequent at the expense of fewer days with weak precipitation or fewer dry days (in other words, whether the rainfall also intensifies at the days with light precipitation[38,39]). Note that even if the intensity at all rainfall levels increases, there would be more very wet days at the expense of days with light rain. From thermodynamic consideration it is not obvious whether we should expect heavy precipitation to scale with total column water vapor, or with local or remote near-surface temperature or

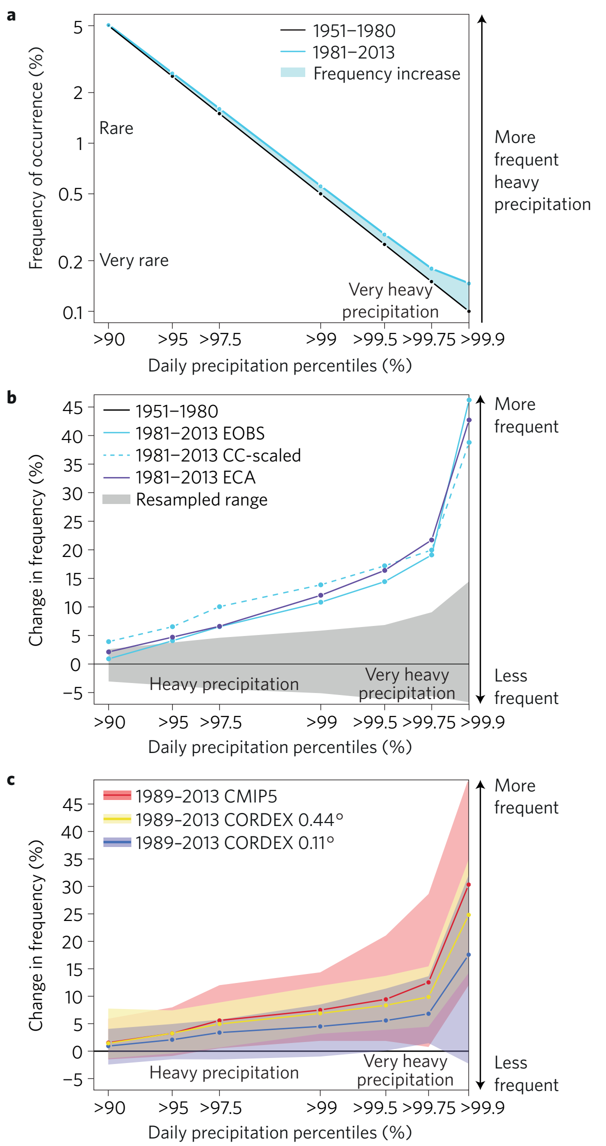

Figure 2 | Heavy rainfall intensification in observations and most recent model generations. a, Observed frequency of occurrence of heavy precipitation in Europe in the periods 1951–1980 (black) and 1981–2013 (light blue solid) according to the EOBS gridded observation data set. Data is binned according to local percentiles calculated for the period 1951–1980 so that for example, 5% of all days fall in the bin 90th to 95th percentiles (see Methods). **b**, Ratio of observed daily precipitation frequency in 1981–2013 versus 1951–1980 according to the EOBS gridded observation data set (light blue solid) and the ECA station series (violet solid). Light blue dashed lines show changes for 1981–2013 as expected from Clausius–Clapeyron (CC) scaling due to the regional mean warming of 0.75 °C between the two periods. Data is aggregated across all EOBS gridpoints in the area 38° N to 72° N and 12° W to 40° E that provide data for all days in both periods. ECA stations in the same area and with less than 20% of missing data in each period are averaged. Grey shading illustrates the changes expected due to internal variability only (two-sided 95% confidence interval) derived by randomly resampling two subperiods of EOBS gridded data across the observational period 1951–2013 (see Methods). **c**, Same as (**b**) but for CMIP5 models (red), EURO-CORDEX models run at 0.44° resolution (yellow) and 0.11° resolution (blue). Models are masked by the observational data set. Shading denotes minimum–maximum ranges across all models in the ensembles, but note that no model follows the upper or lower bound of the shading for all percentiles.

humidity[40]. Furthermore, some dry continental regions are projected to experience a reduction in near-surface relative humidity primarily due to limited moisture availability. Given this complexity it is remarkable that models consistently show an increase in heavy rainfall events over most land regions[41,42]. In mid- to high-latitudes particularly, daily precipitation extremes often scale with local to regional temperatures at rates close to local near-surface specific humidity[40,43,44] — often referred to as Clausius–Clapeyron scaling.

