Approaches, challenges, and applications of climate change impact attribution

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Author contributions according to the https://credit.niso.org/ system

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Acknowledgements:

The authors thank Kris Ebi for friendly feedback on the manuscript draft and the health data in FIG. 2 and Ana M. Vicedo-Cabrera for providing updated information on the MCC data shown in FIG. 2. We also thank Eva-Maria Poerters for help with document formatting.

We also thank Christian Huggel and Ilon Noy as well as two additional, anonymous reviewers for their thorough reviews and suggestions that have helped improve the paper.

The authors acknowledge funding from the Process-based models for climate impact attribution across sectors (PROCLIAS) European Cooperation in Science and Technology (COST) Action (CA19139) for the workshop 'Bridging Climate and Impact Attribution Workshop' held at the Vrije Universiteit Brussel, Brussels, Belgium, which catalysed this collaborative manuscript. We personally thank Christopher Reyer.

S.U., C.G., and W.T. acknowledge support from the CLIMAKID project (grant number 309498/Z/24/Z, funded by the Wellcome Trust) and S.U. and J.K. acknowledge support from the AFRIVERSE project (grant number 309305/Z/24/Z, funded by the Wellcome Trust). (Y.T.)E.L. is supported by the University of Bristol Climate Change and Health Fellowship, which is jointly supported by the Cabot Institute for the Environment and the Elizabeth Blackwell Institute for Health Research. S.S. acknowledges the projects 'Artificial Intelligence for Enhanced Representation of Processes and Extremes in Earth System Models' (AI4PEX; grant agreement 101137682, funded by the EU's Horizon Europe programme) and the climXtreme project (Phase 2, project PATTETA, grant number 01LP2323C, funded by the German Federal Ministry of Education and Research). D.S. was funded by the New Zealand Ministry of Business, Innovation, and Employment through the Whakahura Project. V.H. received a Ramón y Cajal grant (RYC2022-036948-I) funded by MCIN/AEI/ 10.13039/501100011033 and by "ESF Investing in your future". S.L. was supported by a PhD Fundamental Research Grant by Fonds Wetenschappelijk Onderzoek-Vlaanderen (FWO; 11M7725N). W.T. also acknowledges funding from the European Research Council (ERC) under the European Union's Horizon Framework research and innovation programme (grant agreement No 101124572; 'LACRIMA' project). A.J. is supported by the ENS-PSL MACIF Chair and has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 101003469 (XAIDA) and from state aid managed by the National Research Agency under France 2030 bearing the reference ANR-22-EXTR-0005 (TRACCS-PC4-EXTENDING project).

The authors declare no competing interests.

Abstract

Addressing climate change requires knowledge of its impacts on nature and people. In this review, we depict approaches for attributing climate change impacts and the potential uses for such results. Impact attribution studies identify the drivers of observed changes and events, covering links in the causal chain from anthropogenic greenhouse gases and other human-induced climate forcings to effects on natural and human systems via changes in climate and weather. Various approaches are being applied, utilising both existing observations and constructing data that estimate how a world without climate change could have evolved. Different study designs have varying relevance for raising awareness and for supporting policymakers and other actors in risk management and adaptation, informing Loss and Damage mechanisms, or providing evidence for climate litigation. Knowledge gaps remain that call for input from policy experts globally. In the future, tailored study designs may allow attribution of additional impacts and better quantification of the role of climate change against other drivers, whereas increased transdisciplinary collaboration and organisation may provide standardisation to benefit comparability and synthesis across studies. Addressing remaining challenges will help the impact attribution community produce targeted results for well-framed questions that inform development, implementation, and operationalisation of climate policies.

1 Introduction

In tandem with global warming[1], widespread and rapid changes have occurred in the atmosphere, ocean, and cryosphere[2] since pre-industrial times. This includes 'slow-onset changes' such as glacier melt and sea level rise[3] and an increase of weather and climate extreme events such as heat, extreme precipitation, droughts, tropical cyclones, dry and hot compound events, and fire weather[4]. The link between these changes and events in climate-related systems and human activities that perturb the imbalance in the Earth's energy budget (here: 'climate forcings') is evidenced by *climate attribution* studies[5] (FIG. 1a). These attribute the evolution of a climate variable over time[2] (*detection and attribution*[6–8], *trend attribution*[9]) or the change in likelihood or magnitude of classes of weather or climate events (*event attribution*[4,10–12]). Increasing atmospheric greenhouse gas levels are a factor of particular interest. Their influence on observed climate often can be isolated from that of other human (aerosols, land-use changes) and natural (volcanoes and solar variability) external climate forcings and internal variability with established methods.

Climate and weather influence human and natural systems. This has been observed and commented on across history, and is evidenced and quantified by a wide field of research, such as those from fields like disaster economics providing 'identification of weather sensitivity' studies[5] to studies modelling the impacts of past and future climate. Consequently, *changes* in climate-related systems also lead to impacts on natural and human systems[5,13]. This includes widespread and adverse impacts of heat extremes on agricultural production and human mortality and morbidity, and economic damages from tropical cyclones and river floods, for example[3]. Further impacts are associated with changes in mean climate conditions, including many negative and some positive impacts[5]. A rapidly growing number of *impact attribution* studies[5,14–17] identifies and quantifies these climate change impacts through combining both climate attribution and identification of weather sensitivity and impact assessment aspects (FIG. 1a). Compared to climate attribution, this endeavour is more complex[5] as climate is only one non-stationary factor among many that shape natural and human systems, and these confounding factors are typically much harder to assess than in climate attribution. They regard human behaviour, land use, the location of cities, irrigation, population density, infrastructure resilience, and the quality of medical and emergency services, for example, and can have at least as large an influence on outcomes[18,19].

Attribution, defined by consensus across all three Working Groups of the sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC), is the process of evaluating the contribution of one or more causal factors to observed changes or events in the climate system and in climate-related impacts on natural and human systems[20,21]. A series of milestones have led to this definition (FIG. 1b). Here, we define *impact attribution* specifically as any effort that falls within this definition and captures –possibly among other links– a link between climate change and some outcome in natural and human systems. In other words, *impact attribution* is the process of evaluating the contribution of one or more causal factors *which must include climate change or its drivers* to observed changes or events *in a human or natural system*. For robust attribution, just like in climate attribution, the effect of confounding factors needs to be considered. The definition includes studies as varied as the attribution of burned area via changes in vapour pressure to individual carbon majors[22] and the attribution of neonatal deaths to observed climate change[23].

Attribution studies grow in complexity with the number of causal links covered. For concrete impact cases, the causal chain moreover tends to branch into complex causal pathways, where a pathway is the sequence of intermediate steps or mechanisms linking cause and effect. Hence, there are multiple ways of doing impact attribution studies, and studies are rapidly multiplying in number and diversity using data and methods from climate science, economics, behavioural science, epidemiology, conservation biology, or ecosystem science. At the same time, impact attribution results are already influential in society[16], claiming relevance for debates on Loss & Damage, for risk management and adaptation, and for climate litigation, the latter acknowledged by the International Court of Justice's landmark advisory opinion[24]. Given this public attention on attribution results, it is paramount for the scientific community to clarify differences between approaches, unifying concepts and terminologies, and communicate method-related and general limitations.

In this Review, we document and characterise approaches to climate change impact attribution. We first discuss key steps of impact attribution studies: framing of the analysis; identifying the causal pathways to analyse, selecting impact models, defining counterfactual input data, modelling counterfactual outcomes, deriving attribution results, and navigating uncertainty. We illustrate these steps and the variety of associated choices with the aid of five case studies from the published literature, and summarise observational data as key elements of impact attribution studies. We then discuss the possible societal uses of attribution studies and how they relate to methodological choices. Lastly, we discuss challenges and obstacles to overcome, and propose future perspectives for the field.

2 Approaches to impact attribution

Attribution studies consist of a series of steps. Broadly, researchers choose the specific research question to address and identify causal pathways between climate and other relevant drivers and the impact variable of interest. They then run models with factual and counterfactual input data to derive impacts for factual ('as-is') and counterfactual (as might have been e.g., without climate change, or without some other relevant factor) scenarios. Attribution analysis then comprises a comparison between observed or factual impacts on the one hand, and counterfactual impacts on the other hand. The steps are listed in detail below following IPCC AR6 cross-Working Group guidance[20,21], except that 'noting the quality of observations' is integrated as an essential part of each of steps 1-4 rather than a separate step. Different steps are interdependent, e.g., what framings (step 1) are possible needs to consider the causal understanding and complex linkages (step 2), process understanding and modelling tools (step 3), and data availability (BOX1). Steps can be realised in different ways (case studies I-III in section 2.8).

2.1 Framing the analysis

First, the impact sector(s) of interest is chosen, based on expertise or motivated by interest in a specific weather event and its assumed impacts. Second, the specific impact variable is selected. This could be mortality differentiated by sex and age below or above some threshold[25] or neonatal deaths[23], or yields for a particular crop[26] or agricultural total factor productivity[27]. As impact attribution is about understanding *observed* changes or events in natural or human systems[5], the availability of observational data is important for this choice (BOX1). Availability and accessibility of observations differ by variable (FIG. 2a) and geographical region; data are generally much more extensive and accessible in high-income countries (FIG. 2b) and privileged populations. Where observations do exist, it might not be shared due to privacy-related, practical, political or economic reasons, preventing public research.

A next choice is as to whether to study long-term changes or single events, or both[9]. An 'event' may describe an impact event such as anomalously low crop yields[26,28,29] or a climate or weather event such as a hurricane (BOX2), while trend attribution studies look at changes over time such as areas burned by fires (case study I). Either framework can be applied to the same impact, analysing then for example the streamflow during the 2015-2017 Cape Town "Day Zero" drought[30] (case study II) or long-term trends of annual river flow[31]. The spatial scope and aggregation level can differ too, from global coverage aggregated to sub-continental regions (case study I) down to the provincial scale (case study III). More framing choices are made, especially for event attribution, corresponding to nuances in the research question addressed[32]. Which framing is possible for a given impact or event depends on many factors, including data availability and quality (BOX1).

2.2 Identifying the causal pathways

Given the framing, the possible and plausible drivers of the observed outcome are identified next and a hypothesis or theory for the linkage developed[20,21], for example described by a causal network[33–35]. First, this identifies confounding factors that have to be considered so as not to falsely infer a causal relationship[36,37], including factors that affect the exposure, vulnerability, and resilience to a hazard, some of which are quantified as direct human impact drivers (DHF) datasets in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)[38]. Second, this clarifies the pathways of impact analysed out of the many different ways in which climate change and its drivers can typically influence a specific outcome. They regard different parts of the causal chain and cross-connections therein.

