Wealth over Woe: global biases in hydro-hazard research

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Abstract

Floods, droughts, and rainfall-induced landslides are hydro-geomorphic hazards that affect millions of people every year. Anticipation, mitigation, and adaptation to these hazards is increasingly outpaced by their changing magnitude and frequency due to climate change. A key question for society is whether the research we pursue has the potential to address knowledge gaps and to reduce potential future hazard impacts where they will be the most severe. We use natural language processing, based on a new climate hazard taxonomy, to review, identify, and geo-locate out of 100 million abstracts those that deal with hydro-hazards. We find that the spatial distribution of study areas is mostly defined by human activity, national wealth, data availability, and population distribution. Hydro-hazards, which impact large numbers of people, increase research activity, but with a strong disparity between low- and high-income countries. We find that a 100 times higher impact is needed before low-income countries reach comparable research activity to high-income countries. This "Wealth over Woe" bias needs to be addressed by increasing research on hydro-hazards in highly impacted and under-researched regions, or in those sufficiently socio-hydrologically similar. We urgently need to reduce knowledge base biases to mitigate and adapt to changing hydro-hazards if we want to achieve a sustainable and equitable future for all global citizens.

Introduction

Hydro-geomorphic hazards (hydro-hazards), such as floods, droughts, and rainfall-induced landslides, affect millions of people and cause thousands of fatalities annually. According to the Centre for Research on the Epidemiology of Disasters (CRED), floods and droughts together affected more than 130 million people in 2022 alone. Critically, the risk from hydro-hazards will keep increasing due to projected climate and anthropogenic change (Arnell et al., 2019; IPCC, 2022), which already overwhelms disaster risk reduction efforts (Kreibich et al., 2022b). The clear societal threats posed by hydro-hazards suggest that science should tackle knowledge gaps to better guide adaptation policies where the risk is greatest. However, existing natural hazard research overlooks many countries and does not study hydro-hazards in detail. For example, only 6.5% of all natural hazard research studies are performed in Africa (Emmer, 2018) despite having the largest predicted increase in flood exposure (Jongman et al., 2012).

There are still substantial knowledge gaps as to which environmental, anthropogenic, and socio-economic characteristics determine research foci and biases. We lack knowledge regarding which regions are underrepresented in studies of hydro-hazards. Quantifying and mapping these biases is key to revealing and eventually addressing their underlying causes. For hydro-hazards, the high spatial variability of all components of risk complicates bias analyses. Threats from floods, droughts, and landslides are highly heterogeneous, e.g., landslides are gravitational mass movements and occur in rugged terrain. The exposure to any natural hazard depends on hazard magnitude and population distribution (Devitt et al., 2023). Differences in people's vulnerability, e.g., due to their socio-economic situation, further determine how strongly they might be affected when a hazard happens (Benevolenza and DeRigne, 2019). The integration of all three aspects, hazard, exposure, and vulnerability, forms the risk, i.e., the potential for negative impact of hydro-hazards. Therefore, we would not expect the global research landscape to be spatially homogeneous. Instead, we would expect a fair research distribution to follow one or a combination of the following aspects:

1. ***Socio-Hydrological Variations:*** Research is conducted based on scientific gaps. To advance scientific understanding, the scientific community should aim for research that is representative of the underlying socio-hydrological processes, in regard to both hazard generation and risk. Representative knowledge distribution is particularly relevant for assessing vulnerability, as it is spatially heterogeneous and difficult to transfer (King-Okumu et al., 2020; Ward et al., 2020).

2. ***Impact Density:*** Research is conducted where the impact or risk is the largest. Impact can be measured as the number of events, fatalities, people affected, or economic loss. For this type of analysis, we focus on the number of events, people affected, and fatalities. We disregard economic losses here since economic impact data disproportionately favours high-income countries (King-Okumu et al., 2020).

3. ***Population Density:*** Finally, an equitable distribution might simply entail an equal allocation of studies according to population distribution.

Aiming for representative research coverage regarding hydro-climatic, landscape, and socio-economic characteristics is not only important for addressing the current hazard situation but also for predicting and projecting future risk. We investigate a corpus of 100 million scientific abstracts (Kinney et al., 2023) by extracting and geo-locating those studies focused on hydro-hazards. We compare the spatial distribution of these abstracts with hydro-climatic, socio-economic, and disaster impact data to determine biases in the current knowledge base. And finally, to address these biases, we provide recommendations for high-priority regions for future research and funding. Our results integrate knowledge on hydro-hazards for disaster risk reduction and contribute towards a more sustainable and equitable research landscape.

Results

Global distribution of hydro-hazard research

We use Deep Search (Staar et al., 2018) to filter 100 million abstracts and annotate them with location and hydro-hazard mentions. Out of 610,000 abstracts that include variations of the search terms "drought", "flood" and "landslide" further screening (Figure S2) leaves us with 293,156 abstracts for the analysis. We calculate research density as research per cell weighted by the size of the entity (Callaghan et al., 2021). We define highly researched regions as all locations with a research density of more than the 75th quantile of all land cells. The exact regions are shown in Figure S5.

The global distribution of hydro-hazards research densities depicted in Figure 1 (a,d,g) shows a distinct pattern for each hazard. A noticeable hotspot for **drought** research is the west coast of the USA, and further highly researched areas can be found across much of Europe (UK, Switzerland, Italy, and Spain) and Asia (South Korea, Bangladesh). Other highly researched regions are located in Africa. Ethiopia, for example, is among the five most highly researched countries for droughts (Figure S13), though several other African countries are also highly researched, such as Kenya, Nigeria, Tanzania, and Zimbabwe (Figure S5). Drought study numbers are low for Latin America, Central Africa, Russia, Kazakhstan, Mongolia, and Canada. In absolute numbers, Russia is mentioned often (Figure S6), but the size of the country makes individual cell weights low and no small scale studies are detected. **Flood** research density is generally higher due to an overall larger number of articles. Flood research has several clusters around Europe, the USA, and Asia, such as Bangladesh, eastern China, Japan, and South Korea. The cell with the highest flood study count is located in the south of England (a cell including London and the Thames). 5% (8,616 in total) of all flood abstracts target the UK. For comparison, Nigeria is the country with the largest number of flood studies in Africa, with 2,595 abstracts on floods. Flood research in South and Central America and most of Africa is low. **Landslide** research has more distinct hotspots, especially in the Alps, Italy, Taiwan, Hong Kong, the Himalayas, Central China, and Japan. In fact, Taiwan is the cell with the highest research count overall. In terms of absolute numbers, China is the country with the most abstracts on landslide research, with 6,571 abstracts in total.

Research distribution across climate zones

We analyze the research bias between climate zones by comparing study numbers against the numbers of hazard events and population numbers in each climate zone. Temperate regions have, on average, the highest research count for all three hazards (Figure 2a). In terms of hazard event counts (Emergency Management Database, EM-DAT, Figure 2c, upper panel), that distribution is only mirrored by flood event occurrences. Most flood events (mean 28.8 per cell) occur in temperate regions. The average flood count in tropical regions is about half as high as in temperate regions (mean 15.2 per cell), yet the research density is only about a third. This result suggests a flood research bias against tropical regions. A large share of flood events (mean 11.8 per cell) also occurs in polar regions, with the lowest research density by far. Drought events are evenly distributed among climate zones. Drought research effort is much higher in temperate regions than in arid and tropical regions, indicating a bias towards temperate and against tropical and arid regions. For landslides, the identified bias strongly depends on the choice of the event count dataset (e.g., EM-DAT vs. NASA landslide catalogue vs. the Global Fatal Landslide Database—GFLD, Figure 2c, lower panel). The comparison indicates a bias in the event count datasets themselves. Additionally, we compare the research distribution across climate zones with the population distribution across climate zones. The dominance of research in temperate regions matches the higher share of population in that climate zone (36%, Figure 2b). Yet, tropical regions with 22% less population than temperate regions have a 60% (drought), 70% (floods), and 74% (landslides) lower research density.

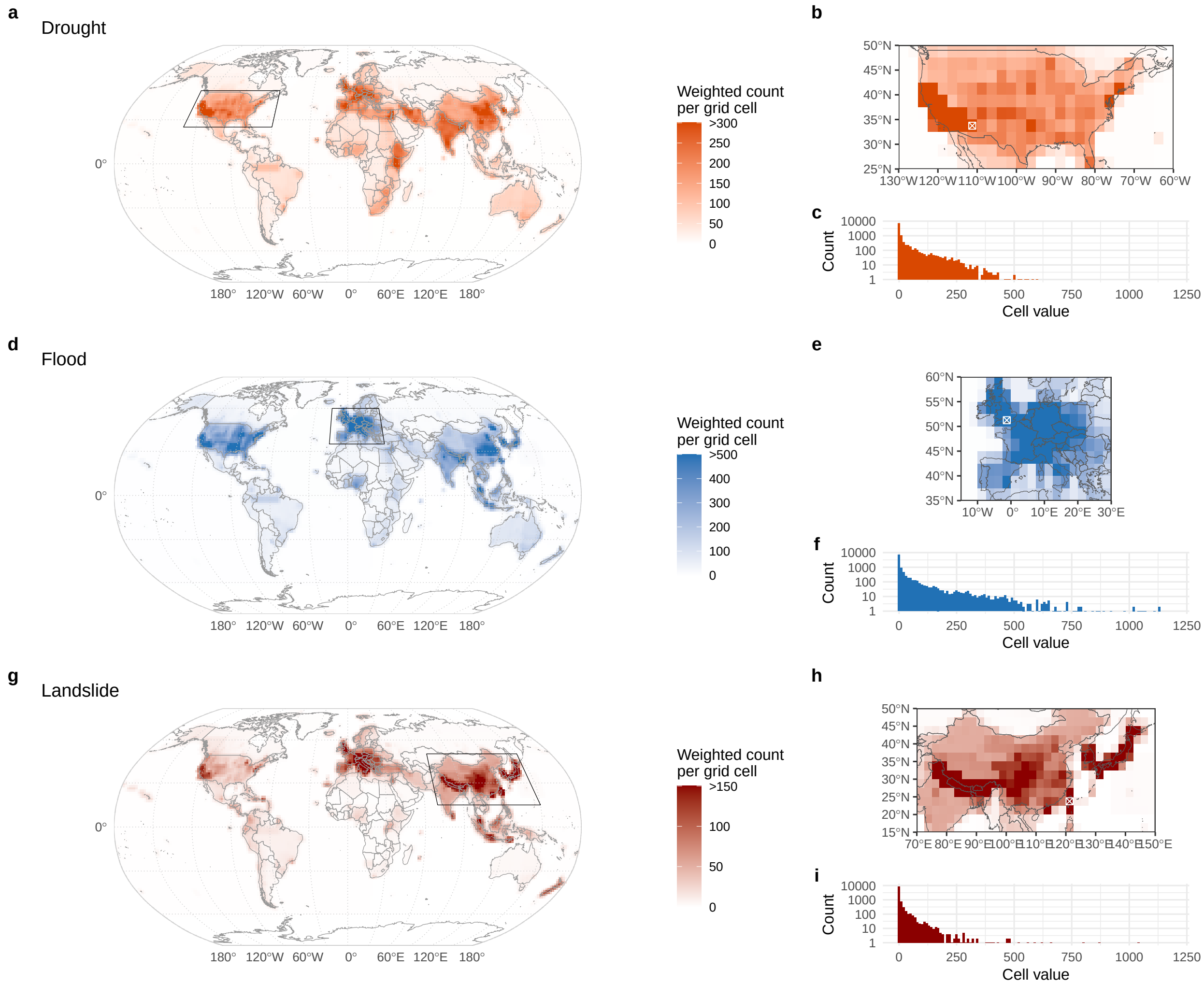

Figure 1. For each water extreme, the research distribution is displayed in three panels. A global map of weighted research count, a detailed map for the highest cell count (marked by x) and a histogram across all raster cells for droughts (**a-c**), floods (**d-f**), and landslides (**g-i**).

Environmental and socio-economic controls on research distributions

We further analyze how these research study distributions co-vary with different environmental and socio-economic characteristics and with the availability of hydro-meteorologic measurements. Hence, we extract the land surface with high research density ($> 75^{\text{th}}$ quantile, Figure S5) and compare its characteristics with those of the whole land surface. Differences between distributions are measured using the Wasserstein metric (Kantorovich, 1960; Krabbenhoft et al., 2022). Figure 3a shows Wasserstein distances for selected variables (all variables: Figure S8).