Progress and open questions

The latest evidence shows that the number of days with very heavy precipitation over Europe has increased on average by about 45% in observations (years 1981–2013 compared to 1951–1980) and by about 25% in the model average, although with substantial spread across models and observations (Fig. 2). These results confirm what was postulated more than 25 years ago, yet there has been crucial progress in our scientific understanding and thus ultimately a strong increase in our confidence. The physical processes controlling heavy rainfall are better understood[34,40,43], our understanding of the role of thermodynamic, dynamical and orographic processes has improved[34,40,45–48], and the role of different forcings[49] and the contribution of internal variability versus the forced response has been quantified[27,42]. Despite these major advances — mainly on heavy precipitation over the northern extratropics — there remain open questions regarding the exact rate of change in heavy precipitation[20,50], the seasonality of changes in precipitation extremes[51], and complex features such as monsoon systems and organized convection. Questions also remain regarding the detailed local- to regional-scale patterns[41,42], where changes could be substantially stronger — for instance over the tropics — or weaker or even negative over parts of the subtropics modified by a poleward expansion of the subtropical dry zones and enhanced subsidence. Furthermore, the rate of intensification depends on the duration of the heavy rainfall events. Recent observational and model evidence suggests that sub-daily rainfall such as hourly downpours scale at rates higher than Clausius–Clapeyron[52–55]. Finally, it is still poorly understood at what rate biweekly to monthly rainfall maxima increase[56], which are relevant in hydrology for streamflow flooding and stagnant floods, respectively. The availability of and unlimited access to high quality long term observations in more regions is critical, but despite large efforts the access to and use of such data remains a challenge[18,57]. Combining those observations with more advanced methods of extreme value statistics and detailed analysis of the dynamics of individual heavy rainfall events[37,58–60] will further advance our understanding of observed trends.

We here show that the earliest predictions made by simple coarse-resolution climate models more than 25 years ago are confirmed by daily rainfall in two regions with dense observational networks and high data quality, and are broadly consistent with simulations by much higher resolution GCMs and RCMs. Also of note is that the newest generation of high resolution models generally parameterize convection. However, even the first available convection-permitting model simulations[61] suggest that, unlike for sub-daily rainfall, the response of daily rainfall maxima in convection-permitting models is broadly consistent with coarse resolution models[52,54,62–64]. Further development and application of convection-permitting models to long term climate change will be key to test whether that reconciles the potentially underestimated rate of change in daily heavy precipitation in models with observations. However, our high confidence in the heavy rainfall intensification over most land regions is not based on a single most advanced convection-permitting model nor only on the most comprehensive observational analysis. Instead it results from the different lines of evidence coming from model, theory and observations. While all of the lines have their strengths and limitations, the heavy rainfall response is consistent across low- to high-resolution models, many observational data sets, many statistical approaches and most importantly supported by improved process understanding that has fostered our confidence. Evidence from model evaluation, projections, observations, or detection and attribution are still often discussed individually, including in recent assessments by the IPCC[65]. For example, model projections treat all models equally as if there were no observations, and as a consequence uncertainty assessments based on those ensembles of opportunity are challenging[66–68]. A tighter formal integration of models, observations and attribution in our view could lead to higher consistency between the lines of evidence and increased confidence about what the future will bring.

