https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

Identifying regions of Europe which may be less prepared for extreme rainfall

Vikki Thompson[1], Erin Coughlan de Perez[2], Dorothy Heinrich[3,4], Karin van der Wiel[5,6], Ed Hawkins[7], Andrew Schurer[1]

[1] School of GeoSciences, University of Edinburgh, Edinburgh EH9 3JW, UK
[2] Friedman School of Nutrition Science and Policy, Tufts University, Boston, 02111, USA
[3] Department of Meteorology, University of Reading, Reading, RG6 6ET, UK
[4] Red Cross Red Crescent Climate Centre, The Hague, The Netherlands
[5] Royal Netherlands Meteorological Institute (KNMI), De Bilt, The Netherlands
[6] Department of Physical Geography, Faculty of Geosciences, Utrecht University, Utrecht, The Netherlands
[7] National Centre for Atmospheric Science, Department of Meteorology, University of Reading, Reading, RG6 6ET, UK

Correspondence to: Vikki Thompson (vikki.thompson@ed.ac.uk)

https://doi.org/10.5194/egusphere-2026-4100
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Abstract. Societal preparedness to extreme rainfall events varies geographically. We present a method to assess assumed preparedness based on observational data alone, investigating record daily rainfall across Europe. To define assumed preparedness, we use two metrics: 1) how recently the record daily rainfall occurred; and 2) how extreme the current record was. In locations where the record occurred further in the past, societal memory of the impacts may have faded, possibly reducing people's interest in preparedness for extreme rainfall. In regions where the current record was not very extreme, a record-smashing event is statistically more likely, yet the region has not experienced such an event so may be less adequately prepared. We show that cities such as Sofia, Barcelona, Munich, and Amsterdam may have low levels of assumed preparedness. Such locations could benefit from communication about possible risks that the population might not be aware of, encouraging adaptation before a record-breaking event arrives.

1 Introduction

On 29th October 2024, the southeastern Iberian Peninsula experienced exceptionally heavy rainfall with the city of Valencia severely impacted by flooding (Llasat, 2024; Campos et al., preprint). Some individual weather stations observed over 600 mm of rain within a day – greater than the region's average annual total (AEMET, 2024). Impacts to society were severe, with over 200 fatalities and billions of Euros of damages (Martin-Moreno et al., 2025).

Just a month earlier, in September 2024, Storm Boris had brought record-shattering rainfall to a broad region of central Europe including Czechia, Austria, and Hungary. The equivalent of 2 to 5 times the climatological monthly rainfall fell over a period of 1 to 3 days (Riboldi et al., 2026). Widespread flooding severely impacted local communities, leading to an estimated insurance costs of over €2 billion (PERILS AG, 2025). In July 2021, we saw a different region of Europe impacted by record breaking rainfall: local records were broken at many sites across Western Germany, Netherlands, Belgium, and Luxembourg – particularly the Ahr catchment (Ludwig et al., 2023). Impacts on society were large – over 40,000 people were affected, with ~220 deaths (Koks et al., 2022). It was within the top 5 costliest disasters in Europe, with insurances costs of €32 billion (Mohr et al., 2022).

Such extreme rainfall events heavily impacting one region act as 'focusing events' (Birkland et al., 2009), leading to questions about risk from both policy makers and the general public around the world. For example, people worry about potentially experiencing a similar event: "Stations near Valencia saw 600 mm in a day, so could that happen where I live?" Or they wonder how this would look in their location: "For Valencia, that amount was >30% of its average annual rainfall falling within a day - could that occur everywhere? If it did happen where I am, are we prepared?" Such questions motivate this study. For Europe, we assess where high proportions of annual rainfall over a short time period are more likely, and we seek to assess which regions are likely to be more prepared for extreme rainfall due to past experience. In a world where resources for risk analysis are limited, such information can aid decision makers on how places where increased preparedness activities could be focused.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

Masukwedza et al. (2025) provide a framework to assess preparedness which we adapt (Fig.1). In their study, the two axes represent the present day return period of the record event and the change in return period of a 100-year event between 1981 and 2021. We adjust the framework to use the two metrics: year of the current record and chance of new record. The change in return period metric used by Masukwedza et al. (2025) assessed the extent to which risk is changing in each location, which we do not include when assessing assumed preparedness. As will be discussed further in later sections, the metrics used here do not take climate change into account.

The year of the current record is used as our first metric of assumed preparedness. In the immediate aftermath of an extreme event people adapt, but as the memory of the event fades, complacency leads to a reduction in preparedness (Ridolfi et al., 2021; Collenteur et al., 2015). Therefore, it could be assumed that regions where the record occurred more recently will be better prepared for similar events, whereas places with longstanding records will be less ready for another event of similar magnitude (de Vries et al., 2026). There are examples where long periods without record-breaking events may have led to reduced preparedness, such as the Ahr floods in July 2021. Despite similar floods in 1804 and 1910 (Roggenkamp and Herget, 2014) it has been shown that people in the impacted region had struggled to imagine what they had never experienced and therefore were less inclined to take early action (Ommer et al., 2023). On a regional scale, gaps in disaster preparedness investment amplified the impact of these floods (da Costa et al., 2026). This is not only the case for extreme weather - Pisa (2024) found that in Japan as tsunamis are infrequent both memory and preparedness reduce over time.

The second metric in the preparedness framework is the chance of a new record. Statistically, some locations are more at risk of experiencing record-breaking extreme rainfall, simply because the observed record is not particularly extreme (Stellema et al., 2025, de Vries et al., 2026). These locations could be called 'soft records' or 'sitting ducks' (Masukwedza et al., 2025); an easy target for the next record-breaking extreme weather event. These regions may have been fortunate so far not to experience a larger extreme, and – as often most adaptation occurs in the wake of an event – are likely to be unprepared.