Multiple variables indicate a strong positive bias in research density towards regions that are highly influenced by human activity. Human footprint, representing aspects of human pressure on the environment (Venter et al., 2016), as well as the variables irrigated land, population count, cropland, and travel time to nearest city as an indicator of urbanization all exhibit high Wasserstein values (> 0.5). Wasserstein values are lower (on average < 0.4) for climatic indices such as potential evapotranspiration, precipitation, and aridity. The average annual precipitation is the only

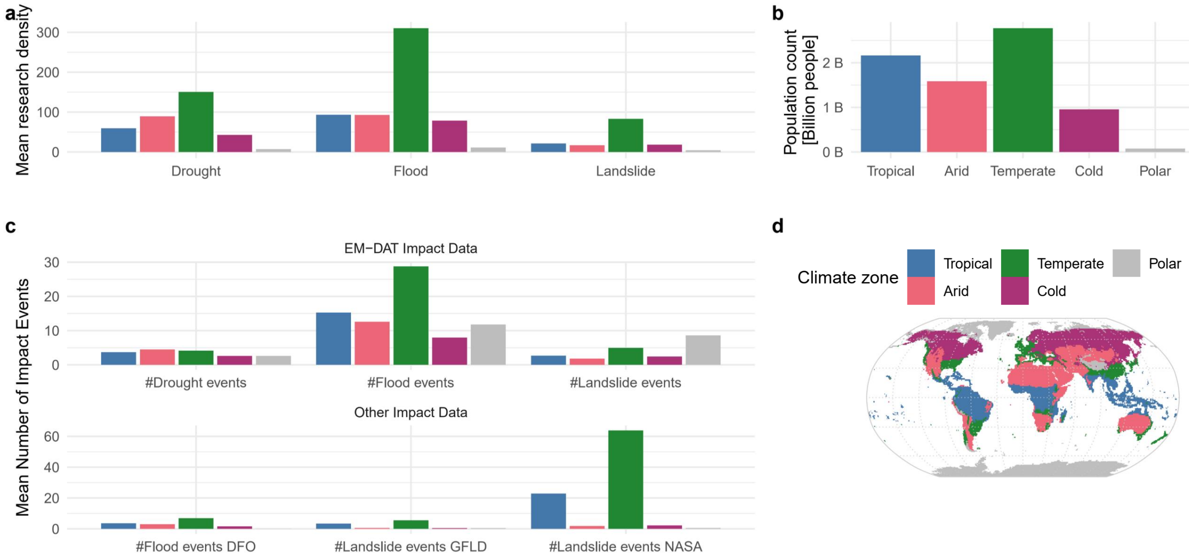

Figure 2. **a**, Mean research density across broad climate zones according to Koeppen-Geiger (Beck et al., 2018), **b**, population count (WorldPop, 2023) by climate zone, **c**, mean number of events per cell and climate zone for EM-DAT event counts as well as one flood and two landslide datasets (Dartmouth Flood Observatory, Global Fatal Landslide Database (GFLD), NASA landslide catalogue), **d**, world map depicting the climate zones.

climatic variable that has a large spread of Wasserstein values across hazards (0.14 for drought, 0.24 for flood, and 0.36 for landslide research). Furthermore, we also observed opposing distribution differences between hazards. While flood and landslide research densities increase with increasing precipitation, drought research density decreases. However, this negative relationship reflects only the average distribution. Examining detailed cumulative distributions (Figure S9), we observe decreasing research density with increasing precipitation from precipitation values $> 1250mm$. We also find biases related to data availability, i.e., the research density is higher in regions with more measurement stations.

Besides human influence, further biases in hydro-hazards research activity can be found in other socio-economic dimensions. There is a positive bias in research density towards countries with a high gross domestic product (GDP) (Wasserstein distance of 0.65 for drought, 0.72 for flood, and 0.74 for landslides). The variable "Scientific and technical journal articles" from the World Bank refers to the number of articles published within the field of science and engineering per country. It can be regarded as a control variable that is expected to exhibit a positive value, which we confirm with an average Wasserstein distance of 0.75 across hazards. Research densities are much less biased towards other socio-economic indices than GDP and population. Income inequality (Gini Index), the ability to adapt to climate change, including hazards (adaptive capacity), and the human development index show only small biases (Wasserstein averaged across hazards: 0.25, 0.24, and 0.19, respectively).

Country income-level, people affected, and research density

We investigate the interactions between research density and the number of affected people to observe whether more impacted regions are also more intensely studied. In Figure 4a, we see

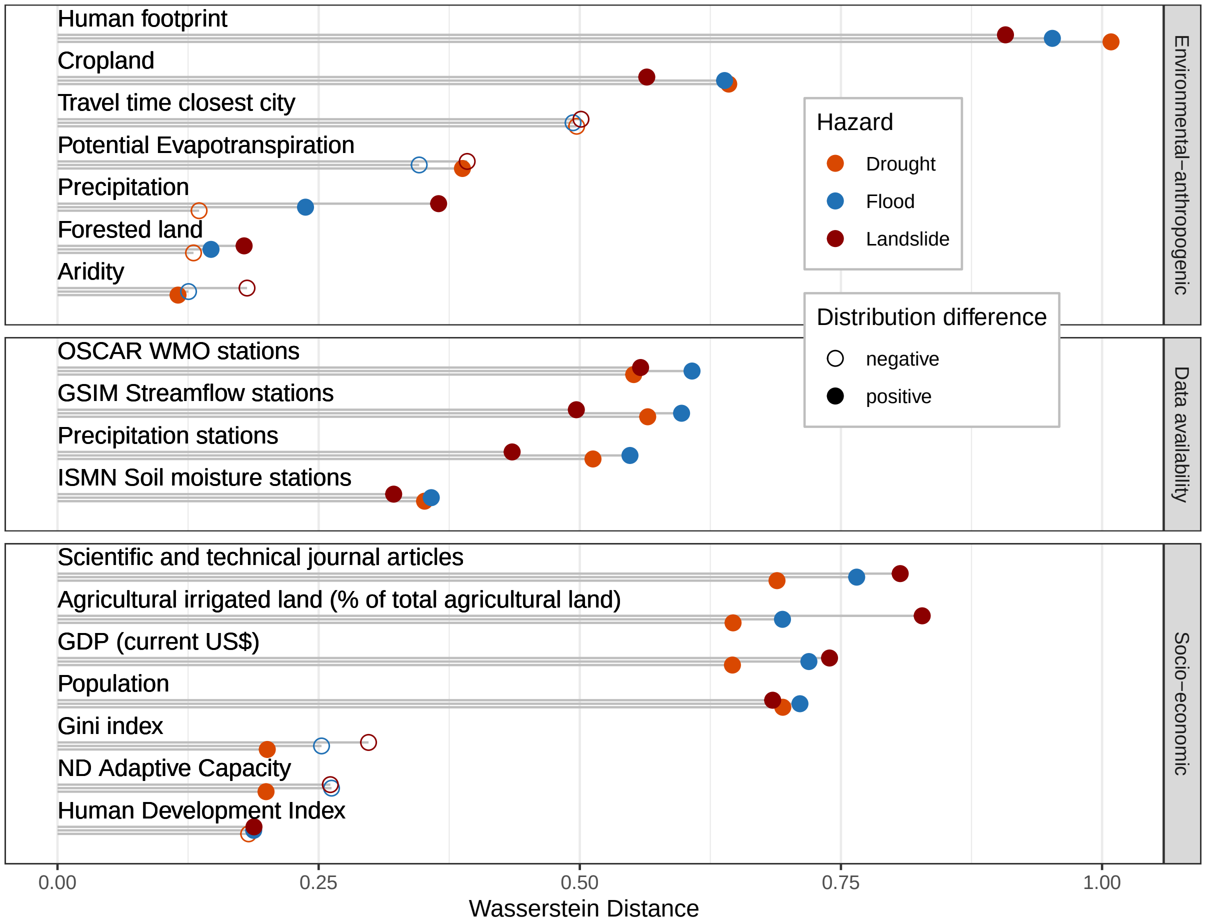

Figure 3. Comparison of climate, land, gauging data, and socio-economic characteristics between regions of high research (> 75$^{\text{th}}$ quantile) and the entire land area. Distribution difference measured as Wasserstein distance (Krabbenhoft et al., 2022). Higher values indicate a stronger bias. A positive (negative) distribution difference indicates more (less) research with increasing characteristics.

that more research is conducted in high-income countries for all hazards, indicated by the higher baseline and earlier onset of the respective curve compared to all other income groups. For some high-income countries (e.g., for droughts in Germany, France, and Japan; or for landslides in the UK, Slovenia, and Uruguay), no people have been recorded as being affected in the EM-DAT database (CRED, 2023a), even though research has been conducted, as indicated by the distribution offset in y-direction. There is no visible offset for the distribution of flooding, given that Malta is the only country for which no affected people are recorded. Low, low-middle, and upper-middle-income countries all report higher numbers of people affected for the same research density than high-income countries. However, for nearly all of these countries, hazard research densities never reach the same level as for high-income countries. The only exception is drought research in lower-middle-income countries, which is largely due to the large amount of drought research in India (Figure S13).

Interestingly, there is a distinct difference in how many people need to be affected before research activity visibly increases for the different income groups. These thresholds are much lower for high-income countries across all hazards. Flood and drought research seems to be triggered when about 100 people are affected in high-income regions, for landslides it is less than 100 people. Flood and drought research activity in low-income countries only starts increasing if more than 10,000 people have been affected. Across all hazards, research density rises with the affected number of people (Figure S15).

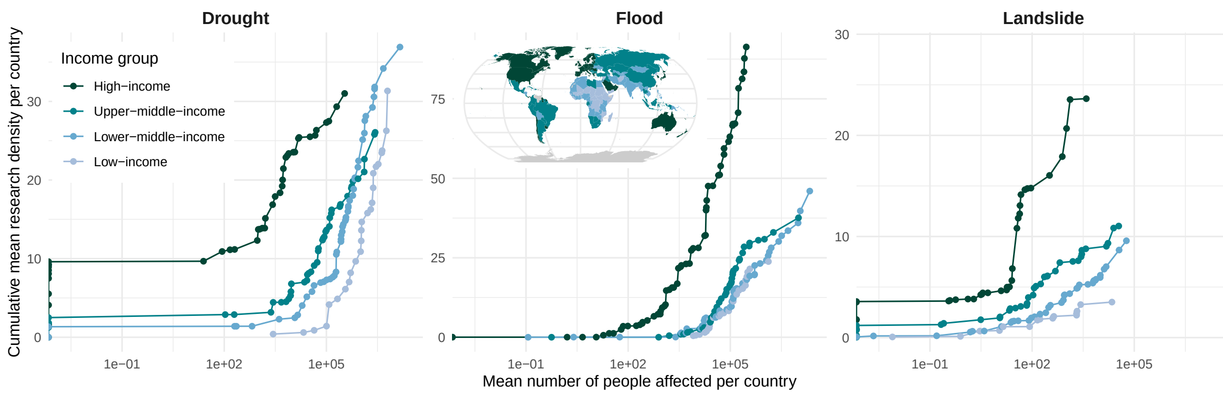

Figure 4. Country-averaged number of affected people against the cumulative distribution of the research density, averaged over all cells per country and separated by World Bank income levels (according to 2021 income classes) (World Bank, 1978). Each dot corresponds to one country.

Discussion

Wealth over woe - poorer countries are less researched despite higher hazard impact

Low-income countries are disadvantaged across all aspects of disaster risk management. They are more impacted by hydro-hazards (Hallegatte et al., 2020), and by climate change, while their risk is increasing in many regions (IPCC, 2022). The need for equality across all aspects of disaster risk management has been recognized by the United Nations Office for Disaster Risk Reduction and in the Sendai Framework, which aims to increase knowledge and disaster risk reduction with a particular focus on low-income countries (https://www.undrr.org/disaster-risk-reduction-least-developed-countries). Our study can contribute to achieving a more equal and sustainable research landscape, especially when local scientists and communities from target regions are involved in the research (Odeny and Bosurgi, 2022) or are being involved in sustainable research partnerships (Gill et al., 2021). Importantly, addressing these knowledge gaps will help the international community reach the Sustainable Development Goals, many of which have synergies with current efforts in disaster risk reduction (Aitsi-Selmi et al., 2016).

Hallegatte et al. (2020) conclude that "Poor people are disproportionately affected by natural hazards and disasters." We find that low-income countries are not just disproportionately affected, but also have a disproportionately lower research density for hydro-hazards. Even though research is more prevalent in all countries where high impact hazard events occur, the threshold for what constitutes "high" is much lower in wealthier countries (Figure 4). For flood and drought research, 100 times more people need to be affected in low-income countries compared to high-income countries for research densities to reach the same level. Hazard impact therefore has a relatively small influence on research activity, while country wealth is much more influential (Wealth over Woe). This disparity is likely due to highly unequal research funding and research capacities between high-income and low-income countries (Skupien and Rüffin, 2020).

Our results show that low-income countries need to base risk assessment decisions, adaptation, or policy changes on less research than wealthier countries. Even if research findings can be transferred from hydro-climatically similar regions, socio-economic and governance conditions will most likely be very different (Figure 4). Yet, local scientific and community knowledge is highly relevant for the effectiveness of disaster risk management (Gaillard and Mercer, 2013) and can reduce disaster impact if combined with resources to implement solutions (Kreibich et al., 2022a). Less research in low-income countries thus means there is less knowledge on how the current impact imbalance might be rectified in the future. Global overviews of research distribution, such as ours, can thus provide valuable guidance by suggesting future research focus regions to funding agencies including the World Bank, the UN, and the European Union.

How can we address current and future hydro-hazard knowledge gaps?

We assess research focus regions based on past impact and identified gaps in socio-hydrological variations covered by research. For an-impact based assessment, we define regions that should become research focus areas as those with combinations of a high number of people affected ($> 75^{\text{th}}$ percentile) and low rates of research activity ($< 75^{\text{th}}$ percentile). For droughts, regions with high research needs are predominantly the Sahel zone, the Horn of Africa, eastern Brazil, and Afghanistan (Figure 5). For floods, the areas are more scattered, but relevant regions are large areas in South and Central America as well as in eastern Africa (e.g., Somalia, Zambia, and Mozambique). In contrast to floods and droughts that affect multiple spatial grid cells, a single landslide event will only be recorded in one cell due to its limited spatial extent. Hence, landslide research focus cells include major cities, e.g., Freetown in Sierra Leone and Abidjan in Côte d'Ivoire (Figure 5). Under-researched landslide regions are mainly located in South America, particularly in Bolivia and Brazil. We find that all of the mentioned locations remain research focus regions even when different impact datasets are used. Though with more data, some additional regions can be added as focus regions, as shown and discussed in the supplemental information.