Implications for the research process

In many fields of science, such as physics, a hypothesis can often be clearly confirmed or rejected by an experiment. However, many environmental phenomena are different: the system is open, physical, chemical and biological processes interact across all timescales and spatial scales, first principles are missing for many processes, and a clean experiment is impossible, too expensive, too dangerous or unethical. In a field like climate research, phenomena are often observed first, and then simulated and explained, and hypotheses are rarely confirmed or rejected unequivocally, but evidence increases gradually. The way the lines of evidence unfolded in the case of increasing heavy precipitation, starting from theory, followed by simple models being confirmed by robust observational evidence only decades later may thus seem unusual to non-scientists but is in fact not an uncommon pattern in climate research. There are numerous changes that have first been predicted based on models and theory before being observed. The most prominent example at the core of climate change research is the warming response to enhanced CO_2 concentrations first predicted more than a century ago[69], simulated in the 1970s[7,70], and now firmly established in both models and observations[71]. Another example is the warming of the global oceans where many studies, based on the seasonal lag of temperature to insolation and the slower warming over the ocean, predicted that the effects of the ocean would delay surface warming by many decades[70,72–76]. As a consequence, the ocean would need to take up most of the energy that Earth has been gaining in response to increased CO_2 concentrations. Only much later was the data of sufficient quality to conclude that the global oceans were indeed warming[77]. Early climate models and observations showed consistent long term trends[78,79], but large decadal variations in the observations were difficult to reconcile with models, as was an apparent observed cooling after 2003[80]. Models showed that much of the variability in the dataset was the result of spatial interpolation[81,82], and progress in calibrating different instruments[83,84] brought more recent observed estimates into much better agreement with both coupled 3D models and energy balance arguments[4,85–88]. This is an interesting example: most of the discrepancies originated from biased observations rather than from models. There are other cases where mismatches between observations and models helped in identifying inhomogeneities in observations, such as for reconstructions of global mean temperature[89], and in observations of upper tropospheric warming. In the latter case, the lack of observed amplification of warming in the upper troposphere that the models predicted was also found to largely be a bias in radiosonde and satellite data[90–93]. Of course this should never imply that we should expect all model-projected changes to be later confirmed by observations. There are many model results and predictions even by the newest generation of models, in which we have low confidence. For example, atmospheric models show too frequent light drizzling precipitation and have difficulties representing blocking, and ocean models struggle to simulate equatorial coastal upwelling. Many of those problems are structural in the sense that models across institutions and generations share biases[94], and as a result long-term projection uncertainties have not decreased over the last decade — despite more detailed observations, process understanding, larger computational capacities, and better agreement of models with data[66,67,95]. Progress can only be achieved through a tighter integration of process understanding, observational data and climate models, through targeted process-based model evaluation on relevant mechanisms and feedbacks, emergent observational constraints that relate to projections[96,97], data assimilation, testing climate models on weather-appropriate timescales[98] and by tracing phenomena through a hierarchy of simple to very complex models[99]. Ultimately, it is the consistency between different lines of evidence — the combination of process understanding based on theoretical first principles, a hierarchy of models and the wealth of observational series — which strengthens our confidence in certain model results and predictions. For predictions to be of value, the challenge is to identify those for which confidence is high, before they actually manifest themselves.

Methods

Methods and any associated references are available in the online version of the paper.

