Challenges in the attribution of river flood events

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Abstract

Recent advances in the field of extreme event attribution make it possible to estimate how anthropogenic global warming affects the odds of climate disasters, such as river floods. Extreme event attribution typically uses precipitation as a proxy for flooding. However, hydrological processes and antecedent conditions make the relation between extreme precipitation and floods highly non-linear. In addition, hydrological science informs us that changes in flood occurrence can be strongly driven by changes in land-cover and by other human interventions in the hydrological system, such as irrigation, and construction of dams and levees. These drivers can either amplify, dampen or outweigh the effect of climate change on local flood occurrence, and neglecting them can lead to incorrect attribution statements. Explicitly including flooding will lead to more robust event attribution, and will account for the role of other drivers beyond climate change. Existing attempts are sparse and incomplete. Key challenges are the lack of flood observations and a dedicated flood attribution framework. We argue that the existing probabilistic framework for extreme event attribution can be extended to explicitly include floods for near-natural cases, where flood occurrence was unlikely to be strongly influenced by land-cover change and human hydrological interventions. However, for the many cases where this assumption is not valid, a multi-driver framework for conditional event attribution needs to be established. Explicit flood attribution will require collaboration between climatologists and hydrologists, and promises to better address the needs of flood risk management.

1. Introduction

A warming climate affects precipitation extremes, through both thermodynamic and dynamic processes (Eden et al., 2016). At two thirds of global weather stations, annual precipitation maxima have increased since 1950 (Sun et al., 2021; Westra et al., 2013), and record-breaking daily extremes have significantly increased, especially since the 1980s (Lehmann et al., 2015). These increases are broadly consistent with the thermodynamic effect prescribed by the Clausius-Clapeyron relationship (Fischer & Knutti, 2016). Besides extreme precipitation, peak river discharge is also changing around the globe (Do et al., 2017; Slater et al., 2021), raising questions on the role of anthropogenic climate change in the occurrence of floods (Blöschl et al., 2017; Kundzewicz et al., 2014).

To address questions about the effect of climate change on specific extreme weather events, a research line has emerged in the last two decades, called extreme event attribution. This field evolved from detection and attribution of the so-called "fingerprints" of anthropogenic global warming (Stone & Allen, 2005; Stott et al., 2004). Several methods have been proposed (Uhe et al., 2016). The key concepts underlying these methods are: 1) to detect trends in the observed historical occurrence of events as the one in question, or more extreme; and 2) if a trend emerges, to assess the potential influence of climate change on the probability of the event, by comparing results from climate models of the factual climate (i.e., with anthropogenic greenhouse forcing) and of the counterfactual climate (i.e., with pre-industrial levels of greenhouse forcing) (NASEM, 2016). This is sometimes referred to as 'probabilistic' extreme event attribution, as it allows to make probabilistic attribution statements. A main motivation behind this research is to address the pressing societal and policy questions about the cause of the disaster. Reflecting the urgency of the questions, these studies are frequently and prominently featured in the media (Osaka et al., 2020). For example, the popular website Carbon Brief maintains an inventory of attribution studies, in an interactive global map (Fig. 1). Out of 504 attribution studies, including both peer-reviewed and 'rapid' studies, 126 concern the attribution of "rain and flooding" events. Most of these studies found that the likelihood of the event was significantly altered by climate change (red markers).

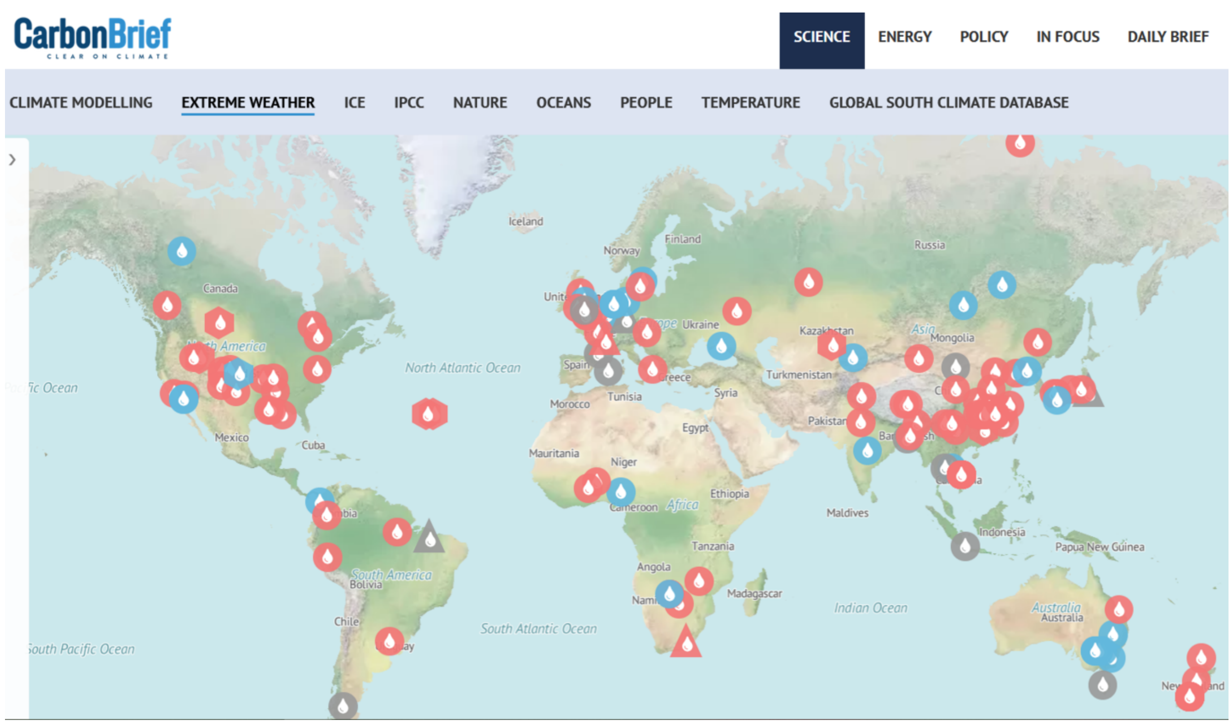

Fig. 1. Global mapping by the website Carbon Brief (2022), including 126 "rain and flooding" attribution studies, published until May 2022. Coloured markers indicate where a significant influence of human alteration of climate is found (red), not found (blue), and where evidence is inconclusive (grey).

