Wealth over Woe: global biases in hydro-hazard research

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Key Points:

- We map the global distribution of almost 300,000 abstracts from published flood, drought, and landslide research studies.
- We find the distribution of published research to be biased against low-income countries and tropical regions, despite more people being affected there.
- We define regions in need of targeted research and funding to reduce knowledge gaps and ultimately disaster impacts.

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Abstract

Floods, droughts, and rainfall-induced landslides are hydro-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 most severe. We use natural language processing, based on a new climate hazard taxonomy, to review, identify, and geolocate 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-hazard events that impact large numbers of people lead to increased research activity, but with a strong disparity between low- and high-income countries. We find that 100 times more people need to be affected by hazards before low-income countries reach comparable research activity to high-income countries. This "Wealth over Woe" bias needs to be addressed by enabling and targeting 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.

Plain Language Summary

Floods, droughts, and landslides are "natural hazards" responsible for the deadliest and most costly disasters globally. The scientific community studies these hazards to reduce their undesired impacts on society. To assess whether these research efforts are well-targeted, we require a global overview of where these hazards are studied and whether impacted regions are considered. Hence, we create a global map of flood, drought, and landslide research that shows whether published research is distributed equitably. We find that there is more research in regions where many people live, in wealthy regions, and in regions that have had disasters happening in the past. However, the level of research in wealthy countries is much higher despite considerably more people being affected by disasters in low-income countries. Based on our findings, we recommend regions where more research is needed for an equitable distribution of research so that all of global society is better prepared for future disasters.

1 Introduction

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., 2022). 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 likely overlooks many countries or regions which are not studied in depth despite their exposure to hydro-hazards. For example, only 6.5% of all natural hazard research studies are performed in Africa (Emmer, 2018) despite this continent having the largest predicted increase in flood exposure (Jongman et al., 2012).

Biased research distributions can be found across several disciplines including medicine (Sumathipala et al., 2004), conservation science (Di Marco et al., 2017), geoscience (North et al., 2020), and climate science (Callaghan et al., 2021). Biases have systemic causes such as differences in research funding (Woelbert et al., 2021; Overland et al., 2022), discrimination in the academic publishing system (Singh, 2006), data availability (Lindersson et al., 2020; Mwampamba et al., 2022) and language barriers (North et al., 2020). However, for hydro-hazards, there are substantial knowledge gaps regarding which environmental, anthropogenic, and socio-economic characteristics determine research foci and biases. We lack quantitative information 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 large spatial variability of the components of risk (i.e. hazard, vulnerability, and exposure) complicates bias analyses. Threats from floods, droughts, and landslides are highly heterogeneous, e.g., landslides are gravitational mass movements and occur predominantly in rugged not flat 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 occurs (Benevolenza & DeRigne, 2019). The potential for negative impacts (or risk) from hydro-hazards depends on the integration of hazard, exposure, and vulnerability. Therefore, we would not expect the global research landscape

to be spatially homogeneous, given that the risk is not spread in this way. Instead, we would expect a fair research distribution to follow one or a combination of the following aspects:

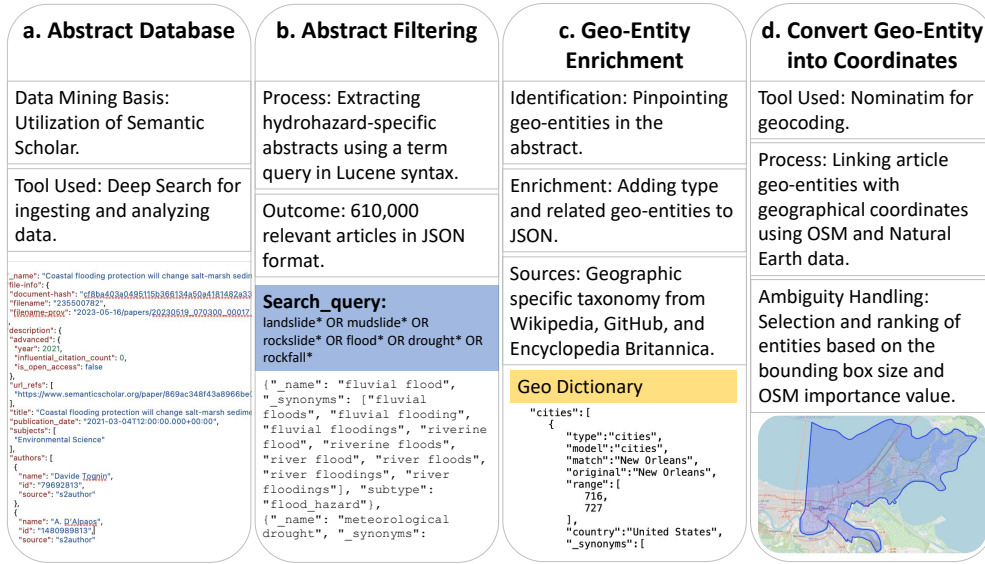1. **_Socio-Hydrological Variations:_** Research is conducted where scientific knowledge gaps have been identified. To advance scientific understanding, the scientific community should aim for research that is representative of the underlying socio-hydrological processes, in regard to both hazard generation and risk. Representative knowledge distribution is particularly relevant in the context of vulnerability, as it is highly spatially heterogeneous and results are difficult to transfer to other communities (King-Okumu et al., 2020; Ward et al., 2020).

2. **_Impact Density:_** Research is conducted where the impact or risk is largest. Impact can be measured as the number of events, fatalities, people affected, or economic loss. For our analysis, we mainly focus on the number of events and people affected. We disregard fatalities and economic losses since fatalities are under-reported for drought events (UNDRR, 2021) and economic impact data disproportionately favors high-income countries (King-Okumu et al., 2020). The only exception is a supplemental analysis of landslide fatalities, as they are considered more accurate than the number of people affected (Froude & Petley, 2018).

3. **_Population Density:_** Finally, an equitable distribution might simply entail an equal allocation of studies according to the distribution of people.

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 geolocating 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 recommend 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 global research landscape.

2 Materials and Methods

2.1 Abstract data mining and annotation with hydro-hazards taxonomy

Figure 1 provides an overview of the database as well as filtering and geolocation steps to identify and geolocate research related to hydro-hazards for subsequent estimation of global research distributions. Each step is described in detail below:

a. Abstract Database	b. Abstract Filtering	c. Geo-Entity Enrichment	d. Convert Geo-Entity into Coordinates
Data Mining Basis: Utilization of Semantic Scholar.	Process: Extracting hydrohazard-specific abstracts using a term query in Lucene syntax.	Identification: Pinpointing geo-entities in the abstract.	Tool Used: Nominatim for geocoding.
Tool Used: Deep Search for ingesting and analyzing data.	Outcome: 610,000 relevant articles in JSON format.	Enrichment: Adding type and related geo-entities to JSON.	Process: Linking article geo-entities with geographical coordinates using OSM and Natural Earth data.
	Search_query: landslide* OR mudslide* OR rockslide* OR flood* OR drought* OR rockfall*	Sources: Geographic specific taxonomy from Wikipedia, GitHub, and Encyclopedia Britannica.	Ambiguity Handling: Selection and ranking of entities based on the bounding box size and OSM importance value.

Figure 1. Overview of methodological steps for 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., 2020).

Abstract Database: The Semantic Scholar Academic Graph (Kinney et al., 2023) formed our basis for data mining. Currently, it contains 215 million scientific documents from all scientific fields, published and indexed by non-profit organizations 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., 2020)(`https://ds4sd.github.io/`), a tool that uses natural language processing to ingest and analyze unstructured data (Figure 1a). Deep Search processes text from the abstract dataset and enriches the metadata (e.g. doi, title, abstract text...), for instance through language detection. As subsequent search and filtering was based on English language keywords, we used this information to filter out non-English abstracts. 95% of all abstracts were in

English (Figure S1). The metadata associated with each abstract includes entries like unique identifiers, language, publication date, or subject (e.g., Environmental Science). 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 (Figure 1b) 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. We then classified each abstract according to all hazards mentioned in that abstract as drought-related, flood-related, or landslide-related. Abstracts mentioning multiple hazards were counted for each category. We created a climate-specific taxonomy for hydro-hazards for the classification, which includes relevant hazard types and sub-types, along with possible 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-entity enrichment: We employed a hybrid rule-based and gazetteer matching approach for location word identification (toponym recognition)(Hu et al., 2023). The rule-based approach identified locations based on natural feature keywords (area, basin, fold, rift, river, range,...), in combination with detecting capitalization. We build a dictionary of location names (i.e. a targeted gazetteer) to identify locations mentioned within the abstract (Figure 1c). We included location names for administrative areas, regions, lakes, rivers, and basins. Geographic taxonomy information about towns and cities with at least 100,000 inhabitants was sourced from Wikipedia's rich open knowledge base (Lehmann et al., 2015) and was further augmented with GitHub open-source collections for smaller capitals and cities by countries, as well as the Encyclopedia Britannica for lakes and rivers (Table S2). By limiting the gazetteer to large, administrative, and natural features we aimed to reduce possible ambiguity (Hu et al., 2023) and directly classified location entities according to type (e.g. match: "New Orleans", type: cities).
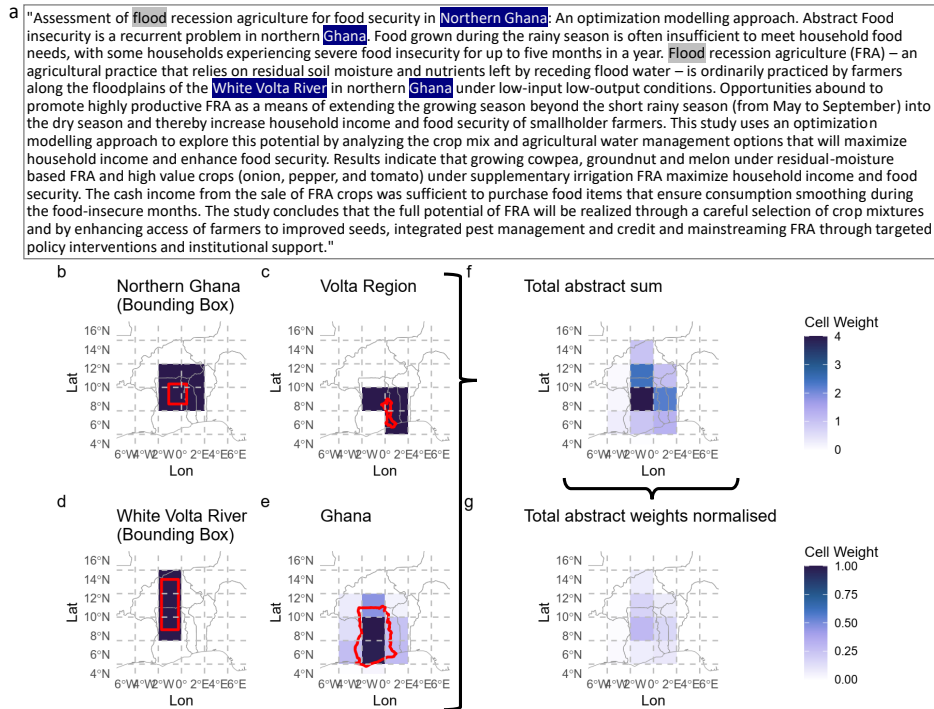
Converting geographic entities into coordinates: We used a combination of the geocoding software Nominatim (Clemens, 2015) and data from Natural Earth Data

159 (NE, `www.naturalearthdata.com`) to geolocate the identified geo-entities. Nominatim

160 searches OpenStreetMap `https://www.openstreetmap.org/copyright` (OSM) (Haklay

161 & Weber, 2008) (Bennett, 2010) data. In case of ambiguity (e.g., multiple identical geo-

162 entities), the five largest entities returned by Nominatim were selected and further ranked

163 based on their OSM importance values, indicating search popularity (e.g., Paris, France:

164 0.8 versus Paris, Texas: 0.5). We used data from NE to supplement the OSM results and

165 to improve shape outlines of large features such as regions and continents. The match-

166 ing was based on geo-entity name and identified type (e.g., "rivers", "countries"). Man-

167 ual evaluation showed that this approach was more accurate in identifying regions and

168 natural features than Nominatim alone. Final coordinates are based on feature bound-

169 ing boxes for OSM and river lines, as well as exact polygon shapes for all other NE data.

