1 Global scaling of rainfall with dewpoint temperature reveals considerable ocean-land 2 difference

3 Haider Ali¹, Nadav Peleg², Hayley J. Fowler¹

4 1. School of Engineering, Newcastle University, Newcastle upon Tyne, UK

5 2. Institute of Environmental Engineering, ETH Zurich, Zurich, Switzerland

6 Abstract

7 Short-duration rainfall extremes are expected to intensify with warming at around 7%/K,
8 following the Clausius–Clapeyron (CC) relation, causing concomitant increases in flash
9 floods. Observed hourly rainfall extremes show consistent CC-scaling with dewpoint
10 temperature across all land regions. Here, we use two global climate reanalysis products
11 (ERA5 and MERRA-2) to examine consistency in scaling with observations, in ungauged
12 regions and over the oceans. We find that reanalyses underestimate observed scaling, but
13 ERA5 provides better estimates than MERRA-2. Scaling rates at high- and mid-latitudes are
14 similar to observations, at CC, while over the tropics mixed negative- and super-CC scaling
15 rates are seen. We show underestimation of scaling rates over the tropics is related to
16 deficiencies in simulations of extreme rainfall over orographically complex and convection
17 dominated regions. Importantly, both reanalyses indicate scaling rates over the ocean are
18 substantially higher than over land, with implications for extreme weather events originating
19 over the ocean.

20 Plain Language Summary

21 As temperatures rise, extreme rainfalls are expected to intensify by 7% per 1°C following the
22 Clausius–Clapeyron relation. Thus, flash floods are predicted to increase in magnitude and
23 frequency with rising temperatures. In the areas where measurements are available,
24 observations confirm the intensification of extreme hourly rainfall with increasing
25 temperatures at the expected rate. Here, we use two global climate reanalysis products to
26 examine the agreement in extreme rainfall-temperature relation with observations, in
27 ungauged regions and over the ocean. High- and mid-latitude rainfall-temperature rates
28 obtained from the climate reanalysis are in accordance with observations. In the tropics, the
29 rainfall-temperature relation is a mix of negative and very high values (in the order of 14%
30 per 1°C). Climate reanalyses indicate extreme rainfall-temperature rates are much higher over
31 the ocean than on land.

32 1. Introduction

33 Short-duration extreme rainfall events can trigger flash floods in rural and urban
34 environments (Fadhel et al., 2018; Fowler et al., 2021a). The hydrological response to these
35 rainfall bursts is very fast, giving no or very little warning to respond (Archer and Fowler,
36 2018; Fowler et al., 2021b). Therefore, understanding the mechanisms of extreme rainfall
37 generation can be useful for the planning and mitigation of hazards and fatalities associated
38 with these events (Wasko et al., 2016). With anthropogenic warming, extreme rainfall events
39 have intensified at the global scale and are projected to further increase (Li et al., 2020;
40 Moustakis et al., 2021; Barbero et al., 2019; Chen et al., 2021; Westra et al., 2014; Fowler et
41 al., 2021a).

42 The intensification of extreme rainfall intensities with warming has been explained
43 thermodynamically by the Clausius–Clapeyron (CC) relationship (Abbott et al., 2020;
44 O’Gorman, 2015). According to the CC relationship, the moisture-holding capacity (specific

humidity) of an air mass increases at approximately $\sim 6.5\%$ per degree warming (K) near to the Earth's surface, and since rainfall extremes tend to occur when the atmosphere is at, or near, saturation, rainfall extremes are also expected to increase in line with CC (Trenberth et al., 2003). Moreover, sub-daily rainfall intensities have been shown to increase with temperature at even higher rates, known as super-CC scaling, of 2CC (14 %/K, Ali et al., 2021; Lenderink et al., 2011; Park & Min, 2017; Zhang et al., 2017) and 3CC (21 %/K, Guerriero et al. 2018) as compared to daily rainfall (Ali et al., 2021; Utsumi et al., 2011). In contrast, sub-daily rainfall extremes have also shown sub-CC or even negative scaling in some studies (e.g. Drobinski et al., 2016; Panthou et al., 2014), particularly where surface air temperature has been used as the scaling variable.

The physical causes of this diversity in scaling are still under discussion (Barbero et al., 2018; Bao et al., 2017). Differences in scaling rates have been reported to occur from processes varying from the microscale to the synoptic scale (Fowler et al., 2021a). Important compounding factors include changes to moisture availability (Barbero et al., 2018; Peleg et al., 2018), the intermittent nature of precipitation (Schleiss 2018; Visser et al., 2020), temperature seasonality (Zhang et al., 2017), different rainfall types (Molnar et al., 2015), and large-scale circulation dynamics (Magan et al., 2020; Pfahl et al., 2017). However, recent work by Ali et al. (2021) has shown consistent scaling at the CC-rate globally. Using hourly observations of rainfall at 7000 gauges from the Global Sub-Daily Rainfall (GSDR) dataset (Lewis et al., 2019) across six macro-regions, they established a consistent scaling relationship with dewpoint temperature overland at around the CC rate, when averaged over large regions, and at around 2CC locally.

