Heavy precipitation hitting vulnerable communities in the UAE and Oman becoming an increasing threat as the climate warms

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Main Findings

- The UAE, Oman and the wider analysed region are located in a so-called hyper-arid region, with on average very little rainfall but with very high variability from year to year. Thus heavy rainfall events such as the one analysed here occur very rarely, leading to short records of similar events which results in high uncertainty in the assessment.
- The El Niño Southern Oscillation, a naturally occurring climate phenomenon, was found to be important to explain the variability in the observed rainfall. Most previous heavy rainfall events in the area occurred during El Niño years.
- To assess the role of human-induced climate change we first estimate if there is a trend in the observations associated with the warming up until today of 1.2°C and find that there is a trend, making heavy rainfall such as observed more likely. Based on the observations, the event was 10-40% more intense than it would have been had it occurred in an El Nino year in a 1.2°C cooler climate.
- To further characterise and quantify the role of human-induced climate change we then also look at climate models with high enough resolution to capture precipitation over the comparably small study region. The available climate models do not consistently exhibit a trend even for the models that were evaluated to simulate rainfall in the region reasonably well. However there is high uncertainty in this finding, again, due to high year to year rainfall variability.
- Based on the IPCC AR6 assessment, which includes scientific literature available up to January 2021, there is “medium confidence” that heavy precipitation would be detectably larger in the Arabian Peninsula at about 1.5°C of global warming compared to pre-industrial climate conditions, which is close to the current level of global warming.
- The disagreement between model results and observations prevents us from concluding with certainty that human-induced climate change is the main driver making this event more likely. However, while multiple reasons could explain the absence of a trend in our model results, we have no alternative explanation for a trend
in observations other than the expectation of heavy rainfall increasing in a warmer climate.

- While the heavy rainfall was well forecasted by national meteorological agencies, floodwaters led to a high number of deaths and extensive damages to homes, shops, offices and cars in the UAE and Oman. The majority of flood related deaths occurred when people were travelling, and many people in Dubai were forced to abandon their cars in floodwaters. The researchers say this suggests warnings may not have reached some people or were not specific enough to the impacts expected in particular regions.

- The high flood risk varies across demographics. In Oman and the UAE, 80 and 85% of the total populations, respectively, live in flood-prone and low-lying areas that are highly exposed. Because of various challenges to their abilities to respond to flood risk, particularly vulnerable groups tend to include older adults, individuals with disabilities, women with caregiving responsibilities, racial/ethnic minorities, migrant workers, and lower-income groups.

- Across both countries, a high degree of surfaces with limited permeability and absorptive capacity from urban developments, inadequate drainage and the hyper-arid soils exacerbate the risk and severity of flash floods.

- UAE and Oman adopt proactive disaster risk management strategies, with functional systems for early warning, early action, and emergency response to floods, along with long-term adaptation planning. However, reducing the high exposure to flood risk, more proactive urban planning and integration of impact-based forecasting in EWS are necessary to reduce impacts associated with similar events in the future.

- Finally, cloud seeding was reported to not have been implemented in the context of this event, and additionally even in case of implementation has no influence on the amount of atmospheric moisture available, which was the main anomalous variable preceding the precipitation event. Hence, we can conclude that cloud seeding had no significant influence in the event

1 Introduction

Beginning on Sunday the 14th of April 2024, the United Arab Emirates (UAE) and the northern parts of Oman were hit by exceptionally heavy rainfall that led to at least 20 fatalities in Oman (NYT, 2024) and four in the UAE and caused massive disruption in infrastructure and public life in the area. In Dubai, most of the rain fell on Monday the 15th of April 2024 and exceeded all previous records of daily rainfall in the last 75 years when records began, with some areas recording more than 250 mm in less than 24h (UAE government, 2024). There are reports of outbreak of water-borne disease in the aftermath of floods already in some parts of the UAE (Farooqui, 2024)

The heavy rain was associated with a low-pressure system that developed from an initial mid-latitude disturbance at 500 hPa, located over Turkey on 13-14/04 (Figure 1). It deepened toward the Persian Gulf and moved slowly to the east, combining with heat over Saudi Arabia. This particular weather
condition, as shown on Figure 1, enhanced vertical motion leading to the formation of mesoscale convective systems (MCS) in the region. MCS are the typical atmospheric systems causing heavy rainfall in the southern Arabian peninsula as well as other arid regions. These systems are generally triggered by moisture advection over the Arabian sea, Gulf of Arabia or Red Sea in combination with cold air aloft and occur predominantly in March and April (Nelli et al., 2021). In this particular case the MCS system developed under a large-scale wavy structure with high pressure and anomalous temperatures in Western Europe and its low-pressure counterpart in the Middle-East. At 500 hPa, a cut-off low from the wavy storm track detached and made a deep excursion into Saudi Arabia and the Persian Gulf (figure 1). The same system also led to low-pressure systems over other parts of Asia, causing for example extremely heavy precipitation over northern Pakistan and adjoining areas of Afghanistan. Authorities in both Afghanistan and Pakistan have reported a death toll of 50 individuals each in just one day (Aljazeera, 2024).

