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Attribution estimates for similar extremes are robust across event definitions

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Event attribution studies assess whether and to what extent human-induced climate change has altered the likelihood or severity of extreme weather events. In recent years, studies have become routine, particularly for heatwaves in many regions, and for heavy rainfall in parts of Asia and Europe. As this body of research grows, a key question emerges: when does a new attribution study add scientific or societal value? We address this question by synthesising findings from existing attribution studies and systematically analysing how results depend on temporal and spatial event definition and dataset. While previous work has shown that quantitative outcomes are sensitive to how events are defined, we find that when similar probabilistic frameworks and comparable datasets are used, attribution results for events of the same type and magnitude within a region are often strikingly consistent. Consequently, additional studies that replicate established methods for well-studied hazards and regions often provide limited new insight unless they incorporate substantial advances in data quality. These findings have implications for operational attribution services and for the use of attribution evidence in decision-making. More broadly, they suggest the need to prioritise understudied regions, and integrative approaches that deepen causal understanding rather than repeatedly reaffirm well-established conclusions.

Studies answering the question of whether and to what extent human-induced climate change has made extreme weather events more likely and/or severe have become routine and for many parts of the world many different attribution studies exist for the same type of extreme event[1–3]. While both globally and over Europe and Asia, studies on heatwaves dominate, more studies on heavy rainfall exist in Asia and North America[4]. Some regions and types of events are still understudied; for example, small island states stand out as having been completely neglected by event attribution studies. The availability of so many studies on certain types of events and regions begs the question of the added value of yet another attribution study on extreme heat in Europe or India, or heavy rainfall in Ireland or China. It also raises a communications challenge: repeatedly "re-proving" findings for which there is already robust and, in many cases, quantitative evidence may inadvertently convey a lower degree of certainty than is scientifically warranted. Continuously restating well-established results can create the impression that the underlying causal link remains unsettled, rather than reflecting the substantial convergence of evidence that already exists. Clarke et al.[2], asked the question on when a new attribution study is indeed not needed, finding that, depending on the combination of region and hazard, new attribution studies are for most purposes unnecessary when sufficient studies exist. In other cases, where many studies exist but are inconclusive, apparently contradictory, or highly sensitive to the specific event and event definition, such as East African droughts[2,5], new studies, carefully designed to actually add new scientific understanding, rather than using just another event definition, are needed.

In this paper, we turn the question around and ask under what circumstances a new attribution study genuinely adds value, and, critically, when it does not. As the number of attribution studies grows and operational attribution services start up, it becomes increasingly important to ensure that such efforts are purposefully designed to advance physical understanding and to provide meaningful decision support. Repeating established approaches for similar events may, under certain circumstances, not add understanding, while also diverting limited scientific capacity from more informative or innovative analyses. Explicitly identifying when additional studies are unlikely to contribute new insights, or how they would need to be designed, can help redirect effort toward approaches that are better aligned with the scientific or societal questions at hand, even when these approaches are more demanding or require a different methodological perspective. For example, combining probabilistic attribution with a

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storyline framework, or vice versa (ref. e.g.,[6]), may offer a more comprehensive understanding of causality and risk than either approach alone.

While it has been shown that the exact definition of an extreme weather event affects the quantitative results of the attribution study[7,8], results are still more similar when the same methodological framing is applied for different event definitions compared to studying the same event with very different framings. A prominent example is the 2021 Heatwave in the Northwest of North America. The event was first studied in a rapid event attribution study[9] based on the probabilistic event attribution methodology combining an observations-based dataset and climate models[10], which found an increase in likelihood of at least a factor of 150 and an increase in intensity of about 2 °C. Other studies, also employing the probabilistic approach, found a similar change in intensity, despite employing a different event definition and using other datasets[11]. More conditional attribution studies on the event, such as one using a forecast-based approach, found a smaller increase of only a factor of 8[12] and an increase in intensity of about 1.3 °C. It is not only heatwaves for which some events assessed by the same methods produce extremely similar results across events and event definitions, but also for heavy rainfall. For instance, attribution studies on extreme winter rainfall related to floods in the UK gave similar results across different years and with differing event definitions[13].

These cases beg an important question: are these similar results only by chance? If not, they illustrate that for a given climatological region, a new attribution study does not provide any new knowledge of the role of climate change unless it also provides some form of additional data or methodological advancement. For instance, by introducing higher resolution or longer observational datasets, or updated climate models with improved capabilities in capturing the extremes of interest, or by disentangling the drivers of a given event through conditioning. This in turn has important consequences for the operationalisation of extreme event attribution, as well as for the compilation of inventories of disasters related to human-induced climate change.

In this paper, we demonstrate that it is indeed generally true for extreme heat events (Section 2.1), and in many cases also for heavy rainfall events (Section 2.2), that the role of climate change is assessed to be extremely similar for the same type and class (magnitude) of event in the same region, even if the event definitions are substantially different. Within the results section, we show several examples to illustrate differences and similarities for different event definitions: a similar event definition (temperature), a slightly changed event definition in terms of region and season (temperature and precipitation), the difficulties arising from differences in observational and model datasets (precipitation). We then generalise the findings for different datasets and event definitions, demonstrating that the dataset is the dominant source of variability in fitted trends (see Methods) in all cases, but especially for rainfall. In Section 3 we discuss the implications of this finding for rapid and operational attribution services, and broader implications with respect to event databases. We conclude in Section 4 that this finding also highlights that for attribution studies that aim to be comprehensive, and for which robust quantification of the role of climate change is important, e.g. because they are intended to provide evidence in damage assessments, the combination of probabilistic and conditional approaches is essential.

Results

Heatwaves

Scientific evidence on the impact of human-induced climate change, primarily caused by the burning of fossil fuels, is strongest for heat extremes compared to other categories of extreme weather events. This is due to three main factors.

First, the magnitude of observed changes in heat extremes is larger than for other types of events, while variability in heat extremes is often smaller than in, for instance, precipitation extremes. Even using the conservative estimates for global changes up to 2020 presented in the IPCC Sixth Assessment Report, the frequency of heatwaves has increased by a factor of four, while heavy rainfall events and droughts (defined as agricultural droughts) have become more likely by factors of approximately 1.5 and 1.7, respectively ([14] Fig. SPM.6).

Second, the physical mechanisms linking greenhouse gas emissions to increases in temperature and extreme heat are well understood and relatively straightforward. The radiative forcing from increased atmospheric greenhouse gases directly results in a warmer climate, which in turn increases the probability and intensity of heat extremes[1].

Third, temperature is the most consistently and accurately observed meteorological variable globally. This leads to a higher degree of confidence in attribution studies, especially with respect to the change in intensity, and limits observational uncertainty compared to other types of extremes.

Consequently, there is no uncertainty around the fact that climate change is making heatwaves more frequent and more intense. Every heatwave (whether terrestrial or marine) occurring today is hotter than it would have been in a counterfactual world without anthropogenic climate change[3,15], unless in very rare circumstances when climate change alters ocean currents or atmospheric circulation to such a degree that a cooling on land is observed[16].

Of course, this does not mean that we know everything there is to know about extreme heat and climate change[17], but it does imply that the question of whether climate change played a role in extreme heat does not require a new study, since is already well answered in the scientific literature (see e.g. refs. 3,15). The quantitative effect of climate change on the likelihood of extreme heat varies by region, season, the severity of the event, and how the event is defined[7]. For example, in the UK, a heatwave defined as temperatures exceeding 28 °C for three consecutive days in the Southeast has become approximately ten times more likely due to climate change. A more extreme event, such as a heatwave reaching 32 °C in the same region, has become around 100 times more likely[18]. This is also shown globally in the same IPCC SPM.6 figure mentioned above. While the change in frequency is sensitive to how a heatwave is defined, the change in intensity is more stable across definitions because the underlying distribution is bounded and asymptotic in shape[17]. This shape makes changes in magnitude relatively insensitive to errors in estimating a fixed return period. At the same time, however, it also means that changes in frequency at a fixed magnitude are highly sensitive to uncertainties in the magnitude estimate, the shape of the distribution and the extremeness of the event considered[19]. In the UK example, this would be 4 °C change in intensity when assessing observations alone – with a range of 3.3 °C to 4.8 °C found across observational data sets – and about 2 °C when using climate models[18].

This shows that the difference in estimated trends in intensity between models and observations, and often also between different observational datasets, is larger than between different definitions of extreme events over the same region in this case. This is not only the case for the UK, but other parts of the world too. We briefly discuss two examples: extreme heat in the Sahel and in South America, before demonstrating the point more generally.