Nevertheless, in many regions, sub-daily scaling rates between extreme rainfall and temperature cannot be computed due to a lack of data or data-sharing constraints. Even the GSDR data, which contains $>20,000$ hourly gauges globally, cannot provide a global solution to estimating the scaling because the dataset is highly variable in terms of spatial coverage, record length, completeness and quality. One solution to overcome the lack of measured data and to extend scaling studies over ungauged areas is to utilize gridded-hourly climate reanalysis products like ERA5 and MERRA-2. Besides, these products can also be used to reveal the currently unknown rainfall scaling relationships over the oceans. Previous studies using this type of pixel by pixel scaling are very limited due to the computational difficulty in handling large datasets and as observational datasets with which to evaluate the results are scarce. Wasko et al. (2016a) evaluated a remotely sensed dataset for use in calculating scaling in ungauged basins at a global scale and found it worked well in tropical regions. Another recent comprehensive study by Moustakis et al. (2020) used the ERA5 product to conduct a quasi-global analysis of rainfall-temperature (surface air and dewpoint temperature; SAT and DPT) scaling, evaluating the scaling results against 1460 hourly rainfall gauges, most of them located in the U.S. ERA5 scaling rates were lower than for observations; however, they suggest that reanalysis products can be useful for providing scaling estimates in regions without gauge data. Here we build on their study to evaluate two commonly-used climate reanalysis products (ERA5 and MERRA-2) against the quality-controlled GSDR dataset on a global scale, including the tropics that were not evaluated so far. We evaluate the scaling rates, explore the reasons for differences in scaling rates between climate reanalyses and observations, and further extend this scaling analysis to the oceans.

2. Data

2.1 Observations

Hourly precipitation data (PPT) were obtained from the GSDR dataset. To ensure sufficient data length for estimating scaling, we selected only those stations with at least 12 years of data (record length shown in Fig. S1) and with less than 20% missing data in any given year (records lie between 1979-2014). The GSDR data has been extensively quality controlled, applying 25 different quality-control checks and removing a range of errors that include physical and spatial consistency issues, flat lines (streaks) and spikes as discussed in Lewis et al. (2019; 2021, in review).

Matching daily DPT were obtained for the nearest record from the Met Office Hadley Centre observations dataset, HadISD, which is based on the Integrated Surface Dataset (ISD) from the National Oceanic and Atmospheric Administration's (NOAA's) National Climatic Data Center (NCDC; Dunn, 2019). DPT was preferred over SAT because it was found to be a more robust climatic variable for scaling studies (Ali & Mishra, 2017; 2018a; 2018b). We considered only the DPT stations that have a correlation greater than 0.9, have a root mean square error (RMSE) smaller than 1.5 °C and an absolute difference in mean DPT of less than 1.5 °C with their neighbouring station (within 100 km distance and 100 m elevation difference; Ali et al., 2021).

Since the GSDR and HadISD stations are not at the same locations, we linked hourly PPT for each location to the corresponding daily (calendar day) DPT from the nearest DPT station, ensuring that the distance between PPT and DPT stations was not more than 40 km and their elevation difference was smaller than 50 m. For more information on the GSDR and HadISD DPT data, their quality control and linking PPT to DPT records, please refer to Lewis et al. (2019) and Ali et al. (2021).

2.2 Climate reanalysis data

We obtained hourly precipitation and DPT data from the ERA5 climate reanalysis product (Hersbach et al., 2020) and the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2, Gelaro et al., 2017) for the period between 1980 and 2018. The data are gridded, with a spatial resolution of 30 km and $0.5^\circ \times 0.625^\circ$, respectively. Hourly DPT values were averaged to estimate the daily DPT for the analysis.

3. Methods

Scaling rates were first computed for the observed and climate reanalysis data. After this, the DPT and PPT variables of the data sources were compared to explain the differences found in the scaling analysis.

3.1 Estimating scaling rates

We estimated scaling using the Binning Method (BM) as Ali et al. (2021) demonstrated it is the most robust method for estimating scaling. To apply the BM, we first classified all wet hours (precipitation ≥ 0.1 mm, except for the observed data from the USA and Japan for which rain gauge measurement precisions were 2.5 mm and 1 mm, respectively). For each PPT, the same hour DPT value was associated in the case of climate reanalysis data, and the same-day DPT value was associated with the observed data. Then, we placed the data into 12 equal-sized bins sorted from lowest to highest DPT and estimated the 99th percentile (P99) of PPT and mean DPT for each temperature bin. Due to the possibility of outliers (low and high DPT values) resulting from specific atmospheric circulations, we fitted a linear regression on the logarithm of P99 and mean DPT for the second bin to the second last bin:

$$\log(P99) = \alpha + \beta DPT \quad (1)$$

Then, we estimated the scaling $\frac{\partial P99}{\partial DPT}$ using an exponential transformation of the regression coefficient (β) given by:

$$\frac{\partial P99}{\partial DPT} = 100(e^\beta - 1) \quad (2)$$

In BM, all wet hours from the same day are used (rather than just rainfall maxima). It was demonstrated by Ali et al. (2021) that the bias due to pairing multiple hourly PPT with the same DPT value is not substantial.