![Figure 1](image-url)

**Figure 1.** Absolute values of geopotential height at 500hPa (top) and anomalies relative to March-May 1991-2020 (bottom). Data source ERA5

The southern Arabian peninsula has a very arid climate with limited and irregular precipitation. In the inland desert areas, annual precipitation typically ranges from 40 to 80 mm, while mountainous regions receive slightly higher amounts, averaging between 120 to 150 mm per year. Rainfall predominantly occurs from November to April. Surrounding the southern Arabian Peninsula are the Arabian Gulf, Arabian Sea, and Sea of Oman, where sea surface temperatures (SSTs) typically range from 17°C to 37°C. Intense surface heating contributes to substantial low-level moisture, especially during warmer months. This moisture-laden marine air is transported inland by the daytime sea-breeze circulation, priming the environment for convection later in the day. The Arabian Peninsula features diverse topographical features, including mountain ranges and plateaus. These topographical variations can enhance atmospheric instability and lift mechanisms, promoting the formation of convective storms (Kumar et al., 2015). In the winter and spring months, when most of the precipitation falls, midlatitude disturbances originating from the Mediterranean or Europe are
generally the source of heavy precipitation (de Vries et al., 2016). They can deliver upper cold air interacting with the local moisture and topography, providing additional lift and triggering convective activity and causing MCS (Francis et al., 2020). Tropical-extratropical interactions can also involve, in spring, moisture contributions from the hot Indian Ocean (de Vries et al., 2016). This influence of mid-latitude disturbances was shown to increase in the last decades, as well as a trend toward heavier precipitation events (Luong et al., 2020) in the region. Nelli et al. (2021) discovered that every significant heavy rainfall event in the southern Arabian peninsula coincided with El Niño years. This supports earlier findings of strong statistical correlations between precipitation trends in the UAE and sea surface temperatures (SSTs) in both the equatorial Pacific and North Atlantic, as noted by Kumar and Ourda (2014). The influence of ENSO on this particular event is further discussed in section 3.2.

The event observed in April 2024 falls well within the typical development of such interactions, despite the magnitude of the storm which, at its particular location, was diagnosed as unusual in a recent study estimating trends in large scale weather patterns using the “analogue technique” (Climameter, 2024).

1.1. On the speculated role of cloud seeding

In the immediate aftermath of the rainfall, while some news and social media reports highlighted the meteorological specificities of the event or a possible link of the precipitation intensity to enhanced greenhouse-gas forcing, some other news and social media reports proposed a causal link of the heavy rainfall in Dubai with cloud seeding experiments carried out in the UAE. There indeed exists a cloud seeding program in the UAE that aims to enhance the precipitation from warm clouds by seeding them with particles large enough to activate the collision-coalescence process (Bruintjes et al., 2012), along with using electrical charges to attempt to enhance this process. Considerable uncertainty remains around the effectiveness of cloud seeding for precipitation enhancement (NRC, 2003, Rosenfeld et al., 2010, Flossmann et al., 2019). Statistical analysis of the UAE program suggests a potential rainfall enhancement in line with previous studies of 10-30%, but with large interannual variability in the proposed response (Al Hosari et al., 2021). Any cloud seeding program depends on identifying the subset of clouds susceptible to modification, limiting the cloud seeding to clouds that were already close to precipitating. This restricts the cases where cloud seeding could theoretically be applied, and the UAE National Centre of Meteorology, who oversee cloud seeding operations in the country, have reported that no cloud seeding missions were carried out targeting the storm (The National, 2024) and given the massive size of the storm system, the clouds would have precipitated regardless of possible cloud seeding influence. Finally, cloud seeding, had it been implemented, has no influence on the amount of atmospheric moisture available, which was the main precipitated variable preceding the precipitation event. Hence, we can conclude that cloud seeding had no significant influence in the event.

1.2 Event definition

As described above, most of the rainfall in the region fell within 24 hours on the 15th of April 2024. Thus, to characterise the event for the remainder of this study we focus on maximum amount of daily precipitation. As this event was the highest on record we also focus on the annual (July-June) maximum which usually falls within this season. Using this ‘RX1day’ variable has the additional advantage that it is one of the routinely calculated indices in most climate projections, thus making it easy to compare our analysis with published literature.
For the spatial definition of the event we focus on the region that saw the impacts during the 1-day heavy rainfall event, indicated by the red box in figure 2. The region includes the UEA, the northern part of Oman, Bahrain and a small part of Saudi-Arabia. We chose this region as it corresponds with the region where the impacts occurred but highlight that it is a relatively small region with very high inter-annual variability which makes it challenging to identify trends in relatively short observed records. We have tested the sensitivity of the choice of region to the results, described in section 3.1.1.

Figure 2: 24 hour rainfall on the 15th of April 2014 in MSWEP. The red box indicates the study region.

1.3 Literature on changes in extreme rainfall in the region

The 6th assessment report of the Intergovernmental Panel on Climate Change (IPCC AR6) assessed that the frequency and intensity of heavy precipitation events have likely increased at the global scale over a majority of land regions with good observational coverage and that heavy precipitation has likely increased on the continental scale over three continents, including Asia (Seneviratne et al. 2021). It also assessed that human influence, in particular greenhouse gas emissions, is likely the main driver of the observed global-scale intensification of heavy precipitation over land regions and that it is likely that human-induced climate change has contributed to the observed intensification of heavy precipitation at the continental scale in North America, Europe and Asia (Seneviratne et al. 2021). The IPCC AR6 further assesses that at the global scale, the intensification of heavy precipitation follows the rate of increase in the maximum amount of moisture that the atmosphere can hold as it warms (high confidence), of about 7% per 1°C of global warming (Seneviratne et al. 2021).
While attribution at smaller scale is challenging for precipitation events, because of decreasing signal-to-noise ratio, attribution assessments for larger regions are relevant for locations within these regions (e.g. Kirchmeier-Young et al. 2019, Tradowsky et al. 2023). There has also been clear attribution of human influence on extreme precipitation in regions of size smaller than those assessed in the AR6 report (e.g. Kirchmeier-Young et al 2019). The attribution at global and continental scales provides clear indication that extreme precipitation at local scale must have also increased in many regions, even though it is more difficult to detect such a change with statistical significance due to increased natural variability at the global level. For example, Sun et al. 2021 showed that for land stations with sufficient observational records, less than 10% of stations showed a statistically significant increasing trend. For the Arabian Peninsula, the IPCC AR6 assessed, based on literature using mainly RX1day as an indication of heavy rainfall, that there was low confidence in observed increase in heavy precipitation for the region as a whole, however, it assessed that there was medium confidence in a projected increase in heavy precipitation at 1.5°C of global warming compared to pre-industrial levels (Seneviratne et al. 2021). This assessment is relevant for the current climate, since we have been getting closer to a level of 1.5°C of global warming in recent years (WMO, 2024). Based on the IPCC assessment from literature available up to January 2021, the warming climate in the Arabian peninsula under a global warming of about 1.5°C, the global tendency towards an intensification of heavy precipitation on global scale with increasing human-induced global warming the heavy precipitation event that took place in Dubai would be expected to show an increase in the occurrence probability of such event and its intensity.