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References

1. Trenberth, K. E. Conceptual framework for changes of extremes of the hydrological cycle with climate change. *Climatic Change* **42,** 327–339 (1999).
2. Hennessy, K. J., Gregory, J. M. & Mitchell, J. F. B. Changes in daily precipitation under enhanced greenhouse conditions. *Clim. Dynam.* **13,** 667–680 (1997).
3. Schmidt, G. A., Shindell, D. T. & Tsigaridis, K. Reconciling warming trends. *Nat. Geosci.* **7,** 158–160 (2014).
4. Huber, M. & Knutti, R. Natural variability, radiative forcing and climate response in the recent hiatus reconciled. *Nat. Geosci.* **7,** 651–656 (2014).
5. Clapeyron, E. Mémoire sur la puissance motrice de la chaleur. *J. l'École Polytechnique* XXIIIe Cahier, Tome XIV 153–191 (1834).
6. Clausius, R. Über die bewegende kraft der wärme und die gesetze, welche sich daraus für die wärmelehre selbst ableiten lassen. *Ann. Phys. (Berlin)* **155,** 368–397 (1850).
7. Manabe, S. & Wetherald, R. T. The effects of doubling the CO_2 concentration on the climate of a General Circulation Model. *J. Atmos. Sci.* **32,** 3–15 (1975).
8. Noda, A. & Tokioka, T. The effect of doubling the CO_2 concentration on convective and non-convective precipitation in a general-circulation model coupled with a simple mixed layer ocean model. *J. Meteor. Soc. Japan* **67,** 1057–1069 (1989).
9. Fowler, A. M. & Hennessy, K. J. Potential impacts of global warming on the frequency and magnitude of heavy precipitation. *Natural Hazards* **11,** 283–303 (1995).
10. Gordon, H. B., Whetton, P. H., Pittock, A. B., Fowler, A. M. & Haylock, M. R. Simulated changes in daily rainfall intensity due to the enhanced greenhouse effect: implications for extreme rainfall events. *Clim. Dynam.* **8,** 83–102 (1992).
11. Whetton, P. H., Fowler, A. M., Haylock, M. R. & Pittock, A. B. Implications of climate change due to the enhanced greenhouse effect on floods and droughts in Australia. *Climatic Change* **25,** 289–317 (1993).
12. Taylor, K. E., Stouffer, R. J. & Meehl, G. A. An overview of CMIP5 and the experiment design. *Bull. Am. Meteorol. Soc.* **93,** 485–498 (2012).
13. Hansen. J. *et al.* Global climate changes as forecast by Goddard Institute for space studies 3-dimensional model. *J. Geophys. Res. Atmos.* **93,** 9341–9364 (1988).
14. Wetherald, R. T. & Manabe, S. Cloud feedback processes in a general-circulation model. *J. Atmos. Sci.* **45,** 1397–1415 (1988).
15. Iwashima, T. & Yamamoto, R. A statistical analysis of the extreme events: long-term trend of heavy daily precipitation. *J. Meteor. Soc. Japan.* **71,** 637–640 (1993).
16. IPCC *Climate Change 1995: The Science of Climate Change* (eds Houghton, J. T. *et al.*) (Cambridge Univ. Press, 1996).
17. Hartmann, D. L. *et al.* in *Climate Change 2013: The Physical Science Basis* (eds Stocker, T. F. *et al.*) Ch. 2 (IPCC, Cambridge Univ. Press, 2014).
18. Alexander, L. V. Global observed long-term changes in temperature and precipitation extremes: a review of progress and limitations in IPCC assessments and beyond. *Weather Clim. Extremes* **11,** 4–16 (2016).
19. Kunkel, K. E. & Frankson, R. M. Global land surface extremes of precipitation: data limitations and trends. *J. Extreme Events* **2,** 1550004 (2015).