1.1 Problem statement and objectives

The interest for attributing an extreme event commonly originates in the severity of the societal impacts (Stone et al., 2021), rather than in its remarkable meteorological features. For instance, there is frequent discussion of a potential role of extreme event attribution in the Loss and Damage Mechanism of the United Nations Framework Convention on Climate Change (Olsson et al., 2022; Parker et al., 2015). Extreme event attribution is typically based on analysis of meteorological variables. During an initial step, called 'event definition' (Philip et al., 2020), researchers define the intensity and domain of the meteorological event that contributed to the disaster (van der Wiel et al., 2017). For example, for the pluvial floods of July 28th 2014 in the Netherlands, the event was defined as equal or surpassing 132 mm of daily precipitation over the whole country (Eden et al., 2018). However, in the case of river floods, which we consider here, it is not the extreme precipitation that directly causes the socioeconomic impacts. Impacts scale rather with the magnitude of the flood hazard, commonly defined as the "temporary covering by water of land not normally covered by water" (Barredo, 2007). While extreme precipitation does not necessarily lead to flooding, flooding can be generated by moderate precipitation, when other factors are at play (Berghuijs et al., 2019; van der Wiel et al., 2020). Thus, the intensity of precipitation is only a proxy for the magnitude of flood impacts. The validity of this proxy depends on the local context and specific event, but is generally not examined. To bring event attribution closer to the impacts of flooding, two solutions have been attempted: 1) using hydrological models to convert precipitation into discharge (e.g., Schaller et al., 2016; see Section 1.2); 2) directly relating the magnitude of the economic impacts to that of the precipitation event, thus bypassing the complications of solution 1 (Frame et al., 2020). Both approaches are infrequent.

Non-climatological changes can also affect river flood hazard, i.e. by regional and local hydrological changes (Boulange et al., 2021; Munoz et al., 2018; Sebastian et al., 2019; Syvitski & Brakenridge, 2013). The effects of these changes can in some cases oppose those of climate change. For example, dam construction can lower flood occurrence on a given location, even when climate change may have increased it; landscape change from forest to urban can increase flood occurrence at the site and downstream, even when climate change may have lowered it. Furthermore, hydrological change can alter sediment fluxes, in turn leading to geomorphic responses, such as in-channel sedimentation and channel enlargement, that affect the flow capacity of river channels and thus its tendency to flood (Hoffmann et al., 2010). If extreme event attribution included representations of these processes and changes, it would better isolate the influence of climate change on flood occurrence, yielding a more accurate climate attribution. Accordingly, it would also inform on the influence of other key drivers of floods. This addresses the mechanisms behind changes in flood hazards, one of the most pressing questions in hydrology and flood risk management (Blöschl et al., 2019). In the wake of a flood disaster, when the urgency of the problem is clearest to citizens and decision-makers, a multi-driver attribution of the event could offer a strong scientific basis for flood risk management. In fact, while stakeholders see general merit in attribution studies (James et al., 2019; Sippel et al., 2015), they seem doubtful about their present usefulness for the practice of climate adaptation and disaster management (Osaka & Bellamy, 2020).

The science of extreme event attribution has quickly advanced, and methods are becoming standardised (Philip et al., 2020; van Oldenborgh et al., 2021). But an explicit attribution of floods to their multiple drivers is still unattempted. In this Perspective: we summarise recent efforts by the scientific community; we examine the challenges to flood event attribution, differentiating between near-natural cases and cases where substantial hydrological change has occurred; and propose separate solutions for either case.

1.2 State-of-the-art: Hydrological modelling in event attribution

A handful of probabilistic extreme event attribution studies include hydrology in their analysis. Pall et al. (2011) propose runoff as a better proxy for flooding than precipitation, and use a simple precipitation-runoff model, fed with daily precipitation input from global climate model simulations, to produce daily runoff series. They do not compare their results to results that would have been obtained from precipitation alone. They calculate, however, the changes in precipitation that would follow thermodynamically from the warming of air masses, concluding that the fraction of attributable risk is similar across the two approaches. Kay et al. (2011) use the same meteorological input as Pall and colleagues, and expand on that study in two respects. They realise 1-year-long continuous simulations of precipitation-runoff with the semi-distributed model CLASSIC. They thus capture the effects of antecedent conditions in the basin and of spatio-temporal variations in precipitation. Further, they include snow-related processes resulting from temperature change, showing that these have a notable effect on runoff peaks. Schaller et al. (2016) also perform continuous simulations, for four years, and include snow processes, with the same CLASSIC model, this time coupled with the hydrodynamic model JFlow+. They highlight the importance of multi-year antecedent conditions. Moreover, they employ an empirical relationship to infer flooded property from peaks in discharge, assuming absence of flood defences. Kay et al. (2018) apply a similar approach to the larger domain of Great Britain, and also highlight the importance of including flood modelling and snow processes. Philip et al. (2019) aim to systematically assess the difference between attribution either based on precipitation only and with inclusion of modelling of river discharge. For the first time, they use multiple hydrological models: PCR-GLOBWB, SWAT, LISFLOOD and RFM. They find that results of discharge attribution differ from those based on precipitation. Sebastian et al. (2019) use hydrological model Vflo® to simulate discharge in the city of Houston resulting from extreme precipitation associated with Hurricane Harvey. Notably, they separate the effects of urban development and climate change in changing peak discharge, finding that urban development had a larger effect. No event attribution study, to our knowledge, has explicitly modelled flood hazard.

