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The evidence gap index: mapping evidence where it matters for climate change impacts

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ABSTRACT

Climate change impacts are already evident and projected to worsen throughout the 21st century, even with mitigation efforts. Systematic mapping is key to organizing scientific evidence and identifying gaps, but current methods lack geographical context in relation to climate impact risk. In this study, we leverage machine learning to scale up systematic mapping and use automatic geolocation to track place-based research. We then enhance conventional systematic mapping by integrating location-based climate risk components—hazard, exposure, and vulnerability—to create an evidence gap index. This identifies high-risk regions that lack sufficient scientific study. We demonstrate this method using fluvial floods, combining research distribution with a flood-risk indicator (hazard), population density (exposure), and the Human Development Index (vulnerability). Our novel approach refines evidence mapping, supporting data-driven policymaking and directing research resources to the most urgent areas.

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Systematic map; evidence gap map; climate risk; climate change impact; vulnerability; machine learning

Introduction

The impacts of climate change can already be observed around the world (Callaghan et al., 2021). Even with ambitious mitigation efforts, the twenty-first century will see increasingly severe effects, such as floods (Hirabayashi et al., 2013), droughts (Kim & Jehanzaib, 2020) and heat waves (Lhotka et al., 2018), driven by the growing frequency and intensity of these events. These impacts are unevenly distributed across the globe, and the ability to effectively manage them depends on a community's capacity and resilience (Smit & Wandel, 2006). Consequently, communities with lower adaptive capacity are likely to bear the brunt of climate impacts (Eckstein et al., 2021).

There is a pressing need to understand where humans are facing which climate change impacts and which strategies form effective responses. Here, place-based research is indispensable as it provides insights into the nuanced requirements for adaptation of different locations. For instance, coastal areas in the tropics might benefit from mangrove restoration to combat rising sea levels, while arid regions might focus on drought-resistant crops tailored to local use. These localized insights help address climate impacts and clarify loss and damage, such as flood-related infrastructure damage or desertification. However, not all impacts and all spatial areas are sufficiently covered by research, resulting in evidence gaps. To prepare humanity for the challenges posed by climate change impacts, it is important to identify evidence gaps well in advance. This early identification of missing knowledge on how to cope with climate change impacts is crucial for informing policymaking, enabling the strategic allocation of research funding to address these gaps effectively (McKinnon et al., 2015; Saran & White, 2018).

Systematic mapping (Bates et al., 2007; James et al., 2016) and evidence gap mapping (Saran & White, 2018; Snilstveit et al., 2016; White et al., 2020) aims to systematically gather, organize and synthesize evidence comprehensively. This is achieved and steadily further refined by following protocols (Bates et al., 2007; James et al., 2016; Saran & White, 2018) which prescribe how to search and screen for evidence on a topic of interest.

Evidence on climate impacts has been already investigated in a systematic map (Callaghan et al., 2021). Here, the authors identified more than 100,000 studies on climate impacts, and detected for each study the affected system, such as ecosystem or human and managed system, and the climate driver such as temperature or precipitation. Additionally, they identified locations mentioned in title and abstract. The study's findings suggest that there may be substantial evidence gaps in less developed countries. However, we currently lack an effective method to identify and prioritize these gaps, making it difficult to determine which ones require the most urgent attention and directed research funding allocation.

One potential way to prioritize gaps is to map scientific evidence against information on climate risks. Following this, evidence gaps are most acute where climate risks are highest. The IPCC defines climate risk in human systems as the interaction between the incidence of a climate-related hazard, the number of people exposed to that hazard, and the vulnerability of the population exposed. In turn, vulnerability is defined by the

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propensity of communities to be adversely affected, for example through a significant dependence on resources affected by the impact, or by low adaptive capacity to respond to or mitigate the effects of an adverse impact (IPCC AR6 WGII, 2022).

In this paper, we propose a new machine-learning enhanced systematic mapping method of identifying and prioritizing evidence gaps on climate change impacts according to the magnitude of climate risk in a given area. Using the example of floods, specifically fluvial floods, we bring together data on fluvial flood risk (hazard), population density (exposure) and human development (vulnerability) to identify under-researched areas where climate risk is highest. Through the development of a new index, an evidence gap index, we achieve a categorization of evidence gaps based on the vulnerability of the affected areas. This methodology can serve as a valuable tool for directing research resources effectively in addressing climate change challenges and to promote climate justice.

Methods and data

Scientific coverage of a climate change impact

Assessing evidence gaps with regards to a specific climate change impact requires the systematic collection of the relevant scientific literature. The underlying methodology is known as a systematic mapping or evidence gap mapping both part of a broader suite of evidence synthesis tools (Bates et al., 2007; James et al., 2016; Nakagawa et al., 2019; Saran & White, 2018; White et al., 2020). While there are slight differences among them all of them follow a stepwise process. First, a definition of a research question sets the stage and scope of the systematic map. Second, scientific literature is collected systematically through a clearly defined search query from bibliographic databases such as Web of Science or Scopus or other specified sources. At a third step the articles are screened for relevance with regards to the research question and further classified into relevant categories to identify the topic of research, the location of the study or other relevant attributes (James et al., 2016; Nakagawa et al., 2019; White et al., 2020). Lastly, the available literature is mapped out and evidence gaps can be identified.

Searches on specific topics yield tens or hundred thousand studies (Callaghan et al., 2020, 2021; Sietsma et al., 2021). Manual-screening of these studies is infeasible. Machine learning as a medium of automation of human labour can be harnessed in these cases (Callaghan et al., 2020, 2021; González-Márquez et al., 2024; Sietsma et al., 2021). Supervised classification, a subset of machine learning methods, is able to sort text into predefined categories. For this purpose, a part of the texts are sorted into the predefined categories by humans – the texts are labelled. The texts and labels are used to train a classifier which then extends the labels to the unseen documents. Named entity recognition, another subset of machine learning methods, extracts information of unstructured texts and can be used to identify locations in abstract and title of scientific publications.