20. Westra. S., Alexander, L. V. & Zwiers, F. W. Global increasing trends in annual maximum daily precipitation. *J. Clim.* **26,** 3904–3918 (2013).
21. Donat, M. G., Lowry, A. L., Alexander, L. V., O'Gorman, P. A. & Maher N. More extreme precipitation in the world's dry and wet regions. *Nat. Clim. Change* **6,** 508–513 (2016).
22. Haylock, M. R. *et al.* A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *J. Geophys. Res. Atmos.* **113,** D20119 (2008).
23. Fischer, E. M. & Knutti, R. Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes. *Nat. Clim. Change* **5,** 560–564 (2015).
24. Jones, C., Giorgi, F. & Asrar, G. The coordinated regional downscaling experiment: CORDEX–an international downscaling link to CMIP5. *Clivar Exchanges* **16,** 34–40 (2011).
25. Kotlarski, S. *et al.* Regional climate modeling on European scales: a joint standard evaluation of the EURO-CORDEX RCM ensemble. *Geosci. Model Dev.* **7,** 1297–1333 (2014).
26. Min, S.-K., Zhang, X., Zwiers, F. W. & Hegerl, G. C. Human contribution to more-intense precipitation extremes. *Nature* **470,** 378–381 (2011).
27. Zhang, X., Wan, H., Zwiers, F. W., Hegerl, G. C. & Min, S.-K. Attributing intensification of precipitation extremes to human influence. *Geophys. Res. Lett.* **40,** 5252–5257 (2013).
28. Fischer, E. M. & Knutti, R. Detection of spatially aggregated changes in temperature and precipitation extremes. *Geophys. Res. Lett.* **41,** 547–554 (2014).
29. Kopparla, P., Fischer, E. M., Hannay, C. & Knutti, R. Improved simulation of extreme precipitation in a high-resolution atmosphere model. *Geophys. Res. Lett.* **40,** 5803–5808 (2013).
30. Rajczak, J., Pall, P. & Schär, C. Projections of extreme precipitation events in regional climate simulations for Europe and the Alpine region. *J. Geophys. Res. Atmos.* **118,** 3610–3626 (2013).
31. Giorgi, F. *et al.* Enhanced summer convective rainfall at Alpine high elevations in response to climate warming. *Nat. Geosci.* **9,** 584–589 (2016).
32. Westra, S. & Sisson, S. A. Detection of non-stationarity in precipitation extremes using a max-stable process model. *J. Hydrol.* **406,** 119–128 (2011).
33. Utsumi, N., Seto, S., Kanae, S., Maeda, E. E. & Oki, T. Does higher surface temperature intensify extreme precipitation? *Geophys. Res. Lett.* **38,** L16708 (2011).
34. O'Gorman, P. A. Sensitivity of tropical precipitation extremes to climate change. *Nat. Geosci.* **5,** 697–700 (2012).
35. Catto, J. L. & Pfahl, S. The importance of fronts for extreme precipitation. *J. Geophys. Res. Atmos.* **118,** 10791–10801 (2013).
36. Pfahl, S. & Wernli, H. Quantifying the relevance of cyclones for precipitation extremes. *J. Clim.* **25,** 6770–6780 (2012).
37. Schaller, N. *et al.* Human influence on climate in the 2014 southern England winter floods and their impacts. *Nat. Clim. Change* **6,** 627–634 (2016).
38. Pendergrass, A. G. & Hartmann, D. L. Two modes of change of the distribution of rain. *J. Clim.* **27,** 8357–8371 (2014).
39. Pendergrass, A. G. & Hartmann, D. L. Changes in the distribution of rain frequency and intensity in response to global warming. *J. Clim.* **27,** 8372–8383 (2014).
40. O'Gorman, P. A. & Schneider, T. The physical basis for increases in precipitation extremes in simulations of 21st-century climate change. *Proc. Natl Acad. Sci. USA* **106,** 14773–14777 (2009).
41. Kharin, V., Zwiers, F., Zhang, X. & Wehner, M. Changes in temperature and precipitation extremes in the CMIP5 ensemble. *Climatic Change* **119,** 345–357 (2013).
42. Fischer, E. M., Sedlacek, J., Hawkins, E. & Knutti, R. Models agree on forced response pattern of precipitation and temperature extremes. *Geophys. Res. Lett.* **41,** 8554–8562 (2014).
43. O'Gorman, P. A. & Schneider, T. Scaling of precipitation extremes over a wide range of climates simulated with an idealized GCM. *J. Clim.* **22,** 5676–5685 (2009).
44. O'Gorman, P. A. Precipitation extremes under climate change. *Curr. Clim. Change Rep.* **1,** 49–59 (2015).
45. Trenberth, K. E., Dai, A., Rasmussen, R. M. & Parsons, D. B. The changing character of precipitation. *Bull. Am. Meteorol. Soc.* **84,** 1205–1217 (2003).
46. Allan, R. & Soden, B. Atmospheric warming and the amplification of precipitation extremes. *Science* **321,** 1481–1484 (2008).
47. Frei, C., Schär, C., Lüthi, D. & Davies, H. C. Heavy precipitation processes in a warmer climate. *Geophys. Res. Lett.* **25,** 1431–1434 (1998).
48. Chavaillaz, Y., Joussaume, S., Bony, S. & Braconnot, P. Spatial stabilization and intensification of moistening and drying rate patterns under future climate change. *Clim. Dynam.* **47,** 951–965 (2015).
49. Pendergrass, A. G., Lehner, F., Sanderson, B. M. & Xu, Y. Does extreme precipitation intensity depend on the emissions scenario? *Geophys. Res. Lett.* **42,** 8767–8774 (2015).
50. Lenderink, G. & Attema, J. A simple scaling approach to produce climate scenarios of local precipitation extremes for the Netherlands. *Environ. Res. Lett.* 085001 (2015).