170 ## 2.2 Abstract to grid conversion

171 We used the geolocated entities to calculate a gridded distribution of the area each

172 abstract covers. Figure 2 demonstrates this process. For each of the four locations iden-

173 tified within the abstract (Figure 2a) the grid cells that are touched by the location poly-

174 gon are given the weight of 1 (unless it is a country, where cell weight is based on cov-

175 erage). The sum of the four grids (Figure 2f) is then divided by the total grid sum (13.56

176 in this case), resulting in a weighted research distribution (Figure 2g). This process pro-

177 duces greater weights for cells where multiple locations overlap.

178 Creating a spatial grid for each abstract enabled us to calculate the density dis-

179 tribution of studies so that we could compare them with other datasets (e.g., popula-

180 tion density) that were also transformed onto the same grid resolution. Similar to Callaghan

181 et al. (2021), we chose a raster grid of 2.5°. However, unlike them, we considered not just

182 the smallest but all locations extracted from an abstract. We commonly found that mul-

183 tiple equally relevant study locations are mentioned in one abstract without relevancy

184 distinction. A country might be mentioned either as a study or modeling domain itself

185 or just to specify the location of a smaller entity for the reader. An alternative count-

186 ing method was used to calculate absolute numbers of abstracts per country. All geolo-

187 cations that fell within a country (excluding continents and marine regions) were counted,

188 and the number of unique abstracts per country was calculated.

a "Assessment of flood recession agriculture for food security in Northern Ghana: An optimization modelling approach. Abstract Food insecurity is a recurrent problem in northern Ghana. Food grown during the rainy season is often insufficient to meet household food needs, with some households experiencing severe food insecurity for up to five months in a year. Flood recession agriculture (FRA) – an agricultural practice that relies on residual soil moisture and nutrients left by receding flood water – is ordinarily practiced by farmers along the floodplains of the White Volta River in northern Ghana under low-input low-output conditions. Opportunities abound to promote highly productive FRA as a means of extending the growing season beyond the short rainy season (from May to September) into the dry season and thereby increase household income and food security of smallholder farmers. This study uses an optimization modelling approach to explore this potential by analyzing the crop mix and agricultural water management options that will maximize household income and enhance food security. Results indicate that growing cowpea, groundnut and melon under residual-moisture based FRA and high value crops (onion, pepper, and tomato) under supplementary irrigation FRA maximize household income and food security. The cash income from the sale of FRA crops was sufficient to purchase food items that ensure consumption smoothing during the food-insecure months. The study concludes that the full potential of FRA will be realized through a careful selection of crop mixtures and by enhancing access of farmers to improved seeds, integrated pest management and credit and mainstreaming FRA through targeted policy interventions and institutional support."

Figure 2. Schematic showing 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 were extracted as bounding boxes for a vague estimate of catchment outline. **e**, for country shapes, each cell is weighted according to the fraction covered by its shape. **f**, Sum of raster **b-e**. **g**, Grid divided by the total sum of all cells to normalize the raster grid for each abstract to a sum of 1. This ensures comparable weights between abstract raster grids, independent of the number of geo-entities tagged.

2.3 Manual evaluation of annotation quality

The combined OSM and NE tagged geo-entity dataset was manually checked, and wrong results that frequently occurred 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. Afterwards, eight evaluators manually assessed 418 abstracts to determine geolocation annotation accuracy. The evaluation focused on three aspects: 1. Accuracy of the identified location words (Is the identified entity a location?). 2. Accuracy of the geolocation. And 3. missed locations. Of the 418 abstracts

288 (69%) had automatically annotated locations, with a total of 779 identified locations across all abstracts. Figure S2 gives a full overview of evaluation statistics.

Regarding aspect 1. Precision and recall are standard information retrieval metrics that are commonly used to evaluate location recognition (Hu et al., 2023). Ting (2010) defines precision as *"Total number of documents retrieved* [locations in our case] *that are relevant/Total number of documents that are retrieved"* and recall as *"Total number of documents retrieved that are relevant/Total number of relevant documents in the database.".* We reach a precision value of 0.91 and a recall value of 0.78 (Figure S2a). In comparison, Hu et al. (2023) evaluate 27 common toponym recognition methods on 26 different datasets. The 27 methods range in precision between 0.477 to 0.868 and in recall between 0.261 to 0.784. Our approach thus reaches state-of-the-art accuracy in location recognition.

Regarding aspects 1. and 2.: 91.1% of all annotated locations have been correctly geolocated (Figure S2b). However, in 22% of abstracts with at least one location and in 3% of abstracts without a location entity, at least one location entity has been missed. This seems like a relatively high number. We therefore further evaluated the influence of missing and wrong locations on the research distributions. In total we identified 202 missed locations. 19% of these missed locations could not be found on OSM by the evaluators either and therefore could not be geolocated. This result reflects the limits of the OSM database. For all abstracts with missing and wrong locations that could be located (120 abstracts, Figure S2c), we test if adding or correcting the locations influences the extent of the covered grid cells to evaluate the reliability of the final research distributions. We find that for 76% of the abstracts, the extent does not change, meaning that missed or wrong locations fall within the already identified locations (e.g. the town "Wakkanai" has been missed, but is contained within the larger entity the island of "Hokkaido", which has been identified). Additionally, the average Pearson correlation between original and corrected abstract density grids is on average 0.89, suggesting a low impact from the additional location entities. We further analyzed if the distribution of evaluated locations across country income groups differs between all evaluated locations as well as missed or wrong locations (Figure S3). A larger share of missed or wrong locations in low-income countries would indicate a bias in our analysis due to a bias in our location dictionary or OSM. However, Figure S3 reveals that this is not the case.

2.4 Bias analysis

Biases in research distributions were determined by comparing the distributions of four data categories: 1. Impact data, 2. Hydro-meteorologic measurement stations, 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 Geocoded Disasters Database (GDIS) (Rosvold & Buhaug, 2021a) to create geolocated impact data. Hazard events are only considered for EM-DAT if certain impact criteria based on severity are met, such as more than 10 dead, more than 100 affected, a state of emergency was declared, or international assistance was called. However, getting accurate impact numbers for disaster events can be a challenge (Guha-Sapir & Below, 2006), and many events are missing information 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 our outcomes to three additional disaster-specific, continually updated datasets commonly utilized by their respective communities: the Dartmouth Flood Observatory (Brakenridge, 2023), the NASA global landslide catalog (Kirschbaum et al., 2010), and the Global Fatal Landslide Database (Froude & Petley, 2018). Both landslide databases focus on rainfall-induced landslides and are widely used within the landslide research community.

We compared **measurement station data** to the identified 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) (World Meteorological Organization (WMO) & Federal Office of Meteorology and Climatology (MeteoSwiss), 2023), Global Precipitation Climatology Centre (GPCC) stations (Rustemeier et al., 2022), 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 the World Development Indicators and Worldwide Governance Indicators (World Bank, 2023; Kaufmann & Kraay, 2022) from the World Bank Open Data Catalog for **socio-economic data** accessed via the "wbstats" R package (Piburn, 2020). Additional socio-economic indices are population (WorldPop, 2023), human development index (Kummu et al., 2018), and the adaptive capacity measure by the Notre Dame Global Adaptation Initiative (ND-GAIN) (C. Chen et al., 2015). We considered

human footprint as a general measure of anthropogenic impact (Venter et al., 2016), and travel time to the nearest city above 100,000 inhabitants as a measure of closeness to urban centers (Nelson et al., 2019a; Hijmans et al., 2023). 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) to determine differences in variable distributions between regions of high research density ($> 75^{\text{th}}$ percentile) and the entire world as a measure of bias. The Wasserstein distance is a measure of the absolute difference between cumulative distributions and does not indicate the direction of bias. We therefore combine Wasserstein difference with a second statistic to calculate the direction of bias. For that we used the summarized difference between cumulative distribution functions (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 6), 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.

3 Results

3.1 Global distribution of hydro-hazard research

Out of 610,000 abstracts that include variations of the search terms "drought", "flood", and "landslide", further screening (Figure S1) leaves us with 293,156 abstracts for analysis. We calculated research density as research per cell weighted by the size of the location entity (Callaghan et al., 2021). We define highly researched regions as all locations with a research density above the 75th quantile of all land cells. The exact regions are shown in Figure S5.

The global distributions of hydro-hazards research densities depicted in Figure 3 (a,d,g) show distinct patterns for each hazard. A noticeable hotspot for **drought** research is the west coast of the USA, while 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). Other African countries that are highly researched are 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 we found no small-scale studies. **Flood** research density is generally higher due to larger number of articles than for the other hazards. 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). About 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. Flood research in South and Central America and most of Africa is low. **Landslide** research has distinct hotspots, especially in the Alps, Italy, Taiwan, Hong Kong, the Himalayas, Central China, and Japan. Taiwan is the cell with the highest research count overall. In terms of absolute numbers, China is the country with the largest number of abstracts about landslide research, with 6,571 abstracts in total.