Some knowledge gained in highly researched regions may be transferable to less studied regions if similar hydro-climatic and landscape characteristics allow the assumption of process similarity (Bertola et al., 2023; Stein et al., 2021). We do find several promising hotspots of highly researched regions where flood, drought, and landslide hazards have been intensely studied. These cover mainly the US, Europe, and parts of Asia. Still, an increase in research will be particularly necessary in regions where increasing hazards and impacts are already noticeable or will likely increase in the future. For example, diminishing water availability in the Southern Hemisphere (Zhang et al., 2023) indicates a need for water management and drought adaptation research, which is currently lacking. Landslide research is predominantly conducted in mountainous and temperate regions in Europe, China, and the USA (Figure 2). Yet, tropical regions, especially tropical cities, have been projected to be future hotspots of landslide risk given both population growth and climate change (Ozturk et al., 2022). While both floods and landslides are well studied in more humid regions, drought research activity is lower in very humid regions and is underrepresented in tropical regions (Figure 2). Hence, we argue that the drought risk for rainforests is likely inadequately studied, given its importance. For example, recurrent extreme droughts in the sensitive Amazon rainforest (Lewis et al., 2011) define a potential critical tipping point for the earth system (Lenton et al., 2008). Additionally,

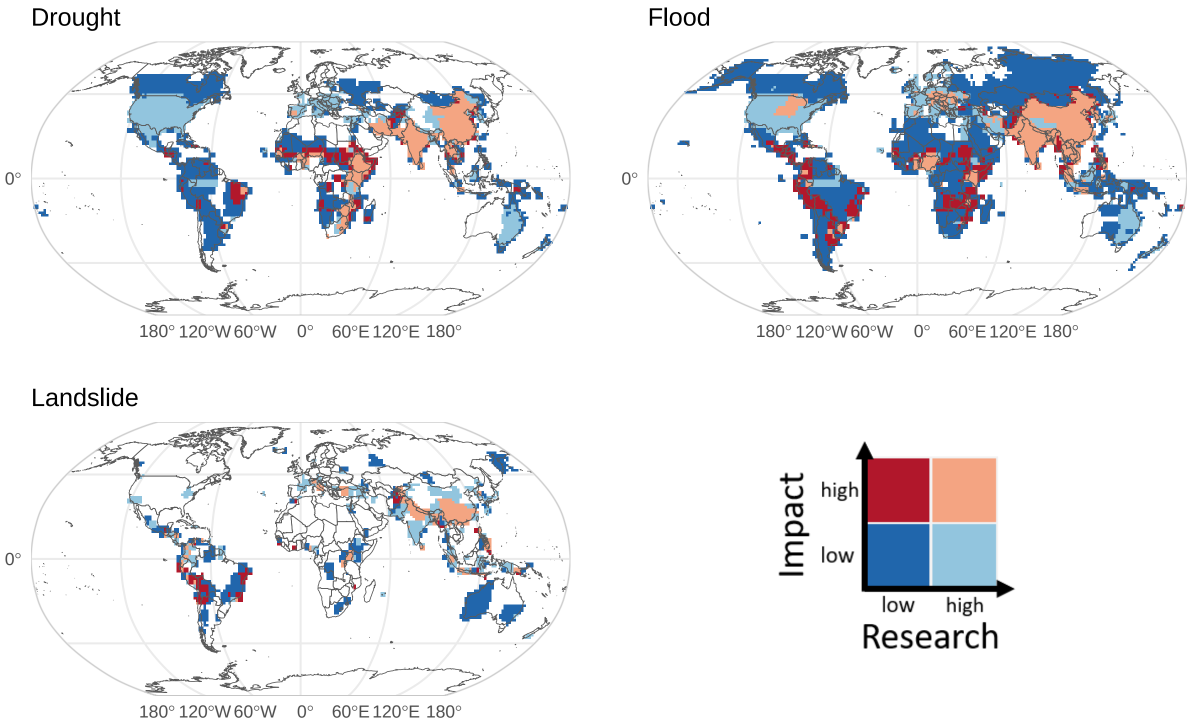

Figure 5. Research focus regions. Each cell is categorized by whether it falls into the high or low research ($> 75^{\text{th}}$ quantile) category and high or low impact category, based on the number of people affected. Most relevant for future research are regions with low research and high impact (dark red). Classification based on 75^{th} quantile of research and impact (number of people affected, EM-DAT).

some poorly explored regions with distinct characteristics, too dissimilar for knowledge transfer, need further exploration from a hazard process understanding viewpoint. A location-specific aspect of risk research is vulnerability, since it is dependent on culture, socio-economic settings, and governance systems (King-Okumu et al., 2020). It is, therefore, paramount to ensure vulnerability to hydro-hazards is studied across different socio-hydrological settings.

Limitations

We have only studied the distributions of knowledge contained within published scientific abstracts because these have so far been compiled as datasets. Our approach therefore cannot adequately recognize that at least some applied research might only occur in technical reports (i.e., grey literature) or in un-published Master's and PhD theses. Importantly, we currently do not consider the wealth of knowledge gathered by local citizens and indigenous people, which is often ignored or overlooked by the scientific community (Chief, 2018), but would require a different type of study to be utilised. Some research might also be overlooked due to the choice of English as the language of analysis. However, Orimoloye et al. (2021) found that 95% of disaster risk management articles are published in English. We therefore assume this limitation to be minor. Similarly, the choice of dictionaries used for geo-location might introduce a bias towards larger entities, high-income countries, and non-natural features (Acheson et al., 2017). Our evaluation on a subset of 175 abstracts showed, that 1/3 of abstracts have missing geo-annotations. However, in 85% the missed annotations would not have changed the geo-location identified. Additionally, location extraction is biased by the limited description contained within abstracts. Although full-text analysis may have yielded more information (Westergaard et al., 2018), it would dramatically reduce the number of articles available. Open access is rapidly growing (Björk, 2017). Hence, reviews like ours will likely become more informative in the future.

Looking forward

In this study, we were able to map hydro-hazard literature and show biases related to where and how often hazards are studied in a specific location. We find that high-income countries experience much higher levels of research activity compared to lower-income countries, despite being less affected. Thresholds for numbers of people affected appear to be significantly higher for lower income countries compared to wealthier regions. Furthermore, the uneven distribution suggests knowledge gaps in hazard understanding since not all hydro-climatic landscapes are covered equally. Where hazard events occur and where they are researched does not align. Tropical regions, for example, are studied less than distributions of flood, drought, and landslide events would suggest. Even more importantly, focusing research on high-income regions means that socio-economic and governance structures found in low-income countries are underrepresented. Such biases reveal where future research might be needed to cover a broad spectrum of hazard research across different environmental and socio-economic characteristics. Additionally, regions where many people have been affected by hazards in the past, but where less research has been conducted yet, offer themselves as future study regions and can thus guide research funding efforts. Specifically, Central and South America should receive more attention for flood and landslide research. In Central and Eastern Africa, more drought and flood research should be conducted.

Overall, our findings provide research funding agencies with the necessary maps to develop programs that target research inequality. Policymakers might use these maps to determine where knowledge gaps might affect their decisions. Researchers should be encouraged to develop collaborative networks within and across under-researched regions to build observational and research capacity where it is most needed. Funding agencies need to develop new funding mechanisms to support such efforts, which are often beyond current funding schemes that focus on funding researchers in the country of the funding agency, rather than build capacity abroad. We currently only show the state of historical research and its impact to date. However, with climate change altering hazard occurrences around the world and with rapidly changing socio-economic conditions in many places, research relevance shifts as well. If we, as a community, want to preemptively address possible future disasters (Ozturk et al., 2022), we need to map current research activities to highlight knowledge gaps in regions that are at risk in the future.

Methods

Abstract data mining and annotation with hydro-hazards taxonomy

The Semantic Scholar Academic Graph (Kinney et al., 2023) forms our basis for data mining. Currently, it contains 215 million scientific documents from all scientific fields, published and indexed by non-profit organisations like Crossref or PubMed, preprint repositories such as arXiv, and academic publishers like Springer Nature. Within the Semantic Scholar corpus, the abstracts dataset provides abstract texts for around 100 million records. We utilized Deep Search (Staar et al., 2018, https://ds4sd.github.io/), a tool that uses natural language processing to ingest and analyze unstructured data. Deep Search processes text from the abstracts dataset and enriches the metadata, for instance with language detection. The metadata associated with abstracts include entries like unique identifiers, language, publication date, or subject (e.g., Environmental Science). Only English language abstracts were analyzed, which make up 95% of the total data available (Figure S2).We further excluded subjects related to the humanities, such as history, philosophy, and art.

Abstract filtering: We first extracted all hydro-hazard-specific abstracts from the 100 million documents using a term query in Lucene syntax (i.e., landslide OR mudslide OR rockslide OR flood OR drought OR rockfall) within Deep Search. As a result, 610,000 relevant articles remained.

Hazard and geo-entity annotation: We created a climate-specific taxonomy for hydro-hazards, which includes several types of hazards and subtypes, along with synonyms. For example, "floods" are classified under "flood hazard", encompassing different forms of floods such as "flash flood", "stormwater", "outburst flood", "fluvial flood", and others. Synonyms for, e.g., "fluvial flood" include "river flood", "riverine flood", etc. A full overview of hazard entities can be found in Table S1, while the entire taxonomy is part of the supplemental data.

Geo-entities were identified in the abstracts and the metadata was enriched by the type of entity (e.g., type: cities, match: "New Orleans"). To perform this step, we compiled a geographic and climate hazard-specific taxonomy. Geographic taxonomy information about towns and cities with 100,000 inhabitants or more was sourced from Wikipedia's rich open knowledge base (Lehmann et al., 2015) and was further augmented with the GitHub open-source collections for smaller capitals and cities by countries, as well as Encyclopedia Britannica for lakes and rivers (Table S2).

Converting geographic entities into coordinates: We used a combination of the geocoding software Nominatim (Clemens, 2015) and data from Natural Earth Data (NE, www.naturalearthdata.com) to add geographic coordinates to the identified geo-entities. Nominatim searches OpenStreetMap https://www.openstreetmap.org/copyright (OSM) (Haklay and Weber, 2008) (Bennett, 2010) data. In case of ambiguity (e.g., multiple identical geo-entities), the five largest entities returned by Nominatim were selected and further ranked based on the OSM importance value, indicating search popularity (e.g., Paris, France: 0.8 versus Paris, Texas: 0.5). We used data from NE to supplement the OSM results and to improve shape outlines of large features such as regions and continents. The matching was based on geo-entity name and identified type (e.g., "rivers", "countries"). Manual evaluation showed that this approach was more accurate in identifying regions and natural features than Nominatim alone. The final coordinates are based on feature bounding boxes for OSM and river lines, as well as exact polygon shapes for all other NE data.

Manual evaluation of annotation quality

The combined OSM and NE tagged geo-entity dataset was manually evaluated, and frequently wrong results were removed. For example, the frequent geo-entity "Mobile" is often misidentified as Mobile County in Alabama. A full list of these manual edits is provided in the supplement. A subset of the final annotated data was evaluated by two independent human reviewers. Each reviewer evaluated 100 abstracts, with 25% overlap between reviewers. Results were judged based on the relevance of the abstract, completeness of the hazard and geo-annotations, and accurate conversion to coordinates. The two reviewers both found 87% of the evaluated abstracts relevant for a hydro-hazards study. Some abstracts might mention the hazard only in a side sentence, with the main focus being, for example, botany, engineering or politics. 3% /9.4% of abstracts (respectively Reviewer 1/Reviewer 2) had hazard annotations missing. Reasons for that could be phrasings such as "wetness" describing a flood. Of the annotated geo-entities, 77% and 86%, respectively, correctly described a location. Common causes of error are country adjectives (e.g., Korean War, Indian export), overlap with common terms (e.g., Cobalt, Salmon), objects named after locations (e.g., Portland cement, Busan clays, Norwegian Computer Center), and names identified as locations (e.g., Allen). When a geo-entity was correctly identified, 95% and 89% were correctly geo-coded using OSM or NE. In 33% and 21%, respectively, of evaluated abstracts, one or multiple geo-entities were missed. Some causes for missed entities are variations in spelling (e.g., "Sumatera" vs. "Sumatra") or locations not included in the dictionary. We randomly chose 20 abstracts out of the review set 1 (100 abstracts) that had missing geo-entities to evaluate the impact those missed entities have on the final spatial coverage identified for each abstract. In 17 out of 20 abstracts, the missed locations fell within regions already identified by other geo-entities within the abstract. We therefore conclude that the impact of missed locations on the final research distribution should be minor.

Abstract to grid conversion

The locations identified for each abstract were combined and rasterized. Creating a spatial grid for each abstract allowed calculating the density distribution of studies to compare them with other datasets (e.g., population density) that were also transformed into the same resolution grid. Comparable to Callaghan et al. (2021), we chose a raster grid of 2.5°. However, unlike them, we considered not just the smallest but all locations extracted from an abstract. We quite commonly found that multiple equally relevant study locations are mentioned in one abstract without relevancy distinction. A country might be mentioned either as a study or modelling domain itself or just to narrow down the location of a smaller entity for the reader. Since smaller (i.e., more specific) locations are likely more relevant, we gave greater weight to smaller locations in an area-based weighting scheme (Figure S3). An alternative counting method was used to calculate absolute numbers of abstracts per country. All geo-locations that fell within a country (excluding continents and marine regions) were counted, and the number of unique abstracts was calculated.

Bias analysis

Biases in research distributions were determined by comparing the distributions of four data categories: 1. Impact data, 2. Hydro-meteorologic station measurements, 3. Socio-economic data, 4. Natural and anthropogenic features of the landscape. All datasets were transformed to the same grid as the abstract data. For **impact data**, the international disaster database EM-DAT (CRED, 2023b) was combined with the Geo-coded Disasters Database (GDIS) (Rosvold and Buhaug, 2021) to create geo-located impact data. Hazard events are only considered for EM-DAT if certain impact criteria based on severity are met. Getting accurate impact numbers for disaster events can be a challenge (Guha-Sapir and Below, 2006), and many events are missing in EM-DAT, e.g., information on the number of deaths and the number of people affected (Jones et al., 2022). Other impact databases exist but have their own biases. A consolidated impact database from different sources is currently missing (Wyatt et al., 2023). We therefore supplement our analysis by comparing it to three additional disaster-specific, continually updated datasets commonly utilized by their respective communities: the Dartmouth Flood Observatory (Brakenridge, 2023), the NASA global landslide catalogue (Kirschbaum et al., 2010), and Global Fatal Landslide Database (Froude and Petley, 2018). Both landslide databases focus on rainfall-induced landslides and are commonly used within the landslide research community.