Sahel - repeated event definition, different years

This section illustrates the similarities in results for similar event definitions applied in different years.

The boreal spring period from March-June normally is the hottest part of the year for the Sahel region. Overall temperatures in the Sahel countries have significantly increased over the 20th and early 21st centuries[20]. This has been accompanied by a rise in the frequency, duration and intensity of heatwaves[21]. Increases have been observed across both day-time and night-time temperatures, in the frequency of events above the 90th percentile, and in very hot days and tropical nights, defined above 35 °C and 20 °C, respectively[21].

At the end of March and the beginning of April 2024, a very large region across North Africa and the Sahel experienced extreme heat, with maximum temperatures in the Sahel region reaching 45 °C and more and minimum temperatures of 32 °C in Burkina Faso (Burkina Faso Meteorological Agency). Kayes in Mali recorded a maximum temperature of 48.5 °C on the 3rd of April (Mali Meteorological Agency). Very high maximum temperatures were also recorded in Senegal, with several cities

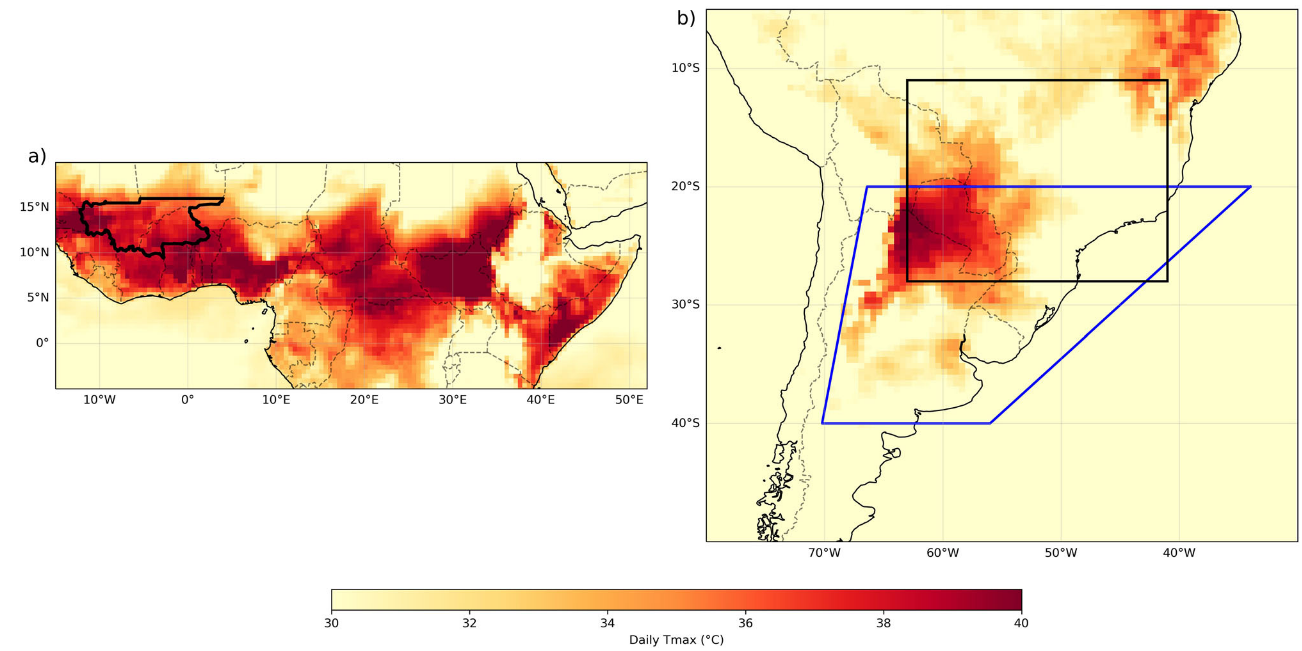

Fig. 1 | (a) Maximum temperature 31 March 2024 based on ERA5 data. The black outline shows the study region. Figure adapted from[22]. (b) Maximum temperatures 15 January 2025 based on ERA5 data. The black box outlines the study region for the 2023 study [11°S-28°S, 41°W-63°W]. The study region in blue (Southeast South America domain or the SES domain) was analysed in the 2025 study (corresponding to data plotted). Figure adapted from[29,32].

Table 1 | Summary of results for Tx5x in Mali and Burkina Faso under 1.2 °C and 1.3 °C of global warming

Data	Mali/Burkina Faso, 1.2 °C			Mali/Burkina Faso, 1.3 °C		
	Return Period (95% CI)	Probability ratio (95% CI)	Intensity change (°C) (95% CI)	Return Period (95% CI)	Probability ratio (95% CI)	Intensity change (°C) (95% CI)
CPC	231 (33, ∞)	**∞ (6.4, ∞)**	**2.3 (0.75, 3.26)**	36 (5, ∞)	**∞ (33, ∞)**	**2.47 (0.78, 3.6)**
ERA5	37 (12, ∞)	**∞ (1.4E + 04, ∞)**	**1.6 (1.12, 2.14)**	17 (6, 838)	**∞ (9286, ∞)**	**1.78 (1.17, 2.31)**
MSWX	264 (34, ∞)	**∞ (38, ∞)**	**2.2 (1.22, 3.38)**	60 (9, ∞)	**∞ (124, ∞)**	**2.39 (0.82, 3.58)**
Models	100	∞	**1.47 (1.4, 1.6)**	50	∞	**1.62 (1.25, 2.01)**
Synthesis	100	∞	**1.58 (1.5, 1.65)**	50	∞	**1.67 (1.13, 2.16)**

The synthesis combines model- and observation-based assessments following Otto et al.[23]. There are no confidence intervals for the return times in the models and synthesis, as these were set to 100 and 50, respectively. Similarly, as not only the upper bounds but also best estimates of the probability ratio are infinite, no confidence intervals (CI) are given. Numbers in bold show statistically significant results.

reporting temperatures well above 40 °C over the first week of April (Senegal Meteorological Agency).

In a rapid attribution study published in April 2024[22], the World Weather Attribution initiative (WWA) looked at three different ways of defining the extreme temperatures in the region, using TX5day over two different regions as well as the highest 5-day minimum temperatures. While temperatures were extreme over this larger region, the highest temperatures were recorded in Mali and Burkina Faso and along a large region encompassing Senegal, Guinea, Mali, Burkina Faso, Niger, Nigeria and Chad. To focus on the most affected region as well as recognising the spatial extent, the original study used two event definitions, one over the larger Sahel and one over the southern part of Mali and Burkina Faso (Fig. 1a, black outline), which we use as an example here.

Table 1 shows the results for the study for the Burkina Faso/ Mali region for the event that occurred in 2024 and if the same event would have occurred in 2025.

Even in a 2024 climate—already warmed by 1.2 °C due to human activities—the extreme heat experienced in the Mali/Burkina Faso region remains a rare event. The 5-day maximum temperatures are estimated to have a return period of possibly 200 years, but 100 years is used in the analysis. As e.g. discussed in the context of the 2021 Pacific Northwest heatwave[19] estimating return periods of record-breaking events is difficult based on observations, due to the bounded nature of the distribution. In regions with short records, this is particularly difficult. To understand the impact of human-caused climate change on this event, results from climate models are combined with those from observation-based products. Both sources confirm that the extreme heat seen in March and April 2024 would have been virtually impossible (shown as infinite probability ratios) without the 1.2 °C of global warming caused by human activity.