3.2 Research distribution across climate zones

We analyze the research bias between climate zones by comparing study numbers against the number of hazard events and population numbers in each climate zone. Temperate regions have, on average, the highest research count for all three hazards (Figure 4a). In terms of hazard event counts (Emergency Management Database, EM-DAT, Figure 4c, upper panel), that distribution is mirrored by flood event occurrences, but not drought or landslide events. Most flood events (mean 28.8 per cell) also occur in temperate regions. The average flood count in tropical regions is about half that of 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, showing 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 though, 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-
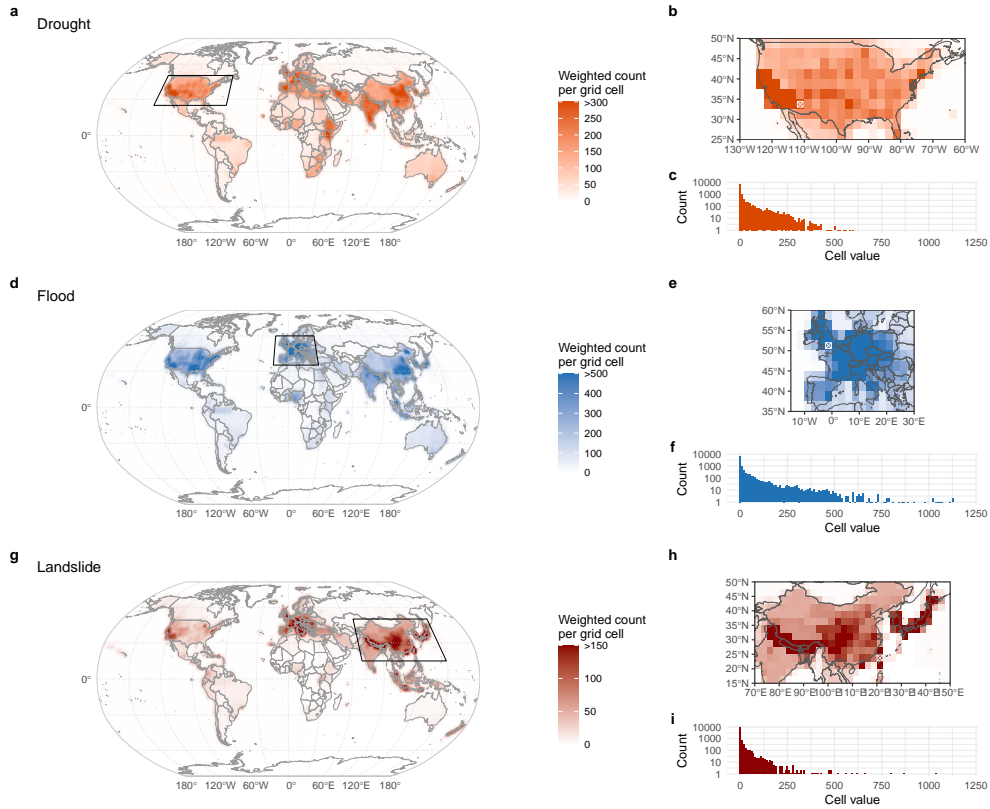
Figure 3. For each water extreme, the research distribution is displayed in three panels. A global map of weighted research count, a detailed map for the highest cell count (marked by x), and a histogram across all raster cells for droughts (**a-c**), floods (**d-f**), and landslides (**g-i**).

DAT vs. NASA landslide catalog vs. the Global Fatal Landslide Database—GFLD, Figure 4c, lower panel). The comparison suggests biases 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 the population in that climate zone (36%, Figure 4b). Yet, tropical regions with only 22% fewer people than temperate regions have 60% (drought), 70% (floods), and 74% (landslides) lower research densities.

3.3 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
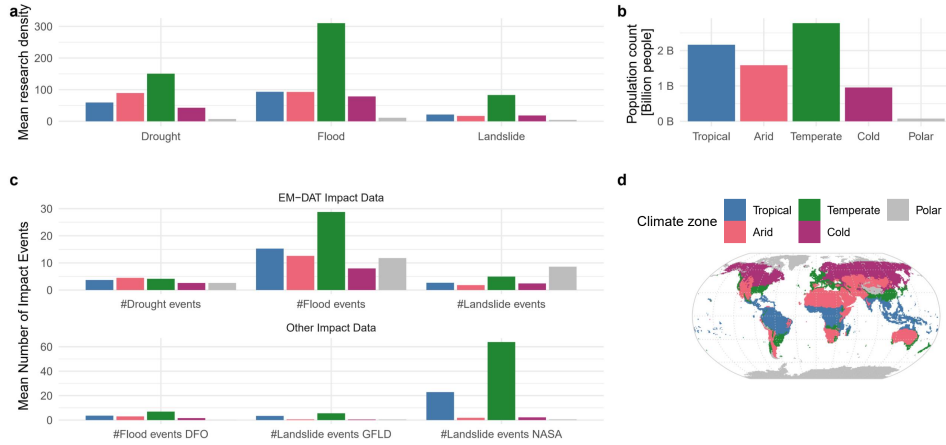
Figure 4. **a**, Mean research density across broad climate zones according to Koeppen-Geiger (H. E. Beck et al., 2018), **b**, population count (WorldPop, 2023) by climate zone, **c**, mean number of events per cell and climate zone for EM-DAT event counts as well as one flood and two landslide datasets (Dartmouth Flood Observatory, Global Fatal Landslide Database (GFLD), NASA landslide catalog), **d**, world map depicting the climate zones.

335   measurements. Hence, we extract the land surface with high research density ($> 75^{\text{th}}$

336   quantile, Figure S5) and compare its characteristics with those of the whole land sur-

337   face. Differences between distributions are quantified using the Wasserstein metric (Kantorovich,

338   1960; Krabbenhoft et al., 2022). Figure 5 shows Wasserstein distances for selected vari-

339   ables (all variables: Figure S8).

340   Multiple variables indicate a strong positive bias in research density towards re-

341   gions that are highly influenced by human activity. Human footprint, representing as-

342   pects of human pressure on the environment (Venter et al., 2016), as well as the vari-

343   ables irrigated land, population count, cropland, and travel time to the nearest city as

344   an indicator of urbanization all exhibit high Wasserstein values (> 0.5). Wasserstein val-

345   ues are lower (on average < 0.4) for climatic indices such as potential evapotranspira-

346   tion, precipitation, and aridity. Average annual precipitation is the only climatic vari-

347   able that has a large spread of Wasserstein values across hazards (0.14 for drought, 0.24

348   for flood, and 0.36 for landslide research). Furthermore, we observed opposing distribu-

349   tion differences between hazards. While flood and landslide research densities increase

350   with increasing precipitation, drought research density decreases. However, this nega-

351   tive relationship reflects only the average distribution. When examining detailed cumu-

lative 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 sta-

tions.

Besides human influence, further biases in hydro-hazard 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 tech-

nical journal articles" from the World Bank refers to the number of articles published

within the fields of science and engineering per country. Due to measuring the quantity

of research similar to our study, it can be regarded as a control variable that is expected

to exhibit a strongly positive value, which we confirm with an average Wasserstein dis-

tance 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 abil-

ity 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).

3.4 Country income-level, people affected, and research density

We investigate the interactions between research density and the number of affected

people to analyze whether more impacted regions are also more intensely studied. In Fig-

ure 6a, we see 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 den-

sities never reach the same level as for high-income countries. The only exception is drought
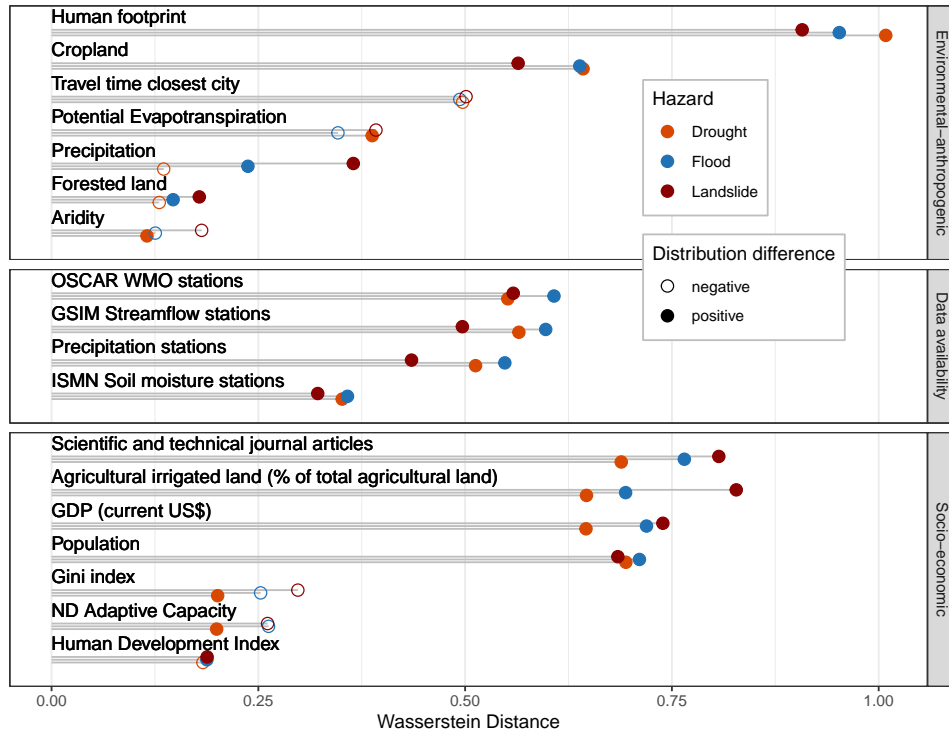
Figure 5. Comparison of climate, land, gauging data, and socio-economic characteristics between regions of high research (> 75th quantile) and the entire land area. Distribution difference measured as Wasserstein distance (Krabbenhoft et al., 2022). Higher values indicate a stronger bias. Wasserstein distance only indicates the strength of bias. We infer the direction of bias from the difference between variable distributions (Stein et al., 2021). A positive (negative) distribution difference indicates more (less) research with increasing characteristics.

research in lower-middle-income countries, which is largely due to the large amount of drought research in India (Figure S13).

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).
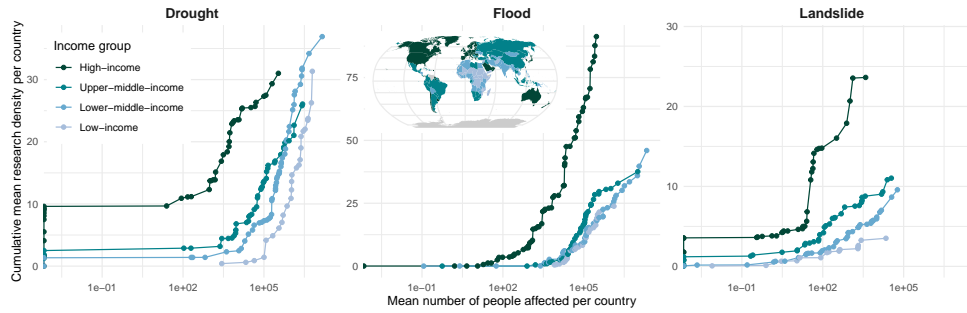
Figure 6. Country-averaged number of affected people against the cumulative distribution of the research density, averaged over all cells per country and separated by World Bank income levels (according to 2021 income classes) (World Bank, 1978). Each dot corresponds to one country.

4 Discussion and Conclusion

4.1 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 already strongly impacted by hydro-hazards (Hallegatte et al., 2020) and by climate change, with accelerating risk 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 (UNDRR) 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 & 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 (SDGs), 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 6). 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 (hence Wealth over Woe). This disparity is likely due to highly unequal research funding, data availability, and research capacities between high-income and low-income countries (Skupien & Rüffin, 2020).

Our results show that low-income countries currently need to base risk assessment decisions, adaptation, and 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 6). Yet, local scientific and community knowledge is highly relevant for the effectiveness of disaster risk management (Gaillard & Mercer, 2013) and can reduce disaster impact if combined with resources to implement solutions (Kreibich et al., 2022). Less research in low-income countries thus means that 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 provide valuable guidance by suggesting future research focus regions to international funding agencies including the World Bank, the UN, and the European Union. Or they can guide international research investments of individual nations, like the Global Challenges Research Fund (GCRF) of the UK Research and Innovation non-departmental body of the UK government.