Climate and non-climate drivers are part of the hypothesis. Studies can focus on a specific climate-impact combination such as heat-mortality[23,25] (case study III) or hurricane-economic damages[39–42] (BOX2) or consider many climate-related hazards at once such as heat during sowing and drought during growing both impacting crop yields[26]. Non-climate factors mediate, complement, or confound the effect of climate and weather and are part of the causal network. This can range from land-use change counteracting climate change impacts on fires[43] (case study I) to improperly built drains combining with heavy rain to cause a fatal derailment[44].

The relevant non-climate drivers can be conceptualised as influenced by climate and weather or not. Impact attribution studies so far tend to focus on how climate affects the hazard, although exposure and vulnerability to this hazard might be affected by climate, too. For drought and heat impacts on crop production on small islands, for example, exposure and vulnerability may depend on the site of production linked to sea level and on people’s ability to irrigate using groundwater recharged by precipitation, respectively. As in all nonlinear systems, the response to one driver changes the sensitivity to another, also described in the IPCC by the concept of ‘multiple drivers’[45,46].

Also the link between the climate driver and climate change can be made in different ways. Studies either consider the link to *observed* climate change (case study I) or trace the signal further back to forcing factors that cause *anthropogenic* climate change (case studies II-III and BOX5; FIG. 1a).

Studies may further differentiate between anthropogenic forcing factors, either treating anthropogenic, non-greenhouse gas factors such as aerosols as individual climate forcings of interest[47–49], or as confounding factors to the greenhouse gas signal[50]. Anthropogenic climate-relevant activities can also directly influence human and natural systems, which may or may not be considered. Land use, for example, affects both climate and ecosystems, playing a dual role as climate forcing and DHF[51–53]. Which causal pathways are included in the analysis dictates the definition of the climate counterfactuals ('conditioning', section 2.4.2). Recent studies trace the causal chain even further back to quantify individual emitters' contributions to climate change impacts[54,55].

2.3 Selecting impact models

Next, impact models test and quantify the hypotheses represented by pathways. Models are understood broadly as simulators of the system of interest, i.e., tools that predict responses in the system when presented with one or more inputs[56]. Impact models span from Earth System models with ecosystem aspects[51,57] to single regression functions (case study III). Two broad groups of model types exist, although in practice models invariably fall somewhere in between: process-based and empirical models.

Some impact models are mainly constructed using mechanistic or process-based understanding to make predictions of the system's future behaviour. These are available for physical systems where process-understanding is high and can be represented by computer code, such as hydrology (case study II). Observational data is needed for model evaluation, calibration, and as input for non-climate drivers. For example, process-based models often rely on DHFs as input data (case study I) or have parameter settings that represent exposure and vulnerability to a hazard, such as the heat thresholds at which the grain number of maize is reduced[58].

Other impact models are predominantly empirical, developed as statistical approximations to observations. They are particularly useful outside purely physical systems when important basic processes are poorly understood or when the interactions between processes are too complex to be simulated explicitly. For example, epidemiological models for heat mortality are commonly empirical[59] (case study III), and crop forecasting and risk assessment is often done with empirical models. In empirical models, non-climate drivers may be accounted for or otherwise addressed, i.e., explicitly estimated or directly or indirectly controlled for.

Other examples of empirical models include climate econometric approaches for the effects of climate and weather on social and economic outcomes. These consist of plausible causal identification designs, for example based on cross-sectional-, time-series-, or hybrid approaches such as the long differences approach[60,61]. For example, econometric analysis of age-specific mortality-temperature relationships based on countries' subnational data finds a U-shaped relationship, flattened by higher incomes and adaptation to local climate[62]. Machine learning (ML) models too are empirical, linking bird migration and environmental predictors using Random Forest and Generalized Models[63] or crop yields and agro-climatic indices using a gradient boosting algorithm for impact attribution[64]. Some studies assume a simplistic one-to-one correspondence between the climate-change attributable component of the climate-related hazard and the outcome of interest, such as extreme-event related economic losses and damages[65] (BOX2).

2.4 Defining counterfactual input data

For impact attribution, models are set up to estimate a baseline condition[20,21] of the climate-sensitive outcome using *counterfactual* input data. Counterfactuals describe hypothetical scenarios that could have occurred in the absence of the causal factors of interest[66]. In attribution studies, these are later compared with *factual* or observed scenarios that reflect present-day or historically evolving conditions. Both the factual and counterfactual scenario might be stationary or change over time due to climate and non-climate drivers and internal processes in human and natural systems[5].

The subset of *climate counterfactuals* is essential and describes climate in the absence of climate change. These are constructed through a simulated intervention in anthropogenic or natural climate forcing or derived from observed historical data. The identification of a relevant climate baseline or forcing intervention is challenging[67], depends on the research question, and affects the outcome[68]. Climate counterfactuals and factuals may be *observations-based* using statistical methods[69], or *climate model-based* using different modelling setups that vary in the degree of conditioning to observed climate variability[70].

2.4.1 Observations-based climate counterfactuals

Observations-based counterfactuals aim to remove with statistical methods the component of climate observations that is related to long-term climate change, which is a combination of slowly-varying internal climate variability and natural and anthropogenic forcing[71]. The most widely used form of observations-based counterfactuals in impact attribution are climate variables detrended with respect to time, with climate data from earlier time periods[72,73], or with a co-variate on global-mean temperature[70,74–76]. The rapid-attribution framework ClimaMeter, for example, uses the weather during atmospheric circulation states identified in reanalysis data for a time period in the second half of the twentieth century as the counterfactual analogs to the factual ones in a more recent time period[72].

This type of counterfactuals has benefits and disadvantages. For example, climate counterfactuals within the ISIMIP project[38] were created by regressing out the change with global-mean temperature (ATTRICI; FIG. 3a-b; Supplementary FIG. 1; case study I). This preserves the timing of historical weather and climate variability (including events) so that studies can focus on impact modelling and related uncertainties[19,23,77–82]. The quality of the observations-based climate counterfactual depend directly on the quality of their factual counterpart, the observations themselves: to take out observed climate change since 1900, the method considers changes in reanalysis data since then, which for regions and cases with low observational coverage (BOX1) gives a less useful baseline[83].

2.4.2 Model-based climate counterfactuals

Climate models are extensively used for deriving counterfactuals of long-term changes[84] and for extreme event attribution[10,16,85]. Climate model-based counterfactuals provide physical consistency between variables and changes as input to impact models. A key consideration for model-based counterfactuals is the degree of conditioning, that is, the degree to which certain model settings are constrained to replicate the observed climate state[68,86].

At one pole of conditioning, model-based climate counterfactuals and factuals can be computed with freely evolving *atmosphere-ocean variability* over the historical period with prescribed forcings such as historical anthropogenic and/or natural forcing (DAMIP[87]; case studies II-III; FIG. 3e-f), fixed pre-industrial forcing, or specific single forcings such as greenhouse gases or aerosols[88]. Because the simulations are freely evolving, the timing of variability is not matched with the observed timing – a disadvantage in some attribution studies. *Atmosphere-only variability* counterfactuals introduce a level of conditioning[89,90] by prescribing sea surface temperatures, and are also used widely[91,92] (case study II).

At the opposite pole, storyline approaches use climate model-based counterfactuals and factuals constrained to observed climate events[93,94]. Detailed simulations of the actual event are compared to similar simulations of a counterfactual event, which is informative about changes in magnitude and physical drivers[95]. Because the simulations are shorter, storyline simulations can be of very high fidelity and realism[96]. Methods to generate climate model-based storyline simulations include nudging models to observed atmospheric circulation[51,95](FIG. 3c-d), data assimilation in reanalysis systems[97] and the use of numerical weather prediction simulations starting from the observed state of the atmosphere[98–100], for example. Nudging is considered to be less constraining in the Tropics compared to the Extratropics, imposing a limit on its applicability in the Tropics. Method-induced differences between counterfactuals are hence clearer to see for Northern Europe (FIG. 3) than for the Amazon region[101] (Supplementary FIG. 1).

The more conditioned counterfactual data are on the observed climate state, the fewer pathways of influence of anthropogenic climate forcing are typically captured. Running a conditioned climate model is typically computationally less expensive than an unconditioned model, which moreover requires larger ensembles for useful attribution analysis. Some impact modelling further needs climate data to be bias-corrected and high-resolution[26,102–108]. Event-specific storyline simulations can not be made readily available.

Hybrid methods use a mixture of models and observations[98,99,109,110]. For example, they may estimate counterfactual temperatures by subtracting attributable anomalies of a given meteorological variable from observations, and the attributable anomaly could be quantified not only using observations, but also models, or both. When estimating counterfactuals via detrending, some methods use an estimate of warming caused by anthropogenic greenhouse gas and aerosol emissions (case study III), for instance from the global warming index[111].

2.4.3 Non-climate counterfactuals

Non-climate counterfactuals estimate baselines without (changes in) non-climate drivers[112]. Just as climate counterfactuals describe an anthropogenically-unforced climate that is *not* the case, non-climate counterfactuals describe other things that aren’t the case. Non-climate counterfactuals too are often derived from their factual equivalents. Non-climate counterfactuals may be ignitions and land-use change estimates for pre-industrial times (case study I) or removal of simple estimates of historical adaptation to heat (case study III) when considering them as values for today.

Useful context can be provided by non-climate counterfactuals, for instance investigating how adaptation measures could have moderated impacts, as used in disaster risk reduction studies[113]. For example, one may estimate counterfactual vulnerability and exposure to cyclones[114], counterfactual flood protection levels[18], or counterfactual river management when attributing streamflow droughts[115] (case study II). Such scenarios may be called exposure and/or vulnerability counterfactuals, counterfactual DHFs, or ‘adaptation counterfactuals’. Practically, defining meaningful non-climate counterfactuals can be challenging where multiple drivers and climatic and socio-economic factors interact in complex ways. All counterfactual scenarios are hypothetical and potentially logically inconsistent. Whether they are still useful or not will depend on the application and subsequent interpretation (section 3).

2.5 Modelling counterfactual outcomes

Next, factual and counterfactual *impacts* are estimated from impact models based on the factual and counterfactual input data that correspond to the pathways of interest. Often multiple models are used in sequence for this, such as process-based hydrological and channel routing models (case study II); process-based fire-vegetation models and meta-regression-Bayesian regularized trimmed splines [82]; or several statistical models such as a ML-based yield model and an epidemiological analysis[64]. A special case interprets climate attribution results as directly translatable to impacts, which has the advantage of being feasible for synthesis across a large number of events[40,116]. However, this approach can also be quite inaccurate for individual events (for an example, see BOX2)[117–119].