To comprehensively map the scientific literature on the climate change impact flood, our example impact for illustrating the evidence gap index, we start with those studies identified in a machine-learning assisted systematic map of scientific literature of all climate change impacts (Callaghan et al., 2021). This study identifies in total 100,724 studies on climate impacts by searching Web of Science and Scopus on 19 October 2020. This means we cover a time range from 1990 to Oct 2020. Utilizing the categorization of affected systems by M. Callaghan et al., we focus on the subset of 12,212 studies that specifically examine impacts on human and managed systems. To further narrow this subset to include only studies on flood-related impacts, we employ text classification. We begin by hand-labelling 600 of these studies at the title and abstract level, recording whether they address flood-related impacts. Included were all studies which mentioned flood, flooding and heavy precipitation which can also lead to flooding. These hand-labelled studies are used to train a ClimateBERT (Webersinke et al., 2022) classifier. We employ a nested cross-validation approach and calculate the F1 score to evaluate the classifier's performance. The F1 score assesses a classifier's effectiveness by combining its accuracy in correctly identifying positive results with its ability in finding all relevant documents. This score ranges from 0 (indicating the least performance) to 1 (indicating perfect performance). For this classification task, we achieve an F1 score of 0.81. The resulting classifier is used to predict whether the remaining 11,612 studies were related to floods, resulting in a final set of 905 studies on flood-related impacts to human and managed systems.

To identify location-based studies we extract locations together from title and abstract using a geoparser (Halterman, 2023) which not only extracts the name of the geographical entity, but also its geographic information. We found that out of 905, 561 (62%) contain a location in title or abstract.

The evidence gap index is designed to highlight evidence gaps based on spatial information, so we need to assign each document to a location on Earth. To do this, we first divide the geographic map into grid cells, each covering 2.5 degrees of latitude and longitude. We then translate the geographic information from the title and abstract, which can range from the continental scale down to towns or villages, to the sets of grid cells congruent with the location, following the approach described in Callaghan et al. (2021). That means we assign each document a value of 1, which is distributed among all relevant grid cells for each mentioned location. For example, if a study references a town contained within a single grid cell, that cell receives an evidence count of 1. Conversely, if a study mentions a continent spanning 100 grid cells, each of those cells receives a count of 0.01 for that study. Additionally, to account for the varying sizes of grid cells – larger near the poles and smaller near the equator – we normalize the count of documents by the area of each grid cell. If two or more locations are mentioned and one contains the other, i.e. a subnational state and its corresponding country, only the smaller location is accounted for.

In this way, we determined the number of scientific publications on flooding for each grid cell representing an area on the globe.

Climate-related hazards

As a component of climate risk, hazard refers to the likelihood of a given adverse impact occurring (IPCC, 2023: Annex I:

Glossary). To effectively incorporate a hazard indicator into the proposed evidence gap index, it must capture the specific hazards relevant to the gaps we aim to identify. It is also important to consider whether the hazard index reflects the current state of the relevant hazard or includes future developments, which are particularly relevant in the context of climate change. Ideally, the hazard index should provide global coverage to enable comprehensive assessments across all regions. Unfortunately, many existing models are primarily focused on Europe and North America (Trigg et al., 2016), which risks perpetuating evidence gaps and limits the ability to address gaps in more vulnerable regions.

To assess the exposure to flood incidents globally, we use a fluvial flood hazard map with a return 10-year period (Dottori et al., 2016). This model estimates both the locations and frequency of flood events. It is based on streamflow data that has been downscaled onto a high-resolution river network, which then serves as input for local flood inundation simulations using a two-dimensional hydrodynamic model. The model's accuracy has been validated through comparisons with historical data and other large-scale fluvial flood models. It is calculated for various return periods, which estimate the intervals between natural hazard occurrences (Dottori et al., 2016). We use a relatively short 10-year return period to ensure that smaller flood events are also included in the analysis.

However, this hazard index does not encompass all potential flood risks, as it only estimates risks from river overflows caused by excessive rainfall or snowmelt. Other types of floods, such as coastal floods triggered by extreme windstorms and pluvial floods caused by intense rainfall that is independent of any overflowing water bodies, are not covered. We were unable to find a suitable global risk analysis for these flood types. As a result, the evidence gap index may fail to highlight evidence gaps in regions where these specific climate risks are prevalent. Additionally, the index does not account for changing flood patterns due to climate change, which may lead to an underestimation of future flood occurrences.

To align the flood risk index with the global scientific coverage produced in the previous chapter, we re-grid the flood risk index map from its original 30" to a 2.5' resolution. This process provides an estimated flood risk exposure for every grid cell in the global map.

Prioritization of evidence gaps: exposure and vulnerability

To prioritize evidence gaps according to their urgency for resolution – the goal of the proposed evidence gap index – defining the concept of urgency is important. In this context, we propose using exposure and vulnerability as a measure of urgency. According to the IPCC exposure defines which system, i.e. human managed system or ecosystem, and how many individuals are affected by the climate change impact. Further, vulnerability describes the lack of adaptive capacity to cope with a climate change impact and the sensitivity or susceptibility to harm (IPCC AR6 WGII, 2022).

In our example, the evidence gap index of flooding in human-managed systems where the evidence describes a general population without a focus on specific groups, we suggest incorporating two key elements: the magnitude of the affected population as an indicator of *exposure* and the socioeconomic characteristics of the population as an indicator for vulnerability. In this context, an under-researched area with a large affected population size and with a high socio-economic vulnerability represents an evidence gap that should urgently be filled. This is a first approximation of assessing exposure and vulnerability and other indicators might be suitable. Properly representing exposure and vulnerability depends on the specific intent of the evidence gap index and the evidence being investigated. For instance, if the focus is on protecting specific population groups such as indigenous people, exposure could be defined as the population density of indigenous people alone. Similarly, vulnerability can be tailored to the particular hazard in question, such as defining vulnerability to floods in terms of economic dependence on fisheries. If ecosystems are captured by the research question of the corresponding systematic map, one might want to include indicators describing the affected ecosystem, such as diversity or fragility.

When considering and structuring suitable data sources, not all of the indicators can be supported through available data or the data might not fulfil the desired quality criteria, i.e. it lacks coverage of the whole world or a desired granularity.

To prioritize evidence gaps in the impact flood we use gridded population density of 2020 (Center for International Earth Science Information Network-CIESIN-Columbia University, 2017) to account for the affected population size and with that the exposure in our proposed framework. Vulnerability is captured by a subnational human development index (HDI) (Permanyer & Smits, 2020; The Subnational Human Development Database | Scientific Data, n.d.) calculated for the year 2019 as a generic indicator for socioeconomic characteristics. It is a translation of the UNDP's official HDI to subnational districts providing a more granular picture and is available for all countries. The HDI and its subnational version (SHDI) are statistical indices based on income per capita, life expectancy, and education levels. While these indices capture key socioeconomic characteristics, other factors such as poverty, inequality, marginalization, social exclusion, and gender discrimination are only indirectly reflected. Explicitly including these would alter the index's focus and interpretation. For this example, we prioritized simplicity and clarity.