2. Challenges to flood event attribution

We argue that two main challenges limit our capacity to accurately attribute river flood events (Fig. 2): 1) Extreme flooding relates to the triggering precipitation event in highly non-linearly ways, because of the mediating hydrological and hydrodynamic processes. 2) Changes to the hydrological systems have occurred during the period of climate change, adding their influence on the occurrence of floods. These changes include natural and human changes in land cover, other human hydrological interventions, and the geomorphic responses of the river channel. In this section we examine these two challenges.

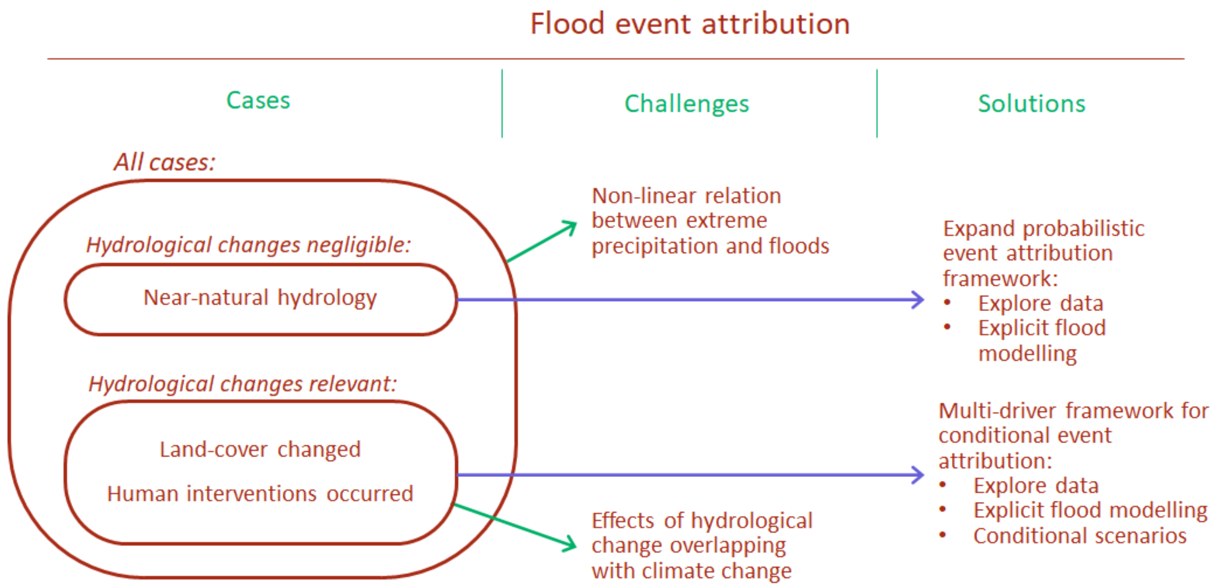

Fig. 2. Conceptual framework of the challenges posed by different cases of flood event attribution, including possible solutions.

2.1 Non-linear relation between extreme precipitation and floods

Shifts in precipitation extremes are not clearly reflected in global flood observations (Berghuijs & Slater, 2023; Blöschl et al., 2017; Do et al., 2017; Kundzewicz et al., 2014; Slater et al., 2021; Zhang et al., 2022). To examine where trends of extreme precipitation and of extreme discharge converge and diverge in sign, we calculated significant trends in annual multi-day extreme precipitation based on the ERA5 climate reanalysis dataset (Harrigan et al., 2020), and in extreme discharge based on the dataset GloFAS, which is modelled based on ERA5 meteorological forcing (Hersbach et al., 2020), for the period 1979-2020 (Fig. 3). Although over most locations the sign of trends in discharge extremes matches that of precipitation extremes (orange and green colours), for many locations an increase in precipitation extremes is matched by a decrease in discharge extremes (blue). Locations where decrease in precipitation extremes is matched by an increase in discharge extremes (purple) are very rare.