2 Data and methods

2.1 Observational data

We use three gridded datasets for analysing extreme rainfall in the study region and trend detection. The first dataset is the European Centre for Medium-Range Weather Forecasts (ERA5) reanalysis product. We note that precipitation from ERA5 is not directly assimilated, but it is a diagnostic variable generated by atmospheric components of the IFS modelling system. Daily precipitation available at 0.5° × 0.5° from the Climate Explorer. The re-analysis is available until the end of the preceding month (31 March 2024). We extend the re-analysis data with the ECMWF analysis (1-18 April) and the ECMWF forecast (19-22 April) to cover the day of the event (April 15, 2024). As the second dataset, we use the Multi-Source Weighted-Ensemble Precipitation (MSWEP) dataset (updated from Beck et al., 2019). This product combines gauge-, satellite-, and reanalysis-based data for reliable precipitation estimates, at 3-hourly intervals from 1979 to near real-time, and at 0.1° spatial resolution globally. We also include the rainfall product developed by the UC Santa Barbara Climate Hazards Group called “Climate Hazards Group InfraRed Precipitation with Station data” (CHIRPS; Funk et al. 2015). The product incorporates satellite imagery with in-situ station data. In this product, daily data are available at 0.05° resolution starting in the year 1981; however, at the time of writing, the data is available only till 31 March 2024 and does not cover the event. Therefore, we limit the use of this dataset only for model evaluation and as a test for the general consistency between the datasets.

As a measure of anthropogenic climate change we use the (low-pass filtered) global mean surface temperature (GMST), where GMST is taken from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (GIstemP, Hansen et al., 2010 and Lenssen et al. 2019).
2.2 Model and experiment descriptions

We use 3 multi-model ensembles from climate modelling experiments using very different framings (Philip et al., 2020): Sea Surface temperature (SST) driven global circulation high resolution models, coupled global circulation models and regional climate models.

1. Coordinated Regional Climate Downscaling Experiment CORDEX-CORE over the West-Asia domain with 0.22 km resolution (WAS-22) (Teichman et al., 2021). The ensemble consists of 3 regional climate models each downscaling 6 GCMs. These simulations are composed of historical simulations up to 2005, and extended to the year 2100 using the RCP8.5 scenario.

2. HighResMIP SST-forced model ensemble (Haarsma et al. 2016), the simulations for which span from 1950 to 2050. The SST and sea ice forcings for the period 1950-2014 are obtained from the 0.25° x 0.25° Hadley Centre Global Sea Ice and Sea Surface Temperature dataset that have undergone area-weighted regridding to match the climate model resolution (see Table B). For the ‘future’ time period (2015-2050), SST/sea-ice data are derived from RCP8.5 (CMIP5) data, and combined with greenhouse gas forcings from SSP5-8.5 (CMIP6) simulations (see Section 3.3 of Haarsma et al. 2016 for further details).

4. ISIMIP: Bias-corrected CMIP6 runs used as input for the impact simulations under the Inter-Sectoral Impact Model Intercomparison Project. The bias correction applied method preserves the absolute changes in monthly temperature, relative changes in monthly values of precipitation, and global warming (Hempel et al., 2013). The runs cover the period from 1960 through to 2099 on a horizontal grid of 0.5° x 0.5° resolution.

2.3 Statistical methods

In this analysis we analyse time series from annual (July-June) maximum 1-day rainfall (RX1day) for a box over UAE, Oman and Saudi Arabia (see event definition: Figure 2), where reasonably long records of observed data are available. Methods for observational and model analysis and for model evaluation and synthesis are used according to the World Weather Attribution Protocol, described in Philip et al. (2020), with supporting details found in van Oldenborgh et al. (2021), Ciavarella et al. (2021) and here.

The analysis steps include: (i) trend calculation from observations; (ii) model evaluation; (iii) multi-method multi-model attribution and (iv) synthesis of the attribution statement.

We calculate the return periods, Probability Ratio (PR; the factor-change in the event's probability) and change in intensity of the event under study in order to compare the climate of now and the climate of the past, defined respectively by the GMST values of now and of the preindustrial past (1850-1900, based on the Global Warming Index). To statistically model the event under study, we usually use a GEV distribution that scales with GMST. Noting from previous evidence on strong links between extreme precipitation in and around the study region with natural modes of variability, we use a GEV distribution that scales with both GMST and NINO3.4. Details of this approach can be found in Kimutai et al. (2024). Next, results from observations and models that pass the evaluation tests are synthesised into a single attribution statement.
3 Observational analysis: return period and trend

3.1 Analysis of gridded data

Figure 3 shows the time series of RX1day in MSWEP, ERA5 and CHIRPS datasets. The datasets are reasonably consistent with each other, capturing the year-to-year variability. The datasets also show consistency in the seasonal cycles and spatial patterns on evaluating for a common climatology period (1990-2020). Therefore, we retain all three observational datasets for evaluating model performance in the attribution step. However, since CHIRPS has not been updated till the day of the event at the time of writing, we do not use CHIRPS for the trend detection analysis, the results for which are discussed below.