To incorporate the population density and the SHDI into the evidence gap index, both data sources are scaled to 1 and re-gridded to a 2.5" grid.

Constructing the index

After collecting data on evidence, hazard, exposure, and vulnerability – each available at a global grid resolution of 2.5' – the next step is to combine these into a single index. This involves addressing two essential components: normalizing the data and determining a methodology for integrating diverse components into a single numerical representation.

Normalization confines each data source to a specific numerical range and defines the separation between data points. For reasons of interpretability, we suggest a fairly simple min–max scaling where the minimum value of a data range is assigned 0, the maximum value 1. We use a

meaningful minimum value which is the smallest value supported by reality, i.e. a meaningful minimum of population density in the original data point does not equal 0, which would be true for large parts of the Atlantic, but the smallest non-zero value. To ensure readability we propose that every data component is scaled to a range of 1 where 1 means there is an evidence gap, the hazard risk is highest, the area is highly exposed to the climate change impact or the area is vulnerable. Taking the logarithm before scaling ensures that differences between smaller values are not obscured by outliers (Figure 1).

We propose a simple and interpretable index that combines study sparsity with the three components of climate risk:

$$EGI = EvidenceSparsity * Hazard *(Exposure + Vulnerability),$$

where EvidenceSparsity is the log normalized inverse of the number of papers per grid cell, Hazard is the normalized impact risk, Exposure and Vulnerability the normalized indicators as described earlier.

With this construction approach, the index is designed to approach 0 in cases where there is either no hazard risk due or when the scientific coverage of an area is very high compared to other regions. These two components are the most crucial elements of the index, ensuring it scales to 0 when there is abundant evidence or no hazard, thereby eliminating the need for evidence.

The final component of the index acts as a location-specific scaling factor, used to further prioritize evidence gaps based on the area's vulnerability and exposure. By summing these factors and integrating them into a single scaling factor, the index allows for flexible weighting, enabling the prioritization of either exposure or vulnerability, depending on the specific needs of the analysis.

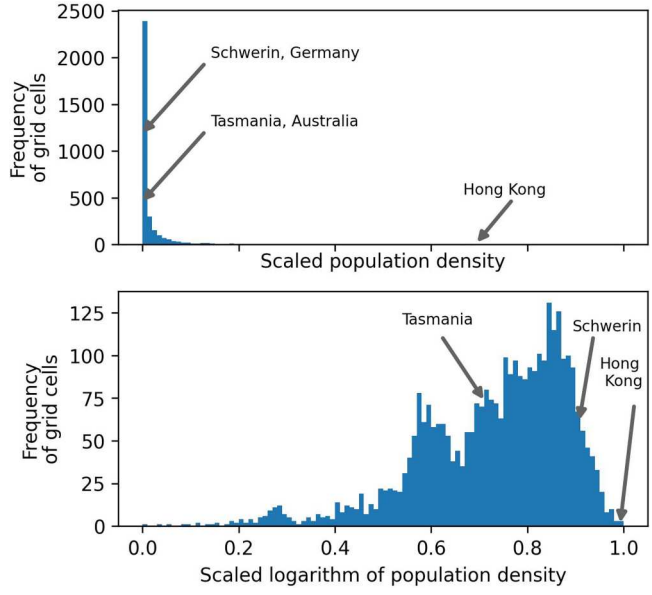

Figure 1. Effect of taking the logarithm on normalization. Distributions of population density without (above) and with (below) taking the logarithm. In the above panel the grid cells containing Tasmania and the grid cell containing Schwerin do not differ strongly. When taking the aking the logarithm of the population density the differences are more pronounced. At the same time differences to areas with higher population density are reduced, see Tasmania vs. Hongkong.

While alternative construction methods, such as multiplying all components to treat them independently, are possible, we favour the flexibility offered by a compound scaling factor. This approach provides the versatility needed to adjust the index according to different contexts and priorities.

With the data we use in our example it is important to note that this specific index captures only evidence gaps with regards to floods and direct human system impacts. Evidence gaps on different impacts would require differently derived data on EvidenceSparsity and a different hazard risk index. Moreover, the Evidence Gap Index can be adapted to capture different elements of exposure and vulnerability by incorporating different data sources, or by weighting the constituent parts differently.

Results

Evidence coverage

Of the 905 publications addressing flood-related impacts on human and natural systems, 561 (61%) contain at least one location in the title or abstract, indicating place-specific research. However, in 170 documents the smallest mentioned location is a country name and 130 documents mention more than one country name – even up to 12 (Miller et al., 2008). While discussing research only on country or supra-country level there is a potential limitation in exploring location-specific details for these documents. Nonetheless, including these documents contributes to the overall knowledge base. Therefore we incorporate them into the analysis by associating them with all corresponding grid cells, as outlined in the Methods and Data section.

263 publications mention places in Asia, followed by North America with 129 studies, replicating an often observed pattern in location coverage of scientific literature (Smith et al., 2023) any publications, namely 110, talk about places in Africa (see Figure 2). However, 63% of the documents that mention an African country also reference at least one other country, suggesting that these studies may use African nations in broader, multi-location research, potentially limiting the depth of location-specific analysis. In comparison, this proportion is smaller for North America, at 47%.

The most frequently mentioned countries are the United States of America (in 96 documents), Bangladesh (in 58 documents) and India (in 53 documents).

Figure 2 shows the distribution of evidence on flood-related impacts on human and managed systems. From the map of scientific coverage one can easily distinguish country borders, and in general rather regionally homogenous coverages. Only a few single places (grid cells) stick out. This is again a sign of low location-specificity in the documents. We observe a particularly low scientific coverage in Russia and Chile, which in future work could potentially be mitigated by searching in multiple languages (Nuñez & Amano, 2021).