51. Rajczak. J., Pall, P. & Schär, C. Projections of extreme precipitation events in regional climate simulations for Europe and the Alpine Region. *J. Geophys. Res. Atmos.* **118,** 3610–3626 (2013).
52. Kendon, E. J. *et al.* Heavier summer downpours with climate change revealed by weather forecast resolution model. *Nat. Clim. Change* **4,** 570–576 (2014).
53. Lenderink, G. & van Meijgaard, E. Increase in hourly precipitation extremes beyond expectations from temperature changes. *Nat. Geosci.* **1,** 511–514 (2008).
54. Westra, S. *et al.* Future changes to the intensity and frequency of short-duration extreme rainfall. *Rev. Geophys.* **52,** 522–555 (2014).
55. Berg, P., Moseley, C. & Haerter, J. O. Strong increase in convective precipitation in response to higher temperatures. *Nat. Geosci.* **6,** 181–185 (2013).
56. Lenderink, G. *et al.* Preparing local climate change scenarios for the Netherlands using resampling of climate model output. *Environ. Res. Lett.* 115008 (2014).
57. Zwiers, F. W. *et al.* in *Climate Science for Serving Society* (eds Asrar, G. R. & Hurrell, J. W.) Ch. 13, 339–389 (Springer, 2013).
58. Shepherd, T. G. A common framework for approaches to extreme event attribution. *Curr. Clim. Change Rep.* **2,** 28–38 (2016).
59. Trenberth, K. E., Fasullo, J. T. & Shepherd, T.G. Attribution of climate extreme events. *Nat. Clim. Change* **5,** 725–730 (2015).
60. Martius, O. *et al.* The role of upper-level dynamics and surface processes for the Pakistan flood of July 2010. *Q. J. Roy. Meteorol. Soc.* **139,** 1780–1797 (2013).
61. Prein, A. F. *et al.* A review on regional convection-permitting climate modeling: demonstrations, prospects, and challenges. *Rev. Geophys.* **53,** 323–361 (2015).
62. Chan, S. C., Kendon, E. J., Fowler, H. J., Blenkinsop, S. & Roberts, N. M. Projected increases in summer and winter UK sub-daily precipitation extremes from high-resolution regional climate models. *Environ. Res. Lett.* **9,** 084019 (2014).
63. Chan, S. C., Kendon, E. J., Roberts, N. M., Fowler, H. J. & Blenkinsop, S. Downturn in scaling of UK extreme rainfall with temperature for future hottest days. *Nat. Geosci.* **9,** 24–28 (2015).
64. Ban, N., Schmidli, J. & Schär, C. Heavy precipitation in a changing climate: does short-term summer precipitation increase faster? *Geophys. Res. Lett.* **42,** 1165–1172 (2015).
65. IPCC *Climate Change 2013: The Physical Science Basis* (eds Stocker, T. F. *et al.*) (Cambridge Univ. Press, 2014).
66. Knutti, R., Masson, D. & Gettelman, A. Climate model genealogy: generation CMIP5 and how we got there. *Geophys. Res. Lett.* **40,** 1194–1199 (2013).
67. Knutti, R. & Sedlacek, J. Robustness and uncertainties in the new CMIP5 climate model projections. *Nat. Clim. Change* **3,** 369–373 (2013).
68. Knutti, R. The end of model democracy? *Climatic Change* **102,** 395–404 (2010).
69. Arrhenius, S. On the influence of carbonic acid in the air upon the temperature of the ground. *London Edinburgh Dublin Phil. Mag. J. Sci.* **41,** 237–276 (1896).
70. Hansen, J. *et al.* in *Climate Processes and Climate Sensitivity* (eds Hansen, J. E. & Takahash, T.) 130–163 (AGU Geophysical Monograph, 1984).
71. Bindoff, N. L. *et al.* in *Climate Change 2013: The Physical Science Basis* (eds Stocker, T. F. *et al.*) Ch. 10 (IPCC, Cambridge Univ. Press, 2014).
72. Hansen, J. *et al.* Climate impact of increasing atmospheric carbon dioxide. *Science* **213,** 957–966 (1981).
73. Hansen, J. *et al.* Climate response times: dependence on climate sensitivity and ocean mixing. *Science* **229,** 857–859 (1985).
74. Siegenthaler, U. & Oeschger, H. Transient temperature changes due to increasing CO_2 using simple models. *Ann. Glaciol.* **5,** 153–159 (1984).
75. Cess, R. D. & Goldenberg, S. D. The effect of ocean heat capacity upon global warming due to increasing atmospheric carbon dioxide. *J. Geophys. Res. Oceans* **86,** 498–502 (1981).
76. Schlesinger, M. E. Equilibrium and transient climatic warming induced by increased atmospheric CO_2. *Clim. Dynam.* **1,** 35–51 (1986).
77. Levitus, S., Antonov, J. I., Boyer, T. P. & Stephens, C. Warming of the world ocean. *Science* **287,** 2225–2229 (2000).
78. Barnett, T.P., Pierce, D. W. & Schnur, R. Detection of anthropogenic climate change in the world's oceans. *Science* **292,** 270–274 (2001).
79. Levitus, S. *et al.* Anthropogenic warming of Earth's climate system. *Science* **292,** 267–270 (2001).
80. Lyman, J. M., Willis, J. K. & Johnson, G. C. Recent cooling of the upper ocean. *Geophys. Res. Lett.* L18604 (2006).
81. AchutaRao, K. M. *et al.* Variability of ocean heat uptake: reconciling observations and models. *J. Geophys. Res. Oceans* C05019 (2006).
82. Gregory, J., Banks, H., Stott, P., Lowe, J. & Palmer, M. Simulated and observed decadal variability in ocean heat content. *Geophys. Res. Lett.* L15312 (2004).
83. Gouretski, V. & Koltermann, K. P. How much is the ocean really warming? *Geophys. Res. Lett.* L01610 (2007).