![Figure 3: Annual RX1day series, area-averaged over the study region based on ERA5, MSWEP and CHIRPS datasets. It should be noted that CHIRPS will not be updated until mid-May 2024 to cover the event, and therefore the 2024 value does not correspond to the event under study.](image)

Figures 4(a-b) show the responses of annual (Jul-Jun) RX1day over the study region to the global mean temperature, based on the MSWEP and ERA5 datasets, respectively. There is no discernible trend in RX1day in either of them. Figure 4(c-d) shows the return period curves, for the 2023/24 climate and a 1.2 °C cooler climate. The 2023/24 event has a return period of 32 years (uncertainty: 7 - 1.5E+05 years) in the MSWEP dataset. The event is rare in the longer ERA5 dataset with a return period of 165 years (uncertainty: 25 years-inf). The best estimates for probability ratio between the present 2023/24 climate vs. 1.2 °C cooler climate centres on no change in both datasets, but with large uncertainty (1.3 for ERA5 (uncertainty: 0 to 40) and 1.2 for MSWEP (uncertainty: 0 to 100)), along with best estimates for intensity change of 3% and 10% increase in rainfall amounts as compared to an event of same rarity as the observed event, respectively, albeit with large uncertainties. The absence of trends in RX1day in these (relatively short) observed datasets is not surprising, because of the known, stronger associations between extreme rainfall in the region to specific natural modes of variability, such as the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD). Therefore, for a realistic estimation of the return period of the event, we need to account for the variation in RX1day due to the accompanying ENSO phase.

In Section 3.2, we repeat the analysis, including average December-February (DJF) Niño3.4 as an additional covariate, for understanding the separate contributions from GMST and Nino to extreme rainfall in the study region.
3.1.1 Spatial patterns in trends

Figure 5 shows maps of the estimated relative change in maximum one-day precipitation associated with a 1.2°C increase in GMST, estimated using a statistical model in which precipitation scales exponentially with both GMST and the Niño3.4 index; the statistical model is fitted independently at each grid cell. Trends in RX1day associated with increased GMST vary widely over the study region and the wider Arabian peninsula, with a wetting trend along the coast of the Arabian Sea - particularly in southern Oman, where the most extreme rainfall has doubled in intensity - but reduced rainfall inland over the Arabian Desert and further to the west. These mixed trends make it difficult to pick out a significant trend over the study region as a whole. The change associated with the current positive El Niño state is much weaker but more consistent over the peninsula as a whole, increasing the intensity of the wettest events by 10-20% over much of the study region.
3.2 Influence of modes of natural variability

Nelli et al., (2021) found that all major heavy rainfall extremes in the southern Arabian peninsula occurred during El Niño years. Corroborating a finding of statistically significant correlations observed between precipitation patterns in the UAE and SSTs in the equatorial Pacific and North Atlantic (Kumar and Ourda, 2014). Conducting a correlation analysis between monthly winter precipitation and global SSTs (covering 60°S to 60°N) (Kumar and Ourda, 2014) found that a substantial portion of precipitation variability is attributable to SST anomalies in the equatorial Pacific, notably associated with El Niño–Southern Oscillation (ENSO) events. They further found through composite analysis of upper tropospheric zonal wind an equatorward shift (approximately 2° latitude) of the subtropical jet stream over the Middle East during ENSO warm phases, impacting weather conditions in the UAE. Suggesting that teleconnections linking ENSO and precipitation in the UAE and neighbouring regions is mediated by the response of the jet stream to Rossby waves.

During the time of the event under study, ENSO had been in the El-Niño phase. We fitted a set of nonstationary models, using time series of detrended Niño3.4 during DJF season as additional covariates, to test whether the phase of ENSO had a significant effect on precipitation in the region or on the estimated trend in GMST (see Kimutai et al., 2024 for details of the statistical model used).

The fitted trend over time is highly variable, reflecting the strong influence of the ENSO on the expected precipitation, but generally captures the peaks of the observed rainfall well.

Figure 6(a-b) shows the response of Rx1day to change in GMST for the two datasets. Trends in RX1day in response to change in ENSO phase are shown in Figure 6(c-d). A slight increasing trend in Rx1day due to GMST change is found to emerge, albeit with large uncertainties. A relatively stronger trend is observed for Nino, consistent with evidence from past studies that establish this link. Figure 6(e-f) shows the return period plots for the present vs. the pre-industrial climate, had the Niño
conditions been constant at the 2023/24 levels. The 2023/24 event comes out to be a 1-in-12 year event (uncertainty: 12-950 years) in MSWEP and a 1-in-60 year event in ERA5 (uncertainty: 12 years to inf). Due to the relatively short and different lengths of the two datasets, we assume that the actual return period of the event is between 12-60 years. For the remainder of the analysis, we use a round value of 1-in-25 years as the return period of the observed Rx1day event. Under the same Nino conditions, the chances of an RX1day event of similar or higher magnitude would have been smaller. Climate change made the chances of the event about 3 times more likely based on MSWEP (uncertainty: 0.1 to 345) and 2 times more likely based on ERA5 (uncertainty: 0 to 111). Following from this, an event with the same rarity as that in the current 2023/24 climate will have precipitated less in the pre-industrial climate. The contribution from climate change is a 40% increase (uncertainty: 50% decrease to 460% increase) in MSWEP and a 12% increase (uncertainty: 26% decrease to 74% increase).