Hazard

The fluvial flood hazard map (Dottori et al., 2016) introduced in the method section indicates where the risk that a flood

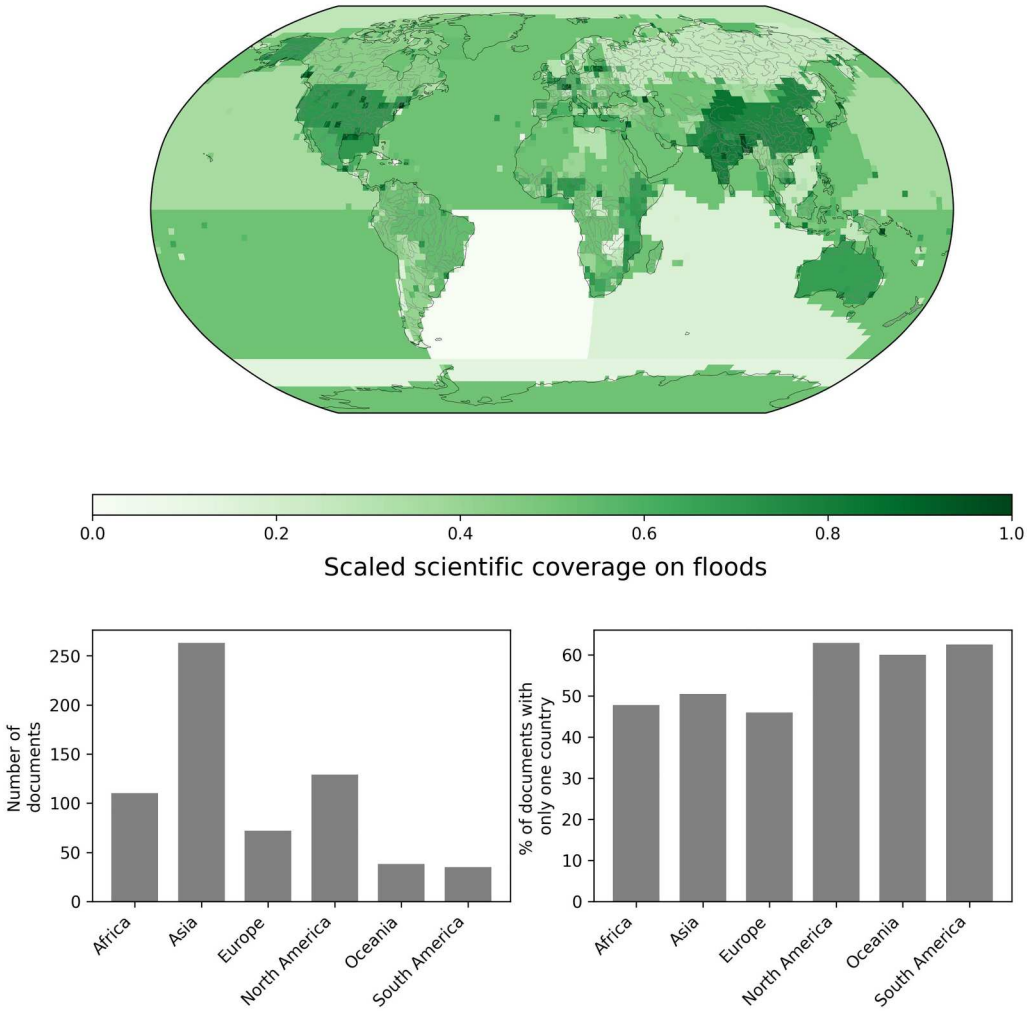

Figure 2. Scientific coverage of world regions with regards to floods and corresponding statistics of the documents. Above: Scientific coverage on floods as described in the Methods and Data section, logged, and scaled to the range (0,1). Below left: Documents with locations in title or abstract by continent, one document can mention several continents. Below right: For each continent the percentage of documents mentioning only one country.

impact is high and replicates river courses of large rivers, such as the Amazon (Espinoza et al., 2013), the Mississippi (Zachos et al., 2016), the Nile (Abdelmoneim et al., 2023; Shamseldin et al., 1999), as well as Russia's many large river systems, and indicates further a high flood risk in Pakistan (Nanditha et al., 2023; Paulikas & Rahman, 2015), Bangladesh (Hoq et al., 2021; Roy et al., 2019) and in large parts of Siberia, where regular Spring floods affect local communities (Kichigina, 2020; Korytny et al., 2009; Tananaev et al., 2020), see Figure 3, above.

Exposure and vulnerability

In order to sort evidence gaps in regions with a high flood risk according to their urgency to address we sum population density and subnational HDI as described in the Method section.

The sum of both ingredients is highest in the north of India because of its high population density and fairly low development and high in much of Sub-Saharan Africa because of a low subnational HDI in the region, see Figure 3. In the figure we look at an equal contribution of population density and subnational HDI to the Vulnerable+population indicator (VP-idx), that means we calculate VP-idx = 0.5* scaled population density + 0.5*scaled subnational HDI. The ratio can be adjusted where we want to weigh either exposure or vulnerability differently.

Evidence gap index

The purpose of an evidence gap index is to pinpoint areas exhibiting a greater demand for research owing to their heightened climate risk. To assess the effectiveness of the index, we juxtapose the ranking determined by flood risk, the hazard component of climate risk against the ranking determined by the evidence gap index.

The most endangered areas for floods according to the flood risk index are in the states of Para and Amazonas, both in Brazil, and Louisiana, USA. According to our proposed evidence gap index, Para and Amazonas remain top, followed by the region of Equateur in the Democratic Republic of the Congo. The number of people exposed, their vulnerability as measured by HDI, and the sparsity of research shows us that there may be a more pressing need for flood-related research in Equateur than in Louisiana.

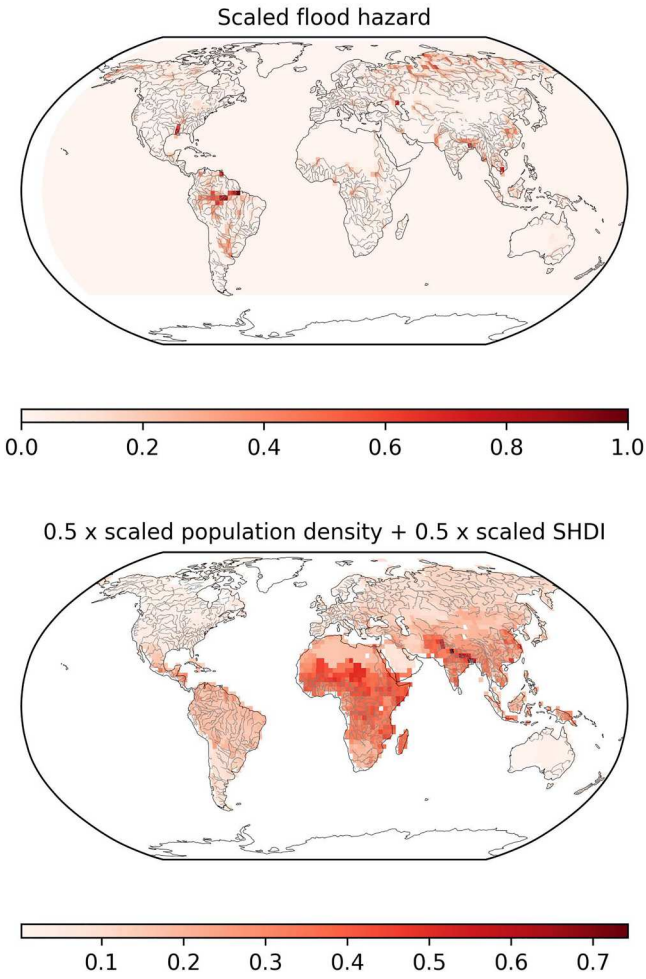

Figure 3. Above: Hazard of floods, regridded to 2.5′ and scaled to a range of (0,1). Note that the flood hazard is only defined for certain parts of the world. Where there is no flood hazard we cannot calculate the evidence gap index. Below: Scaling factor as a combination of the population density and the subnational HDI, both quantities scaled to the range of 1. Both quantities contribute equally to the scaling factor. To achieve a range for the scaling factor of (0,1) both quantities are multiplied with 0.5.