To model counterfactual impacts with a process-based impact model, settings or additional input data often have to be adjusted from those used to model factual impacts. Practical limitations can be a reason, such as hard-coded parameter thresholds in process-based models. In other cases, model parameters have climate dependencies that are not implemented. For example, using sowing dates calibrated to factual climate can result in crops simulated to be sown in wintery conditions, which is a counterfactual scenario far from plausible and hence likely less useful. Conceptually, this example is an edge case between a model technicality and the choice of considering observed adaptation or not. Similar complexities arise in empirical impact modelling (e.g., case study III), and assessing the fit-for-purpose of a model is key. For example, process-based and empirical models may be more or less suitable for making predictions for counterfactual climate conditions beyond the range of their calibration and training data, respectively.

2.6 Deriving attribution results

Finally, the estimated counterfactual and factual or observed impacts are compared to construct attribution statements. For probabilistic event attribution, factual and counterfactual simulation data are typically pooled across years and/or ensemble members, statistical distributions fitted, and the likelihood of exceeding the observed threshold (by magnitude or via observed return period) estimated[26,29,70]. These calculations can be stratified according to groups of events that occur at a specific warming level[120], within a time window[52,121], or accumulated across lifetimes[122,123]. For example, studies can estimate the experienced number of crop failures or wildfires as a function of someone's year of birth[122]. ML approaches are also starting to be used for event attribution[124].

Classical trend attribution quantifies the probability of observations given factual and counterfactual simulations[31,125–130]. Because non-climate drivers may vary over time, the baseline condition can not be assumed to be stationary[20,21], so that trend detection is not a necessary step in trend attribution. Instead, deviation from the expected trend (e.g., a decrease in burned area due to land-use change and other DHFs in case study I) may imply 'attribution without detection'. When using impact observations as a reference, quality considerations again have to be kept in mind[20,21]. Besides the broad categories of trend and event attribution, impact attribution studies can be typologised further[9].

Non-climate counterfactuals can be used in the same statistical framework as climate counterfactuals. Conceptually, this draws together climate attribution including hazard-focused event attribution[70] with the Disaster Risk Management[131,132] and other literature[133] that assesses the impacts of non-climate drivers via changes in exposure and vulnerability. Putting climate- and not climate-driven changes next to each other or just comparing their relative influence is encouraged by the IPCC AR6 glossary definition of attribution[134,135] and seems beneficial for some applications (section 3). Nonetheless, for other analyses this is not generally feasible, and for some applications might not be desirable, either.

2.7 Navigating uncertainty

All these steps are affected by uncertainty, stemming from various factors, including observational quality (BOX1), and from how well an impact model represents the linkages of interest. Framing choices may be considered an additional source of uncertainty or not[32]. Sometimes, apparent uncertainty diagnosed from seemingly conflicting results[136] are rather answers to different research questions and victims of a very generalised communication of results. For example, simplifying impacts on quantitative crop production and impacts on crop nutrient content as 'impacts on food', or quantifying the climate-only contribution or the combined climate and CO_2 contribution may for some crops give different results but is well-explained by the different pathways analysed. Also attributing only the thermodynamic or also the circulation component of climate forcings[32], or treating DHFs such as land use and water management as (in)dependent of climate change, will give different results[137] that might look like uncertainty upon generalised interpretation. A final example is more subtle framing choices such as stating a change in frequency or in magnitude in (also: impact) event attribution[32]. It is important to ensure that the framing is unambiguously stated[20,21] and that nuances of the research question are not lost in communication.

Focusing on *fewer* causal pathways also helps partition the uncertainty, and can derive useful results where an approach with more pathways might not[93]. For example, given large uncertainty regarding the magnitude of crop yield responses to CO_2 fertilisation[138], an attribution of the climate-only component may still be useful to raise awareness for the potential need for adaptation (section 3). In some cases, it is also not clear which pathway should be considered the most 'complete' for societal use cases, or which pathway should be isolated instead. For example, in international negotiations, Loss and Damage (section 3.2) does not differentiate between anthropogenic and natural climate change, and even less established is whether total anthropogenic or greenhouse gas-only forced climate change is relevant.

Considering *shorter* pathways can be useful where uncertainties propagate and accumulate across analysis chains. Uncertainties in the climate response to forcing, for example, will persist throughout the analysis and generally accumulate additional uncertainties in each impact modelling step[139]. Nonetheless, impacts can also aggregate across climate variables, for example by responding to runoff rather than rainfall[140] or to a combination of temperature and precipitation (case studies I-II). In these cases, the impact attribution result may be associated with less uncertainty than an attribution result for the individual climatic driver such as rainfall. Constraining model spread to quantify and reduce uncertainties[141–143] may also be applicable. A diverse array of modelling frameworks and studies focusing on different pathways within the full causal chain is beneficial to increase the robustness of results[144–146].

2.8 Case studies

2.8.1 Case Study I

Burton, Lampe et al. (2024)[19] quantify the impacts of observed climate change on burned area globally via changes in climate that affect vegetation quantity and dryness and fire spread via windspeed (Fig. 4a-b). The attribution analysis focuses on changes in mean burned area and the likelihood of above-average global burned area during 2003–2019, expressed in percentage terms. Impacts are modelled using an ensemble of process-based fire models. Historical land-use change and population density changes are considered as DHFs: Population density affects human ignitions and, together with crop fraction or Gross Domestic Product, fire suppression. The observations-based climate counterfactuals from ATTRICI are used, and as non-climate counterfactuals, pre-industrial estimates of the DHFs are considered. The impact models are weighted by their ability to reproduce historical burned area patterns. The study finds that observed climate change alone increased global burned area by 15.8% [13.1–18.7] (95% confidence interval) and increased the probability of months with above-average global burned area by 22% [18–26]. Direct human impact drivers alone would have lowered burned area by 19.1% [21.9–15.8]. Depending on the region, the DHF or climate change signal dominates and drives the overall observed change.

2.8.2 Case Study II

Holden et al. (2022)[30] (FIG. 4c-d) attribute changes in drought-period streamflow in South Africa to anthropogenic climate change arising from changes in precipitation and reference evapotranspiration. The analysis focuses on the 2015–2017 Cape Town “Day Zero” drought. Additionally, it is assessed how presence/absence of non-native vegetation modulates the attributable climate change impact under three landcover scenarios: i) actual; ii) restored; iii) fully invaded by non-native vegetation. Impacts are modelled with a physically based hydrological model coupled with a river channel routing model, using daily rainfall, reference evapotranspiration, and local stream gauge data for model validation. Climate counterfactuals come from climate model simulations either without constraints or conditioned on observed sea surface temperatures, with counterfactual and factual samples selected as paired factual–counterfactual attribution runs for the observed drought years (2015-2017) in the constrained simulations; and the driest 3-year running-mean periods across two window periods (1869–1899; 2001–2021) as analogues to the observed drought, in the free-running simulations. Climate model data were bias corrected to local station data using quantile-quantile bias correction. Different levels of invasive non-native tree clearing relative to existing coverages that were present during the drought were modelled as adaptation counterfactuals. The analysis finds that climate change reduced drought streamflow by 12-29% relative to a counterfactual with anthropogenic emissions removed, and that climate change impacts on drought flow could have been ameliorated by up to 16% when nature-based solutions were applied (here clearing the non-native trees in the catchment and restoring the natural vegetation in the catchment).

2.8.3 Case Study III

Stuart Smith et al. (2025)[147] (FIG. 4e-f) quantify heat-related mortality in Zürich, Switzerland that is attributable to anthropogenic climate change. The analysis assesses the attributable burden over 1969–2018, with a case study of summer 2018. Impacts are modelled by deriving an exposure-response association between temperature and mortality, using a widely applied epidemiological method. The study also assesses the impact of changes in the exposure-response association over time. Climate counterfactuals are calculated by subtracting temperature anomalies attributable to climate change from observed temperatures. These attributable anomalies are calculated based on historical-natural and historical climate model simulations (the former taken from the Detection and Attribution Model Intercomparison Project) and a hybrid approach that detrends observations based on model-simulated counterfactual temperatures. Data evaluation reduces the set of models used, and the subtraction of attributable anomalies from observed temperatures circumvents the need for bias correction. Different versions of counterfactual impacts are derived under scenarios where exposure and vulnerability to heat (i.e., the exposure-response association) is fixed or allowed to evolve over time. The analysis finds that nearly 1,700 heat-related deaths are attributable to human-induced climate change over 1969-2018. Reductions in vulnerability since 2004 avoided at least 700 heat-related deaths.

3 Applications

Attribution to causally explain observed processes has scientific value. Moreover, impact attribution can generally underpin impacts projected for future levels of climate change (e.g.,[58,148]), just as climate attribution underpins future climate projections[149]. This is the case not when attribution results are quantitatively used to constrain future projections[150–152], but also more generally by adding confidence that models can capture the processes relevant for attribution and projection.

Existing studies have also explored how attribution can inform law, policy, public awareness, and climate risk management[153]. The interpretation and use of climate and impact attribution studies by interested parties[1] vary depending on the actors, the intended use, and the study’s design and communication (TAB. 1). The evolution of attribution towards a “usable science” happens in a general context of the development of climate services[155]. While projects to operationalise

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[1] Defined here broadly as any individual, group, or institution outside of the scientific community who does or might have an interest in the scientific results, synonymous to what is commonly referred to as 'stakeholders' but avoiding negative associations[154].

attribution have been pursued for a few years[156–160], to our knowledge there is no such climate service, and operationalising is still a perspective at this stage.

3.1 Awareness raising

Attribution can raise awareness on the causes, physical manifestations, and impacts of climate change, and it has been suggested that this can motivate climate action[153]. Detection and attribution of climatic changes, such as rising global temperatures, has been at the heart of the IPCC since its first report[161], playing a key role in demonstrating the human causes of global warming. Recent years have seen a substantial increase in media coverage on the attribution of extreme weather events, making the effects of climate change on specific events tangible for the general public[162]. Impact attribution could go further by helping to clarify how changes in extreme weather or slow-onset changes translate into human, socio-economic and environmental impacts and losses at local to global scales (e.g. case studies I-III, BOX5). Empirical studies have investigated the effect of event attribution findings on the public, with mixed results regarding whether they can change opinions on the role of climate change[163–165] or have an impact on action[166–168] beyond prior beliefs, the effects of the events themselves, or other types of scientific information. Recent research has underlined the importance of “subjective attribution” in explaining this variation[169–171].

3.2 UNFCCC Loss and Damage

The increasing frequency and severity of some rapid and slow-onset events due to climate change is leading to losses and damages in human and natural systems. Loss and Damage (L&D) is a ‘third pillar’ in international climate negotiations, together with mitigation and adaptation, with a fund established at COP27 to support vulnerable developing countries in “responding to loss and damage associated with the adverse effects of climate change”[172]. While L&D does not have a legal definition in the United Nations Framework Convention on Climate Change (UNFCCC), its link to escalating climate impacts in a changing climate underscores a possible role for attribution science in the L&D discourse[173–175].

