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Data injustice and attribution of drought events: implications for global climate policy

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ABSTRACT

Extreme event attribution (EEA) studies address the question of the role of anthropogenic climate change in the occurrence of extreme weather events. However, there is an ongoing debate between science and policy actors on whether EEA can inform the Loss and Damage mechanism. Because EEA needs local observational data, it could be affected by the 'data injustice' that plagues data-poor regions. This paper focuses on droughts and assesses whether the geographic location of EEA studies matches the location of recorded drought hazards and observed drought impacts, using a data justice lens and multiple metrics. We find that the location of EEA studies correlates moderately with the location of drought events .56. It does not correlate with the location of countries where droughts generated famine, food shortage, and crop failure .13, of countries where people were most affected by droughts .11, and with countries' agricultural vulnerability to droughts .00; it correlates negatively with countries facing high water stress −.03. Conversely, we found a strong correlation between EEA studies and drought-related economic damages .92. This finding provides compelling evidence that data injustice limits the scope of EEA science. In turn, this questions the suitability of EEA results in the international allocation of climate funds for Loss and Damage.

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Droughts; extreme event attribution; natural disasters; Loss and Damage; data justice; inequalities

Key policy insights

- Extreme event attributions (EEA) that can quantify climate change impacts are seen as a tool for loss and damage fund allocation.
- However, data required for EEA is limited in poorer countries.
- EEA studies are not occurring in places with the most severe drought impacts.
- Hence, EEA may not be suitable for climate finance allocation and can potentially exacerbate injustices.

1. Introduction

The Intergovernmental Panel on Climate Change states that human-induced greenhouse gas forcing is the principal driver behind observed increases in extreme hot weather globally, adding that 'some recent hot events would have been extremely unlikely to occur without human influence on the climate system' (IPCC, 2021, p. 1517). After the occurrence of an extreme event, the public and decision-makers wonder whether anthropogenic climate change has played a role by affecting its likelihood of occurrence or its severity (Kimutai et al., 2023; Philip et al., 2023; Arias et al., 2023; Schumacher et al., 2022; van Oldenborgh et al., 2021). The field of extreme event attribution (EEA) has developed over the last 20 years as an effort to establish

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scientifically sound methods to address these questions (Stott et al., 2004; Stott et al., 2016). Responding to a growing societal need, event attribution aims to quantify how human-induced climate change has impacted the probability or changed the magnitude of specific extreme weather events, such as floods and droughts. These extremes cause loss and damage to habitable territory and livelihood security, affecting developing countries and vulnerable communities the most.

Attribution has several key merits. First, by producing an understanding of the effect of climate change on recent and impactful events, it enhances the effectiveness of communication of climate science to the public and decision-makers. Second, it can assist local decision-making in disaster risk reduction (Scussolini et al., 2024). Third, it represents an initial endeavor toward quantifying the effects of human-induced climate change on damages caused by weather extreme events, which have been used in climate litigation as evidence for human-induced climate change impacts (Lloyd & Shepherd, 2021). Consequently, these findings can be used to inform climate finance mechanisms like the Warsaw International Mechanism for Loss and Damage (L&D), which aims to establish a framework for providing compensation for climate change impacts (Otto et al., 2015). The new fund was established in 2013 at the 19th Conference of the Parties to the Climate Convention, after years of pressure from Small-Island Developing States and Least Developed Countries demanding actions to address the unavoidable losses and damages caused by climate change (Doelle, 2014). L&D occurs when efforts to avoid or minimize climate impacts through mitigation and adaptation fail (UNFCCC, 2012). The underlying idea of this mechanism is to provide economic and technical expertise to developing countries facing climate change's negative consequences, including extreme weather and slow onset events (UNFCCC, 2013b). This is accomplished by promoting knowledge and understanding of risk management, financially supporting action to address loss and damages, providing funding for direct and indirect losses, reducing countries' vulnerability, and improving the adaptive capacity of countries and people (UNFCCC, 2022). One of the tools proposed for quantifying and allocating funds for L&D is EEA. In this paper, we investigate whether data injustice affects the geographical distribution of EEA studies by comparing the locations of these studies with six indicators that reflect drought hazards and impacts. Our comparisons are visually represented through georeferenced maps and statistically analyzed using correlations and regressions.

The paper is organized as followed: (2) Theoretical Background, (3) Methodology, (4) Results, (5) Discussion, (6) Conclusion and Recommendations.

2. Theoretical background

2.1. The use of extreme event attribution

As anthropogenic climate change impact is a worldwide issue (EU Commission, 2022), the outcome of event attribution studies is of interest to different stakeholders (Stott et al., 2016). Methodological debates have focused on the relationship between a so-called probabilistic approach and a more recent storyline approach in event attribution science. The probabilistic approach by comparing model representations of the actual world and a counterfactual world without climate change, it determines the effect of climate change by detecting any significant probability changes. On the other hand, the storyline approach operates as a 'case-study' method and compares plausible model representations of the actual and counterfactual word without the ambition of making statements about the probability of the event (Lloyd & Oreskes, 2018; Thorén et al., 2021; Lloyd & Shepherd, 2021). In legal cases involving liability, combining both the probabilistic and storyline approach to EEA is often more effective for building a robust case (Lloyd & Shepherd, 2021).

The first fields that identified EEA's potential applicability is the insurance sector that is affected by the additional risk resulting from climate change (Allen, 2003). EEA studies are gaining ground also in the legal domain, with several cases investigating the liability of industries or governments for specific damages caused (Ekardt & Heyl, 2022). A further application field is policy, where EEA information can be used by governance actors at different levels (Parker et al., 2017). For instance, at the local and regional levels, NGOs, businesses, and local governments could use information from attribution studies to implement adaptation planning (Pall et al., 2011; Schiermeier, 2011; Stott et al., 2013), for example by improving their expectations about future climate influence on similar events. Nevertheless, there is still debate between scientific and policy actors on whether events need to be attributed to human-influenced climate change, to be included in L&D (Thompson & Otto, 2015; James et al., 2019; Parker et al., 2015; 2017). Paragraph 7 of The Warsaw International Mechanism for Loss and Damage, 'convene meetings of relevant experts and stakeholders' thus providing a good opportunity for dialogue about how scientific insights can inform the mechanism's implementation (Otto et al., 2014). If attribution studies are thought to be useful, the mechanism could also 'promote the development of … information' (paragraph 7(d), UNFCCC, 2013a). These provisions in the Warsaw International Mechanism highlight the potential for attribution science to play a crucial role in addressing the challenges of loss and damage, which got support from many scientists (e.g. Noy et al., 2024; Noy et al., 2023; Wehner & Reed, 2022; Otto et al., 2014) who advocate for the utilization of EEA studies in L&D.