When comparing the unique subnational regions of the first 100 most endangered grid cells with regards to their flood risk to the unique regions of the first 100 grid cells with a highest evidence gap index we see a clear shift in continent distribution, see Figure 4, away from continents with high adaptive capacity such as North America towards continents which have lower adaptive capacity to date such as Africa (Andrijevic et al., 2023; Theokritoff et al., 2023). When changing the weighting of the composite vulnerable+population indicator towards higher weights for population density, densely populated regions in Asia are more strongly represented, see Figure 4.

Particularly, our proposed evidence gap index highlights the Amazon basin in South America, the Congo basin, the Senegal River, and the upper White Nile basin in Africa, as well as the Mekong River in Asia, as regions where research is comparatively scarce and vulnerability is high. This suggests a need for targeted research to support climate change adaptation in these areas. Notably, all of these regions are identified in the IPCC 2022 report as either being at high risk of flooding or having already experienced significant floods (Trisos et al., 2022).

Conversely, the Mississippi basin, clearly identified as a region prone to floods, see Figure 3, is not emphasized by the evidence index due to its already high scientific coverage (see Figure 2), coupled with a low scaling factor. This is largely due to the region's high development or low vulnerability, which reduces its priority in the index. A more nuanced example is the Ganges River, where flood hazards, vulnerability, and exposure are all high (see Figure 3). Despite these risks, the region is also backed by substantial scientific coverage. Consequently, the evidence gap index only highlights this area in regions with particularly dense populations (1500–2300 inhabitants per square kilometre), where the need for further research may be more critical.

Discussion

In this paper we propose and exemplify a new method for systematic mapping rooted in machine-learning that overlays a systematic map of the climate impacts literature on floods with information on climate risk. By doing so we are able to answer a more relevant question for evidence gap mapping. Rather than asking where the evidence is and where it is missing, we are able to respond to a more specific question: do we have scientific evidence in those areas that are most exposed and vulnerable? To achieve this, we construct an evidence gap index that facilitates the ranking of areas based on their need for research.

Our evidence gap index, exemplified on flood hazards, highlights major river basins in South America, Africa, and Asia, prioritizing regions with lower adaptive capacity and less scientific coverage over areas in North America, where both adaptive capacity and scientific coverage are higher. This demonstrates that the index functions as intended, providing a helpful tool to inform the strategic allocation of research resources.

The index primarily identifies river basins rather than coastal flood-prone areas because it is based on a fluvial flood risk index, which does not account for other types of floods, such as coastal floods. Consequently, we are limited in our ability to assess research coverage in areas prone to coastal flooding.

Another aspect to consider is whether the observed scientific coverage accurately reflects reality. It is often harder to identify gaps in knowledge when something is missing, compared to recognizing established findings. However, the low scientific coverage observed in Africa and South America aligns with trends seen in other climate-related topics, such as climate change adaptation (Berrang-Ford, Siders, et al., 2021), climate change and health (Berrang-Ford, Sietsma, et al., 2021), and carbon dioxide removal (Smith et al., 2024), suggesting this could reflect a broader pattern. One contributing factor is that these studies typically only include peer-reviewed and English-language literature, potentially overlooking non-English or grey research such as reports from NGOs. This is partly due to the reliance on machine learning models trained on English and the unstructured nature of grey literature, which complicates the application of automation

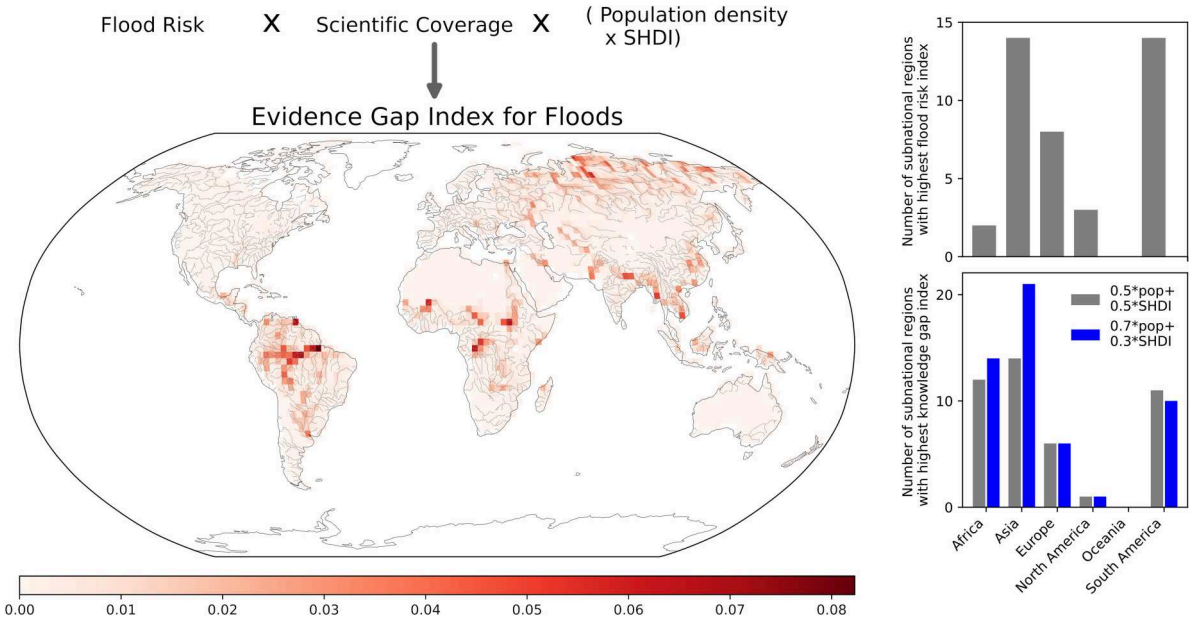

Figure 4. Evidence gap index for floods and its influence in prioritization of regions. Left: The gridded evidence gap index. Population density and subnational HDI contribute equally. Right above: For the first 100 grid cells with the highest flood risk index we found the corresponding sub-national regions. Every region is only counted once. Shown is the distribution for the different continents. Left below: Same as above, however shown are the sub-national regions with the highest evidence gap index. Two versions are shown: in grey population and subnation HDI contribute equally to the index, in blue population is weighted with 0.7, subnational HDI with 0.3 favouring regions with higher population density.

methods needed to process such resources. Furthermore, some regions may have fewer research resources available, further contributing to the disparity in scientific coverage (Blicharska et al., 2017).