Where losses and damages are attributed to climate change, studies could support communities seeking technical and financial assistance for recovery and reconstruction or compensation. Nonetheless, the potential role of attribution results in an L&D mechanism remains debated. It is not clear to what extent attribution will be used to determine eligibility to receive finance from the UNFCCC L&D Fund, and unlikely to be required in the current policy debate and environment.

Attribution could be relevant for L&D decision making, by helping quantify damages associated with climatic changes (e.g.[116]). For this use, uneven coverage of attribution evidence especially for the most vulnerable people and regions remains a hurdle[176–180], and the potential use of detection and attribution of trends, which is better suited to slow-onset events, has so far received less focus. In particular, impact attribution could help with the mismatch with the impacts that L&D are made to deal with, and the hazard-centric studies that are still in majority in the scientific literature.

A current debate in the literature regards the ethical and epistemic consequences of using attribution to guide L&D funding, highlighting the many technical choices to be made in attribution studies that have implications for the research questions addressed and for their results[181]. The weight given to attribution information could moreover impact the framing and scope of L&D and provide only a partial perspective on global climate justice[162,178,182]. For example, this includes the risk of neglecting non-economic losses and damages that are hard to quantify, such as the loss of territory or cultural heritage, in favour of measurable (case studies I-III) and in particular monetisable impacts (BOX2)[183]. Finding a way to deal with these ethical aspects is hence crucial and requires careful interdisciplinary work in collaboration with interested parties. Any L&D remuneration would be a political decision, while attribution and science in general can only inform decision-makers with the best possible information.

3.3 Risk management and adaptation

Risk management and adaptation planning include a phase of risk assessment[184]. Here, impact models are used to quantify the combined effect of the physical hazard, the exposure of people and assets, and their vulnerability, on a potential outcome. For example, health risks can be calculated based on vulnerability relationships between population demographics and heat intensity[185] (case study III). Drivers other than weather or climate often determine the magnitude of the physical hazard. For example, urbanisation makes heatwaves locally more intense through urban heat island effects[186], while land-cover change and water management can either exacerbate or mitigate wildfires (case study I), floods[187] and droughts (case study II).

Moreover, the motivation to implement risk reduction and adaptation strategies is strongest after an impactful event[188]. In this phase, a synergy could be achieved between impact attribution and risk assessment: The same methodological setup can be applied for impact attribution and for risk assessment, where the former focuses on the effects of past changes in risk drivers, and the latter on future changes and on possible interventions[58,189,190]. This needs models to represent the effects of possible interventions to a satisfactory degree and makes use of non-climate counterfactuals (e.g., case study II). There are indications that local actors would find this approach useful[165], but it remains to be tested in specific cases. A few studies question this potential usefulness[165,191], as other sources of information such as climate projections are a more straightforward tool for adaptation planning[192].

3.4 Climate litigation

Climate change is increasingly being contested in the courts: just shy of 3,000 climate-related lawsuits have been filed in recent years[193]. A substantial portion of these cases seek to accelerate state or corporate emission reductions or hold firms liable for the impacts of their greenhouse gas emissions. Successful litigation could force mitigation policy to align with the Paris Agreement[194], and lead to large payouts from high-emitting companies to communities affected by climate change, generating substantial financial risk for firms[195]. Climate science, including attribution, has a key role to play in climate lawsuits[196,197].

Some cases seek emission reductions, such as *Verein KimaSeniorinnen Schweiz and Others v. Switzerland*, in which the European Court of Human Rights found that the Swiss state's inadequate action on climate change constitutes a breach of human rights protected by the European Convention[198]. In these cases, plaintiffs may need to demonstrate (i) that they are affected by the impacts of climate change to have standing to bring the case, and (ii) that continued emissions would lead to further impacts of climate change that would be inconsistent with the rights of the plaintiffs. In the case of *KlimaSeniorinnen*, the applicants cited attribution studies[25,121] (case study III) to demonstrate how climate change was impacting them and therefore establish their status as victims of the Swiss state's alleged violations of the European Convention on Human Rights.

In claims for compensation (e.g., *Lliuya v. RWE*), causation is a key issue. Claimants must prove that their injuries, for which they seek legal redress, were caused by the actions of defendants, in other words, their greenhouse gas emissions. Impact attribution studies can provide a scientific assessment of this causal link, evaluating the extent to which greenhouse gas emissions (as a whole, or of the defendant in question) are responsible for the specific economic, health, or other impacts for which claimants seek compensation[196,199]. In the context of Lliuya v. RWE, an impact attribution study found that the retreat of the Palcaraju glacier was a direct consequence of local warming, of which 95% was attributed to human influence on the climate[200]. The retreat of this glacier had substantially increased the flood risk to the Peruvian city of Huaraz, substantiating one of the main claims made in the lawsuit, that climate change was responsible for the glacial lake outburst flood risk that the claimant now faces. Although legal challenges to the success of climate damages litigation exist, evidence of this type, combined with appropriate legal logic, may support findings for legal causation[197,201].

4 Overcoming obstacles

A number of obstacles arise directly from the requirements of the steps outlined in Section 2. Observational scarcity limits the robustness of attribution calculations[177,202] as well as the accuracy of observations-based climate counterfactuals; poor model quality imposes similar limits. Mismatch in scales and coverage between observations and models present additional challenges. Not all combinations of methods are possible, and substitution of one method for another may not adequately address the intended question.

Users and researchers from across disciplines need to collaborate if relevance for applications is to guide scientists on which methods and study designs are most useful under these constraints. Decisions and compromises on data and methods, framings and pathways may be guided by disciplinary best practices and interdisciplinary discussion. Communication of conclusions needs to balance accessibility versus clarity on framing, the pathway choices made, data sets and tools, and most particularly what was excluded from analysis.

With increasing knowledge of applications, the tradeoff between targeting studies to specific applications and their standardisation and comparability will likely become larger. One application might dictate changes in methods that degrade usability for another application. Synthesis across attribution results though is necessary if impact attribution is to help monitor the progression of climate change impacts across the globe. For the upcoming second and subsequent Global Stocktakes, for example, the UNFCCC explicitly invites the scientific community and the IPCC to provide input[203]. Synthesis across results is also required for impact attribution to help monitor the effectiveness of national adaptation measures, which parties to the Paris agreement are committed to[194].

To make syntheses feasible across a varied landscape of approaches, terminology, data, and start and end points within causal chains, a set of standards would help, flexible enough to account for the diversity of purposes and applications of impact attribution[56]. Regular workshops of a small but diverse group of representative researchers and users could discuss theory and practice that lead to the generation of standards, akin to the annual meetings of the International Ad Hoc Detection and Attribution Group (IDAG) that developed climate attribution protocols[204]. National and regional groups would focus on aspects relevant to the local hazards, policies, and social environments and further act as translators within standard interdisciplinary research settings or in operational impact attribution. Another approach is pioneered by ISIMIP who work towards standardisation by providing modelling protocols for impact attribution and standardised input data[38,205]. AI can help with syntheses across very large numbers of studies[17,206].

For global syntheses and regional applications alike, it will be important to draw on more studies examining impacts in and by authors from low and lower-middle income countries[17,206]. This requires scientific capacity development, which will be difficult to achieve[207,208] but highly beneficial[16,209]. Overcoming geographical biases in attribution coverage[2,4,5,210] and widening the group of experts to represent a diverse set of viewpoints and opinions[211], will provide motivation, resources, and expertise to help overcome shortcomings of existing tools and methods[180]. Nonetheless, attribution results may continue to have lower confidence levels for impacts on smaller spatial scales and with weaker data support. The risk hence persists that comparisons across different hazards, impacts, and regions might be misleading to the disadvantage of the most vulnerable populations (TAB.1). Communicating limitations and pre-empting possible false interpretations of individual and synthesis impact attribution results is paramount. Syntheses that focus on robust metrics of regional and/or sectoral attribution, instead of the number of studies or confidence measures, would help on the latter point[212].

Conceptual challenges become acute when considering attribution as a climate service in an operational setting[32]. For climate attribution – specifically, weather event attribution – meteorological agencies around the world are already working on this [20,21,213–215]. For events that span national boundaries, multiple agencies may each provide an attribution assessment; complementary assessments will be useful but require workflows across agencies to be set up well in advance[70] and reporting standards needed. For weather event attribution, the World Climate Research Programme's new Working Group on Event Attribution aims to facilitate the development of international standards.

Some of the plans for operationalising attribution analyses include some form of impact attribution. The required levels of standardisation and organisation seem a long way off, but reaching a consensus on limitations and benefits of specific methods and impact sector-specific and intersectoral best practices will make progress in this direction. For this, impact attribution needs to continue including experts and users from all the fields with expertise on climate impact assessment, regardless of whether they identify as attribution, climate, or even climate impact scientist. In any further development regarding impact attribution, potential pitfalls, downsides, or side effects of use-cases (TAB. 1) will be paramount to explore and address. In some cases, operationalisation might not be desirable.

5 Summary and future perspectives

Impact attribution science shows that climate change is impacting numerous aspects of natural and human systems. These impacts can often be identified clearly despite the multitude of other drivers that confound the climate change influence. Impacts both happen over longer time periods and occur in individual impact events or impacts associated with a specific weather or climate event. Impact attribution captures various approaches in use, and is rapidly growing to include expertise from additional disciplines. Clear communication of the implications of study design, data, and methods is important for the reliability and reproducibility of impact attribution studies given the potential and risks for societal applications.

To advance the field further, improvements need to be made regarding observational data coverage and quality. This starts with improving access to data held by national meteorological services, academic, public, and corporate actors (such as global re-insurance companies continuously recording damages induced by weather extremes) and with completing existing and creating new databases. Long-term, continued investments are essential given the importance of long-term, ideally continuous, datasets for trend attribution and empirical modelling. Data rescue efforts[97,216,217,] and AI-based techniques, remote sensing data, and citizen science initiatives engaging local communities in data gathering can all help fill gaps and add accuracy to observations. Wider implementation of standardised methodologies for assessing damages and losses from climate-related disasters[218] used by international organisations, and systematic reporting to repositories[219,220], along with shared guidance on strengths and weaknesses of available databases, can advance climate impact attribution for weather events. Qualitative data and/or informal knowledge, including local and indigenous knowledge, as another source of evidence is little used in attribution studies thus far.

Shortcomings of existing climate counterfactuals will be alleviated with the availability of more bias-corrected climate model-derived data, new observations-derived climate counterfactuals, and the construction of hybrid datasets targeted to specific events, studies, and research questions. Advances in impact modelling will come from many sides, including computing investments for effective large-ensemble simulation over AI-based methods[221] to incorporating statistics advances such as climate-economy damage functions[222]. Methods for quantifying impact model uncertainty, and its inclusion in impact attribution, will have to advance in parallel.