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

We assess research focus regions based on past impact and identify gaps in socio-hydrological variations covered by research activity. 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 ($> 75^{th}$ percentile) and low rates of research activity ($< 75^{th}$ percentile). For droughts, regions with high research needs are predominantly the Sahel zone, the Horn of Africa, eastern Brazil, and Afghanistan (Figure 7). 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 con-

trast to floods and droughts, which affect multiple spatial grid cells, a single landslide
event will only be recorded in one cell due to its limited spatial extent. As a consequence,
landslide research focus cells include major cities, e.g., Freetown in Sierra Leone and Abid-
jan in Côte d'Ivoire (Figure 7). Under-researched landslide regions are mainly located
in South America, particularly in Bolivia and Brazil. We find that all of the locations
mentioned 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.
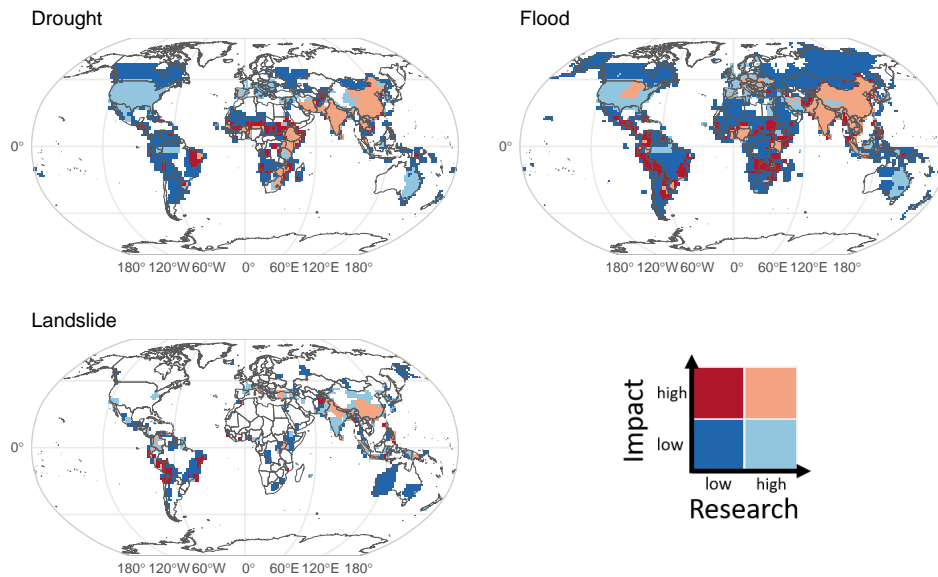
Figure 7. Research focus regions. Each cell is categorized by whether it falls into the high
($> 75^{\text{th}}$ quantile) or low research category and high or low impact category, based on the number
of people affected. Most relevant for future research are regions with low research and high im-
pact (dark red). Classification based on 75th quantile of research and impact (number of people
affected, EM-DAT).

Some knowledge gained in highly researched regions may be transferable to less stud-
ied regions if similar hydro-climatic and landscape characteristics allow the assumption
of process similarity (Bertola et al., 2023; Stein et al., 2021; West et al., 2022). 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 (Y. 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 4). 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 4). Hence, we argue that the drought risk for rainforests is likely inadequately studied, despite 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, 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). Therefore, it is paramount to ensure vulnerability to hydro-hazards is studied across different socio-hydrological settings.

Wealthier countries also collect and share more data (L. Beck et al., 2008), which further adds to the research bias towards data-rich regions (Figure 5). Some countries, such as the US, are likely highly studied simply because they collect large amounts of data through public funding and then make them freely available. In addition to increased research funding, extended data collection and data sharing are necessary. The Sendai framework and UNDRR are targeting gaps in disaster data (Aitsi-Selmi et al., 2016). However, in addition to disaster information, basic and long-term monitoring of variables such as streamflow, soil moisture, precipitation, etc. are equally necessary to improve hazard research, particularly in periods of strong climate change. Closing the data gap can be achieved by funding targeted extension of monitoring networks (Krabbenhoft et al., 2022), or by collecting and combining available data into systematic databases (e.g., Gerbens-Leenes et al., 2024). The most important point is that the data is made open-access for the most effective use (Aitsi-Selmi et al., 2016).

4.3 Limitations

We have studied the distribution of knowledge within published scientific abstracts as these are the only sources of scientific literature compiled as datasets. Therefore our approach cannot adequately recognize that at least some research might only be accessible through technical reports (i.e., grey literature) or in unpublished 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 utilized. 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 geolocation might introduce a bias towards larger entities, high-income countries, and non-natural features (Acheson et al., 2017). We find that this bias did not impact the accuracy of our geolocation (Figure S2). Our evaluation of 418 abstracts showed, that for 26% of the abstracts, one or more locations were missed. However, the impact of missed and wrongly geolocated locations is small, as in 76% of cases the identified location extent does not change when the missing and wrong locations are added. Additionally, location extraction is biased by the limited description contained within abstracts. Although full-text analysis might have yielded more information (Westergaard et al., 2018), it would dramatically reduce the number of articles available. Fortunately, open access is rapidly growing (Björk, 2017), which means that. Hence, reviews like ours will likely become more informative in the future.

4.4 Looking forward

In this study, we were able to map hydro-hazard literature and reveal 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 in relation to increased research activity appear to be significantly higher for lower-income countries compared to wealthier regions. Furthermore, the uneven distributions suggest knowledge gaps in hazard understanding since not all relevant hydro-climatic landscapes are covered equally. Where hazard events occur and where they are researched does currently 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.

An analysis of this scale would not have been possible without automated tools to analyze text-based data. Large language models and other text-mining tools are increasingly necessary to keep up with the vast amounts of research published (Stein et al., 2022). For comparison, based on the person-hours our manual evaluation took, an on par non-automated study would have taken about two years of round-the-clock work for one person to screen all the abstracts in contrast to a few hours of runtime it took us instead (not counting the time it took to develop the approach in the first place). The speed at which text analysis methods are improving will advance opportunities in research analysis. For example, we could add automatically extracted information as "hydrologic" metadata to each article, which could include location, time scale, climate regime, methods used, and more. Research could then easily be found and synthesized along these metadata (Stein et al., 2022). Authors would only need to quality-check the automatic annotations during the submission process, after which their research would immediately be mapped. Beyond search and synthesis, one could additionally generate a training dataset to continuously improve and specialize automation tools. Progress in fair research distributions could thus be tracked and local research made visible.

Overall, our findings provide research funding agencies with the necessary maps to develop programs that target research inequality. Policymakers can use these maps to determine where knowledge gaps might affect their decisions. Researchers should be encouraged to develop collaborative networks with and within 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 often fall outside current funding schemes that focus on funding researchers residing in the country of the funding agency, rather than building capacity abroad. We currently only show the

state of historical research and its impact to date. However, with climate change alter-
ing hazard occurrences around the world and with rapidly changing socio-economic con-
ditions 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 cur-
rent research activities to highlight knowledge gaps in regions that are at risk in the fu-
ture.

5 Open Research

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 evalua-
tion data are 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 Seman-
tic Scholar API (Kinney et al., 2023). 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 (OpenStreetMap,
2023). We use Natural Earth Data (Patterson & Kelso, 2023) accessed via the "rnat-
uralearth" R package (South, 2017). Impact data is sourced from the Emergency Man-
agement Database (CRED, 2023b). Geolocations for EM-Dat were taken from the Geocoded
Disasters (GDIS) Dataset (Rosvold & Buhaug, 2021b). Other impact data was sourced
from the Dartmouth Flood Observatory (Brakenridge, 2023), the NASA global landslide
catalog (Kirschbaum et al., 2010) and the Global Fatal Landslide Database (Froude &
Petley, 2018). Measurement station data was taken from the following sources: Precip-
itation stations - Global Precipitation Climatology Centre (GPCC) (Rustemeier et al.,
2022); streamflow stations - Global Streamflow and Metadata Archive (GSIM) (Do et
al., 2018); soil moisture stations - International Soil Moisture Network (ISMN) (Dorigo
et al., 2011, 2013, 2021); climate stations - WMO Observing Systems Capability Anal-
ysis and Review Tool (WMO OSCAR) (World Meteorological Organization (WMO) &
Federal Office of Meteorology and Climatology (MeteoSwiss), 2023). Precipitation and
evapotranspiration data was taken from CHELSA (Karger et al., 2018). Human foot-
print data was published here (Venter et al., 2017). The fraction of cropland was taken
from the ESA World Cover dataset (Zanaga et al., 2021). Data on travel time from the

nearest city was published here (Nelson et al., 2019b) and accessed via the "geodata"

R package (Hijmans et al., 2023). Socio-economic and other indices were taken from the

World Development Indicators and Worldwide Governance Indicators(World Bank, 2023;

Kaufmann & Kraay, 2022) accessed via the World Bank Open Data Catalog and "wb-

stats" R package (Piburn, 2020). Vulnerability and adaptive capacity data were taken

from the Notre Dame Global Adaptation Initiative (C. Chen et al., 2015). Population

data was taken from WorldPop (WorldPop, 2023). We additionally used Human Devel-

opment Index data (Kummu et al., 2019).

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 (Staar et al.,

2020). 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`). Wasserstein distance was calculated using the "trans-

port" R package (Schuhmacher et al., 2023). The codes to process, analyze, and plot the

data and annotated abstracts are available in this repository: `https://doi.org/10.5281/`

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Supporting Information for "Wealth over Woe: global biases in hydro-hazard research"

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Introduction

Text S1 gives an extended description on quality checks for the geo-annotation procedure. Text S2 provides additional information on the effect different grid types have on the final result. Text S3 gives additional details for the final evaluation. Text S4 offers additional discussion on the identified research needs regions. The supplemental figures

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[*]Work done while at IBM Research

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give a more in-depth understanding of the methodology and provide additional details on the results. Similarly, the supplemental tables provide an overview of details on the methodology including an overview of all datasets used.

Text S1. Abstract 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 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). A special case was made for Rio Grande 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 location:

1. 'Mobile'

2. 'Palmer' (Palmer Drought Severity Index)

3. 'Price'

4. 'Progress'

5. 'Independence'

6. 'Berea' (type of sandstone misclassified as district in Lesotho)

7. 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, and 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:

1. Type 'Rivers' was matched with 'Rivers and Lake Centerlines'

2. Type 'Lakes' was matched with 'Lakes'

3. Type 'Basins' was matched with 'Regions'

4. 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.

5. Type 'Marine Regions' was matched with 'Marine Areas'

6. Type 'Provinces' was matched with the 'States, Provinces' data.

7. Type 'Countries' were matched with 'Countries'.

8. Type 'Continents' were matched with the continental regions supplemented by regional country aggregations, such as 'Central Africa', 'Baltic States', 'Latin America' etc.

Text S2. Raster grid generation

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 on average only half as big as those 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).

Text S3. Extended evaluation

We manually evaluate the annotations of 418 abstracts. In addition to the accuracy reported in the main text, we here extend on the hazard annotation quality. 6% of abstracts reveal a problem with the quality of the Semantic Scholar database. The included text is not an abstract, but instead only the title of a hazard paper (4%) or some kind of news/book review/presentation announcement (1.7%). We deliberately decided to not filter out texts that might be only titles, as any hazard/location mentioned in them will still indicate a hazard research region. Removing the remaining 1.7% error is not straightforward and difficult. 8% of abstracts include incorrectly identified hazards. This includes the use of the word "flood" or "landslide" in a different context (e.g. "flood of writing", "landslide victory"), or the confusion with mining, computational or medical terms that include flooding (e.g. "alveolar flooding"). We tried to reduce the misclassification by

filtering abstracts according to subject (e.g. excluding humanities). However, any further filtering would also remove relevant abstracts, e.g. medical research might report on post-traumatic stress disorder after flooding. Since the biases in research distribution against the Global South are similar in medicine (Sumathipala et al., 2004) and other disciplines (Di Marco et al., 2017; North et al., 2020), we assume that these erroneous hazard mentions should not skew the research distribution for or against Global South countries.