How the evidence gap index orders regions according to their experienced climate risk depends highly on its composition. Here, we relied on just three data sources to serve as proxies for hazard, exposure, and vulnerability. This simplified version provides an initial coarse-grained proof of concept, but it may be advisable to broaden the scope by incorporating data that captures additional elements of climate risk, specifically in terms of vulnerability. For instance, one could consider including economic dependence on agriculture in a region when assessing vulnerability to events like droughts or floods. Also, hazard specific adaptation responses as a counteracting part in vulnerability can be considered to be included into the index (Simpson et al., 2021). Additionally, one needs to carefully investigate the contribution of each component. As we showed, adjusting the relative weights given to vulnerability and exposure can result in the index prioritizing areas in Africa or Asia. Lastly, the grid resolution, determined by the lowest resolution among all the data incorporated in the index, serves as the foundation for index calculations and determines the visibility of structures. In the case of a coarse grid, data related to small structures, like small islands, may be averaged out, leading to an artificial reduction in the evidence gap index for these specific regions.

Any index has to simplify the highly complex interaction between hazard, exposure, and vulnerability that constitutes climate risk. As such the results should be interpreted with caution, and used to guide rather than replace expert knowledge. Additionally, this index only quantifies gaps in the anglophone scientific literature, and does not take into account knowledge and evidence collected in government reports, or indeed local and indigenous knowledge (Ford et al., 2016). Additionally, while the index highlights areas of low scientific coverage, it does not specify the type of scientific coverage needed, as this lies beyond its scope.

Large scale systematic maps are a key in the age of big literature (Callaghan et al., 2020; Minx et al., 2017; Nunez-Mir et al., 2016) and are highly relevant for the IPCC assessments, serving not only as integral components for reporting but also for shaping the scope of assessments. The combination with additional data, as we propose here, makes systematic mapping even more relevant for identifying substantial knowledge hotspots and gaps. This is particularly important for vulnerable groups, who are often disproportionately affected by climate impacts but underrepresented in research (Benevolenza & DeRigne, 2019; Ngcamu, 2023). By directing evidence generation to their specific needs, our methodology supports the development of policies that prioritize their resilience and adaptation. In the context of evidence-based policies, our methodology has the potential to contribute to a more effective scientific knowledge generation process, ensuring that evidence is generated precisely where it is most needed and promoting climate justice.

Disclosure statement

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References

Abdelmoneim, H., Eldardiry, H., Saber, M., Kantoush, S. A., Moghazy, H. M., & Sumi, T. (2023). Integrating multi-sensor observations and rainfall-runoff inundation modeling for mapping flood extents over the Nile River Basin: Example from the 2020 flooding in Sudan. *Geocarto International*, *38*(1), 2197504. https://doi.org/10.1080/10106049.2023.2197504

Andrijevic, M., Schleussner, C.-F., Cuaresma, J. C., Lissner, T., Muttarak, R., Riahi, K., Theokritoff, E., Thomas, A., van Maanen, N., & Byers, E. (2023). Towards scenario representation of adaptive capacity for global climate change assessments. *Nature Climate Change*, *13*(8), 778–787. https://doi.org/10.1038/s41558-023-01725-1

Bates, S., Clapton, J., & Coren, E. (2007). Systematic maps to support the evidence base in social care. *Evidence & Policy*, *3*(4), 539–551. https://doi.org/10.1332/174426407782516484

Benevolenza, M. A., & DeRigne, L. A. (2019). The impact of climate change and natural disasters on vulnerable populations: A systematic review of literature. *Journal of Human Behavior in the Social Environment*, *29*(2), 266–281. https://doi.org/10.1080/10911359.2018.1527739

Berrang-Ford, L., Siders, A. R., Lesnikowski, A., Fischer, A. P., Callaghan, M. W., Haddaway, N. R., Mach, K. J., Araos, M., Shah, M. A. R., Wannewitz, M., Doshi, D., Leiter, T., Matavel, C., Musah-Surugu, J. I., Wong-Parodi, G., Antwi-Agyei, P., Ajibade, I., Chauhan, N., Kakenmaster, W., … Abu, T. Z. (2021). A systematic global stocktake of evidence on human adaptation to climate change. *Nature Climate Change*, *11*(11), 989–1000. https://doi.org/10.1038/s41558-021-01170-y

Berrang-Ford, L., Sietsma, A. J., Callaghan, M., Minx, J. C., Scheelbeek, P. F. D., Haddaway, N. R., Haines, A., & Dangour, A. D. (2021). Systematic mapping of global research on climate and health: A machine learning review. *The Lancet Planetary Health*, *5*(8), e514–e525. https://doi.org/10.1016/S2542-5196(21)00179-0

Blicharska, M., Smithers, R. J., Kuchler, M., Agrawal, G. K., Gutiérrez, J. M., Hassanali, A., Huq, S., Koller, S. H., Marjit, S., Mshinda, H. M., Masjuki, H. H., Solomons, N. W., Staden, J. V., & Mikusiński, G. (2017). Steps to overcome the north–south divide in research relevant to climate change policy and practice. *Nature Climate Change*, *7*(1), 21–27. https://doi.org/10.1038/nclimate3163

Callaghan, M. W., Minx, J. C., & Forster, P. M. (2020). A topography of climate change research. *Nature Climate Change*, *10*(2), 118–123. https://doi.org/10.1038/s41558-019-0684-5

Callaghan, M., Schleussner, C.-F., Nath, S., Lejeune, Q., Knutson, T. R., Reichstein, M., Hansen, G., Theokritoff, E., Andrijevic, M., Brecha, R. J., Hegarty, M., Jones, C., Lee, K., Lucas, A., van Maanen, N., Menke, I., Pfleiderer, P., Yesil, B., & Minx, J. C. (2021). Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies. *Nature Climate Change*, *11*(11), 966–972. https://doi.org/10.1038/s41558-021-01168-6

