EXTREME EVENTS ATTRIBUTION

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AGCM: Atmospheric Global Climate Model
AI: Artificial Intelligence
AMIP: Atmospheric Model Intercomparison Project
BAMS: Bulletin of the American Meteorological Society
CMIP: Coupled Model Intercomparison Project
D: Deliverable
DR: Drought
EE: Extreme Event
EEA: Extreme Event Attribution
ENSO: El Niño-Southern Oscillation
Euro-CORDEX: European branch of the Coordinated Regional Downscaling Experiment
GCM: Global Climate Models
GHGs: Greenhouse gases
HE: Heat Extremes
HW: Heat Wave
HP: Heavy Precipitation
ML: Machine Learning
MS: Milestone
NAO: North Atlantic Oscillation
NWP: Numerical Weather Prediction model
RCM: Regional Climate Model
SIC: Sea Ice Cover
SST: Sea Surface Temperature
TC: Tropical Cyclone
WP: Work Package
WWA: World Weather Attribution

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Figure 9 Illustration of the flow analogue method: A day with an extreme temperature anomaly (map on the top left) has a corresponding circulation, represented by the geopotential height at 500 hPa (map on the bottom left). Flow analogues are days within the database which have a similar circulation to the day of interest (maps on the bottom right). The temperature anomalies of the analogues (maps on the top right) are then compared to the temperature anomalies of the day of interest (map on the top left). After Jézéquel et al. (2018b).

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EXECUTIVE SUMMARY

Extreme event attribution quantifies the influence of climate change on a particular extreme event. However, there are many ways to link an individual extreme event with climate change. This report reviews existing knowledge, data and models for attribution of extreme events to climate change and provides a database collection of about one hundred attribution case studies of different types of extreme events, setting up the roadmap for future avenues on the use of Machine Learning techniques for such scoped in CLINT.

Based on the reviewed literature, attribution approaches can be decomposed in eight key defining elements (called framings). They concern different aspects of the methodological setup, including the definition of the extreme event, the choice of the dataset employed for attribution, the definition of climate change and the quantification of climate change influences on the extreme event. The way these elements are defined (framing choices) constrains the attribution question and affects the attribution results. The report classifies the existing attribution approaches, according to the specific way those elements have been framed in the literature and describes the implications and assumptions of each choice.

This classification is also employed to analyse the case studies of the database collection and identify preferred approaches for the attribution of three major types of extreme events: heat extremes, droughts and heavy precipitation. Some framing choices are clearly preferred (e.g., a generalised tendency to assess extreme events on regional scales), while others are guided by the specific type of extreme event (e.g., the temporal scale of the extreme event). The spread of attribution approaches can be substantially explained by few framing elements, which identify the main sources of disagreement in the database. These critical choices in attribution are related to the dataset employed and the degree of conditionality of the attribution exercise on the specific conditions observed at the time of the event. The report concludes discussing some aspects that can be improved considering the challenges posed by the current understanding and attribution capabilities for different types of extreme events.

1. INTRODUCTION

In climate science, attribution is the process of evaluating the contribution of multiple potential causes to an observed change or event in climate. Early efforts focused on the attribution of observed changes at global or continental scales (e.g., Hegerl and Zwiers 2011, and references therein), including long-term trends in a mean quantity (e.g., global mean temperature) or in the frequency of extreme events (EEs) (e.g., the global increase in the annual frequency of hot days). It is well established that the observed frequency, intensity and/or duration of some EEs have changed in many land areas due to anthropogenic activities (Seneviratne et al. 2021). However, impacts are often caused by individual EEs that illustrate the vulnerability of society and ecosystems and bring climate change into the public's interest. Therefore, it is also natural to ask to what extent climate change is responsible for particular EEs. This has set the ground for a new branch in attribution science (so-called EE Attribution, EEA), specifically devoted to evaluate climate change influences in individual EEs. This question is more challenging than attributing a change in climate because: 1) it concerns a single observed EE, whose specific causes are often affected by multiple (natural and anthropogenic) factors, and 2) the attribution of a trend in the statistics of EEs (e.g., the global increase in hot days) does not mean that all EEs can individually be attributed to climate change.

In the last two decades, scientific advances have allowed attributing specific EEs to climate change, and the number of EEA studies increases every year. These studies address the relative contributions of multiple causal factors to a single EE to assess if and how much climate change has affected the magnitude, probability or physical processes of the EE. Since the seminal study of Stott et al. (2004), different EEA approaches have emerged (e.g., Trenberth et al. 2015; NAS 2016; Shepherd 2016; Stott et al. 2016; Diffenbaugh et al. 2017; Otto 2017; Jézéquel et al. 2018a, and references therein). This Deliverable (D) expands milestone MS16 and reviews existing knowledge, data and models for attribution analysis of different types of EEs addressed in CLINT, setting up the roadmap for future avenues on the use of Artificial Intelligence (AI) and Machine Learning (ML) techniques to attribute EEs to climate change.

2. ATTRIBUTION FRAMEWORK IN CLINT

In attribution science, AI/ML techniques have recently been applied to identify anthropogenic signals in the global spatial patterns of annual mean temperature and precipitation (e.g., Barnes et al. 2019), to evaluate the relative contribution of natural and anthropogenic forcings to global warming (e.g. Pasini et al. 2017), or to map the evidence of anthropogenic influences in mean temperature and precipitation (e.g. Callaghan et al. 2021). However, to the best of our knowledge, AI/ML techniques have never been explicitly applied to quantify climate change influences on individual EEs. Therefore, to assess the potential added value of AI on EEA, a three-step framework (Figure 1) has been designed in WP5:

1. Review of EEA approaches: Review of the state-of-the-art in EEA. For this step, papers published in peer-reviewed journals were identified by a literature search at different sites (e.g., Web of Science, Scopus), including the Climate Attribution Database[1], which contains scientific publications on attribution classified by theme. The search was restricted to studies focusing on EEA (i.e. excluding those related to the attribution of trends in mean or extreme quantities), with emphasis on review and perspective papers, reports or books. This step aims to identify the multiple ways to attribute single EEs to climate change and assess current capabilities on EEA for different types of EEs.

2. Database of EEA studies: Creation of a database collection of case studies, and their classification according to the multiple ways for EEA defined in Step 1. For this step, we analysed the last five reports (2018-2022) of the Special Issue 'Explaining Extreme Events from a climate perspective' of the Bulletin of the American Meteorological Society (BAMS), which provide 107 case studies of EEA. This step explores the EEA approaches that are currently employed by the community and if there are preferred approaches for different types of EEs.

3. AI-based applications: Identification of specific aspects in EEA that are susceptible of ML-based improvements. The exploration of EEA approaches will be tested in a previously defined selection of historical EEs that affected Europe (WP6) and the hotspots (WP7), as outlined in MS25 (Historical EE selected for attribution studies).

Steps 1 and 2 form the basis of the present report, while the results of Step 3 will be described in the next D5.2 (AI-enhaced attribution and projections of EE).

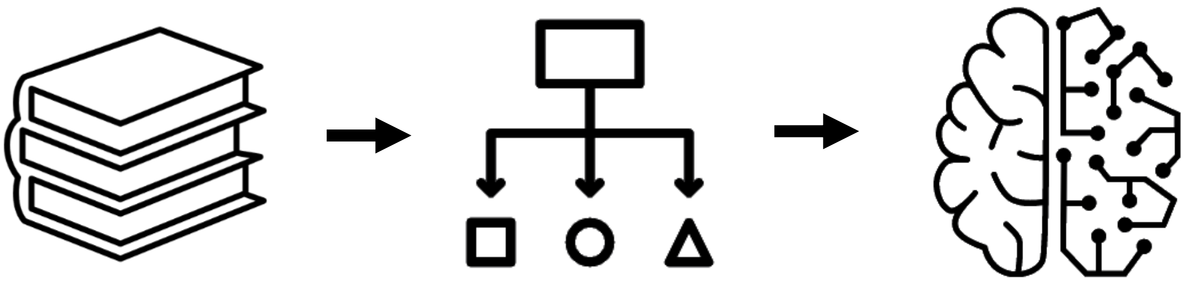

Figure 1 Three-step CLINT framework for EEA: review, database of EEA approaches and AI-based developments.

3. CLASSIFICATION OF ATTRIBUTION APPROACHES

Definitive Yes/No answers to EEA questions (e.g., 'was this EE caused by climate change?') are often ill-posed because most EEs could have happened in an unchanged climate, and hence causal factors can rarely be attributed deterministically. However, it is possible to address the question 'was the

[1] https://climateattribution.org/

EE influenced by climate change[2]?'. The ultimate goal is to quantify changes — more often but not always associated with human activities — in the probability of occurrence, magnitude or driving factors of the EE (e.g., NAS 2016; Stott et al. 2016; Otto 2017). These changes can be inferred by comparing the distributions of a class of EE[3] similar to the observed one in two climates, one with and one without anthropogenic influences (Figure 2).

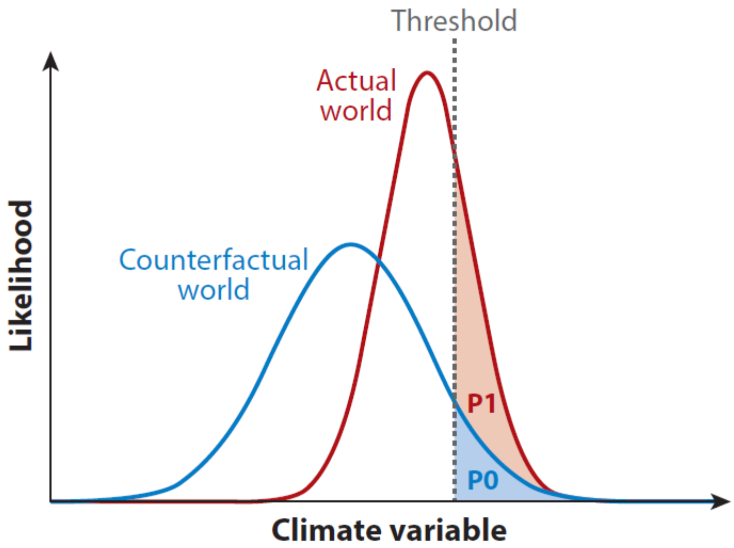

Figure 2 Schematic of the distribution of a climatic variable under current climate conditions (red) and in a world that might have been without climate change (counterfactual world, blue). The class of EE representing the observed EE is defined by a threshold (e.g. the magnitude of the observed EE, vertical dashed line). The probability of occurrence of that class of EE in the factual and counterfactual world is marked as P1 (red shading) and P0 (blue shading), respectively. The comparison of these two probabilities allows to quantify how the probability of the EE occurrence has changed due to climate change. After Otto (2017).

In general, all EE approaches build upon four methodological steps: 1) the definition of the EE; 2) the choice of the dataset employed for EEA; 3) the definition of climate change, and 4) the quantification of climate change influences on the EE (e.g. Otto 2017; Jézéquel et al. 2018a). However, there are multiple ways to attribute an observed EE to climate change. Typical EEA questions include: 'Are EEs of this severity becoming more/less likely because of climate change?', 'To what extent was the EE intensified/weakened because of climate change?', 'How could the EE have been in a world with reduced/augmented anthropogenic influences?' Accordingly, there are also multiple ways of linking the observed EE to climate change, no one providing the best answer to all questions, e.g.: 'climate change doubled the probability of occurrence of the EE', 'climate change made the EE 25% more severe', 'the observed conditions would have caused an EE 2ºC colder in the early 20th century'. There is consensus in the reviewed literature that the results of the EEA depend on the specific research question. In fact, different questions can yield seemingly

[2] The term climate change is preferred to anthropogenic climate change, because EEA can also deal with changes in the EE not related to anthropogenic activities (Jézéquel et al. 2018a)

[3] As the causes of each specific EE are in principle unique to that EE, EEA often considers a 'class of EE' similar to the experienced one, so that the observed EE is a representative of that class.

contradictory attribution results for the same particular EE (e.g., Otto et al. 2012). This is because the framing of questions largely determines how the EE will be studied (i.e. the EEA approach), and the results are sensitive to the EEA approach. For example, Angélil et al. (2017) re-assessed several EEA studies using a common framework for all EEs. When compared to the original studies, the results of the EEA were similar for temperature EEs, but not so much for precipitation EEs (Figure 3).

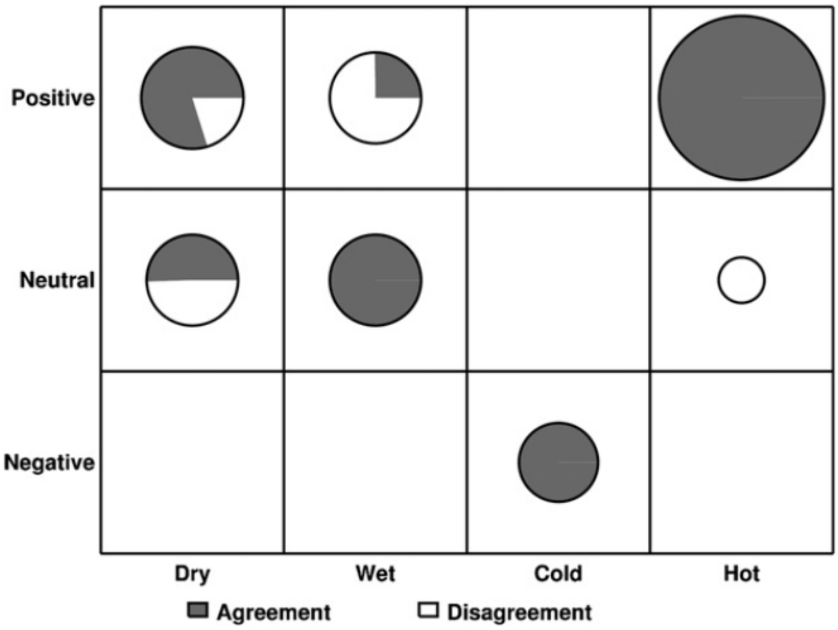

Figure 3 Comparison of EEA statements for different attribution approaches. The areas of the pie charts are proportional to the number of EEs analysed in each category (11 dry, 8 wet, 3 cold and 14 hot EEs). Positive, negative and neutral statements mean increased, decreased and small changes in the likelihood of EE occurrence due to climate change, respectively. Grey and white areas represent the degree of agreement and disagreement in the EEA statements obtained under different framings. After Angélil et al. (2017).