84. Wijffels, S. E. *et al.* Changing expendable bathythermograph fall rates and their impact on estimates of thermosteric sea level rise. *J. Clim.* **21,** 5657–5672 (2008).
85. Domingues, C. M. *et al.* Improved estimates of upper-ocean warming and multi-decadal sea-level rise. *Nature* **453,** 1090-1096 (2008).
86. Church, J. A. *et al.* Revisiting the Earth's sea-level and energy budgets from 1961 to 2008. *Geophys. Res. Lett.* L18601 (2011).
87. Lyman, J. M. *et al.* Robust warming of the global upper ocean. *Nature* **465,** 334–337 (2010).
88. Abraham, J. P. *et al.* A review of global ocean temperature observations: implications for ocean heat content estimates and climate change. *Rev. Geophys.* **51,** 450–483 (2013).
89. Thompson, D. W. J., Wallace, J. M., Kennedy, J. J. & Jones, P. D. An abrupt drop in Northern Hemisphere sea surface temperature around 1970. *Nature* **467,** 444–447 (2010).
90. Mears, C. A. & Wentz, F. J. The effect of diurnal correction on satellite-derived lower tropospheric temperature. *Science* **309,** 1548–1551 (2005).
91. Santer, B. D. *et al.* Amplification of surface temperature trends and variability in the tropical atmosphere. *Science* **309,** 1551–1556 (2005).
92. Allen, R. J. & Sherwood, S. C. Warming maximum in the tropical upper troposphere deduced from thermal winds. *Nat. Geosci.* **1,** 399–403 (2008).
93. Sherwood, S. C., Lanzante, J. R. & Meyer, C. L. Radiosonde daytime biases and late-20th century warming. *Science* **309,** 1556–1559 (2005).
94. Masson, D. & Knutti, R. Climate model genealogy. *Geophys. Res. Lett.* L08703 (2011).
95. Rauser, F., Gleckler, P. & Marotzke, J. Rethinking the default construction of multi-model climate ensembles. *Bull. Am. Meteorol. Soc.* **96,** 911–919 (2014).
96. Hall, A. & Qu, X. Using the current seasonal cycle to constrain snow albedo feedback in future climate change. *Geophys. Res. Lett.* L03502 (2006).
97. Bitz, C. & Fu, Q. Arctic warming aloft is data set dependent. *Nature* **455,** E3–E4 (2008).
98. Palmer, T., Doblas-Reyes, F., Weisheimer, A. & Rodwell, M. Toward seamless prediction: calibration of climate change projections using seasonal forecasts. *Bull. Am. Meteorol. Soc.* **89,** 459–470 (2008).
99. Held, I. Simplicity amid Complexity. *Science* **343,** 1206–1207 (2014).
100. Schär, C. *et al.* Percentile indices for assessing changes in heavy precipitation events. *Climatic Change* **137,** 201–216 (2016).
101. Zhang, X. B., Hegerl, G., Zwiers, F. W. & Kenyon, J. Avoiding inhomogeneity in percentile-based indices of temperature extremes. *J. Clim.* **18,** 1641–1651 (2005).
102. Hofstra, N., New, M. & McSweeney, C. The influence of interpolation and station network density on the distributions and trends of climate variables in gridded daily data. *Clim. Dynam.* **35,** 841–858 (2010).
103. Thomas R. *et al.* (eds) *Weather and Climate Extremes in a Changing Climate. Regions of Focus: North America, Hawaii, Caribbean, and U.S. Pacific Islands* (CCSP, 2008).
104. Cubasch, U. *et al.* in *Climate Change 2013: The Physical Science Basis* (eds Stocker, T. F. *et al.*) Ch. 1 (IPCC, Cambridge Univ. Press, 2014).