The two metrics can be combined, allowing locations to be classified by where they sit in a 2-dimensional space (Fig.1). We introduce the term 'assumed preparedness' to classify places using both metrics. Regions with a high chance of a new record and a longer time since the current record can be assumed to be least likely to be prepared for an extreme event – they have lower assumed preparedness. Changes in either metric could alter how prepared a region is. Those locations with both recent records and low chance of a new record (i.e. the record was statistically extreme) have higher assumed preparedness and are less at risk to impacts from extreme rainfall.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

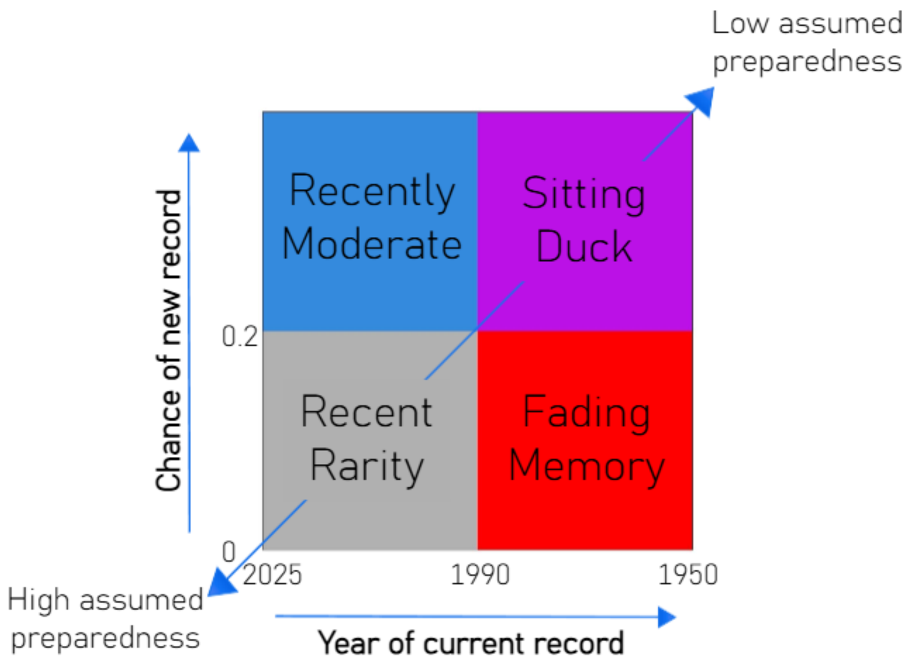

Figure 1: Schematic showing the assumed preparedness framework applied in this study, adapted from Masukwedza et al. (2025).

In this paper, we assess assumed preparedness to extreme rainfall across Europe by implementing the framework to classify locations (Fig.1). We begin by assessing the spatial distribution of daily record rainfall totals across Europe, both in terms of absolute magnitude and proportion of the annual climatology. We identify regions with particularly long-standing records and regions with higher statistical chance of new records. We blend these two metrics to map the level of 'assumed preparedness' to identify the regions that may be most underprepared to extreme rainfall events (locations that would fall in the sitting duck quadrant). Finally, we assess if our assumed preparedness metric does identify regions at risk, based on recent case studies of three impactful events: Ahr floods (July 2021), Storm Boris (September 2024), and Valencia floods (October 2024).

2 Methods

2.1 Data

In this study, E-OBS daily precipitation data from 1950 to 2025 is used (Cornes et al., 2018). E-OBS is a daily gridded land-only observational dataset over Europe. The dataset originates from blended station data from the station network of the European Climate Assessment & Dataset (ECA&D) project. This is a daily dataset – observations over 24 hours per timestep, however the exact 24-hours can vary between regions (e.g. 8 am to 8am, or midnight to midnight). The horizontal resolution

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

is 0.1 x 0.1°, and data from 1950 to 2025 is used. E-OBS has been shown to be superior to alternative gridded datasets of rainfall such as the fifth generation ECMWF reanalysis (ERA5) (Bandhauer et al., 2021; Lavers et al, 2022).

The methodology is applied to a second dataset: HadUK-Grid (Hollis et al., 2019) which provides gridded climate data for the UK based on observations from the UK's land network of weather stations. Daily rainfall data is available from 1891 onwards; we use the 5km gridded data from 1891-2025.

2.2 Metric 1: Year of current record

To calculate the first metric, we identify the record event: the maximum daily rainfall event in the timeseries. We then determine the year in which this event occurred.

2.3 Metric 2: Chance of a new record

To assess the chance of a new record a simplistic, data-driven, statistical method is applied. For every grid point, the 99th percentile (P_{99}), 99.5th percentile ($P_{99.5}$), and current record (P_{MAX}) for daily rainfall totals from all days (1950-2025) is calculated. This is used to assess the risk (chance of a new record), using the equation:

$$RISK = \frac{P_{99.5} - P_{99}}{P_{MAX} - P_{99}} \tag{1}$$

Generally, where the record is closer to P_{99} there is a high likelihood of a new record, and where the record is further above P_{99} a new record is less likely, this is represented by the denominator. However, as the shape of the tail of the distribution can vary spatially, we also incorporate $P_{99.5}$ in the numerator, allowing comparison between different locations with potential differences in skewness (Fig.S1). This remains true under climate change, assuming the signal of climate change is spatially constant – discussed further in later sections.

2.4 Assumed preparedness

We map the assumed preparedness using the proposed framework (Fig.1). Each location is classified into one of 4 categories, based on the values of both the year of the current record and the statistical risk of a new record occurring. We define the two levels of time since current record as pre-1990 and post-1990. Locations are divided into 2 groups based on the risk of breaking a record. For E-OBS, the boundary is placed at 0.2 (Eq.(1)) to split the data roughly into two halves. The exact location of this divide is an arbitrary decision and would require adjustment for different datasets (as shown by differences between E-OBS and HadUK-Grid in Fig.S2).