In a world without this level of warming, the 5-day extreme heat over Mali/Burkina Faso would have been about 1.5 °C cooler when combining climate models and observations in a formal synthesis[23]. However, the detected warming trend is much stronger in two out of the three observations-based and reanalysis datasets. This is a common problem when estimating changes in extreme heat[17,24,25] that can be, e.g., due to models underestimating the effects of aerosols[26] but also have other causes, either from phenomena not captured by the models, or observational-records providing too small a sample to meaningfully estimate strong trends[24,25]. Repeating the same study but for the event occurring in 2025, keeping the event definition the same, but updating the global warming to 1.3 °C, we find that while the return period has decreased quite dramatically, the change in intensity is still very different in the different observational products, and a slightly different set of climate models is used in this case, including only model from the Coupled Model Intercomparison Project

Table 2 | As Table 1 but for a summary of results for Tx10x spring in the first South American region (2023, Fig. 1b), and TxDJFM for the second South American region (2024/25, Fig. 1b)

Data	Tx10x, Central South America, 2023			TxDJFM, Southern South America, 2024/25		
	Return Period (95% CI)	Probability ratio (95% CI)	Intensity change (°C) (95% CI)	Return Period (95% CI)	Probability ratio (95% CI)	Intensity change (°C) (95% CI)
CPC	52 (15, 882)	**∞ (44, ∞)**	**4.9 (3.2, 7)**	24 (6, 424)	∞	**2.5 (1.6, 3.25)**
ERA5	34 (12, 202)	**1.0E + 04 (31, ∞)**	**4.5 (3, 6)**	120 (25, 3048)	**7.0E + 07 (6.0E + 06, 1.0E + 09)**	**1.4 (1, 1.7)**
MSWX	38 (14, 1188)	**∞ (32, ∞)**	**3.4 (2.2, 4.7)**	30 (8, 640)	∞	**1.8 (1.2, 2.48)**
Models	30	**332 (4.13, 2.06E + 04)**	**1.9 (1.0, 2.7)**	10	**3.23E + 03 (77.7, 1.52E + 06)**	**1.04 (0.635, 1.46)**
Synthesis	30	**1.26E + 03 (2.13, 1.39E + 05)**	**2.28 (1.3, 3.29)**	10	**1.87E + 04 (235, 6.39E + 07)**	**1.15 (0.712, 1.6)**

Numbers in bold show statistically significant results.

(CMIP6) but no regional climate models. The increase shown is stronger than for 1.2 °C and also have much larger uncertainty bounds, due to the fact that with fewer models used the sampling uncertainty is larger[23]. However, without any knowledge of whether one of the models or observations-based data sets is closer to representing the real world, no additional knowledge is gained on top of the reduced return time. The fact that the return time was reduced even within a year does suggest that after a few years, or a significant increment of warming, such as 0.1 °C or 0.2 °C of global warming, an identical study will yield new results. Examples of this can be seen in Arrighi et al.[27]. which revisited heat events within the last ten years and found, e.g., for extreme heat in the Amazon, that 10 years and a global warming increment of 0.3 °C doubled the likelihood of the event.

South America - changed event definition, different region and temporal scale

This section illustrates the similarities and differences in results in case the event definition has been substantially changed for a heat event in terms of region, between two partially overlapping areas of similar scale, in terms of temporal scale, from 10 to 120 days, and in terms of season, from winter/spring to summer.

Exceptional heat episodes were observed across much of Brazil during the winter months and early spring 2023. To assess the extent to which human-induced climate change has influenced the occurrence of extremely high temperatures in the region most affected by severe heat (as illustrated in Fig. 1b), Kew et al.[28]. opted to examine the 2-metre land surface temperatures in the region that stretches from São Paulo near the East Coast of Brazil to Paraguay. This region, which is climatologically relatively homogeneous, had the highest positive temperature anomalies in the September period, and includes the states (with the exception of Pará, in the north) where red alerts for heat were issued – therefore, a rectangular box over 11°S-28°S, 41°W-63°W for the spatial definition was selected. As impacts were highest on a time scale of 1 to 2 weeks, the annual maximum of the 10-day average of daily maximum temperatures during August and September only (Aug-SepTX10x) was considered. Figure 1b shows the 1-day maximum temperatures to illustrate the region (black outline). The method of this rapid study follows the peer-reviewed study[29] that looked at a very similar region. The results of the rapid study are shown in Table 2.

As in the Burkina Faso/Mali case, infinite changes in probability and very different changes in the intensity of the heat are shown in different data products. Again, the models show a much smaller increase, approximately half as intense as the observation-based products. This can be compared to another extreme heat in South America, where multiple hot spells hit Argentina and the neighbouring countries of Paraguay, Uruguay and Brazil during the peak summer month of February[30,31]. In a rapid study of the heat event, Zachariah et al.[32]. focus on the summer seasonal (DJFM) mean of the daily maximum temperature, given that there were at least two recorded heat waves since the beginning of February and the first days of March, choosing the IPCC's South East South America domain (SES) as the study region to capture the spread of the event and to facilitate comparison to literature. Figure 1b shows the study region (blue outline). The results are summarised in Table 2. The results in this case are noticeably different to those presented in Table 1, showing that looking at a different region and different temporal scale does impact the results in a similar way to using a different data set. However, some features remain the same, namely that the models underestimate the observed trends by more than a factor of 2. This suggests that to understand changes in extreme heat in South America, an investigation as to why models underestimate observed trends, e.g., as Schumacher et al.[26] found for Western Europe, would provide a more important knowledge gain than an additional attribution study following the same methodology.

General conclusion

The South American example above likely extends beyond the threshold at which attribution studies become too similar to justify a new, standalone analysis. In these examples, the region, temporal scale, and season were all altered simultaneously, yet still the qualitative attribution outcome remains unchanged. This suggests that, while methodological repetition across substantially different settings can provide new useful information, especially if quantitative estimates are needed, e.g., for adaptation purposes[2], it does not necessarily generate additional scientific insight. This would be different if, instead, studies investigated the compounding effects of temperature and humidity[33] or the detailed mechanisms using storyline approaches that so far have mainly been applied to extremes in the global North[34].

The Burkina Faso/Mali example demonstrates that an attribution study conducted for the same season and a similarly defined event of comparable magnitude is unlikely to provide new information. By contrast, modifying key dimensions such as season or region may offer incremental insight, particularly when these changes reflect different physical drivers. Building on this, we now explore more systematically the question of how similar is too similar to warrant a new attribution study.

Despite variations in region, season, and temporal scale, the qualitative conclusions across these studies remain highly consistent. Consequently, unless the objective is to support a narrowly defined application, such as determining event thresholds for early warning or early action systems, a new attribution study employing the same general methodological framework is unlikely to yield substantially new insights. Meaningful advances are more likely to arise from the application of new methods, the use of substantially better datasets such as high-quality station data, or the investigation of processes not captured in previous analyses.

Looking more systematically at the change in intensity over the African continent, we compare the change in intensity for several temporal event

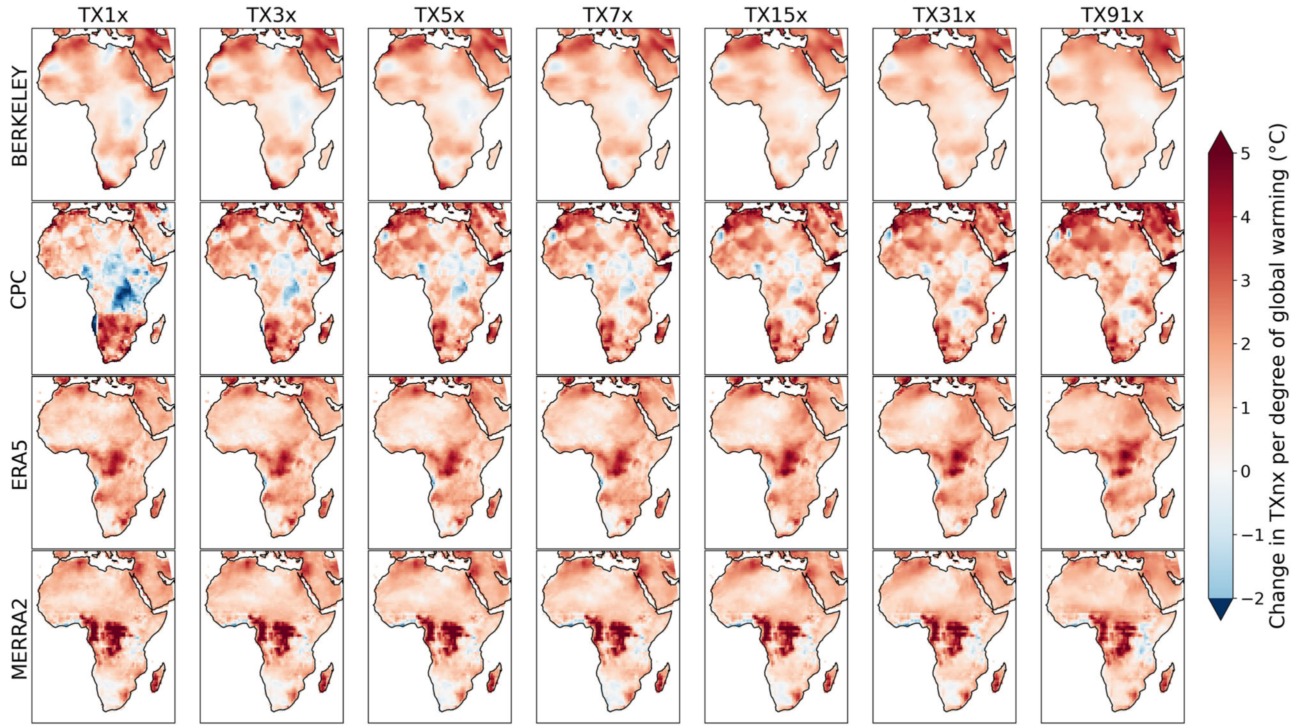

Fig. 2 | Maps of estimated change in extreme temperature indices per degree of Global Mean Surface Temperature (GMST) warming, for different event definitions (columns) and datasets (rows), using data from 1980-2024. Event definitions: TX1x, TX3x, TX5x, TX7x, TX15x, TX31x, TX91x. Datasets: Berkeley Earth, CPC, ERA5, MERRA2.