3.2 Evaluating DPT simulated by the reanalysis

We evaluated the performance of the climate reanalysis at simulating DPT against the observed HadISD DPT using RMSE and Kling-Gupta Efficiency (KGE) statistic (Kling et al., 2012). KGE balances the contributions of bias, correlation and variance, and is estimated as:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\delta - 1)^2 + (\gamma - 1)^2} \quad (3)$$

where r is the Pearson correlation coefficient, δ is the ratio of variances, and γ is the ratio of mean between the climate reanalyses and observed data. KGE ranges between $(-\infty, 1]$ with larger values indicating better performance.

3.3 Evaluating PPT simulated by the reanalysis

We evaluated the performance of the reanalysis products in simulating PPT extremes by estimating the bias in P99. Since the climate reanalysis data are gridded and the GSDR data is at point-scale, i.e. at different spatial resolution, we first applied an Areal Reduction Factor (ARF) to the gridded data to approximate the point resolution before estimating the bias. We used the method of Leclerc and Schaake (1972) to estimate the ARF, given by:

$$ARF = \frac{Z'}{Z} = 1 - e^{-1.1t^{0.25}} + e^{-1.1t^{0.25} - 0.01A} \quad (4)$$

where Z' is the gridded average effective precipitation and Z is the point precipitation, A is the area of the gridded precipitation in km^2 , and t is the temporal resolution, equal to 1 h. In this context, we highlight that ARF is not a universal factor, but a local-specific and non-stationary factor (Kok et al., 2018). ARFs have been found to vary significantly depending on multiple factors, such as rainfall characteristics (specifically weather types, storm shapes, and seasons), data resolution and methods for determining ARFs (Kim et al., 2019; Lee et al., 2015). Lacking studies that fitted ARFs at the global scale, and being aware of the above-mentioned limitations, we used a simple universal constant ARF for evaluating the bias in P99.

The bias in P99 is then defined as:

$$Bias(\%) = 100 \left(\frac{P99_{GSDR} - P99_{gridded}}{P99_{GSDR}} \right) \quad (5)$$

where gridded refers to the reanalyses data.

4. Results and discussion

4.1 Evaluating precipitation scaling rates from climate reanalysis products

We first estimated the scaling rates using climate reanalysis data for the locations where GSDR data are available. The scaling results using the GSDR data are the same as those presented in Fig. 1 in Ali et al. (2021) and therefore not as thoroughly discussed here.

The scaling rates computed using ERA5 are lower ($\sim 1\%/K$ median) than the rates computed from the GSDR data (Fig. 1). Both ERA5 and GSDR data show scaling greater than CC for more than 50% of locations. However, in contrast to the GSDR data, ERA5 shows negative scaling at a few locations in the USA (3.5% of 3003 locations), Australia (1.8% of 602 locations) and India (38% of 42 locations). ERA5 also shows systematic spatial patterns in scaling which are visible in densely gauged regions like the U.S., UK and Japan that we do not see in observations.

For MERRA-2, the computed scaling rates are much lower (except for Australia) than for the GSDR data (Fig. S2). Around 34% of locations in the USA show negative scaling (median - $1.5\%/K$). Unlike ERA5, scaling using MERRA-2 is lower than CC for the majority of gauges, except for in the tropics where it is consistent with the GSDR data and shows scaling greater than the CC rate.

Scaling results over land using the ERA5 product are generally consistent with those from Moustakis et al. (2020). However, with over 700 tropical stations, we were able to demonstrate for the first time that ERA5 significantly underestimates scaling rates in parts of the tropics.

4.2 Differences in P99 and DPT between climate reanalysis products and observations

We next explored the reasons for the differences in scaling rates between the climate reanalyses and observations. These may be due to differences in the representation of extreme precipitation (P99) and/or DPT. We first compared the time series of daily DPT from the reanalysis products against the 6112 locations for which HadISD DPT is available. The comparison was performed at a daily scale as observed hourly DPT was not available.

ERA5 shows high KGE values (close to 1, perfect match) for most locations, except for the west of the USA and a few locations in Russia (Fig. 2), with RMSE values of less than one for most of Europe, the eastern U.S. and southeast Asia. Overall ERA5 performs well against the HadISD observations, suggesting that the differences in scaling found between ERA5 and observations do not occur because of large differences in DPT. However, the performance of MERRA-2 for DPT is relatively poor, with RMSE values greater than $1.8^\circ C$ for most of the locations (Fig. 2c) and poor KGE values especially over Europe (Fig. 2d).