Individual locations can be plotted on the assumed preparedness framework, using the year of record and the risk measure. We plot the locations of 20 major cities across Europe. This enables assessment of locations with lower assumed preparedness - potentially at higher risk of impacts from extreme rainfall. We can also identify cities at the other end of the scale, with higher levels of assumed preparedness through both a more recent record and a lower chance of a new record.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

To investigate the potential value of the methodology presented, we generate versions of the assumed preparedness map as it would have been before impactful events of the past few years. We take three recent impactful extreme rainfall events within Europe: 1) Ahr floods, July 2021 2) Storm Boris, September 2024 and 3) Valencia floods, October 2024. By regenerating the assumed preparedness maps using data only to the end of the year before the event, we can assess if the region would have been identified as a sitting duck with low assumed preparedness.

3 Results

3.1 Annual rainfall and current records

Mapping the climatological annual mean rainfall, from 1950 to 2025, clear geographical variability is apparent (Fig.2a). The greatest total rainfall is shown along the western coastlines and mountainous regions. This pattern is primarily caused by the prevailing westerly winds bringing warm moist air from the Atlantic Ocean to the continent. Mountainous regions are wetter as when the moist air moves eastwards and encounters areas of raised topography the air is forced to rise. This causes it to cool and condense, resulting in rain particularly on the western side.

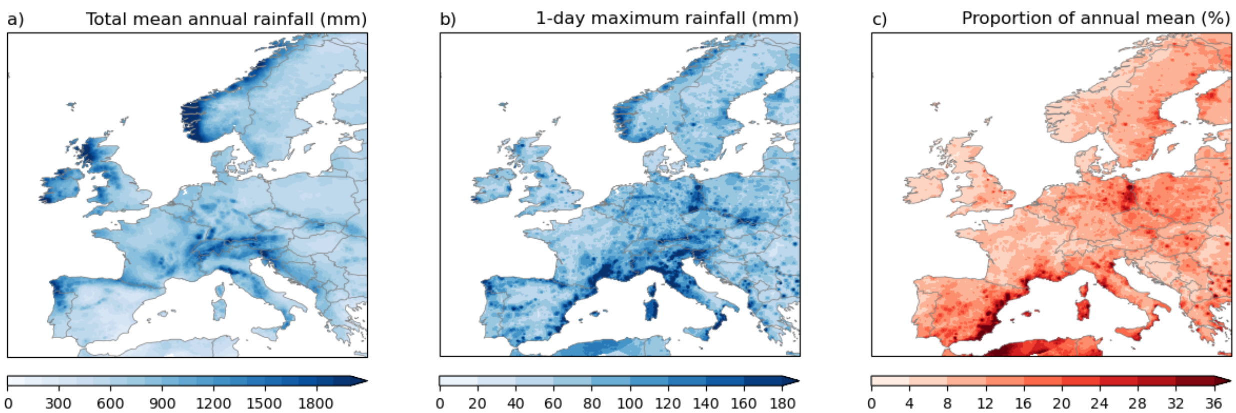

Figure 2: Average annual rainfall. (a) Showing the E-OBS climatological annual rainfall (in mm) from 1950 to 2025 across Europe. (b) The observed record daily rainfall (mm), 1950-2025. (c) The observed daily record as a proportion of the annual mean (%).

The map of daily record rainfall (Fig.2b) shows some resemblance to the annual rainfall totals with western Norway and the northwestern Iberian peninsula showing high values. However, there are also notable differences. In eastern Europe the map shows greater spatial variability – with small patches of high record levels. This could be due to small localised events causing the records, or observational uncertainty due to sparseness of data. In contrast, in western Europe large scale organised weather features – such as cut-off low pressure systems - cause larger scale events.

The daily record rainfall can also be presented as a proportion of the annual mean (Fig. 2c). This highlights clearly that annual rainfall totals alone do not help us understand how a place needs to prepare for that rainfall. In one place a 'month

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

in a day' (around 8%) has happened, and in another it would be totally unprecedented. The eastern coast of Spain and southern coast of France appear particularly likely to receive high proportions of rainfall in a day – as was seen in October 2024. In contrast northern France, Belgium and the Netherlands show much lower levels – suggesting that the meteorological conditions of these regions are not as likely to create such high-proportion events, and perhaps preparing for the same levels is unnecessary.

Similar maps produced using HadUK-Grid are included in Fig.S2. Consistency between datasets improves confidence in the results. The spatial patterns of E-OBS and HadUK-Grid are broadly in agreement and the patterns do not change when including data spanning a longer time period. However, the absolute values for record daily rainfall are generally larger in HadUK-Grid – likely due to the greater number of stations incorporated. Some localised extremes may be missed in E-OBS, yet captured by HadUK-Grid.