Therefore, EEA approaches can be analysed and classified according to the specific way their defining elements are framed. These elements are herein referred to as framings[4]. Important framings include how the EE is defined, the dataset chosen, whether changes in frequency, magnitude or specific processes are assessed, or whether the EE is attributed to the overall climate change, anthropogenic factors or greenhouse gases only (e.g. Angélil et al. 2017; Otto 2017; Jézéquel et al. 2018a). Based on the revised bibliography (e.g. Trenberth et al. 2015; Easterling et al. 2016; NAS 2016; Shepherd 2016; Stott et al. 2016; Knutson et al. 2017; Otto 2017; Jézéquel et al. 2018a; Zhai et al. 2018; Naveau et al. 2020; Seneviratne et al. 2012, 2021; van Oldenborgh et al. 2021, and references therein) we identified up to eight critical framings for EEA. Some of them concern the same methodological step of the EEA approach and can be grouped accordingly (the way of grouping framings does not have any effect in the results, because framings will be assessed separately):

[4] The term framing is often employed in EEA to refer to items or defining elements of the EEA question that need to be stated beforehand. The specific choice of these framings defines the way the EE is attributed to climate change (EEA approach) and affects the attribution results.

1. Definition of the EE. Defining the EE is important because the results of the EEA exercise only apply to the so-defined EE (or class of EE). Several elements contribute to the EE definition, including the selected spatial domain, time scale (temporal duration) and the defining variable. The spatial and temporal frames can range from local to global, and from hourly to multi-annual scales, respectively. Similarly, the defining variable can be a meteorological observable (e.g., precipitation) averaged over those spatio-temporal scales, a field related to the EE (e.g., sea surface temperature, SST) or a more elaborated EE index (e.g., the monthly frequency of hot days).

2. Dataset. Once the EE is defined in observations, one has to decide the type of dataset for the EEA exercise. There are several choices, including observational-based datasets (i.e., observations or reanalyses) and different types of models, ranging from Global Climate Models (GCMs) to Numerical Weather Prediction models (NWPs). They are employed to generate distributions of the EE in two climates with different levels of anthropogenic forcings. Each dataset has its own issues and capabilities to reproduce the observed EE, therefore affecting the EEA results.

3. Definition of climate change. More often, EEA studies compare the intensity or probability of occurrence of the EE in a factual world (the actual world with anthropogenic climate change) and a counterfactual world (the world that would have been without climate change). The former can be a recent period or the present-day climate with all (or just one) anthropogenic forcings. The latter entails several difficulties as it ideally refers to a world that does not exist. Different approaches are employed to construct it, including an early period of the industrial era (e.g., the first half of the 20th century), a preindustrial climate or an idealised natural world (the historical evolution of the climate if anthropogenic forcings would have been fixed at preindustrial levels). These choices affect the results by involving different levels of anthropogenic changes.

4. Quantification of climate change influence. An essential part of the EEA approach is the level of conditionality of the EEA approach on the specific features of the observed EE. Generalised (unconditional) approaches consider all EEs (i.e., regardless of the specific conditions under which they occur). Conditional approaches limit the attribution to particular situations (states of the climate system) that were observed at the time of the observed EE (e.g., El Niño or a specific atmospheric pattern). As the condition constrains the selection of EEs, it affects the quantification of the climate change influence. Another important consideration is the specific aspect of the EE that is being attributed, e.g., changes in intensity for an EE that occurs with a given frequency or changes in the probability of occurrence of an EE with a given magnitude[5]. As an alternative way to this probability-based approach, recent studies have proposed a storyline approach[6], which

[5] This is also known as the 'Oxford' risk-based approach. Changes in intensity are also referred to as scaling factors. Probability changes between the factual p1 and counterfactual p0 world are quantified as the risk ratio (RR, p1/p0) or fraction of attributable risk (FAR, (p1-p0) / p0), with FAR = 0.5 indicating that half of such EEs are attributable.

[6] This is also known as the 'Boulder' or mechanistic approach, although the methodology has not been fully developed and differs between studies. This approach is herein considered as a conditional one, but it is distinguished from the conditional probability-based approach.

disentangles different drivers of the EE and their responses to climate change (without necessarily quantifying their influence on the probability of the EE).

In this report, EEA approaches will be analysed and described according to those items. Each framing entails different possibilities (e.g., the use of observations or model simulations for the dataset), which allows classifying the EEA approaches attending to the specific choice for that framing. To make the assessment manageable, framing choices have been reduced to a limited number of options by constructing qualitative categories (e.g., local, regional or continental-to-global for the spatial scale framing). These categories have been carefully selected based on expert-based judgement and the methods found in the literature, trying to keep them to a minimum, while being as inclusive as possible. For most of the framings, all possible choices are accounted for, and the resulting categories are well constrained. However, other framings are more difficult to categorise (e.g., the definition of the factual world), and the proposed categories involve some degree of subjectivity.

Table 1 classifies the specific choices (or ways of EEA, right column) for the critical framings (middle column) identified in each step of the EEA approach (left column). The structure of the DL will follow that of Table 1, therefore analysing the multiple ways of defining these items (framings) and describing the requirements, assumptions and implications of each specific choice, as reported in the reviewed literature. This classification has also been employed in this DL to analyse a collection of EEA case studies and identify if there are preferred EEA approaches for different types of EE. The designed framework is also expected to help uncover issues (e.g., specific framing choices) that can be subject of ML-based improvements.

Table 1 Classification of EEA approaches. Columns indicate the ways of EEA (right column) for the critical framings (middle column) identified in each step of the EEA approach (left column).

Steps in EEA	Framings	Framing choices (categories)
EE Definition	***Temporal scale***	Sub-monthly
		Monthly
		Multi-month
		Annual – Multi-annual
	Spatial scale	Local
		Regional
		Continental – Global
	Variable	Temperature
		Precipitation
		Other basic fields
		Indices
Dataset	***Dataset***	Observations / reanalyses
		Global Climate Models (GCMs)
		Atmospheric Global Climate Model (AGCMs)
		High-resolution modelling
Climate Change Definition	***Factual***	Historical
		Present-day
		Single Forcings
	Counterfactual	Past / Historical
		Preindustrial
		Natural
	Conditionality	Unconditional

Quantification of Climate Change Influence		Conditional to SST/SIC
		Conditional to other factors
	Metric	Frequency
		Intensity

4. DATABASE OF CASE STUDIES

A database collection of EEA case studies has been retrieved from the Annual Special Issue 'Explaining Extreme Events' of the BAMS, which annually compiles a list of EEA exercises for a selected number of EEs. For the last five special issues (Herring et al. 2018, 2019, 2020, 2021, 2022), we identified 107 case studies, concerning different types of EEs that occurred in 2016-2020 and affected different regions of the world. We disregarded few case studies (14 papers) that focused on the detection and attribution of trends in EEs (rather than on single EEs) or on other issues not related to a specific EE, giving a total of 93 papers. These studies follow different EEA approaches. Therefore, the database provides a sufficient sample of the EEA approaches currently employed by the community and completes previous assessments of BAMS reports (Angélil et al. 2017; Jézéquel et al. 2018a). Other collections of EEA studies (e.g., World Weather Attribution, WWA[7]) were not considered since they follow specific standardised approaches for fast attribution (Philip et al. 2020), which are also applied in BAMS.

For each case study, the EEA approach was classified following the framings and categories defined in Table 1. Note that the number of EEA approaches is larger than the number of case studies considered, because authors more often pose different EEA questions to the same EE or test different framing choices, meaning that for a given framing the same paper can be classified in more than one category.

The database collection of EEA studies and the corresponding classification is summarised in an excel file (available as Annex to this document, stored on the project repository[8]), which contains the following information:

Identifier (columns 1-4): label (number in the list of papers published in each special issue), abbreviated reference (authors), year of the EE and year of publication in the BAMS special issue.

Context (columns 5-7): Type of EE, the motivation to study that specific EE (its rarity, associated impacts, etc.) and the result of the EEA exercise (positive, inconclusive or negative). A negative result

[7] https://www.worldweatherattribution.org/
[8] https://131.175.15.9/share.cgi?ssid=4fb399862356414eba03fd524780f0d1

means that a discernible climate change influence was not found with confidence[9] (i.e., the distributions of the EE in the factual and counterfactual world are not statistically different), whereas an inconclusive result is applied in studies for which robust EEA statements were not possible due to limitations in data availability or model performance. For studies reporting positive results, we do not specify how climate change influenced the EE (i.e., if it increased or decreased the probability or intensity of the EE).

The following groups of columns correspond to the four steps of the EEA approach (left column of Table 1), each one containing as many columns as associated framings (middle column of Table 1). The content of cells (categories for each framing) is as explicit as possible but concise enough to allow classification. The degree of detail varies, depending on the information provided by the authors. We note that for some (very few) case studies one or several categories are missing because there was no way to infer that information:

<u>EE Definition</u> (columns 8-10): spatial scale, temporal scale and defining variable of the EE.

<u>Dataset</u> (column 11): The dataset employed for EEA.

<u>Climate Change Definition</u> (columns 12-13): definition of the factual and counterfactual worlds.

<u>Quantification of climate change influence</u> (columns 14-15): This informs on the specific aspects of the EE attributed to climate change, including the degree of conditionality on the observed EE and the attributed metric (changes in probability and/or intensity of the EE).

The following sections are structured as follows. Section 5 introduces some general statistics of the database, focusing on the types of EE considered. Sections 6-to-9 describe the EEA approaches, following the four methodological steps of EEA, with subsections addressing each framing element. For each item we describe the multiple ways of framing the EEA, including their pros and cons, as inferred from the reviewed literature. Moreover, a statistical analysis based on radial plots for the BAMS case studies is presented to identify the preferred ways for EEA employed by the community. For a given framing, the frequency of each category is expressed in percentage with respect to the total number of case studies. As categories are not mutually exclusive, the sum of frequencies for all categories can exceed 100%. This analysis is carried out for all BAMS articles collectively as well as for those explicitly addressing specific types of EEs.

5. DESCRIPTION OF THE DATABASE

In this section, we describe some general aspects of the database, including the types of EE and some potential biases of the selected collection. For the EEs considered herein, there were mainly two motivations of the authors to choose them: the associated impacts or the rarity of the EE,

[9] This does not necessarily mean that a climate change signal is absent

without a strong preference for any of them (they represent the main motivation in ~15% of the case studies). Although very rare EEs may cause little impact (e.g., if a TC did not make landfall), these terms are often related and hence in most cases (~65% of the studies) both (rarity and impacts) are mentioned as the main motivation of the study. Only in one case (Leach et al. 2020) the EE was selected due to quantitative discrepancies between previous EEA studies. Including the impacts in the decision process is a natural (and desirable) aspect. However, it is challenging to attribute the impacts of EEs in the same way that changes in the climate drivers, and hence considerations affecting the impacts (exposure, vulnerability or management policies) are often disregarded, which introduces some inconsistencies in the EEA exercise (i.e. a hazard-oriented attribution of an impact-selected EE).

Concerning the geographical distribution of EEs, studies tend to address EEs that occur in developed countries (as in previous assessments, Stott et al. 2016; Angélil et al. 2017; Jézéquél et al. 2018a), typically where authors live. This bias is also present in other databases, such as that generated by the Carbon Brief website[10], which has mapped the results of attribution studies on EEs (not only EEA) around the world. For the types of EE addressed in CLINT, there is a clear preference to address EEs that occur in Europe, North America, southern Asia and Australia (Figure 4). Although this geographical bias has been reduced in the last years, the limited number of studies in vulnerable countries is still notorious. There are additional biases affecting the selection of EEs (e.g., NAS 2016). A common one is a publication bias: authors are more prone to publish about EEs with attributable signals to climate change (positive EEA), likely because they are more informative for stakeholders (e.g., consideration of adaptive measures) or public awareness of climate change. Indeed, in the majority of the BAMS cases analysed here (~92% of the case studies), the EE was attributed to climate change. The frequency of positive cases is higher than that provided in older reports (e.g., Black and Baum 2020) or in longer datasets (e.g. Carbon Brief website, going back before 2011). This suggests an accelerating rate at which positive links are being uncovered, likely due to the increasing length of the observational record, continued global warming (higher signal-to-noise) and improved tools (computing power and better models).

[10] https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world/

Figure 4 Spatial distribution of attribution studies on storms, heat, droughts or compound EEs. The database comprises 275 studies, including global analyses (not ascribed to any geographical area) and attributions of trends in EEs (no EEA). Circles and triangles identify formal (peer-reviewed) and fast-attribution studies. Studies reporting human influences, no human influences and inconclusive results are denoted in red, blue and grey, respectively. After https://www.carbonbrief.org/.

Another type of selection bias has to do with the type of EE: authors tend to focus on EEs for which current capabilities and level of understanding make EEA more feasible. This is clearly reflected in the distribution of EEA studies in the database by the type of EE considered (Figure 5). There is a strong preference for heat-related extremes (HEs) (~25%, or >30% when Marine HWs are included in this category), since these are the EEs for which attribution is most straightforward (higher likelihood of successful attribution) and has the longest history. This bias towards heat-related EEs is also present in previous collections of EEA studies, regardless of whether they are (e.g. Angélil et al. 2017; Jézéquel et al. 2018a) or not (Black and Baum 2020; Carbon Brief) restricted to BAMS publications. HEs include heat waves (HWs) and other warm EEs over land on longer spatio-temporal scales (e.g. an extremely warm season). A more detailed classification of HEs (e.g. distinguishing HWs from other warm EEs) was not possible because it would have resulted in small sample sizes, and some studies focus on different temporal scales of the same EE (e.g. a specific HW and the season when it occurred). Comparatively, the number of cold extremes (herein including frost days) is much lower (~8%) than that of HEs, likely because their frequencies and intensities decrease with climate change, as their expected impacts do (another kind of selection bias).