More syntheses or cross-comparisons of different methods will be needed to understand the influence of different methodological choices on similar research questions. Making use of multiple lines of evidence, such as in the "regional attributions" in IPCC's Sixth Assessment Report[223], increases the robustness of results and will help in the interpretation and comparison between different single-method studies. Methods may also be developed to better assess and express confidence levels and incorporate more existing knowledge on uncertainty, integrating physics-based reasoning and previous knowledge[224].

To become useful attribution science for society, these developments need to be accompanied by good practices and additional co-developed research on the potential applications of attribution results. Whenever attribution is motivated or justified by, or implicates, societal uses, these uses should guide methodological choices under consideration of associated risks. Where necessary and possible, priorities between potential uses should be clarified based on input from interested parties[225,226]. For this, more knowledge is needed on the different uses' method needs, possibilities, limitations, and risks, for example by exploring impact attribution results more in real use-case studies in collaboration with policy experts, psychologists, legal experts, philosophers of science, and interested parties. Only then will the rapidly evolving field of impact attribution indeed contribute to a world that better addresses the devastating impacts of climate change worldwide.

Text boxes

BOX 1: Observations

Observations of human systems are diverse. For example, health observations exist from civil and vital registries, electronic records, hospital data, population surveys, cohort studies, surveillance systems, and other sources. Issues include data quality, resolution, collection frequency, scope, geographic and temporal coverage, confidentiality, access, and ethical clearance for survey data (FIG. 2). More generally, a lack of long-term data series at appropriate scales for robustly quantifying the relationships between weather and climate, and the socio-economic indicator of interest –e.g., exposure-response associations[227,228] (case study III) or damage functions[222,229]– is a major challenge in many impact sectors. Data on complex socioeconomic outcomes such as conflicts and migration are very limited and not well harmonised[5]. Other outcomes are difficult, if at all possible, to measure[230].

Observations of biophysical indicators are, for example, related to hydrology (case study II), vegetation (case study I) or biodiversity, and include local instrumental measurements, large-scale remote-sensing data, or aggregated datasets. They too are often local, diverse, sparse, inconsistently measured, and may not be publicly available. For example,river discharge measurements are available from several databases that collate national inventories, however these show substantial differences among each other[189,231,231–233]. Common problems with these datasets are discontinuation of the observational infrastructure and delays in reporting and data sharing[234,235] (Fig. 2).

Climate and weather observations include diverse variables from temperature to cloud fraction and sea level (case studies I-III, BOX5). Spatial and temporal coverage, quality, and homogeneity varies by variable. Most of the global population has by now been covered by temperature data for several decades (FIG. 2), while precipitation, for example, requires higher station network density because of finer-scale spatial variations[236]. Remote-sensing data, homogenised gridded observations that combine different data sources, infilled observational products, and reanalysis data can also be useful. Nonetheless, such products still have gaps and important biases and limitations that must be taken into account[16].

Observations of direct human impact drivers (DHFs) can describe land use changes and population density (case study I), water, agricultural, and ecosystem management (case study II), living conditions and pollution, for example. They are compiled from a variety of different sources, for example in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) attribution protocol[38]. Even observations of changes in biophysical or human systems that may in some studies be scrutinised as an impact variable may in other studies serve as a DHF, such as fishing intensities[38] or national income.

Inventories of emissions and other climate forcing factors report greenhouse gas emissions from individual companies[237–239] or countries[240,241]. Inventory-derived gridded data also inform on other anthropogenic climate forcings factors, such as on anthropogenic aerosol emissions[242] and estimates on land-use changes[243] (case study I). Some observed changes are both non-climate drivers (DHFs) and climate forcings. For example, observed land-use changes both impact ecosystems and agriculture directly, and contribute to climate change, thus impacting ecosystems and agriculture indirectly, too.

BOX 2: Estimates of the climate change costs of Hurricane Harvey

Hurricane Harvey's rainfall caused severe flooding in Houston, Texas in 2017. Frame et al. (2020)[244] combined three estimates of the attributable anthropogenic climate change increase in precipitation[245–247] to calculate attributable damages of a ~20% attributable increase by equating the fractional attributable risk (FAR) to the Fractional Attributable cost. The conclusion was that three-quarters of the then-calcuated US$120Bn damages were due to climate change.

Wehner and Sampson (2021)[248] followed a different approach which explicitly modelled the spatial distribution of flooding based on the factual and counterfactual rainfall. A 20% increase in precipitation corresponded to a 14% increase in flooded area in Greater Houston. Under the assumption that damages were spatially uniform, this led to a much smaller estimate of the cost of climate change, about US$22Bn. Smiley et al. (2022, 2025)[41,42] applied real estate and census map data to these flood maps revealing that damages were not spatially uniform and a 20% increase in precipitation corresponded to a ~30% increase in the flooded homes. Under two different assumptions about the distribution of flooded asset values, they estimated US$50Bn in climate change damages. Human influences other than climate change could also be considered such as the effect of tall buildings[249] or the effect of paving large areas of the urban/suburban environment[250] that magnified the effects of climate change.

This evolution of the estimated attributable climate change cost of Hurricane Harvey reveals that the choice of framing and impact models can strongly influence conclusions. For the particular case of property damages from Hurricane Harvey, the later mechanistic studies followed a framing and modelling detail closer to the attribution question likely posed by most users.

Tables

TAB. 1: Potential applications of attribution results in society, summing up the role of attribution, the relevant interested parties, the type of studies at play, the added value of impact attribution, the potential pitfalls and gaps to fill (non-exhaustive). Sources are indicated when they exist; other statements are not backed up by literature but come from the collective expert judgement of the authors, calling for research. UNFCCC=United Nations Framework Convention on Climate Change, COP=Conference of the Parties, NGO=Non-Governmental Organisation.

<table>
<tr><th colspan="2">Awareness raising(AW)|Risk management and adaptation(RMA)|UNFCCC Loss & Damage(L&D)|Climate litigation(CL)</th></tr>
<tr><td>Specific role of attribution</td><td>AW: Make climate change tangible by linking it to the real-world impacts caused by extremes | Highlight climate change is already a present, not only a future, problem. | RMA: Separation of drivers, identifying the most impactful one. | Highlight impact reduction potential by using adaptation counterfactuals. | Identify vulnerable populations and geographic impact hotspots to enable more effective targeting of interventions. | L&D: Quantify detrimental impacts of climate change in terms of economic and non-economic losses and damages. | CL: Quantify portion of harm/ losses suffered by claimants caused by defendants' emissions[196]. | Demonstrate that claimants are adversely affected by climate change to establish standing.</td></tr>
<tr><td>Relevant actors</td><td>AW: Media, General public, Decision makers. | RMA: Decision makers (public and private sector), insurers, the financial sector, NGOs. | L&D: COP negotiators, politicians, funding agencies, media. | CL: Lawyers, NGOs, judges, claimants, media.</td></tr>
<tr><td>Types of attribution studies</td><td>AW: Attribution of trends, events and impacts to (anthropogenic) climate change. | Resonance amplified by near-real-time studies (e.g., World Weather Attribution[251], ClimaMeter[72,252]). | RMA: Multi-driver (impact) attribution with adaptation-relevant elements such as adaptation and vulnerability counter- factuals. | Inclusion of future projections and scenarios/storylines. | Multi-hazard analysis for sectors or regions. | L&D: Include links to anthropogenic climate forcing. | Slow onset changes and extreme events. | Mapping of impacts of climate changes (anthropogenic or not), especially in most vulnerable countries. | CL: Focus on specific impacts to evaluate causal claims made by parties. | Source attribution quantifying the contribution of defendants' emissions to impacts[201]. | End-to-end attribution to link emissions to harm[201].</td></tr>
<tr><td>Added value of impact inclusion</td><td>AW: Impacts are closer to people's experience. | Clarifies how climate change affects human societies rather than meteorological variables with unclear societal consequences. | RMA: Attributing impacts entails including the elements of risk other than natural hazards, therefore aligning with the goals of adaptation. | L&D: Scoping of remit and requirements for funds. | Inform international discussions on climate justice and reparations. | CL: The harms that legal rights protect against are impacts[197].</td></tr>
<tr><td>Potential pitfalls/ Downsides or side effects of the use-case</td><td>AW: Current attribution inconsistent with expected future climate changes could be misleading. | Negative/pessimistic framing potentially causing despondency and stall motivation to act. | Highlighting the link to climate change potentially decreasing disaster relief due to the polarising nature of climate change in a political context[253]. | RMA: Exaggerate the role of climate change over local governance choices [254] if focusing only on attribution to climate change. | Focus on attributability over adaptation need, risking justice and innovation[255]. | L&D: Lack of tools and data to carry out studies adequately in all regions of the world [176,180]. | Delaying financial support if attribution is necessary but unavailable or inconclusive[182]. | Focus on attributability over vulnerability[256]. | Deplace the political debate from climate justice issues to technical attribution issues[162]. | CL: Differing results for the same event leading to judicial confusion or to a 'battle of the experts'[257].</td></tr>
<tr><td>Gaps to fill</td><td>AW: Little empirical evidence on short-term or long-term effects of different kinds of attribution results on interested parties. | RMA: Aligning attribution methods with existing risk assessment frameworks[189]. | L&D: Metrics for L&D, including non-economic losses. | Inventory of impacts, losses and damages from weather and climate, given existing ones are fragmented, siloed, and uneven[258]. | Interdisciplinary analysis of scientific vs. political understandings of L&D and attribution[182]. | CL: Research that bridges and translates scientific and legal reasoning.
All applications: Methods/guidelines for estimating/communicating robustness/confidence of attribution results based on e.g., existence of multiple lines of evidence or physical knowledge, to aid interpretability, including for non-experts[180,224]. | Research on extreme events and impacts that are challenging to attribute. | Best practices for interdisciplinary research and collaboration with interested parties.</td></tr>
</table>