definitions: TX1x, TX3x, TX5x, TX7x, TX15x, TX31x and TX91x, covering short-term and seasonal-scale heatwaves across the columns of Fig. 2. All datasets shown here cover a common period of 1980-2024. As the discrepancies between observations-based and reanalysis data are at least as large as between models, we limit the systematic analysis to these datasets. A description of all data used can be found in the supplementary information (S2). One can see that the difference between the data source (the rows) is much bigger than the difference between the event definition or duration (the columns), meaning that the results are much more driven by the choice of data than the event definition.

Figure 3 shows a formal decomposition of the variance in trends in extreme heat events globally. The proportion of variability within each of the IPCC AR6 climate reference regions[35], outlined in red in the map, is summarised in Fig. 3. Overall more than 80% of the variability in trends in extreme heat arise from differences between the datasets, with only around 10% arising from differences between event duration, although in some regions - notably northern and western Europe, Russia, central North America, the Sahara - the choice of event duration accounts for a somewhat higher proportion, as much as 40% in northern and central Europe (Fig. 3). When only short-duration events are considered (TX1x, TX3x, TX5x, TX7x), the proportion of variance explained by differences between the event definitions falls to around 5%, with 89% explained by differences between the datasets (Figs. S1 and S2 in the supplementary material); in almost all AR6 regions, less than 10% of the variability is associated with the choice of definition, with the exception again of northern and western Europe, where up to 20% arises from the event duration. When trends are estimated over different spatial extents, the results are also typically very similar (tested here by first averaging the data over 1-, 2-, and 4-degree boxes before regressing against GMST), with only around 3% of the total variance in temperature trends associated with the choice of resolution. This suggests that, while trends in seasonal and short-duration extreme heat may differ slightly in some parts of the world, the dominant source of variability remains the choice of datasets used to estimate the trends.

For heat events, we can thus conclude that new attribution studies for a similar region and event definition can be expected to provide new insights only when they incorporate substantially different observational datasets or employ novel methodological approaches. In their absence, additional studies contribute limited new quantitative information until several years have passed, as discussed above. This further implies that maintaining a diverse ensemble of models and observational datasets is critical when developing operational attribution services, whereas extensive deliberation over precise event definitions may be of comparatively minor importance. In addition, if only qualitative results are required, there is generally no need for a new attribution study on heat extremes.

Heavy rainfall

For extreme heat, the finding that the event definition is much less important than the choice of dataset for the quantitative assessment of the role of climate change is maybe not surprising, given the underlying climate change signal is already known to be large[24]. The question is whether similar conclusions can be drawn for rainfall, where the climate change signal can be very different across regions and event definitions. Recent studies across the world suggest that new attribution studies for precipitation in the same region also do not offer new insights if undertaken with the same methods. When the anthropogenic signal is small, differences between observational datasets dominate, and when the signal is large, the same reasoning that applies to heat events also holds. To illustrate this, we first examine two case studies before proceeding to a broader analysis across multiple datasets and event definitions.

Sahel Region - changed event definition, different region

This section illustrates the similarities and differences in results in case the event definition has been slightly changed in terms of region and temporal scale for a precipitation event.

From July to September 2024, most countries in and adjacent to the Sahel region experienced deadly floods. In August, extreme rainfall led to

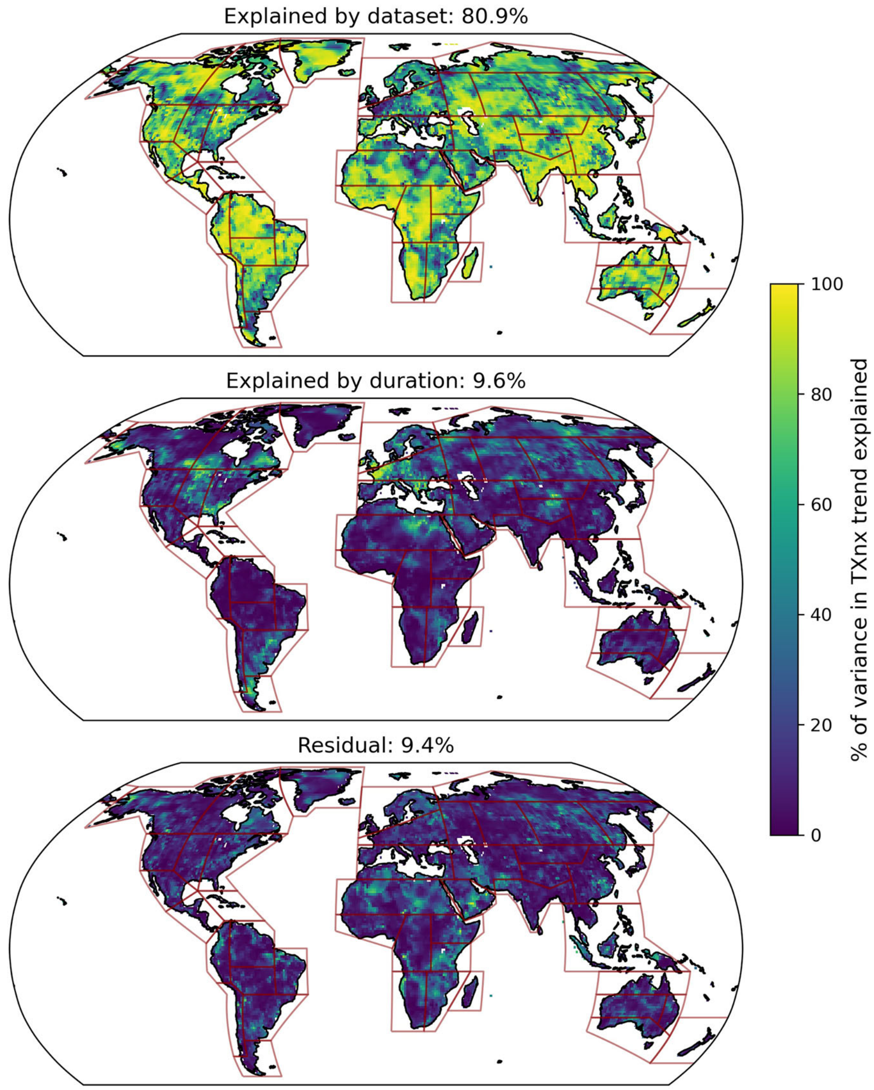

Fig. 3 | Maps of the proportion of the total variance in the trend in extreme heat explained by each factor in each grid cell. Top: proportion explained by choice of dataset; middle: proportion explained by choice of event duration; bottom: proportion not explained by either factor. Red lines denote AR6 regions, used to summarise the total variance explained in Fig. 7 (top).

catastrophic floods in Sudan. At least 205 people have lost their lives[36] and more than 130,000 people have been displaced, with nearly half being people who were already displaced due to the ongoing civil war[37]. In September, further West in the Sahel region, floods killed more than 760 people in Nigeria, 330 in Niger and 30 in Cameroon[38].

The floods in Nigeria, Niger, Chad and Cameroon were nearly identical to the floods that hit the same region at the same time of the year in 2022, killing 612 people in Nigeria and 195 in Niger[39,40].

In 2022, WWA undertook an attribution study[41], looking at two regions: the lower Niger catchment and the Lake Chad basin (see Fig. 4a, black outline). Additionally, WWA also undertook an attribution study of the extreme rainfall in Sudan in 2024[42] (see Fig. 4a, red outline). Below, Table 3 shows the results for the seasonal rainfall over Lake Chad in 2022 and Sudan in 2024. From the synthesis results, in the Lake Chad Basin, very wet seasons like the event from August 2024 are expected to occur much more frequently in today's climate and are made approximately 15% more intense by human-induced climate change. In the Sudan region, the changes are not as great, with the probability ratio being lower compared to the Lake Chad event, while the change in intensity remains very similar. The different region offers quantitatively new information, though; most noticeable in the Sudan region is, statistically, "no change", while this is not the case over Lake Chad in all datasets. This example shows that the relevance of the region/season will depend on what the purpose of the attribution study is.