Text S4. 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 & Petley, 2018). With different impact data, e.g. additional flood and landslide impact data, the earlier mentioned regions based on EM-DAT impact data 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.

| Records identified from: Deep Search (n = 610 000) | → | Abstracts removed before screening: • No geolocation annotated (n =237,181) • Identified language not English (n = 18,632) • Article subject irrelevant (n = 6,751) • Published before 1950 (n = 3,740) • Missing climate hazards (n = 31,489)* • More than 25% of abstract is special characters (n = 1,371) |

↓

| Records screened: (n = 310,836) | → | Abstracts excluded based on location checks: • Location match followed by "et al" indicating citation (n = 191) • Rio Grande provinces misidentified as province (n = 252) • Geo entity of type rivers excluded based on keyword-in-context (n = 22,436) • Non-location geo entity matches (n = 2,439)** • No geolocation possible via Nominatim or Natural Earth data (n = 863) |

↓

| Records screened: (n = 303,639) | → | Abstracts excluded based on hazard checks: • Only other climate annotations besides flood, drought and landslide hazards found (n = 6,203) • Hazard terms not relevant (e.g. "aridity") (n = 4,280) |

↓

| Records included in review: n = 293,156 Drought n = 109,679 Flood n = 171,027 Landslide n = 41,931 |

*missing due to
• Irrelevant search term, e.g. "floodplain" (n = 11,861) or authors with surname "Flood"
• Missed annotation due to connected terms, e.g. ""temperature/drought", "drought-prone", "water-flooded"…
• Missing from dictionary, e.g. "floodgate", "floodwater", "Droughtmaster"…

** "Mobile", "Palmer", "Price", "Berea", "Progress", "Independence"

Figure S1. 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).

a Abstracts   **b** Extracted locations   **c** Impact of missed and wrong locations evaluated by comparing original abstract grid extent against corrected grid extent.

$$Precision = \frac{710\ (tp)}{779\ (tp + fp)} = 0.91$$

$$Recall = \frac{710\ (tp)}{912\ (tp + fn)} = 0.78$$

418 abstracts

130 (31%) no location annotated

13 (3%) missed

117 (28%) no location found

94 (22%) at least one location missed

288 (69%) with at least one location annotated

194 (46%) no location missed

779 locations automatically annotated in 288 abstracts.

69 (9%) not a location (false positive fp)

710 locations (91%) correctly identified as a location by the algorithm (true positive tp)

202 (26%) missed locations (false negative fn)

20 (2%) missing geolocation

63 (8%) wrong geolocation

627 locations (80%) correctly geolocated by the algorithm.

120 abstracts with at least one missed or wrong location

16 (13%) change > 2 cells

12 (10%) change ± 2 cells

92 (76%) abstracts where the extent does not change with corrected location

Figure S2. In-depth evaluation statistics based on 418 manually evaluated abstracts looking for 1. any location entities that might have been missed, 2. any locations entities that were falsely annotated as geo-entity, and 3. if the annotated locations have been correctly geolocated. **a** Total number of abstracts and number of abstracts with missed locations. **b** Total number of all locations extracted from the abstract automatically, and the shares of correctly annotated, correctly geolocated, and missed locations. **c** In-depth evaluation of the impact of missed and wrong geolocation.

Figure S3. Analysis of geolocation bias according to income group. **a**, distribution across income groups of all evaluated locations (where income group assignment was possible). **b**, distribution across income groups of all locations that were missed or wrongly located (where income groups assignment was possible). There is no disproportionately larger contribution of missed or wrong locations for low-income locations than for all locations. We therefore conclude that the biased distribution in Open Street Map (Hu et al., 2023) does not translate into biased geolocation in our analysis against low-income countries.
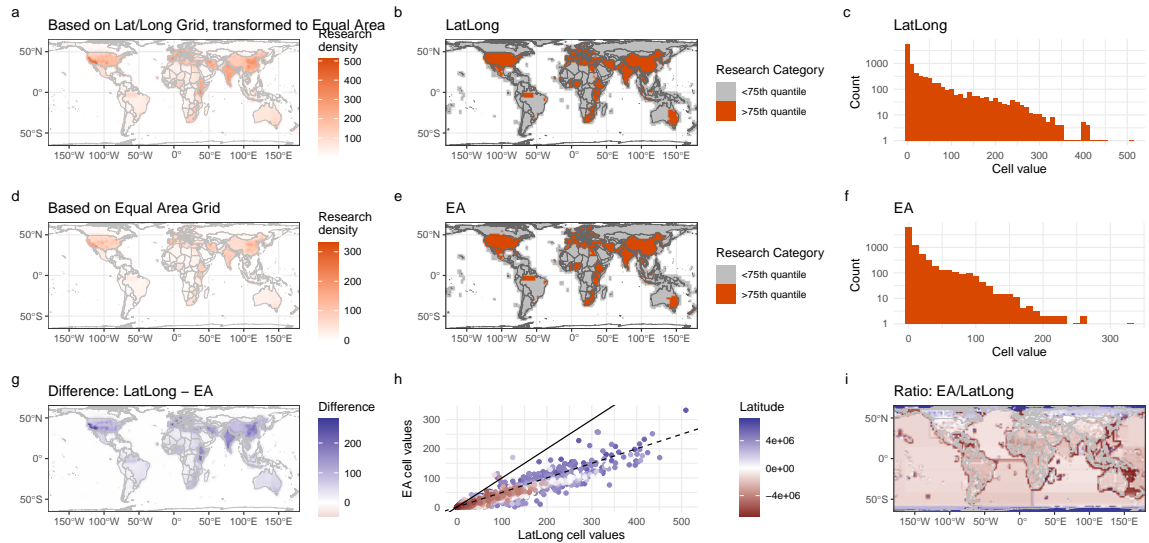
Figure S4. Comparison between research density for drought research between **a**, a latitude-longitude grid (2.5°) and **d**, an equal area (EA) grid (EPSG: 6933). For plotting purposes, the lat/long grid was transformed to equal area as well. **b**, and **e**, highly researched regions (> 75th percentile), **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 ratio between the two grids.

a

b

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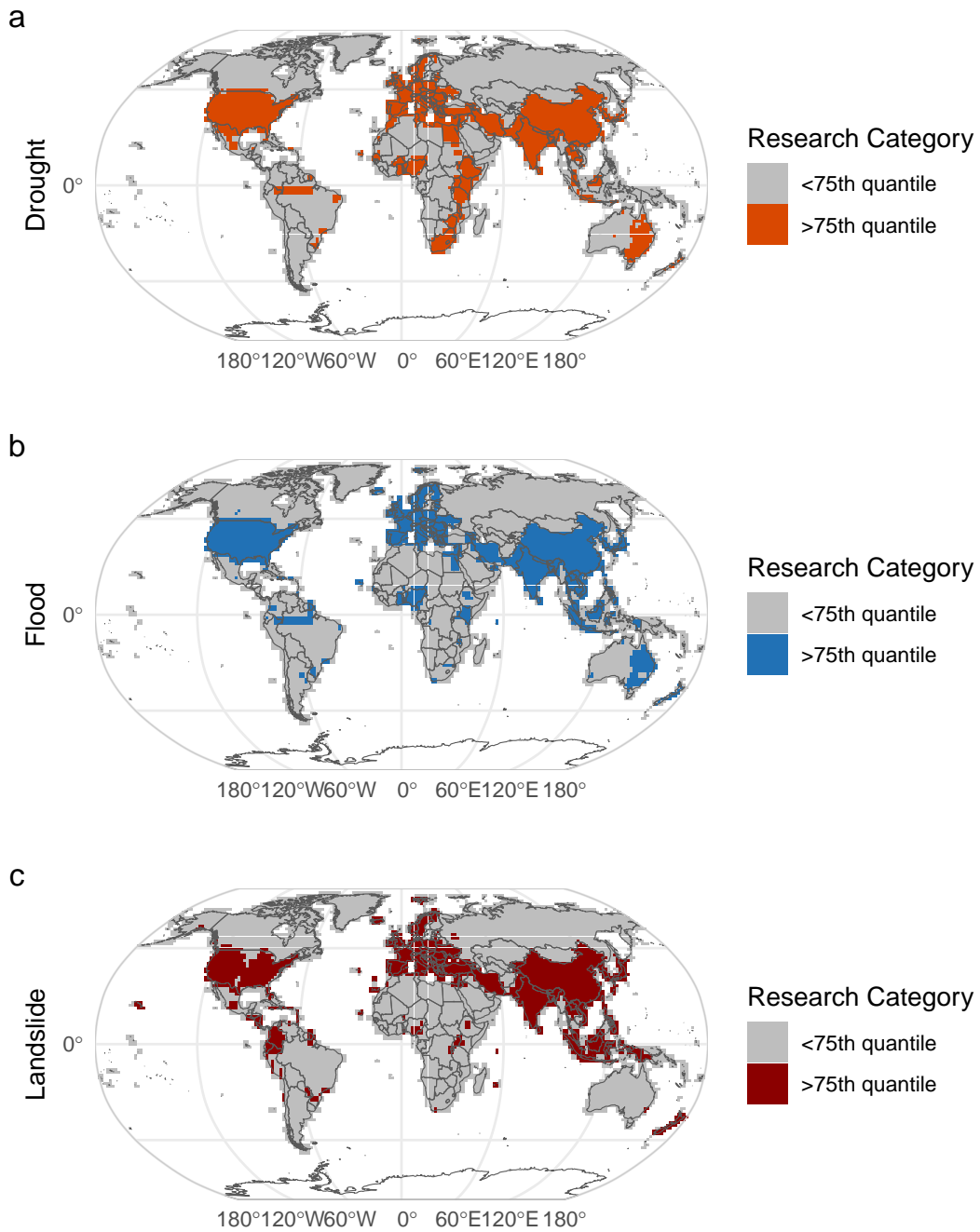
Figure S5. Distribution of highly researched ($> 75^{\text{th}}$ quantile) regions for drought, flood, and landslide weighted research count.