There is awareness of the challenges involved in scientifically associating loss and damage to anthropogenic climate change, namely linking first the meteorological event to anthropogenic climate change, and then the meteorological event to societal impacts (Otto et al., 2014). EEA aims to assess the first of the two causal links, while the second is rarely addressed (Frame et al., 2020).

The key steps in Stone and Allen's (2005) EEA method are: (i) to assess a trend in the occurrence of extreme events of a certain magnitude, using observational time series; (ii) to compare results of climate models simulations reflecting a 'natural' climate and a climate forced by additional greenhouse gas concentrations, and thus (iii) to quantify the effects of the additional greenhouse gas concentrations in the occurrence of these events (Philip et al., 2020a). Crucially, observational data on climate variables such as surface air temperature, humidity, precipitation, and soil moisture need to be available, ideally for the whole period corresponding to anthropogenic global warming, i.e. the last 150 years, or at least for the last ca. 5 decades, corresponding to most of the global warming so far (van Oldenborgh et al., 2021).

This implies that the availability of long-term observational data will determine the possibility of conducting EEA studies for a given location (Otto et al., 2014). A critical problem is that observational hydrometeorological data are not equally abundant across the world. Often, low-income regions are also data-poor; particularly, in Sub-Saharan Africa and South America (Menne et al., 2012; Olsson et al., 2022). Data absence or incompleteness in certain countries is a generally recognized issue known as data injustice (Heeks & Renken, 2018). This scarcity makes it extremely difficult or even impossible to conduct EEA studies in regions emerging as climate impact hotspots and primary recipients of L&D (Olsson et al., 2022). One study already discussed the discrepancy between event attributions and the number of deaths associated with climate extremes (Otto et al., 2020). To date, there is no quantitative assessment of whether in fact the selection of locations of EEA studies may be affected by data injustice. In this study, we assess and quantify discrepancies between the geographical distribution of EEA studies on droughts and the location where drought impacts occur.

2.2. Droughts and EEA

Droughts are complex to quantify (Cammalleri et al., 2020) as they propagate through the water cycle, starting with precipitation deficits that reduce hydrological and agricultural water availability, leading to socio-economic impacts via soil moisture, surface, and groundwater shortages. Characteristics like duration, intensity, and timing evolve during propagation and are affected by human water use and watershed management (Van Loon et al., 2016). Droughts are thus creeping phenomena causing an increased competition over water resources, and are, therefore, linked to costly and damaging direct and indirect impacts. They can have disastrous, long-term effects on agricultural and industrial production, food prices, human and environmental health, migration flows, and energy, in developing and developed countries (UNCCD, 2022; WHO, 2022). An estimated 55 million people across the globe are directly affected by droughts every year, and due to widespread and cascading impacts that are hard to quantify, costs and damages associated with droughts are considered to be largely underestimated (UNDRR, 2021).

Poor people and poor countries are more vulnerable to the adverse effects of droughts, as the capacity to cope with droughts depends on technological and economic development (Naumann et al., 2013). These regions are also highly sensitive due to the pre-existing health conditions of individuals and a high reliance on agriculture (McCarthy, 2001; UNISDR, 2011). For instance, malnourished people are more prone to starvation as a result of food scarcity (Yip, 1997). Similarly, individuals with HIV are at a higher risk of falling ill due to poor water quality (Mason et al., 2005). Whether a drought leads to crop failure, food and water shortage, and ultimately famine depends largely on the country and its government's ability to mitigate, prepare for, and respond to drought impacts, which ultimately depends on the economic, social, and political context (Savelli et al., 2022; Naumann et al., 2013; Sen, 1982; Wilhite & Svoboda, 2000). To capture these important contextual aspects of drought impacts, EEA on droughts requires more than the physical data mentioned earlier. It also necessitates the inclusion of hydro-meteorological indicators like rainfall, soil moisture, and river flow, as well as information pertaining to water consumption and needs. Moreover, it is essential to account for human interventions within the water cycle and ideally, to have quantifiable records of historical societal consequences resulting from drought-related disasters (van Oldenborgh et al., 2021).

2.3. Data justice

The goal of data justice is to ensure that everyone has equal access to the necessary data and services required for a reasonable standard of living (Practice Action Technology, 2015). Nevertheless, resource and capability restraints affecting developing countries present a major impediment toward the achievement of such a goal (Heeks & Renken, 2018). Three forms of data injustice have been identified as occurring in developing nations: procedural, distributive, and instrumental (Heeks & Renken, 2018). We contextualized this classification of climate data in order to depict injustices in EEA studies. *Procedural data justice* pertains to fair data-handling processes, starting with data capture, input to a data system, processing, storage, to data output (Heeks, 2006). Nevertheless, numerous challenges arise in African countries, as well as in many regions worldwide, concerning the stages of data processing (Kaspar et al., 2022). Primarily, the problem stems from data digitalization, wherein early observations may not be fully available in digital format or only partially digitized, resulting in data fragmentation (Brönnimann et al., 2018). The second challenge relates to a deficiency in dissemination capacity tools, which deals with a lack of proficiency in utilizing quality control tools or errors in data entry into the system (Dinku, 2019). Then, the spatial scale at which data is available determines the data quality of the information, resulting often in poor data quality as collecting data at a fine-grained spatial scale is more challenging. Additionally, there has been a reduction in investments in climate infrastructure, leading to significant obstacles in carrying out essential tasks related to weather observation and maintenance (Dinku, 2019). For instance, between 1971 and 2001, Madagascar witnessed a substantial decrease in the number of active stations, declining from 400 to 50 (Dinku, 2019). *Distributive data justice* refers to the fair distribution of data. One of the challenges faced by numerous developing nations is the scarcity of data coverage, with Africa being the continent with the lowest weather station density (Dunn et al., 2014). This issue of data sparsity significantly impacts vast areas of Africa, with rural regions being particularly affected, as in the case of Kenya's station coverage. Indeed, Kenyan cities and densely populated areas reported better data coverage, while lowland areas experienced severe data sparsity (Dinku, 2019). Sparsity can also derive from landscape geographical challenges (such as desert lands) or conflicts. For instance, the meteorological observations network in Rwanda was devastated during the genocide in 1994 (Dinku, 2019). Lastly, *Instrumental data justice* refers to the fair use of data, focusing on the impact of data usage (Johnson, 2016a). We believe that due to procedural and distributive data injustice occurring in developing countries, particularly in Africa, using EEA in loss and damage can lead to instrumental data injustice. Furthermore, the negative effects of droughts, along with potential instrumental data injustice are connected to the broader concept of substantive justice. By employing the Earth system justice (ESJ) framework proposed by Gupta et al. in 2023, we can observe that minimum access to resources and services in Global South countries (Rammelt et al., 2023) is adversely affected by drought impacts like food shortages, famine and water stress and likely to intensify competition over resources. The disproportionate harm to these regions underscores the need for countries most responsible for climate change, and with greater resources, to lead in funding L&D.