Pakistan - differences in datasets

This section illustrates the difficulties with interpreting results in case different observational datasets and model datasets show inconsistent results.

A more typical example of a precipitation attribution study is provided by Pakistan. Monsoon rains are vital for South Asia's water and agriculture, but rapid urban growth, poor drainage, and climate change have made their impacts increasingly severe[43]. Pakistan remains especially vulnerable, having experienced the worst flooding in the country's history in 2022[44] with more than 1700 people killed and an estimated $40 billion in economic damages. From June 2025 throughout the monsoon season 2025, monsoon-related rainfall has impacted much of Pakistan, triggering floods, landslides, and severe weather incidents that have resulted in significant loss of life and widespread damage.

The region of the most severe rainfall was slightly different in both cases, with the 2022 event centred around the Indus basin (Fig. 4b, black outline) and the 2025 event leading to particularly heavy rainfall in a more confined region (Fig. 4b, red outline).

Again, the World Weather Attribution initiative has undertaken rapid as well as peer-reviewed attribution studies[44,45]. In the case of this example, as often with rainfall, the difference between individual models (not shown) and individual observational products (Table 4) is not only in magnitude, but even in the direction of change. This means that conclusions cannot be more confident than physical relationships, such as the Clausius-Clapeyron

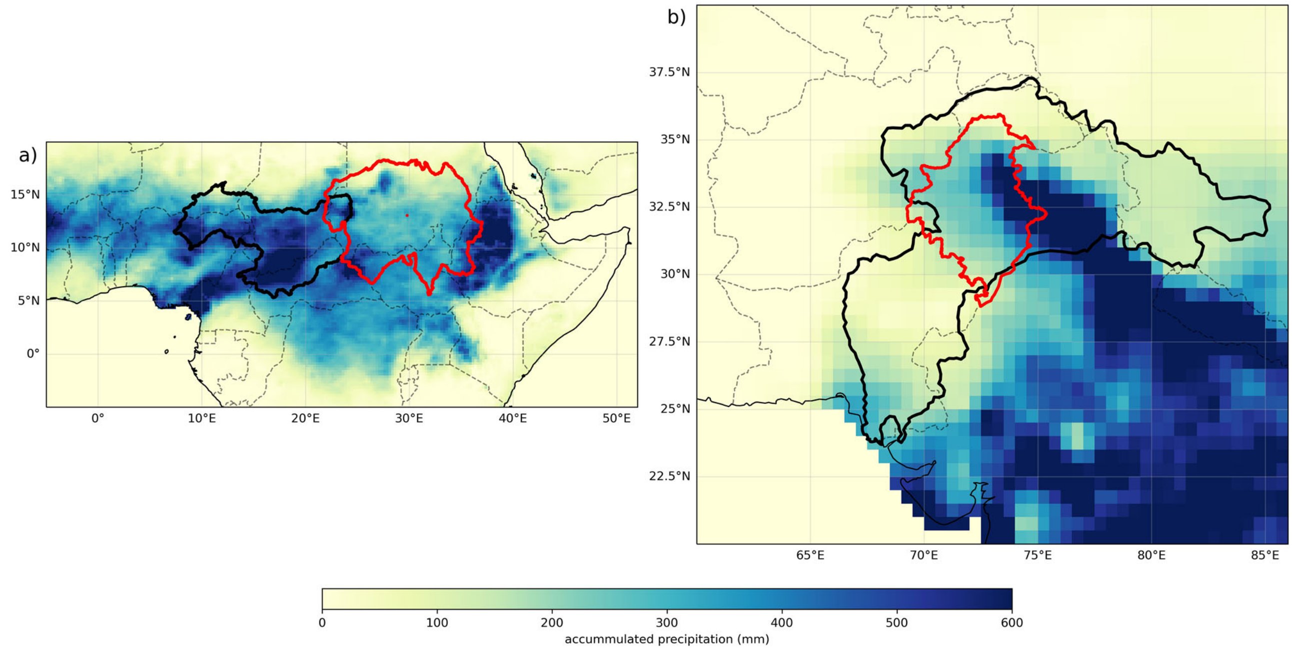

Fig. 4 | a 30-day accumulated rainfall on the 29th of August 2024 in the CHIRPS dataset; the Lake Chad basin is outlined in black, the Sudan study region in red. Figures adapted from[42]. **b** Accumulated rainfall in July and August 2025 over Pakistan in the CPC dataset. The Indus Basin is highlighted in black, the study region from the 2022 study, and the most affected region encompassing the most affected districts in the provinces of Punjab and Khyber Pakhtunkhwa of Pakistan, including the cities of Islamabad, Rawalpindi, Chakwal, Faisalabad, Peshawar, and Lahore, Pakistan, is outlined in red. Figures adapted from[44,45].

Table 3 | Summary of results for Rx30day, Lake Chad 2022 and Sudan floods 2024

Data	Lake Chad, 2022		Sudan Floods, 2024	
	Probability ratio (95% CI)	Intensity change (%) (95% CI)	Probability ratio (95% CI)	Intensity change (%) (95% CI)
CHIRPS	**3.7E + 04 (24, 1.2E + 12)**	**28 (11, 50)**	761 (0.0168, 7.07E + 16)	18.2 (−10.6, 49.6)
TAMSAT	**7.96E + 09 (3.4E + 04, ∞)**	**40 (26, 60)**	-	-
Stations	-	-	Not assessed	**56.6 (15.4, 95)**
Models	**45 (4.33, 570)**	**12.7 (3.8, 23)**	2.06 (0.504, 8.44)	9.28 (−3.64, 23.9)
Synthesis	**188 (2.66, 0.44E + 05)**	**15.1 (5.20, 27)**	2.11 (0.519, 8.66)	10.9 (-1.10, 24.0)

Numbers in bold show statistically significant results. Empty boxes mean that the respective datasets were not included in a study.

relationship, imply. Accordingly, any new studies must be supported by models and datasets that are demonstrably robust, well-validated, and empirically reliable to meaningfully extend or refine existing knowledge. The case of Pakistan differs from the Sahel example. In Pakistan, both the qualitative and quantitative results are entirely driven by the choice of datasets. In contrast, for the Sahel, the dataset mainly affects the quantitative results, while qualitatively the strong influence of climate change is very clear. In both cases, a new attribution study in the same region would only add understanding if either an entirely different approach is used, e.g., conditioning on the atmospheric circulation to disentangle thermodynamic and dynamic drivers or knowledge that would allow datasets to be robustly removed from the analysis. This would be especially important in the case of Pakistan, where, in the studies shown in Table 4, and especially for the 2022 event, the uncertainties in all three observational datasets are so large that they effectively entail very little information.

General conclusion

From the examples above, pronounced regional differences emerge for rainfall, where in the case of the Sahel, precipitation behaves very similarly with respect to the climate change signal as extreme heat in Section 2.1, while for Pakistan even the direction of the trend is totally dependent on the dataset used. Figure 5 shows the same as Fig. 3 in section 2.1 above, but for different event definitions of precipitation events including short duration and seasonal rainfall (Rx1day, Rx3day, Rx5day, Rx7day, Rx15day, Rx31day and Rx91day) across three datasets over the same common timeframe (1981–2024). Despite mixing physically quite different processes of generating rainfall on the seasonal and daily timescales, over 90% of the variance globally can be explained by the dataset chosen, with only 3% explained by differences in the event definition. However, it is important to note that variability in estimates of rainfall trends is typically higher than variability in estimates of trends in temperatures[1]. Again, when only short-duration events are considered (Rx1day, Rx3day, Rx5day, Rx7day), the proportion of variance explained by differences between the datasets increases to 96%, with only around 2% explained by differences between the event durations (Figures S4 and S5 in the supplementary material). Changes to the spatial extent affect the estimated trends more for rainfall than for extreme heat, with around 7% of the variability accounted for by differences in the resolution (Figure S6).