3.2 Fading memory

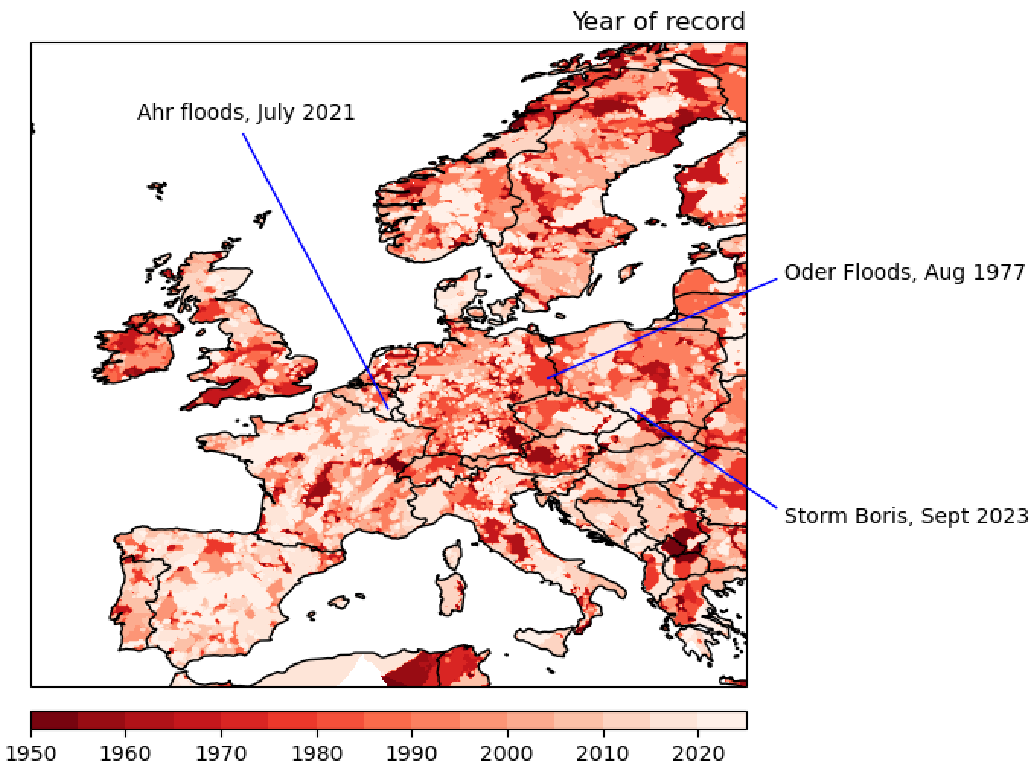

Figure 3: When did the current record occur? Showing the year of E-OBS daily rainfall record (1950-2025).

One component of our assessment of assumed preparedness depends upon how long the current record has stood (Fig.1). We map the year of the current daily record (Fig.3). The E-OBS dataset spans 1950 to 2025, in a static climate we would expect

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

the records to be equally likely to occur at any point within that period. Climate change is increasing extreme rainfall (Seneviratne et al., 2021), and therefore we see more records occurring in the later years (Fig.3). We find 50% of the region has experienced record daily rainfall since 2000 (33% of the data period), and 26% within the last 10 years of the 75 year long record. Several well-reported recent events are evident – such as the Ahr valley event of July 2021 and Storm Boris in eastern Austria and Czechia in September 2024.

However, there are locations with long-standing records. For example, the region around Geneva on the Swiss-French border and much of central Austria stand out as particularly early records. Extreme rainfall in August 1977 provides a large scale long-standing record in the lower Oder river catchment on the northern Germany-Poland border (Sen and Niedzielski, 2010; Pińskwar et al., 2018). There are many regions of dark red, indicating records prior to 1985, in central Europe and in southern UK.

As for Fig.2, similar maps are produced using HadUK-Grid (Fig.S2). The longer timeframe of HadUK-Grid enables us to repeat the analysis using data from 1891 to 2025. In some regions, including much of East Anglia and Caithness, even longer-standing records are present from the early 20$^{\text{th}}$ century.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