Heavy precipitation (HP) is the other most frequent type of EE (~28%). These EEs include synoptic-to-large-scale events, more often related to wet seasons (Quan et al. 2018), anomalous monsoons (Ma et al. 2022) or extratropical systems (e.g., Kawase et al. 2020) and hence they are not classified in the same category as TCs. Indeed, within the 107 reviewed papers, there is only one study explicitly dealing with TCs (and it was not a single TC, but the 2019 September record high typhoon activity over South Korea; Min et al. 2021), with a negative result. Another study specifically addresses the 2021 Hurricane that affected Bahamas (Reed et al. 2021), but the attribution focuses on the associated impacts (HP) rather than on the intensity/frequency of the TC (as an exception, this case is catalogued in both categories: HP and TC). Another recurrent EE is drought (DR) (~16%, or ~19% if we include dryness), more often related to dry monsoon seasons (e.g., Hoell et al. 2022) and meteorological or agricultural DRs (e.g., Nangombe et al. 2020), with other types of DRs (e.g. multi-year hydrological DRs related to depletion of surface or subsurface water) being less commonly assessed. The remaining cases of the catalogue correspond to other types of EEs (e.g., streamflow or sea ice), which are addressed marginally, as well as non-meteorological hazards such as wildfires (~6%) or ecosystem function (~3%).

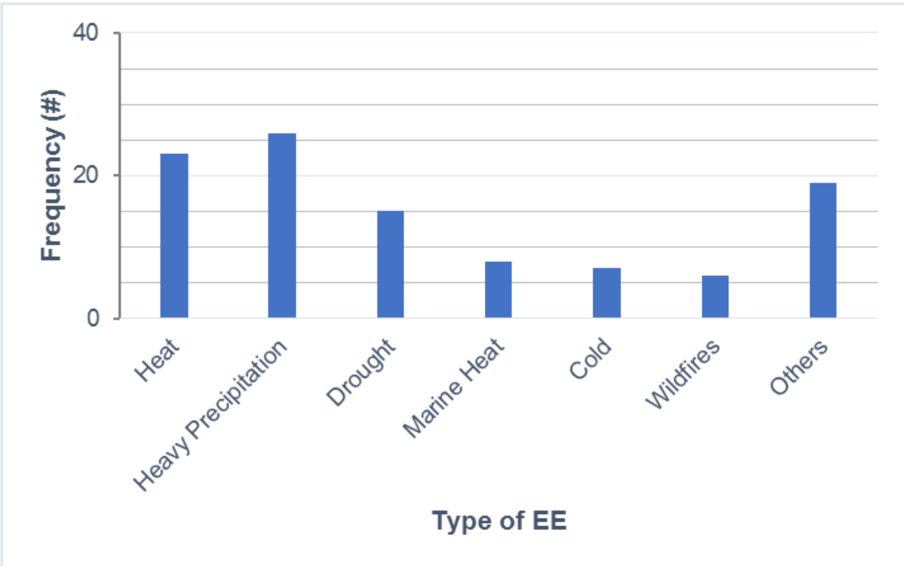

Figure 5 Frequency of studies in the 2018-2022 BAMS annual reports by type of EE.

Although a substantial number of the BAMS case studies could be considered compound / concurrent EEs, this type of EE is not explicitly analysed in this report, since: 1) there are few cases of EEs catalogued as a compound / concurrent EE by the authors[11]; 2) many EEs have to some extent a compound nature (e.g. HWs preceded by DRs), but they are treated as EEs of a single category (or with a separated assessment of their components), partially due to the lack of specific approaches to quantify climate change influences in compound aspects of EEs. When the compound nature of the EE is explicitly stated by the authors, it was classified in the single categories that comprise the EE (e.g., HE-DR compound is considered as both a HE and a DR). Similarly, impact-oriented studies (e.g., coral bleaching responses to a Marine HW; Brainard et al. 2018, or ecosystem function during a DR; Funk et al. 2018) are catalogued by the driving hazard.

[11] The most recurrent one is HE combined with dryness or DRs (4 case studies; e.g. Wang et al. 2021). Other compound or concurrent EEs that are addressed marginally in BAMS include HEs and wetness in humid regions (Min et al. 2022) or DRs combined with wildfires (Du et al. 2021).

In the following, the DL will focus on EEs with enough number of case studies (at least 10) in the BAMS database, namely, HEs, HP and DRs. When the result of the EEA exercise is analysed by type of EE, we find that successful attribution is more likely in temperature-related EEs (HEs and cold EEs; 100% of the case studies) and DRs (with successful attribution in 93% of the cases). This result should be taken with caution (due to the aforementioned publication bias) and not be generalised to all EEs of these types. The only DR where EEA was negative (Martins et al. 2018) largely relied on precipitation data, therefore disregarding the thermodynamical component of climate change in DR severity (via enhanced atmospheric evaporative demand and associated evapotranspiration). Thermodynamical aspects of climate change (e.g., enhanced water holding capacity of the atmosphere via the Clausius-Clapeyron relationship) are also pivotal for the attribution of HP. However, compared to temperature-related EEs, attribution of HP to climate change is more difficult, due to low signal-to-noise ratios at the small spatio-temporal scales of the EE, model biases or small / uncertain dynamical responses to climate change in the weather systems triggering the HP (e.g., NAS 2016, and references therein). This hampers the detection of climate change signals and can yield null EEA results. Indeed, a negative or inconclusive EEA result was reported in ~15% of the HP case studies. Half of them corresponded to EEs on small scales (e.g., 1-day local precipitation; e.g. Tozer et al. 2020) or with a strong dynamical influence (e.g. EEs driven by moisture transport; Hope et al. 2018). This also applies to the case study addressing TC activity (Min et al. 2021), where EEA relied on a gradient index of 200-hPa geopotential height anomalies, although outside of the database there are cases of successful attribution of TCs (e.g., Risser and Wehner 2017). The number of positive EEA results further decreases (~83%) for EEs that are also affected by non-climatic factors (e.g., wildfires). Within the reviewed papers reporting negative climate change influences in the EE, the most recurrent argument is the lack of detectable signals (i.e. non-significant differences between the factual and counterfactual worlds; e.g. Hope et al. 2018, 2019; Min et al. 2021), suggesting natural variability as the main driver of the EE (e.g. Martins et al. 2018; Quan et al. 2018), but few studies discuss the potential limitations of their approaches that may have caused a failed detection, such as the small number of EEs with the observed intensity (i.e. limited sample size; e.g. Tozer et al. 2020) or large uncertainty in the responses to climate change (King 2018).

The following sections describe the different elements of EEA approaches, the ways of framing them, and the preferred choices employed for the three major types of EEs in the database collection.

6. EXTREME EVENT DEFINITION

EEA is often done by considering a class of events similar to the observed one. This involves considering all EEs with intensities above a given threshold (typically the observed one), or constructing an index related to the severity of the EE (e.g., number of hot days). The defining variable is often averaged in time and space, attending to the characteristics scales of the EE, or the duration and spatial extent of the observed EE. Therefore, there are three choices involved in EE definition: the variable chosen to define the event, the region affected (i.e., the spatial scale of the EE) and the duration of the EE (temporal scale). Although decisions are often based on the rarity and associated impacts of the EE, as well as the availability of observations, they are addressed differently (in most cases subjectively), which can yield to different definitions for the same EE. Cattiaux and Ribes (2018) proposed to optimise those choices by selecting the region and period for which the EE has the lowest probability of occurrence, although this approach is not explicitly employed in BAMS, arguably because it could affect the reliability of the statistical tests (e.g., if the observed EE is very extreme, as it often occurs in BAMS).

Despite the high degree of arbitrariness when defining an EE, we assess here the spatio-temporal scales and associated variables that are preferably chosen by the scientific community. As most case studies concluded with a positive EEA, these results could also be interpreted as the minimum spatio-temporal scales for which these specific EEs can be reliably attributed to climate change. We note that there are other considerations related to the definition of the EE, e.g., how close the class of EE is to the observed one. However, this question is related to the level of conditioning on the observed EE (addressed in Section 9), which also considers additional aspects affecting the class of EE (i.e., the environmental conditions or climate states under which the EE occurred).

Studies do not often explore the statistical properties of the EE of interest or how the results depend on the EE definition. However, the latter can have important implications for the attribution statements. For example, for the 2018 summer heat over Europe, Leach et al. (2020) noted quantitative discrepancies between previous attribution studies, with attributed changes ranging between 2-5 (WWA 2018[12]) to more than 30 (McCarthy et al. 2019) increases in its probability of occurrence due to climate change. These discrepancies were reconciled when considering the effects of using different spatial domains and temporal scales in the EE definition. As compared to shorter scales, the use of longer EE scales increases the spatial uniformity and decreases the variance, yielding higher probability ratios (e.g., Angélil et al. 2014).

6.1 Defining variable

The variable used to measure the severity of the EE has implications for EEA, since it defines the specific observable of the EE that is being attributed to climate change. Event definitions should take the limitations of both observations and models into account. For observations, long records of high quality are required, whereas for model-based approaches it is critical that the models can reliably simulate the EE for the right reasons. In both cases, testing the sensitivity of the results across a range of EE definitions is advisable, but this is hardly done in EEA. EEs can be defined in multiple ways, with different variables diagnosing different severities. For example, one may be interested in a given observable of the EE (e.g., the intensity of a TC), or in variables describing a specific impact (e.g. the TC-related storm surge), the answers to these two questions being likely different. Hurricane Sandy represents an example (Knutson et al. 2017): while there is strong evidence that anthropogenic-induced sea level rise made Sandy's surge event worse (Magnusson et al. 2014), there is low confidence in the net impact of climate change on the probability of Sandy-like events (Lackmann 2015).

[12] https://www.worldweatherattribution.org/attribution-of-the-2018-heat-in-northern-europe/

For this framing we consider the following categories: 1) temperature; 2) precipitation; 3) other basic fields of the atmosphere (e.g. pressure), ocean (e.g. SSTs) or land (e.g. streamflow). These fields can be employed for the definition of the EE (its intensity) or to constrain the selection of EEs; 4) indices, including simple metrics related to the persistence of the extreme conditions or more sophisticated indicators of the EE severity. There are two main advantages of using basic fields. First, many of them (in particular temperature and precipitation) are readily available from observations, reanalyses and model simulations. Second, they provide a simple way to characterise the intensity of the observed EE, and to define a class of EE (e.g., all EEs with intensities equal or higher than the observed one), from which one can estimate the risk ratio (i.e. changes in the probability of occurrence of an EE of that magnitude). However, they may miss important processes that contributed to the severity of the observed EE (e.g., the use of precipitation to define an agricultural DR does not fully account for soil drying). While indices can provide a more realistic approach to the EE at hand, some of them do not allow quantifying changes in intensity (e.g., the number of rainy days), can be complex to derive (e.g., Standardised Precipitation-Evapotranspiration Index, SPEI) or suffer from observational uncertainties (e.g. TC indices). As a consequence, they are often employed complementary to the aforementioned basic fields.

Traditional meteorological variables are the most common diagnostics of EEs employed in BAMS (Figure 6). They include temperature for HEs (91%) and cold EEs (86%), and precipitation for HP (92%) and DRs (73%). However, DRs are also very often assessed in conjunction with other fields (73%), typically hydrological variables such as soil moisture (e.g., Hoell et al., 2019), which account for thermodynamical aspects of DRs that are more amenable to attribution. A substantial number of studies (48%) also employ simple extreme indices. For HEs, indices of varying complexity, ranging from simple metrics (e.g., the maximum number of consecutive hot days within a season; Min et al. 2020) to aggregated indicators of HW intensity and persistence (e.g., the HW magnitude index; Zhou et al. 2019), have been employed (39%). They are often employed to attribute specific characteristics of the EE, such as the areal extent of warmth (e.g., Imada et al. 2018), and are also very common for the assessment of Marine HW attributes (e.g., duration; Oliver et al. 2018). Extreme indices are also employed for HP (e.g., the number of rainy or HP days within the season; e.g. Hu et al. 2021), particularly when the assessment deals with anomalous seasons, rather than individual meteorological events, but this approach is less common than in HEs (23%). Some case studies dealing with HP on local scales (Pei et al. 2022) or TC (Min et al. 2021) have also employed atmospheric circulation indices to define the EE, which can be a wise choice if there are strong dynamical influences on the EE and/or the reliability of observations and/or simulations is questionable. For the definition of DRs, the use of indices is very common (~66%), but it is biased towards precipitation indicators (e.g., longest spell of consecutive dry days; Du et al. 2020), with more realistic formulations of water balance (e.g., precipitation minus evapotranspiration, SPEI, etc.) being still relatively uncommon. Because there are few observations of soil moisture and vegetation dynamics, DR assessments based on water balance indices should consider several formulations, and their limitations (Seneviratne et al., 2012).

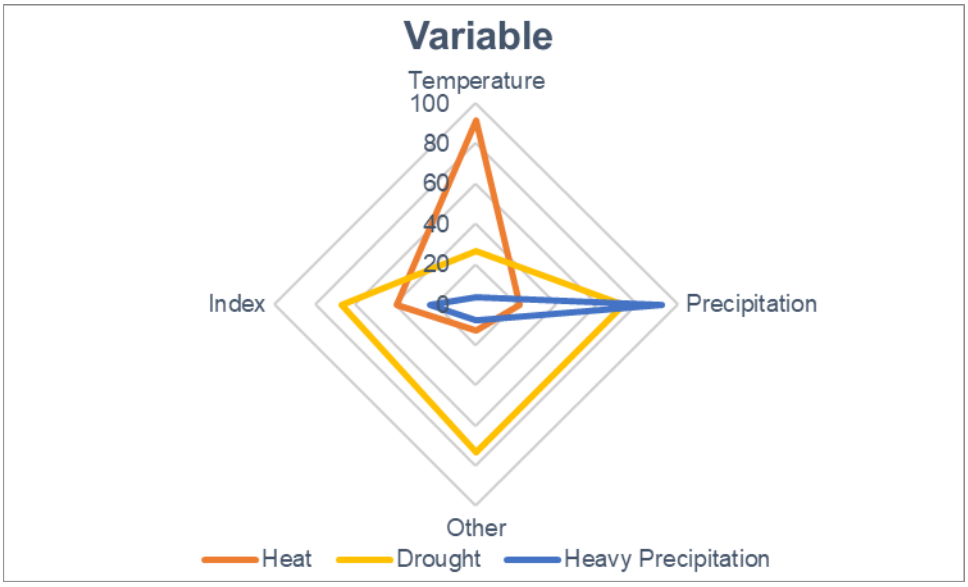

Figure 6 Frequency distribution of categories for the Variable framing by type of EE (in percentage of the total number of case studies for each type of EE). Note that for a given type of EE the sum of frequencies for all categories can exceed 100%, since the same study can use different categories.