Next, we evaluated the performance of the climate reanalyses in estimating P99. We note the use of universal constant ARF may introduce bias uncertainties on top of the bias in P99 that results from the climate reanalysis products. Given this limitation, we find that ERA5 underestimates extreme rainfall (with biases greater than 50% in P99) for the humid, tropical regions (India and Malaysia) and the eastern U.S. (Fig. 3). The biases are comparatively lower for the other regions with the least difference (less than 30%) over the majority of

Europe and Australia. The differences in P99 estimated from the GSDR data are likely due to the poor performance of ERA5 in simulating extreme convective rainfall; this is common in tropical, warm and humid, regions, and for which a high-resolution convection-permitting model is needed (see e.g. Kendon et al. 2014, 2017). However, bias could also remain in the matching of gridded reanalysis data to point observations, even after the application of an ARF. Moreover, the results for MERRA-2 are even worse, with very high biases (greater than 70%) in P99 over the majority of locations (Fig. S3). These differences in P99 highlight that we cannot blindly use reanalysis products to conduct extreme rainfall studies and, therefore, need more observations to first evaluate where and when they can be a good substitute for observations.

The negative scaling found between PPT from reanalysis products and DPT over some regions is governed by various factors such as orography (higher extreme rainfall intensities that are associated with lower temperatures), winter rainfall, convective systems and atmospheric river phenomena. For instance, negative scaling over the south-eastern US and the Gulf of Mexico can be attributed to intense rainfall extremes associated with tropical cyclones occurring in late summer and fall, and therefore, associated with lower DPT values (Knight & Davis, 2009). Similarly, the negative scaling over the coast of Guinea Highlands (north-western Africa) is likely due to the inability of ERA5 to simulate the extreme rainfall occurring because of orographic enhancement in the Highlands (Klutse, 2016). Negative scaling over parts of the Pacific Ocean and Atlantic Oceans can be explained by atmospheric rivers transporting moisture eastwards from the tropics and generating extreme winter rainfall (associated with lower DPT) (Gimeno et al., 2016).

4.3 CC-scaling over the land and oceans

Finally, we estimated scaling rates globally (for land and ocean) using ERA5 (Fig. 4) and MERRA-2 (Fig. S4). We found higher scaling rates over the ocean (mean of 7.8%/K) than overland (mean of 6.6%/K) (Fig. 4). More than 60% of grid cells over the ocean show scaling of greater than CC and 20% of grid cells show scaling of more than 2CC, in comparison to the land where only 52% and 11% of grid cells have scaling rates greater than CC and 2CC, respectively. The tropical oceans (23.5° N-23.5° S) show mixed scaling rates, ranging from negative to very high (>2CC) scaling. However, drier regions, such as along the west coast of Africa (Fig. S5), mostly show negative scaling rates over the ocean (Fig. 4). This region receives an average annual rainfall of less than 200 mm (Fig. S5), and insufficient rainfall data likely give this negative scaling.

Due to the much higher scaling rates over oceans, extreme rainfall intensities will increase more over oceans than on land in a future warmer climate. As a pseudo-observation source, this information can be used to support and verify findings from climate models that have reported stronger intensification of oceanic rainfall (e.g., Pfahl et al., 2017; Suman and Maity, 2020). In addition, there is an open question about how these higher scaling rates may alter not only the intensity of rainfall in extreme storms initiating over the ocean but also the extent of these storms (i.e. extending or diminishing the area of the storm, see Wasko et al., 2016b; Lochbihler et al., 2017). Furthermore, it is yet unclear what impact these modifications to the storm's characteristics will have on the hydro-morphological response over land (Peleg et al., 2020). Based on our evaluation that climate reanalyses underestimate scaling rates overland compared to observations, there is the possibility that scaling rates over the ocean are even

higher than we estimate in this study: greater than CC for 60% of locations. Further studies are required to study this land-ocean contrast in scaling rates and its implications for land-ocean climate dynamics, and impacts on extreme weather events, in the future.

4.4 Differences between the climate reanalysis products

Due to differences in the estimation of the climatic variables used in the scaling analysis (namely precipitation and dewpoint temperature), ERA5 and MERRA-2 produce different scaling results in some regions (Fig. 4 and Fig. S3). Our results imply that ERA5 is a better product to use for scaling analysis; other studies have also suggested the use of ERA5 for the exploration of thermodynamic (convective) environments (e.g. Taszarek et al., 2021). The better performance of ERA5 may be a result of the different assimilation schemes it employs. For example, ERA5 has an advanced parameterization scheme (e.g. radiation and convection schemes) and a better 4D-VAR data assimilation technology (Hersbach et al., 2020). Also, ERA5 estimates surface irradiance (a key parameter governing surface-atmosphere interactions) better than MERRA-2 but their estimates vary from observations due to a deficient cloud prediction, overestimating under cloudy conditions and slightly underestimating under clear skies (Urraca et al., 2018). However, it remains to be explored which factors (such as differences in ocean surface temperature and surface irradiance, model parametrization, and land-surface interactions) largely affect the performance of the reanalysis products in estimating extreme rainfall.