Center for International Earth Science Information Network-CIESIN-Columbia University. (2017). Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 11. November 7, 2023, from https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11

Dottori, F., Salamon, P., Bianchi, A., Alfieri, L., Hirpa, F. A., & Feyen, L. (2016). Development and evaluation of a framework for global flood hazard mapping. *JRC Publications Repository*. November 22, 2023, from https://publications.jrc.ec.europa.eu/repository/handle/JRC93811

Eckstein, D., Künzel, V., & Schäfer, L. (2021). *The Global Climate Risk Index 2021*. Germanwatch. August 20, 2024, from https://www.germanwatch.org/en/19777

Espinoza, J. C., Ronchail, J., Frappart, F., Lavado, W., Santini, W., & Guyot, J. L. (2013). The major floods in the Amazonas river and tributaries (Western Amazon basin) during the 1970-2012 period: A focus on the 2012 flood. *Journal of Hydrometeorology*, *14*(3), 1000–1008. https://doi.org/10.1175/JHM-D-12-0100.1

Ford, J. D., Cameron, L., Rubis, J., Maillet, M., Nakashima, D., Willox, A. C., & Pearce, T. (2016). Including indigenous knowledge and experience in IPCC assessment reports. *Nature Climate Change*, *6*(4), 349–353. https://doi.org/10.1038/nclimate2954

González-Márquez, R., Schmidt, L., Schmidt, B. M., Berens, P., & Kobak, D. (2024). The landscape of biomedical research. *Patterns*, *5*(6), 100968. https://doi.org/10.1016/j.patter.2024.100968

Halterman, Andrew. 2023. Mordecai 3: A Neural Geoparser and Event Geocoder. December 7, 2023, from http://arxiv.org/abs/2303.13675

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., & Kanae, S. (2013). Global flood risk under climate change. *Nature Climate Change*, *3*(9), 816–821. https://doi.org/10.1038/nclimate1911

Hoq, M. S., Raha, S. K., & Hossain, M. I. (2021). Livelihood vulnerability to flood hazard: Understanding from the flood-prone *Haor* ecosystem of Bangladesh. *Environmental Management*, *67*(3), 532–552. https://doi.org/10.1007/s00267-021-01441-6

IPCC, 2023. Annex I: Glossary [Reisinger, A., D. Cammarano, A. Fischlin, J.S. Fuglestvedt, G. Hansen, Y. Jung, C. Ludden, V. Masson-Delmotte, R. Matthews, J.B.K Mintenbeck, D.J. Orendain, A. Pirani, E. Poloczanskaa, and J. Romero (eds.)]. In: *Climate Change 2023: Synthesis Report*. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland (pp. 119–130). https://doi.org/10.59327/IPCC/AR6-9789291691647.002

IPCC AR6 WGII. (2022). Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (1st ed.). Cambridge University Press. December 7, 2023, from https://www.cambridge.org/core/product/identifier/9781009325844/type/book

James, K. L., Randall, N. P., & Haddaway, N. R. (2016). A methodology for systematic mapping in environmental sciences. *Environmental Evidence*, *5*(1), 7. https://doi.org/10.1186/s13750-016-0059-6

Kichigina, N. (2020). Geographical analysis of river flood hazard in Siberia. *International Journal of River Basin Management*, *18*(2), 255–264. https://doi.org/10.1080/15715124.2020.1742136

Kim, T.-W., & Jehanzaib, M. (2020). Drought risk analysis, forecasting and assessment under climate change. *Water*, *12*(7), 1862. https://doi.org/10.3390/w12071862

Korytny, L. M., Kichigina, N. V., & Cherkashin, V. A. (2009). Floods and their risk assessment in East Siberia. In J. Anthony Jones, Trahel G. Vardanian & Christina Hakopian (Eds.), *Threats to global water security*, (pp. 247–52). Springer Netherlands. https://doi.org/10.1007/978-90-481-2344-5_27

Lhotka, O., Kyselý, J., & Farda, A. (2018). Climate change scenarios of heat waves in central Europe and their uncertainties. *Theoretical and*

Applied Climatology, *131*(3), 1043–1054. https://doi.org/10.1007/s00704-016-2031-3

McKinnon, M. C., Cheng, S. H., Garside, R., Masuda, Y. J., & Miller, D. C. (2015). Sustainability: Map the evidence. *Nature*, *528*(7581), 185–187. https://doi.org/10.1038/528185a

Miller, S., Muir-Wood, R., & Boissonnade, A. (2008). An exploration of trends in normalized weather-related catastrophe losses. In H. F. Diaz & R. J. Murnane (Eds.), *Climate extremes and society* (pp. 225–247). Cambridge University Press. November 28, 2023, from https://www.cambridge.org/core/books/climate-extremes-and-society/an-exploration-of-trends-in-normalized-weatherrelated-catastrophe-losses/824B8A29C22EC8D3D2C7D8AF4A57FE1B

Minx, J. C., Lamb, W. F., Callaghan, M. W., Bornmann, L., & Fuss, S. (2017). Fast growing research on negative emissions. *Environmental Research Letters*, *12*(3), 035007. https://doi.org/10.1088/1748-9326/aa5ee5

Nakagawa, S., Samarasinghe, G., Haddaway, N. R., Westgate, M. J., O'Dea, R. E., Noble, D. W. A., & Lagisz, M. (2019). Research weaving: Visualizing the future of research synthesis. *Trends in Ecology & Evolution*, *34*(3), 224–238. https://doi.org/10.1016/j.tree.2018.11.007

Nanditha, J. S., Kushwaha, A. P., Singh, R., Malik, I., Solanki, H., Chuphal, D. S., Dangar, S., Mahto, S. S., Vegad, U., & Mishra, V. (2023). The Pakistan flood of August 2022: Causes and implications. *Earth's Future*, *11*(3), e2022EF003230. https://doi.org/10.1029/2022EF003230

Ngcamu, B. S. (2023). Climate change effects on vulnerable populations in the global south: A systematic review. *Natural Hazards*, *118*(2), 977–991. https://doi.org/10.1007/s11069-023-06070-2

Nunez-Mir, G. C., Iannone, B. V., Pijanowski, B. C., Kong, N., & Fei, S. (2016). Automated content analysis: Addressing the big literature challenge in ecology and evolution. *Methods in Ecology and Evolution*, *7*(11), 1262–1272. https://doi.org/10.1111/2041-210X.12602