We compared **measurement station data** to the research distributions to determine where a lack of data might be a factor in contributing to research gaps. We considered the distribution of stations from the WMO Integrated Global Observing System (called OSCAR), GPCC precipitation stations, the international soil moisture network (ISMN) (Dorigo et al., 2011), and a global streamflow stations dataset (GSIM) (Do et al., 2018). We mainly refer to World Bank socio-economic indices for **socio-economic data**, i.e., population (WorldPop, 2023), human development index (Kummu et al., 2018), and the adaptive capacity measure by the Notre Dame Global Adaptation Initiative (ND-GAIN) (Chen et al., 2015). We considered human footprint as a general measure of anthropogenic impact (Venter et al., 2016), travel time to the nearest city above 100,000 inhabitants as a measure of closeness to urban centers (Nelson et al., 2019). We used ESA World Cover for forest and crop coverage (Zanaga et al., 2021), and precipitation (P), potential evapotranspiration (PET), and aridity (PET/P) as measures of climate zone (Karger et al., 2017). A full list of datasets used, including details and their references, can be found in the supplement (Table S1).

We used the Wasserstein distance (Kantorovich, 1960; Krabbenhoft et al., 2022; Schuhmacher et al., 2023) as a measure of bias as it determines differences in variable distributions between regions of high research density ($> 75^{\text{th}}$ percentile) and the entire world. The Wasserstein distance is a measure of the absolute difference between cumulative distributions. We used the summarized difference between cumulative distribution functions to consider the direction of bias (Stein et al., 2021). A positive difference between distributions indicates that an increase in variable value leads to an increase in research density. Where country-averaged values were used (e.g., for research density or impact calculation, Figure 4), we used a weighted mean average based on the fraction of cells covered by each country polygon. Country averages instead of total sums are used to compensate for different country sizes.

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Author contribution

LS, SKM, TB, and TW designed the study. LS, BP and SKM developed the methods. LS performed the analysis and wrote the manuscript. SKM, CB, and PWJS processed the textual data. UO, TB and TW gave conceptual advice. All authors edited the manuscript.

Conflict of interest

The authors declare no conflict of interest.

Data availability statement

All datasets used in this study are free and publicly available. A full detailed overview of all datasets used is provided in the supplementary information. Results and evaluation data is available in this repository: https://doi.org/10.5281/zenodo.10490256. Due to license restrictions, the Semantic Scholar abstract data cannot be shared directly. However, the Semantic Scholar Academic Graph dataset can be accessed via the Semantic Scholar API (www.semanticscholar.org/product/api). The created hazard and geo-annotations are made available and can be linked to their respective abstracts using the Semantic Scholar ID. The research density raster grids are part of the data repository.

Open Street Map data was accessed using the Nominatim API (nominatim.org). All Natural Earth Data used can be accessed at www.naturalearthdata.com. Impact data from the Emergency Management Database can be requested at www.emdat.be. Geolocations for EM-Dat were taken from the Geocoded Disasters (GDIS) Dataset (sedac.ciesin.columbia.edu/data/set/pend-gdis-1960-2018). Other impact data was sourced from the Dartmouth Flood Observatory (floodobservatory.colorado.edu/Archives/index.html), the NASA global landslide catalogue (landslides.nasa.gov) and the Global Fatal Landslide Database (doi.org/10.5194/nhess-18-2161-2018). Measurement station data was taken from the following sources: Precipitation stations - Global Precipitation Climatology Centre (GPCC, http://gpcc.dwd.de/); streamflow stations - Global Streamflow and Metadata Archive (GSIM, doi.org/10.1594/PANGAEA.887477); soil moisture stations - International Soil Moisture Network (ISMN, ismn.earth/); climate stations - WMO Observing Systems Capability Analysis and Review Tool (WMO OSCAR, oscar.wmo.int). Precipitation and evapotranspiration data was taken from CHELSA (chelsa-climate.org/downloads/). Human footprint data was published here datadryad.org/stash/dataset/doi:10.5061/dryad.052q5. The fraction of cropland was taken from the ESA World Cover dataset (zenodo.org/records/5571936). Data on travel time from the nearest city was published here doi.org/10.1038/s41597-019-0265-5. Socio-economic and other indices were taken from the World Bank Open Data Catalog (data.worldbank.org). Vulnerability and adaptive capacity data were taken from the Notre Dame Global Adaptation Initiative (https://gain.nd.edu/our-work/country-index/). Population data was accessed at www.worldpop.org. The Human Development Index data was published here doi.org/10.5061/dryad.dk1j0.

Code availability statement

Deep Search is a commercial platform and is available with limited features. The Deep Search Toolkit is a Python Software Development Kit (SDK) and Command Line Interface (CLI) allowing users to interact with the Deep Search platform. The Deep Search Toolkit codebase is under MIT license. For individual model usage, please refer to the model licenses found in the original packages (`https://github.com/DS4SD/deepsearch-toolkit`). The codes to process, analyze, and plot the data and annotated abstracts is available in this repository: `https://doi.org/10.5281/zenodo.10490256`.

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Wealth over Woe: global biases in hydro-hazard research

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Contents

1 Supplemental Information

Section 1.1 gives an extend description of how the abstracts were chosen for further analysis. An extended overview of the different steps taken to search for and annotate the abstracts is given in Figure S1. The hydro-hazards terms used in the taxonomy are given in Table S1. The identified abstracts and locations are further filtered using multiple steps as described below. The full filtering statistics can be found in Figure S2.

Section 1.2 provides additional information on how research density was calculated including an evaluation of the effect different grid types have on the final result. Section 1.3 offers additional discussion on the identified research needs regions. Section 1.4, Table S3 shows detailed information on all additional datasets (environmental, socio-economic, station data...) used for the bias analysis. Section 1.5 finally provides additional figures on research distribution (Figures S5-S7), bias analysis (Figures S8-S11), and research needs regions (Figures S12-S15).

1.1 Abstract search, annotation, and filtering

We used keyword-in-context validation for all identified river geo entities. It tests if river-related words were mentioned $\pm$ two words around the entity (including "river", "catchment", "basin", "creek", "stream", "watershed", "delta", "floodplain", "channel", "estuary", "rio", "río") to confirm the named entity actually refers to the river. We excluded some of the world's largest rivers, as their names are well known enough to be mentioned in isolation (Nile, White Nile, Blue Nile, Danube, Yangtze, Ganga, Ganges, Brahmaputra, Mekong, Volga, Indus, Elbe, Amazon, Thames, Rhone, Rhine, Euphrates, Irrawaddy). Rio Grande was treated as specially as it is a common river name in South and Central America. The choice which identified Rio Grande as the correct one was made based on the co-mention of a country or federal state name. Similarly, all rivers and cities were validated against the countries mentioned in the abstract. If a country was mentioned, but the identified smaller location was not located in that country, it was excluded. We excluded very large and well-known cities (e.g. Singapore, Delhi, Berlin) from this criterion.

Geo-entity matches that were manually excluded, since the word often did not refer to a geolocation:

- 'Mobile'
- 'Palmer' (Palmer Drought Severity Index)
- 'Price'
- 'Progress'
- 'Independence'
- 'Berea' (type of sandstone misclassified as district in Lesotho)
- mentioned USA states, but misidentified in other countries, e.g. Florida in Uruguay, Maryland in Liberia, Montana in Bulgaria, Victoria in Malta.

Matching between high-resolution Natural Earth shapefile data and geo-entities was performed based on dictionary type. For example, lakes were matched with lakes outline data, provinces with the states and provinces data, regions with the geographic regions data. Particularly geo-entities from the dictionary types "continental regions" and "provinces" were often replaced by natural earth features. A full overview of entity types and their Natural Earth data matching:

- Type 'Rivers' was matched with 'Rivers and Lake Centerlines'
- Type 'Lakes' was matched with 'Lakes'
- Type 'Basins' was matched with 'Regions'
- Type 'Regions' was matched with 'Physical region features' supplemented by the regions 'Amazonia' according to the Amazon river and "Arctic" according to the arctic circle.
- Type 'Marine Regions' was matched with 'Marine Areas'
- Type 'Provinces' was matched with the 'States, Provinces' data.
- Type 'Countries' were matched with 'Countries'.
- Type 'Continents' were matched with the continental regions supplemented by regional country aggregations, such as 'Central Africa', 'Baltic States', 'Latin America' etc.

1.2 Raster grid generation

We count hydro-hazards research density in two ways. Once as absolute count of number of abstracts per country, and once as research per raster cell (of size 2.5 degrees over the global land area) as demonstrated in Figure S3. For research per cell, we employ a weighted count (Callaghan et al., 2021), that gives higher weight to smaller geographical entities, i.e. mentioning all of Europe will only add a small value to the weighted count, compared to mentioning a river or a specific city within Europe. The smaller geographical entity will be the more relevant study location. However, we do not exclude the large entity (i.e. Europe), as large place names are more distinct and are less likely to be homonyms.

Raster grids based on Latitude-Longitude separation have the problem, that grid cells closer to the equator are larger than grid cells closer to the poles. We test if that difference has an effect on our conclusions. Figure S4 shows the results of that comparison. While grid values based on an equal area grid are in average only half as big as based on a Latitude-Longitude grid, this difference is reproduced across all cells. The resulting patterns of highly researched regions stay the same (e.g. compare Figure S4a and d).

1.3 Research needs regions extended

One consideration with the research focus region is that they are affected by individual historical large-scale hazard events. For example, the large area with high flood impact in the northern United States is mainly caused by a single flood event: The 2008 Midwest flood that affected over 11 million people. This problem is specific to EM-DAT which only includes the most disastrous events based on strict threshold criteria. For comparison, we can also use different impact databases. In Figure S14, we use the Dartmouth Flood Observatory (Brakenridge, 2023) number of displaced people variable for flood impact, and the Global Fatal Landslide Database(Froude and Petley, 2018). With different impact data, e.g. additional flood and landslide impact data, the earlier mentioned regions based on EM-DAT impact data still remain a high priority for additional research, but several new areas appear making the research focus regions even broader (Figure S14). For flood research, e.g. Mali, Niger, and Chad become countries for further research. For landslides, several research focus regions appear in Eastern Africa.

1.4 Supplemental tables

Table S1. Hydro-hazard terms used in the taxonomy for hazard annotation.

Drought Hazard	Flood Hazard	Landslide Hazard
drought, water shortage, meteorological drought, agricultural drought, hydrological drought	flooding,flood damage, flash flood, coastal flood, fluvial flood, stormwater, urban flood, outburst flood, pluvial flood, snowmelt flood, ice jam flood, surface water flood, localized flood, groundwater flooding, dike breach, flood defense failure	landslide, mudslide, rockslide, soil liquefaction, debris flow

Table S2. Summary of Geo-entity Sources and Types

Source	Type of Geo-entity	Description	Link/Reference
Wikipedia	Provinces, Larger Towns, Cities	First level country sub-divisions, Towns and cities with 100,000 inhabitants or more	Subdivisions, Larger towns and cities
GitHub	Smaller Cities	Data on countries by continent, city, capital city, abbreviation	Countries, Cities, Capital Cities, Abbreviations
Encyclopedia Britannica	Lakes, Rivers, Basins	Information on lakes and rivers	Rivers, Lakes

Category	Variable	Dataset	Unit	Resolution		Time period	Reference	DOI	
Data availability	Precipitation Station Density	GPCC	Gauges per grid cell	2.5°		1991-2020	Rustemeier et al. (2022)	10.5676/DWD_GPCC/CLIM_M_V2022_250	
Environmental-anthropogenic	Human Footprint	Data Publication	Numeric categories	1 km2		2009	Venter et al. (2016)	doi:10.5061/dryad.052q5	
Environmental-anthropogenic	Cropland	ESA World Cover v100	Fraction cropland per cell	10 m		2020	Zanaga et al. (2021)	doi:10.5281/zenodo.5571936	
Environmental-anthropogenic	Travel time to the nearest city >100 000 people	Data Publication	Minutes travelled	1 km2		2015	Nelson et al. (2019)	doi:10.1038/s41597-019-0265-5	
Impact	Landslide occurrence NASA	NASA Cooperative Open Online Landslide Repository	-	point	39613 landslides	2007 - …	Kirschbaum et al. (2010)		
Impact	Landslide people affected	Landslide catalogue Froude and Petley	Number of people killed	point	5490 events	2004 - 2016	Froude and Petley (2018)	doi.org/10.5194/nhess-18-2161-2018	
Impact	Dartmouth Flood Observatory	Active Archive of Large Floods	Number of people displaced	polygon	5130 events	1985 - …	Brakenridge (2023)		
Socio-economic	Population	WorldPop	People per pixel	1 km2		2020	WorldPop (2023)	doi/10.5258/SOTON/WP00647	
Socio-economic	Adaptive Capacity	ND Gain Country Index Adaptive Capacity		-		2021	Notre Dame		
Socio-economic	Vulnerability	ND Gain Country Index Vulnerability		-		2021	Notre Dame		
Socio-economic	Human Development Index	Data Publication	-	5 arc-minute		2015	Kummu et al. (2018)	doi.org/10.5061/dryad.dk1j0	
Environmental-anthropogenic	Precipitation	CHELSA	mm	5 arc-minute			Karger et al. (2017, 2018)	chelsa-climate.org/downloads/	Used for aridity
Environmental-anthropogenic	Potential Evapotranspiration	CHELSA	mm	5 arc-minute			Karger et al. (2017, 2018)	chelsa-climate.org/downloads/	Used for aridity
Data availability	OSCAR WMO Stations	WMO Integrated Global Observing System Stations (WIGOS) in the Observing Systems Capability Analysis and Review Tool (OSCAR)	-	point	11508 points	...-2023	World Meteorological Organization (WMO) and Federal Office of Meteorology and Climatology (MeteoSwiss)	oscar.wmo.int/surface//index.html#/	Reporting status "Operational" or "Partly operational"
Data availability	GSIM Stations	Global Streamflow and Metadata Archive	-	point/polygon	26516 stations	…-2016	Do et al. (2018)	doi.org/10.1594/PANGAEA.887477	All stations with min. 10 years of data
Data availability	Soil moisture stations	International Soil Moisture Network	-	point	2903 stations	Accessed: 14.03.2023	multiple citations ISMN	ismn.earth/en/	
Socio-economic	GDP	World Bank Data	current US$	country level		variable (average: 2022)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Agricultural land	World Bank Data	(% of land area)	country level		variable (average: 2020)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Agricultural irrigated land	World Bank Data	% of total agricultural land	country level		variable (average: 20201622)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Land area where elevation is below 5 meters	World Bank Data	% of total land area	country level		variable (average: 2015)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Gini index	World Bank Data	-	country level		variable (average: 2017)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Political Stability and Absence of Violence/Terrorism: Estimate	World Bank Data	-	country level		variable (average: 2021)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Government Effectiveness: Estimate	World Bank Data	-	country level		variable (average: 2021)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Control of Corruption: Estimate	World Bank Data	-	country level		variable (average: 2021)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Proportion of people living below 50 percent of median income	World Bank Data	%	country level		variable (average: 2017)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Scientific and technical journal articles	World Bank Data	-	country level		variable (average: 2020)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Researchers in R&D	World Bank Data	per million people	country level		variable (average: 2017)		data.worldbank.org	Uses most recent available data per country
Socio-economic	Research and development expenditure	World Bank Data	% of GDP	country level		variable (average: 2017)		data.worldbank.org	Uses most recent available data per country
Impact	EM-DAT	Emergency Events Database	-	point/polygon	5291 events	1950 - …	EM-DAT, CRED / UCLouvain, Brussels, Belgium www.emdat.be		
Impact	GDIS	Geocoded Disasters Database	-	polygon		1960-2018	Rosvold and Buhaug (2021)	doi.org/10.7927/zz3b-8y61	

Table S3. Overview of environmental and socio-economic characteristics and data availability gauge datasets used for the bias analysis.