3.3 Statistical chance of a new record

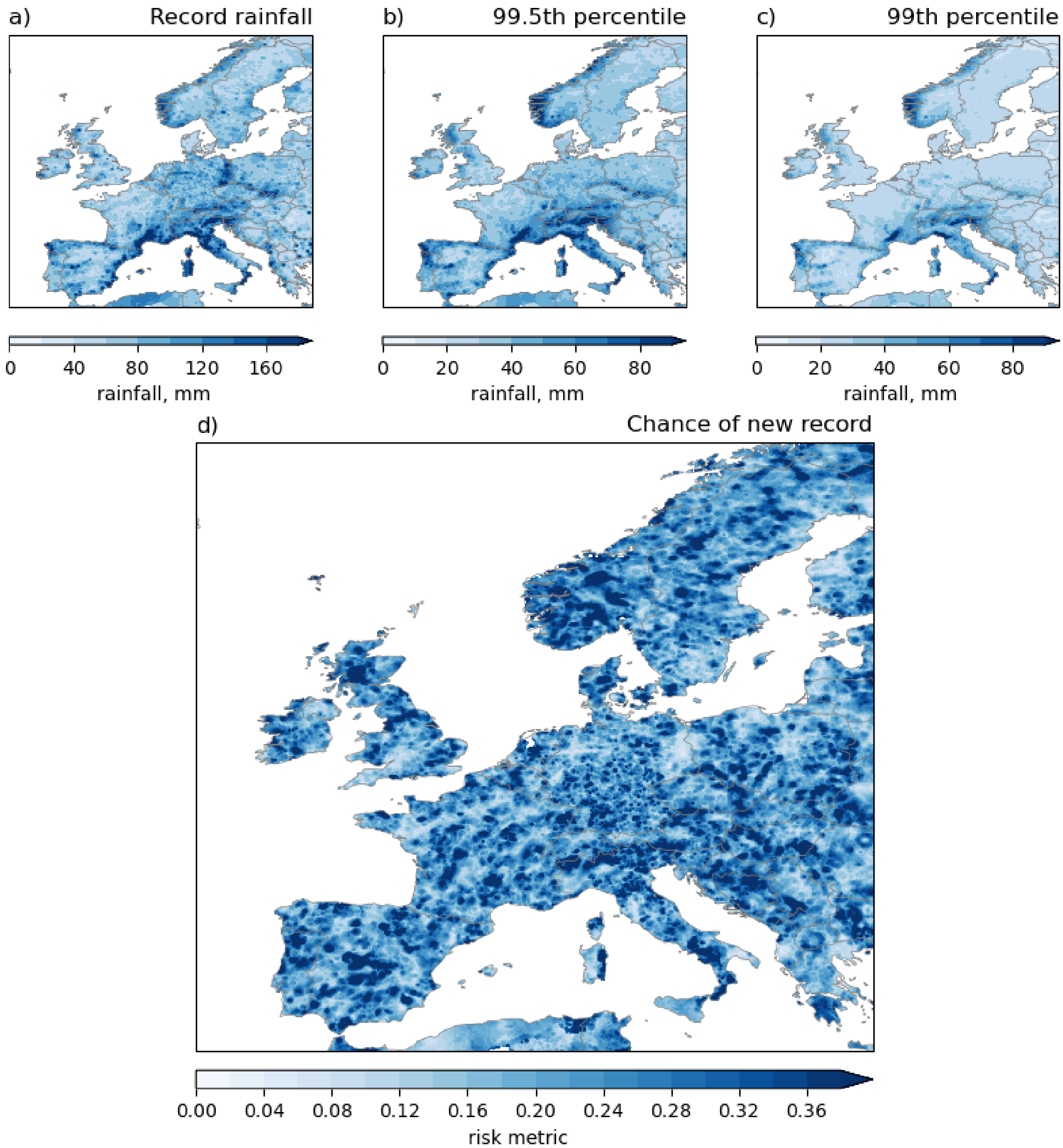

Figure 4: Statistical chance of a new record (a) Map of the daily record total rainfall from E-OBS 1950-2025; (b) map of the 99.5th percentile of all daily rainfall values, 1950-2025; (c) map of the 99th percentile of all daily rainfall values, 1950-2025 and (d) map of the chance of breaking a record calculated using the risk metric (Eq.(1)).

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

From the daily rainfall distribution 1950-2025, we identify the daily record total rainfall (Fig.4a) and the 99th and 99.5th percentile of all daily values (Fig.4b,c). The two percentile maps are smooth compared to the record - as is expected as these values incorporate more (~200 and ~100) daily values instead of only the single maximum. Similar spatial patterns are visible in Fig. 4a-c which reassures that, at least across Europe, using the same approximation of the distribution everywhere may be valid.

The risk metric (see Methods, Eq.(1)) is used as a proxy for the risk of a record-smashing extreme in a specific location (Fig.4d). This map does not show the same spatial pattern as maps 4a-c, instead there is greater spatial variance. There are regions of low risk where the record rainfall is notably greater – such as the Oder catchment in the German Polish border and around the Mediterranean coast. A swath across northern France, following the track of Storm Alex in 2020, is shown as low risk as that event gives a particularly high record compared to the 99th percentile – the areas surrounding appear to be at much higher risk.

The risk ratio shows clear differences in magnitude between E-OBS and HadUK-Grid (Fig.S2), which highlights the need to alter the boundaries in each dataset when categorising locations for assumed preparedness. As stated previously, this difference is likely due to greater number of stations included in HadUK-Grid, however the spatial patterns are generally consistent between datasets.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

3.4 Assumed preparedness

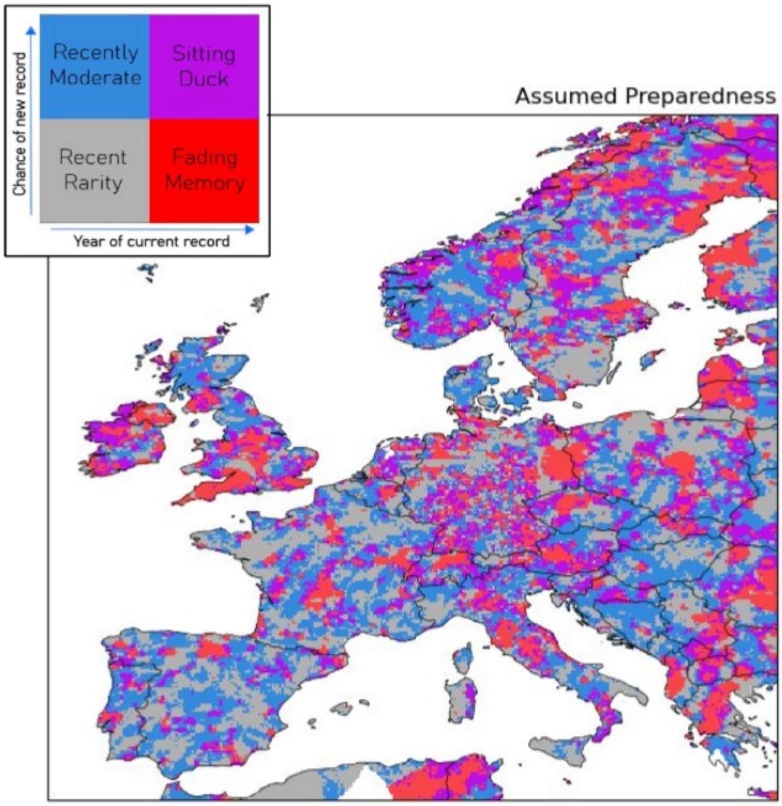

Figure 5: Assumed preparedness across Europe. Showing each location classified by the assumed preparedness framework, using E-OBS 1950-2025.

Next, we can merge the information about the year of the current record (Fig.3) and the statistical risk of a new record event (Fig.4d) to produce a map of assumed preparedness (Fig.5). Presented on a two-way colourbar with 4 categories, this allows us to identify regions where the record is old and statistically low – a region which could be considered a 'sitting duck'. Such regions are where adaptation and communication measures could be most beneficial.

Regions of 'sitting duck' occur throughout the map. Notably, many parts of southern Germany, Austria, and western Ireland stand out as less prepared – i.e. sitting duck regions. The Oder catchment in Polish-German border, highlighted in Fig.3, shows up as a large region of 'fading memory', as it has a particularly early, yet statistically high, record. Much of Bosnia and Herzegovina shows recent but statistically low record events. This may be due to the rainfall in this region following a different statistical distribution, due to the local geography. Some of the regions highlighted as 'sitting ducks', such as south-west Scotland, patches of western France, and patches of northern Spain, are surrounded by areas of greater assumed preparedness. Such areas may be particularly at risk compared to their neighbours suggesting localised policy, such as focused communication programmes, may be required to maintain regional levels of preparedness.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

Regions where recent events have impacted – such as the track of Storm Alex across northern France, Luxembourg and the Ahr valley, and parts of central Europe impacted by Storm Boris, are all classified as "recent rarity" – suggesting a lower risk and higher levels of assumed preparedness.