6.2 Spatial scale

The use of spatial averages is beneficial for a positive EEA, since it increases the signal-to-noise ratio by reducing the internal variability, therefore facilitating the detection of external forcing signals and the quantification of uncertainties. However, the definition of the spatial domain can be challenging for EEs with evolving patterns (e.g., HWs or TCs). Furthermore, it complicates an end-to-end attribution of climate change influences on associated impacts, which strongly depend on local factors.

Concerning the spatial scale of the EE, we distinguish three categories: 1) local; 2) regional; 3) continental global. The classification of this framing requires some degree of subjectivity and there is an unbalance of the areal extents represented by the different categories. In particular, regional domains include a wide range of spatial scales between local (or grid point) values and continental averages. Unfortunately, a more scrutinised classification of this category was not possible, because spatial domains are not always clearly defined, and the use of additional categories (e.g., country-level averages) would be misleading due to the large diversity of areas extents involved.

Almost all BAMS studies apply some level of spatial average in their diagnostics (typically, over a box or political boundaries), and the regional scale is by far the most frequent one (~90%). Although EEs are associated with distinctive spatio-temporal scales, we do not find large differences across the spatial scale categories employed for different types of EEs. This denotes a high degree of arbitrariness, likely related to an intrinsic difficulty to delimit the EE (changes in the spatial extent as the EE unfolds). Despite this, there are some differences in the targeted spatial scales across types of EE. For example, DRs are more frequently addressed at larger spatial scales (e.g., southern Africa, southern China or the northern Plains of USA) than HP (e.g., Yangtze River, southern California or southeastern Australia). Indeed, HP represents the EE for which local scales are more frequently targeted (but still with very low frequencies, ~8%). Examples of local attribution studies include the HP EEs of Beijing in 2022 (Pei et al. 2022) or Hobart (Australia) in 2018 (Tozer et al. 2020), and have also been applied to other hydrological EEs (e.g., the 2019 streamflow in Susquehanna river, USA; Ross et al. 2021). HEs are often addressed at a wide range of spatial scales, including sub-country domains (e.g., central England; Christidis and Stott 2021), small countries (e.g., South Korea; e.g. Min et al. 2022) and subcontinental scales (Scandinavia, western Europe, northeastern Asia, etc.). Continental and global scales are now rarely considered in EEA (~5%), and mainly deal with HEs. The choice of the spatial scale is expected to be more critical for some EEs than for others, since attribution results tend to be robust across different spatial scales for HEs, but not so much for HP (Angélil et al. 2014).

6.3 Temporal scale

Attribution statements for EEs defined at a given temporal (or spatial) scale cannot be extrapolated to EEs occurring at different scales. This framing is classified into the following categories: 1) sub-monthly (i.e., from hourly to multi-daily averages); 2) monthly means; 3) multi-monthly scales (i.e. monthly averages from two months to less than a year, including seasonal means); 4) annual and longer scales. In this case, the classification is straightforward when the defining variable is a basic field (e.g., seasonal mean precipitation in the summer), which occurs in most cases. However, it requires expert-based judgement for extreme indices. For example, when a HE is defined as the maximum number of hot days in a season, it requires a daily index (determination of a hot day) that is accumulated on a seasonal basis, with values ranging from 0 (daily scale) to 90 (multi-month scale). In these cases, the category was chosen based on the most likely values (sub-monthly in the given example).

Unlike the spatial scale, a large diversity of temporal scales is employed in BAMS to define EEs (Figure 7), suggesting that this framing is chosen in closer agreement with the duration of the observed EE. When all types of EE are considered, the multi-monthly category is the most frequent time scale employed in BAMS (~41%). The high frequency of this category is partially due to DRs, which are commonly defined at this time scale (~67%). There are few DR studies focusing on either monthly or yearly averaged fields, indicating that meteorological (e.g., dry monsoons) and agricultural DRs are the most frequent type of DR in EEA. Differently, HP is more frequently addressed at sub-monthly scales (~69%), typically around one week. However, a comparable number of studies also consider longer time scales, such as extremely wet months or seasons. HP is also the EE with the highest number of studies focusing on daily or even sub-daily scales (~15%), the latter corresponding to the precipitation associated with the 2019 TC over Bahamas (Reed et al. 2021). HEs are also defined over a wide variety of temporal scales (from several days to one year), without a strong preference between sub-monthly, monthly and multi-monthly scales (all with frequencies >30%). Multi-day EEs are often employed for land HWs (e.g., Barriopedro et al. 2020), whereas HEs defined at monthly (and longer) scales typically correspond to warm summer periods that affected large areas (e.g. western Europe; e.g. Christidis and Stott 2022) or high latitudes (e.g.

the Arctic; Kam et al. 2018) or HE-DR compound events (e.g. Williams et al. 2020). Unlike the spatial scale, there is an increasing tendency to assess multiple temporal definitions of the EE, although they sometimes apply to different attributes of the EE (e.g., a HW can be defined as the mean temperature anomaly at monthly scales and as the maximum number of consecutive hot days in that month). This increasing tendency agrees with previous studies reporting that the attributable risk to climate change tends to be more sensitive to the temporal than spatial scale (increasing as the duration of the EE increases; Angélil et al. 2014).

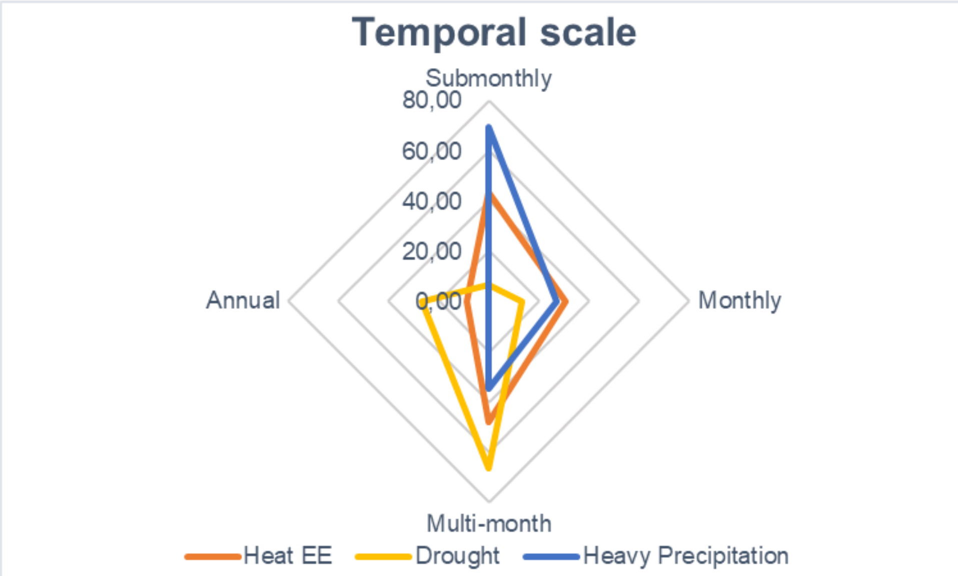

Figure 7 Frequency distribution of categories for the Temporal scale framing by type of EE (in the percentage of the total number of case studies for each type of EE). Note that for a given type of EE the sum of frequencies for all categories can exceed 100%, since the same study can use different categories.

7. DATASETS AND MODELS

Based on the dataset employed, and as a first approximation, EEAs can be divided into those using an observational-based dataset (observations and/or reanalyses) and model simulations, although many studies use both. The type of models employed is important because it often determines the modelling setup and how the factual and counterfactual worlds are constructed, therefore affecting the quantification of climate change influences. In many cases, the decision on the type of model is made based on the needs required (spatial resolution, resolved processes) to fairly represent the specific EE subject to attribution. For this framing, we distinguish the following categories: 1) observational datasets (including reanalyses); 2) coupled GCMs capturing at least the two-way interactions between the atmosphere, ocean, sea ice and land; 3) AGCMs, which require prescribed SSTs and SIC, therefore missing ocean responses to other components; 4) other high-resolution modelling approaches to better represent the EE of interest and its defining variable (e.g. Regional Climate Models (RCMs), weather or seasonal forecasts), herein including specific models for some components of the climate system (e.g., hydrological models for streamflow EEs, ecological models for ecosystem function or wildfires).

Observational datasets: Approaches based on observations or reanalyses compare past and recent periods. The main advantage is that the EEA does not depend on the reliability of the model to capture the forced responses to climate change or its ability to simulate the EE. They also serve to evaluate models (e.g., reject unrealistic models) and are appreciated by users that question the veracity of climate models. However, observations provide limited realizations of EEs, and hence the quantification of climate change influences is difficult, requiring: 1) high-quality data, since uncertainties in observation-based analyses can be considerable; 2) long records to remove internal variability and allow reliable comparisons between the two subperiods (the signal-to-noise ratio decreases with the shortness of the record and the unforced natural variability); 3) understanding of climate change influences on the EE to avoid confounding natural or non-climatic factors. Although studies tend to follow their own ways to deduce climate change influences on the EE (the simplest way is to count threshold exceedances in the factual and counterfactual worlds), there are two common approaches in observational-based datasets:

Statistical fitting distributions: These approaches fit the observed series that define the class of EE to statistical distributions. If an all-data fit to a Gaussian or Gamma function is not appropriate, other theoretical distributions are employed, including the Generalised Pareto Distribution[13] and the Generalised Extreme Value distribution[14]. The quantification of climate change influences requires identifying a trend or covariate related to climate change, typically the global mean temperature, which imposes a time-varying threshold (or parameter of the distribution) that changes with global warming (e.g., Philip et al. 2020 and references therein). This does not account for changes in variability, and assumes that the EE threshold changes proportionally to global warming and that the trend or covariate reasonably captures the climate change influence on the EE. Return periods are thus obtained for the present-day climate (often the year of the EE) and for a past climate (an early year of the covariate record or of the detrended series of the EE). The approach yields estimates of the return periods as a function of the magnitude of the EE for factual and counterfactual worlds (Figure 8), with the intensity of the observed EE (or the associated return period) defining the class of EE. This allows quantifying changes in probability of occurrence for a class of EE with the same magnitude as the observed one, or changes in intensity (for a class of EE that occurs with the same frequency as the observed EE in the present-day climate). This method is also frequently applied to model simulations to quantify changes in the probability/intensity of the EE. In that case, the simulated series in the factual and counterfactual worlds (if available) can be directly fitted to statistical distributions, and hence a covariate may be unnecessary, but the

[13] This is also called Peak-Over-Threshold approach. It is often applied to long timescale EEs above or below a moderate threshold (e.g. monthly mean high temperature or seasonal mean drought) since it requires an enough number of exceedances.
[14] The distribution is constructed from the largest observation within a large sample, or block maxima. It is often applied to EE definitions such as the annual maximum temperature or maximum daily precipitation in a season. A typical approach involves the use of running means (over pre-defined time windows representative of the duration of the EE) of the spatially-averaged variable that defines the EE, from which the annual or seasonal maximum is selected.

approach requires model evaluation (e.g., a reasonable representation of the fitted parameters of the observed distribution in the factual climate of the model).

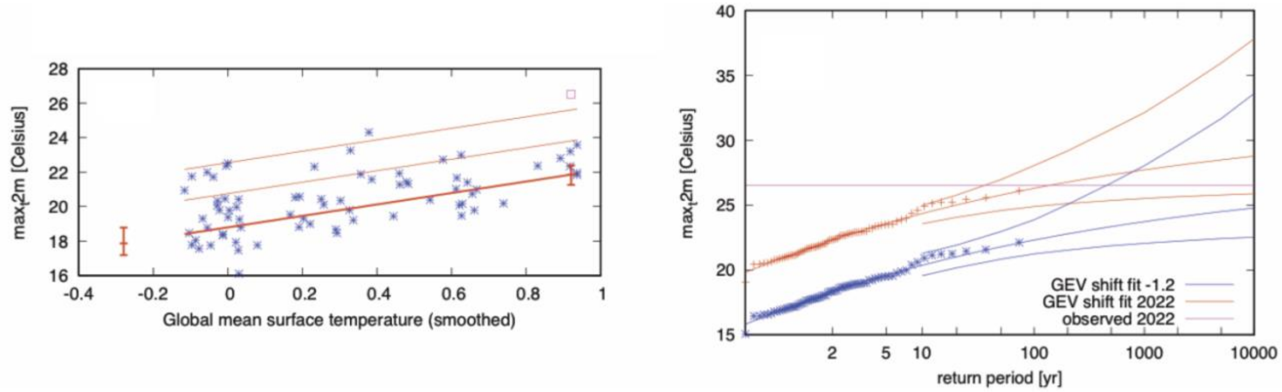

Figure 8 Left: Response of the annual maxima of 2-day mean temperature averaged over central England to changes in global mean temperature. The thick line denotes the time-varying mean, and the thin lines show +1 and +2 standard deviation. Vertical red lines show the 95% confidence interval for the location parameter of the Generalised Extreme Value distribution for the current 2022 climate and the preindustrial (1.2ºC cooler) climate. The 2022 observation from ERA-5 reanalysis is highlighted with the magenta box. Right: Return periods of the annual maximum 2-day mean temperature for the 2022 climate (red lines) and the 1.2ºC cooler climate (blue lines with 95% confidence interval). After Zachariah et al. (2022).

Analogues: A second common approach in observations is the analogue method. The attribution is conditioned on a given observable or state of the climate system (typically the synoptic situation) at the time of the EE (e.g., Cattiaux et al. 2010; Yiou et al. 2007). Accordingly, this approach provides partial attribution (restricted to EEs that occur under the conditional factor). Analogues (similar historical states of the conditional factor) are considered random 'replicates' of the EE, which allow reconstructing distributions of the expected probability of occurrence (or intensity) of the EE (Figure 9). Comparing the distributions reconstructed from analogues of two periods representative of the new and old world (both with different levels of anthropogenic forcings) yields estimates of the changes in the EE (i.e., how the event could have been in the past given the occurrence of the same conditional factor). When using observational datasets, changes can only be attributed to the overall climate change over the period considered (howsoever caused), under the assumption that the considered periods are long enough to cancel low-frequency natural climate variability. In general, it will be challenging to attribute such changes to anthropogenic factors, but these approaches are informative, since they allow determining how long-term changes have affected a given outcome of the EE. The approach also allows diagnosing changes in the frequency of the conditioned states, although they are often ignored. If the conditional factor is the atmospheric circulation, the dynamics of the EE is fixed (flow analogues). In this case, the results emphasize thermodynamic effects of climate change on the EE, which may lead to overestimated statements (false positive), but also avoid null results due to the limited confidence in dynamical aspects of climate change (Shepherd 2016). This approach can also be applied to model simulations, including future projections, although this requires an assessment of model capabilities to reproduce the conditional factor with the observed characteristics and its future responses.