Figure 6. Linear trend in Rx1day over the study region as a function of GMST (top) and as a function of detrended Niño3.4 (center). The thick black line denotes the location parameter of the fitted distribution, and the blue lines show estimated 6- and 40-year return levels. The 2023/24 observation is highlighted in magenta. Bottom: the corresponding return period figure for GMST of 2024 (red lines) and 1.2°C lower GMST (blue lines), assuming Niño level to remain at the 2023/24 level. Shaded regions represent 95% confidence intervals obtained via a bootstrapping procedure. The magenta line shows the observed value of 2023/24 Rx1-day.
4 Model evaluation

In this section we show the results of the model evaluation for the assessed region. The climate models are evaluated against the observations in their ability to capture:

1. Seasonal cycles: For this, we qualitatively compare the seasonal cycles based on model outputs against observations-based cycles. We discard the models that exhibit multi-modality and/or ill-defined peaks in their seasonal cycles. We also discard the model if the rainy season onset/termination varies significantly from the observations.

2. Spatial patterns: Models that do not match the observations in terms of the large-scale precipitation patterns are excluded.

3. Parameters of the fitted GEV models. We discard the model if the model and observation parameters ranges do not overlap.

The models are labelled as ‘good’, ‘reasonable’, or ‘bad’ based on their performances in terms of the three criteria discussed above. A model is given an overall rating of ‘good’ if it is rated ‘good’ for all three characteristics. If there is at least one ‘reasonable’, then its overall rating will be ‘reasonable’ and ‘bad’ if there is at least one ‘bad’.

Out of the three sets of modelling experiments, two sets - HighResMIP and ISIMIP are used in the model-based evaluation and attribution. CORDEX models did not capture the seasonal cycle and therefore, were discarded. Of the 5 ISIMIP models and 18 HighResMIP models evaluated for the study, all of the ISIMIP and 5 HighResMIP models passed the model evaluation.

Table 1: Evaluation results of the climate models considered for attribution analysis of Rx1day over the study region. For each model, the best estimate of the dispersion and the 95% confidence interval obtained via bootstrapping.

<table>
<thead>
<tr>
<th>Model / Observations</th>
<th>Seasonal cycle</th>
<th>Spatial pattern</th>
<th>Dispersion</th>
<th>Shape parameter</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSWEP</td>
<td>0.526 (0.248 ... 0.612)</td>
<td>0.15 (-0.20 ... 1.5)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERA5</td>
<td>0.549 (0.452 ... 0.620)</td>
<td>-0.020 (-0.22 ... 0.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ISIMIP (-)</td>
<td>( ... )</td>
<td>( ... )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GFDL-ESM4 (-)</td>
<td>reasonable</td>
<td>reasonable</td>
<td>0.487 (0.346 ... 0.555)</td>
<td>-0.15 (-0.52 ... 0.47)</td>
<td>reasonable</td>
</tr>
<tr>
<td>IPSL-CM6A-LR (-)</td>
<td>reasonable</td>
<td>reasonable</td>
<td>0.508 (0.350 ... 0.618)</td>
<td>-0.19 (-0.72 ... 0.14)</td>
<td>reasonable</td>
</tr>
<tr>
<td>MPI-ESM1-2-HR (-)</td>
<td>reasonable</td>
<td>good</td>
<td>0.503 (0.299 ... 0.590)</td>
<td>0.0041 (-0.33 ... 1.3)</td>
<td>reasonable</td>
</tr>
<tr>
<td>MRI-ESM2-0 (-)</td>
<td>reasonable</td>
<td>reasonable</td>
<td>0.575 (0.421 ... 0.657)</td>
<td>-0.18 (-0.68 ... 0.48)</td>
<td>reasonable</td>
</tr>
<tr>
<td>HighResMIP (-)</td>
<td>( ... )</td>
<td>( ... )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CMCC-CM2-VHR4 (-)</td>
<td>reasonable</td>
<td>bad</td>
<td>0.404 (0.271 ... 0.489)</td>
<td>-0.091 (-0.31 ... 0.28)</td>
<td>bad</td>
</tr>
<tr>
<td>CNRM-CM6 (-)</td>
<td>bad</td>
<td>reasonable</td>
<td>0.468 (0.342 ... 0.824)</td>
<td>-0.24 (-0.72 ... 0.4)</td>
<td>bad</td>
</tr>
</tbody>
</table>
This section shows Probability Ratios and change in intensity $\Delta I$ for models and also includes the values calculated from the fits with observations.

**Table 6: Probability ratio and change in intensity** of an event such as the Rx1day event under study, due to changing GMST, for the study region, from pre-industrial climate to the present.

<table>
<thead>
<tr>
<th>Model / Observations</th>
<th>Threshold for return period 25 yr</th>
<th>Current warming level [°C]</th>
<th>Probability ratio PR [-]</th>
<th>Change in intensity $\Delta I$ [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSWEP</td>
<td>25.1825 mm/day</td>
<td>1.2</td>
<td>3.4 (0.20 ... 3.5e+2)</td>
<td>41 (-49 ... 4.6e+2)</td>
</tr>
<tr>
<td>ERA5</td>
<td>28.42 mm/day</td>
<td>1.2</td>
<td>2.2 (0.0028 ... 1.1e+2)</td>
<td>12 (-26 ... 74)</td>
</tr>
<tr>
<td>NICAM16-7S ()</td>
<td>34 mm/day</td>
<td>1.2</td>
<td>0.26 (0.015 ... 1.3)</td>
<td>-30 (-59 ... 6.8)</td>
</tr>
<tr>
<td>HadGEM3-GC31 ()</td>
<td>34 mm/day</td>
<td>1.2</td>
<td>0.26 (0.015 ... 1.3)</td>
<td>-30 (-59 ... 6.8)</td>
</tr>
</tbody>
</table>
6 Hazard synthesis