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Additional information
Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to E.M.F (erich.fischer@env.ethz.ch)

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Methods

In Fig. 2 we quantify changes in daily heavy precipitation between the period 1951–1980 and 1981–2013. We first calculate daily precipitation percentiles of all days (dry and wet days)[100] in the period 1951–1980 at each individual gridpoint of the EOBS gridded data set. The 99.9% quantile represents a threshold that on average is exceeded about once in 1,000 days (approximately once in 3 years) and is thereby less intense than very extreme cases like a 1-in-100 year event, which typically has major impacts. We then bin the daily precipitation in the period 1981–2013 at each gridpoint according to the local percentiles defined in the previous period and area-average the occurrence in each bin (see also ref. 23) across the area 38° N to 72° N and 12° W to 40° E. Note that for readability the labels in the figures only include the lower end of the bin, for example, the value indicated at '>90%' counts all days between the 90% and 95% percentiles. We choose the area to minimize the number of gridpoints in which the 90th percentile of all-day precipitation is a dry day, and restrict the analysis to all land gridpoints for which the daily gridded EOBS data set (version 12 at 0.25° resolution)[22] provides continuous data for each day in both periods (see Supplementary Fig. 5). The sign of the changes is insensitive to the exact split between the two observational periods or the choice of two or three subperiods. In order to test whether the changes exceed what would be expected from internal variability only, we randomly resampled subperiods by drawing 30 and 33 individual years, respectively, from the gridded EOBS data across the whole observational period 1951–2013. The analysis was then applied on the resampled subperiods and repeated 500 times to derive a two-sided confidence interval, as a rough estimate for the chances expected due to internal variability. The range is somewhat skewed particularly for high percentiles, illustrating that the number of exceedances is slightly enhanced to the statistical artefact of higher out-of-sample exceedances documented in ref. 101. This may also slightly affect the original analysis but the effect is found to be small and the change almost equally large if the percentiles are defined in the later period 1981–2013 or across the both subperiods together. In order to estimate the Clausius–Clapeyron scaled changes, we increase the raw daily precipitation distribution 1951–80 by 5.25% according to the observed area-averaged temperature change of 0.75 °C (1981-2013 versus 1951–1980 in EOBS gridded temperature data version 12)[22].

The gridding procedure may smooth the actual extremes and in principle artefacts in trends of extremes could result from varying spatial density of stations that are used in the gridding[102]. Therefore we repeat the analysis with raw precipitation station series. We use daily precipitation series from all the ECA stations (non-blended data)[22] across the area 38° N to 72° N and 12° W to 40° E that provided data for more than 80% of the days of each of the periods 1951–80 and 1981–2013 (see Supplementary Fig. 5). To avoid a regional bias to the Netherlands which has exceptionally high station density, we randomly subsampled the data by only using 20% of the stations in the Netherlands. The analysis is performed at each station and then averaged across the area.

For Fig. 2c we repeat the same procedure with the historical and the first years of RCP8.5 simulations of 24 CMIP5 global climate models, 14 EURO-CORDEX regional climate models run at 0.44° resolution and 8 RCMs run at 0.11° resolution (see Supplementary Tables 1 and 2 for a list of models). The climate models are masked to be consistent with the EOBS data.