The assumed preparedness of individual locations can be identified; we show the year of record and risk measure for 20 major cities across Europe (Fig.6). This enables cities at potentially at higher risk of impacts from extreme rainfall, due to less preparedness, to be identified – Sofia, Barcelona, and Munich sit within the 'sitting duck' space. Out of the locations included, Amsterdam is the city with the oldest record – leaving it susceptible to impacts as memory of that event may have faded. Sofia exhibits the highest risk, suggesting the current record is statistically low, and the city has been 'lucky' so far not to experience greater extremes.

We can also identify cities at the other end of the scale, which appear less susceptible (Fig.6). Many cities have experienced their current record in the past 5 years (Vienna, Warsaw, Moscow, Minsk, and Madrid). Although these records are not close to the statistical maximum, the population of these cities will have recent memories of how extreme rainfall impacts them – and therefore may be expected to be more ready for the next big event.

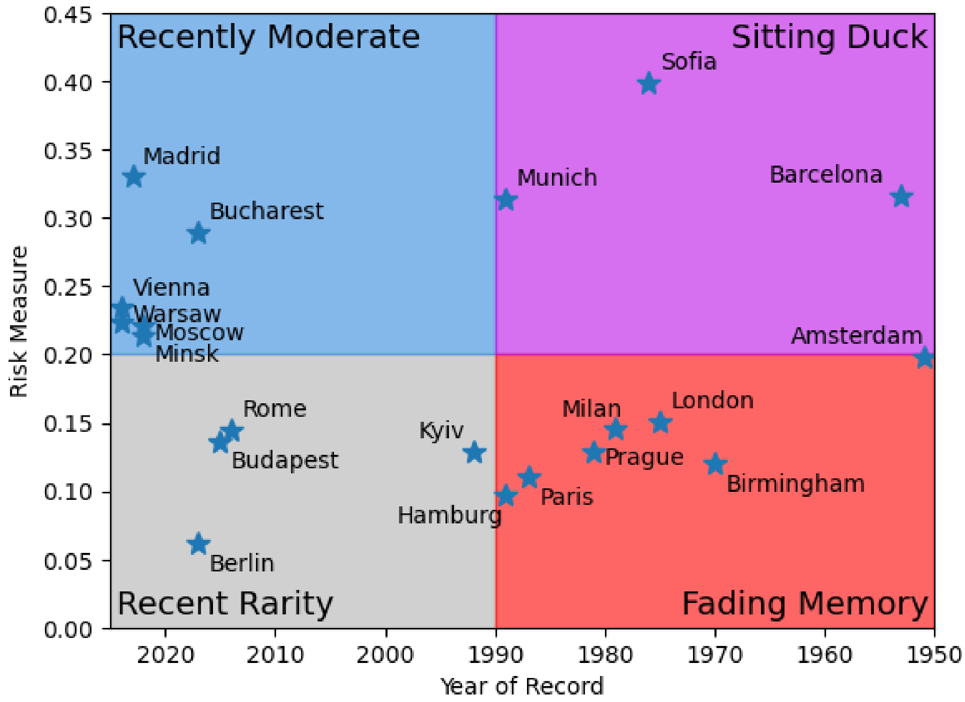

Figure 6: Assumed preparedness of selected cities. Showing the preparedness classification for 20 major European cities.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