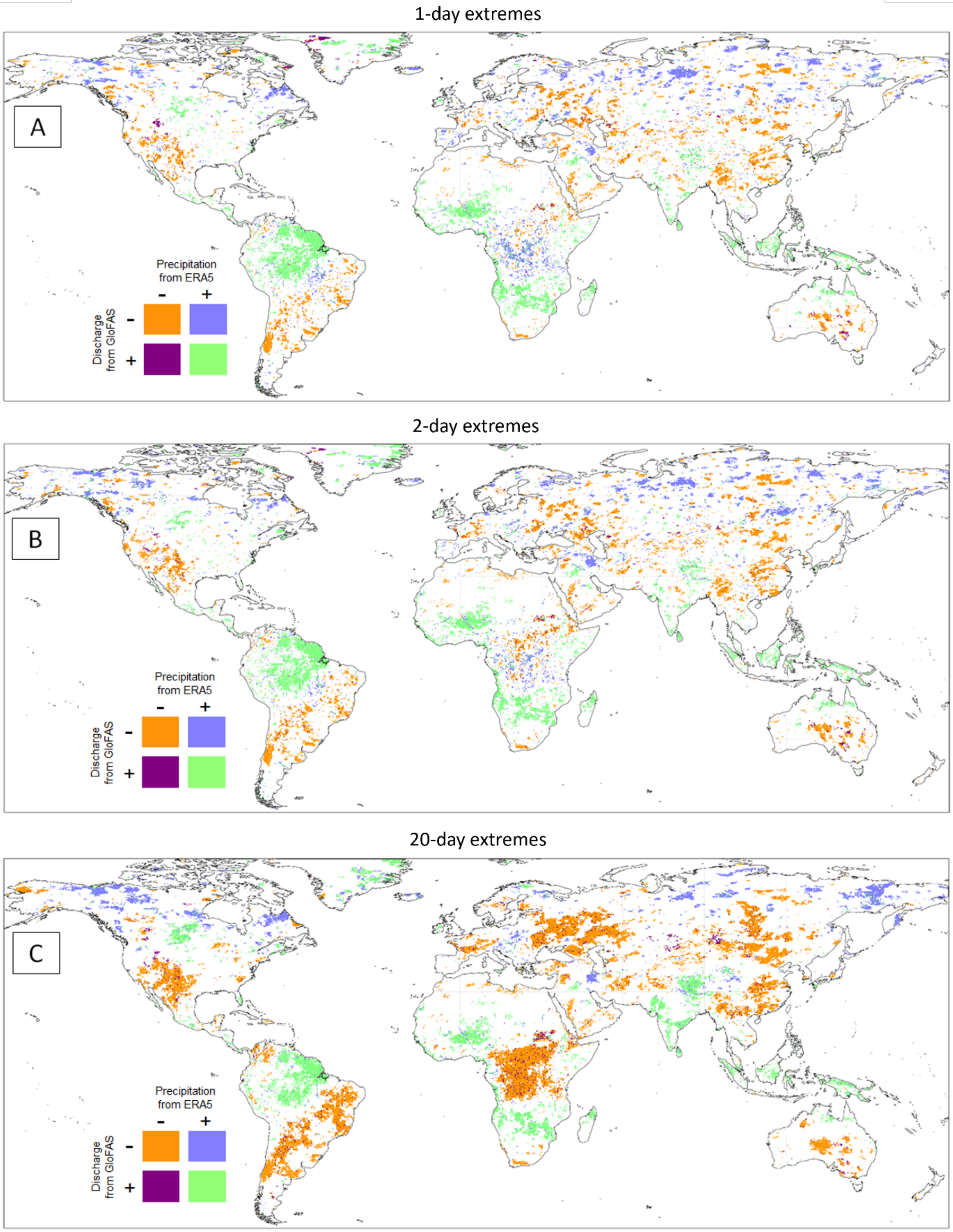

Fig. 3. Convergence and divergence in the sign of significant trends in extremes of precipitation and of

discharge, for period 1979-2020. This is calculated for annual maximum cumulative values of precipitation and of discharge during consecutive periods of 1-day (panel A), 2-day (B) and 20-day (C). Colours show where precipitation and discharge extremes both increase (green), both decrease (orange), where precipitation increases while discharge decreases (blue), and where precipitation decreases while discharge increases (purple). Precipitation data are from ERA5 (Hersbach et al., 2020), and discharge data are from GloFAS (Harrigan et al., 2020). Trend significance is assessed with the Mann-Kendall test.

2.1.1 Mechanisms of river flood generation

The discrepancies in trends are due to non-linear relations between precipitation and flooding, generated by multi-step mediating processes. In a first step, part of precipitation is converted into runoff. In a second step, runoff accumulates into river discharge. In a final step, a portion of discharge can be converted into flood water during an extreme event when river bankfull conditions are exceeded. The first two steps are mediated by processes related to hydrology, like evapotranspiration and infiltration. These are determined by the characteristics of the land surface: slope, soil, vegetation, land-cover, and river network. The second and third steps are mediated by hydrodynamic processes, determined by the hydraulic characteristics of the river channel and of the floodplain.

The spatial and temporal pattern in which these processes play out is essential in determining their outcome. A key determinant is the state of the relevant components of the water cycle at the time of the precipitation event: the antecedent conditions. Key antecedents are: the amount of snow priorly accumulated in the mountainous part of the basin and the timing of its thawing (Berghuijs et al., 2016; Huntingford et al., 2014; Musselman et al., 2018); the level of moisture of the upper parts of the soil (Neri et al., 2019; Tramblay et al., 2019; Wasko & Nathan, 2019); for large-scale basins and events, the level of groundwater. In geographies where these phenomena are seasonal, flood occurrence will typically have strong seasonality (Rottler et al., 2021). For example, the same precipitation event can more likely result in flooding during springtime than summer (Schaller et al., 2014), due to the higher infiltration capacity of summer soils, which contain lower moisture due to higher temperatures and evapotranspiration. More recently, attention is raised to drought as an aggravating antecedent factor for floods (Rashid & Wahl, 2022), whereby soil permeability is reduced by protracted dry conditions (Alaoui et al., 2018). An example of this phenomenon unfolded in spring 2023, over vast parts of Northern Italy (NASA_Earth_Observatory, 2023).

2.2 Hydrological change has occurred

Hydrological changes reduce flood hazard, or increase it; some changes still will reduce it at one location while increasing it at another. The key problem for flood attribution is that often these changes have taken place during the period of climate change. As such, hydrological changes can amplify or counterbalance the effect of climate change on flood occurrence, and failing to take them into account vitiates the attribution.

Effects of land-cover change on river discharge and flood are difficult to predict (Kirchner et al., 2020). Changes in land-cover can be natural or anthropogenic; in the latter case they are called land-use change. Observations show that deforestation in 56 developing countries increased flood occurrence during the last decades (Bradshaw et al., 2007). Similarly, Anderson et al. (2022) show that urbanisation and re-forestation have respectively increased and decreased extreme streamflow, in the context of 729 U.S.A. catchments. Similar indications emerge from many modelling studies (e.g., Du et al., 2012).

Other types of human intervention on hydrology have taken place over a large part of the world's rivers (Grill et al., 2019), altering hydrological and hydraulic properties relevant to flooding. Key interventions are: dam construction and management, river bed encroaching, levees and dikes, channelling and water expansion areas, civil structures like roads, bridges and drainage networks, irrigation and groundwater abstraction, and other flood management measures. While most of these interventions are explicitly meant to have a local hydrological effect, e.g., building a levee to reduce local flood hazard, some have unintended hydrological effects, e.g.: irrigation lowers the water table in the soil; river training may increase flood hazard further downstream (Munoz et al., 2018; Vorogushyn & Merz, 2013).