In this contribution, we address whether there is evidence that data injustice may bias the location of EEA studies. For this, we address these operational questions: Does the geographical location of EEA studies on droughts align with the geographical location of droughts and their impacts? Which impacts are more strongly aligned with EEA study location?

We compare the geographical distribution of EEA studies and of six indicators that reflect drought hazard and impacts. The comparisons are illustrated in georeferenced maps and quantified by statistical correlations/regressions.

3. Methodology

To assess geographical discrepancies of EEA studies distribution, we use six indicators that aim to encapsulate the locations relevant to droughts and their impacts. The indicators are: the occurrence of drought events, the number of drought-related food shortages, famine, and crop failure events, the total number of people affected, countries' vulnerability of rain-fed agricultural systems to droughts, countries' average water stress, and the total economic damages caused by droughts events. The time frame covered in this research is 2010–2022 as most of the attribution studies have been published after 2010. An explanation of the datasets used is provided below.

3.1. Datasets

(i) *Event attribution studies'* geographical distribution. The datasets used are the Carbon Brief (2023) dataset integrated with World Weather Attribution Initiative (2023) data. The Carbon Brief dataset provides a total of 81 drought-related findings for the period post-2011 until 2022 with the oldest study focusing on 1900. The types of studies recorded by the dataset are formal studies, rapid assessments, and trends, while the findings of the studies are classified as human influence found, no human influence found, and inconclusive. In this analysis, we considered all the types of studies and all the findings focusing on drought events that occurred since 2010; The total number of studies considered is 63, of which 42 found human influence, 13 with no human influence found, and 8 had inconclusive/insufficient data. The maps elaborated for this section have been made by using the absolute number of studies and by uploading on QGIS geographical coordinates related to the location of attributed drought events.

(ii) *Drought disaster events* are collected from EM-DAT (2023), the International Disaster Database. Drought disasters are recorded in EM-DAT when they are events that fulfill at least one of the following criteria: an appeal for international assistance has been made, a declaration of emergency has been promulgated, 100 or more people have been reported affected, or 10 or more people have been reported killed. The dataset collects information from a wide range of sources, including government agencies, non-governmental organizations, international organizations, media reports, and other sources. A map displaying the 30-year trend of drought events has been provided (1990-2022) with a total number of 530 events, along with a second map on drought events for the period 2010–2022 with a total number of entries of 220. Statistical testing has been run using this latest time frame.

(iii) *Drought-associated impact* data have been collected from the EM-DAT (2023), where we selected crop failure, famine, and food shortage, for a total of 81 findings. Countries' coordinates affected by the above-cited disasters have been uploaded on QGIS and a comparison with Event Attribution Studies and other indicators has been provided.

(iv) *People-affected* data are collected from EM-DAT (2023) and integrated with DISINVENTAR (2023) databases by adding the country and related data that were not gathered by EM-DAT, resulting in a total of 877 million drought-related affected people. In EM-DAT people affected are classified as those that require immediate assistance during emergencies. EM-DAT data collection can occur by: (a) field reporting of the precise count of affected individuals, (b) reporting the number of damaged houses or families and multiplying it by the average family size in the area, (c) reporting value ranges, from which the average is calculated. In DESINVENTAR the category falls under the voice victims, which refers to individuals whose possession and/or services have suffered severe damage directly associated with the event. This includes: (a) families, computed based on accessible indicators, (b) partial or complete destruction of houses; and (c) loss of crops.

(v) *Vulnerability to droughts* of rain-fed agricultural systems at the country level has been collected from the study conducted by Meza et al. (2019). Specifically, the assessment of countries' vulnerability is determined by applying three macro indicators, namely, social susceptibility, ecological susceptibility, and lack of coping capacity, following the risk framework of the IPCC (2014). Each indicator is composed of several sub-indicators, totaling 36, that have been classified as relevant and weighted accordingly through a global expert survey conducted by the authors (Annex 1). They classify vulnerability on a scale from 0.19 (low vulnerability) to 0.52 (high). For this study, we considered countries with high scores, thus showing the most vulnerable countries (19).

(vi) *Water stress* data have been collected from the World Resource Institute (2023) database and the Aqueduct tool. Country water stress is measured as the ratio of total water withdrawals to available renewable water supply, where water withdrawals include domestic, irrigation, livestock, and industrial consumptive and non-consumptive uses, and available renewable water considers surface and groundwater supplies. High water stress implies high competition among users. The range of values is 0-5, where 0 is low and 5 is extremely high stress. The rank value selected in this study is 5, extremely high water stress, giving a total of 16 countries.

(vii) *Drought-associated total damage* data calculated in US $ have been provided by EM–DAT, reporting total damage for 151 million US $. The total damages section includes the number of damages to livestock, crops and property, and the monetary estimation is expressed in US $. The data corresponds to the damage value occurring in the year of the event (EM-DAT, 2023). Countries' coordinates and total damage values have been uploaded on QGIS, and a comparison with Event Attribution Studies has been made. The relation damages/GDP has been made by calculating the total of damages for the whole period 2010–2022 for each country and making an average of countries' GDP for the whole period by consulting the World Bank (2023) database. The indicator selected was GDP (current US$).

3.2. Models

To quantify discrepancies, we evaluate two models:

(i) the strength of the relationships between indicators is assessed through a Pearson *correlation analysis,* comparing, for each country, the amount of EEA studies (dependent variable) with individual indicators of risk and vulnerability (independent variables: drought events, food shortage and famine, countries' vulnerability rain-fed agriculture, water stress, total damages and people affected). This helps to evaluate whether more vulnerable and more impacted regions indeed have more EEA studies, as expected if the geographical distribution of the studies is a just representation of the drought risk across the world. For each correlation, r value and *p*-value are evaluated. The total number of entries is 256.