5. Conclusions

In this study, we used two climate reanalysis products at the hourly scale (ERA5 and MERRA-2) to check their consistency in estimating precipitation scaling with dewpoint temperature against an extensive observed dataset. We found that ERA5 performs better than MERRA-2 but with lower ($\sim 1\%/K$ median) scaling rates than observations. We further examined the reasons for the difference in scaling rates between reanalyses and observed data. We found that biases in extreme precipitation intensities, not biases in dewpoint temperature, can explain the differences in scaling estimates. Both reanalysis products significantly underestimate extreme precipitation over orographically complex regions and fail to capture rainfall extremes over the tropics, likely due to their convective nature and the coarse resolution of the climate reanalyses.

Since high-resolution rainfall observations are not available for the majority of the globe, particularly the tropics and the poles, we then studied scaling rates globally using the reanalyses, while understanding the associated limitations. We found higher scaling over the ocean compared to land for both ERA5 and MERRA-2. Over the ocean, high- and mid-latitudes mostly show CC scaling, while the tropics show mixed scaling rates, varying from negative scaling (10% grid cells) to greater than 2CC ($>20\%$ grid cells). The implications of the considerably higher scaling rates over the ocean (likely underestimated by the climate reanalysis products) in comparison to the approximately CC-scaling overland in the context of global warming and the potential effect on extreme storms reaching the land are not clear and should be studied.

Important dynamic factors, such as changes to large-scale circulations and vertical wind velocities, and changes to long-scale moisture transport patterns (Ali et al., 2018; Pfahl et al., 2017) have not been considered while estimating scaling rates in this study. This is despite

the suggestion that future changes in rainfall extremes over the tropics will be largely dominated by the movement of the Inter-Tropical Convergence Zone (ITCZ) (dynamics), which might lead to a decrease in rainfall extremes (Pfahl et al., 2017), for example. We, therefore, suggest a need for more studies that include detailed atmospheric dynamics to understand the processes governing rainfall extremes and their changes into the future. Also, we conclude that climate reanalyses likely underestimate scaling rates overland due to their relatively coarse resolution and inability to resolve orographic or convective processes. In the absence of observations, convection-permitting models may be a good alternative for conducting regional or global-scale studies of precipitation extremes (Prein et al., 2017), especially over the tropics where convective rainfall is commonplace. Currently, their use is restricted to continental size domains but these may provide interesting comparisons as a start. For the time being, this study suggests that scaling results based on climate reanalysis products can be useful in regions outside of the tropics. We suggest that in the mid-latitudes these climate reanalyses provide adequate representation of observed scaling rates, with some underestimation, but these should not be used to provide information on scaling rates or indeed for quantitative estimation of extreme rainfall in orographically complex areas or those dominated by convective rainfall extremes (in particular the Tropics).

Acknowledgements

We thank the reviewers for their constructive comments to improve the manuscript. HJF and HA were supported by INTENSE (European Research Council: grant ERC-2013-CoG-617329) and NERC-funded FUTURE-STORMS (NE/R01079X/1). Hayley Fowler is funded by the Wolfson Foundation and the Royal Society as a Royal Society Wolfson Research Merit Award holder (grant WM140025). The GSDR data was used in the previous study (<https://doi.org/10.1029/2020GL090317>; Ali 2021) and can be accessed through it. For the GSDR data sources, see table A1 of doi.org/10.1175/JCLI-D-18-0143.1 (Lewis 2019). HadISD dewpoint temperature data is freely available at <https://www.metoffice.gov.uk/hadobs/hadisd/>.

Author contributions

HA led the work and carried out the analysis with NP. NP managed the reanalysis data. HJF managed the quality-controlled hourly precipitation data. HJF, NP and HA contributed to the design of the methodology. All authors discussed the results and contributed to writing the paper.

Competing financial interests

The authors declare no competing financial interests.

References:

- Abbott, T. H., Cronin, T. W., and Beucler, T. (2020). Convective Dynamics and the Response of Precipitation Extremes to Warming in Radiative–Convective Equilibrium. *Journal of the Atmospheric Sciences* 77, 5, 1637–1660, <https://doi.org/10.1175/JAS-D-19-0197.1>
- Ali, H., Fowler, H. J., Lenderink, G., Lewis, E., & Pritchard, D. (2021). Consistent large-scale response of hourly extreme precipitation to temperature variation over land. *Geophysical Research Letters*, 48, e2020GL090317. <https://doi.org/10.1029/2020GL090317>
- Ali, H., Fowler, H. J., & Mishra, V. (2018). Global observational evidence of strong linkage between dew point temperature and precipitation extremes. *Geophysical Research Letters*, 45(22), 12–320.

352 Ali, H., & Mishra, V. (2017). Contrasting response of rainfall extremes to increase in surface air and
353 dewpoint temperatures at urban locations in India. *Scientific Reports*, 7(1), 1–15.

354 Ali, H., & Mishra, V. (2018a). Increase in subdaily precipitation extremes in India under 1.5 and 2.0 °C
355 warming worlds. *Geophysical Research Letters*, 45(14), 6972–6982.

356 Ali, H., & Mishra, V. (2018b). Contributions of dynamic and thermodynamic scaling in subdaily
357 precipitation extremes in India. *Geophysical Research Letters*, 45(5), 2352–2361.