In regions characterized by weak rainfall seasonality, such as Europe or Australia, the choice of temporal scale used to define the event can lead to substantial differences. In contrast, in regions with pronounced seasonality, these differences are smaller, such as the Amazon, where almost all variance is explained by the dataset. However, this is likely not a finding particularly driven by the climate system itself or the climate change signal but by the combination of the strength of the climate change signal and the quality of observational datasets. When looking at the change in intensity over South America (Fig. 6a), it becomes apparent that there is a drying trend across all event definitions in one dataset, while the other two show an increase in the intensity of rainfall across event definitions over the Amazon. This strong discrepancy explains why the variance is almost exclusively driven by the choice of dataset.

Table 4 | Summary of results for 2022 and 2025 Pakistan floods. Numbers in bold show statistically significant results

Data	2022 Pakistan JJAS Rx60day		2025 Pakistan JJAS Rx30day	
	Probability ratio (95% CI)	Intensity change (%) (95% CI)	Probability ratio (95% CI)	Intensity change (%) (95% CI)
CPC	**4400 (14.5, ∞)**	**120 (16, 330)**	**222 (2.6, 1.38E + 8)**	**94 (13.7, 192)**
IMERG	25 (0.08, ∞)	68 (−33, 420)	2.2 (0.7, 400)	23.6 (−17, 98)
MSWEP	-	-	0.4 (0.09, 1.6)	−20 (−41, 12.5)
CHIRPS	-	-	**30 (2.2, 7.7E + 04)**	**40 (0.35, 108)**
ERA5	0.8 (0.007, ∞)	−2.3 (−35, 43)	-	-
Stations	-	-	1.2 (0.06, 8.7)	2.9 (−21, 28)
Models	1.53 (0.009, 2820)	2.92 (−17.7, 31.3)	1.44 (0.318, 15.7)	12.3 (−26.4, 70.7)
Synthesis	2.11 (0.0104, 4690)	10.3 (−25.7, 98.8)	1.61 (0.190, 37.8)	14.7 (−31.8, 92.2)

Figure 6b shows the same changes in intensity across datasets and event definitions for Australia; here, the patterns of change are the same across both datasets and event definitions, but the strength of the climate change signal varies substantially between datasets and is overall much smaller; hence, a lot more noise explains the variance.

Thus, for rainfall, we can conclude that in most regions, the discrepancies between observational datasets (and models) are so substantial that conducting an attribution study using only a single dataset should be avoided, unless exceptionally high-quality station data are available for validation of the gridded product. In turn, this also means that for an additional attribution study in a region that has already been studied, the added value of a new study is very low if no additional information on excluding certain datasets can be given. It is important to highlight that this does not mean that the climate change signal is the same in different types of rain-producing systems, as is clearly shown by the large discrepancy between the Lake Chad results and those for Pakistan. Rain-producing systems, such as storms of similar type, however, may exhibit comparable responses, but we will not be able to identify these clearly by repeating a similar type of study, but by adding new methods aimed at understanding the processes, such as Weisheimer et al.,[46] did for the Pakistan floods 2022. In this forecast-based conditional attribution study, they identified the influence of greenhouse gas forcing on the water transport while also concluding that climate change increased the intensity of the event by about 10%, similar to the synthesised results in Table 4. This underscores that precipitation attribution remains more uncertain than temperature attribution, but these uncertainties can only be reduced through a better mechanistic understanding of how different storm types respond to warming.

Discussion

Attribution studies play a crucial role in connecting lived experience with abstract scientific understanding, thereby supporting effective climate action. They are also very crucial in communicating the reality of climate change[47]. The analysis presented above demonstrates that robust, attributable climate change signals in temperature extremes are not confined to temperate climates but are observed within tropical and subtropical regions when evaluated in their respective regional contexts (Section 2.1). While quantitatively the influence of climate change differs in different regions, these are robust with respect to short- and long-duration heatwaves and are also consistent across datasets (Section 2.1.2) and are qualitatively the same. This means even the choice of dataset only affects the quantitative result. As shown in Section 2.2, this finding is not limited to heat waves; heavy rainfall events are also robust across event definitions within a region, albeit seasonality is a more important factor and unsurprisingly, given the signal is generally smaller than temperature, internal and natural variability plays a more important role. When it comes to rainfall, differences between datasets can strongly affect the conclusions we draw. In some cases, they can determine whether we detect a climate change signal at all. In certain regions, such as Pakistan (mentioned above), this can even lead to fundamentally different conclusions. In other regions, like Lake Chad, rainfall patterns behave much more consistently across datasets, similar to temperature. Figure 7 summarises the findings for temperature (top) and precipitation (bottom), displaying the variance explained by event definition (green), dataset (blue) and noise (orange) for the different regions.

Across different regions, changes in event intensity tend to be consistent, even when different event definitions are used or when focusing on more or less extreme events. Seasonal choices can matter—particularly in transitional "shoulder" periods—but these effects are typically secondary. Distinguishing between qualitative, quantitative, and intermediate (e.g., order-of-magnitude) differences further highlights that what is required is a *useful* event definition rather than a uniquely "correct" one.

The choice of climate variable or event definition should be guided by physical relevance and societal impact, rather than by post-hoc optimisation. Alternate variables (e.g. Tmin versus Tmax, or compound metrics such as heat indices) are most appropriately introduced when there is a clear mechanistic link to the impact or vulnerability under consideration[48], or when stakeholder-relevant exposure pathways are known to be inadequately captured by a single metric. Therefore, a transparent, hypothesis-driven selection of datasets and metrics, with explicit justification grounded in data quality, physical understanding, and relevance to impacts is required, rather than an exhaustive or opportunistic exploration of all available options.

At the same time, strong dependency on datasets should not be interpreted as an argument for indiscriminately expanding the number of datasets considered. Where data quality is poor, sparse, or inhomogeneous, adding additional datasets can be counterproductive, increasing noise or introducing structural biases that obscure rather than clarify the underlying signal. In the existing literature, this risk is typically assessed through systematic dataset evaluation, including checks of observational coverage, homogenisation procedures, physical consistency, independence between products[49,50]. What it highlights instead is that sensitivity analyses that explicitly quantify how results change when individual datasets are included or excluded are necessary to render especially quantitative attribution studies useful.

Conclusion

Overall, our results demonstrate that methodological choices and, especially, differences among observational datasets exert far greater influence on attribution outcomes than variations in event definitions or selected years. This finding is not surprising, and implicitly known by most scientists undertaking attribution studies, even though, to our knowledge, it has not been systematically shown and published.

The consequences of these findings have certainly not been implied in the community. These are, firstly, that unless a study introduces substantially new data or methods, additional full attribution analyses for the same region often do not provide new insights. This has direct implications for the development of operational attribution systems.

If an event recurs in a region that has already been studied, the added value of performing another comprehensive attribution analysis including