August 28, 2024, 10:26am
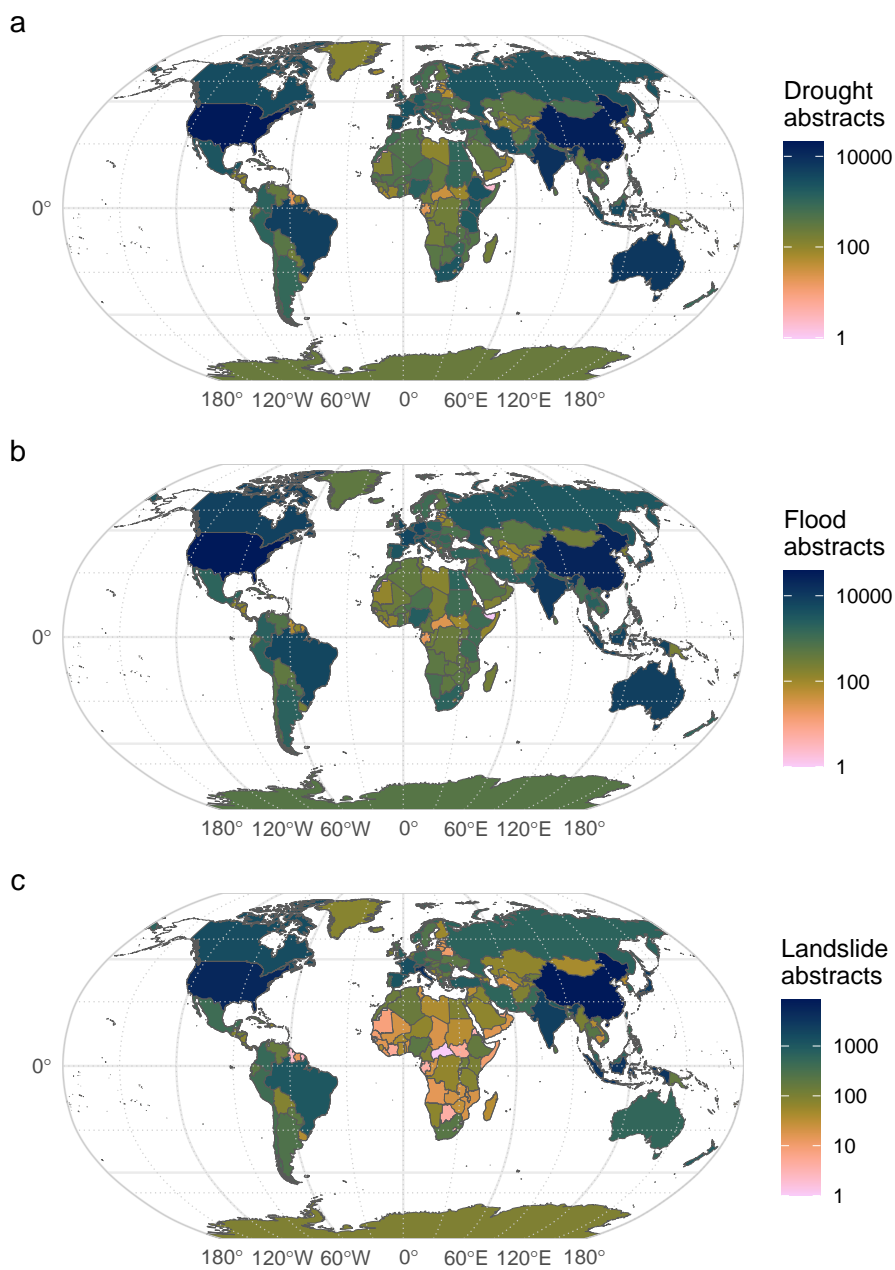
Figure S6. Number of abstracts per country for all abstracts tagged for **a**, drought, **b** flood, **c**, landslides. Double counts for multi-hazard mentions are possible. Not counted in this figure is coverage from continental regions, e.g Central America, Africa, and Europe.
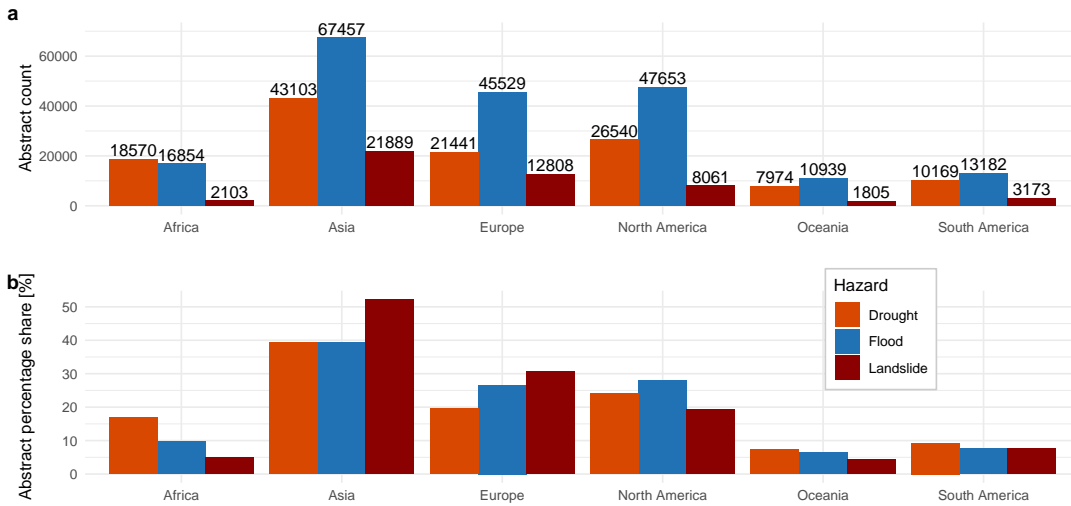
Figure S7. **a**, Number of abstracts per continent for each hazard and **b**, percentage share of abstracts from the total number of abstracts per hazard. The percentage share adds up to more than 100 per hazard since abstracts can cover multiple continents.
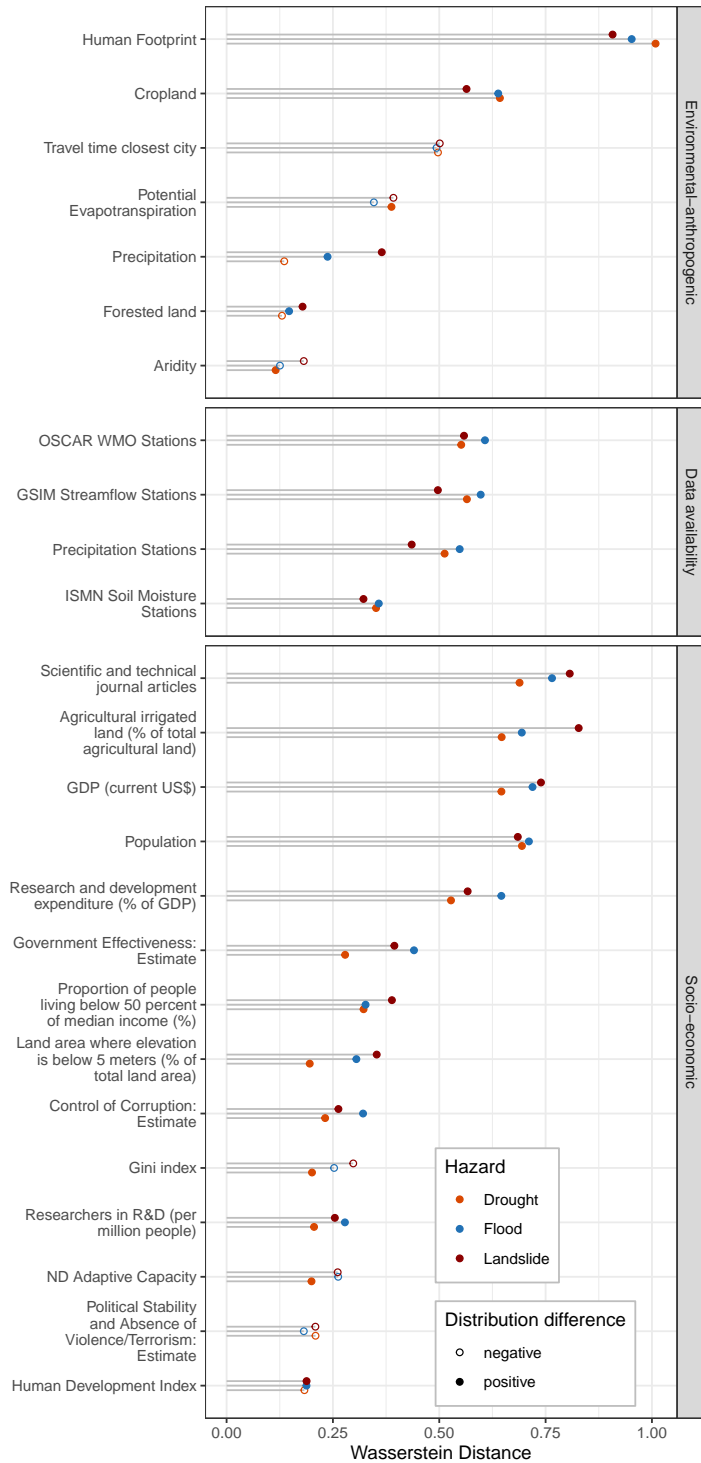
Figure S8. Comparison of climate, land, gauging data, and socio-economic characteristics between regions of high research ($> 75^{\text{th}}$ quantile) and the entire land area. Distribution difference measured as Wasserstein distance (Krabbenhoft et al., 2022). Higher values indicate a stronger bias. A positive (negative) distribution difference indicates more (less) research with increasing characteristic.
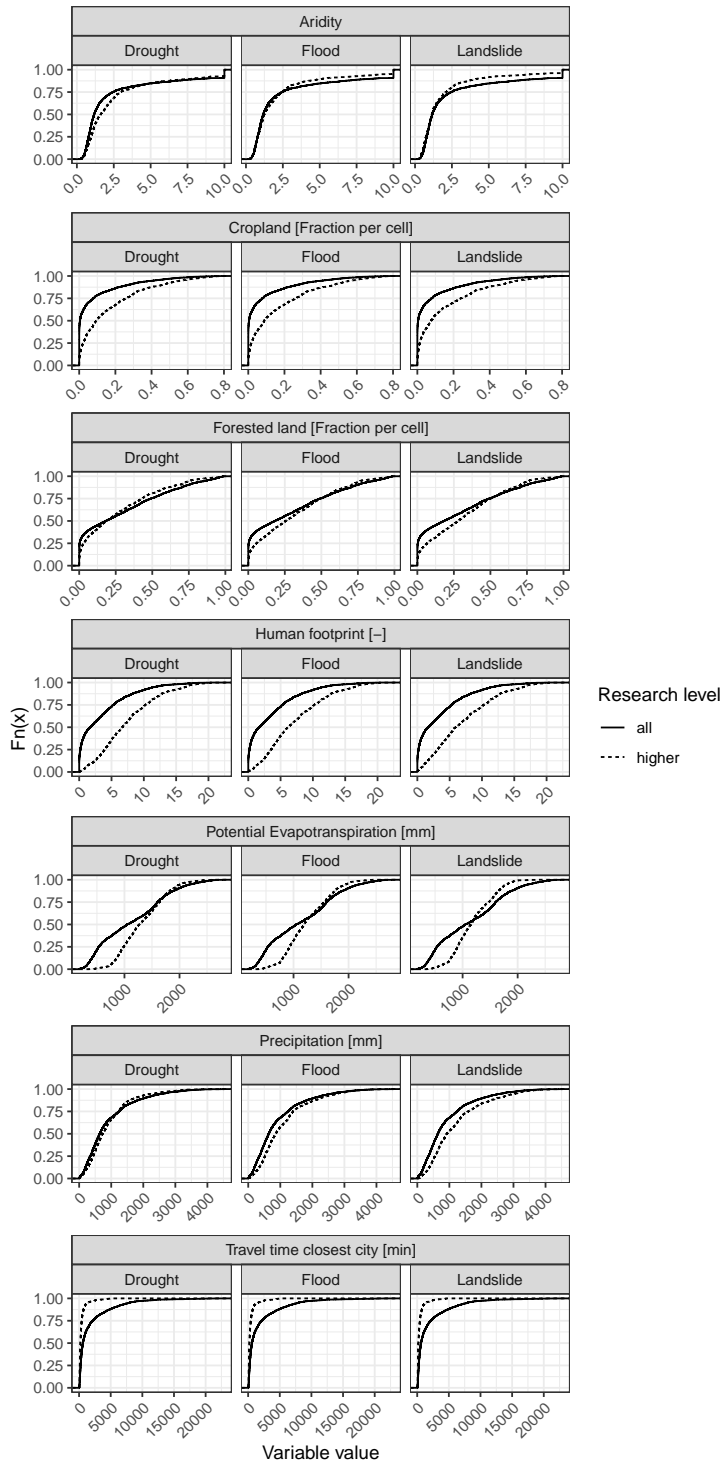
Figure S9. Cumulative distribution functions for environmental and anthropogenic character-istics split into regions with higher ($> 75^{\text{th}}$ quantile) and lower ($< 75^{\text{th}}$ quantile) research density in comparison to all land area.