3.5 Case studies

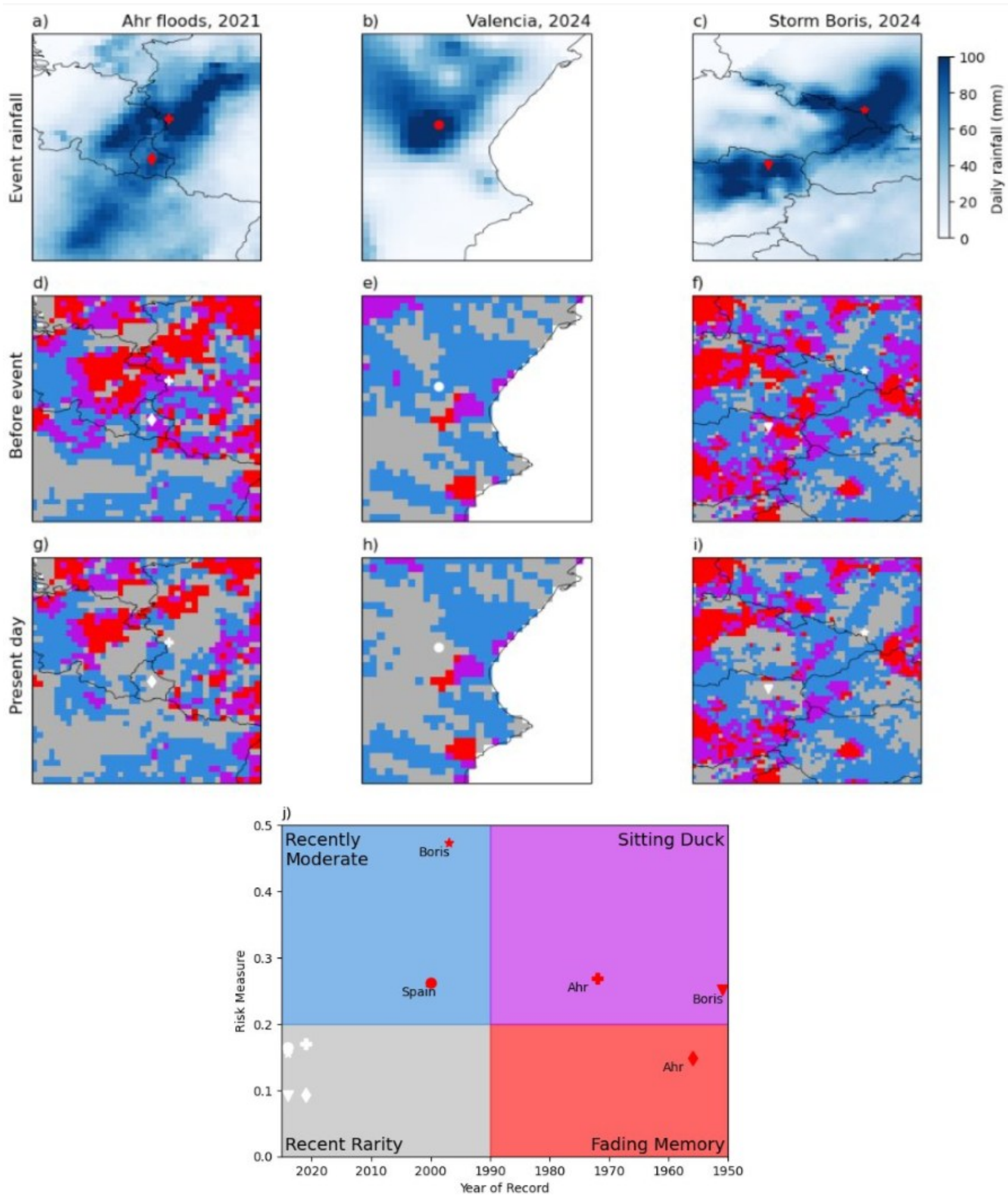

Figure 7: How recent events alter assumed preparedness. Upper row, daily rainfall of 3 recent events, (a) Ahr (14th July 2021); (b) Valencia (30th October 2024); and (c) Storm Boris (14th September 2024). Middle row, assumed preparedness of the regions prior to the three events, including data: (d) up to December 2020 and (e/f) up to December 2023. Lower row, (g-i) assumed preparedness for the regions using data up to December 2025. Colours as in Fig.5. (j) as in Fig.6, with categorisation of the locations (shown in upper plots with same marker styles) before (in red) and after (in white) the event.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

To assess the usefulness of such an assumed preparedness map (Fig.5) we can produce the map as it would have been prior to impactful events (Fig.7). For this, three recent events are chosen: Ahr floods (July 2021), Valencia floods (October 2024), and Storm Boris (September 2024). Rainfall fields for the three events are shown in Fig.7 a-c. For each case, the assumed preparedness map is produced twice, once using data to the end of the year before the event (Fig.7, d-f) and once using all available data (Fig.7 g-i). We show how some locations have changed within the matrix (Fig.7j). We would expect that prior to an impactful event the region would be highlighted as at risk, further from the lower left corner in the matrix. The previous record could be recent but statistically low, or historical though high risk. In Fig.S3 we also show the preparedness maps for the whole of Europe using subsetted data, to show how other regions change through time.

For the Ahr region prior to the event in July 2021 much of Luxembourg, south eastern Belgium, and western Germany is red or purple (Fig.7d) – suggesting regions of fading memory (red) and sitting duck (purple). After the event (Fig.7g) the region has been reclassified lower down the axes, indicating less risk of a record event and a higher level of assumed preparedness due to the recent extreme.

In the case of the Valencia event (Fig.7b) the greatest rainfall is not over the region where greatest impacts were documented. There is less change in classification after the event (Fig.7e/h). Further inland there are regions where ‘recently moderate’ (blue) changes towards ‘recent rarity’ (grey) - the recent event has reduced the chance of a new record. The discrepancy between greatest rainfall and greatest impacts may be because some impacts were downstream of the rainfall itself, or it may be that extreme rainfall over Valencia itself occurred over timescales not captured by the daily timeframe of E-OBS. Close to Valencia, records were broken on 1-, 3- and 6-hourly timescales – though not daily (C3S and WMO, 2025). The third event, Storm Boris in September 2024, shows regions moving towards ‘recent rarity’ (grey). The areas of greatest rainfall (Fig.7c) are most altered between Fig.7f and Fig.7i. Many of the change is from 'recently moderate’ (blue), suggesting although there had been records in recent years they were not particularly extreme. Storm Boris set new records, leading to an assumed reduction in risk and increase in preparedness after the recent extreme.

4 Discussion and Conclusions

We assess observed daily rainfall totals across Europe. We show that rainfall varies spatially, as does the daily record as a proportion of the annual mean. This suggests that not everywhere needs to prepare for 30 % of their annual rainfall in a day, as was seen near Valencia in October 2024. In some places such quantities of rainfall are highly unlikely, due to differing climate and geography. We present a map of assumed preparedness to daily rainfall extremes across Europe (Fig.5). This map can be used to identify regions which may have lower levels of preparedness, based on their past experiences and statistical likelihood of a new record.

We identify several cities with low assumed preparedness: Sofia, Barcelona, Munich, and Amsterdam. However, we also find many cities with either fading memory (old record) or high chance of a record (statistically low current records)

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

where further investigation could be beneficial to ensure suitable risk management planning. Different methods to increase preparedness may be relevant depending on where a region sits – for example locations with 'fading memory' may be at risk as people could have forgotten previous extremes, whereas in 'recently moderate' locations recent extremes are statistically low, highlighting how much worse it could be would aid preparedness.

We show that for some example events, prior to that event the region would have been flagged as low assumed preparedness, and so could have been targeted by policymakers for focused adaptation or risk management plans. For both the Ahr floods and Storm Boris prior to the event the regions impacted show less levels of assumed preparedness with areas marked 'sitting duck' – and could have benefited from additional attention in terms of local education and communication to reduce risks (Ommer et al., 2023; da Costa et al., 2026). The case studies also highlight how regions in all three coloured quadrants are at risk.

However, we cannot assess preparedness solely on statistics - local knowledge is required to understanding local preparedness. In the case of the Valencia floods the assumed preparedness map would not have indicated a lack of preparedness in the region most impacted. Geographical knowledge is key – as in some places impacts from extreme rainfall will not be spatially coherent with the location of greatest rainfall. In some regions adaptation may be driven by the greatest event within a larger (e.g. political) region rather than just locally. Some regions may have longer 'memory', perhaps due to notable impacts to the community, and how that memory is transmitted (e.g. local oral history and education) (Metcalfe et al., 2020). Some recent events may have occurred within a period of lesser vulnerability – perhaps the most intense rainfall occurred at night, or at a time when the water infrastructure had greater capacity – and so impacts were lower than our map would suggest. Our map of assumed preparedness can guide policymakers to identify locations potentially at risk, but local insight is essential to compliment this information.