(ii) The relationship between the amount of EEA studies (dependent variable) and multiple independent variables (drought events, food shortage and famine, countries' vulnerability rain-fed agriculture, water stress, total damages and people affected) as predictors through a *multiple linear regression* model. This is used to understand which variables better explain the geographical location of EEA studies around the world. We report the significance (*p*-value) and effect size of each indicator in explaining the EEA distribution, and the r^2 of the full model. There are relevant differences in values between EEA studies and two variables – people affected and total economic damages-, and to deal with the wide range we scaled the data to million. Calculations are run on R software and SPSS, and summary output are included in Annex 1.

4. Results

To analyze the geographical overlap or discrepancy between the distribution of EEA studies and that of drought impacts, we first show a series of maps overlying EEA geographic distribution with the variables studied. Then, we present a table with the correlation coefficients (Table 1) and a table with multilinear regressions output (Table 2). (Annex 1, Figure 1) shows drought events occurring (a) over thirty-two years, 1990–2022, to

Table 1. Pearson correlation coefficient (r).

	EEA studies (Y)	
	r	*p*
N. of drought events (EM-DAT)	0.56	**< 2.2e-16**
Food shortage, famine, crop failure	0.13	**0.04**
Countries' vulnerability for rain-fed agriculture	0.00	0.97
Water scarcity	−0.03	0.60
Total damages US$	0.92	**< 2.2e-16**
People affected	0.11	0.08

Values in bold are considered to be significant.

provide the long-term historical context, and (b) from 2010 to 2020 which is the time frame considered in the analysis and statistical testing.

We found discrepancies in the geographic distribution of, on the one hand, EEA studies and, on the other hand, of drought-related impacts, countries' vulnerability, countries' water stress, and people affected by drought events. This shows that EEA studies are not geographically distributed according to drought impacts. Contrastingly, a strong correlation is registered between the number of EEA studies in countries and total drought damages in the same country, and a moderate correlation between EEA studies and drought events.

Figure 1 overlays drought events with EEA studies, including information about whether human influence on drought occurrence was detected, for 2010-2022. The correlation between the occurrence of EEA studies and of droughts across countries is moderate .56. Countries that experienced more than 7 drought events are the US and China which are also the countries with the highest number of EEA studies that found a human-influence (14 and 5, respectively), which is 33% and 12% respectively of the total number of such studies. Both countries also reported one inconclusive EEA study each, and for the US there are also 5 EEA studies that found no human-influence (38% of the total number of such studies). At a regional level, we can find a correlation also with Southern Africa and the Horn of Africa. Specifically, Southern Africa reported 6 EEA studies that found a human-influence (11%), and 1 no-human influence found reported in Madagascar. While the Horn of Africa – Ethiopia, Kenya, and Somalia-, reported 5 human-influence found studies, 4 no human-influence found, and 3 studies that were inconclusive, which correspond to 12%, 31%, and 38%, respectively of the total of each study type. The Horn of Africa presents the highest value of inconclusive studies (3 out of 8).

Figure 2 displays the overlays of EEA studies, drought-associated impacts, such as food shortage, famine, and crop failure, and countries with high vulnerability to droughts for rainfed agricultural systems. A first analysis between EEA studies and drought associated impacts reveals some overlapping between the two indicators in southern Africa and the Horn of Africa. However, the majority of food shortage, famine, and crop failure disasters are occurring in Sub-Saharan Africa and Central America, highlighting a deep discrepancy between the two indicators. Indeed, the correlation value is .13, meaning that there is no correlation between the distribution of event attribution studies and drought-related disaster impacts. In the time frame analyzed 81

Table 2. Regressions.

Models Total entries = 256	Coefficients	Std. Error	t	Sig.	95.0% Confidence interval for B	
					Lower Bound	Upper Bound
EEA (Y) n. of droughts event (X1)	.563	.052	10.806	.000	.460	.665
EEA (Y) Food shortage, (X2)	.196	.097	2.022	.044	.005	.386
EEA (Y) Vulnerability rain-fed agriculture (X3)	.014	.356	.040	.968	-.687	.715
EEA (Y) Water scarcity (X4)	-.2	.385	2.725	.604	-.958	.558
EEA (Y) Total damages $ (X5)	.248	.007	37.768	.000	.235	.261
EEA (Y) People affected (X6)	.007	.004	1.723	.086	-.001	.015

Table 2 offers a data summary. From the table, we can see that there are two variables individually useful in the prediction of Y, and these are drought events (X1) and total damages (X5). Indeed, they are statistically significant (Sig.) and also reported the highest coefficient values and lowest standard errors.