Nuñez, M. A., & Amano, T. (2021). Monolingual searches can limit and bias results in global literature reviews. *Nature Ecology & Evolution*, *5*(3), 264–264. https://doi.org/10.1038/s41559-020-01369-w

Paulikas, M. J., & Rahman, M. K. (2015). A temporal assessment of flooding fatalities in Pakistan (1950-2012). *Journal of Flood Risk Management*, *8*(1), 62–70. https://doi.org/10.1111/jfr3.12084

Permanyer, I., & Smits, J. (2020). The Subnational Human Development Index: Details on Inequality. *N-IUSSP*. November 30, 2023, from https://www.niussp.org/environment-and-development/the-subnational-human-development-index-details-on-inequality-lindice-de-developpement-humain-infranational-details-sur-les-inegalites/

Roy, B., Islam, A. K. M. S., Islam, G. M. T., Khan, M. J. U., Bhattacharya, B., Ali, M. H., Khan, A. S., Hossain, M. S., Sarker, G. C., & Pieu, N. M. (2019). Frequency analysis of flash floods for establishing new danger levels for the rivers in the northeast Haor region of Bangladesh. *Journal of Hydrologic Engineering*, *24*(4), 05019004. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001760

Saran, A., & White, H. (2018). Evidence and gap maps: A comparison of different approaches. *Campbell Systematic Reviews*, *14*(1).

Shamseldin, A. Y., Abdo, G. M., & Elzein, A. S. (1999). Real-time flood forecasting on the Blue Nile river. *Water International*, *24*(1), 39–45. https://doi.org/10.1080/02508069908692132

Sietsma, A. J., Ford, J. D., Callaghan, M. W., & Minx, J. C. (2021). Progress in climate change adaptation research. *Environmental Research Letters*, *16*(5), 54038–54038. https://doi.org/10.1088/1748-9326/abf7f3

Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., Lawrence, J., Lempert, R. J., Muccione, V., Mackey, B., New, M. G., O'Neill, B., Otto, F., Pörtner, H.-O., Reisinger, A., Roberts, D., Schmidt, D. N., Seneviratne, S., Strongin, S., … Trisos, C. H. (2021). A framework for complex climate change risk assessment. *One Earth*, *4*(4), 489–501. https://doi.org/10.1016/j.oneear.2021.03.005

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, *16*(3), 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Smith, S. M., Geden, O., Gidden, M. J., Lamb, W. F., Nemet, G. F., Minx, J. C., Buck, H., Burke, J., Cox, E., Edwards, M. R., Fuss, S., Johnstone, I., Müller-Hansen, F., Pongratz, J., Probst, B. S., Roe, S., Schenuit, F., Schulte, I., & Vaughan, N. E. (2024). *The state of carbon dioxide removal* (2nd ed.). The State of Carbon Dioxide Removal. May 23, 2024, from https://osf.io/f85qj/

Smith, S. M., Geden, O., Nemet, G. F., Gidden, M. J., Lamb, W. F., Powis, C., Bellamy, R., Callaghan, M. W., Cowie, A., Cox, E., Fuss, S., Gasser, T., Grassi, G., Greene, J., Lück, S., Mohan, A., Müller-Hansen, F., Peters, G. P., Pratama, Y., … Minx, J. C. (2023). *The state of carbon dioxide removal* (1st ed.). Available at: https://www.stateofcdr.org

Snilstveit, B., Vojtkova, M., Bhavsar, A., Stevenson, J., & Gaarder, M. (2016). Evidence & gap maps: A tool for promoting evidence informed policy and strategic research agendas. *Journal of Clinical Epidemiology*, *79*, 120–129. https://doi.org/10.1016/j.jclinepi.2016.05.015

Tananaev, N. I., Efremova, V. A., Gavrilyeva, T. N., & Parfenova, O. T. (2020). Assessment of the community vulnerability to extreme spring floods: The case of the Amga River, Central Yakutia, Siberia. *Hydrology Research*, *52*(1), 125–41. https://doi.org/10.2166/nh.2020.124

The Subnational Human Development Database | Scientific Data. n.d. November 30, 2023, from https://www.nature.com/articles/sdata201938

Theokritoff, E., van Maanen, N., Andrijevic, M., Thomas, A., Lissner, T., & Schleussner, C.-F. (2023). Adaptation constraints in scenarios of socio-economic development. *Scientific Reports*, *13*(1), 19604. https://doi.org/10.1038/s41598-023-46931-1

Trigg, M. A., Birch, C. E., Neal, J. C., Bates, P. D., Smith, A., Sampson, C. C., Yamazaki, D., Hirabayashi, Y., Pappenberger, F., Dutra, E., Ward, P. J., Winsemius, H. C., Salamon, P., Dottori, F., Rudari, R., Kappes, M. S., Simpson, A. L., Hadzilacos, G., & Fewtrell, T. J. (2016). The credibility challenge for global fluvial flood risk analysis. *Environmental Research Letters*, *11*(9), 094014. https://doi.org/10.1088/1748-9326/11/9/094014

Trisos, C., Adelekan, I., Totin, E., Ayanlade, A., Efitre, J., Gemeda, A., Kalaba, K., Lennard, C., Masao, C., Mgaya, Y., Ngaruiya, G., Olago, D., Simpson, N., Zakieldeen, R., & Thorn, J. (2022). Africa. In *Climate change 2022: Impacts, adaptation and vulnerability. Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change* (pp. 1285–1456). Cambridge University Press. December 8, 2023, from https://www.cambridge.org/core/books/climate-change-2022-impacts-adaptation-and-vulnerability/africa/9E657A48555494EF46C0DD4550D9C006

Webersinke, N., Kraus, M., Bingler, J. A., & Leippold, M. (2022). ClimateBert: A pretrained language model for climate-related text. September 30, 2022, from http://arxiv.org/abs/2110.12010

White, H., Albers, B., Gaarder, M., Kornør, H., Littell, J., Marshall, Z., Mathew, C., Pigott, T., Snilstveit, B., Waddington, H., & Welch, V. (2020). Guidance for producing a Campbell evidence and gap map. *Campbell Systematic Reviews*, *16*(4), e1125. https://doi.org/10.1002/cl2.1125

Zachos, L. G., Swann, C. T., Altinakar, M. S., McGrath, M. Z., & Thomas, D. (2016). Flood vulnerability indices and emergency management planning in the Yazoo basin, Mississippi. *International Journal of Disaster Risk Reduction*, *18*, 89–99. https://doi.org/10.1016/j.ijdrr.2016.03.012