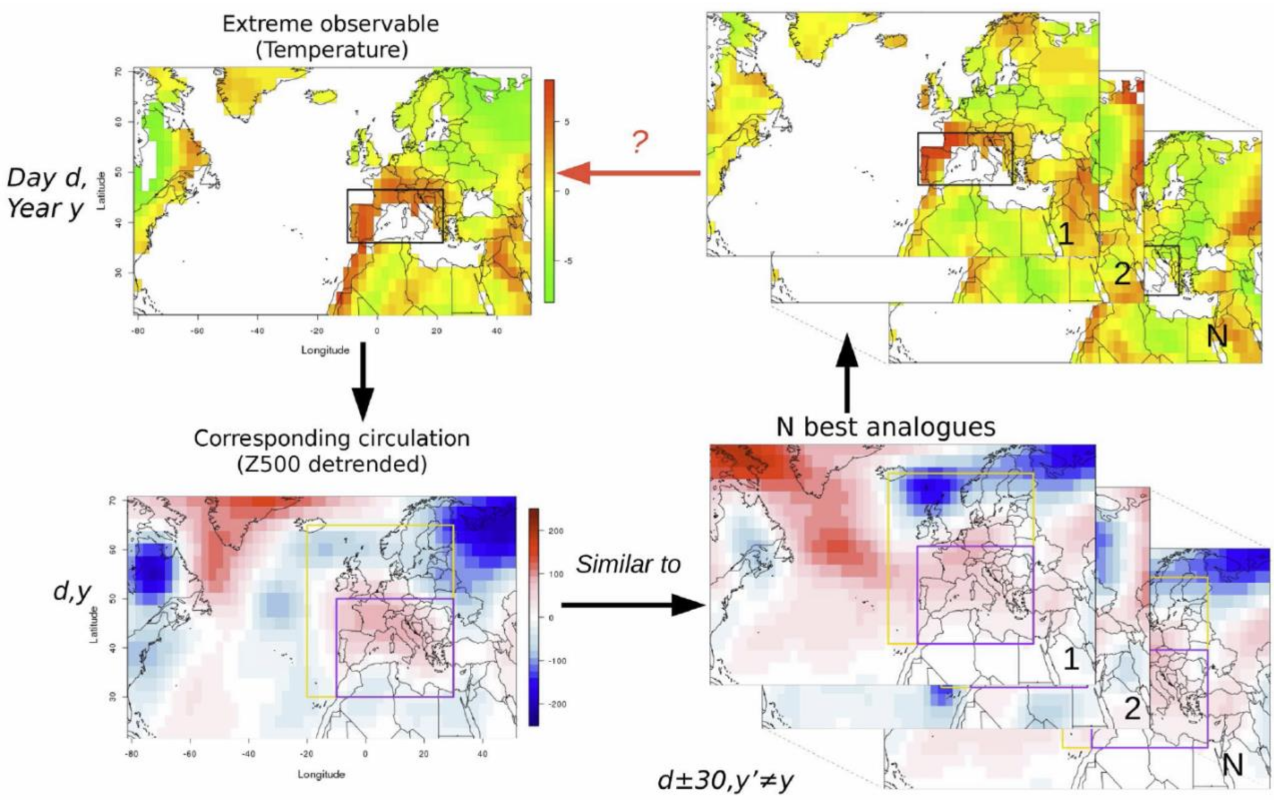

Figure 9 Illustration of the flow analogue method: A day with an extreme temperature anomaly (map on the top left) has a corresponding circulation, represented by the geopotential height at 500 hPa (map on the bottom left). Flow analogues are days within the database which have a similar circulation to the day of interest (maps on the bottom right). The temperature anomalies of the analogues (maps on the top right) are then compared to the temperature anomalies of the day of interest (map on the top left). After Jézéquel et al. (2018b).

Unlike observations, model-based approaches allow an explicit treatment of anthropogenic forcings (and their separated influences) and better estimation of uncertainties and internal variability (e.g., Hegerl and Zwiers 2011). An advantage is that multiple and/or long simulations can be conducted to generate a large sample free of inhomogeneities, and the possibility of quantifying the influence of specific anthropogenic forcings (greenhouse gases (GHGs), aerosols, land changes) on the EE (e.g., Pall et al. 2011). However, model-based approaches suffer from other types of uncertainties (e.g., model biases), which affect the attribution of EEs to climate change (Bellprat et al. 2019). Accordingly, model evaluation is required, since the results of EEA rely on the model ability to simulate the EE (e.g., the associated statistics, the specific weather situation and feedbacks that may have affected the observed EE) and its changes. Confidence on the skill of the model is often assessed with simple diagnostics on the climatology, interannual variability or dynamic features in factual simulations, which may be insufficient to ensure that the mechanisms are well simulated (e.g., land–atmosphere coupling, troposphere-stratosphere interactions; Vautard et al. 2019). For studies using multiple GCMs, a selection is often made based on those evaluations, which further allows overcoming some structural deficiencies in individual models. Other studies apply bias correction techniques (e.g., subtracting the mean bias or adjusting the variance or the quantiles), although some of them might not properly account for model errors in the probabilities of EEs (Bellprat et al. 2019). For other types of models (AGCMs, forecasts, etc.), results further rely on the model's ability to simulate the climate conditions that generate the EE under the observed constraint and hence model evaluation should be assessed conditionally (given the forcings and conditioning factors). In all cases, biases are assumed stationary (i.e., the same in factual and counterfactual simulations) and are difficult to quantify, particularly for EEs with large observational uncertainties.

The choice of the model type is influenced by the data availability (and capacity to run model simulations) and the model's ability to simulate reliably the specific EE. As the modelling design is different in each case, and requires different specifications of the initial and boundary conditions, the type of model chosen somewhat determines the level of conditioning (Section 9.1). In addition to observational datasets, model-based approaches are also considered in this framing, and classified in the following categories:

<u>GCMs</u>: This is the most recurrent approach for EEA, and enjoys several advantages: 1) it does not require model capabilities and computing facilities due to the availability of existing collections of GCM simulations under the same forcings (e.g. the Coupled Model Intercomparison Project, CMIP), which provide an explicit representation of factual and counterfactual worlds, allowing fast EEA; 2) it offers the possibility of performing multi-model assessments and exploring model-related uncertainties in EEA, although the latter is often overlooked. As a drawback, the coupling nature of these simulations imposes limitations to: 1) the ensemble size which can affect the reliability of the statistics of the EE and estimates of internal variability; 2) the type of EEs that can be addressed due to the limited spatial resolution and complexity of the model (representation of processes).

<u>AGCMs</u>: These simulations require specifying the observed historical evolution of SST/SIC (AMIP runs), or more commonly, the observed SST/SIC anomalies at the time of the EE (from less than a year to a decade; e.g. Pall et al 2011). Therefore, they are constructed specifically for a particular class of EE and involve some level of conditioning on the observed states accompanying the EE. By prescribing the SST/SIC patterns, AGCM simulations are cheaper to run, which has several benefits: 1) model biases can be reduced; 2) the model can be run for a large ensemble (between tens to hundreds of simulations) typically generated by perturbing the initial conditions; 3) model simulations allow higher spatial resolution and more complex representations of key model components (typically, improved representation of the atmospheric dynamics and land-surface processes). On the cons side, AGCM simulations: 1) do not fully capture atmosphere–ocean coupling, which could lead to misrepresentations of EEs affected by air-sea interactions; 2) are often restricted to a single AGCM model, with the risk of model-dependent results; 3) require estimation of the counterfactual SST/SIC conditions (how the observed SST/SIC pattern would have been without anthropogenic influences).

<u>High-resolution models</u>: For EEA on local scales or EEs that require high resolution, the output of global climate models can be used to run downscaling experiments with high-resolution models.

They include RCMs nested in either GCMs (e.g., Euro-CORDEX) or, more typically, AGCMs, but also hydrological or land models. GCM-driven simulations allow the use of multiple RCMs (driven by a restricted subset of GCMs), whereas AGCM-driven runs provide a large ensemble of simulations (conditioned on the SST/SIC pattern that is prescribed to the AGCM and its biases). Some recent studies have also employed highly-constrained model approaches, constructed specifically to represent the EE of interest, by using numerical weather prediction models or seasonal forecast systems initialised within the respective predictability window (a few days/month in advance of the EE). By constraining the initial and boundary conditions (land surface, SST/SIC, atmospheric circulation) to the actual states of the EE the class of EE in the factual simulation can be directly compared with the observed EE and model evaluation is more straightforward. However, methodological approaches have not been fully developed yet, and the description of the counterfactual world remains challenging, since it requires natural estimates of the initial and boundary conditions.

In BAMS 2018-2022, studies use observations or reanalysis to define and/or contextualise the EE, evaluate models or perform EEA, but almost none supports its EEA statements on observational datasets only. For the dataset, there is a preference for GCM (~67%) over AGCM models (~43%), although the majority of studies use more than one dataset (typically GCMs and AGCMs; Figure 10). About two-thirds of the GCM studies employ a multi-model approach based on CMIP5 or CMIP6 collections. For EEA studies using a single GCM, there is a clear preference (~15% of GCM-based EEA studies) for the Community Earth System Model (CESM) (e.g., Winter et al. 2020), which provides a large ensemble of full and single forcing simulations for the last millennium. Differently, AGCM-based approaches often rely on a single model, typically the HadGEM3-A (e.g., Christidis et al. 2019), the global model of the Hadley Centre near-real time attribution system. This initiative generates two 15-member ensemble sets of simulations at high-resolution (0.56° × 0.83°) for the historical period (1960-2013) (Christidis et al. 2013; Ciavarella et al. 2018): one with the observed SST/SIC and external forcings, and another one with natural forcings only, for which an estimate of the anthropogenic change in the SST/SIC pattern is subtracted from the observations. An additional pair of short ensembles (with 525 members) for the last year on record is also run on a seasonal-to-seasonal basis to perform near real-time attribution of recent EEs. Other ongoing international initiatives following similar protocols with different AGCMs are the Climate of the Twentieth Century Detection and Attribution Project (Stone et al. 2019).

In some works (~14%), the output of these global climate models is downscaled via RCMs, but very few (~6%) use specific model components related to the EE at hand (e.g. hydrological, land or ecosystem models). About 38% of the high-resolution approaches (e.g. Lewis et al. 2020) exploit the resources of the initiative Weather@Home2, a climate modelling project that uses the distributed computing system climateprediction.net (Massey et al. 2015; Guillod et al. 2017) to run very large ensembles (typically hundreds of members) of short simulations with two land-atmosphere models on volunteers' home computers: an AGCM (HadAM3P) and an embedded higher resolution (50 km) RCM (HadRM3P), both from the UK Met Office Hadley Centre. The AGCM provides the anthropogenic forcings, boundary (SST/SIC) and initial atmospheric conditions to the RCM for the factual and counterfactual runs (the latter often based on preindustrial levels of anthropogenic forcings and corresponding SST/SIC estimates; e.g. Schaller et al. 2016). On the other hand, few (~15%) of the high-resolution approaches rely on existing GCM-driven RCM simulations from CORDEX (e.g., Leach et al. 2020), likely due to the limited ensemble size and availability of experiments.

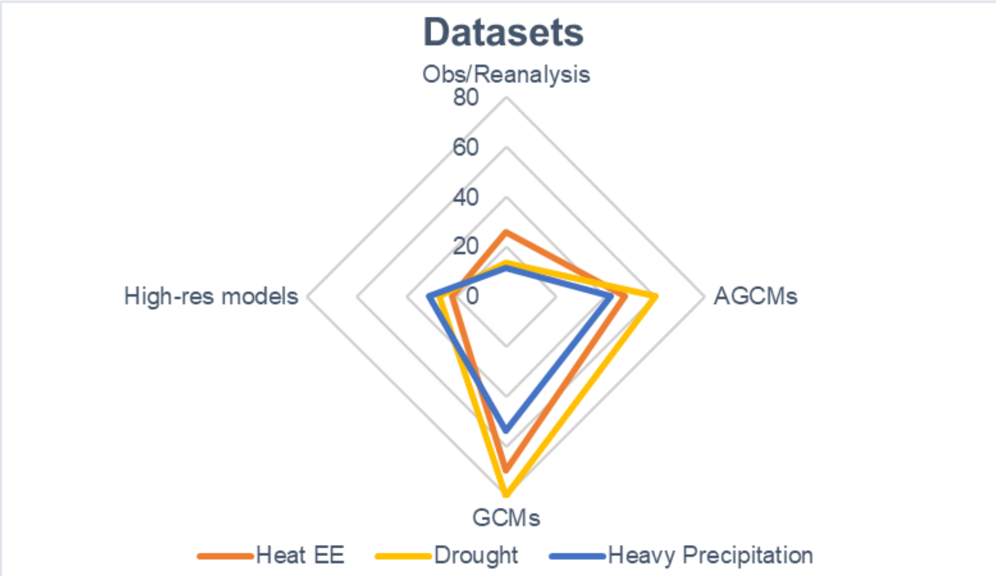

Figure 10 Frequency distribution of categories for the Dataset framing by type of EE (in percentage of the total number of case studies for each type of EE). Note that for a given type of EE the sum of frequencies for all categories can exceed 100%, since the same study can use different categories.

Forecasts are also employed (~27% of high-resolution approaches). They include Numerical Weather Prediction (NWP) models (e.g., the non-hydrostatic Weather Research and Forecasting (WRF) model; Ma et al. 2022), seasonal forecast systems (e.g. Hope et al. 2019) and in very few cases high-resolution global models run in a forecast mode (e.g. Reed et al. 2021). All NWP-based studies address HP (with positive results), being run under the initial and boundary conditions of the EE, and counterfactual estimates typically derived from the recent historical period. Seasonal forecasts are present marginally in BAMS, including three studies on wildfires, HP and frost in Australia (Grose et al. 2018; Hope et al. 2018, 2019), and with a high frequency of negative results. They use two ensembles of seasonal forecasts with the operational seasonal forecast system of Australia by imposing the observed initial and boundary conditions (IBCs) of the ocean, atmosphere and/or land for the factual world, and corresponding estimates for a counterfactual world. Although the number of studies using high-resolution approaches has increased, very few EEA exercises (only 7 cases in BAMS) rely on high-resolution models only.