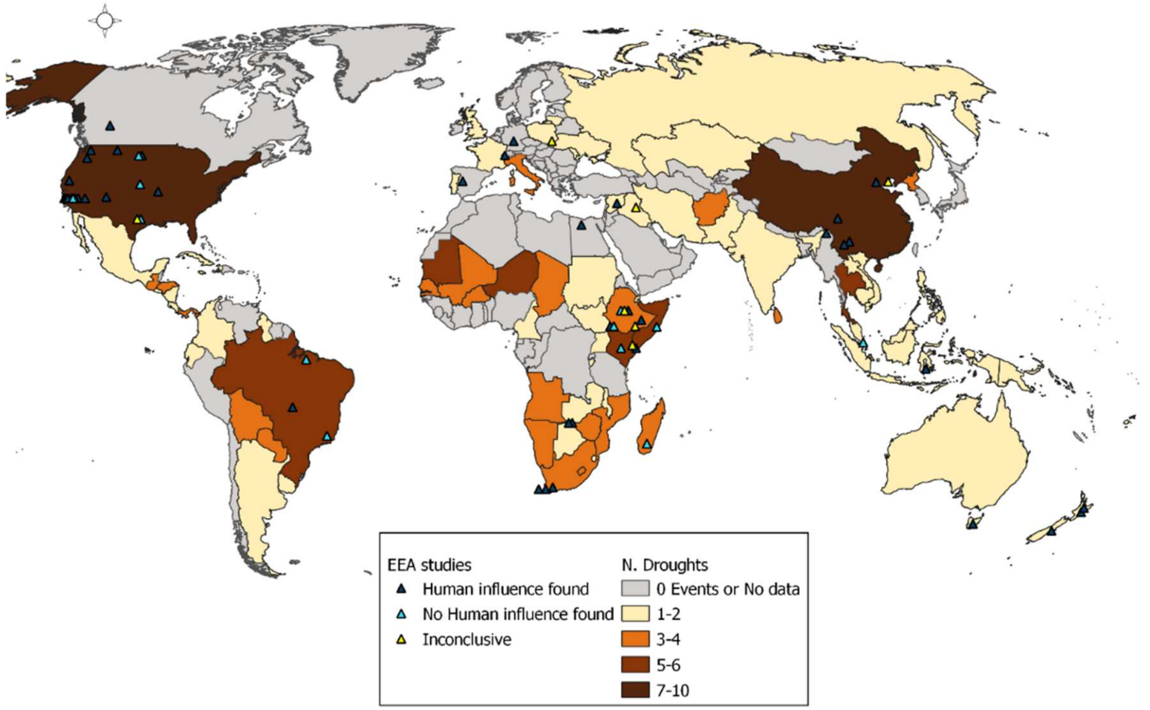

Figure 1. Global map displaying in the red shading colors the number of drought events, according to the EM-DAT database, from 2010 to 2022, and the geographical focus of event attribution studies showed with the blue triangle for studies with human influence found, the light blue triangle for no human influence found studies, and yellow triangle for inconclusive studies, for the same time period according to Carbonbrief.org integrated with WWA.

drought-associated disaster events occurred affecting 32 countries. A second analysis entails EEA studies, countries with high vulnerability to droughts for rainfed agricultural systems. The most impacted regions are Sub-Saharan Africa, particularly the Sahel. Rain-fed agriculture contributes largely to the national GDP in Africa, serving as a primary source of livelihood for a large portion of the rural population (Dinku, 2019). Almost 80% of global agriculture is rain-fed, however, in some African areas, it can be up to 95% (Alexandratos & Bruinsma, 2012). For example, Sub-Saharan Africa is vastly dependent on rain-fed agriculture, resulting in 60% of the region being highly vulnerable to frequent and severe droughts (Esikuri, 2005). Furthermore, when dealing with climate change, climate variability, and adaptive capacity, Africa is one of the most vulnerable continents at the global level (Boko et al., 2007; IPCC, 2022) as climate models agree that rainfall patterns are very likely to change with the advance of climate change resulting in more frequent droughts and having disruptive effects in poorer regions that lack infrastructure and adequate policies (Distefano & Kelly, 2017). The discrepancy in distribution between EEA and vulnerability is evident from the map, reporting a correlation value of .00.

Figure 3 overlays EEA studies, drought-related impacts, and countries experiencing extremely high levels of water stress. As water stress is expressed as the ratio between demand and supply, high water stress levels imply competition between users over the resource, which can worsen during drought events. Considering that droughts are likely to increase in the future both in frequency and intensity, this can exacerbate drought impacts and inequalities between and within countries (Elkouk et al., 2022). Furthermore, countries facing economic water scarcity often lack the financial resources to meet the demand for water and may not have extensive and well-maintained hydro-climatic monitoring networks. As a result, these countries are underrepresented in publications on drought indices, while high-income countries have more extensive reporting (Kchouk et al., 2022). This is reflected also in our results, where the correlation between water stress and EEA distribution is negative −.03.

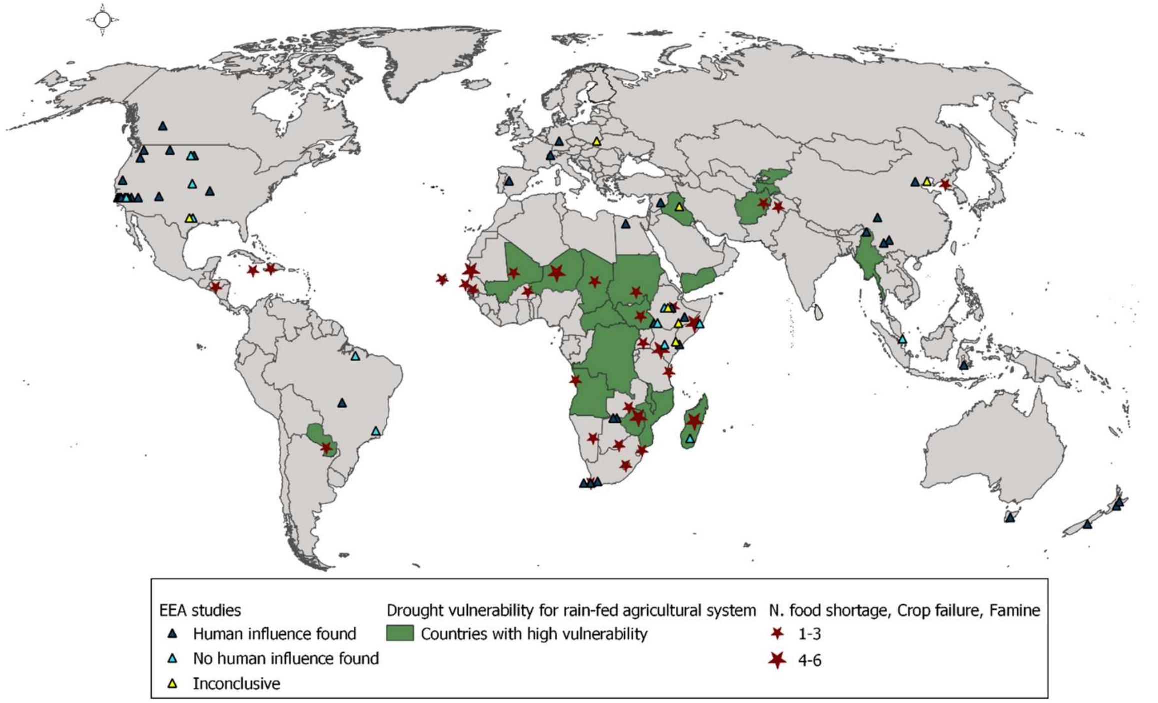

Figure 2. Global map displaying with the red star drought-associated impacts (food shortage, famine, and crop failure) from 2010 to 2022 according to EM-DAT database, and with the green color countries drought vulnerability rain-fed agricultural systems according to Meza et al. (2019) and the geographical focus of event attribution studies showed with the blue triangle for studies with human influence found, the light blue triangle for no human influence found studies, and yellow triangle for inconclusive studies, for the same time period according to Carbonbrief.org integrated with WWA.