Figures

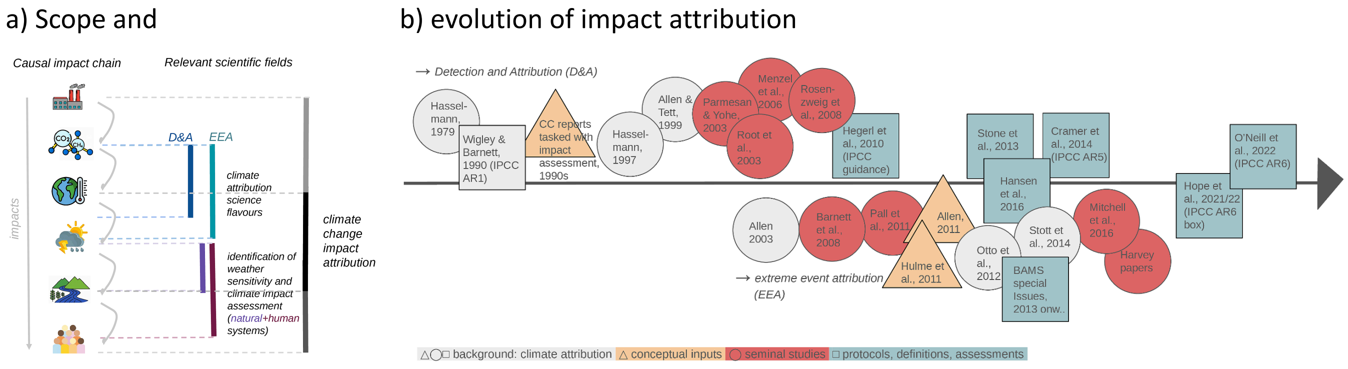
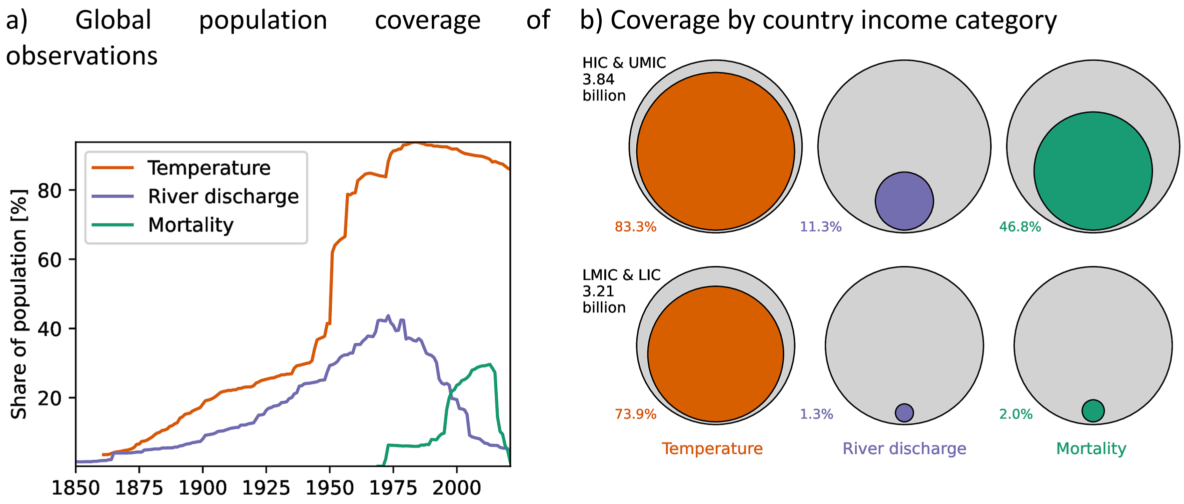


FIG. 1: Impact attribution from source to effect, from its scientific beginnings to now. (a) (Left) The causal chain (straight gray arrow) and steps (curved grey arrows) between causal elements (symbols) from emissions to climate change impacts. (Right) Mapping (horizontal dashed lines) between the elements of the causal chain and scientific fields that analyse them (vertical bars), including climate attribution science flavours (dark blue – D&A; turquoise – EEA), identification of weather sensitivity and climate impact assessment studies (purple – regarding natural systems; aubergine – regarding human systems), and climate change impact attribution studies (black/grey). Darker shading (black) indicates steps required for a study to qualify as climate change impact attribution, while lighter shading (grey) indicates optional steps. (b) Milestones and influences that have shaped the evolution of impact attribution science[5–8,10,20,21,36,56,125,126,128,129,140,259–264] (for Harvey papers, see BOX2). D&A=Detection and Attribution; EEA=Extreme Event Attribution; IPCC=Intergovernmental Panel on Climate Change; ARx=xth Assessment Report.



a) Global population coverage of observations

b) Coverage by country income category

FIG. 2: Share of population covered by (proxy) observations for (orange) daily maximum temperature from Global Historical Climatology Network (GHCN-Daily)[265,266], (purple) monthly or daily river discharge measurements from the Global Runoff Data Centre (GRDC)[267], and (green) daily mortality counts from the Multi-Country Multi-City Collaborative Research Network (MCC)[268] and personal communication with Ana M. Vicedo-Cabrera, October 2024. Coverage is shown as (a) annual time series of the percentage of the global population covered by observations and (b) the 1996-2015 average share of the total population covered in (top) high and upper-middle income countries (HIC & UMIC) and (bottom) low and lower-middle countries (LMIC & LIC), where equal areas represent an equal absolute number of people. Economic classification is based on the 2022 gross national income from the World Bank[269]. For details, see Supplementary Text 1.

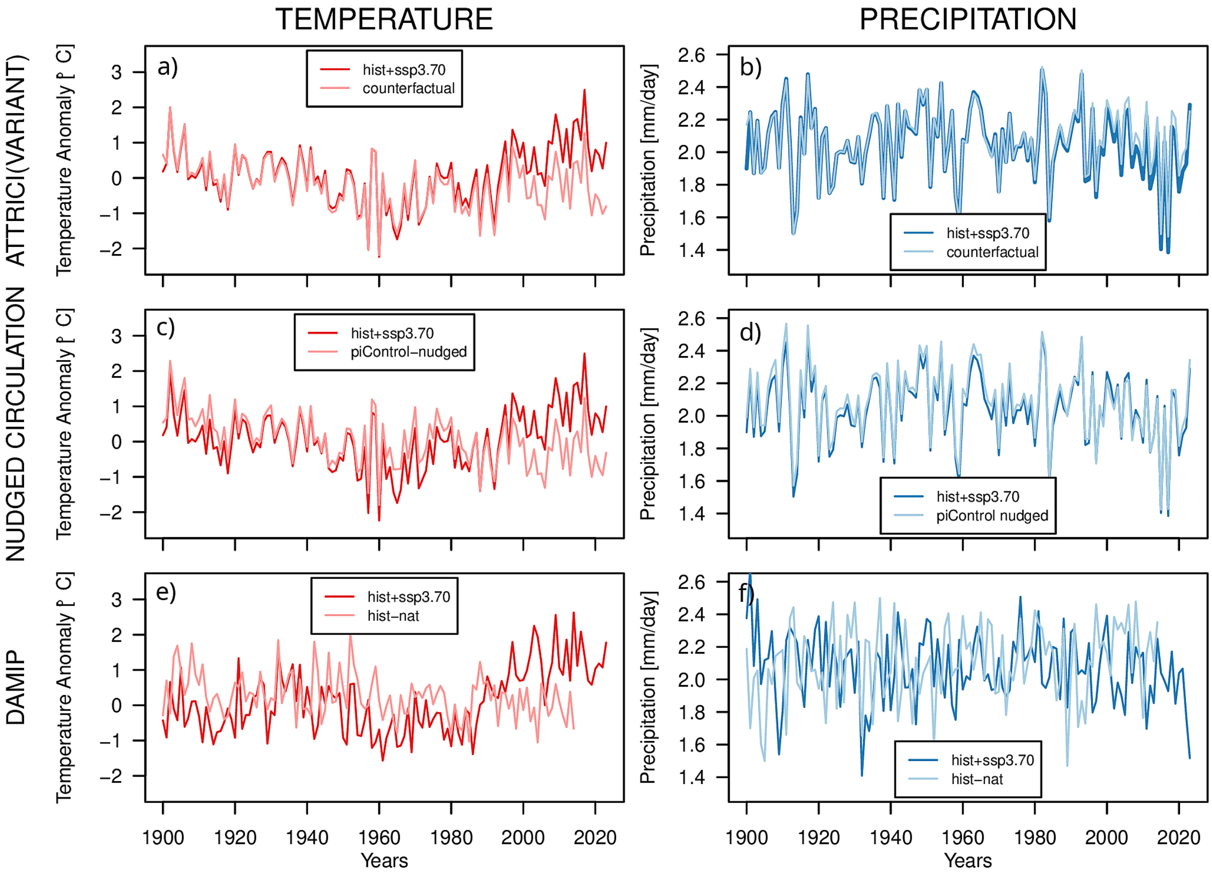


FIG. 3: Illustration of methods to generate counterfactuals for June-August (JJA) over Northern Europe for CESM2[270] climate model simulations. Results from (top, a-b) Statistical counterfactual generation via a variant of the ATTRICI method[83], (middle row, c-d) nudged circulation climate model simulations[51], and (bottom, e-f) natural forcing historical simulations from the Detection and Attribution Model Intercomparison Project[87] (DAMIP; one run only shown), showing for each data for (left, a,c,e) temperature and (right, b,d,f) precipitation for the factual (hist+SSP3-7.0; dark red/blue/grey) and the counterfactual (light red/blue/grey) scenario. For details, see Supplementary Text 2 and for the same figure for the Amazon region, see Supplementary FIG. 1. CESM=Community Earth System Model, ATTRICI=ATTRIbuting Climate Impacts, SSP=Shared Socioeconomic Pathway.