For the event definition described above we evaluate the influence of anthropogenic climate change on the RX1day heavy rainfall event by calculating the probability ratio as well as the change in intensity using observation-based products and climate models. Models which do not pass the evaluation described above are excluded from the analysis. The aim is to synthesise results from models that pass the evaluation along with the observations-based products, to give an overarching attribution statement. Fig. 7 shows the changes in probability and intensity for the observations (blue) and models (red). Before combining them into a synthesised assessment, first, a representation error is added (in quadrature) to the observations, to account for the difference between observations-based datasets that cannot be explained by natural variability. This is shown in these figures as white boxes around the light blue bars. The dark blue bar shows the average over the observation-based products. Next, a term to account for intermodel spread is added (in quadrature) to the natural variability of the models. This is shown in the figures as white boxes around the light red bars. The dark red bar shows the model average, consisting of a weighted mean using the (uncorrelated) uncertainties due to natural variability plus the term representing intermodel spread (i.e., the inverse square of the white bars). Observation-based products and models are combined into a single result in two ways.

Usually, we first neglect common model uncertainties beyond the intermodel spread that is depicted by the model average, and compute the weighted average of models (dark red bar) and observations (dark blue bar): this is indicated by the magenta bar in Fig. 7. As, due to common model uncertainties, model uncertainty can be larger than the intermodel spread, secondly, we also show the more conservative estimate of an unweighted, direct average of observations (dark red bar) and models (dark blue bar) contributing 50% each, indicated by the white box around the magenta bar in the synthesis figures.

When looking at the synthesised statistics alone, the best estimate indicates no change due to human induced climate change. The uncertainties around this statistical assessment are however very high, and thus the best estimate is not a useful indicator to combine all lines of evidence.

The observational data products all show an increase in RX1day. This observed change is not significant from a statistical point of view, but with short records and very high interannual variability, significant trends are not to be expected. Both datasets have best estimates well above “no-change” indicating potentially a very high increase in both intensity and probability of occurrence. The range of the increase in intensity for the best estimates of both observational datasets is 12-40%.

The number of climate models available on the short timescale of this report is limited, firstly due to the fact that many models with high enough resolution do not pass the model evaluation. In fact all
models from the CORDEX ensemble exhibit a seasonal cycle that has the peak rainy season in boreal summer, which is very much in contrast to observed seasonal cycles. Furthermore, as it is important to include the detrended Nino3.4 as a covariate in the statistical model to simulate the correct inter-annual variability only models that had the SSTs readily available could be included which limited the number of models further. None of the models evaluated scored high on all three categories of evaluation and thus we do not find any “good” models. All “reasonable” models that could be used show a very large range of uncertainty with best-estimates around “no-change” on average but individual models showing quite different trends.

Figure 7. (a) Synthesis of intensity changes (%; left) and probability ratios (right) when comparing the return period and magnitudes of the DJF rainfall over study region in the current climate and a 1.2°C cooler climate.

Given the observed increase in heavy rainfall already at today’s 1.2°C and the IPCC assessment discussed above shows an increase in the larger region of the Arabian peninsula at 1.5°C of warming this could indicate that the models underestimate the increase in heavy rainfall with global warming for this region.

Combining lines of evidence from the synthesis results of the past climate, results from future projections and physical knowledge that suggest an increase in heavy rainfall on the RX1day timescale from the Clausius-Clapeyron relationship we cannot give a quantitative attribution statement, but highlight that heavy rainfall in the area could have potentially increased considerably due to human-induced climate change. Thus investing in adaptation and decreasing vulnerability to such events is important and urgent.

7 Vulnerability and exposure

To understand the drivers of risk and impact in the 2024 April floods in the United Arab Emirates (UAE) and Oman, the preceding hazard analysis must be complemented by the vulnerability, exposure, and coping capacity factors at play in this event. Rapid attribution studies endeavor to pinpoint the key themes that likely shaped the event's trajectory, discussing the factors that either decreased or exacerbated the impacts of the meteorological event. This case of Middle East flooding, resulting from a record-breaking rainfall event, underscores the importance of resilience in these countries to climate change. One way of assessing this is through the ND-GAIN Index (2021), which
summarizes a country's vulnerability to climate change and other global challenges along with its readiness to improve resilience. The UAE and Oman, both categorized as upper-income countries, have high ND-GAIN index scores of 32 and 60, respectively, ranking among 185 countries. Pakistan and Afghanistan, with ND-GAIN scores of 150 and 179 respectively, experienced extreme precipitation in their northern regions through the same meteorological system, as depicted in Figure 1. However, the combined death toll in Pakistan and Afghanistan exceeds 100, compared to a combined total of 24 in the UAE and Oman. This disparity signifies the varying levels of preparedness and measures already implemented in some of the middle eastern countries to enhance resilience, as highlighted in the following sections. To fully understand and learn from the floods requires further research, including after action reviews.

7.1 Intersecting vulnerabilities

The vulnerability to flood risk in the UAE and Oman intersects across various demographics, highlighting disparities in exposure and coping capacities.

Residents inhabiting low-lying coastal regions and flood-prone areas across both countries are significantly at risk due to their high exposure to flood risk (UNDRR, 2021). Studies in Fujairah City, UAE underscore the susceptibility of such areas, exacerbated by continuous urban expansion and the ground’s diminished natural absorption capacity (Subraelu et al., 2023). Likewise, urban sprawl along the coast in Oman renders numerous communities exposed to flooding (Nair, 2022). In the 2020 census, it was reported that about 80% of the population resides in flood-prone areas such as coastal plains (Sultanate of Oman, 2019).