Figure 4 overlays drought-associated total economic damage, computed as damages to properties, crops and livestock, event attributions studies, and drought events. The positive correlation between economic damages and event attribution studies is very strong with a correlation value of .92. The geographical overlapping of both indicators has been reported in countries/regions such as the US, Brazil, the Horn of Africa, Southern Africa, Southeast Asia (Vietnam and Thailand), China, and New Zealand. We should specify that even if the highest value damages are occurring in the US and China, these counted as 0.044% and 0.019% of the countries' GPD respectively, while in Somalia the damages in relation to the GDP accounted for 0.342% and in Vietnam for 0.250%.

Figure 5 overlays EEA studies, drought events, and people affected whose data have been collected from EM-DAT and DesInventar. India recorded the highest value of people affected, surpassing 338 million people impacted by droughts, of which 330 million only due to the 41-month-long dry spell starting in 2015; China follows with 85 million people affected during 2010–2022. The map reveals that the distribution of impacted people is in Central America, South America, Sahel, the Horn of Africa, Southern Asia, and the Middle East/South Asia area. Since the data are presented in millions, larger countries will inherently show a higher number of people affected. The correlation between EEA studies and people affected is found to be .11, indicating no correlation between the two indicators.

5. Discussion

Our findings indicate a lack of correlation between, on the one hand, the geographical distribution of EEA studies and, on the other hand, the occurrence of drought-associated impacts, vulnerability of rain-fed agricultural systems, water stress levels, and the number of people affected. These features are the most problematic because regions reporting drought-related impacts, such as Central America and Sub-Saharan Africa are also

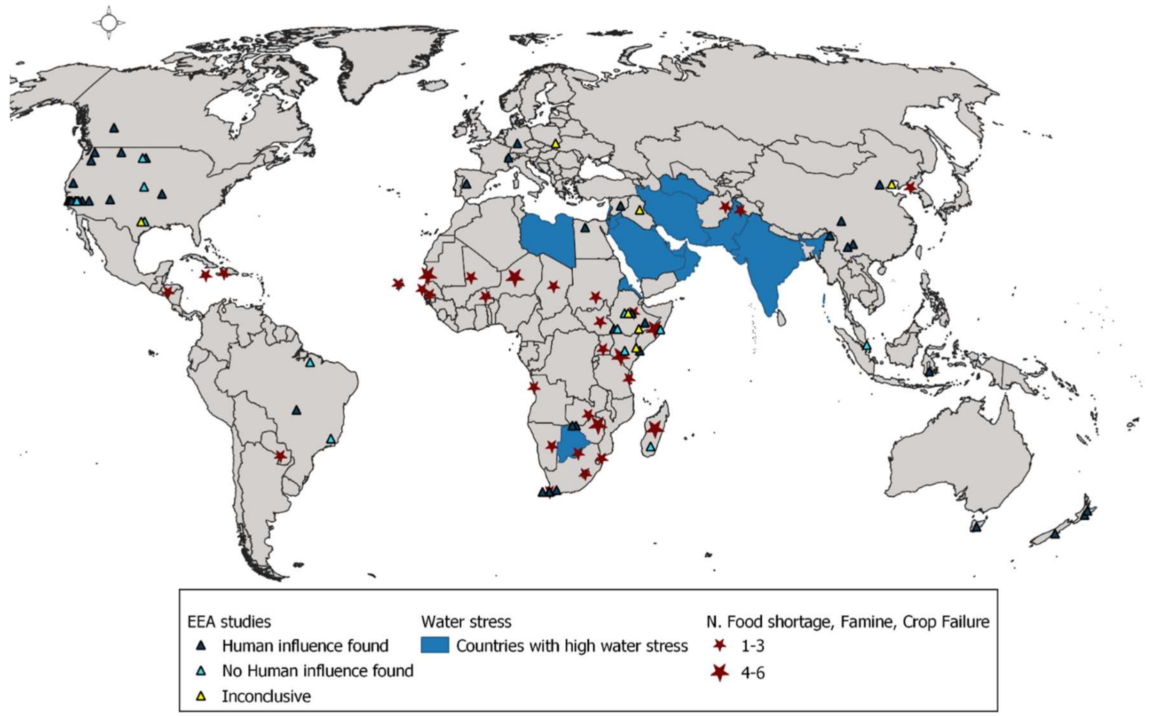

Figure 3. Global map displaying with the red star drought associated impacts (food shortage, famine, and crop failure) from 2010 to 2022 according to EM-DAT database, and with the light blue color countries that experience extremely high level of water stress according to WRI rank. The geographical focus of event attribution studies is showed with the blue triangle for studies with human influence found, the light blue triangle for no human influence found studies, and the yellow triangle for inconclusive studies, for the same time period according to Carbonbrief.org integrated with WWA.

ranked as highly vulnerable for rain-fed agricultural systems, which means they are likely to face food security issues. Similarly, countries experiencing extreme water stress levels, such as South Asia and India particularly, also have large numbers of people affected by droughts. EEAs are lacking in the case of Central America, Sahel, and South Asia, and the majority of inconclusive studies occur in the Horn of Africa, an area severely affected by all the indicators. These countries are likely the intended target of the L&D, but miss strong EEA analysis.

Thus, applying EEA as a requirement to access L&D will create high inequality, leaving behind the countries that need it the most. This lack and inconclusiveness of EEAs due to insufficient data is explained by the existing literature. Otto et al. (2020) conclude that long records of temperature observations are not available in the GHCN-D dataset, for Central America, South America, India, part of the Middle East, and Southeast Asia; hence, other data more relevant to depict droughts like soil moisture, discharge, and precipitation, which are typically measured less frequently than temperature, are also likely missing.

Furthermore, in Sub-Saharan Africa, the decline in investment in weather stations (i.e. Madagascar), unequal distribution of stations through countries' territory (i.e. Kenya), and temporal observations gaps due to conflicts (i.e. Rwanda) severely challenge the availability, accessibility, and therefore utilization of data (Dinku, 2019). Significant gaps persist in the accessibility of relevant data in southern and eastern Africa.