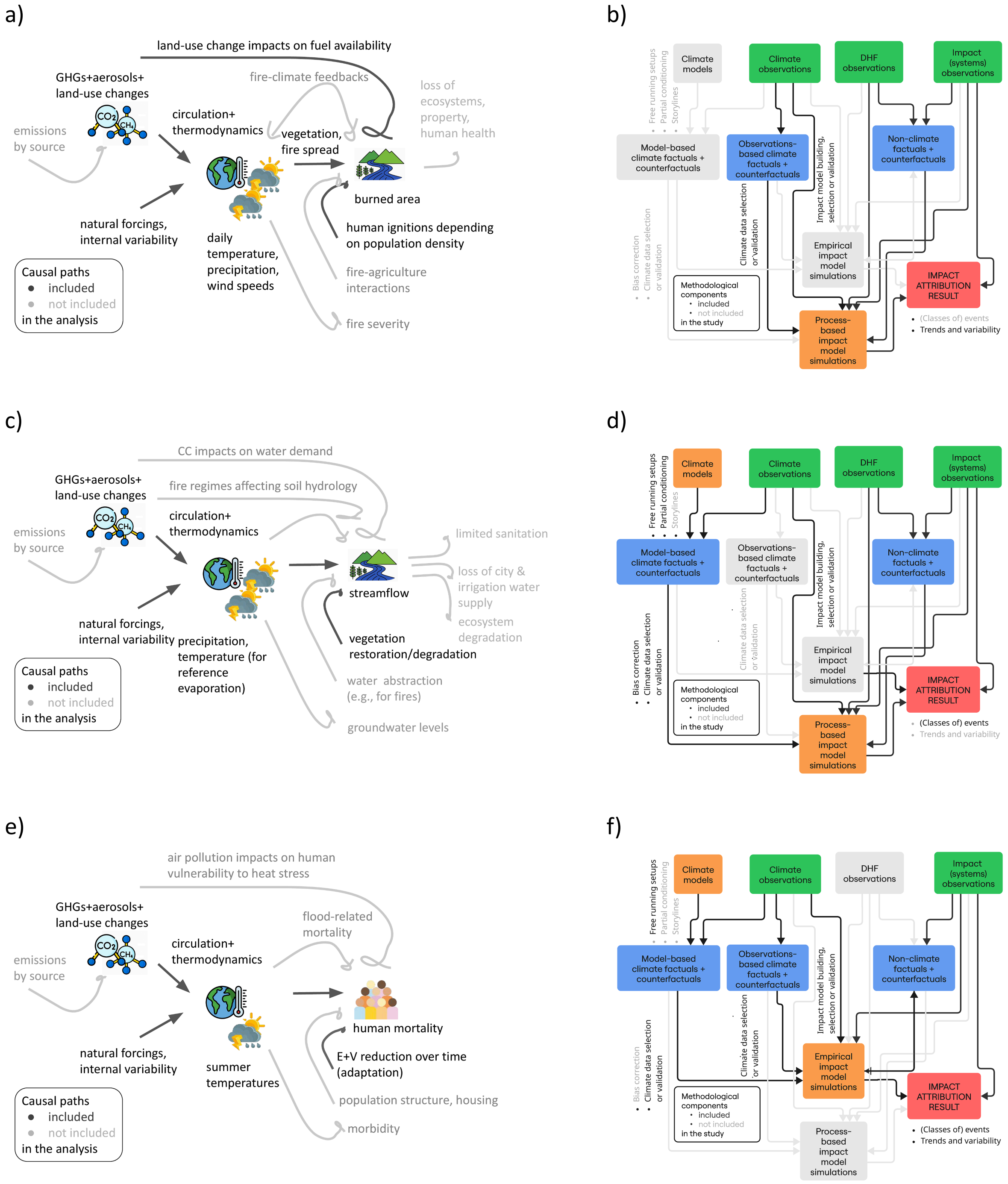


FIG. 4: Scope and methods of the case studies from section 2.8., including (top) Burton, Lampe et al. (2024)[19], (middle) Holden et al. (2022)[30], and (bottom) Stuart Smith et al. (2025)[147]. For each case study, (left) causal pathways and (right) methodological steps included (black/colour) and not included (grey, illustrative only) are shown. (Left) The paths not included are selected here based on discussion in the original publication and additional suggestions by the literature. Land-use changes affecting human and natural systems via effects on climate may include biogeophysical and/or biogeochemical effects. (Right) Observations – green; models – orange; factuals and counterfactuals – blue; impact attribution result – red; analysis steps – no box. For the generalised flowchart, see Supplementary FIG. 2. For a more detailed FIG. f), see Fig. 1 in the original publication.

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Supplementary information to:
“Approaches and challenges in attributing climate change impacts”

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Supplementary texts

TEXT S1. Technical details on FIG. 2

To illustrate the observational coverage of variables that might, and have been, used in attribution studies, we choose to show daily-maximum temperature, river discharge, and mortality. This choice was made to spread across the spectrum of variables more directly or indirectly linked to global warming, moving across the spheres relevant for impact attribution (FIG. 1). Depending on the attribution study, lower or higher spatial and temporal scales may be considered necessary or acceptable than those used here for illustration (e.g., monthly rather than daily mortality, or higher-frequency river discharge).

Income classification data and processing

Data on the countries’ current income group was taken from the World Bank classification[1] of economies with populations of more than 30,000, distinguishing between low (LIC), lower-middle (LMIC), upper-middle (UMIC), and high income countries (HIC) defined by a 2022 gross national income (GNI) per capita of $1,135 or less; $1,136 to $4,465; $4,466 to $13,845; and $13,846 or more, respectively. For the mapping between gridded data and national data, the 1:10m Cultural Vectors: Admin0 shapefile from Natural Earth[2] was used.

A 0.5°×0.5° latitude/longitude file was created that specifies for each grid box the country from those in the Natural Earth shapefile within which it mostly lies. These countries were then matched to the World Bank classifications and LIC and LMIC aggregated, and UMIC and HIC, to create two binary masks indicating grid boxes lying in either of the two country groups. Note that 63 countries listed in the Natural Earth dataset are too small to have a grid box assigned to them. The mapping procedure resulted in 17 grid boxes being assigned to more than one country, of which 12 were classified in different categories and excluded from further analysis. Very few grid boxes were not assigned to any country and hence also excluded. Entries of the Natural Earth Datasets with disputed political status are also not included in the World Bank list, so manual appointment to the income category of another country based on author judgement (e.g., SOL, SAH, KAB, CYP, FL, KAS) or exclusion from the analysis (PSX, BRT, ATA, COK) was necessary, contributing a very small share of global population. Venezuela is currently not classified by the World Bank and was hence excluded from the analysis.

Temperature

Station data availability information for daily maximum temperature was taken from the National Oceanic and Atmospheric Administration (NOAA)'s Global Historical Climatology Network daily (GHCNd) dataset[3,4] for the period 1850-2021. To calculate population coverage, population data from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) phase 3a histsoc dataset at 0.5°×0.5° resolution was used[5,6].

For a), an annual binary coverage mask was created at the regular 2.5°×2.5° latitude/longitude resolution that indicated for each grid point/box whether or not there is at least one station in the grid box the record for which includes that year. The population data was then remapped (summed) to the same 2.5°×2.5° resolution. Data from both files were multiplied and the result aggregated to the global level to derive the global sum of the global population covered by temperature observations. This was compared to the total, unmasked, sum of the population. For b), the analysis is repeated after masking the gridded population data with the income classification mask (HIC+UMIC; LMIC+LIC) before reaggregation of the latter to 2.5°×2.5° resolution.

The underlying assumption is that the temperature data from one station are representative for temperatures within the same grid box at 2.5°×2.5° resolution. Grid box size decreases with distance from the equator, so station data in the Tropics are effectively assumed to be representative of a larger area than at the Poles, which will in b) lead to potentially overestimating the relative share of data in LMICs vs HICs. The plot is solely based on an inventory file which lists instrumental sites and gives a start data and end date in years. In consequence, data quality might vary and the number of days covered per year is not specified, although completeness is presumed fairly high for station data.

River discharge

River discharge data was obtained from the Global Runoff Data Centre (GRDC)[7], for the period 1850-2021. A global river flood hazard map with a 50-year return period at 1 km resolution was obtained from the Joint Research Centre Data Catalogue[8]. Population data was obtained from the ISIMIP phase 3a histsoc dataset at 0.5°×0.5° resolution[5,6].

For a), the population map was masked with the 50-year river flood map (anywhere with flood depth > 0 m) to estimate the total number of people globally potentially exposed to river floods. Based on metadata from GRDC, stations were filtered based on (i) the length of the available time series (at least 1 year – daily or monthly both included) and (ii) the amount of missing data (max 50%). The population living within 100 km of each station meeting these criteria was then summed to obtain the number of people exposed to river floods and living in data-covered regions. For b), the analysis was repeated after masking the gridded population data with the income classification mask (LMIC+LIC; HIC+UMIC) at 0.5°×0.5°.

Note, the estimate is that e.g., in 2021, 988 million people, corresponding to 12.6% of the global population, live in areas exposed to river floods with a 50-year return period. Historical coverage in this most widely-used global database peaks in the 1970s and then falls due to a declining number of stations in all continents except Oceania from the late 1970s or early 1980s. This decline is in part due to a discontinuation of observational stations, and in part to a delay in reporting, in particular in phases of social upheaval, to international networks such as GRDC[9–16]. Sensitivity tests to the choice of discharge dataset (alternative: Riggs' data[12]), of the population dataset (alternative: Gridded Population of the World for 2020 from CIESIN[17]), result in a historical time series of similar shape, with population coverage peaking between the 1970s and 1980s (regardless of the fact that the number of stations does not decline in Riggs' data[12]), with maximum values of coverage ranging between 30% and 44% of the exposed population, across datasets.

Mortality

For coverage of daily mortality data we used information from the Multi-Country Multi-City (MCC) Collaborative Research Network[18], an international collaboration of research teams working at the intersection between environment, climate, and health. The network has assembled the largest dataset on daily mortality, drawing from 847 locations in 50 countries around the world, in order to analyse various environmental-health associations such as ambient temperature and mortality. The data span the period from 1969 to 2021 and cover largely cities and metropolitan areas. Membership to the MCC network is based on collaborative work and data sharing and data are not freely accessible for non-members.

Available proxy observations for mortality in FIG. 2 were estimated by firstly compiling a list of countries in the MCC database with daily mortality data for urban populations, irrespective of how many cities within a country these data refer to, based on data available at the time of writing[18] and updated, unpublished data provided by Ana M. Vicedo-Cabrera in personal communication, October 2024. Annual country-level urban population and total population data were taken from the UN World Urbanisation Prospects[19].

For a), we extracted the total urban population for each country and year included in the MCC database and combined it with the total global population estimates to compute the fraction of the total urban populations of all MCC countries in the global population. This gives the estimated coverage proxy for the share of the global population in each year of the record for which attribution-relevant mortality data (i.e., daily mortality) are available. For b), the analysis is repeated separately for the countries classified as HIC and UMIC and for the ones classified as LMIC and LIC. An important underlying assumption in the calculations is that any health risk functions derived from the MCC data are representative for all urban populations in the MCC countries.

Visualisation

In panel a), the estimated shares of the global (temperature, mortality) or globally exposed (discharge) population that is covered by temperature, discharge, and mortality proxy data are shown as an annual time series. Panel b) shows the average estimated share of the total population in LICs or LMICs (left) and in UMICs or HICs (right) covered by data during the period 1996-2015. The area of the black square frame is proportional to the total population in each income category, while the area of the red, blue, and purple filled squares are proportional to the share of the population covered by temperature, discharge, and mortality data, respectively.

Text S2. Technical details on FIG. 3 and FIG. S1

FIG. 3 in the main text and FIG. S1 illustrate three conceptually different methods to generate climate counterfactuals, which have all been used for climate impact attribution.