Older adults, individuals living with disabilities, and women with caregiving responsibilities also face heightened risks, notably because of mobility challenges to evacuate during floods (Bukvic et al., 2018; Bailie et al., 2022; Gutnik & Roth, 2018; Cvetkovic et al., 2018; Azad & Pritchard, 2023). The marginalization of racial and ethnic minorities, including certain migrant worker groups, hinder their access to critical information such as early warnings and evacuation routes (Lacuata, 2024; MICIC, 2016; Abubakar & Aldridge, 2022). For example, three of the four fatalities from the UAE were reported to be Filipino migrant workers (Lacuata, 2024). Undocumented migrants can be even more marginalized, often lacking access to adequate knowledge, resources and support systems to cope with extreme weather events (Méndez et al., 2020).

Socioeconomic disparities also exacerbate vulnerability, with lower-income groups generally bearing a disproportionate burden (Ibrahim et al., 2024). Limited access to insurance, education, and resources impede their ability to prepare for and recover from floods effectively (Lindersson et al., 2023; Poussard et al., 2021; SAMHSA, 2017).

Addressing these intersecting vulnerabilities necessitates comprehensive strategies that consider the diverse needs of vulnerable populations, human settlements, and exposed systems, from enhancing access to resources and education to improving infrastructure resilience.

7.2 Urban planning

Urban planning in the UAE and Oman is at a critical juncture, playing a decisive role in exacerbating or mitigating flood risks amid the backdrop of rapid urbanization and climate change. In the UAE, particularly in cities like Dubai and Abu Dhabi, the pace of coastal development has surged on lands
only a few meters above sea level, rendering over 85% of the population and 90% of infrastructure vulnerable to rising sea levels and extreme weather events (Melville-Rea et al., 2021). The proliferation of impermeable concrete surfaces and inadequate drainage infrastructure amplifies flooding during heavy rainfall, a vulnerability compounded by the concentration of tall buildings in urban areas (Shanableh et al., 2018; Szyprawska-Glodzik, 2023). Further, arid regions experience more severe flash floods due to limited permeability of the soils and the characteristics of rainfall in such areas, as it tends to be sporadic and intense while generally difficult to forecast accurately (Saber et al., 2021). Recent extreme weather events have underscored these challenges, disrupting vital infrastructure like the Metro, intercity buses, major roads, and airports, affecting thousands of local commuters and international travelers (CNA, 2024; Badam, 2024).

The UAE’s Sharjah faces a significant challenge of increasing flood risk due to rapid urbanization, with built-up areas in the city having grown four-fold from 1976, in turn having reduced the minimum rainfall needed to generate runoff from about 15 to 10 mm (Shanableh et al., 2018). Efforts to retrofit stormwater management systems face hurdles once infrastructure is established, highlighting the importance of proactive planning (CNA, 2024; Almheiri et al., 2023).

In Oman, insufficient consideration of flood risks in urban planning has led to continued construction in flood-prone zones, encroaching upon natural drainage systems (Al Yaqoubi, 2022). Muscat, in particular, faces a growing threat from floods exacerbated by unchecked urban sprawl into flood-prone areas in conjunction with more frequent extreme weather events (Al Yaqoubi, 2022).

Addressing these challenges requires adaptive and future risk-informed urban planning, integrating climate change projections, enhancing infrastructure resilience, and harmonizing land use with water management strategies. In the UAE, urban planning initiatives, such as integrating climate considerations into frameworks like the Abu Dhabi 2030 Urban Structure Framework Plan (Government of Abu Dhabi, 2023), showcase a commitment to resilience in urban areas. In Ras Al Khaimah, ambitious plans are underway to mitigate flood risks through the strategic construction of 38 dams, 87 collection ponds, and 193 kilometers of drainage channels (UNFCCC, 2024). In Sharjah, measures such as mangrove planting and seagrass restoration are being implemented to bolster coastal resilience (Quagliolo et al., 2022; Ministry of Climate Change and Environment, 2019). Engineering interventions, including coastal setbacks and flood defense structures, are also underway to protect critical infrastructure, as well as innovative risk-sharing mechanisms and insurance schemes to mitigate flood impacts and discourage settlement in high-risk areas (Ministry of Climate Change and Environment, 2019).

Oman is employing comprehensive flood risk assessments and advanced modeling techniques to identify high-risk areas (Al-Hinai & Abdalla, 2021). Embracing nature-based solutions like mangrove restoration and investing in structural defenses such as dams and flood walls are part of its strategy (Sultanate of Oman, 2018). Urban planning practices are evolving to steer development away from flood-prone zones (Al Ruheili, 2017; Sultanate of Oman, 2018). Embracing a holistic approach, combining nature-based and engineered solutions with comprehensive adaptation strategies, is crucial for building climate resilience and safeguarding urban environments against future flood risks. Ensuring community consultation or stakeholder engagement is also critical for designing equitable and effective adaptation actions, and it is unclear to what extent this took place in said plans and measures.
7.3 Disaster risk management

7.3.1 Disaster risk management policy

Disaster risk management policies in the UAE and Oman represent proactive responses to the increasing challenges posed by climate change. In the UAE, a forward-looking strategy focuses on climate-resilient infrastructure as a key defense against future disasters by investing in green building and infrastructure design, alongside research into future-proof construction materials, and restoration of mangrove forests (UNFCCC, 2023). On a national scale, the UAE's commitment to climate adaptation is evident through initiatives like the National Climate Change Adaptation Program in which it outlines its assessments of climate risk exposure across key sectors including energy, infrastructure, insurance, and health, and plans for each sector to develop an adaptation plan with prioritized actions and execution timelines (UNFCCC, 2023). The UAE Council on Climate Action streamlines federal and emirate-level policies, emphasizing a comprehensive approach to disaster risk management (UNFCCC, 2023).