References to the International Soil Network and all its contributing networks: Al-Yaari et al. (2018); Albergel et al. (2008); Alday et al. (2020); Ardö (2013); Bell et al. (2013); Beyrich and Adam (2007); Biddoccu et al. (2016); Bircher et al. (2012); Blöschl et al. (2016); Bogena et al. (2018, 2012); Bogena (2016); Brocca et al. (2009, 2008, 2011); **?**); Calvet et al. (2016, 2007); Canisius (2011); Capello et al. (2019a,b); Cappelaere et al. (2009); Chen et al. (2015a,b); Cook (2016, 2018); Darouich et al. (2022); Dente et al. (2012); Dorigo et al. (2013, 2021); Flammini et al. (2018a,b); Fuchsberger et al. (2021); Galle et al. (2015); González-Zamora et al. (2019); Hajdu et al. (2019); Hollinger and Isard (1994); Ikonen et al. (2016, 2018); **?**); Jackson et al. (2011); Jensen and Refsgaard (2018); Jin et al. (2014); Kang et al. (2019, 2014); Kirchengast et al. (2014); Larson et al. (2008); Leavesley (2010); Lebel et al. (2009); Liu et al. (2001); Loew et al. (2009); Marczewski et al. (2010); Mattar et al. (2014, 2016); MOGHADDAM et al. (2016); Moghaddam et al. (2011); Morbidelli et al. (2011, 2017, 2014); Mougin et al. (2009); Musial et al. (2016); Nguyen et al. (2017); Ojo et al. (2015); Osenga et al. (2019, 2021); Peischl et al. (2012); Pellarin et al. (2009); Petropoulos and McCalmont (2017); Raffelli et al. (2017); Robock et al. (2000); Rosnay et al. (2009); Rüdiger et al. (2007); Schaefer et al. (2007); Schlenz et al. (2012); Shuman et al. (2010); Smith et al. (2012); Su et al. (2011); Tagesson et al. (2014); Van Cleve et al. (2015); Vreugdenhil et al. (2013); Wigneron et al. (2018); Xaver et al. (2020); Yang et al. (2013); Young et al. (2008); Zacharias et al. (2011); Zappa et al. (2019, 2020); Zhang et al. (2018); Zhao et al. (2020); Zheng et al. (2022); Zreda et al. (2012, 2008)

1.5 Supplemental Figures

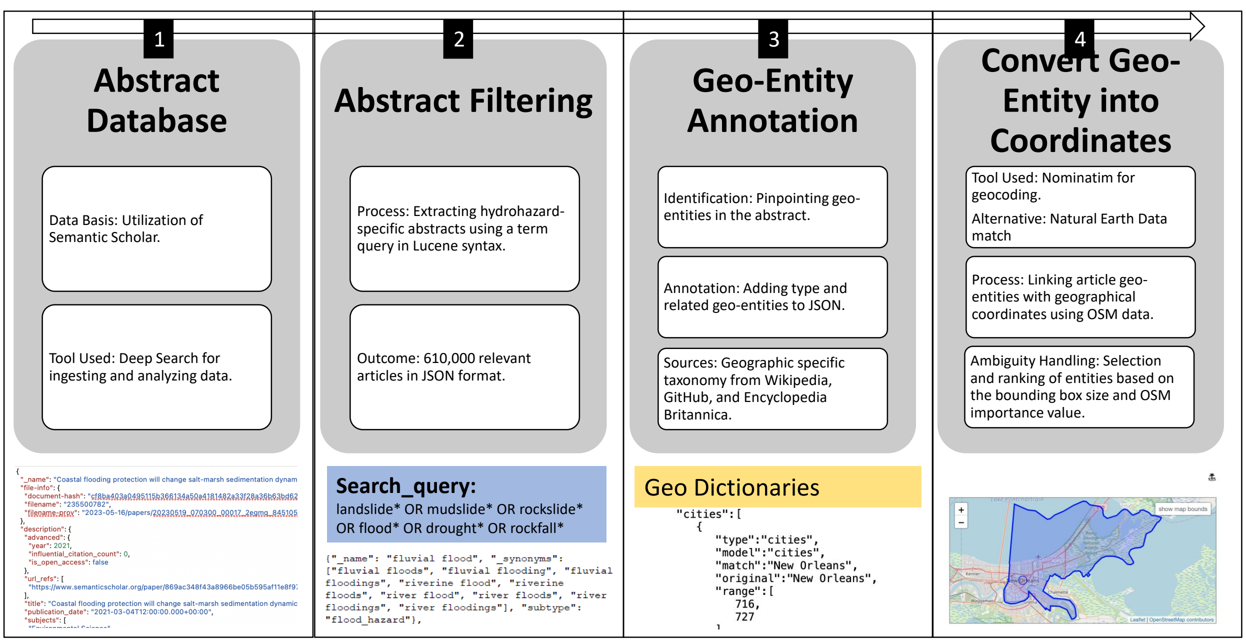

Fig. S1. Overview of methodological steps for the abstract search, annotation and geolocation. The abstract database (Kinney et al., 2023) was processed using DeepSearch (Auer et al., 2022; Pyzer-Knapp et al., 2022; Staar et al., 2018).

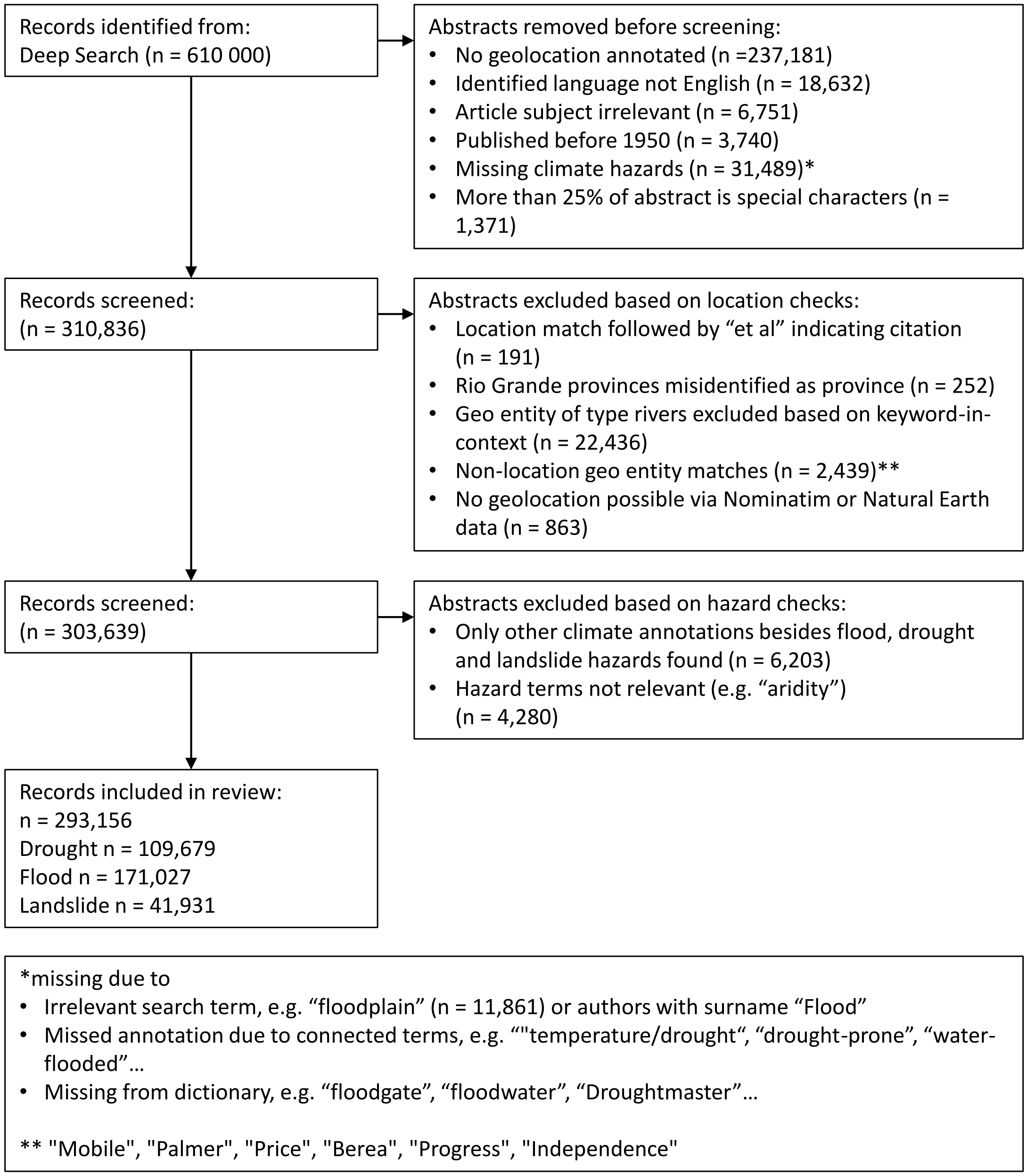

Fig. S2. Overview of extracted abstract numbers and filtering statistics. Any numbers reported refer to entire abstracts. Filters that did not affect the total number of abstracts (e.g. duplicate location matches) are not shown, but described in the supplemental methods section. This overview follows the PRISMA flow diagram chart (Preferred Reporting Items for Systematic Reviews and Meta-Analyses, Page et al., 2021).

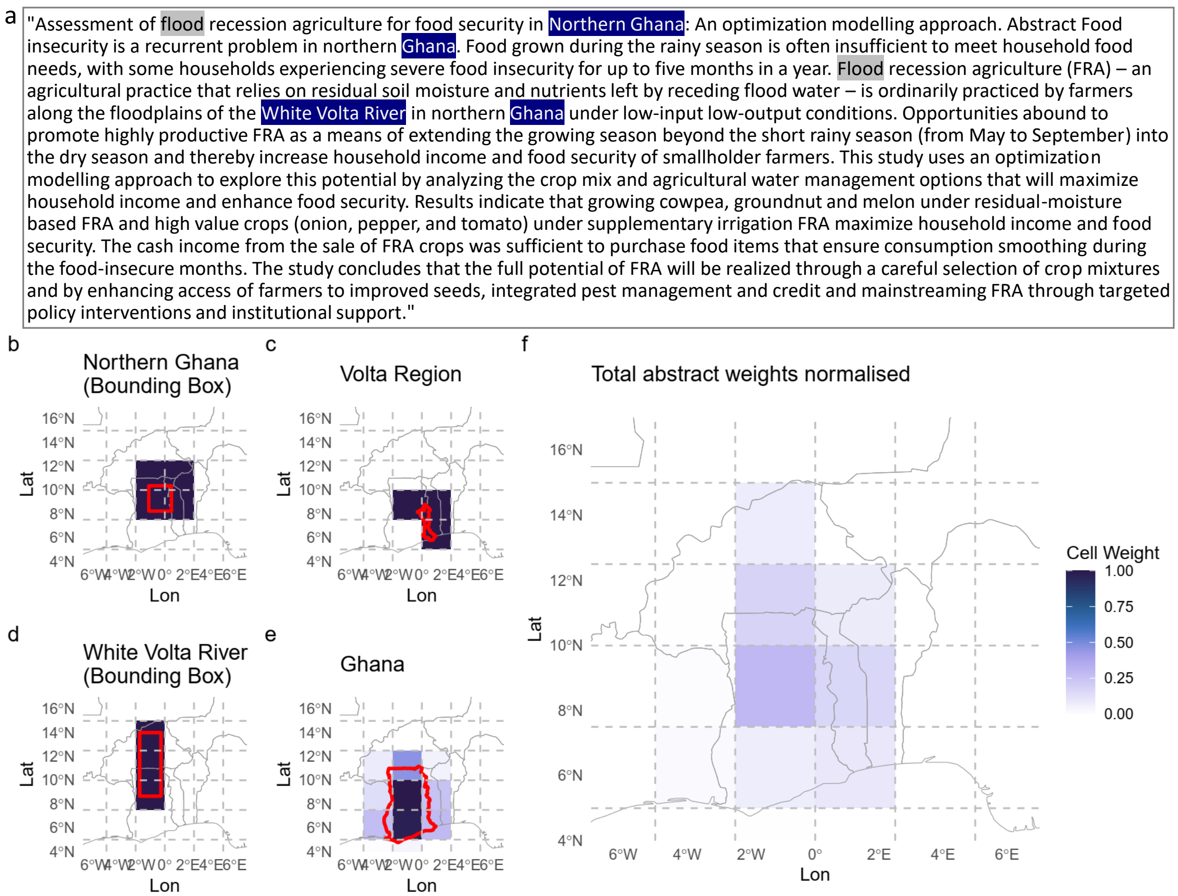

Fig. S3. Schematic for single abstract processing. **a**, Abstract (Balana et al., 2019) with annotated hazards (grey) and geolocations (blue), **b-e**, geo entity polygon (red) with underlying raster weights. **b**, bounding box of Open Street Map entity. **c-e**, polygons/bounding box extracted from Natural Earth Data. Rivers extracted as bounding boxes for vague estimate of catchment. **e**, for country shapes, each cell is weighted according to the fraction covered by its shape. **f**, Sum of raster **b-e**, divided by the total sum of all cells to normalise the raster for each abstract to a sum of 1. This ensures comparable weights between abstract rasters, independent of the number of geo-entities tagged.