Using just two simple metrics to assess preparedness leads to many assumptions and simplifications. For instance, the map of record event (Fig.3) shows only the greatest event in the record. There may be other impactful events that fell just short of the record but happened much more recently. In such locations, the year of the record will be less likely to be indicative of the local preparedness. We assess preparedness based on daily rainfall alone, but the impacts will depend on much more. For example, in urban area shorter duration intense rainfall has greatest impacts, river basins are susceptible to longer-duration rainfall collecting water over larger areas and longer times. Dam management, river conditions and pre-conditioning will influence the timescales of rainfall which will lead to impacts.

This research highlights many outstanding questions surrounding how we can determine preparedness levels. Further research into how memory of an extreme weather event fades and over what timescales past experiences still matter is essential. For the Ahr valley floods in 2021 seemed unprecedented – but similar events had occurred in the deeper past (Roggenkamp and Herget, 2014), ensuring the memory of these remain can reduce the surprise of future extremes (Kelder et al., 2025). Our preparedness map shows 'sitting duck' locations bordering 'recent rarity'. The 'sitting duck' locations could be considered to have been lucky so far. Some of these at-risk locations may have implemented adaptation based on nearby events, yet

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

identifying ‘sitting ducks’ next to ‘recent rarities’ could enable us to highlight the regions of ‘lucky escape’ so far. We need better understanding of how places adapt when they are not directly impacted but are close to regions impacted.

The metric used to assess the chance of a new record (Eq.(1), Fig.S1) uses only record daily rainfall and 99th and 99.5th percentiles of daily rainfall for each location. The full distribution of daily rainfall is not incorporated. An alternative could be to fit a statistical distribution such as a gamma distribution to the daily rainfall and assess the percentile of the current record event. The simplified method is expected to give comparable results, and it allows the method to be applied to datasets covering larger regions or higher spatial and temporal resolutions where fitting a distribution to every grid point could prove unfeasible.

In this assessment, we do not account for spatial variance in climate change. Globally, extreme rainfall is increasing with climate change and this is projected to continue (Seneviratne et al., 2021). There is evidence that variability is increasing, leading to more record breaking extremes (de Vries et al., 2024). We assume a spatially uniform change, but this is unlikely to be true, even just across Europe. Some regions show greater increase due to dynamical changes enhancing thermodynamic changes. Across Europe, a north-south gradient in extreme rainfall trends has been shown in several datasets, with the Mediterranean showing greater increases (Beranová et al., 2025; Hänsel, S. et al., 2022). Changes in daily rainfall also vary seasonally, leading to reduced preparedness at times of the year previously unlikely to experience extreme events. Masukwedza et al. (2025) used the metric of change in return period to incorporate climate change and indicate locations that might not realize that the risk of extreme weather is changing, having not experienced a recent extreme. Over a continental region these assumptions could be considered a valid first estimate however, to assess preparedness over larger regions the assumptions become increasingly invalid and alternative methods should be investigated.

Comparisons with other observational datasets, including those with global coverage, would be beneficial. Here, we show results from E-OBS and HadUK-Grid – even comparing two land-only station-based datasets we find similarities and discrepancies. Reliable and accurate precipitation datasets are crucial to allow us to quantify the risks of extreme rainfall but numerous studies have highlighted the disagreement between precipitation datasets (e.g. Sun et al., 2018; Cattelan et al., 2025; Bernová et al., 2025; Bhattacharyya et al., 2022). Cross validating across multiple datasets can help reduce uncertainties. Furthermore, using longer datasets when available can place recent extremes into a longer context. For example, HadUK-Grid provides data back to the 19th century providing further insights about very early record events (Fig.S2), and Kelder et al. (2025) highlights an even older record from Oxford (UK) in the 18th century. Climate model data provides a further information source. Large ensembles of climate models can be used to better understand the tails of the distribution (Thompson et al., 2017; van der Wiel et al., 2019). Using model datasets from different climate states or transient simulations, the changing risks can be assessed (Kelder et al., 2020; Masukwedza et al., 2025).

In conclusion, we present a method to assess spatial variability in assumed societal preparedness to extremes using observational data alone. In this warming world we know record breaking extreme rainfall events will become more common. Society needs to prepare for future record rainfall events, and the current preparedness to these events differs by location. Understanding where the risks are greatest, both in terms of statistical chance of a record breaking event and local memory of

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

past events, is essential to ensure suitable targeted adaptation and risk management strategies. We must move away from reactive adaptation, and use the information we have to encourage targeted proactive adaptation measures.

Code and data availability

The E-OBS dataset used, version 33.0e, is available from the Copernicus Climate Change Service (C3S, https://surfobs.climate.copernicus.eu) and the data providers in the ECA&D project (https://www.ecad.eu). The HadUK-Grid dataset is available from the UK Met Office (https://www.metoffice.gov.uk; https://catalogue.ceda.ac.uk/uuid/4dc8450d889a491ebb20e724debe2dfb/).

The code used to generate the figures in this paper and the Supplementary Materials is available from github and zenodo: https://github.com/vikki-thompson/rain_preparedness and [to be added]. All data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials.

Author contributions

V.T. designed the study and performed the data analysis of E-OBS. E.H. performed the data analysis of HadUK-Grid. V.T., E.CP., D.H., K.vdW., E.H., and A.S. contributed to the interpretation of the result and the writing of the article.

Competing interests

The authors declare no competing interests.

https://doi.org/10.5194/egusphere-2026-4100
Preprint. Discussion started: 21 July 2026

Financial support

E.H. received financial support from the UK National Centre for Atmospheric Science, and UK Research and Innovation (UKRI) via the International Science Partnerships Fund (ISPF) under Grant number [22/CC/11103] at the Co-Centre for Climate + Biodiversity + Water.

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