Similarly, Oman adopts a proactive stance toward disaster risk management. In 2019, Oman approved the National Strategy for Adaptation and Mitigation to Climate Change (2020-2040), centering on three themes: 1) developing climate information, air monitoring, and regional climate modeling, 2) assessing and monitoring vulnerabilities to climate change, and adaptation planning, and 3) sustainable development (Sultanate of Oman, 2019). Scientific research and hydrological modeling play crucial roles in Oman's disaster resilience efforts, especially concerning wadi (dry river bed) flash floods (Tetsuya et al., 2022). The Ministry of Agriculture, Fisheries, and Water Resources leads initiatives such as updating flood hazard maps and formulating emergency plans for cities, emphasizing data-driven risk management (Muscat Daily, 2023). Projects like the Wadi Al Ansab flood protection dams highlight Oman's commitment to enhancing infrastructure resilience (Sultanate of Oman, 2022).

7.3.2 Early Warning Early Action (EWEA)

In the UAE, the National Center of Meteorology (NCM) (n.d.) monitors, forecasts, and issues warnings about severe weather events. Prior to the onset of the heavy rainfall in April, the NCM provided estimates indicating substantial precipitation, with some areas predicted to receive up to 100 mm of rain in 24h (Parrish, 2024, X). Leveraging the National Emergency Crisis and Disaster Management Authority, the UAE government disseminated warnings through social media platforms, advising residents to remain indoors and adhere to safety protocols (NDTV, 2024). Based on this information, Dubai government entities and private schools transitioned to remote operations to ensure minimal exposure to risks, starting on the Sunday preceding the heavy rainfall (NDTV, 2024). In anticipation of the heavy rainfall, the Department of Municipalities and Transportation coordinated with stakeholders to ensure the continuity of infrastructure and basic services (Khaleej Times, 2024). Once specialized teams confirmed that the floods would exceed predictions, emergency response teams were deployed to the most impacted communities (Khaleej Times, 2024).

The Oman Flash Flood Guidance (OMANFFG) system is designed to provide real-time guidance and information regarding potential flash flooding (HRC, n.d.). Utilizing data from a new radar network, the OMANFFG system rapidly evaluates the threat of flash floods based on rainfall estimates and soil saturation levels (HRC, n.d.). On 12 April, the National Early Warning Center (NEWC) issued alerts
about the expected heavy rainfall across the country (Times of Oman, 2024). Further, the National Committee for Emergency Management in Oman had issued a warning pertaining to the expected floods, which prompted preemptive measures by government and emergency services, including keeping schools and government offices closed (Blaskovic, 2024; Zhuang, 2024). NEWC has also previously issued alerts about expected heavy rains and thunderstorms across the country, allowing residents to prepare and take necessary precautions, such as for the 2024 March floods (Singh, 2024).

Faced with such intense rainfall, the early warning messaging and ensuing early action are likely to have reduced the impact on exposed individuals and communities across both countries. However, both countries’ early warning systems lack impact-based forecasting, which could facilitate the translation of warning messages into early action, thus further improving their effectiveness. To build this capacity, in November 2023, the World Meteorological Organization (WMO)’s Panel on Tropical Cyclones and Gulf Countries Council (PTC/GCC), of which the UAE and Oman are members, held a workshop on impact based forecasting and warning services (WMO, 2023a; WMO, 2023b).

7.3.3 Emergency response

In response to the April 2024 floods in the UAE and Oman, both countries enacted comprehensive emergency response measures to address the immediate aftermath. President Sheikh Mohamed bin Zayed Al Nahyan of the UAE promptly initiated a quick response to the floods (Evans, 2024). Emergency response teams in the UAE were immediately deployed to provide assistance to the most affected areas, addressing infrastructure impacts and clean-up efforts (Khaleej Times, 2024). The UAE government, in collaboration with relevant agencies, focused on restoring infrastructure and services as floodwaters receded (Evans, 2024). It is reported that authorities maintained constant communication with residents and businesses to address concerns and provide support where necessary (Khaleej Times, 2024). For example, the Department of Municipalities and Transport (DMT) played a pivotal role in coordinating efforts with stakeholders to address the adverse weather conditions experienced across Abu Dhabi (Khaleej Times, 2024). Additionally, the central bank of the UAE has directed banks to postpone payments for personal and vehicle loans for a period of six months for individuals impacted by the recent flooding (Kumar, 2024). A task force has been established to investigate the impact of the weather event and develop strategies to enhance future preparedness and community resilience, including an investigation into the resilience of its infrastructure (Khaleej Times, 2024).

In Oman, the Royal Oman Police conducted extensive rescue operations, carrying out 152 emergency operations and rescuing 1,630 individuals who had been stranded by the floods (Zhuang, 2024; Oman Moments, 2024). The Ministry of Education suspended school operations in several governorates as a precautionary measure, ensuring the safety of students and staff (Gritten et al., 2024; The Economic Times, 2024). Furthermore, over 1,400 individuals were evacuated to shelters, and government offices suspended work in affected regions to prioritize public safety (Gritten et al., 2024).

V&E conclusions

The high flood risk in Oman and the UAE varies among different demographic groups. Around 80% and 85% of the total populations, respectively, reside in flood-prone or low-lying areas, rendering them highly exposed to this risk. Due to various challenges to their abilities to respond to flood risk, older adults, individuals with disabilities, women responsible for caregiving, racial/ethnic minorities,
migrant workers, and those from lower-income brackets, tend to be particularly vulnerable when faced with flooding.

In both countries, the frequency and severity of flash floods are exacerbated by the prevalence of impermeable surfaces due to urban development, coupled with inadequate drainage and hyper-arid soil conditions limiting the ground’s absorptive capacity. The proactive disaster risk management strategies in place, such as systems of early warning, early action and emergency response likely reduced impacts, but there remains a pressing need for more proactive urban planning and the incorporation of impact-based forecasting into early warning systems.

**Data availability**

Almost all data are, or will be made available via the Climate Explorer.

**References**

All references are given as hyperlinks in the text.