August 28, 2024, 10:26am
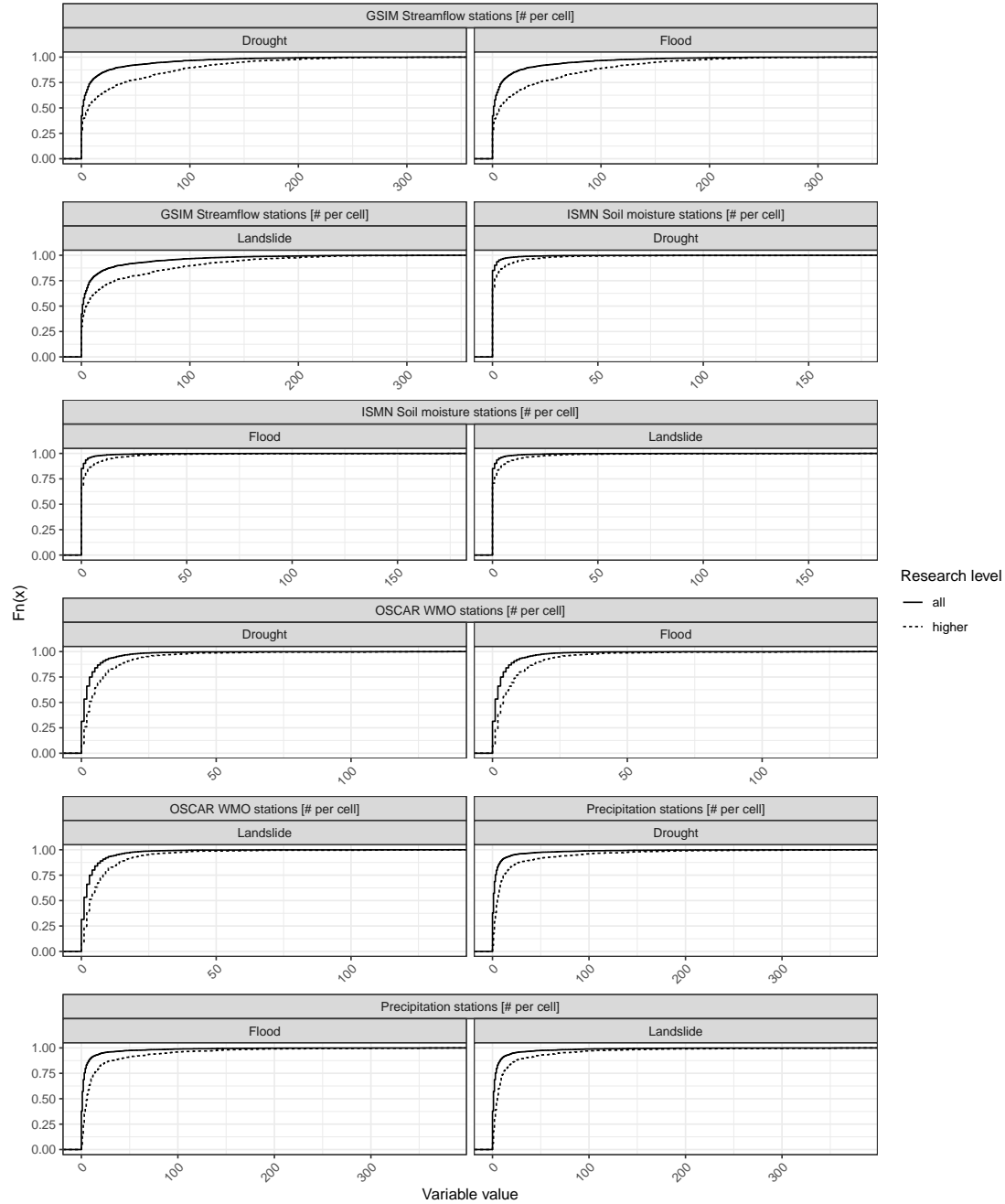
Figure S10. Cumulative distribution functions for data density for various gauging datasets split into regions with higher ($> 75^{\text{th}}$ quantile) and lower ($< 75^{\text{th}}$ quantile) research density in comparison to all land area.
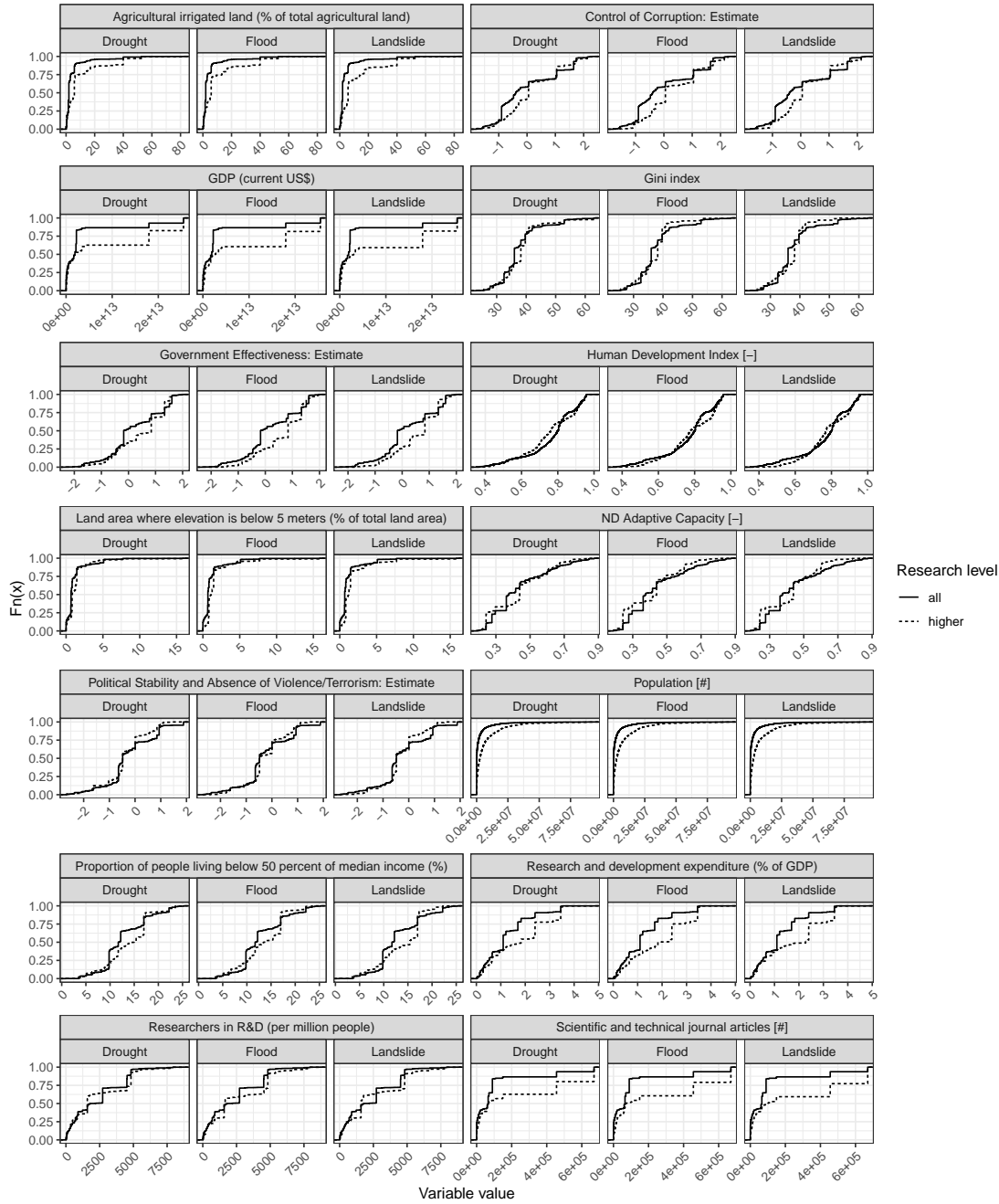
Figure S11. Cumulative distribution functions for socio-economic characteristics split into regions with higher ($> 75^{\text{th}}$ quantile) and lower ($< 75^{\text{th}}$ quantile) research density in comparison to all land area.

a

b

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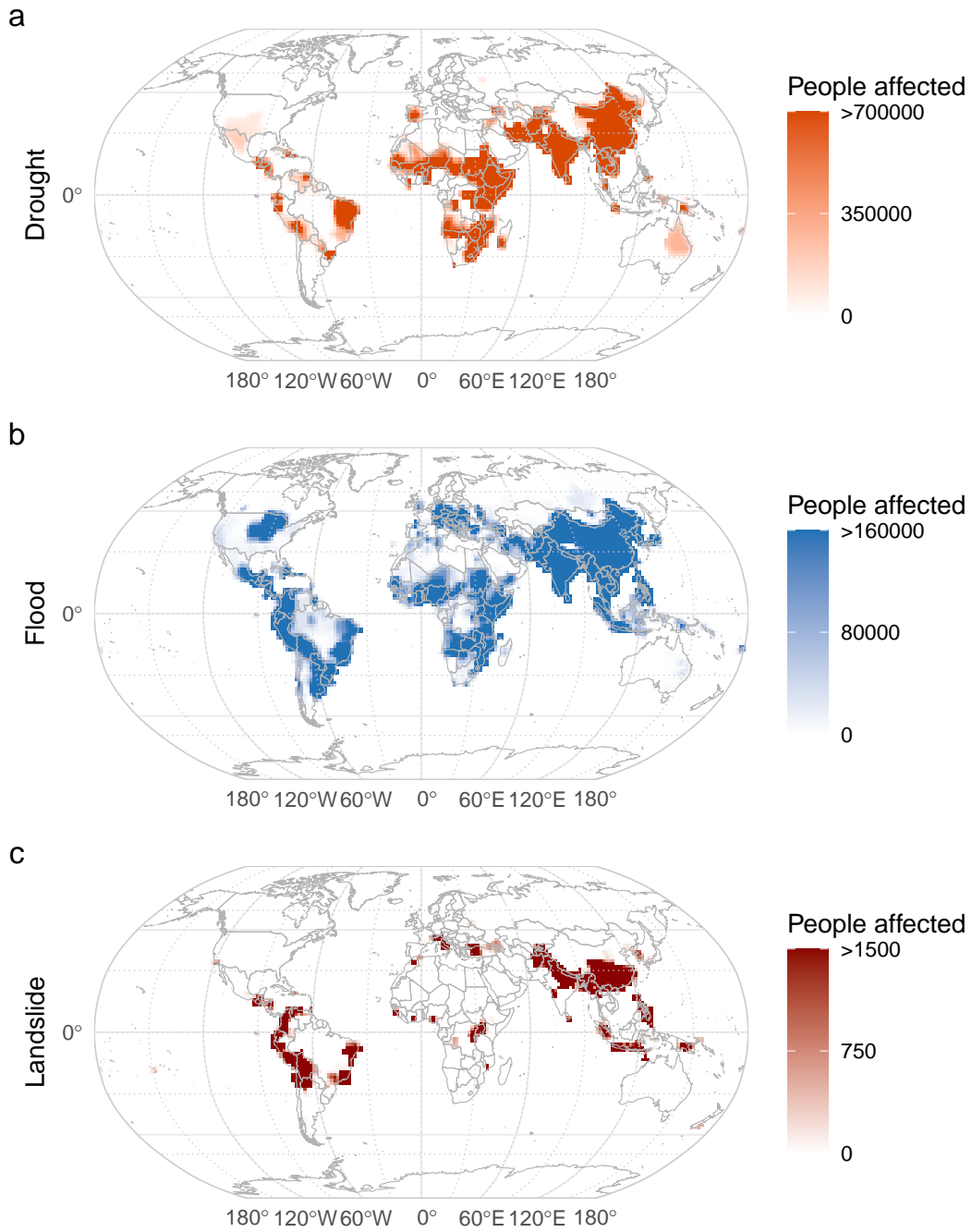
Figure S12. EMDAT impact data. Number of people affected per grid cell for **a**, Droughts, **b**, Floods, **c**, Landslides