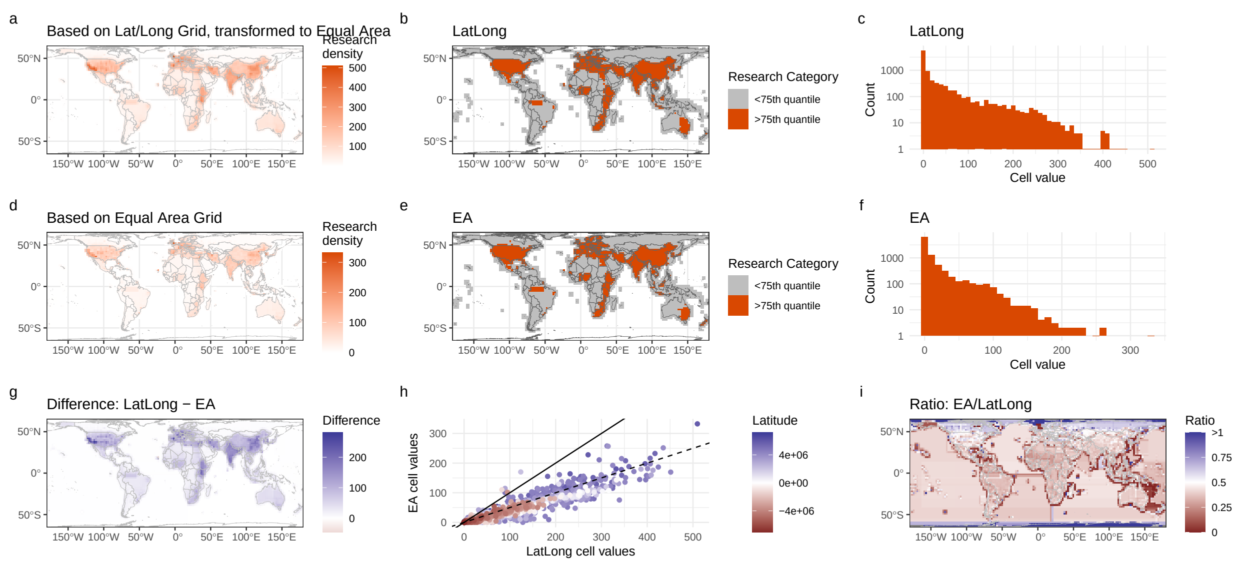

Fig. S4. Comparison between research density for drought research between **a**, a latitude-longitude grid (2.5°) and **d**, an equal area (EA) grid (EPSG: 6933). For plotting purposes the lat/long grid was transformed to equal area as well. **b**, and **e**, highly researched regions ($> 75^{\text{th}}$ percentile), **c**, and **f**, the value histogram for the global maps. **g**, is the difference between the LatLong-based grid and the EA based grid. **h**, plots the LatLong grid values against the EA grid values. For comparison a line with a slope of 1 (solid) and 0.5 (dashed) is added. **i**, shows the ration between the two grids.

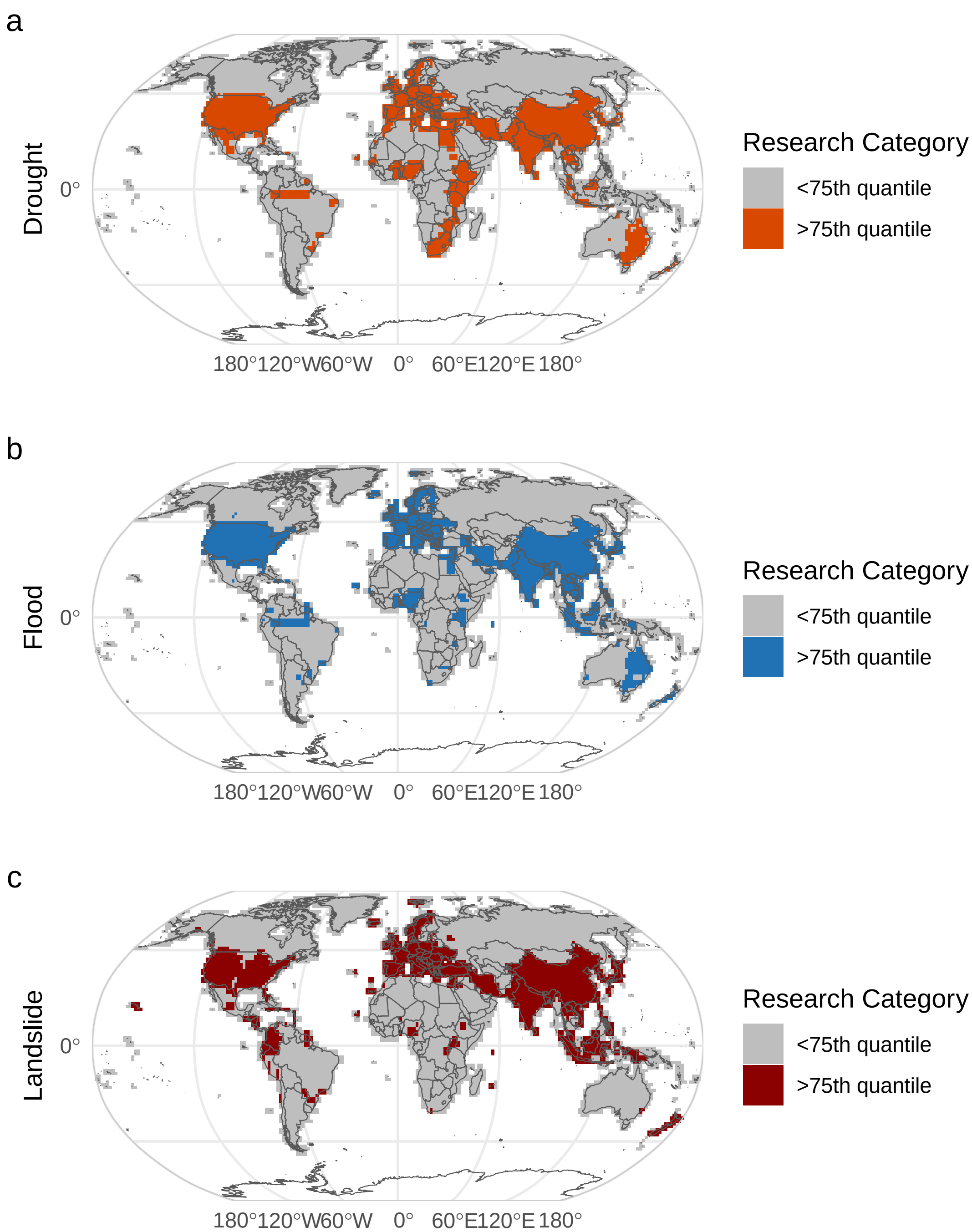

Fig. S5. Distribution of highly researched ($> 75^{\text{th}}$ quantile) regions for drought, flood and landslide weighted research count.

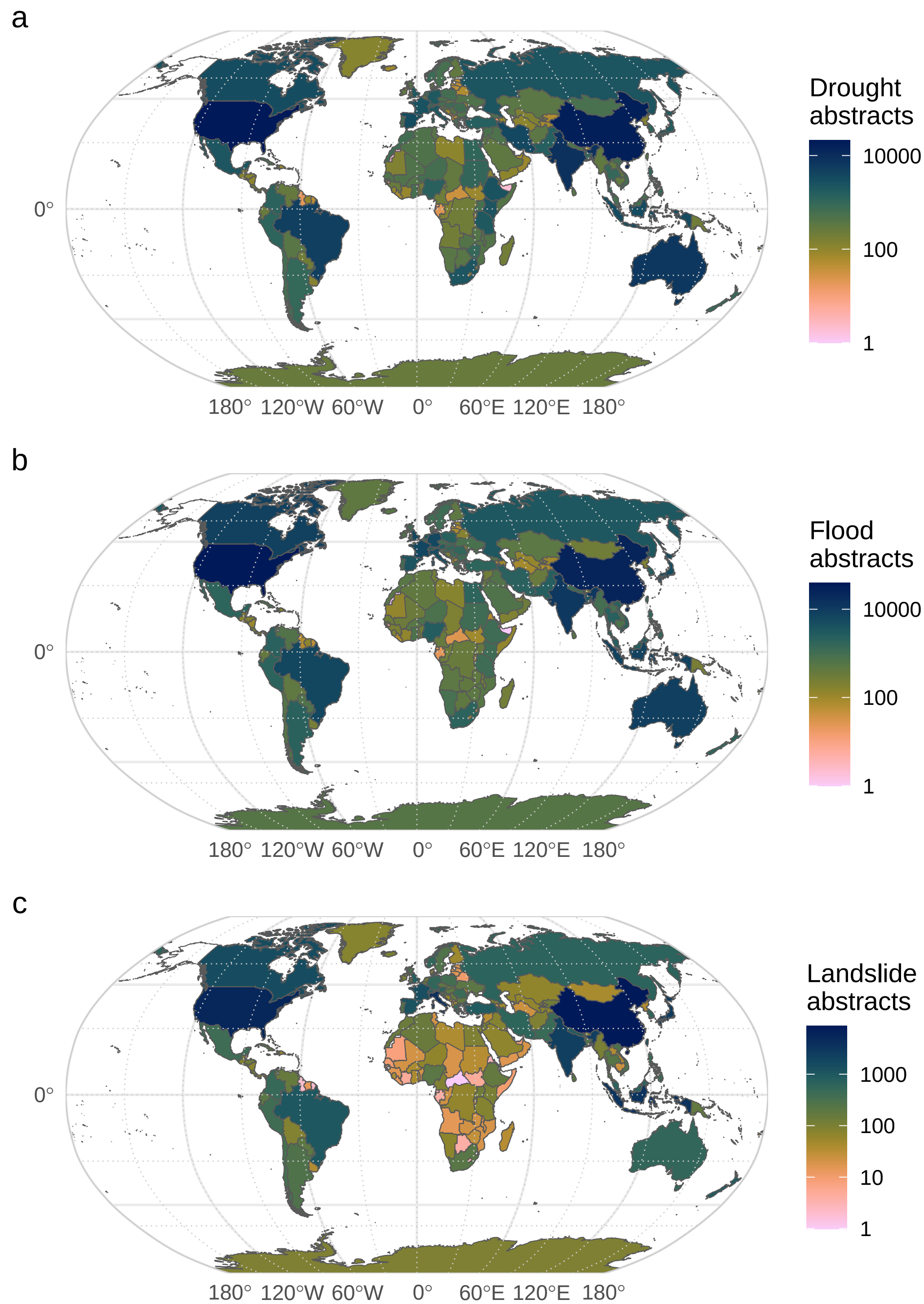

Fig. S6. Number of abstracts per country for all abstracts tagged for **a**, drought, **b** flood, **c**, landslides. Double counts for multi-hazard mentions are possible. Not counted in this figure are coverages from continental regions, e.g Central America, Africa, Europe.

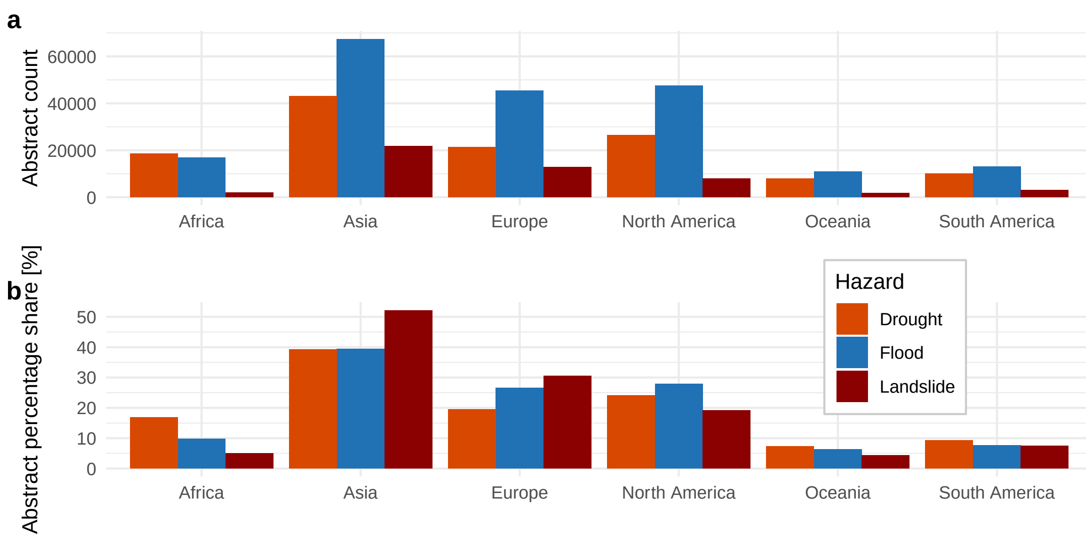

Fig. S7. **a**, Number of abstracts per continent for each hazard and **b**, percentage share of abstracts from the total number of abstracts per hazard. The percentage share adds up to more than 100 per hazard, since abstracts can cover multiple continents.