By type of EE, GCMs are the preferred tools for both HEs (~70%) and DRs (80%), in both cases with frequencies ~20% above AGCMs. GCMs are also employed more frequently than AGCMs for HP, but by a smaller margin (of ~10%) than for other EEs. This reflects the need of higher resolution and improved representation of atmospheric processes. Indeed, high-resolution modelling is more frequently employed for HP (~30%) than for the other types of EE, followed by DRs (20%), where high-resolution approaches often rely on GCM-driven hydrological models (e.g., Ross et al. 2021).

8. CLIMATE CHANGE DEFINITION

Once the EE is defined, EEA relies on the comparison of that class of EE in a factual and a counterfactual world, which represents the climate conditions of a world with and without (or with reduced levels of) anthropogenic forcings. The difference between these worlds is key to quantify the role of climate change. While the factual world is readably available from observations and can be simulated straightforwardly from the observed evolution of external forcings and/or other boundary conditions observed at the time of the EE, the counterfactual world is challenging, since it refers to a world that might have been. The construction of a counterfactual world involves different levels of assumptions, depending on its definition (e.g., NAS 2016; Stott et al. 2016; Knutson et al. 2017; Otto 2017, Jézéquel et al. 2018a), although for some approaches it may not be necessary (e.g., if the hypothetical counterfactual world is replaced by an observed period of the past with reduced anthropogenic influences). Attribution results can differ depending on whether an EE is attributed to the overall observed climate change (i.e., the difference between the present-day and a past period, due to anthropogenic and natural factors), to anthropogenic factors (GHGs, aerosols, land-use/land-cover changes) or to a given anthropogenic forcing (e.g., GHGs).

8.1 Factual world

Quantifying climate change influences depends on how close the factual world is to the actual climate. Indipendently from the dataset, the factual world often depends on the available period, more often being: 1) the entire or part of the historical period, defined as those intervals extending before the satellite era (1980s); 2) present-day conditions (any period starting after the 1980s, including or not the actual year of the EE). By definition, this category includes model ensemble approaches initialised at the time of the EE (i.e. simulations for the actual year, season or weather horizon of the EE); 3) Single forcing experiments forced with the observed evolution of only one anthropogenic forcings. Unlike 1) and 2), which include the effect of all anthropogenic forcings, this category represents the 'factual' world that would have been given the observed changes in that single forcing only (with the remaining ones set at preindustrial levels). The CMIP6-component Detection & Attribution Model Intercomparison Project (DAMIP[15]) provides relevant historical GCM simulations (e.g., aerosols-only, CO_2-only, solar-only and volcanic-only forcing) to facilitate an improved estimation of the climate response to individual forcings (Guillet et al 2016). The main difference between 1) and 2) is that the latter brings the factual world closer to the actual (warmer) world where the EE occurred (increasing the likelihood of EEA), but also reduces the sample size, which affects the uncertainty estimates.

[15] https://damip.lbl.gov/

The classification of this framing was difficult and should be considered with caution, since authors do not always explicitly state the factual period (or the specific forcings considered in the model exercises) and the defined categories involve some degree of arbitrariness. As historical simulations in CMIP5 and CMIP6 ended in 2005 and 2014, respectively (which does not cover the time of the EEs addressed in BAMS), some studies extend the historical simulations with projections based on future scenarios of climate change. When the factual period is not specified, the case study was classified in the first category unless future projections are used (in that case the present-day category is assumed).

There is a clear preference for present-day factual definitions (81% of the case studies; Figure 11), closer to the time of the EE, than historical factual worlds (~22%), although the latter is more often employed in observational-based studies to minimise the influence of natural variability over the factual period considered. On the other hand, most BAMS studies pose the framing question in terms of overall climate change influences in general, and hence anthropogenic forcings are often considered altogether, with marginal assessments of their separated influences (only in ~7% of the case studies). Single forcing experiments are often (but not always) run with GCMs and allow more constrained statements on the role of specific anthropogenic forcings, further avoiding opposite effects that may result from their historical evolution (e.g., increasing GHGs and aerosols in North America, Europe and southeastern Asia), although at expense of reducing the multi-model ensemble, since they are often available for a more restricted subset of GCMs. Only few BAMS studies separate the effect of GHGs (8%; e.g., Kam et al. 2021) or aerosols (4%; e.g. Lu et al. 2021), or explore the effects of different types of land cover (only Ji et al. 2020). However, single forcing experiments are always used as a complementary analysis to full-forcing EEA assessments.

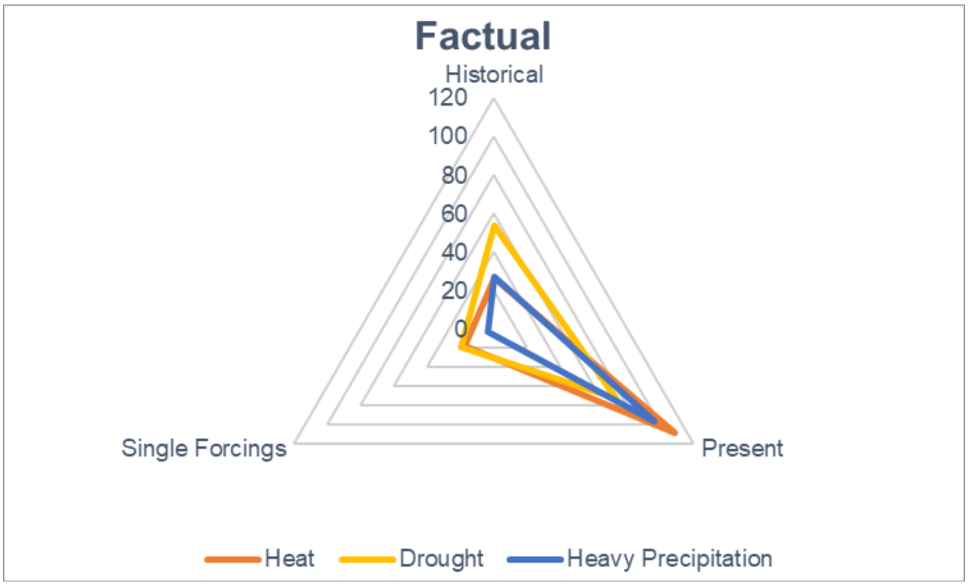

Figure 11 Frequency distribution of categories for the Factual framing by type of EE (in percentage of the total number of case studies for each type of EE). Note that for a given type of EE the sum of frequencies for all categories can exceed 100%, since the same study can use different categories.

In general, BAMS studies barely assess the sensitivity of the results to the factual period chosen, with only very few exceptions (e.g., Wang et al. 2019a). However, there is an increasing tendency, albeit still limited to a few studies (~10%), to include future projections in EEA. This can lend support to attribution statements, being also useful to explore the time of emergence of climate change signals (mainly for negative attribution results) and to assess additional changes in the frequency/magnitude of the EE with unabated global warming. These studies typically focus on mid- and/or late-century projections (e.g., Sun et al. 2019), but rarely consider different scenarios or levels of global warming (an exception being Perkins-Kirkpatrick et al. 2019).

We identified some differences between the factual choices depending on the type of EE. Although all EEs are preferentially framed with respect to the present-day climate, DRs are more frequently addressed in factual worlds of the historical period (53%) than the other EEs (~26%). Present-day framings can further be distinguished between those focusing on recent periods or the actual year of the EE (this separation is not applied herein, because it often depends on the type of models employed). Actual conditions are more frequently employed for HP (65%), whereas HEs are more often framed with respect to recent periods (61%). HEs are also the ones for which future changes are more frequently addressed (~17%), likely due to the higher confidence on (reduced spread of) projections. Despite the indirect effects of aerosols on precipitation, none of the BAMS studies dealing with HP addressed the influence of anthropogenic aerosol changes alone.

8.2 Counterfactual world

The choice of the counterfactual world depends on how much one needs to (or can) go back to fairly represent the conditions of a world 'without' climate change. There are different ways to build a counterfactual world, and, as in the case of the factual choice, they are often constrained by the type of dataset employed. For this framing, the different categories include: 1) a past/historical period (e.g., early 20th century) or year. This category is applied to any period of the 20th century, therefore referring to an 'old' world with reduced anthropogenic influences. This will not give a complete account of the effects of climate change but allows to rely on observations only; 2) preindustrial conditions, defined as any period or year before 1900. The category includes pi-control GCM simulations from CMIP, which are run for long periods with time-fixed external forcings, typically set at 1850 levels; 3) natural forcing simulations (also available for GCMs participating in CMIP), equivalent to historical runs (since 1850) in that they impose the observed evolution of natural forcings, but anthropogenic forcings are fixed at preindustrial levels (as in 2). They allow inferring how the historical period could have been without increasing levels of anthropogenic forcings (but with the same natural forcings as in observations).

For most observational-based datasets, category 1) is the only possible choice (with the exception of the 20th Century Reanalysis Project, which now extends back to 1851, allowing the possibility of defining a preindustrial counterfactual). For GCMs participating in CMIP (and associated downscaling exercises), all choices are possible, allowing a straightforward construction (and comparison) of counterfactual estimates. Differently, conditional approaches require counterfactual estimates of the conditional factors (Schaller et al. 2016). In the case of AGCMs this entails inferences on how the observed SST/SIC pattern could have been without anthropogenic forcings. To estimate the anthropogenic contribution to the observed SST/SIC field, a warming signal[16] is removed from the observed SST/SIC. As this step is not straightforward and involves a substantial degree of uncertainty, several studies use different estimates of counterfactual SST/SIC. The counterfactual world is even more challenging for EEA approaches based on forecast models, since they require estimates for the IBCs. Studies follow different approaches, which typically imply re-simulating the EE after removing thermodynamical signals from the IBCs used for the actual ensemble. The climate change signal can be defined as the climatological difference of free runs with high and low CO_2 (Wang et al. 2016), but most studies simply detrend the IBCs over the available historical period, including (e.g., Kawase et al. 2020; Ma et al. 2022) or not (Reed et al. 2021) the corresponding adjustment of the atmospheric dynamical fields. Ignoring the anthropogenic changes could be justified for atmospheric dynamical fields, but not for others with strong thermodynamical influences (e.g., humidity), which represents an additional source of uncertainty.

Overall, there is a slight preference to use preindustrial conditions (~48%) over a historical natural world (37%), with past/historical periods being less frequently considered (26%; Figure 12). As these definitions are characteristic of specific model families, these framings also correspond to the most frequent choices employed in studies based on AGCMs, GCMs and observational-constrained approaches, respectively. Studies framing a preindustrial counterfactual world mainly rely on: 1) pi-control simulations (e.g., Knutson et al. 2018) or a preindustrial period of the historical simulation of GCMs; 2) preindustrial estimates of SST/GHG/SIC in the case of AGCMs and their embedded RCMs (e.g., Imada et al. 2018). The preindustrial climate typically refers to conditions of a year or period between 1850 and 1900, either simulated explicitly (e.g., pi-control runs) or inferred by statistical approaches (e.g. a trend-based analysis of the variable over the historical period against the global mean temperature; Section 7). Concerning the category of natural forcings only, there is no preferred period to define the counterfactual world. When the chosen interval is stated, studies use either the entire (or most of the) historical period (e.g., Oliver et al. 2018) or a recent period closer to the observed EE (e.g. second half of the natural 20th century; e.g., Yuan et al. 2018). The same lack of consistency applies to Past/Historical periods, which are often chosen in terms of data availability (this category is dominated by observational-based studies). When possible, they cover the early or first half of 20th century (e.g., Pei et al. 2022), but in some cases, the counterfactual period does not extend before the 1980s, particularly for HP or DRs defined from land-surface data (e.g., Hoell et al. 2019). Only very few global model studies consider historical periods as counterfactual, including: 1) AMIP-like AGCM simulations, run with the observed evolution of SST/GHG/SIC conditions for some historical period (e.g., Wang et al. 2019b); 2) weather or seasonal forecast ensembles initialised with past/historical IBCs (e.g., Reed et al. 2021); 3) RCMs driven by GCMs, for which preindustrial or natural simulations are not available (e.g., Vautard et al. 2018; Kew et al. 2019).

[16] This anthropogenic signal is often obtained by subtracting historical and preindustrial simulations, or historical and natural runs, although in some cases, only the GHG (or the atmospheric composition) part of the anthropogenic forcing is considered, which does not account for all anthropogenic influences.

As many EEA studies use different datasets (which often imply different counterfactuals), this results in a balanced distribution of counterfactual categories for all EEs, with small differences in the preferred choices across types of EEs. However, the comparison of counterfactual periods within the same dataset is not common in BAMS, although it has an impact (Hauser et al. 2017). In all types of EE, preindustrial estimates tend to dominate (with frequencies above 46%). However, natural forcings only are also very common, particularly for thermodynamical EEs (HEs and DRs). HP is the EE for which past/historical counterfactuals are more frequently employed (~42%), reflecting the influence of highly-conditioned approaches.

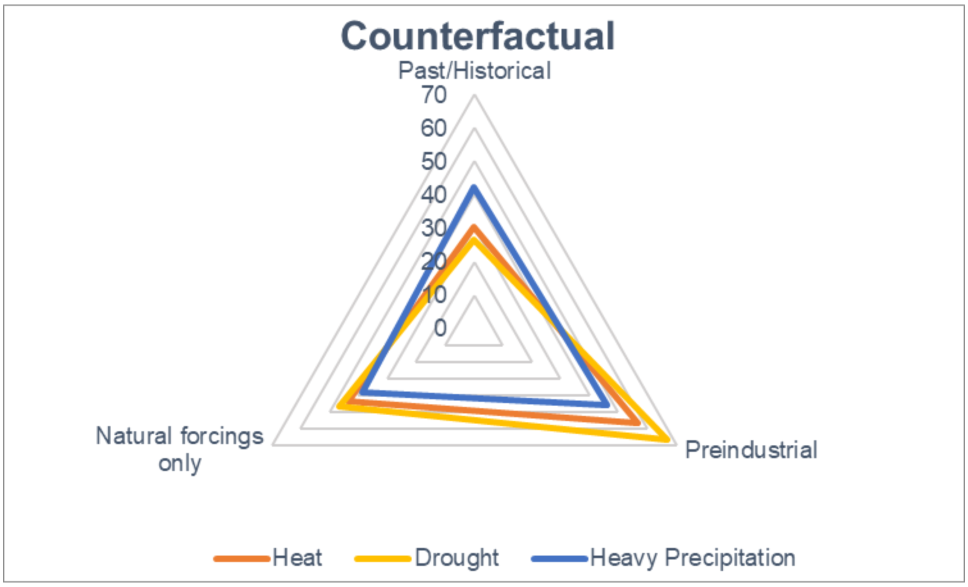

Figure 12 Frequency distribution of categories for the Counterfactual framing by type of EE (in percentage of the total number of case studies for each type of EE). Note that for a given type of EE the sum of frequencies for all categories can exceed 100%, since the same study can use different categories.