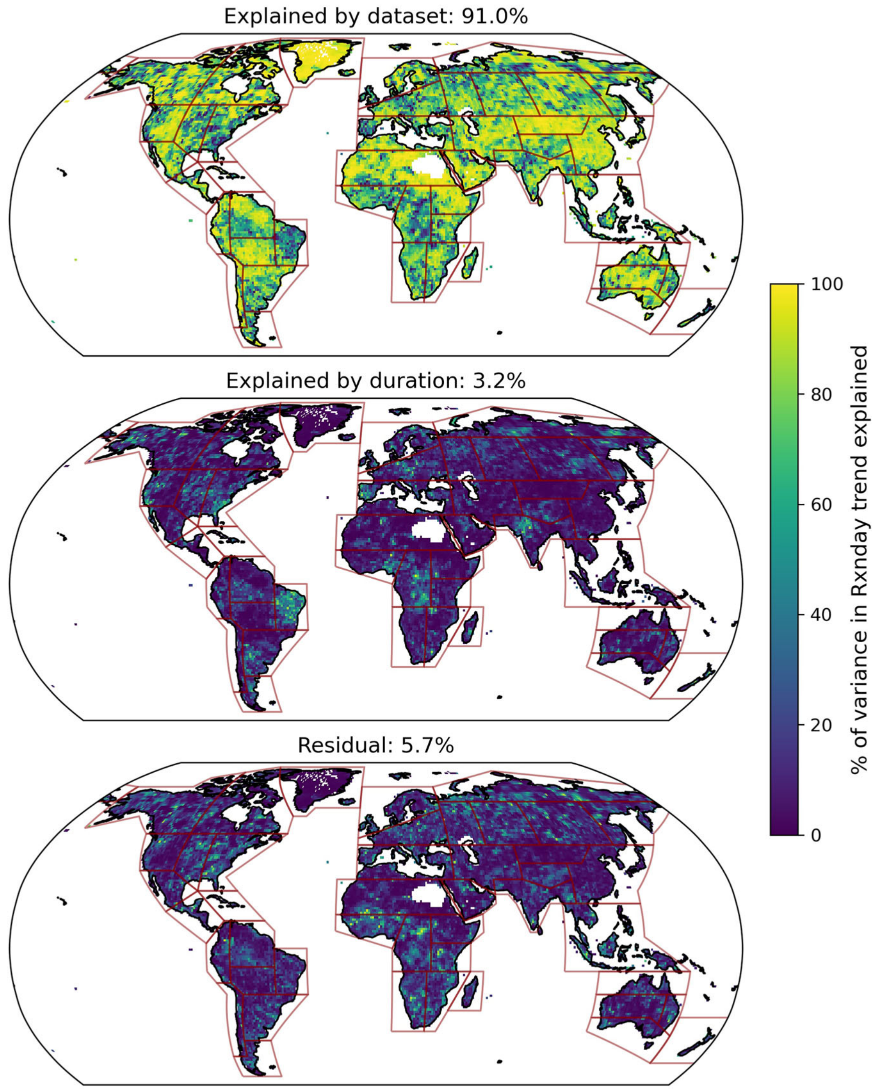

Fig. 5 | Maps of the proportion of the total variance in the trend in heavy precipitation explained in each grid cell by each factor. Top: proportion explained by choice of dataset; middle: proportion explained by choice of event duration; bottom: proportion not explained by either factor. Red lines denote AR6 regions, used to summarise the total variance explained in Fig. 7 (bottom). Blank grid cells indicate that there was at least one year with infinite log precipitation, indicating a year with zero rainfall in one of the datasets.

new observational synthesis, full model ensembles, and a reassessment of dynamical drivers is very limited. Therefore, in such cases, for operational attribution services intended primarily to inform decision-makers and the public in the immediate aftermath of an extreme event, an analysis based solely on observations would provide all genuinely new information available if a previous attribution study exists. This includes determining the extremity of the current event and assessing whether subsequent warming since the previous study has significantly increased its intensity. All other relevant information, such as confidence in the findings based on observational quality, discrepancies between models and observations, and whether the climate change contributions can likely be explained by thermodynamic factors alone, can be drawn from earlier studies.

Secondly, providing attribution studies for studied events also presents a communication concern: continually re-establishing conclusions that are already supported by strong and, in many cases, quantitative evidence may unintentionally suggest that the science is less settled than it actually is. Repeatedly demonstrating the same causal relationships can give the impression of ongoing uncertainty, rather than signalling the high level of confidence and consistency that characterises the existing body of research and inadvertently also "train" the media to only talk about climate change in the face of extreme weather events when a new attribution study is available.

In contrast, scientific attribution studies focusing on regions that have not previously been analysed, or employing methods that differ substantively from those used in earlier work, remain urgently needed to address substantial gaps in our understanding, including those relevant to global stocktake processes. Such studies are particularly important for events that have not yet been examined, as well as for those where existing results are inconclusive or characterised by high uncertainty.

Methods

M.1 Probabilistic attribution of extreme weather events

The case studies of extreme heat and precipitation discussed in Sections 2.1 and 2.2 below follow the probabilistic event attribution method described in ref. 10, with supporting details found in ref. 23,51.

For each time series, a nonstationary GEV distribution is used to model the dependence of extreme temperatures (Section 2.1) and precipitation (Section 2.2) on smoothed global mean surface temperatures (GMST). For temperatures, the distribution is assumed to shift linearly with GMST, while the variance remains constant; for precipitation, the distribution is assumed to scale exponentially with GMST, with the dispersion (the ratio between the standard deviation and the mean) remaining constant over time. 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[52,53]. The parameters of the statistical models are estimated using maximum likelihood and used to calculate the return period of the event of interest (the inverse of the probability of exceeding the observed magnitude), for the GMST

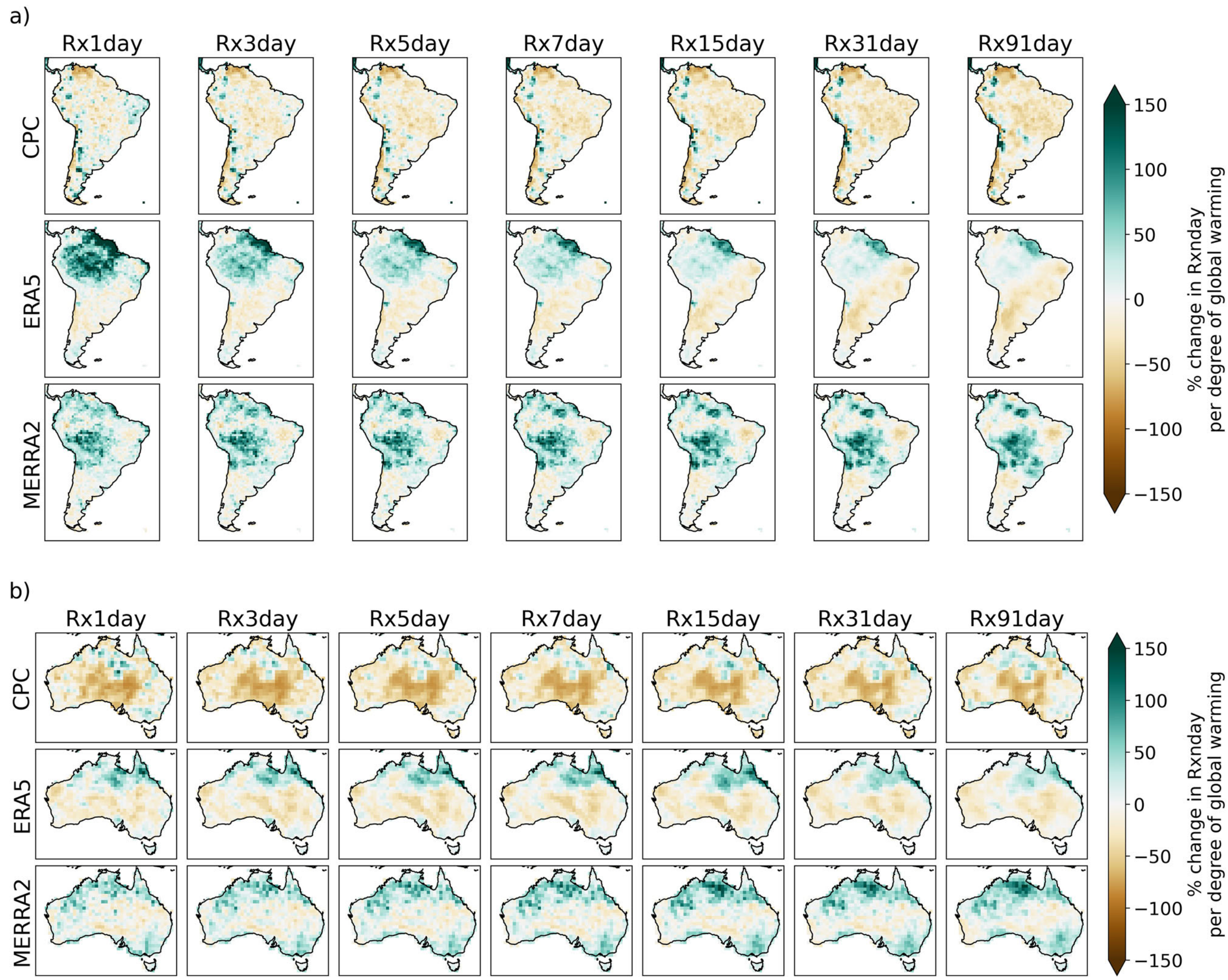

Fig. 6 | Maps of estimated % change in extreme rainfall indices per degree of GMST warming, for different event durations (columns) and datasets (rows), using data from 1980−2024 for **a** South America and **b** Australia. Event durations: Rx1day, Rx3day, Rx5day, Rx7day, Rx15day, Rx3day, Rx91day. Datasets: CPC, ERA5, MERRA2.

corresponding to both the year in which the event occurred (the 'factual' climate) and a 'counterfactual' preindustrial climate without human-caused warming that is either assumed to be 1.2 or 1.3 C cooler than today, based on the time of the event, corresponding to the human-induced warming estimated in the global warming index[54]. This is used to estimate the probability ratio (the factor change in the likelihood of an event of the observed magnitude) and the change in intensity (the change in magnitude of an event of the same rarity) associated with a specified degree of human-caused global warming.