This analysis also shows that the occurrence of drought events relates poorly to the occurrence of drought-related impacts. This is due to the fact that differ in their vulnerability to droughts, defined by both biophysical and socioeconomic drivers that together determine the capacity to cope with extreme events (Naumann et al., 2013). Indeed, the countries recording the highest number of drought events during 2010–2022 were the US and China, while the most impacted by food shortage and famine were Central America, the Caribbean, and Sub-Saharan Africa. Additionally, Sub-Saharan Africa faces significant vulnerability to drought due to its heavy reliance on rainfed agricultural systems (Meza et al., 2019). Results also reveal that, whereas the location

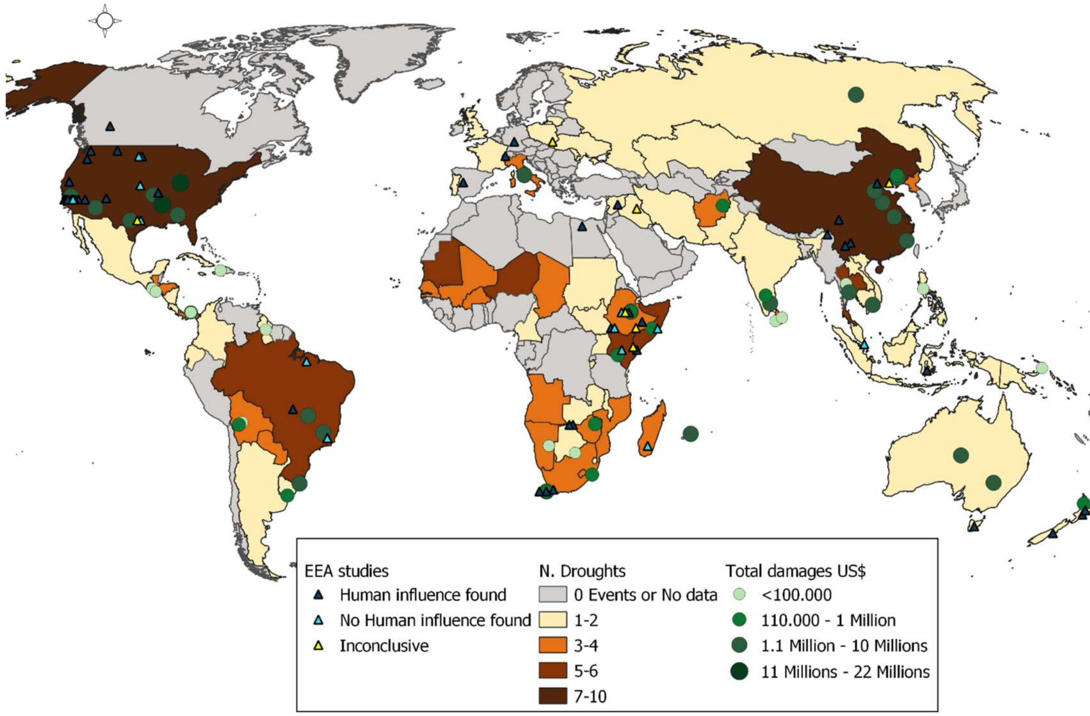

Figure 4. Global map displaying in the red shading color the number of drought events, according to the EM-DAT database, from 2010 to 2022, and the green shades scale showing the total damages associated with droughts expressed in (US$) (amount of damages to crops, livestock, and property) for the same time period according to EM-DAT database. The geographical focus of event attribution studies is showed with the blue triangle for studies with human influence found, the light blue triangle for no human influence found studies, and yellow triangle for inconclusive studies, for the same time period according to Carbonbrief.org integrated with WWA.

of EEA studies correlates only moderately with the occurrence of drought events, it correlates very strongly with drought-associated total damages. We show that EEA studies are preferentially carried out in countries experiencing at least one economically damaging drought. The largest economic damages are recorded in developed countries, and this is in line with the fact that developed countries are characterized by a higher number and value of insured exposed assets compared to developing countries, therefore more subject to economic damage (Panwar & Sen, 2020). Furthermore, developing countries' economies cannot absorb shocks in the same way as developed economies having also higher repercussions on their GDP. This highlights the importance of considering additional indicators, such as the percentage of income/GDP impacted by a disaster and the greenhouse gas emissions produced by person/country, in addition to data justice, when discussing L&D access criteria. Moreover, non-economic losses must be considered, such as loss of life, cultural heritage, and Indigenous knowledge, as well as degraded health and territory. These losses often face challenges in data gaps, reporting, measurability, and integration into economic valuation, significantly affecting Indigenous communities due to their unique value systems (UNFCCC, 2016). L&D mechanism aims to address these challenges by ensuring the inclusivity of Indigenous and local communities in the development of the mechanism's general technical guidelines, so to ensure that their values and interests are represented and implemented in the framework (UNFCCC, 2022).

5.1. Limitation of the indicators

There are several limitations to our indicators. Firstly, the number of droughts assessed by EM-DAT does not reflect the duration of each event; a two-month drought and a forty-one-month drought are both counted as a single event. This is due to EM-DAT's criteria for reporting events (see methodology). While the database