ATTRICI

The ATTRICI approach (ATTRIbuting Climate Impacts[20] identifies the long-term shifts in the factual daily climate statistical distributions that are correlated to global mean temperature change. The approach assumes a smooth cycle of the associated distribution of climate variables through the year. The estimated shifts since 1901 are then removed from the observational data by projecting the observed data on counterfactual distributions that assume a fixed 1901 level of global mean temperature. The projection is done through quantile mapping, a method borrowed from the bias adjustment literature. In this way, the ATTRICI approach preserves the internal variability of the observed data in the sense that factual and counterfactual data for a given day have the same rank in their respective statistical distribution. The impact model simulations forced by the counterfactual climate inputs therefore allow for quantifying the contribution of the observed climate change (no matter from where the trends originate) to observed long-term changes in impact indicators but also for quantifying the contribution of the observed trend in climate to the magnitude of individual impact events. The method treats each climate variable individually, so the multivariate dependencies are not fully preserved, though the ranks are. The method does not explicitly separate out anthropogenic climate change. For the illustration in FIG. 3 we use a simplified variant (ATTRICI-VARIANT) in which we detrend the spatially aggregated time series of yearly means directly, using global mean temperature as predictor variable. The counterfactual data provided as part of ISIMIP3a is produced on the grid level and has daily resolution.

Nudged Simulations in the CESM2 Earth System Model

To generate climate counterfactuals in the absence of thermodynamic climate change, we utilise two simulations from the Community Earth System Model Version 2 (CESM2) Earth System Model[21]. A standard coupled forced simulation covers the historical (1850-2014) and SSP3-7.0 (2015-2100) scenarios, incorporating prescribed CO_2 emissions and dynamic land-use change. This simulation follows the CESM2 Large Ensemble protocol, with CAM6 running at a resolution of 1.25° longitude, 0.9° latitude, and 32 vertical levels. In addition, a “paired” unforced simulation maintains constant 1850-level forcings (piControl scenario) while nudging horizontal winds towards those in the forced simulation. This setup uses pre-industrial CO_2 and land-use conditions for 1850-2100, applying a "linear-weak" nudging configuration with a 6-hour relaxation timescale. Nudging ensures that both simulations exhibit similar variability on interannual and shorter timescales, driven primarily by atmospheric circulation, while differing in long-term trends due to thermodynamic anthropogenic influences. By comparing the forced and nudged circulation simulations in FIG. 3, this method isolates the thermodynamic component of anthropogenic effects on climate, such as temperature increases and altered precipitation. This technique may be productively used to generate climate counterfactuals via the nudging methodology.

Visualisation

Daily data near-surface temperature (TREFHT) and precipitation (TOTPREC) data from three extended historical (historical+SSP3-7.0) simulations from CESM2 are produced. The data is then spatially averaged to the Northern Europe (FIG. 3) or Amazon (FIG. S1) IPCC region[22] and seasonal means for June-August (JJA) are taken. These are shown in FIG. 3 (bottom row) together with one DAMIP hist-nat counterfactuals as annual time series (which does not match variability by construction). To one of the extended historical runs, either method to derive counterfactuals is applied, as would be for the observed climate realisation to derive counterfactuals for the production of impact attribution results. The ATTRICI-VARIANT method applied here gives by design time series at the region’s aggregation level, both for daily-mean temperature and precipitation. The correlation between the annual data for temperature, and precipitation, respectively, is shown in the right-most column, with grey lines indicating the same year in the factual and counterfactual data. For the DAMIP data, this does not apply as the interannual climate variability is independent between factual and counterfactual simulations. In consequence, no meaningful correspondence is expected for the time period shown between the respective members with the same initial conditions (aka ensemble member labels r,i,p,f in CMIP6).

Supplementary Figures

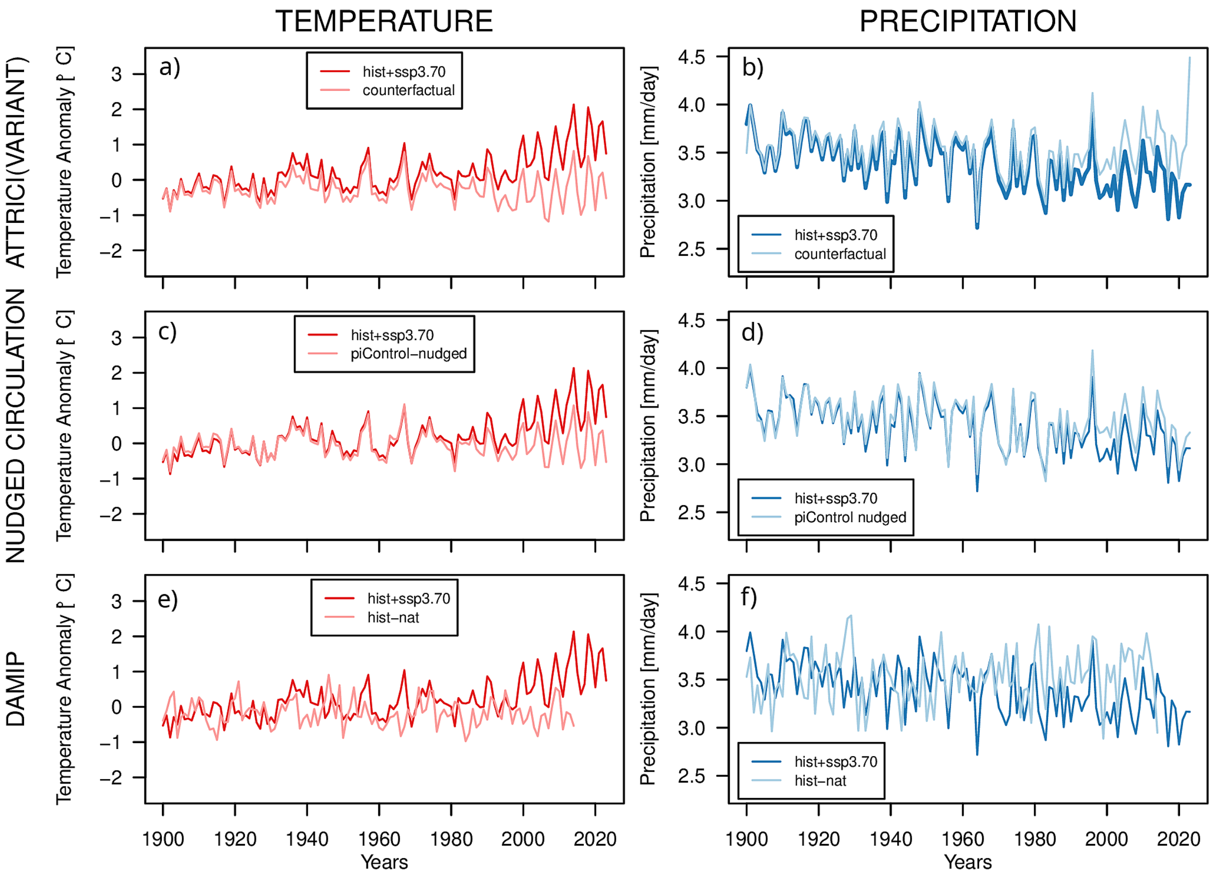

FIG. S1: Illustration of methods to generate counterfactuals for June-August (JJA) over the Amazon region (AMZ)[23] for CESM2[21] climate model simulations. As FIG. 3 in the main text, but for a different region.

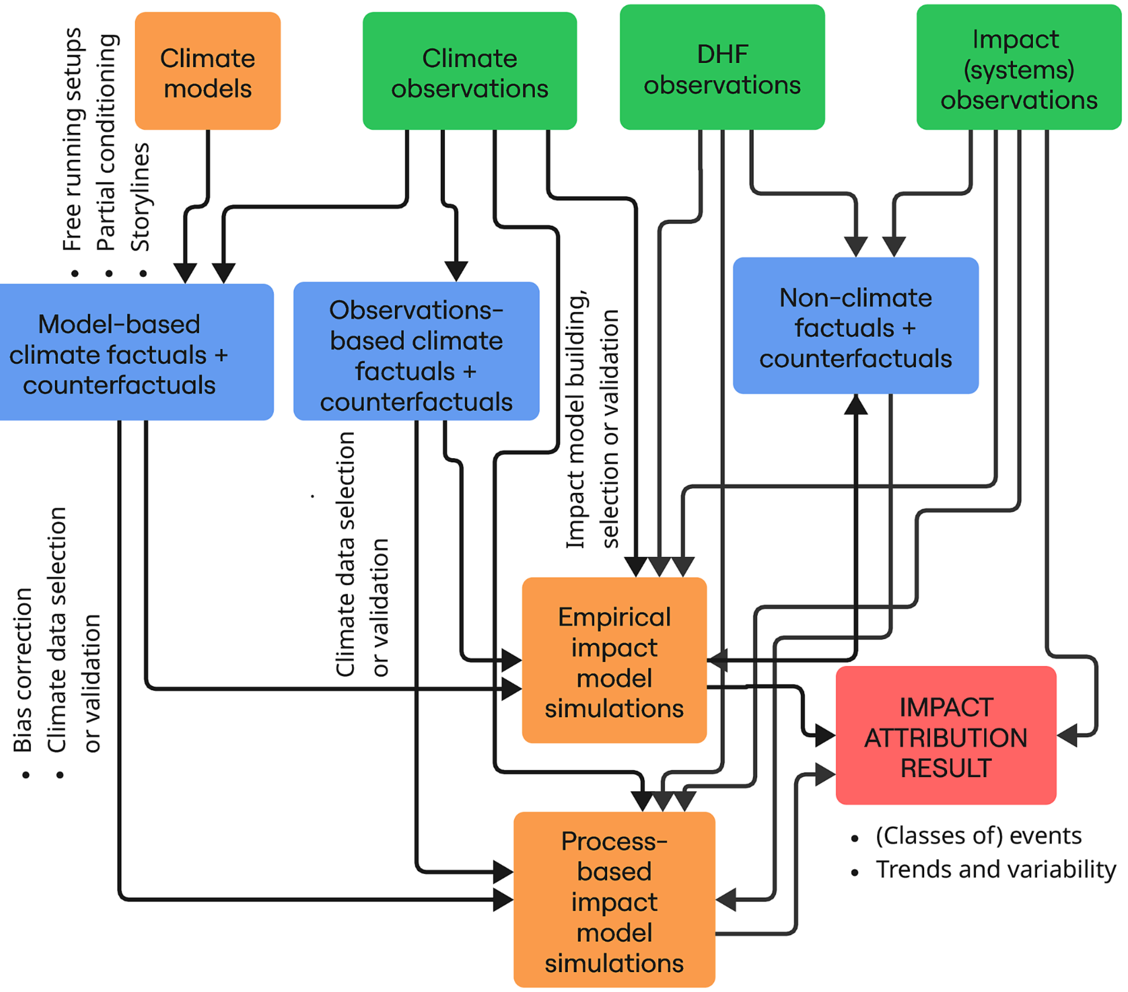

FIG. S2: Methodological steps typical for climate change impact attribution studies. As FIG. 4b),d),f) in the main text, but without specifying the steps taken in any specific, existing study.

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