August 28, 2024, 10:26am
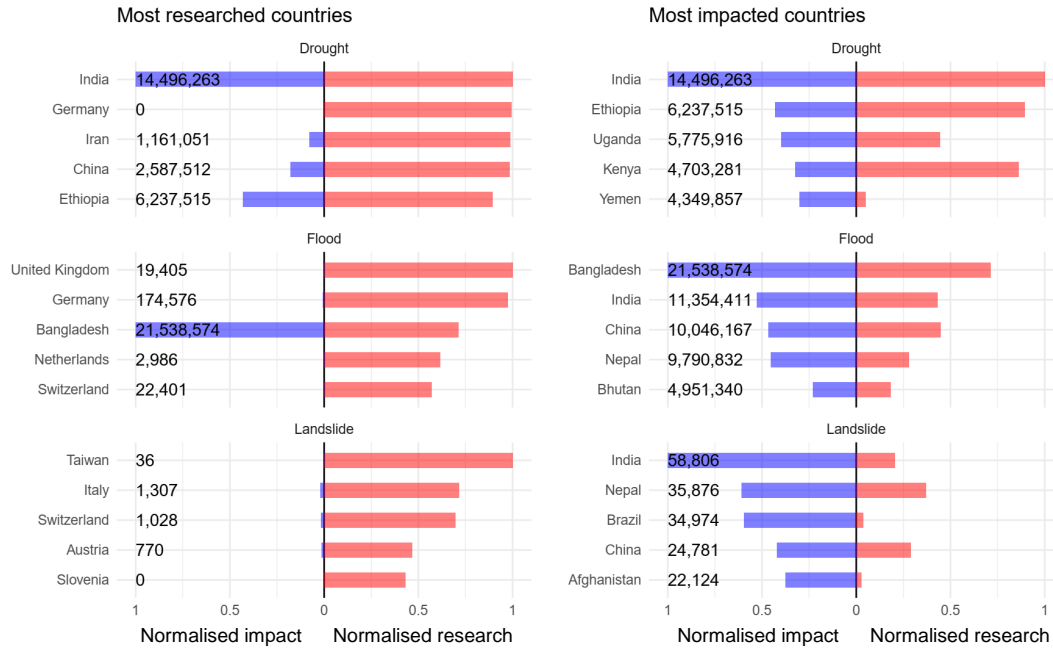
Figure S13.   Most researched (according to average research density) vs most impacted countries and their research (red) compared to their impact (blue) comparison. Numbers on the impact bars indicate the number of affected people per country according to EM-DAT
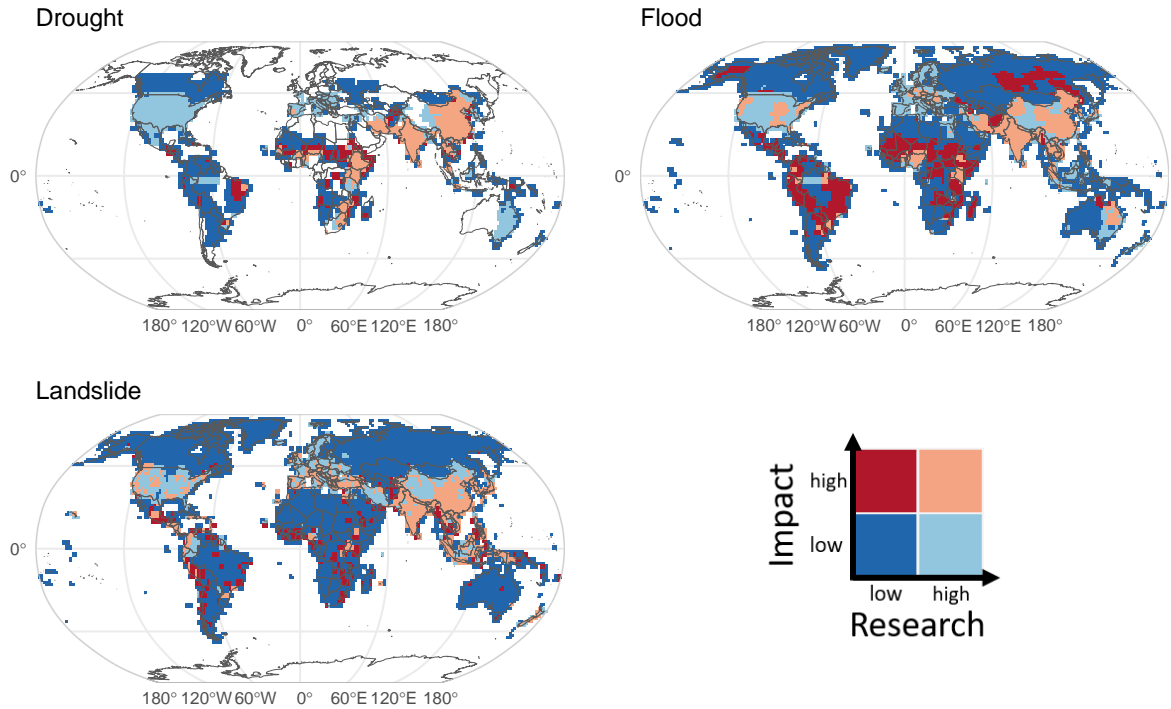
Figure S14. Research needs regions. Most relevant for future research are regions with low research and high impact (dark red). Splits based on 75th quantile of research and impact. The impact here varies between hazards. Drought: Number of people affected (EM-DAT). Flood: Number of people displaced (Dartmouth Flood Observatory, (Brakenridge, 2023)), Landslide: Number of fatalities (Froude & Petley, 2018).
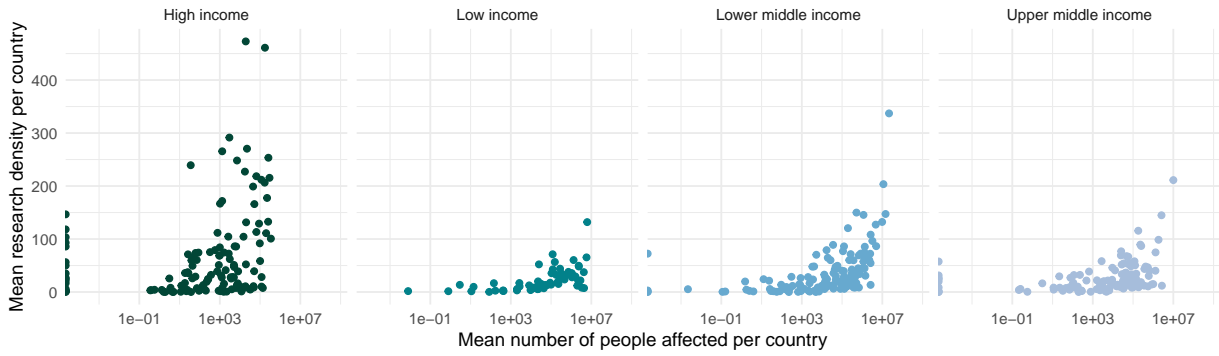
Figure S15. Country-averaged number of affected people against the distribution of the research density, averaged over all cells per country and separated by World Bank income levels (according to 2021 income classes) (World Bank, 1978). Each dot corresponds to one country. For a distinction by hazard refer to Figure 4.

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

Supplement to Table S3: 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 & Adam, 2007; Biddoccu et al., 2016; Bircher et al., 2012; Blöschl et al., 2016; H. Bogena et al., 2018, 2012; H. R. Bogena, 2016; Brocca et al., 2009, 2008, 2011; Calvet et al., 2016, 2007; Canisius, 2011; Capello et al., 2019; Cappelaere et al., 2009; Chen, Xiao, et al., 2015; Chen, Zhang, & Wang, 2015; D. R. Cook, 2016; D. Cook & Sullivan, 2018; Darouich et al., 2022; Dente et al., 2012; Dorigo et al., 2013, 2021; Flammini, Corradini, et al., 2018; Flammini, Morbidelli, et al., 2018; Fuchsberger et al., 2021; Galle et al., 2015; González-Zamora

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

Category	Variable	Dataset	Unit	Resolution	Sample Size	Time period	Reference	DOI	Notes
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	polygon	5490 events	2004 - 2016	(Froude & Petley, 2018)	doi.org/10.5194/nhess-18-2161-2018	
Impact	Dartmouth Flood Observatory	Active Archive of Large Floods	Number of people displaced	point	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	GSM Stations	Global Streamflow and Metadata Archive	-	point	26516 stations	Accessed: 14.03.2023	(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		multiple citations ISMN	ismn.earth/en/	
Socio-economic	GDP	World Development Indicators	current US$	country level		variable (average: 2022)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Agricultural land	World Development Indicators	(% of land area)	country level		variable (average: 2020)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Agricultural irrigated land	World Development Indicators	% of total agricultural land	country level		variable (average: 2020)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Land area where elevation is below 5 meters	World Development Indicators	% of total land area	country level		variable (average: 2015)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Gini index	World Development Indicators	Gini index	country level		variable (average: 2017)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Political Stability and Absence of Violence/Terrorism: Estimate	Worldwide Governance Indicators	-	country level		variable (average: 2021)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Government Effectiveness: Estimate	Worldwide Governance Indicators	-	country level		variable (average: 2021)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Control of Corruption: Estimate	Worldwide Governance Indicators	-	country level		variable (average: 2021)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Proportion of people living below 50 percent of median income	World Development Indicators	%	country level		variable (average: 2017)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Scientific and technical journal articles	World Development Indicators	-	country level		variable (average: 2020)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Researchers in R&D	World Development Indicators	per million people	country level		variable (average: 2017)	data.worldbank.org	data.worldbank.org	Uses most recent available data per country
Socio-economic	Research and development expenditure	World Development Indicators	% of GDP	country level		variable (average: 2017)	data.worldbank.org	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 & Buhaug, 2021)	doi.org/10.7927/zz3b-8y61	

et al., 2019; Hajdu et al., 2019; Hollinger & Isard, 1994; Ikonen et al., 2016, 2018; Jackson et al., 2011; Jensen & Refsgaard, 2018; Jin et al., 2014; C. S. Kang et al., 2019; J. Kang et al., 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 & 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)

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