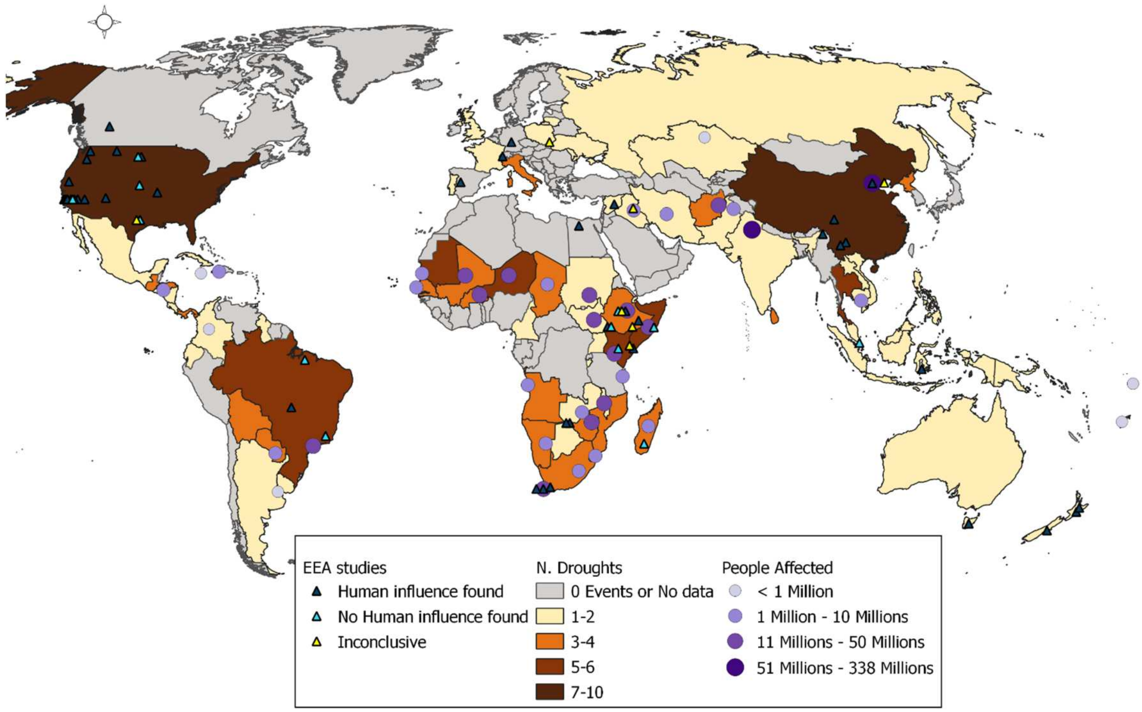

Figure 5. Global map displaying in the red shading color the number of drought events, according to the EM-DAT database, from 2010 to 2022, and the purple shades scale showing the total number of people affected classified as people that requires immediate assistance during emergencies by EM-DAT and individuals whose possession and/or services have suffered severe damage directly associated with the event by DesInventar database. The geographical focus of event attribution studies is showed with the blue triangle for studies with human influence found, the light blue triangle for no human influence found studies, and yellow triangle for inconclusive studies, for the same time period according to Carbonbrief.org integrated with WWA.

provides information on the duration of events, our analysis focused on the number of events, and we adopted other indicators to measure impacts. Other limitations concern geographic biases and data collection. Geographic biases arise from unequal reporting quality and coverage across regions, with relatively worse coverage for Sub-Saharan Africa regarding the occurrence and accounting of impact variables. Any disaster type may be subject to geographic biases in EM-DAT due to discrepancies in reporting systems between countries (EM-DAT, 2023). Reporting biases also exist, with unequal quality and coverage for different impact variables. For instance, insured damages are reported more frequently than uninsured damages, creating a geographic bias in areas lacking insurance coverage, such as Africa. Furthermore, for droughts, EM-DAT often fails to capture associated mortality, as it is overlooked as an indirect impact (EM-DAT, 2023). Lastly, that might be geographical bias towards big countries having more droughts, however, normalization to countries' surface areas would have not benefit our analysis as larger countries are more likely to be hit by more droughts but also to be targeted by more attribution studies, thus making normalization not relevant.

5.2. Future research

To even better assess the coherence, or the lack thereof, of EEA and the foci of drought impacts, the number of deaths associated with droughts should be included. This was considered, for example, by Otto et al. (2020) in their aggregate analysis of other extreme events (heatwaves, storms, and floods). However, reported deaths associated with droughts are typically very low, as it is hard to objectively quantify the number of people that incur fatal consequences from the indirect effects of a drought, i.e. famine, food scarcity, extreme poverty (Berman et al., 2017; Wilhite, 2000).

Furthermore, we could have assessed a dataset based on meteorological events to compare the data from EM-DAT. Despite EM-DAT being recognized as the most comprehensive global dataset on the impact and frequency of natural disasters (UNDRR, 2020), there are still instances of missing data (Jones et al., 2022).

Lastly, regarding the attribution of heatwaves, even though these are intensified and made more frequent by human-caused climate change (IPCC, 2023), it must be noted that in regions like Africa, heatwaves are often unrecorded as disasters in databases like EM-DAT (Harrington & Otto, 2020). As we previously discussed, for a disaster to be recorded in EM-DAT, there must be documented impacts on people, which are rarely available for heatwaves in Africa as this region lacks reliable records on how heatwaves increase hospital admissions and deaths and damage crops (Carbon Brief, 2023). This underreporting implies that the impacts of heatwaves are less visible compared to events like floods.

Nevertheless, the attribution of flood events could also be impacted by data injustice, though potentially to a lesser extent as precipitation and discharge data are generally more available than soil moisture data (GRDC, 2024). However, floods might cause fewer impacts than droughts in regions like Africa, where droughts have more severe and widespread consequences (CRED, 2022).

6. Conclusions and recommendations

In the last fifteen years, event attribution studies have contributed to the understanding of the consequences of anthropogenic climate change, through its effect on extreme events, and assisted the media in the communication of climate change effects to the large public (van Oldenborgh et al., 2021; Stott & Walton, 2013). Whereas the idea of a problematic distribution of event attribution studies has been hinted at in the literature (Otto et al., 2020), our research clearly shows that event attribution studies on drought are not geographically distributed according to their impacts. Besides data injustice, the limited capacity of regional and national technical institutions is possibly another reason for the fewer attribution studies in Africa (IPCC, 2019, chapter 6.2). Addressing this gap will involve strengthening local expertise, empowering developing countries to finance their own research initiatives, and facilitating north–south knowledge exchange (Otto et al., 2020; King et al., 2023). Still, geographic discrepancies in attribution studies could be attributed also to other factors. For instance, funding sources could play a significant role. A subset of countries in the Global North holds the most resources and expertise for conducting attribution studies, resulting in a significant gap in availability; also, studies conducted by external scientists might lack the local context and framing that scientists with regional expertise can provide (Otto et al., 2020). Media coverage biases could also influence which events are studied, as near-real-time information about impacts often relies on media reports, which can be uneven and biased (Carbon Brief, 2023). Additionally, null result publication bias may also skew the literature, as in general studies without conclusive or negative results may struggle to get published (Fanelli, 2012), and there are no clear indications that climate science deviates from this tendency.

Therefore, the potential use of event attributions as a criterion for accessing L&D gives rise to concerns regarding justice, fairness, and ethical considerations in the distribution of funds. We suggest that before considering EEA studies to inform loss and damage, it is crucial to first advance EEA studies in developing countries by addressing the existing research gap. This can be achieved through capacity-building efforts supported by the Global North and by investing in weather station distribution. Additionally, developing impacts-based EEA analyses would improve our understanding of the costs associated with human-induced climate change (Philip et al., 2020b). Integrating EEA with knowledge on vulnerability and exposure, and fostering collaboration between scientists, policymakers, and humanitarian aid experts, will further enhance decision-making related to L&D.

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