3. Possible solutions for flood event attribution

The challenge of non-linear relations between extreme precipitation and flooding applies to all flood cases, and thus also to cases of near-natural hydrology, where hydrological changes during the time interval of interest can be neglected (Fig. 2). We argue that for these simpler cases an approach that can be explored is the expansion of the existing framework of probabilistic extreme event attribution.

On the other hand, cases where relevant hydrological changes have occurred, i.e., land-cover changes and human hydrological interventions, present the additional challenge that the effect of these flood drivers overlaps with the effect of climate change. For these more complex cases, we argue that it is necessary to establish a multi-driver framework for conditional event attribution.

3.1 Possible solution for near-natural cases

The methods of probabilistic event attribution can be expanded to include representation of the relevant hydrological and hydrodynamic processes, by explicitly using flood data and flood modelling. This allows overcoming the problem posed by the non-linearity between precipitation and floods, in two main respects. First, explicit flood attribution overcomes the errors associated with the initial step of event definition. When using precipitation as a proxy for floods, the precipitation event needs to be defined in terms of intensity and extent in space and time, such that it most closely captures the generation of the flood. This involves arbitrary choices (van Oldenborgh et al., 2021). For example, after consultation with local experts and consideration of impacts, it can be defensible to define the triggering event as the cumulative precipitation over either 2 or 5 days, and over an area of either 500 or 2000 km^2. However, the results of the attribution may strongly diverge in either case (Angélil et al., 2018), requiring sensitivity tests (Luu et al., 2021). If, instead, the definition is an observed metric of flood hazard, this problem is largely negated. Second, explicit flood attribution addresses the issue of antecedent conditions. Multi-year hydrological simulations, followed by flood simulations, can adequately reproduce the state of, e.g., soil moisture and snow pack.

In the following, we explore possible solutions for: the definition of an appropriate flood metric; the availability of suitable flood data; and the flood modelling.

3.1.1 Flood metric

Adding explicit consideration of floods to attribution means that all analysis is based on a metric of flood hazard, instead of precipitation. As established in event attribution science, the event definition should be closely informed by the socio-economic impacts of the event. For any type of exposed element, the impact is primarily determined by the depth of the flood waters. Other relevant quantities are the flow velocity, flood duration, and any pollution or sediment carried by the water (Vogel et al., 2018). The total impact of the event is determined by the sum of the impacts at each point over the flooded area. Therefore, a flood metric that reasonably relates to the total impact is the total flood area. However, since exposure widely varies over the territory, to better approach impacts, a finer analysis should take into account the location of population and of valuable and critical assets.

3.1.2 Flood data

Probabilistic extreme event attribution requires the following categories of data: 1) observed magnitude of the event, for the event definition; 2) time-series of observations, for trend detection; 3) model-based time-series, representing both factual and counterfactual climates, for the actual attribution (Philip et al., 2020).

For the magnitude of the flood event, it is ideal if collaboration with the local relevant institutions is established; the change is then higher that data from remote sensing, gauges or field surveys can be accessed. Sometimes, local measurements are compromised by the flood (Kreienkamp et al., 2021). In the absence of local data, recent products at continental or global scale are potentially suitable replacements:

- Global Drought and Flood Catalogue (He et al., 2020). Includes data on severity, inundation area, inundation fraction and flood duration for events during 1950–2016. It is obtained by merging in situ and remote sensing datasets with land surface and hydrodynamic modelling. Available at https://registry.opendata.aws/global-drought-flood-catalogue/.
- Global Flood Database (Tellman et al., 2021). Includes satellite maps of 913 floods from 2000 to 2018, documented by the Dartmouth Flood Observatory, at 250 m resolution. https://global-flood-database.cloudtostreet.ai/.
- WorldFloods database (Mateo-Garcia et al., 2021). 422 flood maps, satellite-based and validated, for 119 events between 2015 and 2019, assembled from disaster response organisations. https://www.nature.com/articles/s41598-021-86650-z#data-availability.
- European Flood Database (Hall et al., 2015). Includes discharge time-series from >7000 European stations, and coordinates and dates of >170,000 floods during 1960-2010. https://www.eea.europa.eu/data-and-maps/data/external/european-floods-database.
- HANZE dataset (Paprotny & Mengel, 2023). Includes dates, locations, area inundated, number of persons killed and affected, and losses for more than 1500 European floods during 1870-2020. https://www.nature.com/articles/s41597-023-02282-0.
- Flood Phenomena dataset of European floods (EEA, 2018). Includes flood area, impacts and other flood characteristics for more than 11,000 floods during 1980-2015. https://www.eea.europa.eu/data-and-maps/data/european-past-floods.

For future events, ongoing developments in remote sensing are promising. New flood observation data are becoming available, e.g., in the Fractional Water data from NASA's Soil Moisture Active Passive satellite (Du et al., 2021). New algorithms may soon reconstruct near-real time observations of flood area, integrating imaging from satellite and aerial sensors with elevation maps (Muñoz et al., 2021).

Time-series of local observations should have sufficient length for trend detection, ideally covering the whole period of climate change, i.e., the last 150 years, or as a minimum the last 4-5 decades, to capture most of climate change. The key issue is that complete, uniform time-series of floods are very rare. For a few locations, the data listed in the previous section may contain a short time-series of historical floods. Failing that, the next best option is to resort to a flood proxy better than precipitation: river discharge. If that is also not available, the best approach is to use modelling reconstructions that are based on observations or on climate reanalysis. The key datasets are:

- Global Runoff Data Centre (GRDC). Comprises observations for 9900 stations globally of daily or monthly discharge. Length varies, up to 200 years, and reaching until near-present. https://www.bafg.de/GRDC/EN/01_GRDC/grdc_node.html.
- Global Flood Monitoring System (GFMS; Wu et al., 2019). Contains 3-hourly quasi-global (50°S - 50°N) modelled precipitation, runoff, discharge and flood depth, from 2001 to the present with real-time update; the simulation resolution is 1/8°, and results are downscaled to 1 km. It takes precipitation input from several products to run the VIC hydrological model coupled with the DRTR flood model. http://flood.umd.edu/.
- Global Flood Awareness System (GloFAS; Harrigan et al., 2020). Contains daily discharge at 0.1° resolution, from 1979 to the present with real-time update. It takes runoff from hydrological model HTESSEL (part of ERA5 climate reanalysis) to run the hydrodynamic model LISFLOOD. https://www.globalfloods.eu/.
- Global Reach-scale A priori Discharge Estimates (Lin et al., 2019) and Global Reach-Level Flood Reanalysis (Yang et al., 2021). Contains model-based daily discharge for ~2.94 million

river reaches, for 1980-2019. It takes meteorological input from MSWEP v2.1 and other datasets, to run the hydrological model VIC at 0.25° and the river-routing model RAPID. https://www.reachhydro.org/home/records/grades.

3.1.3 Flood modelling

Flood modelling should be used to produce time-series of flood events, based both on observed and on modelled boundary conditions. In probabilistic attribution, the former are needed in the step of trend detection, and the latter are needed in the model-based attribution step that compares floods in factual and counterfactual climates.

To produce an observation-based flood time-series, the modelling chain needs to include both a hydrological and a hydrodynamic modelling step. The hydrological model uses meteorological observations on precipitation and temperature, typically at daily time-step; solve key processes like evapotranspiration, infiltration, exchanges between storage in snow, soil and groundwater; and produce time-series of discharge or runoff at a suitable resolution. In turn, the discharge or runoff series are used in the hydrodynamic model, which solves processes related to the surface flow of water more accurately than the hydrological model, and yields peak discharge and flood metrics.

To produce the entirely model-based flood time-series representing factual and counterfactual climate, the modelling chain is the same, but will take precipitation and temperature from climate models. These could come from the simulations coordinated by the Coupled Model Intercomparison Project Phase 6 (CMIP6). CMIP6 includes simulations called 'piControl', i.e., 'pre-industrial control', reflecting the counterfactual climate of AD 1850 (Eyring et al., 2016), unaffected by anthropogenic greenhouse gas emissions, using constant forcing along the whole duration, of at least 100 years. The factual climate is addressed by the 'historical' simulations of CMIP6. These simulations are transient, meaning that increasing levels of greenhouse gas are applied to reflect the history of anthropogenic emissions during 1850-2014. To extend the series until the present, results of the 'scenarioMIP' experiments of CMIP6 can be used. CMIP6 results are available at https://esgf-node.llnl.gov/projects/cmip6/. Such results have been used to globally simulate high-resolution floods for the pre-industrial (counterfactual) climate (Scussolini et al., 2020), and both pre-industrial and modern (factual) climates (project ISIMIP2b; Lange et al., 2020).

Additionally, to force flood models at higher resolution, results from regional climate models can be used. A group of dynamical downscaling experiments using different regional climate models is coordinated by CORDEX (Diez-Sierra et al., 2022; https://cordex.org/data-access/). These experiments cover 14 continental domains, at resolution between 12 and 50 km. Simulations start at 1950, and thus do not include the pre-industrial, fully counterfactual climate. Also, they are presently based on CMIP5 global climate models, but results based on CMIP6 will become available in the near future.

However, it is necessary to consider whether the meteorological input from global or regional climate models has adequate resolution and skill, especially with respect to convective precipitation events. These fine-scale events are not adequately represented by parameterisation schemes in those models (Coppola et al., 2020). This can be overcome by the recent emergence of convection-permitting climate models, with resolution finer than 4 km (Luu et al., 2022; Manola et al., 2018). Such input into the flood modelling can improve skills in reproducing flood properties. However, this comes at massive computing costs; hence cannot be performed over a large area or for a large ensemble and their application is rare (Pichelli et al., 2021).

Hydrological simulations for attribution should be carried out continuously for multiple years, as first evidenced by Schaller et al. (2016). This is the only way to capture antecedent conditions, as it allows the hydrological model to adjust to long term effects on, e.g., storage of snow, lakes and groundwater (Ajami et al., 2014). Thus, results will also include floods generated by moderate precipitation, for example, when it coincides with snow-melt, or when it occurs after prolonged cold/wet conditions that have saturated the soil in the basin. Ideally, simulations should be run continuously over the whole interval covered by the multi-decadal climate time-series available. If that is computationally too expensive, and if long-term changes in water storage are negligible, a reasonable choice is to apply a threshold to extract extreme events from the precipitation time-series, and to simulate hydrology and floods during multi-year intervals culminating with these events.

The step of model evaluation should include, besides precipitation and temperature, comparison of modelled floods and discharge with the respective observations, both for the event and for historical time-series. For this, the datasets mentioned above can be used.

3.2 Possible solution for complex cases

When relevant hydrological change has occurred, changes in flood occurrence have more than one driver. This is not contemplated in the probabilistic attribution framework, where the question is a variant of "has anthropogenic climate change increased the frequency of events like this one?" (NASEM, 2016).

3.2.1 A multi-driver framework for conditional event attribution

A multi-driver framework should be formulated to address driver-specific questions that condition the attribution on the states of the other drivers. By systematically including and excluding, in the hydrological and hydrodynamic modelling steps, the effect of land-cover change and of human hydrological interventions, explicit flood attribution can disentangle the relevance of each driver, including climate change. Such framework takes inspiration from and goes beyond emerging literature on storyline attribution for flood management (de Bruijn et al., 2016; Sillmann et al., 2021).

The core steps should be: event definition; definition of hydrological drivers; evaluation of the modelling chain; conditional model-based attribution. Whereas in probabilistic attribution the step of trend detection is essential to determine if attribution even makes sense, in a multi-driver framework this is not pertinent, as any driver-specific trends are confounded by the effects of the other drivers. The event definition and the evaluation of the modelling chain present the same challenges as in the near-natural cases discussed above. We here discuss available data about hydrological changes, to inform the definition of the relevant hydrological drivers, and how to represent hydrological changes in models, to enable the conditional model-based attribution.