358 Archer, D.R. and Fowler, H.J. 2018. Characterising flash flood response to intense rainfall and
359 impacts using historical information and gauged data in Britain. *Journal of Flood Risk Management*,
360 11, S121–S133, DOI: 10.1111/jfr3.12187

361 Barbero, R., Westra, S., Lenderink, G., & Fowler, H. J. (2018). Temperature-extreme precipitation
362 scaling: A two-way causality? *International Journal of Climatology*, 38, e1274–e1279.

363 Barbero, Renaud, Fowler, H. J., Blenkinsop, S., Westra, S., Moron, V., Lewis, E., Chan, S.,
364 Lenderink, G., Kendon, E., & Guerreiro, S. (2019). A synthesis of hourly and daily precipitation
365 extremes in different climatic regions. *Weather and Climate Extremes*, 26, 100219.

366 Bao, J., Sherwood, S. C., Alexander, L. V., & Evans, J. P. (2017). Future increases in extreme
367 precipitation exceed observed scaling rates. *Nature Climate Change*, 7(2), 128–132.

368 Chen, Y., Paschalis, A., Kendon, E., Kim, D., & Onof, C. (2021). Changing spatial structure of
369 summer heavy rainfall, using convection-permitting ensemble. *Geophysical Research Letters*, 48(3),
370 e2020GL090903.

371 Drobinski, P., B. Alonzo, S. Bastin, N. Da Silva, and C. Muller (2016), Scaling of precipitation
372 extremes with temperature in the French Mediterranean region: What explains the hook shape?, *J.*
373 *Geophys. Res. Atmos.*, 121, 3100– 3119, doi:10.1002/2015JD023497.

374 Dunn, R. J. H. (2019). HadISD version 3: Monthly updates. *Met Office Hadley Centre Technical*
375 *Note*.

376 Fadhel S, Rico-Ramirez MA, Han D. 2018 Sensitivity of peak flow to the change of rainfall temporal
377 pattern due to warmer climate. *J. Hydrol.* 560, 546–559. (doi:10.1016/j.jhydrol.2018.03.041)

378 Fowler, H.J., Lenderink, G., Prein, P., Westra, S., Allan, R.P., Ban, N., Barbero, R., Berg, P.,
379 Blenkinsop, S., Do, H.X., Guerreiro, S., Haerter, J.O., Kendon, E., Lewis, E., Schaer, C., Sharma, A.,
380 Villarini, G., Wasko, C., Zhang, X. 2021a. Anthropogenic intensification of short-duration rainfall
381 extremes. *Nature Reviews Earth and Environment*, DOI: 10.1038/s43017-020-00128-6.

382 Fowler, H.J., Ali, H., Allan, R.P., Ban, N., Barbero, R., Berg, P., Blenkinsop, S., Cabi, N.S., Chan, S.,
383 Dale, M., Dunn, R.J.H., Ekström, M., Evans, J.P., Fosser, G., Golding, B., Guerreiro, S.B., Hegerl,
384 G.C., Kahraman, A., Kendon, E.J., Lenderink, G., Lewis, E., Li, X.-F., O’Gorman, P.A., Orr, H.G.,
385 Peat, K.L., Prein, A.F., Pritchard, D., Schär, C., Sharma, A., Stott, P.A., Villalobos-Herrera, R.,
386 Villarini, G., Wasko, C., Wehner, M.F., Westra, S., Whitford, A. 2021b. Towards advancing scientific
387 knowledge of climate change impacts on short-duration rainfall extremes. *Phil. Trans. Roy. Soc. A*,
388 20190542, DOI: 10.1098/rsta.2019.0542.

389 Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., .. & Zhao, B. (2017). The
390 modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *Journal of*
391 *climate*, 30(14), 5419–5454.

392 Gimeno, L. et al. Major mechanisms of atmospheric moisture transport and their role in extreme
393 precipitation events. *Annu. Rev. Environment Resources* 41, 117–141 (2016).

394 Guerreiro, S. B., Fowler, H. J., Barbero, R., Westra, S., Lenderink, G., Blenkinsop, S., Lewis, E., &
395 Li, X.-F. (2018). Detection of continental-scale intensification of hourly rainfall extremes. *Nature*
396 *Climate Change*, 8(9), 803–807.

397 Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., ... & Thépaut, J.
398 N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological*
399 *Society*, 146(730), 1999-2049.

400 Kendon, E. J., Roberts, N. M., Fowler, H. J., Roberts, M. J., Chan, S. C., & Senior, C. A. (2014).
401 Heavier summer downpours with climate change revealed by weather forecast resolution
402 model. *Nature Climate Change*, 4(7), 570-576.

403 Kendon, E. J., Ban, N., Roberts, N. M., Fowler, H. J., Roberts, M. J., Chan, S. C., ... & Wilkinson, J.
404 M. (2017). Do convection-permitting regional climate models improve projections of future
405 precipitation change?. *Bulletin of the American Meteorological Society*, 98(1), 79-93.