9. QUANTIFICATION OF CLIMATE CHANGE INFLUENCE

9.1 Level of conditionality

The level of conditionality refers to the degree of consideration of potential drivers of the EE in the EEA exercise. It affects the class of EE that is being attributed and hence the quantification of climate change influences. Attending to the level of conditionality, and as a first approximation, there are basically two major approaches in EEA, which can lead to very different results (Harrington 2017):

Unconditional: Unconditional attribution links climate change with a class of EE or its impacts, howsoever caused. In this case, the framing question applies to all EEs of that class (e.g., all HWs above a threshold), even if they have not happened yet. As a consequence, the quantification of changes is only conditional on the climate change definition (Section 8) and the specific biases of the datasets employed. This choice is only possible in studies based on observations / reanalyses or GCMs unless they attempt to control some feature of the state of the climate system (e.g., by selecting specific years with a given state such as El Niño).

Conditional: Conditional attribution links the class of EE with the combined influences of climate change and a certain state of the climate system that accompanied the occurrence of the observed EE. This conditional factor is an internal element of the climate system which arguably played a role in the occurrence of the EE (e.g., a precursor). In conditional approaches, the class of EEs becomes closer to the conditions under which the actual EE occurred. This choice is contingent upon the hypothesis that the causal chain that triggered the observed EE can be reproduced in whole or in part. Highly conditioned approaches (e.g. forecasts) are extreme cases of this kind, which try to recreate the observed EE so that the attribution question is whether an exact replicate of the singular EE is influenced by climate change. As conditional approaches only consider a subset of EEs (e.g., all HWs above a threshold that happened under the occurrence of the conditional factor) they deal with conditional probabilities. Therefore, conditional EEA can address changes in the magnitude of the EE but cannot fully account for the overall changes in its probability of occurrence because the conditional probability is different to the total (unconditional) probability, unless there is no influence of the conditional factor on the EE. By imposing and fixing some observed constraints, conditioning may help to control the sources of uncertainty and improve signal-to-noise ratios. As a drawback, conditional analyses do not explicitly account for potential climate change influences in the likelihood of occurrence of the conditional factor.

There are too many variants and degrees of conditioning on EEA. Therefore, according to the reviewed papers, this framing was classified in the following categories: 1) Unconditional; 2) Conditional to SST and/or SIC patterns; 3) Conditional to other factors (atmospheric, land and/or oceanic states). The latter includes several degrees of conditionality, ranging from some canonical patterns (e.g., North Atlantic Oscillation, NAO, or El Niño-Southern Oscillation, ENSO) to the actual atmospheric and oceanic patterns of the EE. We note that there is some overlap between 2) and 3) in what concerns the consideration of oceanic factors. However, the distinction is opportune, since the observed SST fields do not necessarily match onto the canonical patterns of oceanic variability, and even when they do, global SST patterns can also account for additional influences unrelated to these oceanic modes. Some datasets are by construction conditional approaches, whereas others allow conditional or unconditional framings. Conditional approaches can be employed in observations/reanalysis (e.g., the flow analogue method, which is conditional to the atmospheric circulation) or GCMs (e.g., when the conditioning deals with large-scale modes of internal variability such as ENSO). Approaches based on AGCMs (or RCMs nested in AGCMs) are by definition conditional approaches (on the SST/SIC), since they prescribe the same SST/SIC states in all members. Moreover, they neglect any effect of the atmosphere on the air-sea coupling at the temporal scale of the EE (Risser et al. 2017), a hypothesis that might not be justified, particularly for HP (Angélil et al. 2017). Overall, assumptions increase with the degree of conditionality, as do the uncertainties related to counterfactual estimates (e.g., IBCs in forecast approaches).

In BAMS (2018-2022), there is some tendency to use unconditional approaches (61%), partially reflecting the preference for GCM-based studies (Figure 13). Conditional approaches often rely on thermodynamical constraints (typically SST/SIC patterns; 46%), for which the influence of climate change is clear. However, other ways of conditioning are also employed (~42%). Within this category, the most common conditional factor (~18% of studies) is an SST-related internal mode of variability (typically ENSO) being in a given phase (e.g., El Niño; Brainard et al. 2018; Williams et al. 2020). This approach can help to better isolate causal factors, but could also blur or misinterpret the signal (e.g., if there are different influences of eastern vs central Pacific El Niño events). Conditioning can also be constrained by a precursor not clearly related to climate change, i.e., a dynamical conditioning (Trenberth et al. 2015; Shepherd 2016; Yiou et al. 2017), this choice being used in ~16% of the BAMS case studies. The constraints used in this approach are of varying nature in terms of the metric (e.g., sea level pressure, tailored indices, etc.) and the approach to define when the conditional factor occurs. They include the identification of spatial patterns similar to the observed one (by using flow analogues, e.g., Jézéquel et al 2018b; Barriopedro et al. 2020; Yiou et al 2020; Qian et al 2022 or highly correlated patterns, e.g. Christidis et al. 2018; Zhou et al. 2018; Lu et al. 2022), specific thresholds for pre-defined indices of atmospheric circulation (e.g. Funk et al. 2019; Zhou et al. 2021) or simply the states of a given atmospheric mode of variability (e.g. Arctic Oscillation/NAO; Du et al. 2020; Kam et al. 2022; Qian et al. 2020). In most of these cases, ignoring the climate change signal on the conditional factor is a justifiable decision (being more likely small or very uncertain), which further avoids the need of constructing counterfactual estimates for the conditional factor. The remaining cases (~7%) correspond to highly conditioned forecast approaches constrained by the atmospheric and oceanic states at the time of the EE.

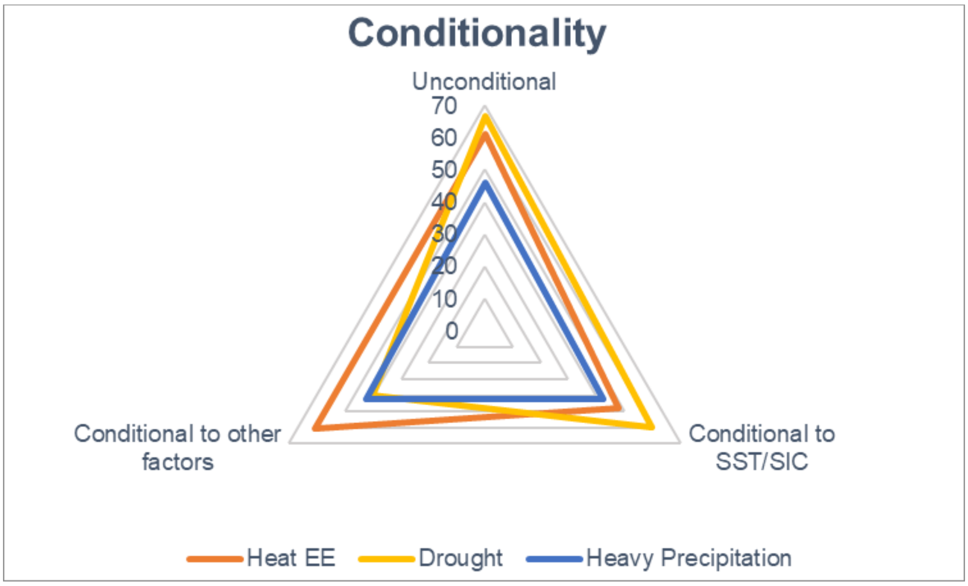

Figure 13 Frequency distribution of categories for the Conditionality framing by type of EE (in percentage of the total number of case studies for each type of EE). Note that for a given type of EE the sum of frequencies for all categories can exceed 100%, since the same study can use different categories.

Frequently, authors tend to adopt unconditional and conditional approaches for the same EE, which results in high frequencies of all categories in Figure 13. However, conditional approaches more often do not assess the influence of the conditional factor on the EE or the sensitivity of the attribution statements to different states of the conditional factor (e.g., whether results differ under El Niño or La Niña conditions). Concerning the types of EEs, all of them are preferably addressed in an unconditional manner (with frequencies ~60% or higher), although there is also a high frequency of studies conditioning on either SST/SIC (particularly for DRs, 60%) and other factors (particularly for HEs, ~69%). The distribution of categories is more balanced for HP than other EEs (all categories with frequencies above 40%). They are the only EEs for which highly conditioned approaches are applied (~19%). Other ways of conditioning are more commonly employed to address HEs and DRs, with some differences in the preferred conditional factor (the atmospheric circulation for ~35% of HEs and oceanic states for ~27% of DRs). The latter could be explained by the dissimilar characteristic time-scales of these EEs and reflects that different drivers are considered relevant for different types of EEs.

A novel conditional approach that is missing within the reviewed BAMS papers is the storyline approach (e.g., Shepherd 2016), although it still lacks from an established methodology. This approach addresses the EE in a strongly conditioned manner by dissecting different relevant factors, being particularly attractive to assess the associated impacts and narratives of compound EEs. To do so, the atmospheric circulation is often nudged to the observed one, and experiments are run for different states of other relevant factors affecting the EE (e.g., different levels of anthropogenic forcings and SST warming) so that the contributing role of these causal factors can be assessed separately or in combination (e.g., van Garderen et al. 2021). Nudging to the observed atmospheric circulation is also applied to the counterfactual experiments, thus avoiding counterfactual estimates under the assumption that circulation responses to climate change are so small and/or uncertain that can be ignored. That way, several storylines can be constructed to infer how the EE could have been (or will be in the future) under combined influences of its drivers.

9.2 Metric

When climate change influence is detected on a EE, the change of the EE that is being attributed needs to be specified, because changes in climate result in changes in the magnitude and probability of EEs. Being traditionally ignored, this issue has been shown to draw seemingly conflicting conclusions for the same EE. For example, for the 2010 Russian HW, one study stated that the EE was largely natural because temperature anomalies were more than those explainable by long-term trends (Dole et al. 2011), whereas another work concluded that climate change increased the probability of occurrence of such an EE (Rahmstorf and Coumou 2011). This apparent contradiction can be reconciled by understanding that these two studies answered the attribution question in different ways (Otto et al. 2012): a small change in warming corresponded to a large change in frequency and hence the interpretation of a climate change influence depends on whether the interest is in changes in frequency for a given magnitude or changes in magnitude for a given frequency (e.g., Seneviratne et al., 2021; Figure 14). A similar situation occurred for the 2011 Texas HW – DR compound event. Hoerling et al. (2013) concluded that the EE was largely caused by natural variability and La Niña conditions at the time of the EE, whereas Rupp et al. (2012) reported that HWs in Texas were ~20 times more likely for 2008 La Niña conditions than during the 1960s. The first analysis focused on what caused most of the magnitude of the anomalies, whereas the latter focused on the changes in the probability of the EE.

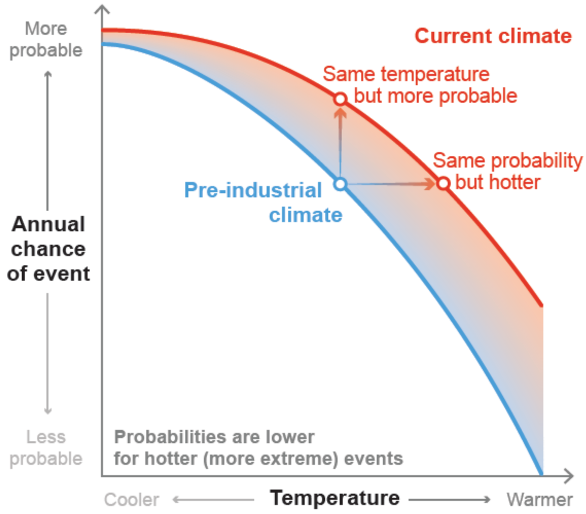

Figure 14 Example of changes in EEs between factual (orange) and counterfactual (blue) climates. The horizontal axis shows the magnitude of the EE, while the vertical axis shows the corresponding annual chance of occurrence. For a given EE in the counterfactual world (white dot in blue curve), the vertical coloured arrow measures the increase in its probability of occurrence, whereas the horizontal one gives the increase in magnitude due to climate change. Depending on the considered EE, these two changes can be very different. After Seneviratne et al. (2021).

Therefore, it is of paramount importance to clearly state whether changes in probability or intensity are being attributed to climate change, since these different metrics can give seemingly conflicting results, without fundamental contradiction. This framing choice is now clearly stated in most BAMS reports, and it is considered herein, distinguishing between studies that address: 1) changes in frequency (probability); 2) changes in intensity. There are not specific pros and cons on choosing one or another category. However, we should note that changes in probability may refer to the overall changes in the frequency of occurrence of the class of EE or changes that occur under a given precursor (conditional probability). The quantification of changes in intensity can also vary with conditioning and is more often stated in a deterministic way (e.g., 'climate change made that HW 2ºC warmer'), which partially hinders the probabilistic nature of EEA, but it is less liable to misinterpretation by the public. In both cases, the quantification should be accompanied by confidence estimates.