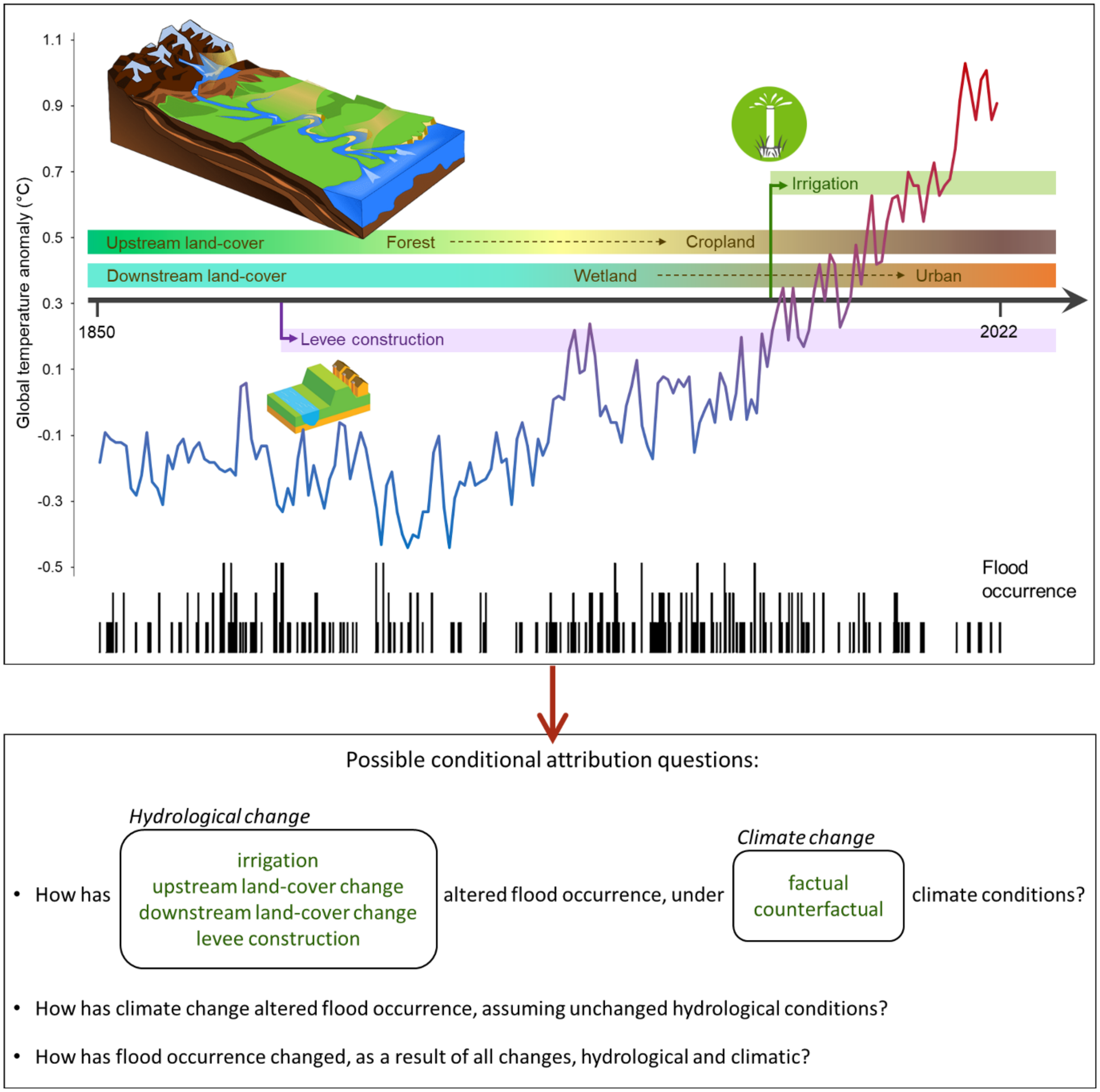

Fig. 4. Conceptual representation of changes through time in drivers of river floods. Global warming, and associated changes in temperature and precipitation, often overlaps with changes in the hydrology, such as land-cover change, construction of levees and large-scale irrigation. Global temperature data are from the National Centers for Environmental Information of NOAA. Flood occurrence data is hypothetical. The bottom box illustrates the questions pertinent to a multi-driver framework for conditional attribution.

To judge which hydrological changes should be included, it is necessary to know the hydrological history of the basin (Fig. 4). Different relevant hydrological changes have likely occurred at different times, and can be very old, as in the case of the Netherlands, where water management has a famously long history (Hoeksema, 2007). Restricting the analysis to the period coinciding with most of climate change, i.e., the last century, makes the problem more tractable, and seems more relevant from the perspective of flood risk management. In the following, we review information on land-cover change and on other human interventions.

3.2.2 Land-cover change

For flood attribution, land-cover (land-use) maps need to be available for the present and also for past periods. Ideally, to ascertain whether changes overlap with climate change, maps should cover ca. the last century. Other relevant aspects are accuracy, resolution and the number of land-cover classes that are differentiated. Fine resolution is especially useful for detailed hydrodynamic modelling in urban contexts, whereas for hydrological modelling of large basins, resolution can be coarser. The priority should be to access any local data curated by regional institutions, which will typically be finer, more accurate, and may extend further back in time. Should this not be available, potentially useful global and continental datasets are:

- Global Land Survey. Global maps curated by the US Geological Survey, for years 1975, 1990, 2000, 2005, 2010, at 30 m of resolution. Available at https://www.usgs.gov/landsat-missions/global-land-survey-gls.
- Global Land Cover and Land Use Change (Potapov et al., 2022). Global maps from satellite imagery, for period 2000-2020, at 30 m of resolution. https://glad.umd.edu/dataset/GLCLUC2020.
- Climate Change Initiative Land Cover V2. Global maps curated by the European Space Agency, from each year between 1992 and 2015, at 300 m of resolution. https://www.esa-landcover-cci.org/.
- Land-Use Harmonization (Hurtt et al., 2020). Global modelled maps for period 850-2100, at 0.25° of resolution. https://luh.umd.edu/.
- Corine Land Cover. Maps over Europe for years 1990, 2000, 2006, 2012, and 2018, at 100 m of resolution. https://land.copernicus.eu/pan-european/corine-land-cover.
- LUCAS LUC V1.1 (Hoffmann, 2022). Annual maps for Europe from 1950 to 2100, at 0.1° of resolution, based on multiple datasets and methods.