406 Kling, H., Fuchs, M., Paulin, M., 2012. Runof conditions in the upper Danube basin under an
407 ensemble of climate change scenarios. *J. Hydrol.* 424, 264–277.

408 Klutse, N. A. B. et al. Daily characteristics of West African summer monsoon precipitation in
409 CORDEX simulations. *Theoretical Appl. Climatology* 123, 369–386 (2016)

410 Knight, D. B. & Davis, R. E. Contribution of tropical cyclones to extreme rainfall events in the
411 southeastern United States. *J. Geophys. Res.* 114, D23102 (2009).

412 Leclerc, G., and J. C. Schaake (1972), Derivation of hydrologic frequency curves, *Rep.* **142**, 151 pp.,
413 Mass. Inst. of Technol., Cambridge.

414 Lenderink, G., Mok, H. Y., Lee, T. C., & Van Oldenborgh, G. J. (2011). Scaling and trends of hourly
415 precipitation extremes in two different climate zones-Hong Kong and the Netherlands. *Hydrology and*
416 *Earth System Sciences*.

417 Lewis, E., Fowler, H., Alexander, L., Dunn, R., McClean, F., Barbero, R., Guerreiro, S., Li, X.-F., &
418 Blenkinsop, S. (2019). GSDR: A global sub-daily rainfall dataset. *Journal of Climate*, 32(15), 4715–
419 4729.

420 Lewis, E., Pritchard, D., Villalobos-Herrera, R., Blenkinsop, S., McClean, F., Guerreiro, S.,
421 Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rustemeier, E., Fowler, H.J. Quality
422 control of a global hourly rainfall dataset. Submitted to Environmental modelling and software,
423 January 2021 (in review).

424 Li, X.-F., Blenkinsop, S., Barbero, R., Yu, J., Lewis, E., Lenderink, G., Guerreiro, S., Chan, S., Li, Y.,
425 & Ali, H. (2020). Global distribution of the intensity and frequency of hourly precipitation and their
426 responses to ENSO. *Climate Dynamics*, 54(11–12), 4823–4839.

427 Lochbihler, K., Lenderink, G., and Siebesma, A. P. (2017), The spatial extent of rainfall events and its
428 relation to precipitation scaling, *Geophys. Res. Lett.*, 44, 8629– 8636, doi:10.1002/2017GL074857.

429 Magan, B., Kim, S., Wasko, C., Barbero, R., Moron, V., Nathan, R., Sharma, A., 2020. Impact of
430 atmospheric circulation on the rainfall-temperature relationship in Australia. *Environ. Res. Lett.* 15,
431 094098. <https://doi.org/10.1088/1748-9326/abab35>

432 Molnar, P., Fatichi, S., Gaál, L., Szolgay, J., & Burlando, P. (2015). Storm type effects on super
433 Clausius–Clapeyron scaling of intense rainstorm properties with air temperature. *Hydrology and*
434 *Earth System Sciences*, 119(4), 1753.

435 Moustakis, Y., Onof, C. J., & Paschalis, A. (2020). Atmospheric convection, dynamics and
436 topography shape the scaling pattern of hourly rainfall extremes with temperature
437 globally. *Communications Earth & Environment*, 1(1), 1-9.

438 Moustakis, Y., Papalexiou, S. M., Onof, C. J., & Paschalis, A. (2021). Seasonality, intensity, and
439 duration of rainfall extremes change in a warmer climate. *Earth's Future*, 9(3).

440 O'Gorman, P. A. (2015). Precipitation extremes under climate change. *Current Climate Change*
441 *Reports*, 1(2), 49– 59. <https://doi.org/10.1007/s40641-015-0009-3>.

442 O'Gorman, P. A., & Schneider, T. (2009). The physical basis for increases in precipitation extremes in
443 simulations of 21st-century climate change. *Proceedings of the National Academy of*
444 *Sciences*, 106(35), 14773-14777.

445 Panthou, G., Mailhot, A., Laurence, E., & Talbot, G. (2014). Relationship between surface
446 temperature and extreme rainfalls: A multi-time-scale and event-based analysis. *Journal of*
447 *hydrometeorology*, 15(5), 1999-2011.

448 Park, I.-H., & Min, S.-K. (2017). Role of convective precipitation in the relationship between subdaily
449 extreme precipitation and temperature. *Journal of Climate*, 30(23), 9527–9537.

450 Peleg, N., Marra, F., Fatichi, S., Molnar, P., Morin, E., Sharma, A., & Burlando, P. (2018).
451 Intensification of convective rain cells at warmer temperatures observed from high-resolution weather
452 radar data. *Journal of Hydrometeorology*, 19(4), 715-726.

453 Peleg, N., Skinner, C., Fatichi, S., and Molnar, P.: Temperature effects on the spatial structure of
454 heavy rainfall modify catchment hydro-morphological response, *Earth Surf. Dynam.*, 8, 17–36,
455 <https://doi.org/10.5194/esurf-8-17-2020>, 2020.