It is worth mentioning that in some cases the EE is not directly attributed to climate change but to a precursor of the EE and the role of climate change on that specific precursor. However, this category was not considered herein because we did not find studies that strictly follow this approach (without quantifying changes in the frequency/intensity of the EE). A possible exception is Navarro et al. (2019). They explored the contribution of low sea ice extent over the Barents-Kara sea to the heavy 2016-2017 winter precipitation over Europe by running hindcast simulations initialised for that season and the same ensemble set but with sea ice conditions close to climatology. The sea ice state was found to play an important role on the EE, which can be linked to climate change on the basis of the anthropogenic influences in the recent sea ice decline. Examples of this kind represent the so-called multi-step or indirect attribution (e.g., Knutson et al. 2017): the EE is indirectly attributed based on a change in closely related climate conditions (or precursors) that can be attributed to climate change. This approach can be used to address challenging EEs or impacts associated with EEs (where there are multiple confounding factors), as long as a chain of mechanisms based on physical understanding is provided (e.g., an unusually high intensity of a TC may be attributable if it can be related to concurrent extremely warm SSTs and if the latter can be attributed to climate change). The EEA results can reduce the chances of a false negative (incorrectly concluding that climate change had no influence) but increase those of false positives (incorrectly concluding that anthropogenic climate change had an influence, by e.g., disregarding other factors contributing to the EE).

In the analysed BAMS reports, there is a clear tendency towards a frequency framing (76%), although a substantial number of studies quantify changes in intensity or in both (24%). The frequency-based framing is slightly more common in HEs (~83%) than in the other types of EEs (about 70%). We also note that changes in intensity are more often addressed in conditional studies for which the overall changes in frequency cannot be quantified, including forecast-based approaches (e.g., Ma et al. 2022), flow-analogue methods (e.g., Jézéquel et al. 2018b) and ENSO-conditioned approaches (e.g., Quan et al. 2018).

10. CONCLUSIONS

EEA quantifies climate change influences in the probability of occurrence, magnitude or driving factors of a particular EE. However, the extent to which an EE is attributable to climate change is a question that can be framed in various ways, and the answer depends on the framing. This D reviews current approaches for EEA, and provides a database collection of EEA case studies for different types of EEs. The D builds upon a review of EEA literature and 107 EEA studies published in the last five BAMS reports (2018-2022) 'Explaining Extreme Events from a climate perspective'.

Based on the reviewed literature, the multiple ways to attribute single EEs to climate change are defined in terms of eight key framing elements of the methodological setup. They concern different aspects of the definition of the EE, the choice of the dataset employed for EEA, the definition of climate change and the quantification of climate change influences on the EE. That way, EEA approaches are decomposed in their defining elements (framings) and classified according to the specific way these items are defined (framing categories). The D describes the implications and assumptions of each framing choice and the preferred one employed for the attribution of the three most frequent types of EEs of the database collection: HEs, DRs and HP.

The analysis has been performed considering each framing element of the EEA approach separately. However, the EEA approach only becomes completely defined when all choices of the methodological design have been made. Therefore, in this section, the EEA studies of the database are analysed in terms of the eight-tuple of categories (the specific combination of choices made for all framings) that define the EEA approach. This makes the ensemble of EEA approaches (all combinations of categories) amenable to analysis. As a summary, Table 2 presents the most likely combinations of framing categories for each type of EE (note that the number of BAMS studies that follow a specific EEA approach can be low). Based on this joint analysis and the separated assessment of EEA approaches by framing, the following conclusions are obtained:

Critical framings: When constructing the EEA approach, some choices are clearly preferred by the authors and for all types of EEs (e.g., regional spatial scales, preindustrial counterfactual worlds and metrics related to changes in the frequency of the EE). While these choices might not always be the optimal ones for all cases, they denote a general consensus in the scientific community (and a general perception that those methodological aspects are not the most critical ones for EEA). Other framings vary with the type of EE, but show relatively high consistency within studies addressing that type of EE. They include the temporal scale (longer periods as one moves from HP, to HEs and DRs) and the defining variable (a tendency to use basic meteorological fields for HEs and HP, and more complex indicators for multi-variated EEs such as DRs). A third group of framings are those that are loosely defined by the authors (meaning that they are not considered decisive for the results), an example being the choice of the factual world. Finally, other elements of the EEA approach show a balanced distribution of categories for all types of EEs, and hence little agreement on any choice. This results from a generalised tendency to test the sensitivity of the results to changes in those framings, meaning that they are perceived as sensitive choices. In particular, critical decisions are related to the choice of the dataset and the degree of conditionality on the observed conditions at the time of the EE (i.e., the proximity of the class of EE to the observed EE). These two framings are somewhat related (by the way model experiments are designed) and explain a substantial part of the spread in the adopted approaches (Table 2).

Table 2 Preferred approaches for EEA of different types of EE (rows). Columns show the eight framing elements of the EEA approach. Each EEA approach is described by eight categories representing the specific choices made during the methodological design. For each EE, the most frequent combinations of framing choices in the database collection of BAMS reports (2018-2022) are shown. They account for at least 50% of all approaches adopted for that type of EE. Only EEs with a minimum number of (at least 10) case studies are considered.

<table>
<tr><th>EE Type</th><th colspan="3">EE Definition</th><th>Dataset</th><th colspan="2">Climate Change Definition</th><th colspan="2">Quantification of climate change influence</th></tr>
<tr><th></th><th>Spatial</th><th>Temporal</th><th>Variable</th><th>Dataset</th><th>Counterfactual</th><th>Factual</th><th>Conditionality</th><th>Metric</th></tr>
<tr><td rowspan="3">HE (23)</td><td rowspan="3">Regional</td><td>Multi-month</td><td>Temperature</td><td>GCMs</td><td>Natural</td><td>Present</td><td>Unconditional</td><td>Frequency</td></tr>
<tr><td rowspan="2">Sub-monthly</td><td rowspan="2">Temperature</td><td>AGCMs</td><td>Preindustrial</td><td>Present</td><td>Conditional to SST/SIC</td><td>Frequency</td></tr>
<tr><td>Observations</td><td>Historical</td><td>Present</td><td>Conditional to other</td><td>Intensity</td></tr>
<tr><td rowspan="3">DR (17)</td><td rowspan="3">Regional</td><td rowspan="3">Multi-month</td><td rowspan="2">Precipitation</td><td>AGCMs</td><td>Preindustrial</td><td>Historical</td><td>Conditional to SST/SIC</td><td>Frequency</td></tr>
<tr><td>GCMs</td><td>Natural</td><td>Historical</td><td>Unconditional</td><td>Frequency</td></tr>
<tr><td>Index</td><td>AGCMs</td><td>Preindustrial</td><td>Historical</td><td>Conditional to SST/SIC</td><td>Frequency</td></tr>
<tr><td rowspan="3">HP (28)</td><td rowspan="3">Regional</td><td rowspan="2">Sub-monthly</td><td rowspan="2">Precipitation</td><td>AGCMs</td><td>Preindustrial</td><td>Present</td><td>Conditional to SST/SIC</td><td>Frequency</td></tr>
<tr><td>GCMs</td><td>Natural</td><td>Present</td><td>Unconditional</td><td>Frequency</td></tr>
<tr><td>Multi-month</td><td>Precipitation</td><td>AGCMs</td><td>Preindustrial</td><td>Present</td><td>Conditional to SST/SIC</td><td>Frequency</td></tr>
</table>

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Types of EE: Concerning the critical elements identified here (the pair dataset-conditionality) studies tend to follow different approaches for different types of EE (Table 2). Assuming that for a given type of EE the most frequent way of EEA is the most suitable one to address that EE, a key conclusion is that the optimal approach varies with the type of EE (even if the same method can be applied to different types of EE). If so, different types of EE may require different approaches, which would hamper the transference (and inter-comparability) of methodologies to other types of EE. For EEs with large thermodynamical influences (HEs and agricultural DRs) the most frequent approach uses GCMs and unconditional attribution. For precipitation-based EEs (herein considering meteorological DRs and HP), the most popular way of EEA relies on high-resolution modelling (AGCMs, RCMs or forecasts) and conditional approaches. There are also differences in the type of conditioning across types of EEs. DRs are frequently addressed by conditioning on some oceanic aspect (even in GCMs) and HEs are more often constrained by the atmospheric states at the time of the observed EE, whereas HP are the only EEs explored in a highly conditioned manner (forecasts).

Therefore, decisions on the EEA approach are guided by the type of EE. This reflects the fact that different types of EE pose different requirements for model fidelity. GCMs are more suitable for EEs on large spatial scales and under a strong thermodynamic control (e.g., HWs, agricultural DRs). EEs that occur on small spatio-temporal scales, depend on precipitation (e.g., meteorological DRs) or are strongly affected by the dynamics (e.g., TCs) are better simulated by high resolution models (e.g. AGCMs or RCMs). Similarly, the degree of conditioning often depends on the type of EE because some EEs are only reasonably represented in specific types of model simulations that are only affordable in a conditional manner. For rare EEs (e.g., TCs), unconditional attribution is challenging and forecasts are often required to guarantee high-resolution and explicit simulation of the EE. Therefore, decisions on the EEA approach are often not made independently of the type of EE, because it somewhat determines its definition (based on the characteristic spatio-temporal scales), and the decision on the type of dataset (the one that can better resolve the EE of interest), which in turn constrains the affordable periods for defining the factual and counterfactual worlds and level of conditioning.

Limitations: For some EEs, the possible ways for EEA are restricted to a few ones, which pose additional challenges and constrain the margin of improvement. This is because advances in EEA do not only depend on the development of novel approaches, but also on the level of understanding of climate change influences and our current capabilities to observe and simulate these EEs. Typical issues hampering EEA confidence include limited observations, inadequate model performance at the required time scales, low signal-to-noise ratio, model spread or multiple confounding factors. Table 3 shows a summary of current capabilities on EEA for HEs, DRs and TCs, the three major types of EEs defined in CLINT. For this assessment, several aspects have been considered, as identified in the BAMS case studies and the reviewed literature.

Attribution capabilities are higher for some EEs than for others, depending on the length and quality of observations, the spatio-temporal scale of the EE, the ability of climate models to simulate it, and the level of understanding of the physical processes whereby climate change affects the EE. HWs are the simplest events on which to perform attribution because they enjoy long records of observations, are reasonably simulated by models and have direct relationships to global warming (although they are still challenging at local scales). DRs are more complex but still affordable in what concerns their climate drivers (i.e., neglecting non-climate components of the DR such as water use management). TCs are among the most challenging EEs to attribute due to their small spatio-temporal scales, limited capabilities of global climate models to simulate them adequately, and the low confidence in the climate change responses of their dynamical drivers. HWs and DRs have been attributed with multiple observational-based datasets and different types of models (typically GCMs and AGCMs), whereas TCs often require specialised model simulations (e.g., large ensembles of strongly constrained high-resolution forecasts) and the lack of long-term records is still a major limiting factor for EEA. Therefore, future ML developments in D5.2 will focus on improving EEA for EEs that are currently affordable (HWs and DRs) with the CLINT datasets.

Ways of improvement: Focusing on the critical framings identified herein (the pair dataset-conditionality), there are two preferred approaches for EEA: GCM-based unconditional and AGCM-based conditional attribution. This choice does not only affect the EEA results. It has also profound implications in terms of causality and understanding. The first one emphasises the overall changes in the probability / intensity of the EE, irrespectively of how the EE was caused and hence the approach is more statistical (somewhat aligned with the traditional probability-based approach). The second one assumes a role of the conditioning factor on the EE and requires some understanding of the involved processes, therefore being more oriented towards a process-based attribution (or storyline approach).

We identify ways of improvement in both approaches. For example, the GCM-unconditional approach would benefit from the development of methodologies that quantify changes in the spatial pattern of the EE (i.e., fingerprints) and its temporal evolution. An explicit EEA on the evolving patterns of the EE would allow extending the attribution question to other attributes of the EE (e.g., duration, spatial extent, etc.), and to smaller spatio-temporal scales, minimising the sensitivity of the results to the EE definition. On the other hand, the conditional approach (either applied to AGCMs, RCMs or forecasts) requires the design of model experiments for the particular EE, which makes multi-model approaches difficult, and the attribution statements dependent on the chosen model. In addition, conditional approaches more often focus on one single precursor of the EE (typically SST/SIC). Advances would require the development of well-established conditional methodologies that can be applied to GCM simulations to generate multi-model assessments. Moreover, the consideration of multiple drivers of the EE (and their non-linear interactions) would represent a step forward towards a process-based attribution of EEs quantifying the roles of these drivers (and their changes) on the probability / intensity of the EE.

The next D5.2 will explore the added value of ML techniques in this avenue. The application of the same AI strategy (with different implementations or arrangements in architecture) to conditional and unconditional EEA approaches would be highly desirable to define a common framework that allows comparability and transferability to different types of EEs and avoids additional framings to the attribution question. Special attention will be paid to approaches compatible with the datasets employed in CLINT, and the ML developments designed in WP3 and WP4 for the detection and causation of EEs.

Table 3 Summary of current level of understanding and attribution capabilities for different types of EEs, as reported in the literature. This information should be interpreted qualitatively. The assessment is based on subjective judgement of issues (columns) related to the EE definition, EEA approaches, data availability and model performance, physical understanding of climate change influences and current challenges.

EE Type	EE Definition	EE Attribution	Data & Replication	Understanding	Challenges
Heat Extremes 	· Temperature or extreme indices · Diversity of spatio-temporal scales	· Multi-method EEA · Multi-data approaches (observations, reanalyses, GCMs, AGCMs, RCMs)	· Long records · Reasonably represented in models	· Long-term changes attributed to human influence at global and regional scales	· Modelling of land-surface feedbacks · Urban HWs & impacts
Droughts 	· Indices biased to meteorological or agricultural droughts · Large spatio-temporal scales	· Sensitivity to the drought definition (rainfall deficit vs hydrological variables) · GCMs, AGCMs (few hydrological models)	· Regional contrasts in data availability · Medium confidence in model performance	· Robust trends in agricultural droughts for some regions · Role of warming in non-meteorological droughts (evaporation & snowmelt)	· Multiple (& non-climate) factors and timescales · Modelling of vegetation dynamics · Subsurface data & historical trends · Low-frequency variability
Tropical cyclones 	· Index-dependent severity (precipitation storm surge, size, etc.) · Small spatio-temporal scales	· Few EEA studies (none based on observations) · Highly-conditioned approaches (e.g. forecasts) or multi-step EEA	· Short records & uncertainties · Limited GCM resolution (except HighResMIP) and model performance	· Challenging detection of observed trends · Opposing climate change influences in frequency & intensity	· Sample size & continuous indicators · Large ensembles & high-resolution modelling · Low-frequency variability

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