If different datasets have comparable merits, including multiple datasets in the modelling could enable quantifying the uncertainty relative to the land-cover. When land-cover changes affect large areas of the river basin, they should be included in the hydrological modelling step. When land-cover changes affect the urban areas adjacent to the flood, it may be appropriate to include them in the hydrodynamic modelling step. Most distributed hydrological models have internal representation of land use for processes as evapotranspiration, canopy interception, infiltration, irrigation (e.g., Horton et al., 2022); however, the associated parametrizations are not evident and are model-dependent. Another aspect that should be considered is whether the land-cover changes had implications for soil properties. Deforestation, for example, is known to cause loss of soil, especially on steep terrain. If this is the case, soil changes should be included in the modelling, either using direct available information, or recurring to assumptions.

3.2.3 Other human interventions on hydrology

Flood attribution requires information on human hydrological interventions: their key features relevant to the modelling, and the timing of their realisation. Similarly, progressive changes to the channel geometry and channel bed elevation as a result of fluvial aggradation or incision need to be assessed. As with land-cover, often the best information should be accessed in collaboration with local authorities. However, there are a few global datasets that can function as alternatives:

- Global Dam Watch. This can be used to assess the presence of dams and reservoirs in the basin upstream of the study area, and the date of construction thereof. http://globaldamwatch.org.
- Global Water Watch (Donchyts et al., 2022). This contains time series of surface area for 71,000 reservoirs. https://www.globalwaterwatch.earth/.
- Historical Irrigation Database (Siebert et al., 2015). This contains information on which global areas are equipped for irrigation, in time-series covering 1900-2005, at 5'of resolution. https://aquaknow.jrc.ec.europa.eu/en/content/historical-irrigation-dataset-hid.
- OpenDELvE (Nienhuis et al., 2022). This contains maps, locations and metadata of known levees over global river deltas. https://www.opendelve.eu/.

These datasets might still miss data for data-poor regions. It could be therefore valuable to try to assess the presence and extent of interventions indirectly, using more general datasets that have recently emerged. For example, HydroATLAS (Linke et al., 2019) contains information on hydrological, climatological, environmental and anthropogenic characteristics of river basins and segments, at 15" of resolution; the database of free-flowing rivers (Grill et al., 2019) contains information about human pressure on river segments, notably on: degree of fragmentation and of regulation by dams; on urban areas, enabling assumptions on the presence of levees and river confinement structures.

The hydrological and hydrodynamic modelling will then need to adopt methods to represent these interventions in the simulations, often by 'burning' them into the elevation map (Wing et al., 2019), and drawing from the large experience documented in the literature (e.g., Remo et al., 2018; Zhao et al., 2016).

4. Whither flood attribution?

We have proposed our view that explicit inclusion of flooding in extreme event attribution is necessary, but complicated by challenges at several levels. In all cases, hydrological/hydrodynamic modelling has to be included, as no existing dataset includes flood events under the factual and counterfactual climate conditions needed for the attribution. An area of advancement will therefore be to tackle these challenges in an expanded probabilistic attribution framework (Section 3.1). This can benefit from the huge progress recently made towards generating historical and near-real-time flood information. Such a framework should include propagation of uncertainties over the additional steps of hydrological and flood modelling, and we expect that uncertainties will grow considerably compared to attribution of precipitation. For most basins and river segments, hydrology is altered (Grill et al., 2019). Here, other drivers of flood occurrence need consideration, and future research should establish and test novel frameworks for attribution. We have illustrated the broad ideas of a multi-driver framework for conditional attribution (Section 3.2). As this framework enables isolating the hydrologic from the climatic drivers, it could also be adapted to include and isolate other climatic drivers, to link the occurrence of the event to specific climate mechanisms. For example, thermodynamic versus dynamic drivers (Diffenbaugh et al., 2017), teleconnections with climatic oscillations, or sea surface temperatures. In the future, efforts could also be made towards a framework to also enable attribution of compound fluvial and coastal floods (Zscheischler & Lehner, 2022).

An interesting advantage offered by an attribution framework that includes representation of past hydrological change, is that with relatively small additional effort, it could also include simulations with possible future changes in land-cover and possible river/flood management measures, in addition to possible climatic scenarios. This would directly connect flood attribution with adaptation and with the policies of flood management (Lahsen & Ribot, 2022; Osaka & Bellamy, 2020).

Besides flood managers, flood attribution could benefit from collaborations with fluvial geomorphologists and paleoflood hydrologists. While dealing with the last decades or century makes the attribution more tractable, historical records or sedimentary evidence for extreme events can expand the limited window of modern observations, and inform on rare high-magnitude events that occurred in the past (Wilhelm et al., 2018). Usually, the offset between the past setting (land-use and river morphology) and the present requires assessment, which may be a challenge for heavily engineered Anthropocene rivers. Despite the uncertainty associated with discharge estimates from paleoflood studies, their inclusion could benefit flood risk attribution as they provide the precedent and the synoptic conditions for such extremes to have occurred in the past (St. George & Mudelsee, 2019). Besides, paleo flood information could enable attribution of older historical floods (Blöschl et al., 2020).

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