456 Pfahl, S., O'Gorman, P. A., & Fischer, E. M. (2017). Understanding the regional pattern of projected
457 future changes in extreme precipitation. *Nature Climate Change*, 7(6), 423–427.

458 Prein, A. F. et al. The future intensification of hourly precipitation extremes. *Nat. Climate Change* 7,
459 48–52 (2017).

460 Schleiss, M. (2018). How intermittency affects the rate at which rainfall extremes respond to changes
461 in temperature. *Earth System Dynamics*, 9(3), 955-968.

462 Suman, M., Maity, R. Southward shift of precipitation extremes over south Asia: Evidences from
463 CORDEX data. *Sci Rep* 10, 6452 (2020). <https://doi.org/10.1038/s41598-020-63571-x>.

464 Trenberth, K. E., Dai, A., Rasmussen, R. M., & Parsons, D. B. (2003). The changing character of
465 precipitation. *Bulletin of the American Meteorological Society*, 84(9), 1205–1218.

466 Urraca, R., Huld, T., Gracia-Amillo, A., Martinez-de-Pison, F. J., Kaspar, F., & Sanz-Garcia, A.
467 (2018). Evaluation of global horizontal irradiance estimates from ERA5 and COSMO-REA6
468 reanalyses using ground and satellite-based data. *Solar Energy*, 164, 339-354.

469 Utsumi, N., Seto, S., Kanae, S., Maeda, E.E., Oki, T., 2011. Does higher surface temperature intensify
470 extreme precipitation? *Geophys. Res. Lett.* 38, L16708. <https://doi.org/10.1029/2011GL048426>

471 Visser, J. B., Wasko, C., Sharma, A., & Nathan, R. (2020). Resolving Inconsistencies in Extreme
472 Precipitation-Temperature Sensitivities. *Geophysical Research Letters*, 47(18), e2020GL089723.

473 Wasko, C., Parinussa, R. M., & Sharma, A. (2016a). A quasi-global assessment of changes in
474 remotely sensed rainfall extremes with temperature. *Geophysical Research Letters*, 43(24), 12-659.

475 Wasko, C., Sharma, A., and Westra, S. (2016b), Reduced spatial extent of extreme storms at higher
476 temperatures, *Geophys. Res. Lett.*, 43, 4026– 4032, doi:10.1002/2016GL068509.

477 Westra, S., Fowler, H. J., Evans, J. P., Alexander, L. V., Berg, P., Johnson, F., Kendon, E. J.,
478 Lenderink, G., & Roberts, N. M. (2014). Future changes to the intensity and frequency of short-
479 duration extreme rainfall. *Reviews of Geophysics*, 52(3), 522–555.

480 Zhang, X., Zwiers, F. W., Li, G., Wan, H., & Cannon, A. J. (2017). Complexity in estimating past and
481 future extreme short-duration rainfall. *Nature Geoscience*, 10(4), 255–259.

482
483
484
485
486
487
488

489

Figure 1. Scaling rates ($\% \text{ K}^{-1}$) estimated using hourly precipitation and dewpoint temperature from ERA5 (top panel) and the GSDR dataset (bottom panel). Scaling is estimated using the binning method at the 99th percentile. NS stands for the number of gauges/grids in each region. The numbers in blue indicate the median negative scaling (blue numbers in parenthesis indicate the percentage of locations showing negative scaling). The number in black indicates the median scaling ($\% \text{ K}^{-1}$) for each region. The numbers below each panel indicate the percentage of gauges within each region which show scaling rates ranging from 0-0.5CC (green), 0.5CC-CC (yellow), CC-1.5CC (orange), 1.5CC-2CC (pink), and greater than 2CC (red) respectively, where CC is 6.5%/K.

Figure 2. The root mean square error (RMSE) in $^{\circ}\text{C}$ and Kling-Gupta Efficiency (KGE) statistic of dewpoint temperature from (a-b) ERA5 and (c-d) MERRA-2, against available HadISD dewpoint temperature.

Figure 3. The mean percentage bias ($= \frac{P99_{GSDR} - P99_{ERA5}}{P99_{GSDR}} \times 100$) in the 99th percentile of rainfall (P99) in ERA5 against GSDR data for the selected regions.

Figure 4. Scaling rates ($\% K^{-1}$) estimated using hourly precipitation and dewpoint temperature from ERA5, (b) latitudinal distribution of scaling over the land (red), ocean (blue) and land+ocean (black), (c) scaling distribution (in terms of percentage of locations) overland (brown) and oceans (blue) within different scaling ranges ($\times CC$), where CC is $6.5\%/K$. Scaling is estimated using the binning method at the 99th percentile. The numbers in black in panel (a) indicate the median scaling ($\% K^{-1}$) over the land and ocean respectively.

Figure1.

ERA5

USA (NS: 3003)

Australia (NS: 602)

Europe (NS: 1974)

Japan (NS: 1364)

Malaysia (NS: 89)

India (NS: 42)

GSDR

USA

Australia

Europe

Japan

Malaysia

India

Figure2.

RMSE

Kling–Gupta Efficiency

ERA5

MERRA2

Figure3.

Figure4.