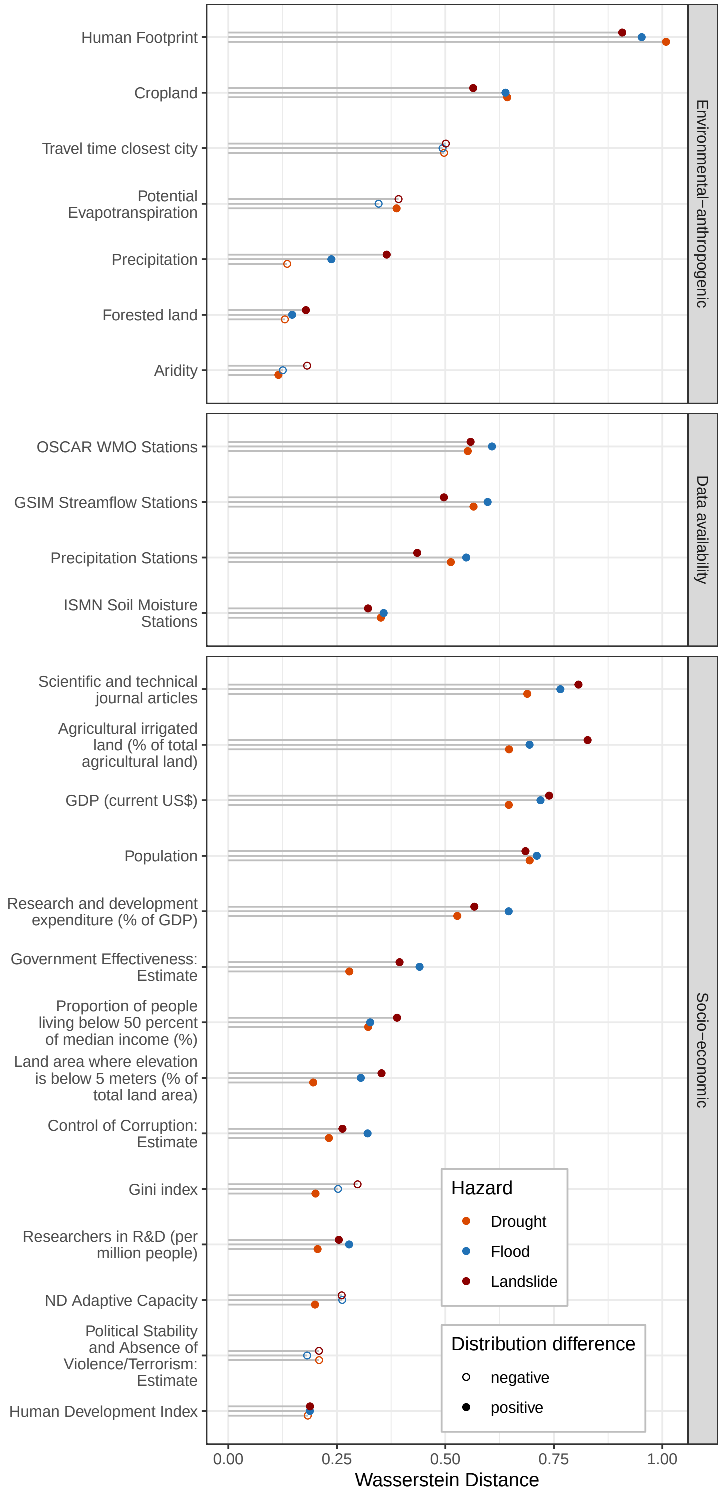

Fig. S8. Comparison of climate, land, gauging data and socio-economic characteristics between regions of high research ($> 75^{\text{th}}$ quantile) and the entire land area. Distribution difference measured as Wasserstein distance (Krabbenhoft et al., 2022). Higher values indicate a stronger bias. A positive (negative) distribution difference indicates more (less) research with increasing characteristic.

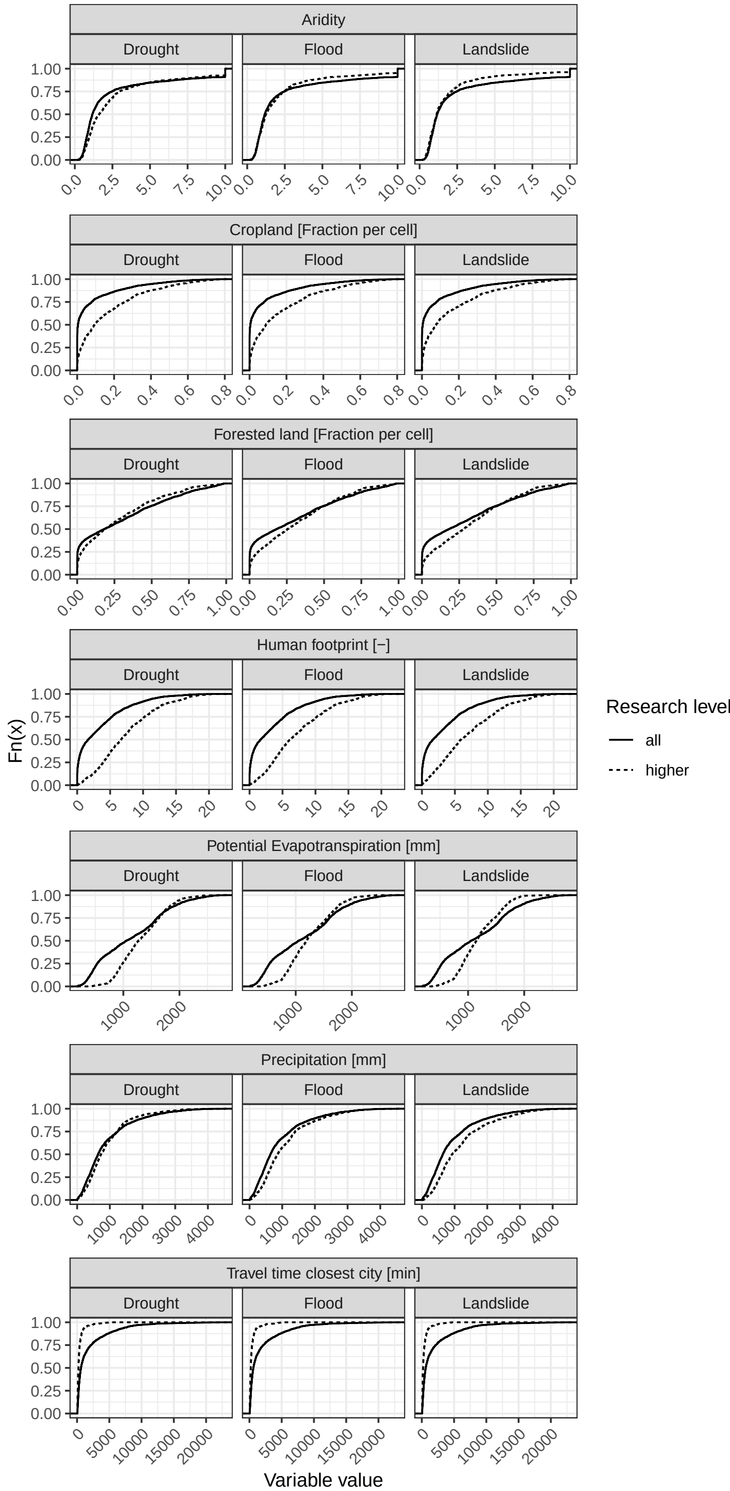

Fig. S9. Cumulative distribution functions for environmental and anthropogenic characteristics split into regions with higher ($> 75^{\text{th}}$ quantile) and lower ($< 75^{\text{th}}$ quantile) research density in comparison to all land area.

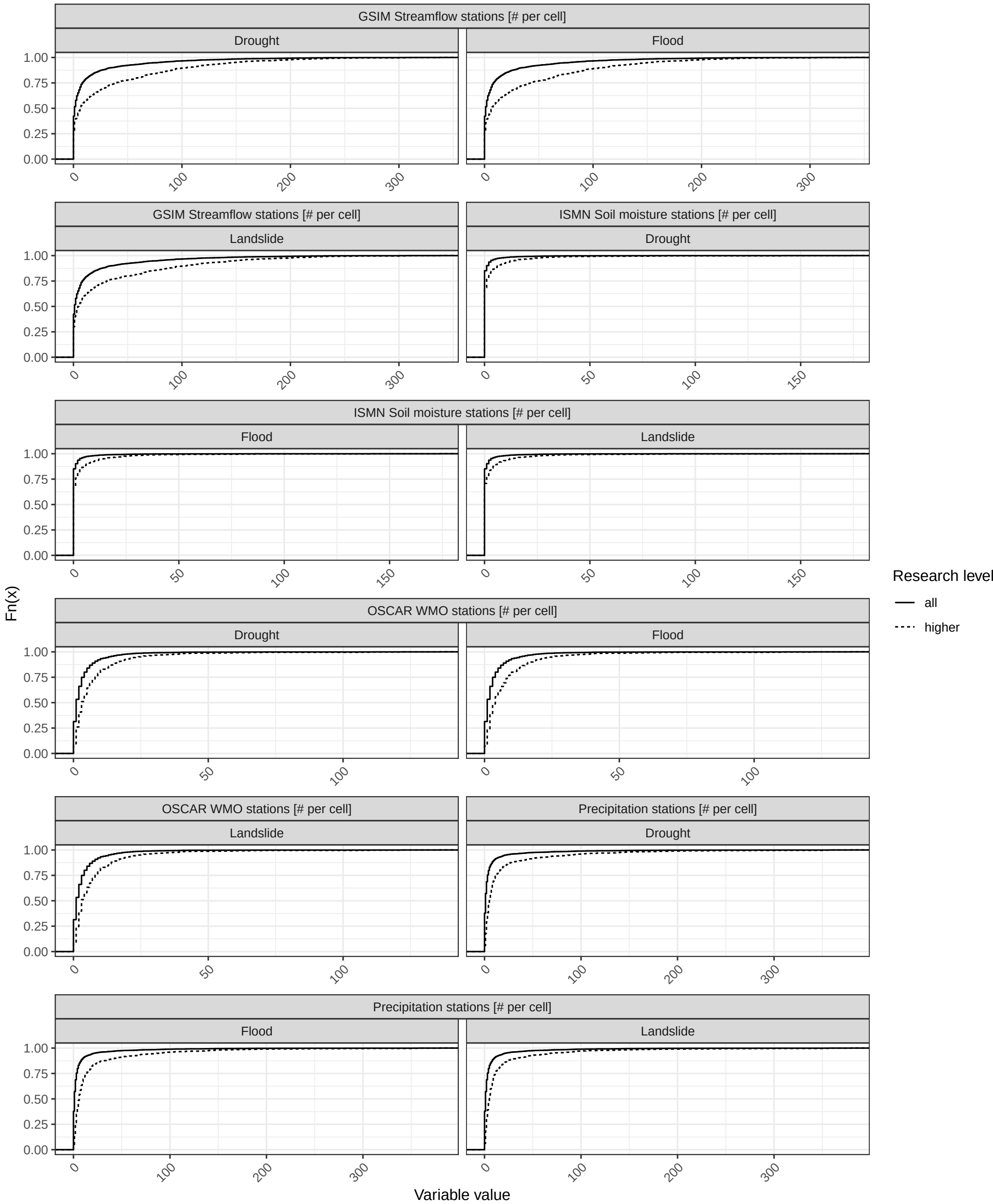

Fig. S10. Cumulative distribution functions for data density for various gauging datasets split into regions with higher ($> 75^{th}$ quantile) and lower ($< 75^{th}$ quantile) research density in comparison to all land area.

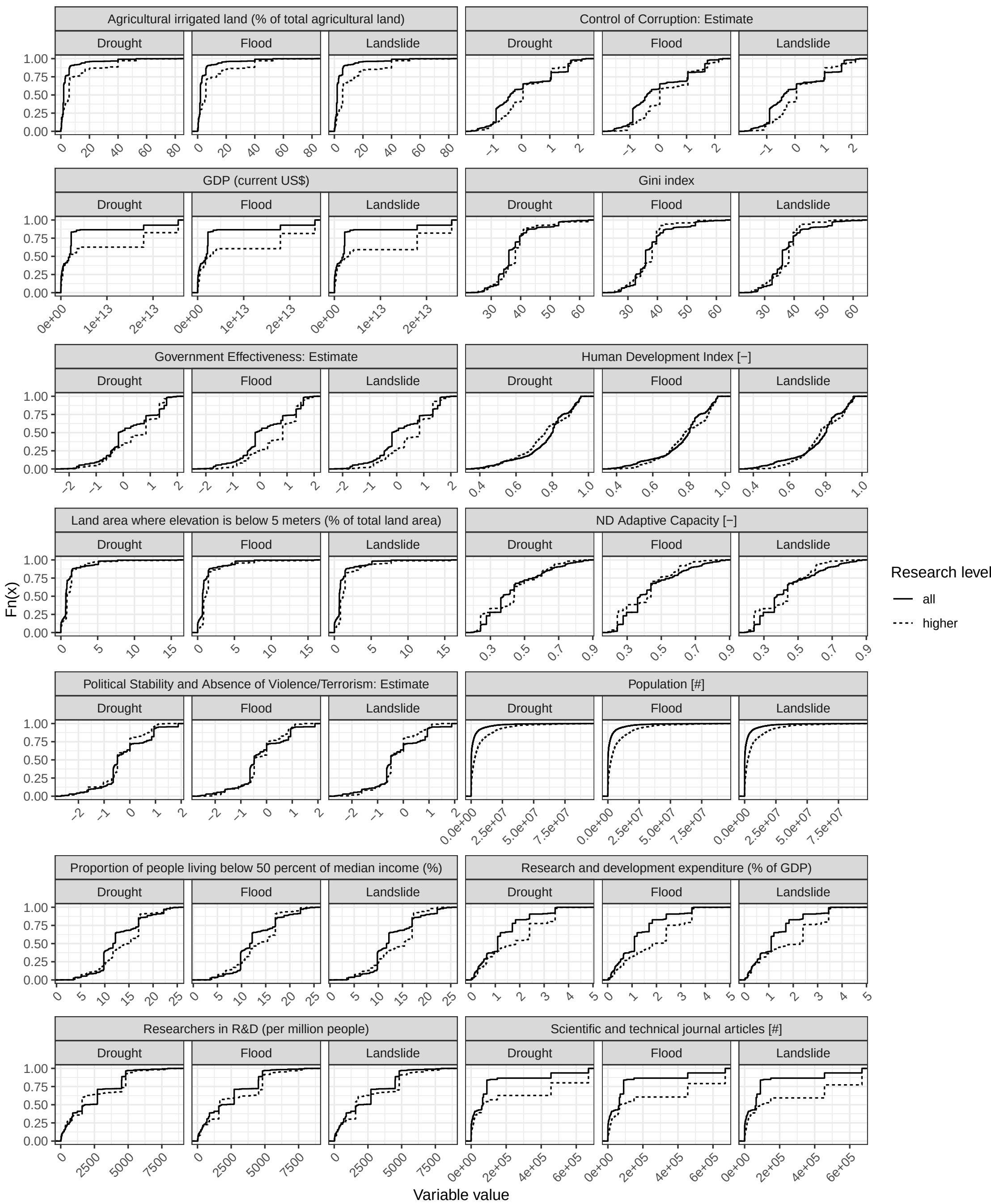

Fig. S11. Cumulative distribution functions for socio-economic characteristics split into regions with higher ($> 75^{th}$ quantile) and lower ($< 75^{th}$ quantile) research density in comparison to all land area.