The analysis is repeated for multiple observational datasets and also for climate models, using the same event definition in each case. The results of this analysis are synthesised into a single result using a precision-weighting algorithm described in Otto et al.[23].

M.2 Identifying sources of variability in fitted trends

To quantify sources of variability in estimated trends in the intensity of extreme temperature and precipitation events, we use a multivariate Analysis of Variance (ANOVA)-based technique[55,56]. Global gridded daily maximum temperatures and daily accumulated precipitation were obtained from multiple observational or reanalysis datasets: ERA5 reanalysis at 0.25° resolution[57]; MERRA2 reanalysis at 0.625° x 0.5° resolution[58]; CPC at 0.5° resolution[59]; Berkeley Earth at 1° resolution (temperature only[60]). Global mean surface temperature (GMST) is taken from NASA's Goddard Institute for Space Science surface temperature analysis (GISTEMP[52,53]. We use a four-year running mean of GMST, centred on the third year, to remove natural variability associated with El Niño Southern Oscillation (ENSO).

For each gridded data product, a land-sea mask was applied, and for each land cell the annual maximum of the n-day rolling mean was calculated for $n = \{1, 3, 5, 7, 15, 31, 91\}$, resulting in a total of seven temporal event definitions per variable. For precipitation, these n-day maxima were log-transformed, and any cells where any log-transformed value was infinite were also masked from the dataset; this removes arid regions with years of zero accumulated precipitation from the trend fitting process. The annual maxima are then regressed against the four-year running mean of GMST, and the estimated regression parameters are averaged over a 1° x 1° grid to facilitate comparison between the various data sources. To save computation time, we do not fit the full GEV as in the individual case studies because the focus here is on variability in the mean trend, rather than in changes in the likelihood of particular events, which are very sensitive to both the shape of the distribution and the extremity of the event. For temperatures, we consider the absolute change Δ per degree of global warming, and for rainfall we present the relative change calculated as $100(\exp(\Delta)-1)$, where Δ is the change in log(precipitation) per degree of global warming.

To identify the main sources of variability in the fitted trends, we first stack the interpolated slope estimates into a single $KD \times S$ data matrix $\mathbf{Y}$, where K is the number of datasets, D is the number of event durations, and S is the number of grid cells with parameter estimates. The trends estimated

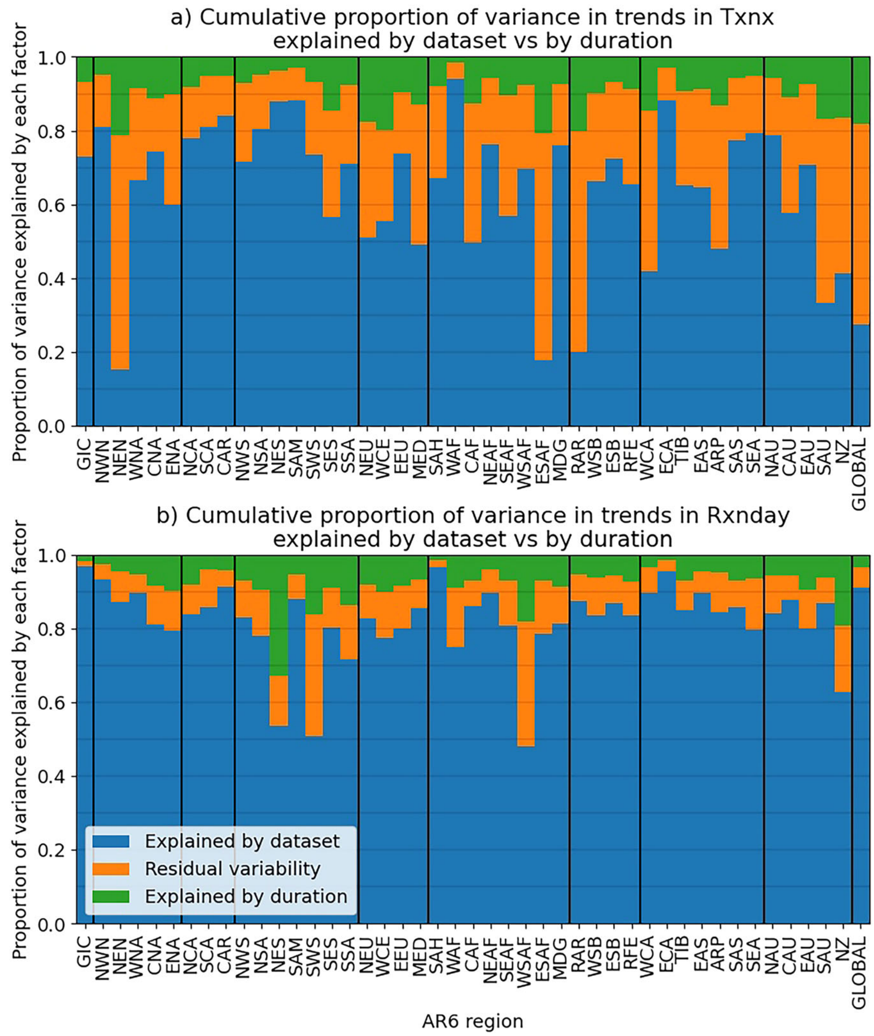

Fig. 7 | Cumulative proportion of variance in estimated trends in extreme temperatures (top) and rainfall (bottom) explained by each factor in each AR6 region (red outlines in Figs. 4 and 7). Blue segments represent proportion associated with different datasets; green segments represent proportion associated with the event duration; orange segments represent residual variability not systematically explained by either factor.

from the kth dataset and the dth event duration can be written as

$$\mathbf{Y}_{\mathrm{kd}} = \boldsymbol{\mu} + \boldsymbol{\alpha}_{\mathrm{k}} + \boldsymbol{\beta}_{\mathrm{d}} + \boldsymbol{\varepsilon}_{\mathrm{kd}} \quad where\, k = 1, \ldots, K\, and\, d = 1, \ldots, D.$$

Here, $\mathbf{Y_{kd}}$ is a vector of length S containing the parameter estimates at each grid cell; $\boldsymbol{\mu}$ is the overall mean trend; $\boldsymbol{\alpha_k}$ is the systematic difference between this mean trend and the trends in the kth dataset; $\boldsymbol{\beta_d}$ is the systematic difference between the mean trend and the trends in the dth event duration; and $\boldsymbol{\varepsilon_{kd}}$ is a residual term representing variability that cannot be explained by either the choice of dataset or the choice of event duration.

Following Chandler et al.[55]., we compute the total variance of the trends in the Sth grid cell as

$$V_s = \sum_k \sum_d \left(Y_{skd} - \mu_s\right)^2,$$

while the variance associated with the choice of dataset and event duration, respectively, are

$$V_{sK} = D\sum_k \alpha_{ks}^2 \text{ and } V_{sD} = K\sum_d \beta_{ds}^2$$

with residual variance $V_{sE} = V_s - V_{sK} - V_{sD}$.

By dividing V_{sK}, V_{sD} and V_{sE} by V_s, we can determine the proportion of the total variance in each grid cell associated with the dataset and event duration, and also the proportion that is not systematically explained by either factor. The proportion of variance explained by each factor over larger regions is calculated by first summing the variance associated with each factor over each region, and dividing by the total variance over the same region, as

$$V_K = \frac{\sum_s V_{sK}}{\sum_s V_s},\ V_D = \frac{\sum_s V_{sD}}{\sum_s V_s} \text{ and } V_E = \frac{\sum_s V_{sE}}{\sum_s V_s}.$$

Data availability

All input data for the tables used in this study are available to download on the KNMI Climate Explorer under the flowing url: https://climexp.knmi.nl/attribution_studies/pages/2026-attribution-robust.cgi. This is a permanent repository, hosted by the Royal Netherlands Meteorological Institute (KNMI) and supported by the WMO. The link will work once you are registered. The data used in Figs. 1 and 4 are the same as in Tables 1 &2 for Fig. 1 and Table 3&4 for Fig. 4.The data and code needed to reproduce Figs. 2–3 and 5–7 are available via Zenodo: https://doi.org/10.5281/zenodo.22027134.

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Author contributions
F.E.L.O. conceptualised the study and wrote the initial draft. F.E.L.O. and C.R.B. did the data analysis. S.Y.P., C.B., T.R.K., B.C., M.Z., I.P. and J.K. contributed equally to the editing and reviewing of the drafts of this manuscript.

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Competing interests
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