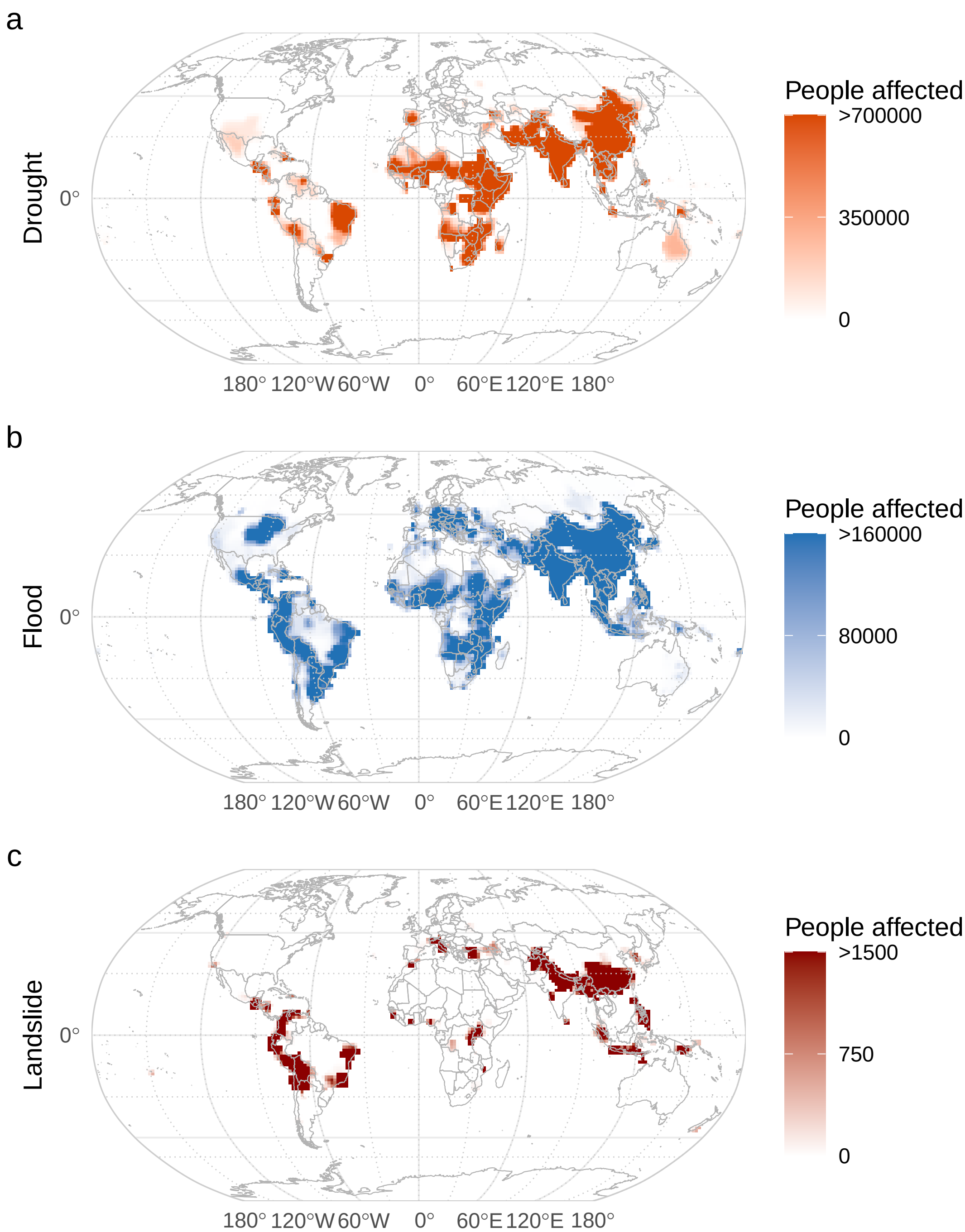

Fig. S12. EMDAT impact data. Number of people affected per grid cell for **a**, Droughts, **b**, Floods, **c**, Landslides

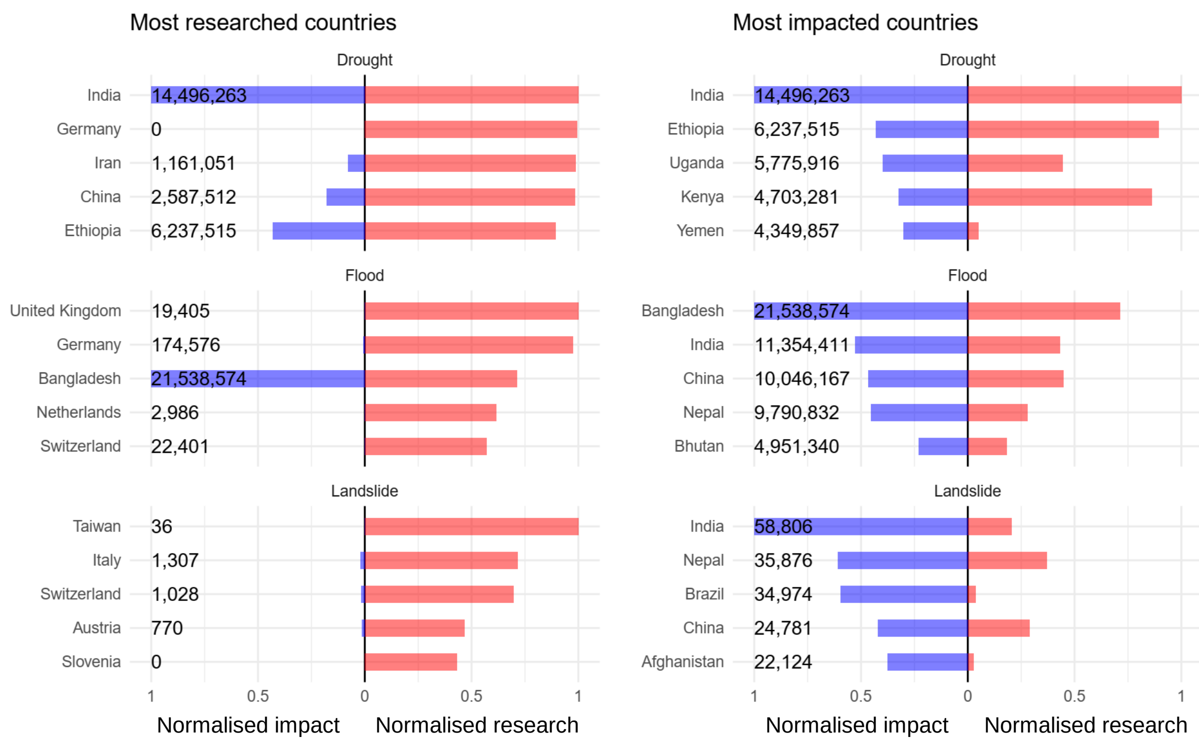

Fig. S13. Most researched (according to average research density) vs most impacted countries and their research (red) compared to their impact (blue) comparison. Numbers on the impact bars indicate the number of affected people per country according to EM-DAT

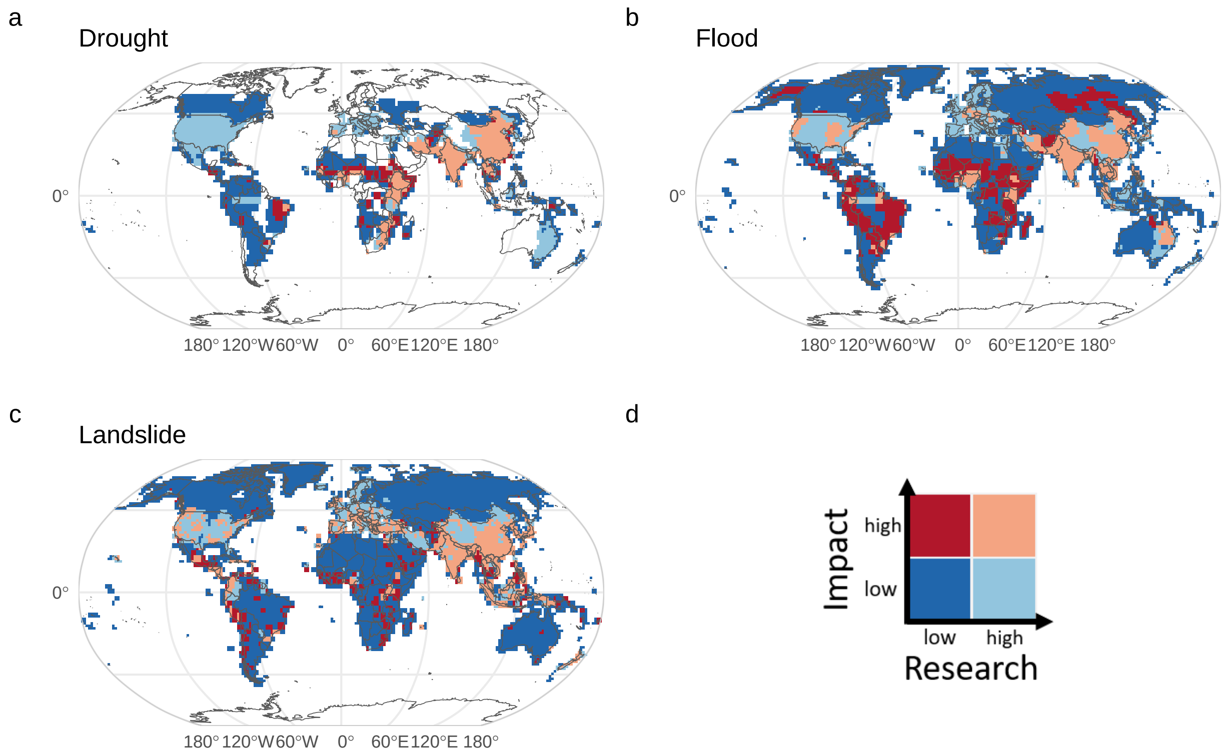

Fig. S14. Research needs regions. Most relevant for future research are regions with low research and high impact (dark red). Splits based on 75^{th} quantile of research and impact. Impact here varies between hazards. Drought: Number of people affected (EM-DAT). Flood: Number of people displaced (Dartmouth Flood Observatory, (Brakenridge, 2023)), Landslide: Number of fatalities (Froude and Petley, 2018).

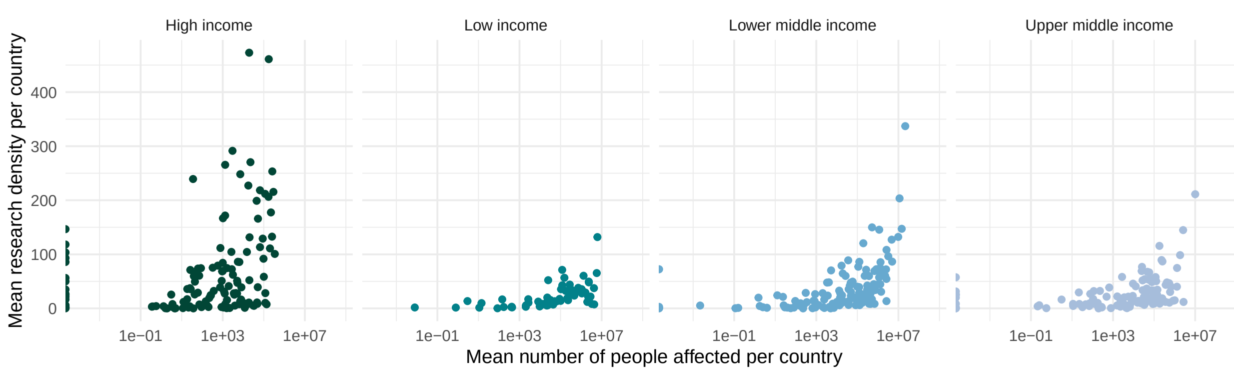

Fig. S15. Country-averaged number of affected people against the distribution of the research density, averaged over all cells per country and separated by World Bank income levels (according to 2021 income classes) (World Bank, 1978). Each dot corresponds to one country. For a distinction by hazard refer to Figure 4.

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1 Introduction